Operationally robust offshore bidding zones

Market design for efficient balancing

SEN233: CoSEM Master Thesis

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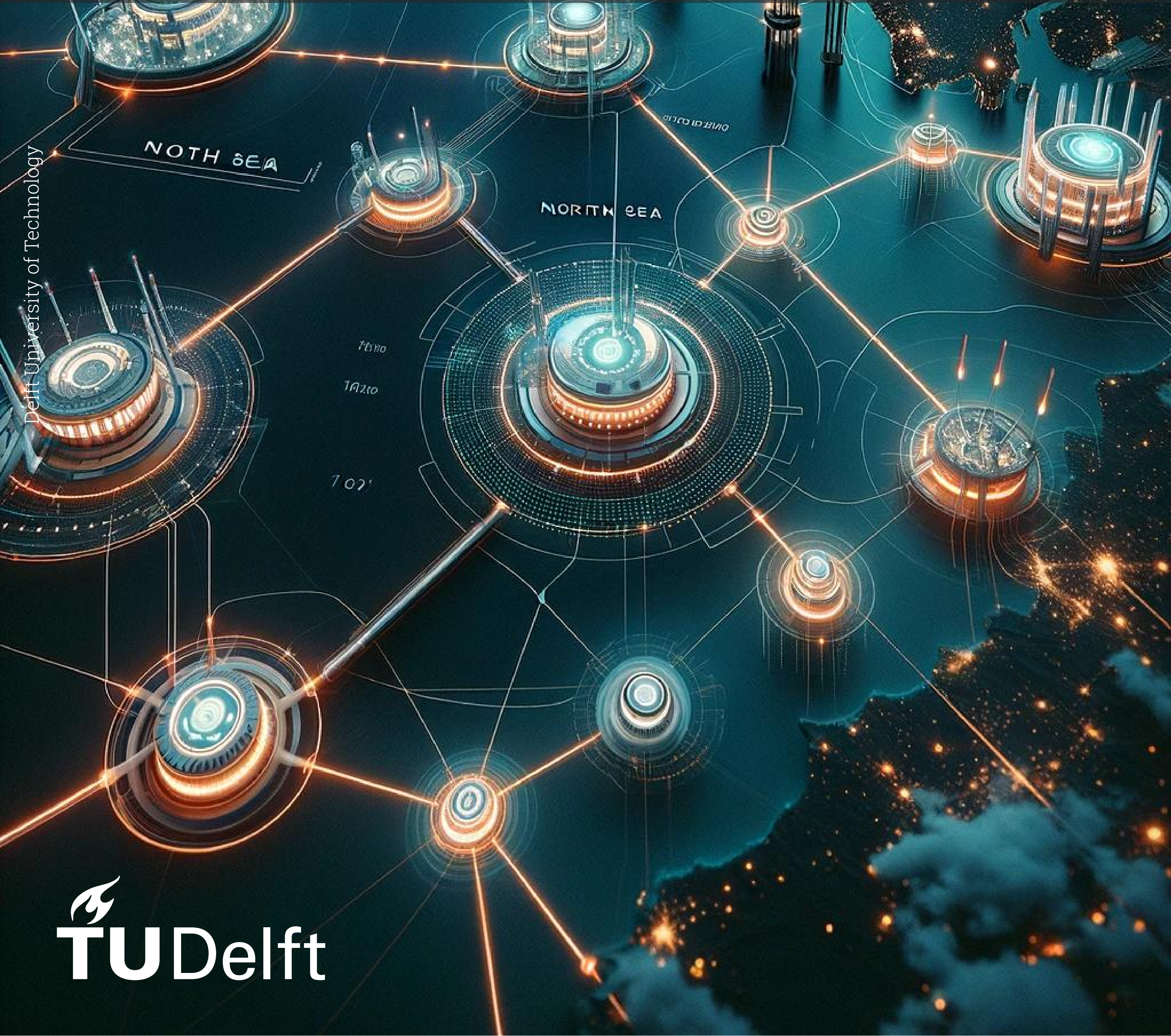
Delft University of Technology



TU Delft

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by

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Nomenclature

Abbreviations

Abbreviation	Definition
TSO	Transmission system operator
BRP	Balancing responsible party
OWF	Offshore wind farm
OBZ	Offshore bidding zone
HVDC	High voltage direct current
HM	Home market
ACH	Advanced hybric coupling
SOS	Special orderd set
DAH	Day-ahead
GCT	Gate closure time
PTU	Program time unit
E-program	Energy program
vRES	Variable renewable energy sources
PDF	Probability density function
MILP	Mixed integer linear programming
...s	Pluralisation of abbreviation

Executive summary

A promising way to transition to a carbon-neutral power system is the large scale deployment of off-shore wind farms in the North Sea, with a planned capacity of approximately 300 GW by 2050. However, due to the increased rate of wind farm connections, coupled with the growing distance of OWFs from the coast, the conventional method of connecting OWFs to the energy grid through radial connections is becoming increasingly untenable. By connecting OWFs to multiple countries with interconnectors they can be used for trade between countries when the wind is not blowing, thereby increasing the utilisation rate of these expensive assets. Under current regulation these OWFs which are connected only trough interconnectors, form their own off-shore bidding zones.

A crucial aspect of realising the potential of these offshore biddings zones lies in addressing the challenge of maintaining grid balance in these zones. This because in contrast to on-shore bidding zones, there is only large volumes of variable generation without any dispatchable demand and generation within the offshore bidding zone, which help ensuring that energy generation matches demand at all times, so that the frequency of the grid does not deviate too far from 50 Hz. It is currently still unclear to what extent the structural differences between onshore and offshore bidding zones will affect the imbalance management. This thesis thus aims to identify the differences between on-shore and off-shore bidding zones, how these differences impact the bidding behaviour of balancing responsible parties operating off-shore windfarms and to what extend this could impact the capacity for imbalance management.

To investigate these dynamics, a model of the bidding behavior of offshore wind farms in sequential electricity markets was developed using Linny-R, a visual representation language for mixed-integer linear programming. The model simulates balancing responsible parties operating offshore wind farms trading first in the day-ahead market and then in the intraday market, as production uncertainty decreases over time and various levels of price uncertainty are introduced. Production uncertainty, resolved at different forecasting horizons, is modeled using special order set constraints. Other uncertain factors influencing BRP decisions, such as interconnector capacity allocation mechanisms, separate imbalance prices in the offshore bidding zone (OBZ), and varying gate closure times (GCTs), are examined through a full factorial experimental design.

By modeling these dynamics, the approach captures how BRPs adapt their strategies under different levels of uncertainty and constraints. It provides a framework to analyze trade-offs, quantify risks, and assess the efficiency of market designs under many scenarios.

The results in Figure 1 shows that moderate expected imbalance penalty (2x the intraday price, IMB-2) results in imbalance volumes that are close to the imbalance volumes that would occur if the BRP bid its most accurate expected (EXP) production forecast. At this imbalance price and a gate closure time of 5 minutes (GCT05), the maximum volume of shortages and surpluses are 24.2 and 25.3 percent of installed capacity respectively. The total volume of imbalances as percentage of total production is equal to 7.51 percent. However, at lower imbalance penalties, the shortages that may be generated by the OWF could peak as high as 77 percent of the installed capacity of the OWF.

In contrast, higher imbalance penalties could significantly reduce these shortages because the BRP will bid lower volumes into the market, but the downside is that curtailment, represented by surpluses, may peak as high as 70 percent of the installed capacity. This trade-off between shortages and curtailment is present for all imbalance price scenarios.

Reducing the gate closure time of the intraday market from 60 to 30 minutes could reduce both shortages and surpluses to about 30% (peak) and 5% (total). Reducing the GCT to only 5 minutes could reduce them to about 25% (peak) and 4% (volume). The effectiveness of reducing the gate closure time greatly depends on the imbalance penalties.

The effect of wind forecasting uncertainty on the imbalances off-shore wind farms create in this thesis are generally higher than other studies because of the following reasons. First off all, in other studies

	Frequency of shortages in a year [#]			Max shortage as percentage of installed capacity [%]			Total volume of shortages as percentage of total energy production [%]		
	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05
IMB-1	6843	6871	6875	77.3	55.8	45.2	44.6	27.7	21.0
IMB-2	3658	3600	3540	49.2	31.4	24.2	7.83	4.77	3.77
IMB-5	1554	1419	1552	30.3	21.9	15.1	1.84	1.16	0.96
IMB-10	777	705	759	20.4	14.9	11.1	0.66	0.43	0.35
15	497	474	515	16.1	10.6	7.47	0.33	0.21	0.18
FORECAST	3995	3890	4029	40.4	27.5	21.5	8.19	5.17	3.77

	Frequency of surplusses in a year [#]			Max surplus as percentage of installed capacity [%]			Total volume of surplusses as percentage of total energy production [%]		
	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05
IMB-1	0	0	0	0	0	0	0.00	0.00	0.00
IMB-2	3428	3441	3450	48.3	31.1	25.3	8.07	5.12	3.74
IMB-5	5844	5809	5604	62.1	41.5	34.7	19.2	12.1	9.00
IMB-10	6805	6656	6471	67.4	48.3	38.1	25.7	16.4	12.3
IMB-15	7219	6926	6747	70.8	48.3	40.8	29.5	18.8	14.0
FORECAST	4034	4131	3814	43.4	30.3	23.4	8.10	4.91	3.85

Figure 1: Frequency, maximum and total shortages and surpluses including the expected production scenario

the forecasting errors of load and variable generation can be aggregated over large geographical areas, and this significantly reduces the forecasting error. Secondly, in these studies it is assumed that OWFs bid their expected production into the markets, rather than adjust their bid for profit maximization.

Both of these assumptions do not hold true In an OBZ, as there are no loads, and the geographical area is considerably smaller. Furthermore, BRPs cannot join pool markets as they have no control over which onshore bidding zone the electricity they bid into the market is sent to, or where their imbalances are sent to. Although this does not entirely preclude BRPs operating OWFs from participating in pool markets in onshore bidding zones, such participation will be less profitable when the balancing prices between the onshore bidding zones and the OBZ differ significantly, or when dual price imbalance moments become more frequent.

On the basis of these results the following policy recommendations are made. First, reducing the gate closure time so as to reduce the forecasting horizon can be an effective policy measure, but only if the following conditions are met. (1) For an reduced GCT to be effective, large amounts of flexible demand are necessary to ensure ample liquidity in the intraday markets with which the OWFs can adjust their intraday positions. The need for this liquidity can be reduced by mitigating the price and volume risks that OWFs face. This because the results show that the presence of price and volume risks can lead to higher intraday volumes traded. These findings provide a new perspective on transmission access guarantees and financial transmission rights that are being developed to mitigate these risks for OWF developers. (2) For an reduced GCT to be effective, the imbalance penalties need to incentivize the OWFs to bid as close to their expected production as possible. As shown in the results the use of separate imbalance prices might not give the right incentives for OWFs to do so. By coupling the imbalance prices in the OBZ with the on-shore bidding zone that the imbalances are transported makes it possible for OWFs to pool their imbalances, incentivising them to bid their expected power production.

1 Introduction

As the world grapples with the need to sustain an energy-intensive lifestyle while minimising its environmental impact, the drive towards variable renewable energy sources (vRES) has become paramount. Among the options, the North Sea presents a feasible avenue for large-scale renewable energy generation through wind turbines. Ambitious targets aim to significantly increase offshore wind farm (OWF) capacity — from about 21 GW today to around 300 GW by the year 2050 (NSWPH, 2022). This rapid expansion puts pressure on wind turbine supply chains and production capabilities and presents transmission system operators (TSOs) with the complex challenge of integrating a growing number of OWFs into the onshore grid.

Due to the increased rate of wind farm connections, coupled with the growing distance of OWFs from the coast, the conventional method of connecting OWFs to the energy grid through radial connections is becoming increasingly untenable (Ruijgrok et al., 2019). The hub-and-spoke concept emerges as a solution to these challenges, proposing large offshore transformer platforms (hubs) that connect to surrounding OWFs via radial connections, which then link to the mainland through fewer but larger cables (NSWPH, 2021). Figure 1.1 provides a simplified representation of both approaches.

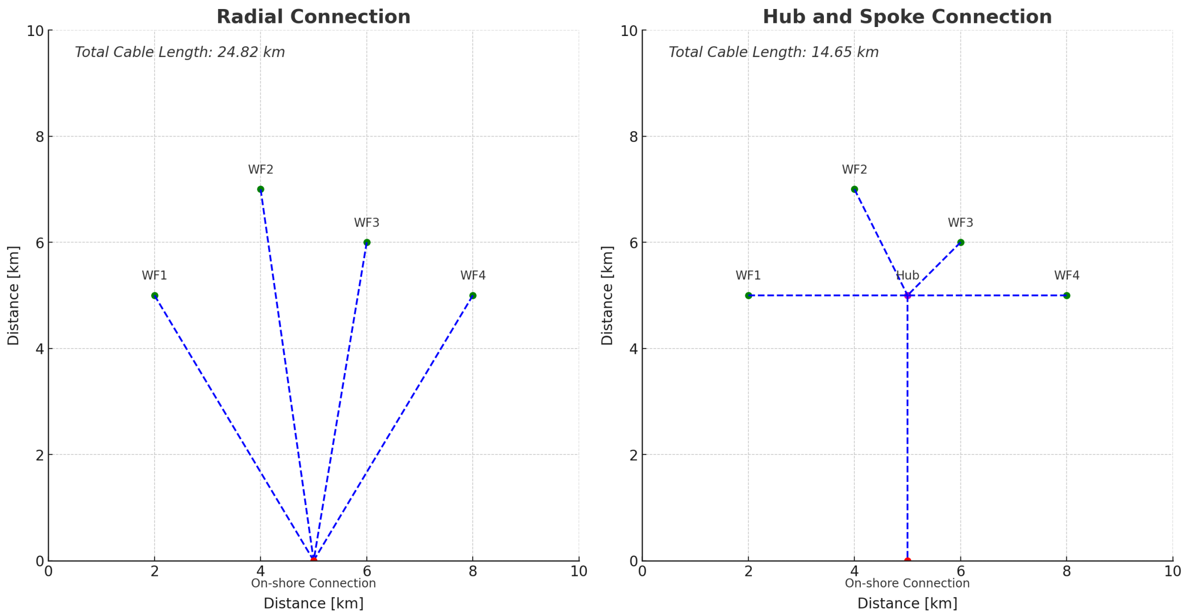

Figure 1.1: Difference between radial and hub-and-spoke connection

Yet, the hub-and-spoke concept still faces the issue of underutilised infrastructure during low wind periods. To address this challenge, the hybrid concept evolved. By connecting OWF hubs to multiple different bidding zones across countries, the connections can be used both for feeding in energy from the OWFs and for trading between bidding zones, thereby increasing cable utilisation (NSWPH, 2019). While this is one of the main drivers, there are more indirect benefits of this setup. For example, by connecting countries close to large generation areas instead of other places on the mainland, this would also reduce congestion on the meshed AC grid. Figure 1.2 provides a graphical representation of the cable utilisation benefits.

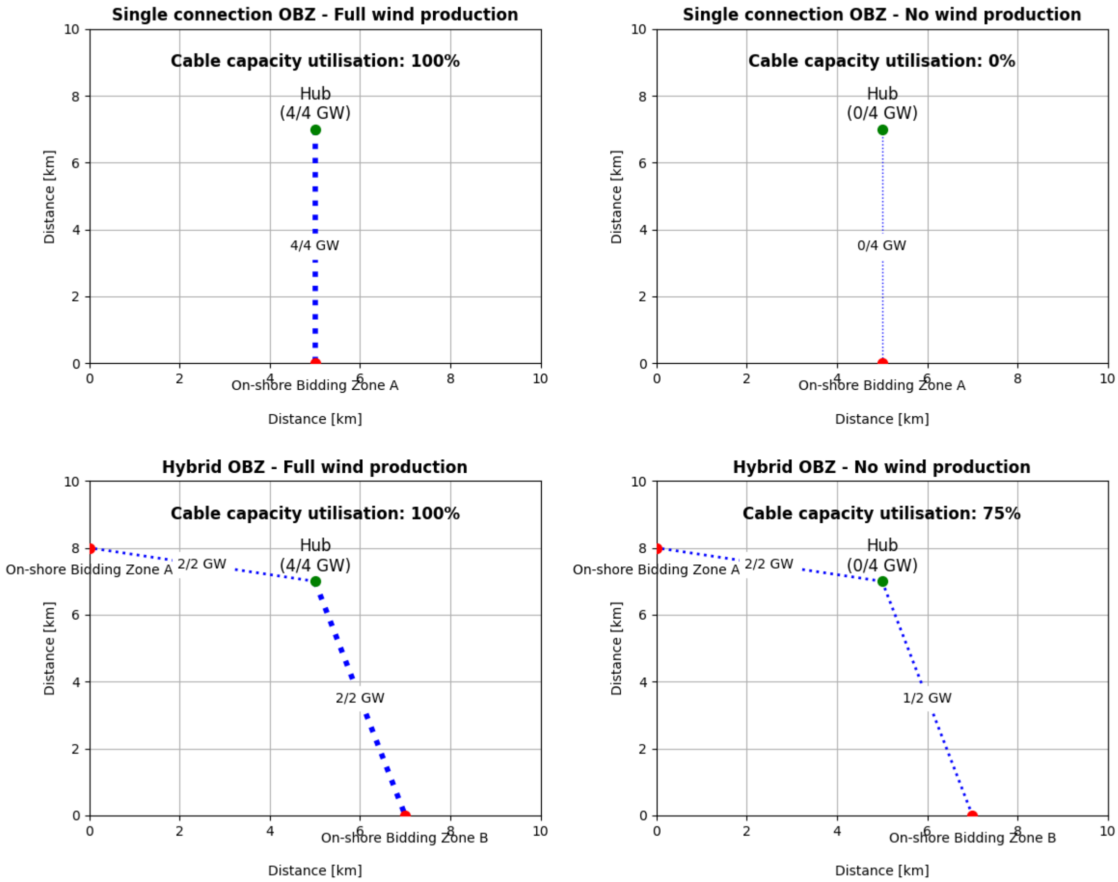

Figure 1.2: Cable utilisation benefit of OBZ

While this concept for OWF grid infrastructure development is more efficient, it conflicts with some existing regulations (NSWPH, 2020). In a home market (HM) approach, only the cables between the hubs are designated as interconnectors, while the cables leading to shore are simply long connection cables, as shown in Figure 1.3(a). By also designating the cables connecting various OWF hubs to shore as interconnectors, these hubs form their offshore bidding zones (OBZs), as shown in Figure 1.3(b). While both market designs have their trade-offs, a leading consortium, the North Sea Wind Power Hub, including partners like TenneT, has concluded that OBZs will be the way forward. However, one of the remaining challenges still needs to be addressed: the balancing of OBZs (NSWPH, 2023-a).

1.1. Balancing Offshore Bidding Zones

A crucial aspect of realising the potential of OBZs lies in addressing the challenge of maintaining grid balance in these zones. As hubs connect multiple wind farms, OBZs typically have a large amount of variable generation and little or no consumption (NSWPH, 2023-a). Ensuring that energy generation matches demand at all times so that the grid frequency does not deviate too far from 50 Hz is critical to prevent TSOs from taking severe remedial actions like disconnecting consumers and

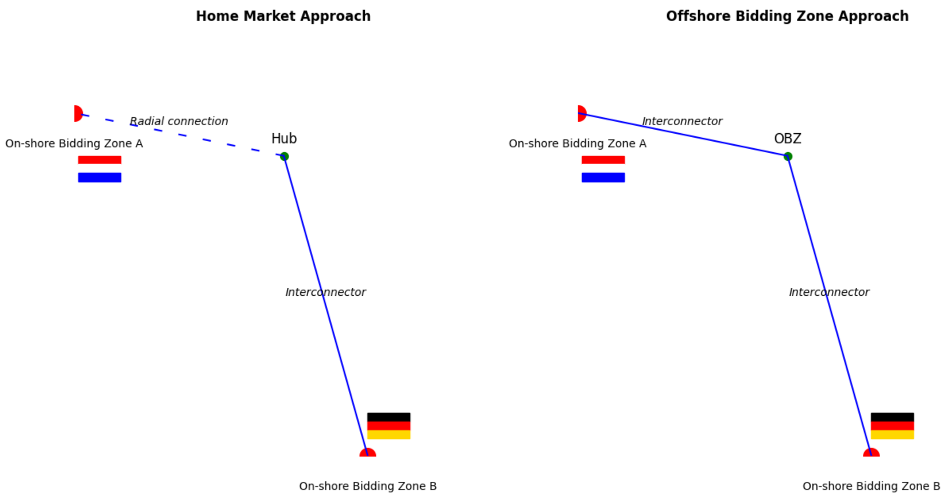

Figure 1.3: (a) Home market setup and (b) offshore bidding zone market setup

producers. In a worst-case scenario, large frequency deviations can trip system protection measures, leading to cascading blackouts, which can be incredibly difficult to resolve. Extended blackouts, lasting several hours, can have devastating consequences for society as a whole, as many critical processes, such as public transportation, health care and communication services, are entirely dependent on an uninterrupted supply of electricity (Ministry of Economic Affairs and Climate Policy, 2022).

To ensure that production and consumption match at all times, each BRP is required to adhere to their delivery schedule (e-program), ensuring the supply or withdrawal of electricity precisely as planned (TenneT, n.d.-a). BRPs managing inherently uncertain vRES, such as OWFs, typically balance their portfolios by adjusting their day-ahead positions through intraday markets. Failure to do so transfers the responsibility for real-time balancing to TSOs, who must then correct these imbalances using services obtained via bilateral contracts, market auctions, or incentives for active balancing participation (TenneT, n.d.-b). BSPs provide various balancing services to TSOs, which vary in activation method, duration, and control speed. These services are categorised into up-regulation, which involves increasing generation or reducing consumption, and down-regulation, which involves decreasing generation or increasing consumption.

Frequency containment reserves (FCR) are contracted bilaterally between TenneT and BSPs, typically months in advance. These reserves are automatically activated when the grid frequency deviates too far from 50 Hz. Frequency Restoration Reserves are divided into two categories: automatic frequency restoration reserves (aFRR) and manual frequency restoration reserves (mFFR), also known as incident reserves. TenneT determines the required volumes of each type and contracts BSPs accordingly.

Offer is activated automatically based on a merit order, compensating BSPs based on their bids when reserve capacity is needed. To ensure minimum reserve availability, TenneT also requires mandatory bids from BSPs, who receive capacity payments in return. This dual mechanism guarantees a baseline supply while promoting a more liquid market through voluntary energy bids. mFFR, in contrast, is contracted through capacity agreements, obliging BSPs to maintain the agreed capacity at all times so TenneT can manually activate it when necessary.

The balancing mechanisms used by BRPs and TSOs in onshore bidding zones may not translate effectively to OBZs. For electricity markets to function efficiently, conditions such as sufficient liquidity and effective capacity allocation are crucial (EPEX SPOT, n.d.-a). This necessity is reflected in European regulation 2019/943, which emphasises that day-ahead and intraday markets must maximise the ability of market participants (in this context, BRPs) to manage imbalances (EU, 2024).

The issue with OBZs lies in their composition—entirely non-dispatchable production assets without local generators capable of providing frequency containment or restoration reserves. This absence significantly reduces market liquidity, which is vital for a well-functioning market. To address this, a proposed solution is leveraging the assets in neighbouring countries connected via interconnectors to serve as the balancing side for the OBZ (NSWPH, 2023-b). Integrating OBZs can compensate for their structural limitations, ensuring grid stability and market viability despite the lack of local balancing resources.

Intuitively, this results in the same situation as for on-shore bidding zones. However, the subtle but crucial difference is that under the OBZ setup, the TSO does not guarantee transportation capacity between the OWF and the market. For example, a TSO may reduce an interconnector's transportation capacity if it deems this necessary for operational security, e.g., for the transportation of balancing energy (NSWPH, 2023b). Furthermore, if interconnector capacity is allocated implicitly through market mechanisms like flow-based market coupling, this could also lead to a reduction in transportation capacity, as this coupling algorithm is designed to maximise social welfare while taking into account grid congestion within bidding zones (NSWPH, 2023a).

Grid congestion can significantly influence the bidding behavior of BRPs operating OWFs by exposing them to various price and volume risks. First, if both interconnectors connecting the OBZ are fully utilised, a price collapse occurs within the OBZ, reducing the value of electricity to its marginal cost—effectively zero for wind power. Second, if sufficient interconnector capacity is curtailed, the BRP may be unable to sell all the electricity it generates, leading to stranded production.

Additionally, one of the primary motivations for establishing OBZs is to leverage flow-based market coupling, which automatically curtails interconnector capacity to prevent congestion within the onshore bidding zone. While this approach improves the efficiency of onshore grids, it prevents BRPs from engaging in portfolio balancing with their assets located in the connected onshore bidding zone. This limitation forces BRPs to position themselves in the market with inherent forecasting errors, increasing the likelihood of costly imbalances. The heightened risks associated with congestion may lead OWFs to adjust their bidding strategies, potentially influencing the imbalances they create.

Many of these potential risks, like the reduction of transport capacity, are widely recognised, and a variety of hedging instruments like long-term transmission rights, feed-in premiums, and reallocation of congestion rents are being discussed to mitigate these risks (TenneT, 2024). However, more attention should be paid to how these risks affect the ability of BRPs and TSOs to effectively manage imbalances so as to guarantee the operation of the grid. As the need for imbalance management increases with a growing amount of vRES, a clear understanding of the potential risks is imperative.

1.2. Research challenge

In conclusion, the OBZ concept can greatly contribute to the transition towards an increasingly rapidly evolving emission-free energy system. However, this may not jeopardise operational robustness by compromising the ability of TSOs to maintain grid balance at all times. It is currently still unclear to what extent the structural differences between onshore and offshore bidding zones will affect the capacity for imbalance management. This thesis therefore aims to clarify the following:

1. in what ways OBZs are different from on-shore bidding zones,
2. how these differences may affect the bidding behaviour of BRPs operating OWFs and
3. to what extent this could impact the capacity for imbalance management.

This knowledge will be crucial for TSOs, policymakers, and energy market participants as they work towards optimising the design and operation of OBZs to support the transition to a more sustainable and resilient energy system. By highlighting the operational intricacies and potential risks, this research will contribute to the development of more robust regulatory frameworks and market mechanisms that can effectively accommodate the unique characteristics of OBZs.

1.3. Thesis outline

The next chapter of the thesis will present the aspects of the electricity system that are relevant to this study, summarise existing literature on the differences between offshore and onshore bidding zones, formulate specific research questions, and explain why a model-based simulation approach is taken. Chapter 3 explains the basic idea behind the simulation model, presents the model structure, and provides details on its operationalisation. Chapter 4 presents the model implementation and examines the dynamic model behaviour to demonstrate that the model is adequate for the purpose of this study. Chapter 5 motivates the chosen experimental design and presents the results of the experiments. Chapter 6 discusses these results, addresses the study's limitations, and suggests further research options. Chapter 7 concludes this thesis by revisiting the research questions and formulating policy recommendations.

2

Problem Analysis and Research Question

The preceding chapter introduced some distinct differences and associated challenges in balancing OBZs, notably the absence of demand, dispatchable generators, and guaranteed transmission capacity. To clarify how these differences affect operational robustness, this chapter first summarises the current electricity market setup in Europe, focusing on methods used to ensure constant balancing of the grid while considering the competing interests of BRPs and TSOs. It then explains how OBZ limit the ability of BRPs to manage their imbalance, why this introduces price and volume risks, and why this may change the BRPs' bidding behaviour and the resulting imbalances that the TSOs must resolve. Finally, it argues that bidding strategies of BRPs in an OBZ that simultaneously consider the financial risk of curtailment and imbalance penalties appear to be a knowledge gap and outlines how this thesis will address this gap.

2.1. European electricity markets

The process of liberalisation and unbundling of electricity provisions started in the 1990s. To create an electricity market, production and consumption roles within the system had to be unbundled from the construction, operation, and maintenance of the grid, which became the sole responsibility of TSOs. Because of their monopolistic position, certain fundamental rights are granted to market participants (producers and consumers) to ensure fair competition. Since then, electricity markets have evolved, and continue to evolve, to integrate the growing amount of electrification and variable renewable energy sources (vRES). Some examples of this are the growing share of electricity traded in the continuous intraday markets and the introduction of intraday auctions (EPEX SPOT, 2024).

Bidding zones and the copper plate principle

A fundamental market freedom of market participants is that, within the contractual limits of their connection agreement, they have the right to produce and consume what they choose. Additionally, they have the freedom of transaction, meaning that market participants can enter into any form of contractual agreement with regard to demand and supply (TenneT, n.d.-f).

Bidding zones are core to facilitating these market freedoms, where electricity can be traded freely without considering grid constraints (TenneT, n.d.-d). This "copper plate" principle forms a guarantee that all electricity can be sold and bought at every single point in the grid within the bidding zone, as long as it is within the limits of the contracted capacity between BRPs and TSOs. In reality, however, grid constraints pose issues for TSOs in the form of congestion, which requires expensive counter-trading and re-dispatch measures to resolve. In 2023 alone, TenneT spent 470 million Euros on congestion management compared to 239 million Euros in 2022 (ACM, 2022). As European regulation dictates that bidding zones need to accurately represent congestion (TenneT, 2024), they mostly follow the existing borders of various nations, as shown in Figure 2.1.

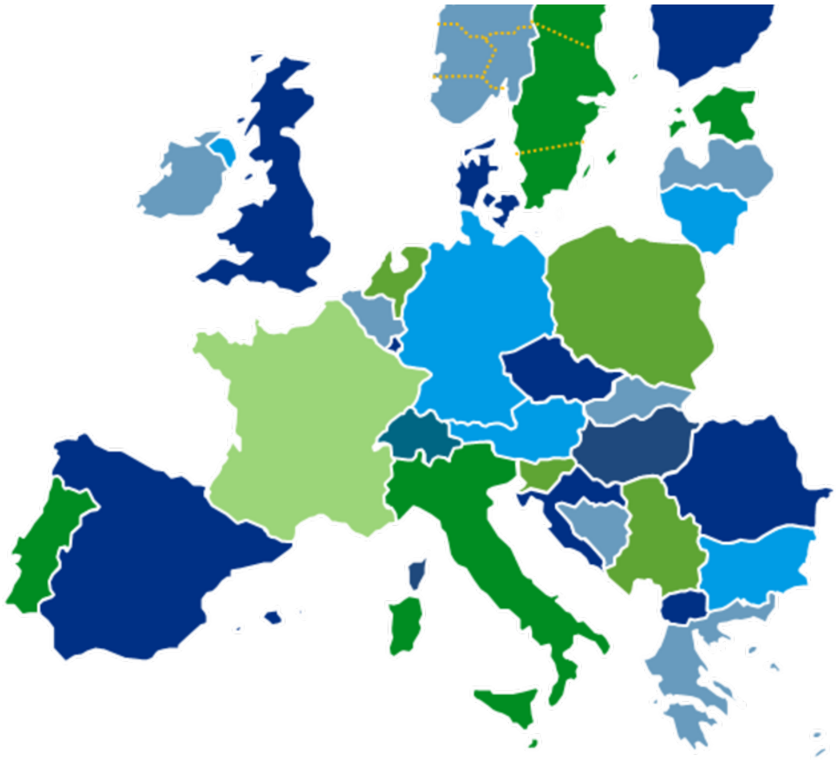

Figure 2.1: Bidding zone borders (TenneT, n.d.-e)

Interconnectors

Electricity between these bidding zones is transported over interconnectors. Due to their thermal, voltage, and stability limits (ENTSO-e, 2020), these interconnectors break with the copper plate assumption because they constrain the amount of electricity that can be traded between bidding zones. TSOs can estimate available cross-zonal capacity based on preemptive load, production, and grid topology forecasts, also called the reference flow (Fref). Additionally, TSOs assign a flow reliability margin (FRM) needed to cover various uncertainties like the forecast of topology (planned and unplanned outages), forecasted flow over HVDC, and increased renewable energy production. The remaining available margin (RAM) is the amount of capacity allocated to the day-ahead market and can be calculated as: $RAM = FMAX - Fref - FRM$ (ENTSO-e, 2020). This domain is then given to the market coupling algorithm in both the day-ahead market and the intraday market of the two interconnected bidding zones.

Day-ahead markets

The day-ahead (DAH) market (also referred to as the spot market or wholesale market) is cleared once per day at 12 CET in central Europe. Bids cover the 24-hour time period from 00 CET to 24 CET the next day. In these DAH markets, participants can make buy and sell bids in various market time units (blocks), ranging from an hour to 15 minutes. Bids have to be in by 12 CET, and the results are published around 13 CET (TenneT, n.d.-f). In these markets, the electricity price is set according to the highest successful bid in the order book. This process, also known as pay-as-cleared pricing, together with marginal pricing theory, is key to the proper functioning of this market (EU, n.d.). As this is a blind auction, participants do not know who their counterparty actually is; they just have to produce/consume the amount of energy that they contracted through this auction and hence include this in their e-program.

Marginal pricing theory suggests that it is most profitable for generators to bid into the day-ahead auction at marginal cost (EU, n.d.). Generally, the marginal cost is assumed to be 0 for vRES like wind and solar, although some suggest it is prudent to include the possible balancing cost into the bid as well. For dispatchable generators like gas power plants, the marginal cost is often a function of fuel price, efficiency, and CO_2 prices. For the demand side, participants set their prices based on their willingness to pay, i.e., how much a unit of electricity is worth to them.

Single Day-Ahead Coupling (SDAC, also known as flow-based market coupling) aims to connect the day-ahead markets of multiple bidding zones. It does this by shifting production from one zone to another until either the clearing price in both bidding zones is the same, resulting in maximum social welfare, or no more interconnector capacity (RAM) is available. In this second scenario, prices in both zones will converge somewhat, but a non-optimal price difference will remain.

The SDAC algorithm also takes into account other practical limitations that can affect the price convergence across bidding zones, such as ramping limits and transportation losses of the physical infrastructure (EU, 2021). Ramping limits refer to the maximum amount of power a physical asset can ramp up or down within a specific period of time. In the case of HVDC interconnectors, ramping limits are often put at around 100 MW/min (TenneT, 2024). The inclusion of transportation losses means that a minimum price difference between two bidding zones is required to ensure that the welfare gains outweigh the transportation losses. However, the impact of this is limited: the losses for some of the largest interconnectors in the North Sea, Norned and Nordlink are 3.2 and 3.1 percent respectively.

Continuous intraday markets

After the day-ahead market clearing, market participants can adjust their positions and the amount they sold/bought on the continuous intraday market. Depending on the nominated market operator (NEMO) that operates in these markets, the intraday markets start between 3 and 5 hours after the day-ahead market closes. In recent years, these markets have rapidly increased in market share, partly due to an increased amount of vRES (EPEX SPOT, 2024). Unlike the day-ahead auction, the continuous intraday trade works on a pay-as-bid principle, which eliminates producer surplus. Within a bidding zone, parties are free to trade the whole day up to 30 to 5 minutes before delivery, depending on the bidding zone.

Similar to day-ahead markets, the intraday markets are coupled through the single intraday coupling (SIDC). As there is only continuous trade, the coupling algorithm does not attempt to optimise social welfare. Instead, when two matching cross-border trades are found, the SIDC checks whether there is sufficient cross-border capacity available to transfer the electricity. Similar to the SDAC, this check also considers the congestion of the grids within the bidding zones, capacity domains, transportation losses and ramping limits.

Over-the-counter trading

Within bidding zones, market parties are allowed to make over-the-counter trades. Such trades often take the form of long-term bilateral power purchase agreements (PPAs). One benefit of these over-the-counter markets, compared to the day-ahead and intraday markets, is that they permit BRPs and other market participants to hedge volume and price risks through all kinds of instruments besides PPAs. Although over-the-counter trades fall outside the strictly regulated markets, price setting often refers to average prices in these markets to ensure that parties do not underpay or overpay on the regulated market.

2.2. Balancing markets

Balancing means ensuring that the grid has a frequency of around 50 hz at all times. Failing to do so can result in large-scale blackouts with very large societal consequences. In the EU, balancing is based on two principles: *prevention* of imbalance by incentivising BRPs to adhere to their e-program and the ability of TSO to *solve* real-time imbalance (TenneT, 2019).

The e-programs submitted by BRPs have to match so that the sum of all generation is equal to the sum of all consumption. When there is indeed too much electricity on the grid, production needs to be ramped down, and more electricity needs to be consumed. In case of surplus production, a BRP that has promised to deliver 1000 MW could ramp down to deliver 800 MW instead and would be paid by the TSO for this passive balancing. However, in case of shortage, such a ramp-down would aggravate the grid imbalance, and then the BRP would have to pay for the imbalance it causes.

This implies that imbalance is perceived differently by BRPs and TSOs: for BRPs, the imbalance equals the difference between their actual production and their submitted e-program, whereas, for a TSO, the imbalance equals the net sum of all real-time BRP imbalances. Although improbable, it is conceivable that all BRPs have large imbalances, while from the TSO's system perspective, there is no imbalance at all.

How BRPs manage imbalances

Depending on the kind of generators the BRPs use, they have different tactics for managing their imbalances. BRPs that own dispatchable generators can adjust their output with the switch of a lever (within the ramping and other constraints of their assets). When BRPs are unable to produce the electricity contracted in the day-ahead market, they can adjust their position in the intraday market, paying other parties to either produce more or consume less. BRPs that are unable to do so are exposed to the imbalance price. As most conventional generators have very high reliabilities, such imbalances are rare for BRPs having such assets, but because of the unpredictability of the weather, BRPs operating OWFs are much more exposed to uncertainties.

One of the most efficient ways for BRPs to manage their imbalances due to prediction errors for their renewable sources is portfolio balancing. When BRPs can submit their e-program for a large set of producers and consumers, the relative prediction error of aggregated production and consumption like vRES and consumer demand is much smaller. Portfolio balancing also protects parties from price uncertainty in the intraday and imbalance markets, which is increasingly becoming more relevant as the volatility in these markets has been increasing.

The difficulty with managing vRES assets is that production can only be ramped down, not up. BRPs can curtail the energy they produce by turning off solar inverters or changing the pitch angle of the wind turbine blades. This can cause problems as it is difficult to estimate the production of these assets a day before the production takes place. Even one hour before delivery, the production prediction error can be 30-40 percent. This poses a dilemma for BRPs managing these assets: do they sell electricity on the market that they aren't sure can be delivered, with the risk of paying a lot of money for the imbalances they cause, or do they wait and sell everything on the intraday market minutes before delivery, with the risk of selling it at a much lower price or not selling it at all and having to curtail their generation?

Failure of BRPs to correctly manage these risks can have large consequences for the system imbalances. For example, on the 9th of October 2023, a forecast deviation occurred that the market apparently did not anticipate. "Tennet had to activate well over 600 MW of reserves to tackle a 964 MW shortage" (TenneT, n.d.). It was not so much the forecasting error that caused the system imbalance but rather how the BRPs managed the uncertainty of the forecast and positioned themselves in the market. When BRPs wait until the last moment before delivery to trade their electricity, when their production forecast errors are smallest, this requires a high amount of liquidity in the intraday market.

How TSOs solve imbalances

TSOs are responsible for managing the system imbalances; to do so, they need to be able to generate and consume electricity on the grid. As TSOs are by law not allowed to own such assets themselves, they acquire four standard balancing products to manage system imbalances: Frequency Containment Reserve (FCR), automatic and manual Frequency Restoration Reserves (aFRR and mFRR), and Replacement Reserves (RR) (TenneT, 2023). While all these products deliver either up or down-regulation energy, the products vary in activation speed and duration. TSOs are obligated to reserve a certain amount of FCR capacity to ensure grid stability in case of large supply shocks, such as the failure of a large generator (TenneT, 2024). Since this capacity is reserved far ahead of time and has little connection to the day-ahead and intraday markets, FCR, mFFR and RR fall outside of the scope of this study.

Part of the aFRR capacity is contracted similarly to the FCR capacity by TSOs ahead of time. The main difference is that after this capacity has been reserved, balancing service providers (BSPs) can submit bids in the balancing energy market up to 25 minutes before the period of delivery (TenneT, 2024). Thus, the capacity reservation ensures that the TSOs have ample capacity available in a worst-case scenario, while the balancing energy market introduces competition, so balancing energy is supplied at the lowest possible cost. Additionally, the TSO publishes real-time balancing prices to the market every minute to incentivise active participation in the balancing market.

A more recent and very successful method TSOs use for balancing is the International Grid Control Cooperation (IGCC), which permits net balancing between different bidding zones. For example, if The Netherlands has an overproduction of 100 MW and Germany has an underproduction of 100 MW, these imbalances can be netted against each other by sending the energy from the Netherlands to Germany over an interconnector. Such a netting prevents the activation of aFFR in both bidding zones. Currently, this cooperation is only possible in bidding zones located in the synchronous zone of central Europe. Moreover, IGCC balancing is limited by the available interconnector capacity.

Portfolio balancing and balancing service providers
Balancing services can only be provided by first going through a pre-qualification process that requires a lot of digitisation on the side of the BSPs, as they have to be able to reliably and accurately follow signals from the TSO. Also, the BSP assets must have high ramping speeds, limiting the set of assets that BSPs can use for balancing. Finally, bids made in the balancing capacity market and balancing energy market also need to be a 100 percent certain they can actually deliver the contracted ramping. Failure to deliver the contracted energy can result in disqualification as BSP. This tends to exclude assets with uncertain ramping capacity, such as renewable generators or vehicle-to-grid demand response.

The main issue for TSOs is that the use of portfolio balancing means that there will be different amounts of generation at different locations than they planned initially. This means that the flows over the grid change compared to what was planned. This could increase the congestion management cost that will eventually be transferred to the consumer. The benefit of knowing these possible congestions ahead of time is that TSOs like TenneT can contract these services through local auctions. In some cases, they may even contract individual producers to not bid in the markets to prevent congestion. However, acquiring these services ahead of time is effective only when the predicted flows over the grid do not change too much in real-time.

Balancing as interplay between TSOs and BRPs
Managing system imbalances in real-time is essential for the safe operation of the electricity grid and the electricity markets. Failure to do so can lead to TSOs taking drastic measures (activating emergency power reserves or disconnecting parts of the grid) that come with a large social cost. To ensure real-time balancing, TSOs like TenneT set passive balancing incentives for BRPs and acquire a certain amount of FCR and aFFR capacity ahead of time. Given limited contracted capacity and the operational difficulty of balancing in real-time, TSOs prefer to prevent imbalances. Portfolio balancing by BRPs reduces their financial risk while also helping TSOs prevent imbalances. Portfolio balancing may change the predicted flows on the grid, resulting in unexpected congestion, but this also holds for the balancing interventions by TSOs.

2.3. Differences between onshore and offshore bidding zones

One of the key requirements for electricity markets within a bidding zone to work efficiently is that there is ample supply and demand within that bidding zone (ACER, 2023). Having only wind generation capacity, OBZs break with this principle. This means that all electricity produced in an OBZ has to be transported over interconnectors. As this interconnector capacity is allocated implicitly through market coupling, BRPs operating OWFs in an OBZ are limited to trading in the day-ahead auctions and the continuous intraday market of this OBZ. This structure also means that the price formation in an OBZ depends on the prices in the bidding zones to which it is exporting.

Price formation
Price formation in an OBZ connected to two other bidding zones is expected to work as follows: Electricity will be transported to the bidding zone with the highest prices until no more capacity on that interconnector is available, and then to the lower-priced bidding zone (NSWPH, 2020). This means that, as a rule of thumb, the prices in the OBZ will converge to those in the first bidding zone where the interconnector still has transport capacity available. When both interconnectors are congested, the prices in the OBZ become equal to the marginal costs of the wind farms in the OBZ, which is zero. This implies that BRPs are worse off when their OWFs are in an OBZ than when their OWFs are connected to one of the onshore bidding zones with a standard connection, because then they always get the lowest price of that bidding zone. This means that an OWF in an OBZ exposes BRPs to different price risks than if it were located in an onshore bidding zone.

Risks induced by flow-based market coupling

To ensure that the copper plate principle holds within bidding zones, advanced hybrid coupling (AHC) takes into account the effect of cross-border flows on the congestion within a bidding zone. ADHC allocates interconnector capacity based on a trade-off between increased congestion costs and greater price convergence. If the reliability margins are too strict compared to the actual possible flows, this decreases the amount of electricity that can be transported, leading to less price convergence and welfare losses. If they are too loose, the grid gets congested, and the TSO has to increase the amount of congestion management. When one unit of flow in a certain location can prevent multiple units of flow somewhere else, OWFs need to be curtailed because of limited interconnector capacity. AHC calculates the optimal flows through the grid based on the bids made in the day-ahead markets, and the bids in the OBZ greatly impact these flows. Thus, SDAC may introduce additional price and volume risks for BRPs.

If BRPs operating OWFs in an OBZ were able to anticipate these interconnector capacity reductions, they could compete for interconnector space in the electricity markets. Because the error in the power generation forecast for the next day is relatively high, BRPs may be hesitant to bid the maximum expected production volume into the DAH market, preferring to wait for the intraday market instead, as then their forecast errors will be smaller. However, because interconnector capacity is allocated through the SDAC and is based on how much volume BRPs bid into the DAH market, a BRP may not be able to shift trade to the intraday market because all available capacity has already been allocated to an OWF of some other BRP that was comfortable with bidding their maximum expected production volume into the DAH market. Even when all BRPs wait for the intraday market to bid in their capacity, the same competition for interconnector capacity can occur because the SIDC works on a first come, first served basis.

In summary, price formation in OBZs poses additional price and volume risks for BRPs compared to onshore bidding zones. These risks may lead to bidding behaviour that increases the amount of imbalances, because the volume risks of flow-based market coupling may incentivise BRPs to over-commit volume in the day-ahead and intraday markets, which could lead to larger imbalance shortages.

Imbalance management in OBZs

The current plan for resolving imbalances in OBZ is to include these imbalances in the imbalances of the onshore bidding zones (TenneT, n.d.). This ensures that imbalances will always be transported towards the onshore bidding zone, where the imbalances can be resolved most cheaply. This also means that the price formation of balancing energy in OBZs would be similar to the price formation in the onshore bidding zones.

However, as portfolio balancing is only allowed within the bidding zones themselves, while OBZs have neither demand nor dispatchable generation capacity, portfolio balancing is impossible in OBZs. As explained in the previous section, this limits the hedging opportunities of BRPs in dual-price scenarios. In the case of single-price scenarios, a BRP could still use passive balancing in multiple bidding zones to achieve a similar result. However, as balancing prices between bidding zones is heavily influenced by local price-setting mechanisms and the use of imbalance netting or IGCC, this is likely to be less effective than in onshore bidding zones.

Another factor that could influence the imbalance management is the gate closure time (GCT) of trading allowed over interconnectors. The GCT is currently 1 hour before delivery. This severely limits the ability of BRPs to wait for a lower forecast error before making a trade in the market. TenneT also recognises this, hence the plan to reduce the GCT to 30 minutes before delivery. But even then, the difference between the forecasted and actual power generation of OWFs may be considerable, and this poses a dilemma for BRPs: either bid a higher volume at the risk of their portfolio being in imbalance, or bid a lower volume at the risk of not selling it and having to curtail their production. This dilemma is analysed in more detail in the next section.

2.4. Bidding behaviour of BRPs operating OWFs in OBZs

As explained in the previous sections, imbalances are not caused by wind forecast errors *per se*, but rather result from how BRPs manage the risks that these uncertainties entail. This section elaborates on how these different risks may affect the bidding behaviour of BRPs operating OWFs, assuming that they aim to maximise their expected profit.

Wind power uncertainty

The power production P of a wind turbine can be approximated using the formula:

$$P = 0.5C_p \rho \pi r^2 v^3 \tag{2.1}$$

Where C_p is the power coefficient of the wind turbine, indicating what percentage of the incoming energy in the wind can be extracted, depending on the rotational speed of the wind turbine. ρ is the density of the incoming wind, which can vary depending on temperature and moisture content. r is the length of the wind turbine blades. As power P has a cubic dependence from wind speed v, this wind speed forms the largest source of uncertainty.

The wind power curve in Figure 2.2 reflects that wind turbines have a minimal *cut-in speed* that is needed to overcome the resistance of the wind turbine before it starts producing power, a *rated output speed* beyond which it cannot produce more power because the turbine has reached its maximum rotation speed, and a *cut-out speed* beyond which the turbine must be turned out of the wind to prevent storm damage. While only the wind speed is shown on the X-axis, these power curves are often already corrected for things like wake effects and air density.

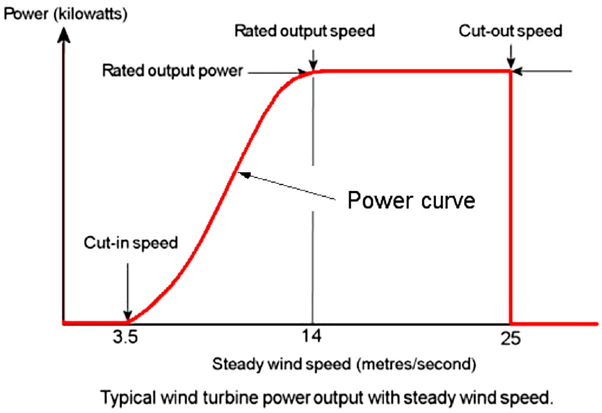

Figure 2.2: Power curve of a wind turbine (Libii, 2013)

The Root Mean Square Error (RMSE) is a commonly used metric to measure the differences between predicted values by a weather forecast model and the actual observed values (Piotrowski et al., 2022). The forecasting error strongly depends on the forecasting horizon. For example, Zhang et al. (2020) show that for wind speed forecasts with a 24-hour forecast horizon, the RMSE equals about 2.1 m/s, and about 1.7 m/s for a forecast with a 1-hour time horizon. Even closer to real-time, the RMSE can be reduced to 0.6 m/s. Forecasting errors can be idealised as a normal distribution $N(\mu, \sigma)$, where the mean μ corresponds to the most likely point prediction, and the standard deviation σ corresponds to the RMSE (Libii, 2013).

Under extreme weather conditions, approximation with a normal distribution is less suited because a relatively small variation in wind speed can then result in a much larger power deviation. For example, with a wind speed standard deviation of 1.7 m/s and a mean of 10 m/s, the 95 percent confidence interval ranges from 6.6 m/s to 13.4 m/s. This translates into a power deviation between 1164 kW at a speed of 6.6 m/s and 9500 kW at a speed of 13.4 m/s. Therefore, TSOs use specialised forecasting tools to help TSOs to plan accordingly to reduce the impact and risk of large ramping speeds and changing flows in the grid.

Bidding strategies

The differences between onshore and offshore bidding zones change the risks faced by BRPs that operate OWFs. Most of these risks are recognised with respect to their long-term effects, but little attention has been paid to how they might affect the bidding behaviour of BRPs and, consequently, the balancing of the grid. How these risks impact BRPs operating OWFs located in an OBZ is especially relevant as they can only participate in the day-ahead and intraday markets, and have no other hedging possibilities to mitigate these risks. Assuming that BRPs bid against marginal cost in both markets, their only decision variables are the volumes they bid into these markets. BRPs will make these bids to maximise their expected profits.

When their bid is accepted, BRPs are obliged to deliver this electricity. As the wind speed prediction becomes more certain and a BRP operating an OWF expects a deviation from its e-program, it has to buy or sell electricity in the intraday market to adjust its position. This implies that each volume bid they make in the day-ahead market has a corresponding expected value for overproduction or underproduction. For example, assume that, based on its forecast, a BRP expects that its OFWs will produce somewhere between 600 and 1200 MW. If it bids 600 MW into the market, its underproduction is likely to be zero, but its overproduction may be as high as 600 MW. Conversely, bidding 1200 MW could result in up to 600 MW underproduction. Such deviations from its e-program can result in high balancing costs for the BRP.

As the power production and associated gains and losses are uncertain, BRPs have to make decisions based on how much risk they are willing to take. For example, if the expected price in the day-ahead market is very high compared to the expected prices on the intraday and balancing markets, a rational actor would bid the maximum forecasted power production in the day-ahead market. However, as electricity market prices and available volumes are uncertain and volatile (partly because of the increased amount of vRES), BRPs operating OWFs are always exposed to some risks. As the price and volume risks are larger, and in some instances very different, for OWFs in OBZs as compared to onshore bidding zones, this poses the question of how this will change their bidding behaviour.

The first effect of risk-averse or risk-taking behaviour in the electricity markets is that it greatly affects the volumes offshore wind farms offer into the market. Studies by Vahedipour-Dahraie et al. (2021), Zhang et al. (2023) and Ju et al. (2019) show that more risk-averse BRPs trade less electricity into the market to prevent exposure to market risks. This effect becomes stronger when they also have the ability to use their own resources to manage their risks through portfolio balancing.

In almost all cases, this risk-averse approach leads to a larger amount of imbalances generated by the BRP, and this could potentially also lead to more system imbalances. The study by Ramirez-Burgueno et al. (2023) indeed indicates that the uncertainty of renewable energy sources leads to a higher total amount of balancing capacity that was necessary. Studies by Wozabal and Rameseder (2020) and Vahedipour-Dahraie et al. (2020) show that for a risk-averse approach, larger forecasting uncertainties result in higher curtailment costs.

In contrast, BRPs with a less risk-averse approach generally bid more volume into the market, both in cases with and without the ability to dispatch other assets. Even though this increases the imbalance volumes in almost all cases, most studies conclude that this higher risk appetite generally leads to more profits for the BRPs (Alahyari and Pozo, 2022; Castillo et al., 2019; Rahimiyan & Baringo, 2019).

In this context, a risk-averse approach means that BRPs assume the imbalance prices to be quite high relative to the income they receive for selling their electricity in the market. In most of the cited studies, BRPs act as price takers, meaning that their bidding behaviour does not affect the balancing prices at all. This assumption is often made because of the difficulty of accurately modelling real-world balancing prices. In reality, however, large power deviations like those modelled in some studies, would have a significant effect on the imbalance prices in bidding zones like The Netherlands. This effect will, in turn, influence the bidding behaviour of BRPs, complicating the study of imbalances in OBZs.

2.5. Knowledge gap and research questions

The aim of this thesis is to clarify to what extent the introduction of OZBs will affect the capacity of TSOs for imbalance management. Although, in theory, imbalances of multiple BRPs could balance out on the system level, larger imbalances caused by a BRP will generally aggravate the balancing problems for TSOs. The main research question for this thesis is therefore:

MRQ: *Will BRPs that operate OWFs in an OBZ generate more imbalances than if they would operate in an onshore bidding zone?*

The preceding sections have made clear that the primary trade-off for BRPs operating OWFs is between the volume of curtailment and the volume of imbalances, and that the risk associated with this trade-off is reduced when forecast uncertainty decreases, but becomes larger when BRPs are unable to hedge against market risks. This also implies that these trade-offs might grow as market risks increase.

Generally, research findings indicate that BRPs with a less risk-averse approach are more profitable but also have large imbalance positions more often. Different risk approaches lead to very different volumes being bid into the markets. The variety of approaches used to price imbalances in earlier studies makes it difficult to generalise the results to the case of OBZs. Hence, this first sub-question:

SQ1: *What is the effect of the greater price and volume risks in an OBZ on the imbalances generated by BRPs operating OWFs in an OBZ?*

The premise that larger forecast uncertainty generally leads to larger imbalances or curtailment (depending on the risk appetite of BRPs) implies that TSOs can reduce imbalances by shortening the interconnector gate closure time, as this will reduce forecasting errors for OWF operators. However, as the cited studies often do not specify the forecasting horizon of the errors used, or when they do, the forecasting horizon does not match up with those relevant to this study, these results cannot be generalised to this case. Hence this second sub-question:

SQ2: *What is the effect of reducing the intraday gate closure time on the imbalances generated by BRPs operating OWFs in an OBZ?*

One of the main discouragements for BRPs to generate imbalances, or to operate in a way that benefits the system balance, are the potential costs for creating such imbalances. The expected differences between the short-term market and balancing energy prices will strongly affect bidding behaviour. In the cited studies, these imbalance prices are often modelled to be quite low, and parties act as price takers, but in practice, if one assumes all other BRPs to be in balance, the imbalance of a single OWF could greatly affect the prices. This makes it challenging to generalise the results of the cited studies to the case of OBZs, especially as it is currently unclear how imbalance prices will be formed in OBZs. Although an in-depth analysis of the dynamics of the imbalance market is beyond the scope of this thesis, the influence of imbalance prices (relative to intraday prices) can be factored into the perceived financial risk for BRPs. Hence, this third sub-question:

SQ3: *What is the effect of relative imbalance prices in an OBZ on the imbalances generated by BRPs operating OWFs in an OBZ?*

2.6. Research approach

As presently no offshore bidding zones have been implemented in practice, the impact of creating an OBZ on the bidding behaviour of BRPs cannot be investigated by an empirical cross-case comparison. As argued in the previous section, findings from simulation-based studies of the bidding behaviour of BRPs in onshore bidding zones cannot be generalised to OBZs because an OBZ poses very different price and volume risks and virtually no options to manage these risks via portfolio balancing. Therefore, a model-based simulation approach is used to explore the influence of forecasting uncertainty on the frequency and range of system imbalances that a TSO has to solve, taking into account how BRPs make the trade-off between the costs of imbalance penalties and revenues lost due to curtailment,

The model used in this simulation approach is based on the idea that BRPs seek to maximise their expected profit by placing their bids in the day-ahead and intraday markets such that for each hour, their expected sales revenue minus their expected balancing costs is as high as possible. As will be explained in detail in the next chapter, these expected values will depend on the probability density function (PDF) of the forecasting error and the differences in prices on the day-ahead, intraday and imbalance market. The literature provides methods and data for estimating the PDF of the forecasting error for different times to market gate closure. As in an OBZ, the markets have different characteristics, and the price differences can not be estimated on the basis of empirical market data. Therefore, simulations will be run for a range of price ratios between the intraday market, the day-ahead market and the imbalance market. This, at least, will provide insight into how these relative price differences affect the bidding behaviour of BRPs and the resulting system imbalances.

To explore the interaction between the independent variables (gate closure time and market price ratios), simulations are run following a full-factorial design, i.e., one model run for each possible combination of inputs. The outcome of these experiments can support TSOs like TenneT in their search for robust policies under high degrees of system uncertainty. The current regulatory uncertainty surrounding OBZs translates into an investment risk for OWF developers. If these uncertainties are not addressed, it is unlikely that the ambitious goals of installing many gigawatts of wind farms in the North Sea will be realised.

3

Simulation Model Design

To explore how the specific properties of offshore bidding zones affect the bidding behaviour of BRPs operating OWFs in such a zone, and to what extent this may impact system imbalances, a model-based simulation approach is used.

3.1. Type of model

The simulation model was implemented in Linny-R, an executable graphical language for specifying mixed integer linear programming (MILP) models developed by Pieter Bots at Delft University of Technology (Linny-R, 2024). It captures the bidding behaviour of BRPs operating OWFs as they participate sequentially in the day-ahead and intraday markets. The model simulates the resulting imbalance, defined as the difference between actual production and the final intraday market position. To account for production uncertainty driven by wind speed variability, special order sets are used to model wind generation uncertainty at different forecasting horizons. Since less is known about other uncertainties, such as price risks faced by OWFs, these are explored across a wide range of possible values using a full factorial experimental design.

MILP-based models are widely applied in electricity studies to analyse operational and market dynamics due to their ability to handle complex decision-making under constraints. They are particularly suitable for modelling electricity markets where discrete decisions (e.g., market bids, and curtailment choices) interact with continuous processes (e.g., generation, forecasting). The use of MILP in this study ensures that the bidding behaviour of BRPs operating OWFs can be tested under various wind power forecasting errors and market uncertainty scenarios.

3.2. Important assumptions and simplifications

Before discussing the details of the model design, it is important to outline several assumptions and simplifications that have been made to ensure the study's focus and feasibility.

First, it is assumed that all electricity generated in the OBZ is sold exclusively via interconnectors, as there is currently no local demand planned within the first OBZs. While future installations, such as electrolysers for hydrogen production, might introduce local demand, these developments are not part of the initial plans. Additionally, interconnector capacity allocation is assumed to occur implicitly through the SDAC and SIDC.

Second, the model assumes that all interconnector capacity is allocated implicitly via market coupling, which introduces additional market risks for BRPs. These risks stem from the possibility of interconnector capacity being curtailed. Market coupling might curtail interconnector flows for two reasons. First, while DC interconnectors allow for controllable power flows, these flows can influence the AC grid within bidding zones and across borders, potentially causing congestion. Flow-based market coupling prioritises social welfare optimisation across all cross-border transmission capacities. As a result, capacity on the OBZ interconnector might be restricted to free up capacity on other interconnectors that generate greater social welfare. Second, interconnector flows might be restricted if they risk overloading the meshed AC grid within a bidding zone. Unlike interconnector capacity, TSOs guarantee transportation capacity within bidding zones, meaning that if intra-zone grid congestion arises, interconnector capacity might be curtailed to prevent overloading.

Modelling these volume risks accurately is challenging. Assessing the first risk would require modelling the social welfare benefits of all potential cross-border transmission flows. Addressing the second would involve simulating onshore grid congestion, which depends on numerous assumptions about planned flows and grid constraints. To simplify this, the model incorporates a wide range of price risks to evaluate their impact on the bidding behaviour of OWFs without directly modelling these complex volume risks.

This study also assumes that BRPs lack the ability to hedge their risks through long-term financial transmission rights. While such long-term transmission rights, are being developed to provide hedging opportunities for OWFs, these instruments are not yet available, and their exact structure remains uncertain. Consequently, the financial flows in this model are based solely based on implicit allocation through markets to reflect the current situation accurately. The potential impact of introducing transmission rights is addressed in the discussion chapter.

Finally, the model assumes that any overproduction, defined as the difference between actual production and the final intraday market position, is always curtailed by the OWF. In real-world operations, this energy could potentially be utilised in balancing markets or transported via physical transmission rights. However, since physical transmission rights for OBZs are unlikely and there is limited adoption of vRES assets for automatic and manual frequency restoration reserves (aFRR and mFRR), these options are excluded from this study. Additionally, the curtailed energy could passively contribute to balancing system imbalances within the OBZ, but this too, falls outside the scope of the model as it is assumed that BRPs operating OWFs in OBZs

3.3. Model outputs

The simulation model should compute outputs in two categories: performance indicators and validation metrics. The performance indicators are the outcomes of interest for TSOs, as they provide a measure for the severity of the imbalance problems that may occur:

- the frequency of positive and negative imbalances;
- the highest positive and negative imbalance observed during the simulation period (1 year), relative to the installed OWF capacity in the OBZ;
- the total volume of imbalances (surpluses and shortages), relative to the total amount of energy generated.

3.4. Representation of bidding behaviour

Assuming that all BRPs bid to maximise their expected profit on the basis of the same wind speed and market price forecasting data, the model need only compute the bidding volumes of a single BRP for each market for each program time unit (PTU) of the year. In this thesis, a PTU of 1 hour is assumed. The day-ahead market closes at noon every day, at which time the BRP has to make a volume bid for each of the 24 hours in the next day. This means that the forecasting horizons range from 12 to 35 hours before the start of delivery, as depicted in the upper part of Figure 3.1.

As the forecasting error increases as a function of this time-to-delivery, the risk of bidding more (or less) electricity into the market than will actually be generated at the time of delivery will likewise increase.

As depicted in the lower part of Figure 3.1, the BRP can compensate for its day-ahead position for each of the 24 hours by buying or selling in the intraday market. Presently, the intraday market closes 1 hour before actual delivery, but this time horizon may be reduced to half an hour or possibly even shorter. Here, too, a longer period between market closure and actual delivery means a higher forecasting error, but this error will be considerably smaller than the errors on which the day-ahead bids were based.

For the model, this means that per day, the BRP decides on 48 bid volumes: 24 on the day-ahead market (with time-to-delivery ranging from 12 to 35 hours) and 24 on the intraday market (with time to delivery

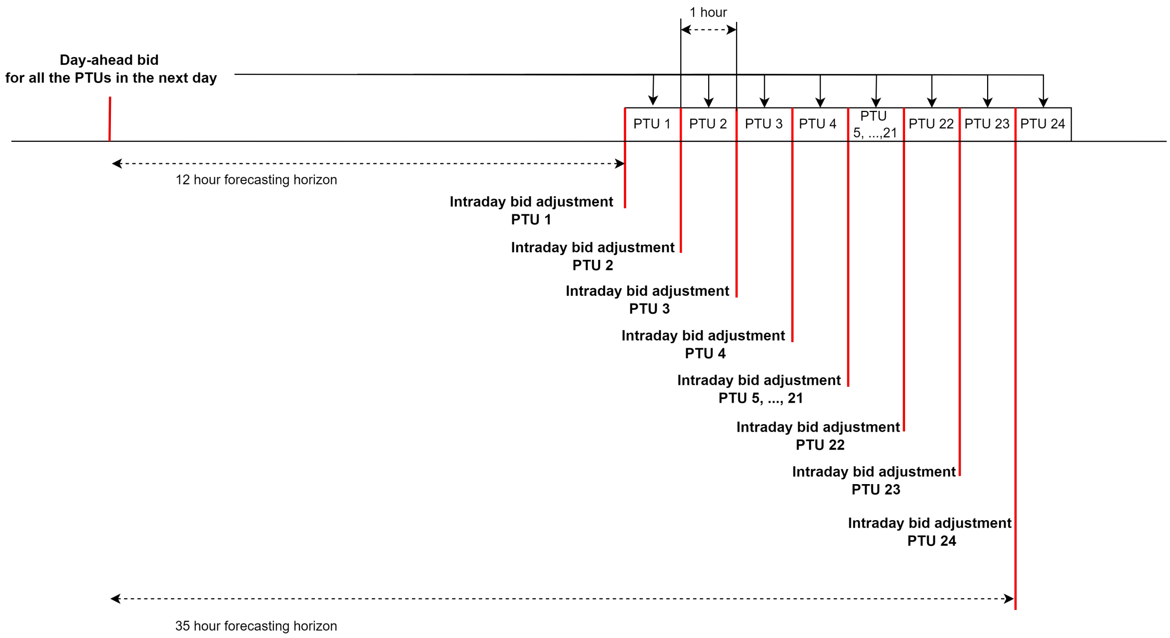

Figure 3.1: Timeline of RBP decisions in the day-ahead market

1 hour, or possibly less if gate closure time is reduced).

The financial risk of bidding into the day-ahead market has two components: the error in the power generation forecast and the price ratio between the day-ahead market and the intraday market. When the actual generation volume turns out to be lower than the bid volume, the BRP has to buy the expected difference in the intraday market, which will be a cost if the intraday market price is higher. Conversely, when the actual generation volume turns out to be higher than the bid volume, the BRP has to sell the expected difference in the intraday market, which will be a cost if the intraday market price is lower.

Bidding close to the upper limit of the power generation forecast will almost certainly cause a shortage, while bidding close to the lower limit will almost certainly cause a surplus. Therefore, the BRP is assumed to bid (for each PTU_i in Figure 3.1) never more than the most probable generation volume Q_{GEN} plus two standard errors of the power generation probability distribution forecasted for that PTU, and never less than Q_{GEN} minus two standard errors.

The chart in Figure 3.2 illustrates how (for a wind farm with 1 GW nominal capacity) the expected surplus can be computed as a function of bid volume and the probability density function of the power generation forecast when this is truncated to 2 standard errors. For the bid volume indicated by the red vertical line, the shaded surface area under the curve to the right of this line is the expected surplus, while the surface area under the curve to the left of this line is the expected shortage.

The *expected* financial profit of a bid into the day-ahead market will then be equal to the expected surplus times the price difference (intraday minus day-ahead) minus the expected shortage times the price difference (day-ahead minus intraday). The BRP will choose to bid the volume for which this sum is lowest, which evidently depends on the anticipated prices in the two markets.

The BRP makes its intraday decisions each hour (just before the market closes), choosing the volume to buy or sell on this market based on the more accurate forecast. Here, too, the BRP seeks to minimise the financial risk of bidding too low (and having to curtail wind energy, missing revenue) and that of bidding too high (and incurring an imbalance penalty). When the BRP has bid volume Q_{DAH} into the day-ahead market and now has a more accurate power generation forecast Q_{GEN}, then it should bid volume $Q_{\text{INT}} = Q_{\text{GEN}} - Q_{\text{DAH}}$ into the intraday, i.e., sell volume Q_{INT} if $Q_{\text{INT}} > 0$, or buy $-Q_{\text{INT}}$ if $Q_{\text{INT}} < 0$, if this forecast Q_{GEN} is perfectly accurate. But as forecast Q_{GEN} will still be imperfect, the shortage and surplus that can be expected when bidding volume Q_{INT} into the intraday market can be

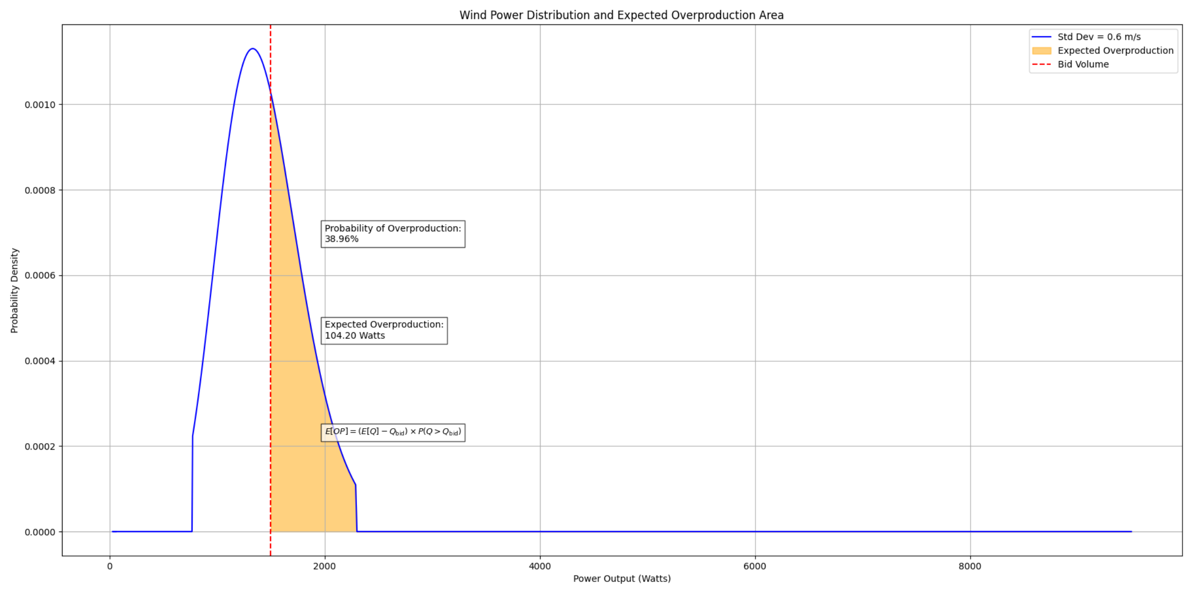

Figure 3.2: Expected overproduction calculation example

computed similar to the expected shortage and surplus on the day-ahead market, i.e., as in Figure 3.4. The BRP will choose the intraday bid volume such that it maximises its expected profit, which is equal to the intraday bid volume Q_{INT} times the intraday market price minus the expected shortage for this volume (if any) times the imbalance penalty. The shortage equals $max(0, Q_{\text{ACT}} - Q_{\text{INT}})$ as the BRP can itself compensate a surplus by curtailing its generation.

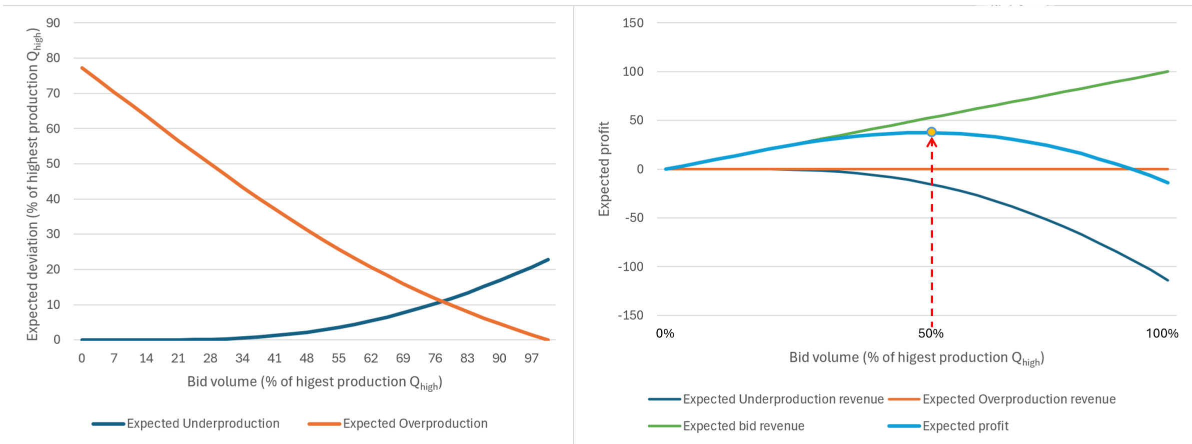

Figure 3.3: Example of optimising intraday bid volume

To illustrate how the BRP can optimise its profit, the left-hand chart in Figure 3.3 shows the expected overproduction and expected underproduction as functions of the bid volume. Note that both axes have been scaled as a percentage of what the BRP estimates to be the maximum power generated. This highest production volume Q_{high} is calculated as the generation volume that corresponds with the forecasted wind speed plus 2 standard deviations. The right-hand chart then shows the three components of revenue for the BRP. The straight line is the bid volume times the market price; the curved lines are over- and underproduction times their associated revenue. For this example, overproduction is assumed to be curtailed, and hence generate no revenue, while underproduction is assumed to mean a penalty that is 2 times the market price. For these conditions, the profit is highest when the BRP bids a bit more than half of its highest production volume into the market.

3.5. Computation of expected shortage and surplus per bid volume

For each hour t, the expected shortage and the expected surplus depend on the bid volume and the probability density function (PDF) of the power generation forecast. To obtain this power forecast PDF, the PDF of the wind speed forecast is combined with the wind turbine power generation curve of the OWF. The uncertainty of the wind speed forecast is approximated by using a Normal distribution $N(\mu, \sigma)$ where μ is the forecasted mean wind speed for time t, and σ the empirically measured standard error. This standard error depends on the time horizon of the forecast h (in hours).

Figure 3.4 illustrates how the relation between bid volume and expected shortage and surplus is established. The mean wind speed in the time series data (chart 1 at the top) ranges between 0 and 23 m/s. This continuous interval is made discrete with a resolution of 0.1 m/s. This results in a total of 231 possible wind speeds. For each of these wind speeds v combined with the forecasting error σ corresponding to each forecasting time horizon h (24 for the day-ahead market bids with a forecasting horizon between 36 and 12 hours, and 3 for the intraday bids representing forecasting horizons of 1 hour, 30 minutes, and 5 minutes, cf. chart 2), the wind speed forecast $PDF(v, h)$ is approximated by a truncated normal distribution (chart 3). Combining these PDFs with the power curve of the wind farm turbines defined by equation 2.1 (chart 4) results in $231 \times 27 = 6,237$ power generation forecasts $PDF(v, h)$ (chart 5). Using the method illustrated by Figure 3.4, the 6,237 relations between bid volume Q and the expected shortage (underproduction) $EU(v, h, Q)$ and also the 6,237 relations expected surplus (overproduction) $EO(v, h, Q)$ can be computed (charts 6 and 7).

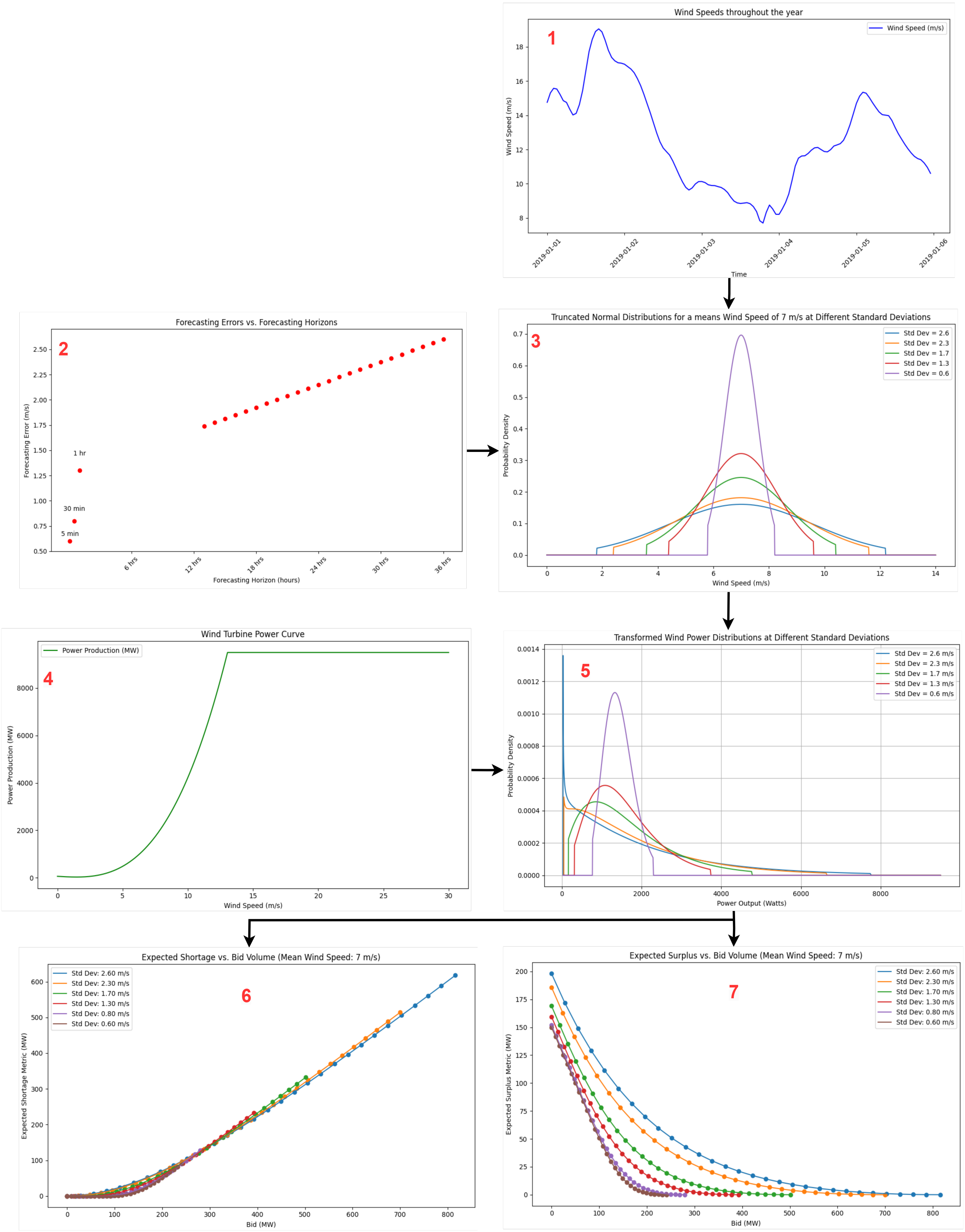

Figure 3.4: Steps to calculate the relationship between bid volumes and expected surpluses/shortages for different scenarios

3.6. Model inputs

Currently, the locations for these wind parks are auctioned off by the Dutch government in 1 GW size blocks. The first OBZs under construction will follow a 2-2-2 configuration with 2 × 2 GW of interconnector capacity and 2 GW of installed wind turbine capacity, similar to those depicted in the introduction. As other network variants are also being considered, a 1 GW configuration will be studied. Given the model design, simulation results will scale linearly with installed capacity. Figure 3.5 shows a representation of the configuration under study.

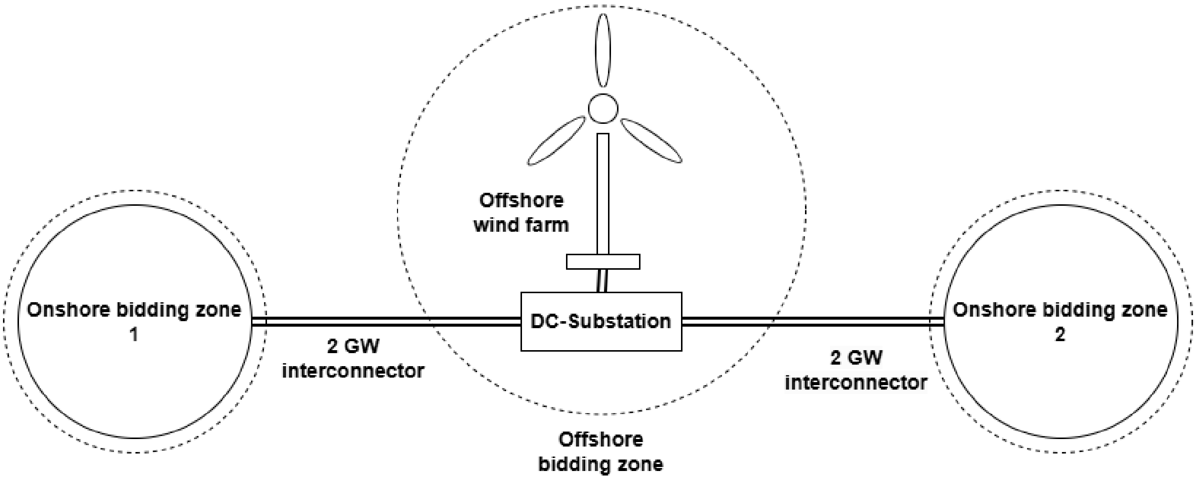

Figure 3.5: Representation of OBZ

According to TenneT, one of the most prominent locations is located in the North Sea at coordinates 54°20’48.1"N; 4°24’20.4"E (NSWPH, 2019-b). Therefore, wind speed time series for this location are used.

The power curve of the wind turbine describes the relationship between the wind speeds and power production. While the power curves of most wind turbines are quite similar, there is a small difference between onshore and offshore wind turbine power curves. The power curve of one of the types of offshore wind turbines that is currently installed in the North Sea is used.

Forecasting uncertainty

Different types of models are used to forecast the weather and wind power. It is assumed that BRPs use the models that provide the greatest accuracy. For the day-ahead forecasting horizons, numerical weather prediction models generally provide the best predictions. For the shorter forecasting horizons in the intraday market, persistence-based forecasting methods provide the best forecasting accuracy. With a 35 hour time horizon, the standard error is about 2.6 m/s, and this decreases to about 1.7 m/s for a time horizon of 12 hours. As the decrease in forecasting uncertainty is linear between these two points, error values for the hours between 12 and 35 are based on linear interpolation. The wind speed forecast horizon errors outlined above are based on Brand’s (2006) forecast method, categorised as long-term forecasting.

For the shorter intraday forecasting horizons (1 hour, 30 minutes and 10 minutes), the forecasting errors are based on Ju et al. (2019) and Zhang et al. (2020), who found standard deviations of 1.3 m/s for 1 hour and 0.8 m/s for 30 minutes. But as renewable energy sources like wind will most likely bid for 15 min time blocks instead of 1 hour time blocks, a gate closure time of 5 minutes would mean a forecast horizon between 5 and 20 minutes. As no such short forecasting horizons could be found in the literature, a standard deviation of 0.6 m/s is used, based on the assumption that uncertainty will then be considerably lower, still.

Gate closure time

The gate closure time (GCT) for electricity for interconnectors is presently 1 hour. Reducing the GCT of markets would allow BRPs to adjust their positions in the market with improved wind speed forecasts. A GTC of 30 minutes would be feasible, as it is higher than what is currently possible within bidding zones. For example, in the Netherlands, the gate closure time in the intraday market is 5 minutes before delivery. Hence, TenneT is considering lowering the gate closure time of the interconnectors to this level as well. Therefore, gate closure time is an input parameter for the model, which will then use the corresponding standard errors of the wind speed forecast.

Price and volume risks

All markets have price and volume risks. However, BRPs operating OWFs in an OBZ face additional and different price risks compared to onshore bidding zones because of advanced hybrid coupling. The risks introduced by AHC depend on the amount of installed capacity per generator type, total demand, willingness to pay and flexibility, fuel prices, and many more variables. Modelling these risks endogenously in a valid way would require modelling the generation and demand in all the connected bidding zones as well as the advanced hybrid coupling algorithm that optimally matches these. As this is beyond the scope of this thesis, price and volume risks are represented as an exogenous factor: the ratio between intraday price and day-ahead price. A ratio less than 1 then represents that the BRP expects intraday prices to be lower than day-ahead prices, and a ratio greater than 1 that the BRP expects intraday prices to be higher than day-ahead prices. As the volume risks in an OBZ result in additional price risks, volume risks need not be represented separately.

Imbalance penalties

As is made clear by TenneT in one of their position papers, the imbalance prices should incentivise the BRPs operating OWFs in an OBZ to avoid imbalances within the OBZ itself and within the offshore meshed grid, and limit the impact on the frequency of the onshore grid. Currently, it is clear that the OBZs will have a separate imbalance pricing mechanism, but it is still unclear how these imbalance prices will be decided upon (TenneT, 2024). As BRPs are able to manage their surpluses of electricity by curtailing their generation, this thesis assumes that the expected cost of positive imbalances is always zero, so only imbalance penalties for shortages are considered. Because no real-world data is available to model these imbalance prices, the penalty for negative imbalances is represented as a model input parameter that specifies the imbalance penalty as a dimensionless multiplier relative to intraday price.

3.7. Validation metrics

The validation metrics serve to assess the validity of the imbalance results. As the mutual interdependency between bid volumes and market prices is not represented in the model, the volumes bid into the markets may be unrealistic. For example, when BRPs bid a lot of electricity into the intraday market, prices in this market may drop, increasing the difference between the intraday prices and the expected imbalance prices. This could incentivise BRPs to lower their intraday position by buying electricity in the intraday market to prevent high expected imbalance costs for the shortages they create. Conversely, when BRPs buy a lot of electricity in the intraday market, prices in that market might go up and incentivise BRPs to bid more electricity into the intraday market.

To be able to verify that the relative volumes sold and bought by BRPs in the three markets are realistic enough, the volume ratios are computed by the model:

- intraday volume sold / volume bid into the day-ahead market;
- intraday volume bought / volume bid into the day-ahead market;
- intraday volume relative to lowest and highest forecasted power generation;
- day-ahead volume relative to lowest and highest forecasted power generation.

These ratios provide an indication of the possible impact market volumes may have on market prices and are discussed in the next chapter.

Model diagram

The diagram in Figure 3.6 summarises the overall design of the model. To address the research questions, the model will be used in a full-factorial experiment where the market price ratios and the intraday gate closure time will be varied; the properties of the OBZ (total installed wind farm capacity, wind turbine power curve, hourly wind speed time series and forecasting error for each time horizon) will be the same for all model runs.

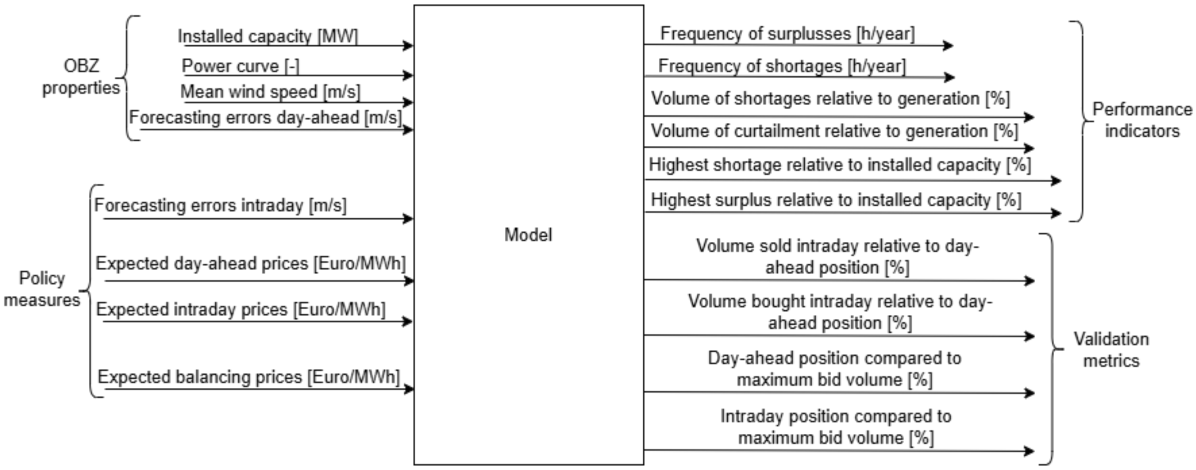

Figure 3.6: Model diagram

3.8. Mathematical optimisation model

The simulation model can be formalised as a mathematical optimisation model. When a full year is simulated, the BRP makes two decisions for each hour t (where $t = 1, 2, \dots, 8760$):

1. *Day-ahead market:* The BRP first decides on the bid volume $Q_{\text{DAH},t}$ for the day-ahead market for hour t. In this first stage, 12 to 35 hours before delivery, the uncertainty in power generation is relatively high.
2. *Intraday market:* In this second stage, one hour or less before actual delivery, the uncertainty in power generation is considerably lower, and the BRP can adjust its position on the day-ahead market $Q_{\text{DAH},t}$ by deciding on its intraday bid volume $Q_{\text{INT},t}$ for the same hour t.

To compute the system imbalance that needs to be solved by the TSO, the model computes the actual power generation $Q_{\text{ACT},t}$ by drawing a random number from the probability distribution of the forecasted power generation at the closure of the intraday market (1 hour or less before actual delivery).

First stage decision (day-ahead market)

In the first stage decision, the BRP aims to maximise its expected profit in the day-ahead market while considering the expected costs associated with underproduction and overproduction:

$$\text{MAX:} \quad \pi_{\text{DAH},t} = Q_{\text{DAH},t} P_{\text{DAH}} + (EO_{t,h}(Q_{\text{DAH},t}) - EU_{t,h}(Q_{\text{DAH},t})) P_{\text{INT}} \tag{3.1}$$

For $t = 1, \dots, 8760$ under the constraint:

$$0 \leq Q_{\text{DAH},t} \leq Q_{\text{high},t} \tag{3.2}$$

Where for each hour t:

$\pi_{\text{DAH},t}$ the profit (in €) the BRP expects to make on the day-ahead market;

$Q_{\text{DAH},t}$ the volume (in MWh) the BRP bids into the day-ahead market;

P_{DAH} the electricity price (in €/MWh) on the day-ahead market;

$EO_{t,h}(q)$ the expected overproduction (in MWh) as a function of bid volume (chart 6 in Figure 3.4);

v_t wind speed time series data (in m/s) used as mean for the probability density function of the forecasted wind speed;

$h = 12 + t \bmod 24$ the forecast horizon (in h); this horizon ranges between 12 to 35 hours before delivery;

$EU_{t,h}(q)$ the expected underproduction (in MWh) as a function bid volume (chart 7 in Figure 3.4);

$P_{\text{INT}} = r_{\text{INT:DAH}} P_{\text{DAH}}$ the electricity price (in €/MWh) on the intraday market, relative to the day-ahead price; the dimensionless price ratio $r_{\text{INT:DAH}}$ is an input parameter.

$Q_{\text{high},t} = WTPC(v_t + 2\sigma_h)$ the high end of the power generation forecast, based on the wind speed forecast plus twice the forecast error for time horizon h (chart 5 in Figure 3.4).

Expected over- and underproduction
When the stochastic wind speed forecast for hour t with time horizon h is represented as:

$$V_{t,h} \sim \mathcal{N}(v_t, \sigma_h^2) \tag{3.3}$$

Then, the stochastic power generation by the OWF follows from the wind turbine power curve:

$$PG_{t,h} \sim WTPC(V_{t,h}) \tag{3.4}$$

This power curve is defined as

$$WTPC(v) = \begin{cases} 0 & \text{if } v < v_{\text{cut-in}} \lor Vt > v_{\text{cut-out}} \\ P_{\text{ro}} & \text{if } v > v_{\text{ro}} \\ \theta v^3 & \text{otherwise} \end{cases} \tag{3.5}$$

where P_{ro} is the rated output power of the OWF, v_{ro}, $v_{\text{cut-in}}$ and $v_{\text{cut-out}}$ the turbine-specific wind speed limits, while θ captures the other static properties of the OWF (cf. Equation 2.1).

When the BRP bids volume q into the market, the expected overproduction in hour t for forecasting time horizon h then equals the integral

$$EO_{t,h}(q) = \int_q^\infty PG_{t,h}^{\text{inv}}(x)\,dx \tag{3.6}$$

Where $PG_{t,h}^{\text{inv}}$ is the probability density function of the power generation (the blue line in Figure 3.2).

Likewise, the expected underproduction in hour t for forecasting time horizon h then equals the integral

$$EU_{t,h}(q) = \int_0^q PG_{t,h}^{\text{inv}}(x)\,dx \tag{3.7}$$

The continuous non-linear functions EO and EU are implemented as piecewise linear constraints as explained in Appendix A.

Second stage decision (intraday market)
In the second stage decision, the BRP adjusts its position based on updated forecasts. The goal is to maximise profit in the intraday market by adjusting the bid volume while considering the expected costs associated with underproduction.

$$\text{MAX:} \quad \pi_{\text{INT},t} = Q_{\text{INT},t} P_{\text{INT}} - EU_{t,GCT}(Q_{\text{DAH},t} + Q_{\text{INT},t}) P_{\text{SP}} \tag{3.8}$$

Under constraint:

$$0 \leq Q_{\text{DAH},t} + Q_{\text{INT},t} \leq Q_{\text{high},t} \tag{3.9}$$

Where for each hour t:

$\pi_{\text{INT},t}$ the profit (in €) the BRP expects to make on the intraday market;

$Q_{\text{INT},t}$ the volume (in MWh) the BRP bids into the intraday market;

$Q_{\text{DAH},t}$ the volume (in MWh) that the BRP has bid into the day-ahead market in stage 1;

P_{INT} the electricity price (in €/MWh) on the intraday market;

$EU_{t,GCT}(q)$ the expected underproduction (in MWh) as a function of bid volume (chart 7 in Figure 3.4); note that now the time horizon equals the gate closure time GCT of the intraday market.

v_t wind speed time series data (in m/s) used as mean for the probability density function of the forecasted wind speed used to compute the expected underproduction;

$P_{\mathrm{SP}} = r_{\mathrm{SP:INT}} P_{\mathrm{DAH}}$ the shortage penalty price (in €/MWh), relative to the intraday market price; the dimensionless price ratio $r_{\mathrm{SP:INT}}$ is an input parameter.

$Q_{\mathrm{high},t} = WTPC(v_t + 2\sigma_h)$ the high end of the power generation forecast, based on the wind speed forecast plus twice the forecast error for time horizon GCT (chart 5 in Figure 3.4).

Imbalance calculation

When the actual power generation exceeds the volume that the BRP bid into the intraday market, the BRP can solve this imbalance by curtailing its power generation. Thus, only a shortage causes a system imbalance that must be solved by the TSO. The volume $Q_{\mathrm{RES},t}$ (in MWh) that the TSO needs to feed in to restore balance in hour t is computed as:

$$Q_{\mathrm{RES},t} = max(0, Q_{\mathrm{DAH},t} + Q_{\mathrm{INT},t} - Q_{\mathrm{ACT},t}) \tag{3.10}$$

Where $Q_{\mathrm{ACT},t}$ is the electricity that is actually generated in hour t (in MWh). This actual generation is computed by drawing a random number from the probability distribution of the power generation forecast for the specified gate closure time GCT.

3.9. Model summary

In summary, the conceptual bidding behaviour model captures the decision-making process of a BRP operating an OWF under wind power forecasting uncertainty in both the day-ahead and intraday markets. By transforming the wind speed forecasting errors into power forecasting errors, the BRP can estimate the expected shortages and surpluses associated as a function of wind speed, time-to-delivery and bid volume. Approximating this non-linear relationship as piece-wise linear constraints for each combination of wind speed and time horizon (and hence standard error) allows the model to infer optimal bid volumes in a computationally efficient manner for different market price ratios. This model provides a robust framework for exploring the imbalances that result from a BRP that optimises its bidding strategy for expected profits while considering the risks associated with power generation uncertainty.

4

Model Implementation and Validation

4.1. Model implementation

The simulation model was implemented in Linny-R, an executable graphical language for specifying mixed integer linear programming (MILP) models developed by Pieter Bots at Delft University of Technology (Linny-R, 2024).

The Linny-R diagram in Figure 4.1 represents the bidding process on the day-ahead market. The rectangle in the centre represents the bid volume decision variable (range 0-1000), which will generate a revenue equal to the bid volume times the expected price on the day-ahead market (100); the other two rectangles represent the expected under- and overproduction. The curved arrows represent the piecewise linear constraints that define the non-linear relation between these variables and the bid volume. In each time step of 1 hour, these constraints will be different, depending on time t and the associated wind speed forecast and time horizon of this forecast (12-35 hours). The expected underproduction volume is bought on the intraday market, the overproduction is sold on that market. In this example, the ratio intraday market price : day-ahead market price is set to 0.5. The MILP solver will maximise (for all 8760 time steps t) the sum of the expected revenues in these two markets.

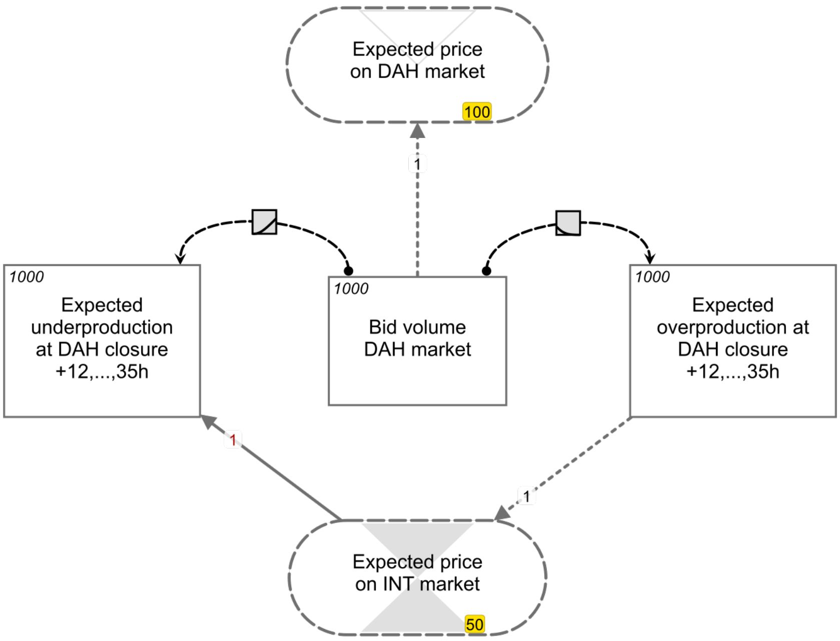

Figure 4.1: Linny-R diagram for first stage decision (day-ahead market)

The Linny-R diagram in Figure 4.2 represents how the BRP adjusts its position by either buying or selling on the intraday market. The upper bound for the volume that the BRP will bid into the intraday market is assumed to be equal to its forecasted generation plus two standard errors. If the BRP buys on the intraday, then this will be at most, the volume that it has bid into the day-ahead market. Hence, the lower bound of the intraday bid equals minus the total volume bid by the BRP has bid into the day-ahead market. A negative bid volume indicates buying (at the intraday market price), and a positive bid volume indicates selling (at the same price). In this example, the ratio imbalance market price: intraday market price is set to 2.

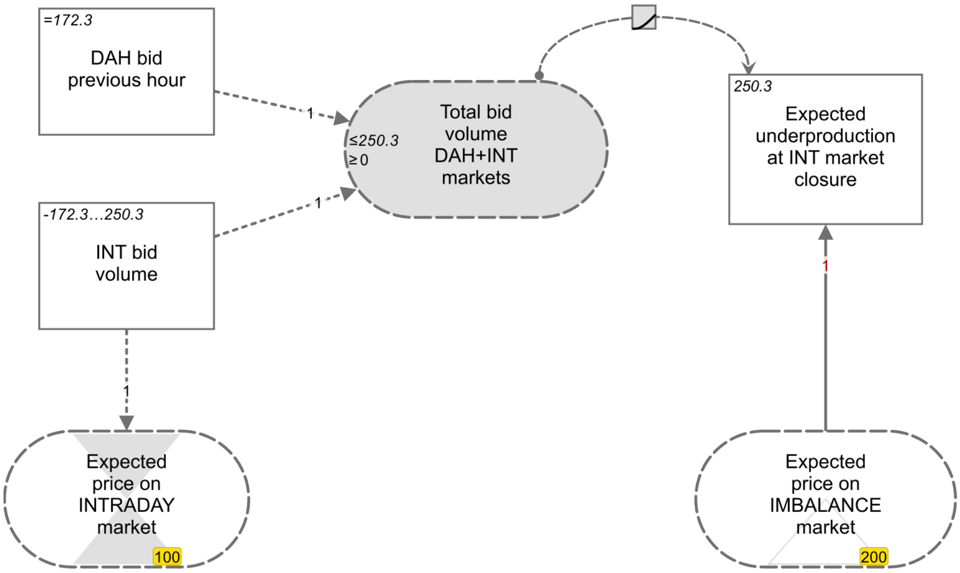

Figure 4.2: Linny-R diagram for second stage decision (intraday market)

The expected underproduction is a function of the total volume (day-ahead plus intraday) bid by the BRP. This function, visualised by the curve in the small square in the middle of the constraint arrow, varies depending on the forecasted wind speed. The expected underproduction must be compensated for by buying on the imbalance market at (in this example) twice the intraday price.

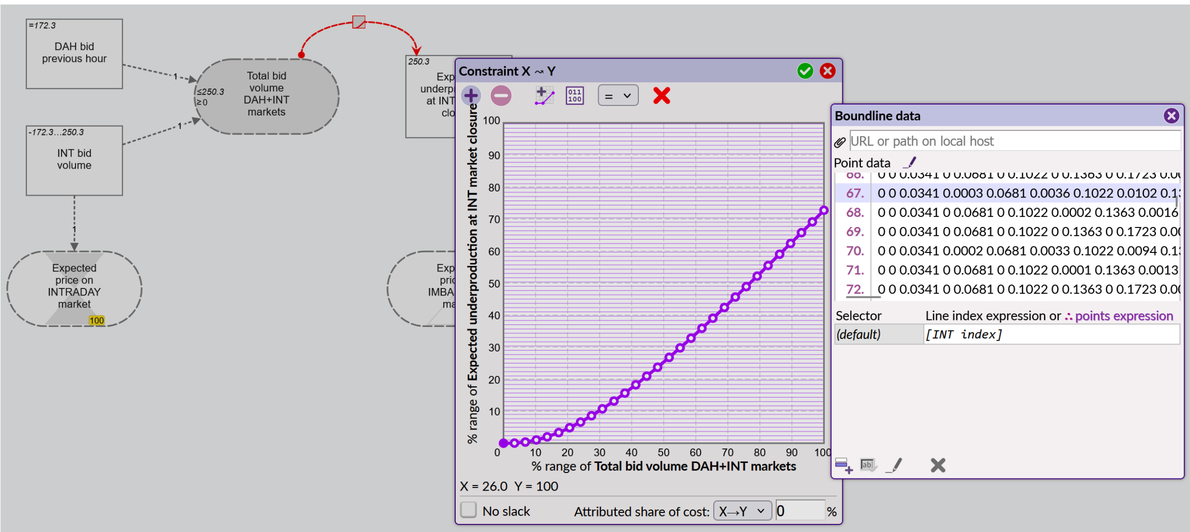

Figure 4.3: Linny-R dialogs for piece-wise linear constraint with dataset

Figure 4.3 illustrates how the piecewise linear constraint in Figure 4.2 is defined in Linny-R: for each combination of wind speed forecast and forecast time horizon (12-35 hours for the day-ahead market, 60, 30 and 5 minutes for, the expected underproduction is defined as a series of 30 data points (X, Y) where X is a percentage of the bid volume relative to the highest expected production (based on wind speed forecast plus 2 standard errors) and Y is a percentage of the total revenue. These data points have been calculated using a Python script that implements the procedure outlined in Figure **??**.

For the intraday market (Figure 4.2), the number of the curve to use `[INT index]` is computed as:

`3 * [Wind speed forecast INT] + [GCT index]`

Where `[Wind speed forecast INT]` is a time series with numbers between 0 and 160 (wind speed minus 2 m/s in dm/s) and `[GCT index]` equals 1, 2 or 3 for forecasting horizons of 60, 30 and 5 minutes, respectively.

Model parameters

The model simulates an offshore wind farm with 1 GW installed capacity. The relation between wind speed and power generation is based on the empirical power generation curve of a modern offshore wind turbine with a cut-in speed of 1,8 m/s and a cut-out speed of 18 m/s.

Wind speed forecast data are based on empirical time series data obtained for the year 2019 for one of the planned wind farm locations in the Noth Sea. This hourly time series (8760 data points) is used as the day-ahead point forecast. The intraday point forecasts are computed by drawing for each data point a random value from a truncated normal distribution with the data point as μ and the standard error for the 1 hour forecast horizon as σ.

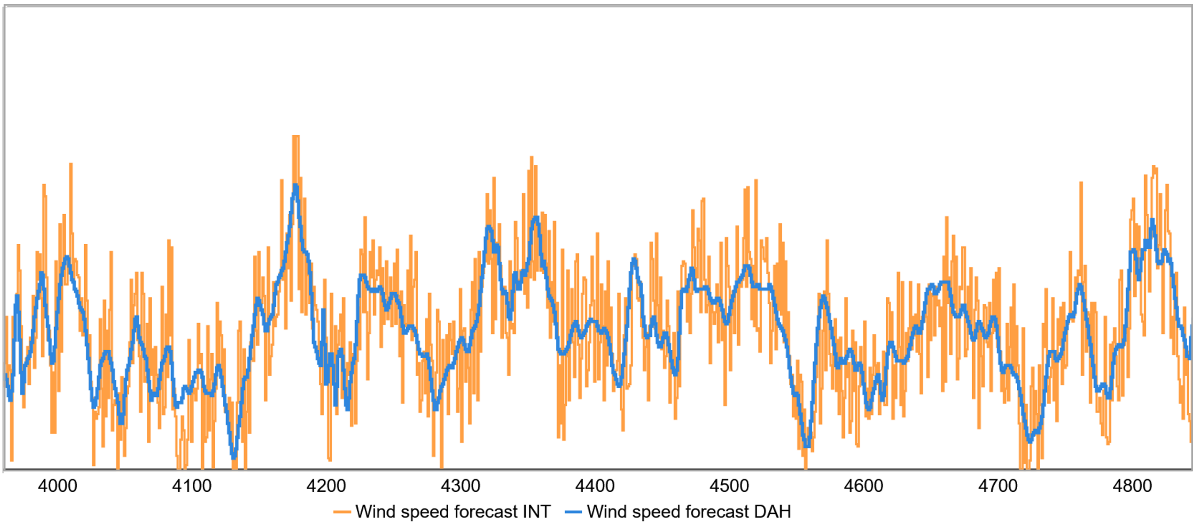

Figure 4.4: Wind speed forecasts day-ahead and intraday

The chart in Figure 4.4 shows a part of the day-ahead and intraday wind speed forecast data sets. As can be seen, the intraday forecast deviates considerably from the day-ahead forecast, but the mean of this deviation is zero.

Model validation

In this section, the validation of the model developed in Linny-R for simulating bidding strategies on the day-ahead and intraday electricity markets is presented. The validation process focuses on key aspects of the model to ensure that its assumptions, constraints, and outcomes align with expectations. The primary objectives of validation are to confirm that the model's implementation accurately represents the bidding behaviors of a BRP operating am OWF.

The validation process targets several key components of the model. These include the accuracy of input data, such as wind speed forecasts and their transformation into power generation estimates, the correctness of piecewise linear constraints governing market relationships, and the validity of underlying assumptions like price ratios and forecasting errors. The results of this validation provide confidence in the model's ability to simulate market behaviour accurately and its applicability for further analysis and decision-making.

The chart in Figure 4.5 shows the observed imbalances over time. As expected, the imbalances for longer time horizons have a greater amplitude. This is confirmed by the descriptive statistics in Table 4.1, which clearly shows that the mean is close to zero, while the dispersion and range of the imbalances decreases as the forecasting horizon is reduced.

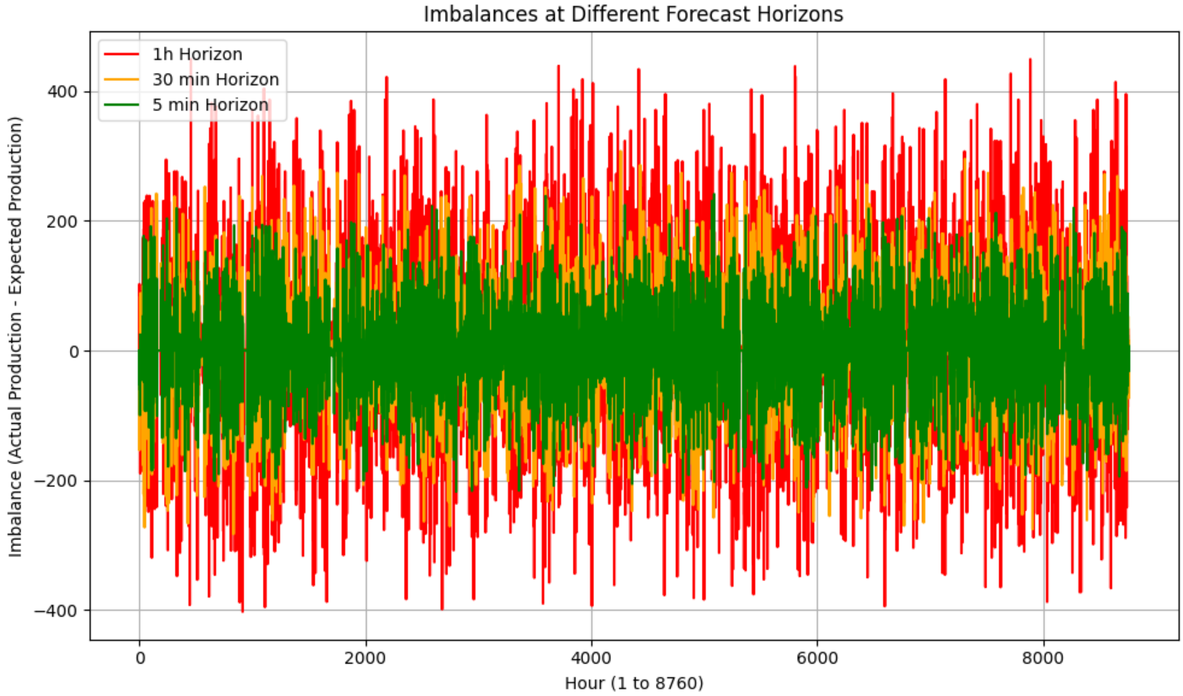

Figure 4.5: Imbalances throughout the year (Actual production - Expected production)

Table 4.1: Summary Statistics for Imbalances at Different Forecast Horizons

	1h	30 min	5 min
Mean	1.35	0.24	0.84
Standard Deviation	115	72	56
Min	-403	-283	-219
Max	450	308	242

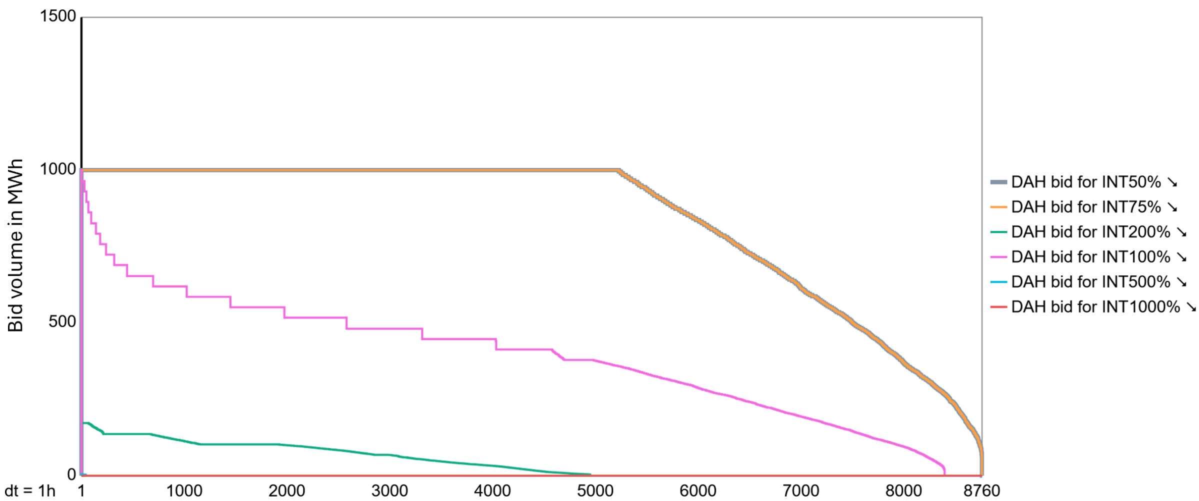

Figure 4.6: Bid volume Day-ahead market as a percentage of the maximum possible bid volume

The chart in Figure 4.6 shows the day-ahead bid volumes of the BRP for each hour over a year, sorted from high to low, at different price ratios between the day-ahead and intraday market. As expected, the chart shows that the BRP consistently bids lower volumes into the day-ahead market when the BRP estimates that intraday prices will be higher than day-ahead prices. The higher the intraday : day-ahead price ratio, the lower the curve of the day-ahead bid volume. This gives confidence that equations 3.1 and 3.2 adequately represent the day-ahead bidding behaviour of the BRP.

The "staircase steps" in the lines can be explained by the piecewise linear approximation of the relationship between the bid volume and expected overproduction and underproduction: each step corresponds with one of the 30 corner points like those shown in Figure 4.3, as the solver will typically find an optimum in such points.

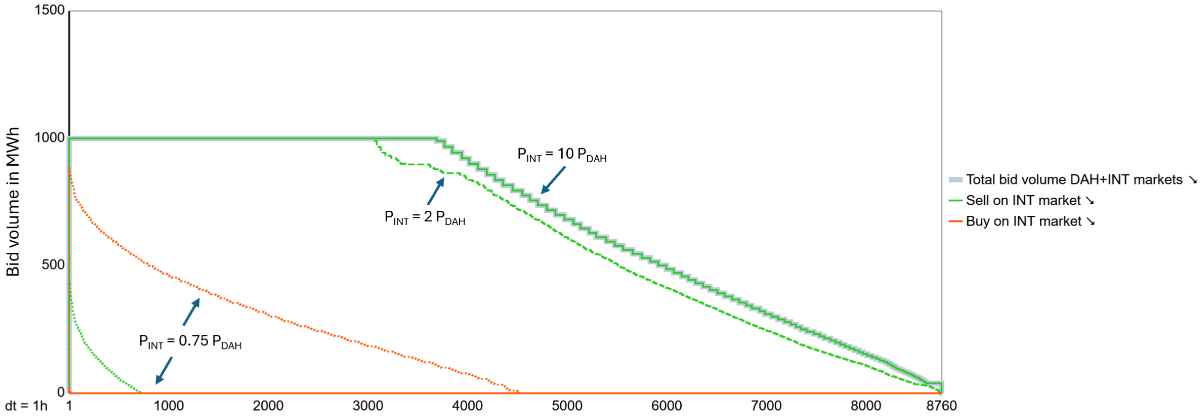

Figure 4.7: Volume traded on the Intraday market for different INT:DAH price ratios

The chart in Figure 4.7 shows the volumes bought (red) and sold (green) on the intraday market for different price ratios. The top line represents the total volume (day-ahead + intraday). As expected, the BRP bids its entire volume into the intraday market when the intraday : day-ahead price ratio is very high, and less so when this ratio is lower but still higher than 1. When the price ratio is lower than 1, the BRP will sell only 10% of the time, and buy about 50% of the time.

These model outcomes confirm that the model simulates the bidding behaviour of the BRP for both markets in a reasonable way, and hence can be used for a more extensive analysis.

5 Results

To investigate how the bidding behaviour of a BRP affects the imbalances that must be solved by the TSO, the simulation model has been run in a full factorial experiment for the following input variable ranges:

- Intraday: Day-ahead price ratio 0.5, 0.75, 1, 2, 5 and 10;
- Imbalance: Intraday price ratio 1, 2, 5, 10 and 15;
- Intraday gate closure time: 1 hour, 30 minutes and 5 minutes.

For a full factorial experiment, this means $6 \times 5 \times 3 = 90$ model runs. For these runs, first the amount of imbalances to be solved by the TSO is analysed by displaying the following output variables of the model:

- Frequency of shortages (hours per year)
- Highest shortage that occurred relative to the installed capacity of the OWF (as percentage)
- Total volume of shortages (sum over 8760 hours) relative to the actual amount of generated electricity (as percentage)
- Frequency of surpluses (hours per year)
- Highest surplus that occurred relative to the installed capacity of the OWF (as percentage)
- Total volume of surpluses (sum over 8760 hours) relative to the actual amount of generated electricity (as percentage)

Here, shortage means that the power that was actually generated by the OWF was less than the total volume (day-ahead plus intraday) bid by the BRP. Because of imbalance penalties, shortages indicate a cost for the BRP. A surplus means that the actual power generation was higher than the total bid volume. Although the BRP can resolve surpluses by curtailing the power generated by the OWF, such curtailment implies a waste of energy and hence is also undesirable.

The model outcomes for shortages and surpluses are shown in tables with a colour scale where red indicates high values (as imbalances are undesirable) and green indicates low values. The tables include the following abbreviations: GCT (Gate Closure Time), IMB (Imbalance/Intraday Price Ratios), and INT (Intraday/Day-ahead Price Ratios). For example, IMB-5 indicates that the expected imbalance price is five times higher than the intraday price, while INT200 signifies an expected intraday price that is double the day-ahead price.

Figure 5.1 shows the run results for shortages. The most remarkable finding is that the shortages seem to be completely insensitive to the intraday : day-ahead price ratio, even though this ratio results in very different volumes bid into the day-ahead market (cf. Figure 4.6). An explanation for this outcome is that the forecasting error relates to the total generation volume. The BRP adjusts its market position so that its total bid volume matches this total generation volume. This means that the BRP selects its intraday bid position such that the sum of day-ahead and intraday bid volumes will be the same, independent of the day-ahead bid volume. By consequence, the shortages are also independent of the day-ahead bid volume.

Another remarkable finding is that the *frequency* of shortages is quite insensitive to the gate closure time (GCT). The relatively small differences in this frequency follow from the differences in the time series for the actual generation for each GCT. The effect that a shorter GCT results in a lower highest shortage, as well as a lower total shortage, follows from the smaller standard error in the wind speed forecast as the forecast time horizon becomes shorter.

The strongest effect shown by the shortages table is that their frequency, maximum and total drop radically as the imbalance : intraday price ratio increases. This confirms the idea that the BRP will bid less volume into the market when the financial risk of a shortage is higher due to a higher imbalance penalty relative to the opportunity cost of curtailing overproduction.

The simulation outcomes show that even an extremely high imbalance penalty will not completely prevent shortages from occurring. The lowest observed frequency is 474 hours, which is about 5% of the time. The highest observed shortage then drops by about 4/5, and the total volume by 99%. Such extreme imbalance prices are not very realistic, but even when the imbalance market price level is only twice that of the intraday market price level, this results in a very significant reduction of shortages.

		Frequency of shortages in a year [#]			Max shortage as percentage of installed capacity [%]			Total volume of shortages as percentage of total energy production [%]		
		GCT60	GCT30	GCT05	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05
IMB-1	INT50%	6843	6871	6875	77.3	55.8	45.2	44.6	27.7	21.0
	INT75%	6843	6871	6875	77.3	55.8	45.2	44.6	27.7	21.0
	INT100%	6843	6871	6875	77.3	55.8	45.2	44.6	27.7	21.0
	INT200%	6843	6871	6875	77.3	55.8	45.2	44.6	27.7	21.0
	INT500%	6842	6870	6874	77.3	55.8	45.2	44.6	27.7	21.0
	INT1000%	6843	6871	6851	77.3	55.8	45.2	44.6	27.7	21.0
IMB-2	INT50%	3658	3600	3540	49.2	31.4	24.2	7.83	4.77	3.77
	INT75%	3657	3603	3540	49.2	31.4	24.2	7.83	4.77	3.77
	INT100%	3657	3603	3541	49.2	31.4	24.2	7.83	4.80	3.77
	INT200%	3657	3600	3540	49.2	31.4	24.2	7.83	4.77	3.77
	INT500%	3658	3599	3539	49.2	31.4	24.2	7.83	4.77	3.77
	INT1000%	3659	3603	3527	49.2	31.4	24.2	7.83	4.80	3.77
IMB-5	INT50%	1554	1419	1552	30.3	21.9	15.1	1.84	1.16	0.96
	INT75%	1554	1419	1552	30.3	21.9	15.1	1.83	1.16	0.96
	INT100%	1553	1420	1541	30.3	21.9	15.1	1.83	1.16	0.95
	INT200%	1553	1422	1541	30.3	21.9	15.1	1.84	1.16	0.95
	INT500%	1552	1424	1551	30.3	21.9	15.1	1.83	1.16	0.96
	INT1000%	1553	1424	1548	30.3	21.9	15.1	1.83	1.16	0.96
IMB10	INT50%	777	705	759	20.4	14.9	11.1	0.66	0.43	0.35
	INT75%	777	707	758	20.4	14.9	11.1	0.66	0.43	0.34
	INT100%	779	707	758	20.4	14.9	11.1	0.66	0.43	0.34
	INT200%	780	707	759	20.4	14.9	11.1	0.66	0.43	0.34
	INT500%	780	701	758	20.4	14.9	11.1	0.66	0.42	0.34
	INT1000%	780	707	757	20.4	14.9	11.1	0.66	0.43	0.34
IMB15	INT50%	497	474	515	16.1	10.6	7.47	0.33	0.21	0.18
	INT75%	497	474	514	16.1	10.6	7.47	0.33	0.21	0.18
	INT100%	497	474	515	16.1	10.6	7.47	0.33	0.21	0.18
	INT200%	497	474	516	16.1	10.6	7.47	0.33	0.21	0.18
	INT500%	497	474	512	16.1	10.6	7.47	0.33	0.21	0.18
	INT1000%	489	474	511	16.1	10.6	7.47	0.33	0.21	0.18

Figure 5.1: Frequency, maximum and total volume of shortages

		Frequency of surplusses in a year [#]			Max surplus as percentage of installed capacity [%]			Total volume of surplusses as percentage of total energy production [%]		
		GCT60	GCT30	GCT05	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05
IMB-1	INT50%	0	0	0	0	0	0	0.0	0.0	0.0
	INT75%	0	0	0	0	0	0	0.0	0.0	0.0
	INT100%	0	0	0	0	0	0	0.0	0.0	0.0
	INT200%	0	0	0	0	0	0	0.0	0.0	0.0
	INT500%	1	1	1	1.15	0.52	1.34	0.0	0.0	0.0
	INT1000%	0	0	24	0	0	2.77	0.0	0.0	0.0
IMB-2	INT50%	3428	3441	3450	48.3	31.1	25.3	8.07	5.12	3.74
	INT75%	3429	3438	3450	48.3	31.1	25.3	8.07	5.10	3.74
	INT100%	3429	3438	3449	48.3	31.1	25.3	8.07	5.10	3.74
	INT200%	3429	3441	3450	48.3	31.1	25.3	8.07	5.12	3.74
	INT500%	3428	3442	3451	48.3	31.1	25.3	8.07	5.12	3.74
	INT1000%	3427	3438	3463	48.3	31.1	25.3	8.07	5.10	3.76
IMB-5	INT50%	5844	5809	5604	62.1	41.5	34.7	19.2	12.1	9.00
	INT75%	5844	5809	5604	62.1	41.5	34.7	19.2	12.1	9.00
	INT100%	5845	5808	5615	62.1	41.5	34.7	19.2	12.1	9.02
	INT200%	5845	5806	5615	62.1	41.5	34.7	19.2	12.1	9.02
	INT500%	5846	5804	5605	62.1	41.5	34.7	19.2	12.1	9.00
	INT1000%	5845	5804	5608	62.1	41.5	34.7	19.2	12.1	9.00
IMB10	INT50%	6805	6656	6471	67.4	48.3	38.1	25.7	16.4	12.3
	INT75%	6805	6654	6472	67.4	48.3	38.1	25.7	16.4	12.3
	INT100%	6803	6654	6472	67.4	48.3	38.1	25.7	16.4	12.3
	INT200%	6802	6654	6471	67.4	48.3	38.1	25.7	16.4	12.3
	INT500%	6802	6660	6472	67.4	48.3	38.1	25.7	16.5	12.3
	INT1000%	6802	6654	6473	67.4	48.3	38.1	25.7	16.4	12.3
IMB15	INT50%	7219	6926	6747	70.8	48.3	40.8	29.5	18.8	14.0
	INT75%	7219	6926	6748	70.8	48.3	40.8	29.5	18.8	14.0
	INT100%	7219	6926	6747	70.8	48.3	40.8	29.5	18.8	14.0
	INT200%	7219	6926	6746	70.8	48.3	40.8	29.5	18.8	14.0
	INT500%	7219	6926	6750	70.8	48.3	40.8	29.5	18.8	14.0
	INT1000%	7227	6926	6751	70.8	48.3	40.8	29.5	18.8	14.0

Figure 5.2: Frequency, maximum and total volume of surpluses

Figure 5.2 shows the run results for surpluses. Here, too, the colour pattern reflects that the frequency of imbalances occurring is not sensitive to the GCT. It also reflects the effect of shorter GCT and of the imbalance : intraday price ratio on surpluses is the reverse of their effect on shortages: when the BRP expects that the imbalance price will be equal to the intraday price, it will bid all its capacity into the market, as then the penalty for imbalances is effectively zero.

The simulation outcomes show that a very high imbalance penalty can result in peak curtailments of as much as 70% of the installed capacity, and a total curtailment of almost 30%. But again, as such high penalties are not realistic, the total amount of energy that is curtailed is likely to be less than 10% when the imbalance market price level is twice that of the intraday market price level.

		Intraday position as percentage of maximum production [%]			Day-ahead bid volume as percentage of maximum production [%]
		GCT60	GCT30	GCT05	GCT60-30-05
IMB-1	INT50%	100	100	100	100
	INT75%	100	100	100	92.9
	INT100%	100	100	100	48.4
	INT200%	100	100	100	5.67
	INT500%	100	100	100	0.02
	INT1000%	100	100	99.7	0.00
IMB-2	INT50%	57.5	66.5	71.9	100
	INT75%	57.5	66.5	71.9	92.9
	INT100%	57.5	66.5	71.9	48.4
	INT200%	57.5	66.5	71.9	5.67
	INT500%	57.5	66.5	71.9	0.02
	INT1000%	57.5	66.5	71.8	0.00
IMB-5	INT50%	45.3	56.4	63.1	100
	INT75%	45.3	56.4	63.1	92.9
	INT100%	45.3	56.4	63.1	48.4
	INT200%	45.3	56.4	63.1	5.67
	INT500%	45.3	56.4	63.1	0.02
	INT1000%	45.3	56.4	63.0	0.00
IMB10	INT50%	40.1	52.0	59.2	100
	INT75%	40.1	52.0	59.1	92.9
	INT100%	40.1	52.0	59.1	48.4
	INT200%	40.1	52.0	59.2	5.67
	INT500%	40.1	52.0	59.1	0.02
	INT1000%	40.1	52.0	59.1	0.00
IMB15	INT50%	37.7	49.9	57.4	100
	INT75%	37.7	49.9	57.4	92.9
	INT100%	37.7	49.9	57.4	48.4
	INT200%	37.7	49.9	57.4	5.67
	INT500%	37.7	49.9	57.4	0.02
	INT1000%	37.6	49.9	57.3	0.00

Figure 5.3: Intraday and Day-ahead bid volumes as a percentage of maximum production

Figure 5.3 shows the position of the BRP on the intraday market, i.e., its total bid volume day-ahead + intraday, as percentage of the highest expected production (based on wind speed forecast plus two standard errors), and likewise the bid volume of the BRP on the intraday market, relative to this maximum production. The blue shading, proportional to the percentages, highlights that the eventual position of the BRP on the intraday market is independent of the volume bid into the day-ahead market. And here, too, the intraday position data shows that the BRP bids less volume as the imbalance penalty becomes higher, and more as the GCT becomes shorter and hence the forecasting error becomes smaller. For the highest imbalance penalty used in the experiment, the BRP bids less than 2/5 of its expected highest generation.

		Volume of electricity bought in intraday as percentage of total bid volume [%]			Volume of electricity sold in intraday as percentage of total bid volume [%]			Volume of electricity sold&bought in intraday as percentage of total bid volume [%]		
		1h	30Min	5Min	1h	30Min	5Min	1h	30Min	5Min
IMB-1	INT50%	22.7	37.7	45.4	1.52	0.52	0.29	24.3	38.2	45.7
	INT75%	18.5	31.0	37.3	7.25	5.06	4.22	25.7	36.0	41.5
	INT100%	1.64	4.14	5.74	40.0	34.5	32.1	41.7	38.7	37.9
	INT200%	0.0	0.0	0.1	93.6	92.9	92.5	93.6	93.0	92.6
	INT500%	0.0	0.0	0.0	100	100	100	100.0	100.0	100.0
	INT1000%	0.0	0.0	0.0	100	100	100	100.0	100.0	100.0
IMB-2	INT50%	75.4	75.7	75.4	0	0	0	75.4	75.7	75.4
	INT75%	63.2	63.5	63.2	2.28	2.31	2.26	65.5	65.8	65.5
	INT100%	13.8	13.8	13.8	24.6	24.6	24.6	38.4	38.4	38.4
	INT200%	0.6	0.6	0.6	91.4	91.4	91.4	92.0	92.0	92.0
	INT500%	0.0	0.0	0.0	100	100	100	100	100	100
	INT1000%	0.0	0.0	0.0	100	100	100	100	100	100
IMB-5	INT50%	111.8	96.3	90.7	0	0	0	112	96	91
	INT75%	95.7	81.6	76.7	1.22	1.57	1.73	96.9	83.2	78.4
	INT100%	26.3	20.6	18.8	18.7	20.9	21.8	45.0	41.5	40.6
	INT200%	1.56	1.09	0.94	90.5	90.7	90.9	92.1	91.8	91.9
	INT500%	0.0	0.0	0.0	100	100	100	100	100	100
	INT1000%	0.0	0.0	0.0	100	100	100	100	100	100
IMB10	INT50%	133.7	108.2	99.2	0	0	0	134	108	99.2
	INT75%	115.2	92.1	84.3	0.83	1.27	1.48	116	93.4	85.8
	INT100%	34.9	24.8	21.7	16.0	19.2	20.4	50.9	44.0	42.1
	INT200%	2.41	1.45	1.18	90.2	90.4	90.8	92.6	91.8	92.0
	INT500%	0.0	0.0	0.0	100	100	100	100	100	100
	INT1000%	0.0	0.0	0.0	100	100	100	100	100	100
IMB15	INT50%	147.0	114.9	103.6	0	0	0	147	115	104
	INT75%	127.2	98.5	88.4	0.64	1.15	1.40	128	100	89.8
	INT100%	40.3	27.4	23.2	14.7	18.2	19.8	55.0	45.6	43.0
	INT200%	2.95	1.67	1.30	89.9	90.4	90.9	92.9	92.0	92.2
	INT500%	0.0	0.0	0.0	100	100	100	100	100	100
	INT1000%	0.0	0.0	0.0	100	100	100	100	100	100

Figure 5.4: Intraday volumes bought and sold as percentage of total bid volume

Figure 5.4 shows how the BRP adjusts its position by buying or selling electricity on the intraday market. The blue shading in the two leftmost tables highlights two things:

- When the intraday : day-ahead price ratio is low, the BRP will have bid more volume into the day-ahead market, so it has to buy more volume on the intraday to adjust its position based on the more accurate forecast. Conversely, when the intraday : day-ahead price ratio is high, the BRP will have bid little or no volume into the day-ahead market, and then it will have to sell more to adjust its position.
- The BRP buys more and sells less on the intraday as the imbalance penalty becomes higher. This pattern is more evident from the shading in the leftmost table (volume bought), but the percentages in the middle table do show that volumes sold decrease as the imbalance : intraday price level ratio increases.

The rightmost table combines volumes bought and sold to reflect how strongly the BRP must adjust its position. The green-yellow-red shading reflects that high adjustments are considered undesirable. The colour pattern highlights that the BRP has to make more adjustments as the imbalance : intraday price level ratio increases. The percentages indicate that the adjustment may be as high as 1.5 times the total bid volume.

	Frequency of shortages in a year [#]			Max shortage as percentage of installed capacity [%]			Total volume of shortages as percentage of total energy production [%]		
	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05
IMB-1	6843	6871	6875	77.3	55.8	45.2	44.6	27.7	21.0
IMB-2	3658	3600	3540	49.2	31.4	24.2	7.83	4.77	3.77
IMB-5	1554	1419	1552	30.3	21.9	15.1	1.84	1.16	0.96
IMB-10	777	705	759	20.4	14.9	11.1	0.66	0.43	0.35
15	497	474	515	16.1	10.6	7.47	0.33	0.21	0.18
FORECAST	3995	3890	4029	40.4	27.5	21.5	8.19	5.17	3.77

	Frequency of surplusses in a year [#]			Max surplus as percentage of installed capacity [%]			Total volume of surplusses as percentage of total energy production [%]		
	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05	GCT60	GCT30	GCT05
IMB-1	0	0	0	0	0	0	0.00	0.00	0.00
IMB-2	3428	3441	3450	48.3	31.1	25.3	8.07	5.12	3.74
IMB-5	5844	5809	5604	62.1	41.5	34.7	19.2	12.1	9.00
IMB-10	6805	6656	6471	67.4	48.3	38.1	25.7	16.4	12.3
IMB-15	7219	6926	6747	70.8	48.3	40.8	29.5	18.8	14.0
FORECAST	4034	4131	3814	43.4	30.3	23.4	8.10	4.91	3.85

Figure 5.5: Frequency, maximum and total shortages and surpluses, including the expected production scenario

As the amount of imbalances is not sensitive to the intraday : day-ahead market price level ratio, the tables in figures 5.1 and 5.2 can be summarised in 5×3 tables. Figure 5.5 shows these tables plus one additional row that shows the frequency, maximum and total volume of shortages and surpluses that would have resulted if the BRP had bid the production volume corresponding to its best wind speed forecast, i.e., at the intraday gate closure time.

These "bid as forecast" imbalances provide a useful metric for comparison because they reflect how the BRP would have bid simply to minimise imbalances without considering the potential profit and opportunity cost related to differences in market prices. The data show that the statistics computed for shortages and surpluses that result from "bid as forecast" are quite close to those that result when the imbalance penalty is assumed to be twice the intraday price.

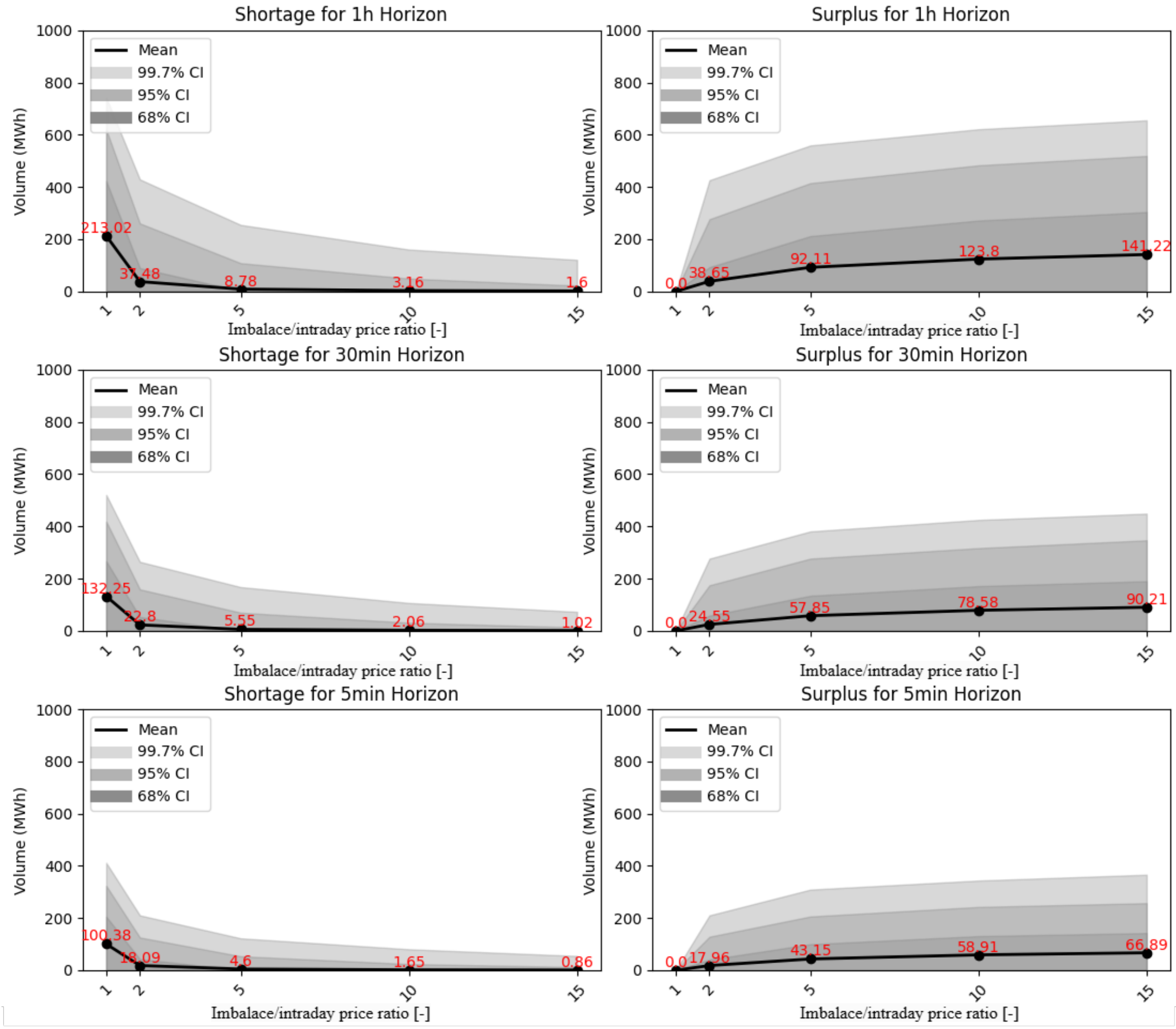

Figure 5.6: Confidence intervals of shortages and surplusses at different forecasting horizons

To put the highest shortage and surplus in the tables charts in more perspective, Figure 5.6 plots, for each intraday gate closure time, the mean value of the shortage (in MWh) as a function of the imbalance : intraday price level ratio. The shaded areas reflect the confidence intervals around this mean. These charts clearly show that the marginal effect of a higher imbalance penalty becomes quite small beyond a price ratio of 2. However, for the TSO, the highest imbalance value is most relevant as this is indicative for the balancing capacity that would need to be reserved.

In summary, the results from the full factorial experiment show that when a BRP operating an OWF in an OBZ follows a profit-maximising bidding strategy in the intraday market:

- the shortages that may be generated by the OWF could peak as high as 77 percent of the installed capacity of the OWF unless such shortages are penalised;
- imbalance penalties could significantly reduce shortages because the BRP will bid lower volumes, but this has as downside that curtailment may peak as high as 70 percent of the installed capacity;
- a moderate imbalance penalty (2x the intraday price) results in imbalance volumes that are close to the imbalance volumes that would occur when the BRP would bid its most accurate production forecast (peak shortage ≈ 40%, total shortage volume ≈ 8% of total actual generation, peak surplus ≈ 40%, total surplus ≈ 30% of total actual generation);
- reducing the gate closure time of the intraday market from 60 to 30 minutes could reduce both shortages and surpluses to about 30% (peak) and 5% (total); reducing the GCT to only 5 minutes

could reduce them to about 25% (peak) and 4% (volume).

The model is based on an OWF with 1 GW capacity, but results can easily be generalised to other capacities because the model scales linearly.

6 Discussion

This chapter takes a closer look at the results of the simulation model and places them in the context of how OWFs operate and behave in the market. It focuses on the challenges of validating these results against real-world data, especially given the lack of detailed information about how BRPs bid in OBZs. Each BRP has unique incentives depending on their contracts and the onshore markets they operate in, making direct comparisons difficult—even if empirical data were available.

The chapter is divided into four sections. First, it examines how the forecasting errors used in the simulation stack up against real-world datasets, including data from Elia and studies by NREL, to see how realistic the assumptions are. Next, it explores the bidding strategies of BRPs, highlighting how market risks influence imbalances and profitability. The third section discusses the effect of shortening the GCT on forecasting accuracy and imbalance frequency, providing insights into the trade-offs involved. Finally, the chapter discusses possibilities for future research, pointing to ways more advanced tools and better data could refine our understanding of how OWFs manage uncertainty and market dynamics.

6.1. Comparison of forecasting errors with empirical data

To better appraise the validity of the findings, the time series data used as power generation forecasts in the model are compared to similar data sets.

A dataset published by TSO Elia (Elia, 2024, 2018) contains short term forecasts of offshore wind power production, based on a multivariate autoregressive persistence based model of the aggregated OWF capacity (2.1 GW) installed in Belgium. This means that each hour the power production for the next four 15-minute PTUs is calculated, which translates into a forecasting horizon ranging from 0 to 1 hour. Additionally, this dataset provides the 10P and 90P values of these hourly forecasts. Finally, this dataset contains some of the metered values of production for that quarter hour.

The total difference between the short term forecasting prediction and the actual metered production ranges between 7 and 16 percent of total production, depending on the month. Data was analysed from 1 September 2023 to 30 August 2024, resulting in an average difference of 11.9 percent compared to total production. This is quite similar to the total imbalance results found in the simulation runs for imbalance : intraday ratio = 2, where for GCT = 1 hour the total imbalance (shortages + surpluses) relative to the actual production is just below 16 percent, and for GCT = 30 minutes slightly above 12 percent. As the forecasting horizon in the Elia model ranges from 0 to 1 hour, the average forecasting horizon is equal to 30 minutes, so the results are best compared to the 30 minute scenario.

The simulation results show that at very high or low imbalance prices, the BRP bids at the extremes of its power forecasts. This results in either very large shortages or very large surpluses created by the OWF. Assuming that in the Elia data BRPs do not consider imbalance prices, outcomes for extreme bidding can be approximated using the P10 and P90 data. If BRPs would bid at the P10 levels, the shortages would be 1.3% of the total production, and surpluses 28.4%, while bidding at the P90 level would result in shortages of 31.6% and surpluses of 2.3% of the total production. These finding are similar to those found in the simulation results for GCT = 30 minutes: for low expected imbalance prices shortages are 27.7% and surpluses 0% of the total production, while for high imbalance prices shortages are 0.21% and surpluses 18.8% of total production.

For an even shorter forecasting horizon, no empirical data on the relation between offshore wind power production forecasts and resulting imbalances could be found. Therefore, the forecasting errors used in the simulations are compared to the forecasting errors used in a study by NREL, which tries to asses the system cost of additional reserve capacity required to balance wind power (NREL, 2010; Ela et al., 2011). In this NREL study, a pure persistence based forecasting model was used to assess the wind power variability, meaning that the forecast error is equal to the difference between the measured power at 10 minute intervals. The forecasting errors were normalized by scaling the standard deviation to the installed capacity. For a small isolated wind farm of 500 MW, this normalised standard deviation was 6.5 percent of the installed capacity. For aggregated wind farms totalling 40 GW, this forecasting error was only 1.7 percent of the installed capacity.

At a forecasting horizon of 5 minutes, the simulation model used in this thesis assumes a wind speed forecasting standard error of 0.6 m/s. As explained in Section 3.4, the resulting normal distribution was truncated at two standard deviations, meaning a range of 2.4 m/s. The time series data sampled randomly from the wind speed distribution was then converted to a time series for actual power generation. For this time series, the difference between the lowest generation and highest generation equals 45 percent of total capacity. For two standard deviations of the isolated wind farm in the NREL study, this range would be 4x6.5 = 26 percent of the installed capacity, and for three standard deviations 6x6.5 = 39 percent of installed capacity.

This suggests that the power generation forecast errors used in the simulation model are almost twice the errors derived from the NREL study. However, it is unclear whether the NREL examples concern onshore or offshore wind farms, or a combination of both. This is relevant, as the forecasting errors for offshore wind farms can be much higher than for onshore wind farms. Data analysis by Elia showed that the forecasting error (mean absolute error) for offshore wind is almost twice as large as that of onshore wind at short-term forecasting horizons (from 3.18 percent to 6.08 percent) (Elia, 2019). The normalised standard deviation of 6.5% percent found in the NREL study suggests that their forecasting errors are more representative of onshore wind power.

The NREL study found that the additional costs associated with balancing OWFs were relatively low, but its authors noted that "The large size of the market areas assumed in the study allows substantial benefits of geographic diversity to be realised" (NREL, 2011-a). Moreover, unlike the simulation model used in this thesis, the NREL study assumes that BRPs are not influenced by balancing prices in their decisions, and bid their best power generation forecast. This makes sense because this strategy is the most profitable for renewable energy sources that share balancing costs in a pool market with one-sided balancing pricing (Vinel & Mortaz, 2019). But as pointed out in Section 2.3, portfolio balancing is not possible in an OZB.

6.2. Bidding behaviour

The simulation results show that when BRPs follow a bidding strategy that considers market risks, this can lead to more imbalances being generated by OWFs compared to bidding the expected production, i.e., the P50 value of the forecasts. This finding is supported by a study by Chavez-Ávila et al. (2014), who found that the amount of imbalances increases from around 26% of total generation when BRPs bid their expected production to 61% of total generation when BRPs optimise their bids for the expected balancing costs. This happens because the OWF optimises for its expected revenue, and if it is able to increase its profits by selling more energy in the intraday market it accepts the possibility of creating more imbalances. In this study a forecasting horizon ranging between 1 and 6 hours was used.

Vilim & Botterud (2014) also investigated the optimal bidding strategy, but did not limit how much the BRP operating an OWF can bid into the market, allowing BRPs to freely speculate on the balancing market. Their simulation also showed that the more profitable bidding strategies create more imbalances compared to strategies that simply bid the forecasted value. In the most extreme case, the BRP sold 80 GWh in the market while only producing 21 GWh in that time frame.

The simulation results also show that in all the scenarios the position in the day-ahead market has very little impact on the position in the intraday market. As the market price ratios are exogenous variables, the BRP can buy and sell large volumes in the intraday market without affecting prices. While this assumption may well hold for an OBZ with only 1 or 2 GW capacity, it may be much less realistic for an OBZ with a planned capacity of 89 GW of OWFs (26 percent of total planned OWF capacity in the North Sea).

When BRPs sell a lot of electricity in the market there is an increase in supply. Assuming that the demand stays constant, this would result in a decrease in prices. Conversely, when an BRPs buy a lot of electricity in the market while all other demand stays the same, the prices would increase. As a lower imbalance : intraday ratio leads to more shortages but less curtailment, and vice versa, the interaction between intraday bid volume and imbalance : intraday ratio could affect the imbalances.

Studies that simulate market clearing of day-ahead markets show that small forecasting errors in load and variable energy sources can lead to large price changes in the market. In some cases, just a 3 percent forecasting error can lead to a price increase/decrease of the clearing price of 20 percent (Carpinelli et al. 2018). This suggests that ignoring the interaction between bid volumes and market prices limits the validity of the simulation outcomes.

In summary, that other studies found considerably lower imbalances caused by OWFs can be explained by the these underlying assumptions:

- The forecasting errors of load and variable generation can be aggregated over large geographical areas, and this significantly reduces the forecasting error.
- BRPs bid their expected production into the markets, rather than adjust their bid for profit maximisation. This is a valid assumption in markets where market participants are free to share such risks which is made possible by the copper plate assumption and one sided balancing mechanisms.

However, these assumptions do not hold in the case of offshore bidding zones. In an OBZ, there are no loads, and the geographical area is considerably smaller. BRPs cannot join pool markets as they have no control over to which onshore bidding zone the electricity they bid into the market is sent to, or where their imbalances are sent to. Although this does not preclude that BRPs operating OWFs participate in pool markets in both onshore bidding zones, such participation will hardly be profitable when the balancing prices between the onshore bidding zones and the OBZ differ much, or when dual price imbalance moments become more frequent. Secondly, it is unlikely that BRPs in an OBZ will bid their expected output into the market when they are unable to hedge their balancing risks.

6.3. Effect of reducing the forecasting horizon

The simulation results show that the effect of reducing the GCT from 1 hour to 30 minutes is considerably stronger than that of reducing the GCT from 30 minutes to 5 minutes. This can be explained by the smaller reduction in forecasting error (from 0.8 m/s to 0.6 m/s), which is a relatively modest decrease.

The results also show that reducing the forecasting horizon from 30 to 5 minutes does not decrease the frequency of imbalances in all scenarios. One explanation is that reducing the forecasting horizon, thereby reducing the forecasting error of the wind speed, only reduces the power forecasting error in certain scenarios.

For example, if the entire wind speed probability density function for a 1 hour forecasting horizon spans the horizontal part of the wind turbine power curve, reducing this forecasting error has no effect on the expected power production. A similar phenomenon, but less strong, happens before or close to the cut-in speed of the wind turbine. These findings are also supported by other papers like NREL (2011-b), that show a much lower reduction in power forecasting error when wind farms are operating close to minimum or maximum production capacity, when better forecasting tools are employed.

One peculiar outcome is that in runs with imbalance/intraday ratio = 5, a shorter forecasting horizon leads to a higher frequency of imbalances. To verify that the reduced forecasting horizon used in the model actually reduces the uncertainty in power generation, the expected power production for all forecasting horizons was analysed and compared with the actual generation time series used in the model. This showed a standard deviation of 114 MW for a 1-hour time horizon, 72 MW for a 30-minute time horizon and 55 MW for a 5-minute time horizon, so indeed a shorter forecasting horizon makes for more accurate predictions.

However, in some cases a reduced forecasting horizon increases the risk of underproduction, which leads to more conservative bids by the BRP in the case of higher imbalance prices. This is partially due to the shape of the wind power curve of the turbines. When the high wind speed forecasting uncertainty overlaps largely with the rated speed of the wind turbine, the change of underproduction is very small, as most of the possible scenarios lead to a maximum production of 1 GW. This leads to situations where for the same bid volume and mean wind speed, the expected underproduction of the shorter forecasting horizon is actually larger than that of the larger forecasting horizon. In these cases the BRP is more conservative with its intraday position when it has a shorter forecasting horizon and more often bids at the lower end of its power production range.

6.4. Further research

A key focus of this thesis has been on how offshore wind farms (OWFs) handle forecasting uncertainty in energy markets. While the approach taken offers a straightforward, computationally efficient way to simulate this uncertainty, further research should aim to improve forecasting precision and incorporate more granular data. Future studies should explore advanced forecasting tools and use actual generation data to refine the understanding of OWFs' forecasting uncertainty in different market scenarios. Additionally, further research into the trade-offs between network congestion and forecasting uncertainty is explored.

6.4.1. Improved methods

Advanced forecasting tools, such as machine learning models and ensemble forecasting techniques, should be tested across various forecasting horizons. Research indicates that different methods yield optimal results depending on the forecast time frame; for example, numerical weather predictions (NWPs) are often more accurate for longer horizons, while persistence-based models may excel at shorter intervals. By integrating these forecasts and comparing them with actual measurement data, researchers can more accurately represent the uncertainty that OWFs face.

Wind regime properties vary significantly by location and height, with offshore wind showing nearly twice the forecasting error compared to onshore wind, especially at sites further from the coast and at higher altitudes. Future research should thus include an in-depth examination of how different locations and hub heights impact forecasting uncertainty. This investigation could help forecast the reliability of OWFs sited farther offshore, where conditions are generally less predictable but energy potential is high.

The operational constraints of wind turbines, such as ramp rate limits, yawing speeds, and wake effects, should also be better simulated to assess their impact on forecasting accuracy. These factors influence turbine responsiveness to changing wind conditions and thus contribute to power output variability. Recent studies also suggest that wake effects between adjacent wind farms might be higher than previously assumed, especially as offshore wind deployment increases. A more comprehensive simulation of these constraints would clarify their effect on forecasting error and, subsequently, on market behaviour.

Another important research avenue is to further investigate the bidding behavior of OWFs by incorporating the dynamic formation of price and volume risks, as well as real-time market prices and imbalance penalties. These simulations would enable a deeper understanding of how risk exposure affects OWF profitability, as well as the impact of different trading strategies on system stability. Such studies could also explore various market designs, including those like the HM and AHC approaches, to assess their effectiveness in aligning OWF incentives with grid stability.

6.4.2. Trade-offs between forecasting uncertainty and network congestion

During the literature review, a key trade-off was identified between network capacity and forecasting uncertainty, highlighting an important area for further research. This trade-off could significantly influence the efficiency of market design and operation. Two main aspects of this trade-off warrant closer examination:

First, forecasting uncertainty in production creates a dilemma when allocating interconnector capacity in the day-ahead market. A decision must be made whether to reserve capacity on an interconnector for the potential production of the OWF in the OBZ or to allocate it to other interconnectors that might yield greater social welfare due to flow-based market coupling. While such trade-offs are also present in existing interconnectors and wind farms located within bidding zones, they are likely to be more pronounced in the case of OBZs. This is because all production from the OBZ directly impacts flows over the interconnectors, as the OBZ is positioned between two interconnectors. Future research should quantify the differences in social welfare between day-ahead optimization based on the most accurate forecasts and real-time optimisation based on actual production values. Such investigations should also account for varying levels of renewable energy penetration and network constraints.

Second, there is a trade-off between network capacity and the ability of BRPs to aggregate forecasting errors. The concept of OBZs emerged partly because implicit capacity allocation through market mechanisms prevents network congestion within bidding zones, as interconnector capacity is automatically curtailed via flow-based market coupling. However, this setup prevents BRPs from aggregating the forecasting errors of their geographically dispersed variable generation and demand sources, thereby increasing relative forecasting errors. These larger forecasting errors can lead to greater imbalances or require more cautious positioning by BRPs operating OWFs. Further research should explore this trade-off by quantifying the financial losses BRPs face due to these larger relative forecasting errors and assessing how these losses affect market performance.

By investigating these trade-offs in detail, future studies can provide insights into how to better balance forecasting uncertainty and network congestion in market designs that include OBZs.

7 Conclusion

The increasing costs of connecting wind farms further offshore have led to the development of hybrid interconnectors that serve a dual function: connecting bidding zones and transporting energy generated by offshore wind farms (OWFs) to shore. To address interconnector capacity allocation issues arising from this dual function, the concept of offshore bidding zone (OBZ) was introduced. Since OBZ deviates from some fundamental principles of the electricity market, including the absence of demand, it remains an open question how these deviations impact the real-time balancing of the grid. Specifically, the study reported in this thesis aimed to find out whether BRPs that operate OWFs in an OBZ generate more imbalances than if they would operate in an on-shore bidding zone.

The primary differences between onshore and offshore bidding zones concerning balancing lie in how BRPs manage the uncertain generation of their vRES. In contrast to onshore bidding zones, BRPs in offshore zones cannot use portfolio balancing and over-the-counter contracts, reducing their hedging possibilities and exposing them to greater price and volume risks. Additionally, due to different price formation mechanisms under AHC and the reliance on interconnectors for electricity sales, these risks become even larger. Finally, trade closer to real-time is limited by the gate closure time of the interconnectors, leaving OWF operators with much larger forecasting uncertainties than those in onshore bidding zones.

This gave rise to three questions that will be addressed one by one, leading to an overall conclusion with recommendations.

SQ1: *What is the effect of the greater price and volume risks in an OBZ on the imbalances generated by BRPs operating OWFs in an OBZ?*

The price and volume risks in offshore bidding zones can lead to differences between expected day-ahead (DAH) and intraday prices, resulting in two scenarios: one where intraday prices are expected to be higher than DAH prices, and another where intraday prices are expected to be lower. When intraday prices are expected to be higher, OWFs bid a small amount in the intraday market and wait to sell their electricity in the DAH market. This strategy minimises over-commitment in the DAH market, allowing for more informed decisions with lower forecasting uncertainty in the intraday market. Conversely, when intraday prices are expected to be lower than DAH prices, OWFs tend to overcommit, leading to much larger volumes being bid into the DAH market.

In contrast to scenarios where the DAH and imbalance prices are expected to be equal, these price and volume risks lead to large differences between the volume bid into the DAH market and the volume bid into the intraday market. This means the OWF has to sell or buy more electricity to adjust its position in the intraday market which can lead to larger differences between the intraday and expected balancing prices.

This provides a new perspective on the ongoing discussion around financial transmission rights and transmission access guarantees which are being discussed to mitigate the additional price and volume risks that OWFs in OBZs are exposed to. While the quantitative impact of these mitigation measures on the price and volume risks in OBZs are still being researched, they might potentially impact the amount of imbalances generated by OWFs in OBZs.

Literature indicates that decreased hedging possibilities due to the lack of portfolio balancing, combined with greater price and volume risks under higher uncertainties from wind production, can result in bidding behaviour of BRPs operating OWFs that leads to larger shortages and surpluses of energy. Unlike imbalance surplusses, shortages cannot be simply resolved by the curtailment of wind energy. Transmission System Operators (TSOs) recognise this and believe that reducing gate closure time for trade over interconnectors could mitigate these risks. This raised the next sub-question:

SQ2: *What is the effect of reducing the intraday gate closure time on the imbalances generated by BRPs operating OWFs in an OBZ?*

Reducing the intraday gate closure time from 1 hour to 30 minutes significantly decreases the total volume and maximum amount of shortages, with consistent effects across various simulated price and volume risks. Reducing the gate closure time even further from 30 minutes to 5 minutes further decreases the total and maximum amount of shortages throughout the year.

While reducing the gate closure time decreases the amount of shortages, this comes at the cost of higher amounts of curtailment. However, this effect is quite minimal compared to the reduction in shortages. By reducing the gate closure time from 1 hour to 30 minutes, the total amount of shortages decreases by a factor between 13-20 more compared to the amount of curtailment. Reducing the GCT to only 5 minutes does decrease the amount of shortages in some scenarios, but this decrease is much smaller.

In light of these results, this thesis recommends policymakers to reduce the gate closure time from 1 hour to 30 minutes as this is an effective measure to reduce the amount of imbalance shortages that are created by OWFs, without impacting its volume of curtailment and, thus its business case. As the effect of reducing gate closure time even further to 5 minutes is much smaller this reduction is not recommended outright. Before such an measure should be considered the impact on the operation of the grid should first be assessed.

Furthermore, for an reduced GCT to be effective, large amounts of flexible demand are necessary to ensure ample liquidity in the markets at these short gate closure times. While TenneT might be able to provide incentives for this flexible demand within its own bidding zones, this might be insufficient to make an impact when, for example, OWFs in OBZs can only sell to the other on-shore bidding zones that are connected. Thus, for this policy measure to be effective TenneT also needs to cooperate with other on-shore bidding zones it is connected to.

SQ3: *What is the effect of relative imbalance prices in an OBZ on the imbalances generated by BRPs operating OWFs in an OBZ?*

Compared to a shorter forecasting horizon leading to better predictions, the expected imbalance prices have a strong effect on the amount of imbalances that OWFs generate. In cases where the expected imbalance prices are equal to the intraday prices, shortages make up between 44 and 20 percent of the total production capacity. This shows that while reducing the forecasting horizon is an effective measure to reduce shortages this policy measure alone does not provide the OWFs with the right incentives to reduce their imbalances to an acceptable level.

MRQ: *Will BRPs that operate OWFs in an OBZ generate more imbalances than if they would operate in an on-shore bidding zone?*

This study has shown that the differences between onshore and offshore bidding zones can significantly impact the imbalances, both shortages and surpluses, generated by OWFs. Without the ability to reduce the relative forecasting error or use their own assets to better manage their imbalances, BRPs operating OWFs in an OBZ may generate shortages that can result in higher system imbalances. Financial incentives to reduce these shortages may result in high amounts of surplus curtailment, which will negatively impact the business case for OWFs, and lead to higher costs for consumers.

Reducing the gate closure time so as to reduce the forecasting horizon can be an effective policy measure, but only if the following conditions are met. (1) For a reduced GCT to be effective, large amounts of flexible demand are necessary to ensure ample liquidity in the intraday markets with which the OWFs can adjust their intraday positions. The need for this liquidity can be reduced by mitigating the price and volume risks that OWFs face. This is because the results show that the presence of price and volume risks can lead to higher intraday volumes traded. These findings provide a new perspective on transmission access guarantees and financial transmission rights that are being developed to mitigate these risks for OWF developers. (2) For a reduced GCT to be effective, the imbalance penalties need to incentivise the OWFs to bid as close to their expected production as possible. As shown in the results, the use of separate imbalance prices may provide insufficient incentives for OWFs in OBZs to manage their imbalances in ways that limit the system imbalances. By coupling the imbalance prices in the OBZ with the on-shore bidding zone where the imbalances are transported to makes it possible for OWFs to pool their imbalances, incentivising them to bid their expected power production.

8 Reflection

Completing this thesis has given me an opportunity to reflect on the entire process and recognize both its strengths and areas for improvement. A key strength of my work was implementing the uncertainty of production using SOS (Special Ordered Sets) constraints. This approach allowed for the development of a model that was not only fast but also highly interpretable, accurately accounting for the forecasting uncertainty of wind turbines. I am proud of this particular aspect, as it contributed significantly to ensuring a realistic representation of the wind power generation challenges, which ultimately enhanced the quality of my results.

I must acknowledge that my communication with my supervisors was not as frequent or effective as it should have been. This lack of communication led to delays and ultimately necessitated an extension, causing more difficulty than was necessary. If I could go back, I would prioritize keeping my supervisors updated regularly throughout the entire process, seeking more feedback early on to prevent misunderstandings or misaligned expectations. The challenges I faced as a result of my insufficient communication have been valuable lessons that I will carry forward into future projects, reminding me of the importance of collaborative guidance and timely interaction.

Another key lesson I learned from this experience is the importance of thorough validation and proper documentation throughout the modeling process. In hindsight, I realize that conducting more extensive validation at each stage and documenting these steps more comprehensively would have greatly benefited my work. This would have given me greater confidence in my model and made communication with my supervisors more effective, as I would have had clearer evidence to support my decisions and results. Additionally, more rigorous validation would have helped catch potential bugs and mistakes earlier, preventing them from impacting the later stages of the project. Moving forward, I aim to prioritize validation and documentation to ensure both the robustness of my work and better communication with collaborators.

A

Appendix A: SOS Constraints

A.1. Modeling uncertainty with special ordered sets (SOS)

In wind power generation, the amount of electricity produced depends heavily on wind conditions, which are unpredictable. This uncertainty poses a challenge for an OWFs when deciding how much electricity to bid into the day-ahead (DAH) and intraday (INT) markets. To handle this uncertainty in our optimization model, we use a mathematical technique called special ordered sets (SOS).

A.1.1. Time horizon and sequential decision-making

Our model operates over a full year, consisting of 8760 hours. For each hour t (where $t = 1, 2, \ldots, 8760$), a two stage optimisation is performed. As the OWF moves from the first stage to the second stage the forecasting horizon decreases, thereby reducing the forecasting uncertainty. The final stage only serves to calculate the final imbalance position of the OWF. The stages are as follows:

1. First Stage (Day-Ahead Market): The OWF decides on the bid volume $Q_{\text{DAH},t}$ for the day-ahead market for hour t. At this stage, the uncertainty in wind production is relatively high.

2. Second Stage (Intraday Market): Based on the day-ahead bid $Q_{\text{DAH},t}$, the OWF adjusts its position by deciding the intraday bid volume $Q_{\text{INT},t}$ for the same hour t. After the day-ahead market, updated forecasts reduce the uncertainty in wind production by adjusting the special order sets.

3. Final Stage (Imbalance Calculation): At this stage no more decisions are made. Based on the intraday bid $Q_{\text{INT},t}$ and the actual production $Q_{\text{ACT},t}$ the imbalance position of the OWF is calculated.

A.2. How do special ordered sets work?

Special ordered sets (SOS) are a way to model non-linear relationships within a linear programming framework. They allow the model to approximate a curve (non-linear function) using piecewise linear functions. This approach enables us to model the non-linear relationship between the bid volumes in the market and the expected overproduction or underproduction.

In SOS modeling, we have:

- A set of decision variables α_i that represent weights at specific points along the curve.
- Only two adjacent α_i can be positive (non-zero) at the same time.
- The sum of these two non-zero α_i is equal to 1.

To illustrate this, consider an example where we have a relationship between the bid volume in the day-ahead market (X) and the expected underproduction (Y). The bid volumes are represented as fractions between 0 and 1, corresponding to 0% (minimum production capacity) to 100% (maximum production capacity) of the offshore wind farm (OWF). The data is provided in Table A.1 and visualized in Figure A.1.

Point i	Bid Volume Fraction X_i	Expected Underproduction Fraction Y_i
1	0.00	0.00
2	0.25	0.05
3	0.50	0.15
4	0.75	0.30
5	1.00	0.60

Table A.1: SOS variables for example

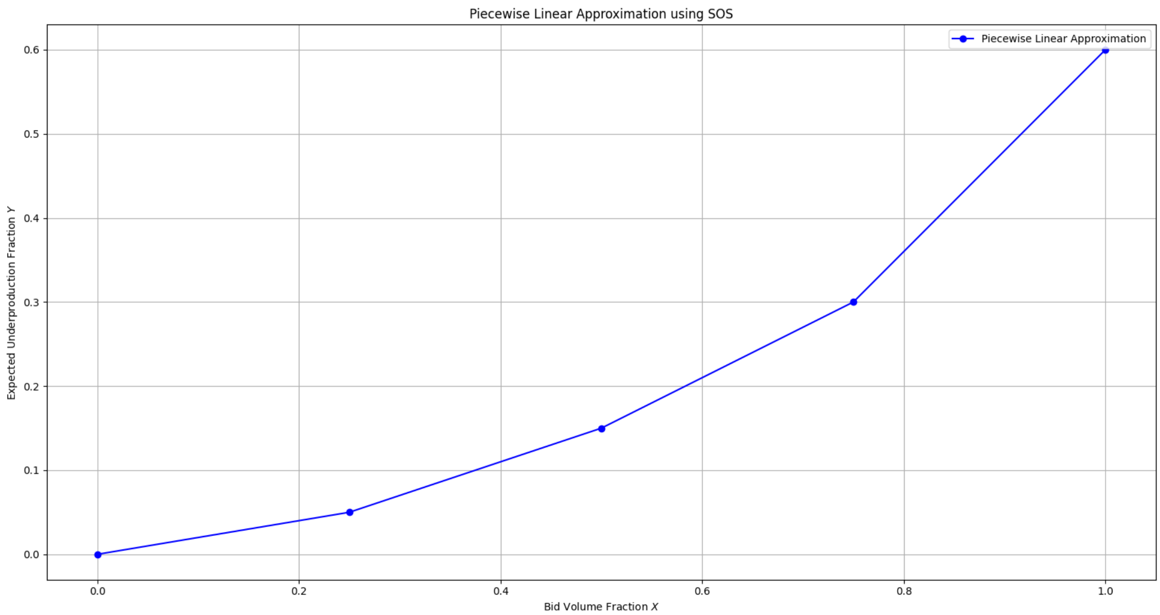

Figure A.1: Graph representing SOS variables

Using the SOS variables α_i, we interpolate between the points to find the bid volume fraction X and the expected underproduction fraction Y as follows:

$$X = \alpha_i X_i + \alpha_{i+1} X_{i+1}$$

$$Y = \alpha_i Y_i + \alpha_{i+1} Y_{i+1}$$

Here, only two adjacent α_i can be non-zero at the same time, and they must satisfy:

$$\alpha_i + \alpha_{i+1} = 1$$

All other $\alpha_j = 0$ for $j \neq i, i+1$.

The bid volume Q_{Bid} and the expected underproduction $EU(v, h, q)$are then calculated using:

$$Q_{\text{Bid}} = Q_{\max} \cdot X$$

$$EU(v, h, q) \; = Q_{\max} \cdot Y(X)$$

Here, Y is a function of X, and the relationship between X and Y is piecewise linear. Specifically, $Y(X)$ is defined in different intervals based on the values of X:

$$Y(X) = \begin{cases} a_1X + b_1 & \text{for } 0 \leq X < 0.25 \\ a_2X + b_2 & \text{for } 0.25 \leq X < 0.5 \\ a_3X + b_3 & \text{for } 0.5 \leq X < 0.75 \\ a_4X + b_4 & \text{for } 0.75 \leq X < 1 \end{cases}$$

By defining $Y(X)$ in this piecewise manner, we explicitly show that the expected underproduction Y is a function of the bid volume fraction X. The piecewise linear functions capture the non-linear relationship between X and Y using linear segments between the data points in Table A.1.

Summary of Variables:

- X is the interpolated bid volume fraction (between 0 and 1).
- Y is the interpolated expected underproduction fraction (between 0 and 1), defined as $Y = Y(X)$.
- Q_{Bid} is the bid volume in megawatt-hours (MWh), calculated as $Q_{\text{Bid}} = Q_{\text{max}} \cdot X$.
- $EU(v, h, q)$ is the expected underproduction in megawatt-hours (MWh), calculated as $EU(v, h, q) = Q_{\text{max}} \cdot Y(X)$.
- Q_{max} is the maximum production capacity of the OWF.

By using the SOS variables α_i and defining $Y(X)$ as a piecewise linear function, we ensure that X and Y correspond to a point on the piecewise linear approximation of the non-linear relationship between bid volume and expected underproduction. This method allows us to capture the non-linearities in the relationship while keeping the model linear and computationally efficient.

A.3. Special ordered sets in the first and second stage decisions

Now that the basic principles of special ordered sets are clear, this section details the full implementation of these special ordered sets in the model. To more accurately represent the non-linear functions that describe the relationship between the bid volumes and the expected underproduction or overproduction, this thesis uses 30 points in the uncertainty set instead of 5 as in the example presented above. Additionally, multiple special ordered sets are used; which one is applied at time step t depends on the forecasting error and mean wind speed associated with that time step.

For each hour t in the model, we define SOS variables $\alpha_{i,t}$ for the day-ahead market and $\beta_{j,t}$ for the intraday market, where $i = 1, 2, \ldots, 30$ and $j = 1, 2, \ldots, 30$ represent the 30 points of each relationship.

Constraints of the SOS Variables:

- $\alpha_{i,t} \geq 0$ for all i, and only two adjacent $\alpha_{i,t}$ can be positive at the same time, summing to 1:

$$\alpha_{i,t} + \alpha_{i+1,t} = 1$$

- $\beta_{j,t} \geq 0$ for all j, and only two adjacent $\beta_{j,t}$ can be positive at the same time, summing to 1:

$$\beta_{j,t} + \beta_{j+1,t} = 1$$

A.3.1. First stage decision (Day-Ahead Market)

In the first stage decision, the OWF aims to maximize its profit in the day-ahead market ($\Pi_{\text{DAH},t}$) while considering the expected costs associated with underproduction and overproduction. For each hour t, the following objective function is maximized:

1. Day-Ahead Market Profit ($\pi_{\text{DAH},t}$)

$$\text{MAX:} \quad \pi_{\text{DAH},t} = Q_{\text{DAH},t}P_{\text{DAH}} + (EO(v_t, h, Q_{\text{DAH},t}) - EU(v_t, h, Q_{\text{DAH},t}))P_{\text{INT}} \tag{A.1}$$

Where $Q_{\text{DAH},t}$, $Q_{\text{UP},t}$, and $Q_{\text{OP},t}$ are functions of the bid volume and are defined using SOS variables:

$$X_t = \alpha_{i,t}X_i + \alpha_{i+1,t}X_{i+1}$$

$$Y_t = \alpha_{i,t} Y_i + \alpha_{i+1,t} Y_{i+1}$$

$$Z_t = \alpha_{i,t} Z_i + \alpha_{i+1,t} Z_{i+1}$$

Then:

$$Q_{\mathrm{DAH},t} = Q_{\max} \times X_t$$

$$EU(v_t, h, Q_{\mathrm{DAH},t}) = Q_{\max} \times Y_t = Q_{\max} \times Y(X_t)$$

$$EO(v_t, h, Q_{\mathrm{DAH},t}) = Q_{\max} \times Z_t = Q_{\max} \times Z(X_t)$$

Here, $Y(X_t)$ and $Z(X_t)$ are piecewise linear functions of the bid volume fraction X_t, capturing the expected underproduction and overproduction fractions, respectively.

Constraints for the SOS Variables:

- $\alpha_{i,t} \geq 0$ for all i.
- Only two adjacent $\alpha_{i,t}$ can be positive at the same time, and they must sum to 1:

$$\alpha_{i,t} + \alpha_{i+1,t} = 1$$

- All other $\alpha_{j,t} = 0$ for $j \neq i, i+1$.

Non-negativity and Capacity Constraints:

$$0 \leq Q_{\mathrm{DAH},t} \leq Q_{\max}$$

$$0 \leq EU(v_t, h, Q_{\mathrm{DAH},t}),\ EO(v_t, h, Q_{\mathrm{DAH},t}) \leq Q_{\max}$$

Variables and Parameters:

- $\Pi_{\mathrm{DAH},t}$ [€]: Profit from the day-ahead market.
- $Q_{\mathrm{DAH},t}$ [MWh]: Bid volume in the day-ahead market.
- $EU(v_t, h, Q_{\mathrm{DAH},t})$ [MWh]: Expected underproduction, a function of $Q_{\mathrm{DAH},t}$.
- $EO(v_t, h, Q_{\mathrm{DAH},t})$ [MWh]: Expected overproduction, a function of $Q_{\mathrm{DAH},t}$.
- P_{DAH} [€/MWh]: Price in the day-ahead market.
- P_{INT} [€/MWh]: Price in the intraday market.
- $Q_{\max}$ [MWh]: Maximum production capacity.
- $\alpha_{i,t}$ [unitless]: SOS variables for the day-ahead market at point i and time t.
- X_i, Y_i, Z_i: Data points for bid volume fractions and expected underproduction and overproduction fractions.
- $i = 1, 2, \ldots, 30$: Index for the breakpoints in the SOS approximation.

A.3.2. Second stage decision (Intraday Market)

In the second stage decision, the OWF adjusts its position based on updated forecasts. The goal is to maximize profit in the intraday market ($\Pi_{\mathrm{INT},t}$) by adjusting the bid volume while considering the expected costs associated with underproduction.

2. Intraday Market Profit ($\Pi_{\mathrm{INT},t}$)

$$\text{MAX:} \quad \pi_{\mathrm{INT},t} = (Q_{\mathrm{INT},t} - Q_{\mathrm{DAH},t})P_{\mathrm{INT}} - EU(v_t, GCT, Q_{\mathrm{INT},t} - Q_{\mathrm{DAH},t})P_{\mathrm{SP}} \tag{A.2}$$

Where $Q_{\mathrm{INT},t}$ and $Q_{\mathrm{DAH},t}$ are functions of the bid volume in the intraday market and are defined using SOS variables:

$$X_t^{\mathrm{INT}} = \beta_{j,t}X_j + \beta_{j+1,t}X_{j+1}$$

$$Y_t^{\mathrm{INT}} = \beta_{j,t}Y_j + \beta_{j+1,t}Y_{j+1}$$

Then:

$$Q_{\mathrm{INT},t} = Q_{\max} \times X_t^{\mathrm{INT}}$$

$$EU(v_t, GCT, Q_{\mathrm{INT},t} - Q_{\mathrm{DAH},t}) = Q_{\max} \times Y_t^{\mathrm{INT}} = Q_{\max} \times Y(X_t^{\mathrm{INT}})$$

Constraints for the SOS Variables:

- $\beta_{j,t} \geq 0$ for all j.
- Only two adjacent $\beta_{j,t}$ can be positive at the same time, and they must sum to 1:

$$\beta_{j,t} + \beta_{j+1,t} = 1$$

- All other $\beta_{k,t} = 0$ for $k \neq j, j+1$.

Non-negativity and Capacity Constraints:

$$0 \leq Q_{\mathrm{INT},t} \leq Q_{\max}$$

$$0 \leq EU(v_t, GCT, Q_{\mathrm{INT},t} - Q_{\mathrm{DAH},t}) \leq Q_{\max}$$

Variables and Parameters:

- $\Pi_{\mathrm{INT},t}$ [€]: Profit from the intraday market.
- $Q_{\mathrm{INT},t}$ [MWh]: Bid volume in the intraday market.
- $EU(v_t, GCT, Q_{\mathrm{INT},t} - Q_{\mathrm{DAH},t})$ [MWh]: Expected underproduction in the intraday market, a function of $Q_{\mathrm{INT},t}$ and $Q_{\mathrm{DAH},t}$.
- $Q_{\mathrm{DAH},t}$ [MWh]: Bid volume in the day-ahead market for hour t (as defined in the first stage).
- P_{INT} [€/MWh]: Price in the intraday market.
- P_{SP} [€/MWh]: Shortage penalty price.
- $Q_{\max}$ [MWh]: Maximum production capacity.
- $\beta_{j,t}$ [unitless]: SOS variables for the intraday market at point j and time t.
- X_j, Y_j: Data points for bid volume fractions and expected underproduction fractions.
- $j = 1, 2, \ldots, 30$: Index for the breakpoints in the SOS approximation.

A.4. Summary of SOS constraints

By optimizing the day-ahead bid first and then adjusting the intraday position based on the day-ahead bid, the sequential decision-making process of the OWF is accurately modeled. The reduction in forecasting uncertainty between these two time steps is captured by using different uncertainty sets for the SOS variables. The SOS variables for the day-ahead ($\alpha_{i,t}$) are based on the broader uncertainty in wind

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