Energy Economics 144 (2025) 108316

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Coordinated bidding in sequential electricity markets: Effects of price-making

Kim K. Miskiw [a,*], Emil Kraft [b], Stein-Erik Fleten [c]

[a] Karlsruhe Institute of Technology (KIT), Institute for Information System and Marketing (IISM), Karlsruhe, Germany
[b] Karlsruhe Institute of Technology (KIT), Institute for Industrial Production (IIP), Karlsruhe, Germany
[c] Norwegian University of Science and Technology (NTNU), Department of Industrial Economics and Technology Management, Trondheim, Norway

ARTICLE INFO

JEL classification:
C61
C63
D44
Q40
Q41
L94

Keywords:
Balancing reserve market
Coordinated bidding
Electricity markets
Multi-market trading
Multi-stage stochastic programming
Uncertainty

ABSTRACT

As the uncertainty and time granularity of short-term electricity markets increase and as intraday trading gains importance, deriving good trading decisions becomes increasingly complex. This paper analyses the potential benefit of coordinating bids in three sequential electricity markets using a three-stage stochastic optimisation. The modelled markets include a typical European market setting consisting of a balancing reserve, a day-ahead, and an intraday market. Due to limited intraday market liquidity, the trading strategies also take price impacts into account. The results indicate that coordinated bidding can increase profitability, with the extent of gains depending on the price impacts. In a case study with a biomass and photovoltaic portfolio operating in Germany, we find that coordinated bidding increases the average revenue by around 18% over all analysed type days. As renewable generation continues to increase, trading strategies that coordinate bids across markets are expected to become increasingly important.

1. Introduction

In recent years, the share of intermittent renewable energy generation in the European power system has increased, introducing greater uncertainty and volatility into electricity markets. To address this uncertainty, the markets have adapted, successfully maintaining the balancing requirements at a stable level (Koch and Hirth, 2019). Among other market adaptations, the temporal granularity increased, with a trend towards around-the-clock, real-time trading (Kraft et al., 2023). Notably, the Intraday Market (IDM) plays a significant role in absorbing uncertainty from renewable energy sources, leading to a high increase in liquidity and traded volumes (SE, 2022a). While the Day-Ahead Market (DAM) was traditionally the most important electricity auction, the IDM is catching up in importance (Kraft et al., 2023).

As the IDM becomes increasingly important relative to the DAM, the need for a profit-maximising bidding strategy that accounts for the interdependencies of profit opportunities across consecutive electricity markets grows (Vardanyan, 2016; Ottesen et al., 2018; Wozabal and Rameseder, 2020). This is especially true since bidding decisions in each market sequentially influence the others (Klæboe et al., 2022). Additionally, the growing proportion of renewable energy sources within the system alters their representation in the power plant portfolios of market participants. This introduces new challenges for participants in dealing with the inherent quantity uncertainty in portfolios. Combined with the market interdependencies, this leads to a new role of the market participants. Stochastic coordinated bidding addresses these interconnections by considering multiple uncertainties across sequential markets. In contrast, deterministic bidding heuristics — also known as separate, sequential, or myopic bidding — focus solely on individual markets without accounting for such interdependencies (Klæboe et al., 2022). Hereafter, we will refer to these heuristics as myopic bidding heuristics.

Stochastic coordinated bidding models the interdependencies and increased uncertainty by defining bidding strategies using multi-stage stochastic optimisation. However, this approach requires more computational resources and modelling effort compared to myopic bidding heuristics. Quantifying these benefits of coordinated bidding helps electricity producers to decide which methods they should focus on to

* Correspondence to: Chair for Information and Market Engineering, Institute for Information System and Marketing (IISM) at Karlsruhe Institute of Technology (KIT), 76131 Karlsruhe, Germany.
E-mail address: kim.miskiw@kit.edu (K.K. Miskiw).

https://doi.org/10.1016/j.eneco.2025.108316
Received 22 June 2023; Received in revised form 20 October 2024; Accepted 9 February 2025
Available online 25 February 2025
0140-9883/

enhance their dispatch and trading decisions, as discussed by Aasgård (2022). For a power plant operator, the difference in the contribution margin between coordinated and myopic bidding strategies — commonly referred to in the literature as the gain of coordinated bidding — is particularly relevant (Klæboe et al., 2022; Löhndorf and Wozabal, 2022). Studies on bidding strategies that speculate on spot market price differences indicate high gains from coordination are possible in certain cases (Löhndorf and Wozabal, 2022). Incorporating the IDM into bidding strategies significantly affects these benefits, as suggested by previous research (Boomsma et al., 2014; Narajewski and Ziel, 2022). As the IDM's relevance and liquidity continue to grow, the advantages of coordinated bidding are expected to increase. Thus, the literature shows growing interest in coordinated bidding, as we discuss further in the next section. However, a research gap persists regarding the benefits of coordination, particularly for three-stage market settings with increasingly liquid short-term trading (Ottesen et al., 2018) and case studies that reflect the increasing uncertainty in power plant portfolios, including renewable generation.

This work contributes the following points to the literature. In a typical European market setting comprising spot and reserve markets, it:

- quantifies the effect of price impacts in selected markets, thus enhancing the analysis of limited liquidity in the context of coordinated bidding across three markets (balancing reserve market, day-ahead, and intraday market),
- analyses determined strategies and the differences in the revenue structure obtained from coordinated and myopic bidding, both with and without price impacts considered,
- sheds light on the emerging coordinated bidding strategies for the new role of generation portfolios (biomass and Photovoltaic (PV)) exposed to limited liquidity as well as price and quantity uncertainty,
- captures the effects of the recent surge in renewables' penetration, its implied uncertainty, and the increased importance of intraday trading in a case study for the German electricity market.

The rest of this work is structured as follows. First, the literature body is examined in Section 2. Afterwards, Section 3 introduces the model and how the different markets and the price impact are specified. Following that, Section 4 presents the case study used for the analysis. The results of the case study are presented in Section 5, followed by a discussion in Section 6. Section 7 concludes with a summary and an outlook.

2. Literature review

The short-term operational optimisation problems in electricity markets can be distinguished into the optimal dispatch problem (also known as the unit commitment problem) and the optimal bidding/trading problem. Much of the literature on these topics takes a deterministic approach, disregarding the impact of uncertainty (Kraft et al., 2023).

Recent studies have typically examined single revenue streams within liberalised electricity markets in isolation, a limitation highlighted by Löhndorf and Wozabal (2022) and Klæboe et al. (2022). In contrast, this paper presents a selection of the most relevant papers dealing with multi-stage, stochastically optimised bidding and dispatch decisions in sequential electricity markets from the perspective of a single market participant. For additional literature reviews, see Mazzi et al. (2018) and Finnah et al. (2022).

The studies under consideration exhibit variations in market settings. Some investigate a two-stage model encompassing the DAM and the realisation stage, as in Castillo et al. (2015). Others, like Heredia et al. (2018), expand to a three-stage model that also includes the IDM, the Automatic Frequency Restoration Reserve (aFRR), and imbalance settlements. While these studies focus on optimal bidding behaviour in sequential market setups, only a few of the current studies quantify the gain of coordinated bidding, as pointed out by Ottesen et al. (2018) and Ayón et al. (2017). The studies that quantify the gain of coordination find that it varies highly across different markets and regions. For instance, a gain of coordination of 1% is observed in the Scandinavian market (Kongelf et al., 2019), and 20% in the Spanish market (Wozabal and Rameseder, 2020), respectively. These variations are attributed to differences in market design and liquidity, for example, of the IDM, as stated by Löhndorf and Wozabal (2022).

In line with this finding, the model specifications, and especially the price impact resulting from the market liquidity, require careful analysis. Kraft et al. (2023) show coordinated bidding strategies for a portfolio comprising one PV and biomass power plant with 100 MW each in the aFRR market, the DAM and IDM. They conclude that the optimal bidding strategy often takes an open position in the DAM, speculating on higher IDM prices. However, this model assumes that the market participant has no price impact, a simplification that overlooks the effect of a bid on the market price. Conversely, several studies emphasise the significance of price impact on optimal bidding strategies and, by extension, the gain of coordinated bidding (Finnah et al., 2022; Narajewski and Ziel, 2022).

Such a price impact can be incorporated by modelling the limited liquidity of different markets. In literature, the price impact is implemented as a negative linear relation between the bid volume and price, which is estimated with historical time series. Plazas et al. (2005) apply this approach to the balancing market, Boomsma et al. (2014) to both the spot and balancing markets, and Löhndorf and Wozabal (2022) to continuous trading on the IDM. An alternative approach is employed by Steeger et al. (2018). Here, the effect is not modelled solely by a linear relation but by the step-wise drop-out of different competitors' bids. Although this modelling approach is possible because of the high data availability in the German market setting, it does require significantly higher modelling detail and complexity.

To the best of our knowledge, there are neither studies analysing the gain of coordinated bidding for three consecutive markets of a common European market framework, nor do they also integrate a price impact depiction in the market setup. The focus on modelling price effects and establishing a benchmark narrows the scope of relevant literature to the list in Table 1. Yet, none of these studies explores a three-stage market setting that includes two spot markets alongside an ancillary market. Moreover, only the study by Löhndorf and Wozabal (2022) examines the German market, considering price impacts in the IDM. They analyse a battery and two hydro storages but do not capture the technical characteristics of dispatchable power plants or the portfolio's quantity uncertainty introduced by volatile renewable infeed. Consequently, their findings are more applicable to a different market participant role than the one we investigate. Löhndorf and Wozabal (2022) report a coordination gain of up to 28% for different storage types, whereas our analysis indicates a gain of approximately 18% for the specific days considered.

3. Method

The subsequent sections outline the approach for modelling sequential electricity markets. First, we detail the representation of the markets and their uncertainty. Next, this section introduces two strategies for bidding within these markets: myopic and coordinated. Finally, we discuss how a price impact can be incorporated.

3.1. Modelling sequential electricity markets

The European power market comprises a multitude of different markets. There is the possibility of trading electricity over-the-counter or on exchange markets. Fig. 1 illustrates a simplified timeline of the latter. In general, a distinction can be made between the provision of

Table 1
Overview of the literature dealing with coordinated bidding in multiple electricity markets.

Source	Modelled markets				Model Specifications	
	DAM	IDM	Ancillary	Market area	Technologies considered	Price impact
Löhndorf and Wozabal (2022)	x	x		Germany	Pumped hydro and battery storages	IDM
Plazas et al. (2005)	x		AGC, BM	Spain	Thermal power plant	BM
Boomsma et al. (2014)	x		BM	Norway	Hydro power plant	DAM + BM
This work	x	x	aFRR	Germany	Biogas, PV	IDM

aFRR = Automatic Frequency Restoration Reserve, AGC = Automatic Generation Control, BM = Balancing Market, DAM = Day-Ahead Market, IDM = Intraday Market, PV = Photovoltaic.

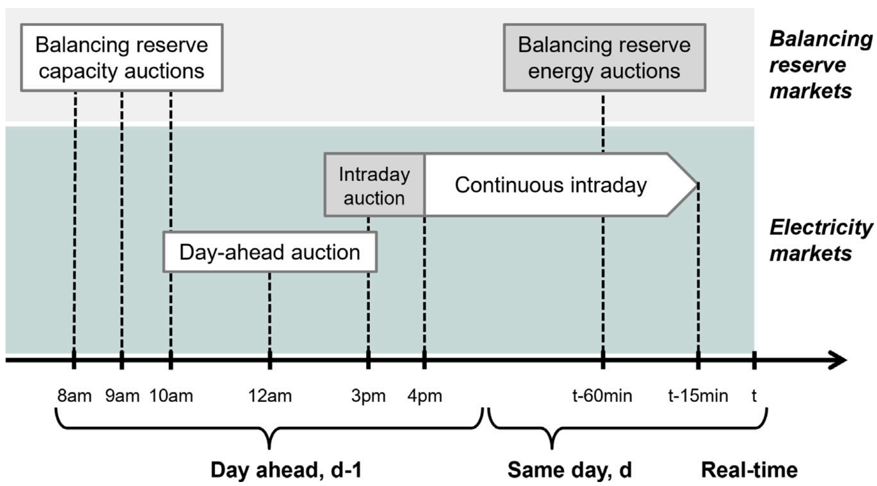


Fig. 1. Sequence of markets for electricity and balancing reserve with gate-closure times for the German market design (following Kraft et al., 2023). The modelled markets are marked with white boxes.

reserve (grey shaded background), which is used to balance the system, and electricity (teal shaded background).

The first auction of the day is for the capacity of the balancing reserve market. Here, several auctions take place for three products with different lead times. Participants in these auctions need to be pre-qualified beforehand. These providers bid a price and volume to reserve capacity for positive and/or negative adjustments. The bids can be made for six four-hour time slices and are auctioned via pay-as-bid by 10 a.m. every day. The capacity allocated in the balancing reserve market is obligated to be immediately accessible for ramp-up at the Transmission System Operator's request. Consequently, offering reserve to the Transmission System Operator is a binding obligation. Afterwards, the day-ahead auction takes place at 12 a.m. for the next day. Here, the energy delivery for the 24 h of the next day is traded with an hourly resolution and settled with a uniform pricing scheme. Closest to delivery is the IDM, where trading in hourly, half-hourly and quarter-hourly resolution takes place. The IDM can be divided into a start auction at 3 p.m. and the subsequent continuous market, where products can be traded up to 30 min before delivery. Unlike the balancing reserve market, a market participant can take long and short positions in the DAM since they can be closed by a respective counter trade in the IDM. Deviations from the commitments on the modelled markets, namely imbalances, are penalised with different pricing mechanisms. Following this auction, an energy auction takes place for the activation of the balancing reserve.[1]

From this timeline, we choose the market setup visualised with differently shaded boxes in Fig. 1. This choice is motivated by the rising interest in markets with shorter lead times. It includes a balancing reserve market with separate positive and negative power products, a DAM, and a continuous IDM. For the balancing reserve market, we only consider the capacity auction and focus on aFRR. Hence, we further use the specific product aFRR when referring to the balancing reserve market. We focus on the capacity auction only since the energy auction can be seen as an independent opportunity for generating more revenue and does neither impose risk nor a restriction on the other trading decisions in the DAM or IDM. Moreover, the participation in the energy auction does not require successful participation in the capacity auction (Kraft et al., 2023). We focus on the continuous IDM, given its increased trading volume in the last years compared to the start auction. Between 2022 and 2023, the traded volume on the continuous IDM rose by 30%, while the volume traded on the German intraday start auction only increased by 8% (SE, 2022b, 2024). The appeal of the continuous IDM lies in its ability to take advantage of price fluctuations by adjusting positions multiple times up to delivery. However, we aim to illustrate the interdependencies between the modelled markets. When deciding on DAM or aFRR bids one day in advance, the sequential release of information in continuous trading can hardly be anticipated. Therefore, we model the continuous market as a single hypothetical auction, reflecting the ID3 price (SE, 2022b). This is a simplification. Yet, it aligns with standard abstractions in the literature (Kraft et al., 2023). The following section explains how the model addresses uncertainty in the chosen markets.

3.1.1. Gradual disclosure of information

Within the presented market timeline, market participants face numerous uncertainties when deciding how much electricity to offer in each spot market and how much capacity to reserve for aFRR. These uncertainties stem from unpredictable renewable energy infeeds and fluctuating market prices, leading to risks in both price and quantity. Given the sequential nature of the market setup, information is revealed over time. Fig. 2 illustrates the availability of information at each bidding decision further denoted as stages. The timeline of bidding decisions on these stages is indicated below the time axis, while the upper part visualises the information availability.

[1] The energy auction only takes place for two of the three reserve products, as frequency containment reserve is activated automatically simultaneously for all providers from the capacity reserve auction.

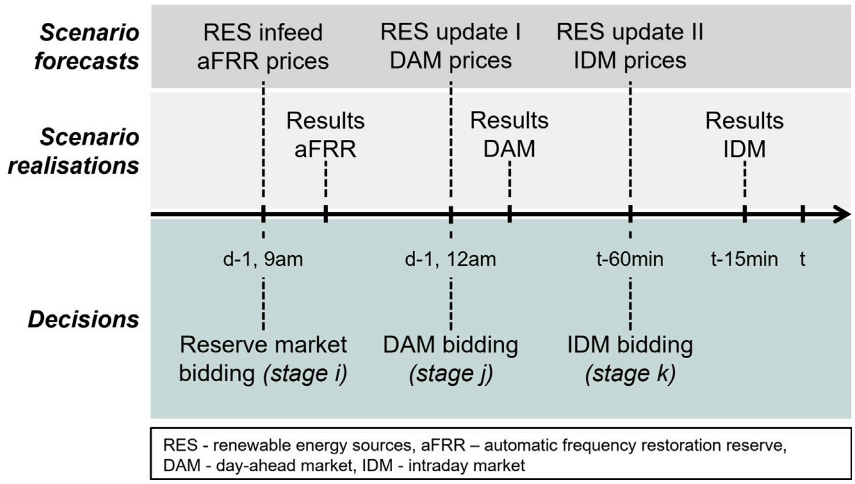


Fig. 2. Timeline of information availability (above time axis) and decision-making (below time axis) of the multi-stage decision problem and its translation to modelled stages (following Kraft et al., 2023).

The initial stage decision i relies on information that is available at the beginning of the day (before 9 a.m.), including Renewable Energy Source (RES) infeed and aFRR price forecasts. The following decision at stage j then considers aFRR market results from the clearing process, as well as updated renewable infeed forecasts and DAM price forecasts. Finally, the stage k decision incorporates the new updates about the DAM results, the renewable infeed, and IDM price forecasts.[2] For stage i the uncertainty of e.g., the aFRR prices, is represented as the discrete scenario realisations $i_l \in I = \{i_1, \dots, i_L\}$, for stage j as $j_m \in J = \{j_1, \dots, j_M\}$, and for stage k as $k_n \in K = \{k_1, \dots, k_N\}$. Thereby, l, m, and n index the scenarios within each stage. These scenarios collectively form a scenario tree and represent the finite probability space, Ω. For simplicity, any further references to scenarios across stages i, j, and k will use the notation $(i, j, k) \in \Omega$.

The underlying uncertainty in prices and quantities necessitates representing potential outcomes across various scenarios. The construction of the scenarios $(i, j, k) \in \Omega$ follows Russo et al. (2022) and Kraft et al. (2023). The discrete scenario realisations are quantified based on historical realisations of the prices and the renewable generation. In general, we generate multiple scenario trees for which we each fit an additive time series model and one for the stochastic residuals for all three stages. Individual models are fitted for weekends, weekdays, and seasons. Following Russo et al. (2022), we further distinguish between three PV generations and corresponding residual load levels based on initial clustering results. This results in 18 additive time series and stochastic residual models, each generating a separate scenario tree. Within one scenario tree, all stages use the same deterministic components of the additive time series models and, hence, depend on each other. Regarding the stochastic component, we assume independence of the second stage (j) from the first stage (i), indicating that the outcomes of aFRR prices do not affect DAM prices. We make this assumption due to the relation of the trading volume (2 GW aFRR market (regelleistung.net, 2022), 26 GW DAM (SE, 2020)) and the diverging technology mixes on the markets that leads to potential different price setting units. On the contrary, we assume a dependence between the stochastic component of the DAM and IDM prices. These and other market-specific uncertainty modelling lead to the following distinction between the stages.

For the first stage i, the additive time series model comprises a logarithmic regression based on the following fundamental variables: the product's mean seasonal price, the day-ahead PV generation forecast, the day-ahead residual load forecast, and the price of the previous day's auction for the product. The stochastic residuals not explained by the fundamental variables in the logarithmic regression are further simulated by applying a mean-reverting process with jump regimes (Keles et al., 2012). With this mean-reverting process, we simulate the stochastic residuals 1000 times. The resulting prices are then reduced using k-means clustering. Through the k-means clustering process, we derive ten clusters for the aFRR prices, thereby considering ten discrete scenario realisations for stage i.

The second stage, labelled as stage j, addresses the uncertainty in DAM prices. This uncertainty arises primarily from two factors: potential changes in the forecasts of renewable energy generation and load between the closing times for aFRR (9 am, day-1) and the DAM (12 am, day-1) and the DAM's inherent stochastic nature. The third stage, denoted as stage k, updates the forecast for renewable generation and load based on conditional expectations in relation to stage j, leading to a revised forecast of the residual load. Our approach to modelling the impact of changing residual load forecasts on DAM and IDM prices focuses on three main sources of uncertainty: solar power generation variability, the stochastic nature of the residual load, and the inherent uncertainty in day-ahead and IDM prices. To account for these interdependencies, we extend the methodologies of Keles et al. (2012) using multivariate mean-reverting processes and stochastic differential equations based on empirical data and Monte Carlo simulations as detailed in Kraft et al. (2023). The prices from the Monte Carlo Simulation are reduced by assuming a standard deviation from which two distances from the mean are symmetrically drawn, resulting in five discrete price scenarios for stage j and k. The transition between stages in the model incorporates conditional expectations to ensure consistency and avoid arbitrage across scenarios.

The combination of ten discrete scenarios in i and five discrete scenario for j and k results in 250 scenario paths per scenario tree. For each of the discrete scenarios the different prices $y^{\text{aFRRpos}}_{i,ts}$, $y^{\text{DAM}}_{j,h}$, and $y^{\text{IDM}}_{j,k,qh}$ are defined. Based on these prices, the binary acceptance parameters for bids are defined respectively. The distinct modelling of bidding decisions in these markets is described in the following sections.

3.1.2. Balancing reserve auctions

Addressing the aFRR market's design presents a challenge in formulating the trading problem, given that pay-as-bid pricing inherently involves both price and volume as decision variables. To avoid nonlinear relationships in the optimisation problem, we use the following approach. The modelling of uncertainty results in discrete aFRR price

[2] Please note, we do not model the uncertainty between the second RES update and the realisation of the renewable infeed.

values for both positive $y_{i,ts}^{\text{aFRRpos}}$ and negative $y_{i,ts}^{\text{aFRRneg}}$ directions for each aFRR price scenario i. The bid volume $x_{lp,i,ts}^{\text{aFRRpos,bid}}$ and $x_{ln,i,ts}^{\text{aFRRneg,bid}}$ (MW) at different discrete price levels ($lp \in LP$ or $ln \in LN$) become the decision variables for positive (negative) aFRR bidding. Similar to the specification in Kraft et al. (2023), the discrete price levels equal the predefined price levels in each scenario, as the optimisation has no incentive to bid between two scenario price levels in a uniform price auction. We define them for all four-hour time slices $ts \in TS$. This approach allows us to construct a bidding curve with volumes at various $|LP|$ or $|LN|$ price levels for each aFRR product.

A bid is accepted and hence traded if the price level $y_{lp,i,ts}^{\text{aFRRpos,bid}}$ at which it is placed lies below the realised market price $y_{i,ts}^{\text{aFRRpos}}$. This is captured by a binary acceptance variable $\beta_{i,lp,ts}^{\text{aFRRpos,bid}}$, as shown in (1). Based on the acceptance of a bid, the expected revenue ρ_i^{aFRRpos} can be calculated, as shown in (2). The pay-as-bid remuneration for aFRR is accounted for by including the price level $y_{lp,ts}^{\text{aFRRpos,bid}}$ of the bid in the revenue. Hence, the expected revenue is calculated considering the probability pr_i of the discrete scenario i and summed up over all four-hour time slices ts and price levels lp.

$$\beta_{i,lp,ts}^{\text{aFRRpos,bid}} = \begin{cases} 1, & \text{if } y_{lp,i,ts}^{\text{aFRRpos,bid}} \le y_{i,ts}^{\text{aFRRpos}} \quad \forall i, ts \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$\mathbb{E}_{i\in\Omega}\left(\rho_i^{\text{aFRRpos}}\right) = \sum_{i=1}^{I} pr_i \sum_{ts=1}^{TS} \sum_{lp=1}^{LP} \left(y_{lp,ts}^{\text{aFRRpos,bid}} \beta_{i,lp,ts}^{\text{aFRRpos,bid}} x_{lp,i,ts}^{\text{aFRRpos,bid}}\right). \tag{2}$$

3.1.3. Spot market auctions

In contrast to bidding for aFRR, the DAM and the IDM are modelled using a uniform pricing mechanism. In this context, $y_{j,h}^{DAM}$ and $y_{j,k,qh}^{IDM}$ represent the uniform prices in the DAM and IDM for the respective hourly $h \in H$ and quarter-hourly $qh \in QH$ resolution. Although the DAM and IDM have different time resolutions and stage dependencies, the modelling for both markets is equivalent. We further present the formulation for the IDM. The respective equations for the DAM can be found in Appendix A.

The decision variables for the IDM include the bid volume $x_{lid,i,j,k,qh}^{\text{IDM,gen,bid}}$ on discrete price levels $lid \in LID$. This formulation allows the submission of a bid curve with volumes at various price levels lid for each quarter hour qh. Unlike the aFRR auction, the spot markets allow for open positions in the DAM that must be closed in the IDM. Therefore, in addition to the generation bid, we introduce the decision variables $x_{lid,i,j,k,qh}^{\text{IDM,long,bid}}$ and $x_{lid,i,j,k,qh}^{\text{IDM,short,bid}}$ for the IDM as well as for the DAM. A market participant's short volume corresponds to the energy that has been sold and is not planned to be generated with the underlying asset. Conversely, long volume refers to additional energy bought at the respective stage. The acceptance of these bids is modelled using the binary acceptance variable $\beta_{lid,j,k,qh}^{IDM}$ for the respective price levels ldi, as shown in (3) to (5). The volume of long and short trades is limited to a fixed percentage $q^{\text{short/long}}$ of the capacity of the underlying portfolio, which is set to 10%. The overall traded volume on the IDM in scenario realisation j, k comprises the accepted generation offers $x_{i,j,k,qh}^{IDM,gen,trade}$ as well as short $x_{i,j,k,qh}^{IDM,short,trade}$ and long positions $x_{i,j,k,qh}^{IDM,long,trade}$ of the trader, see (6).

$$x_{i,j,k,qh}^{\text{IDM,gen,trade}} = \sum_{lid=1}^{LID} \beta_{lid,j,k,qh}^{\text{IDM}} x_{lid,i,j,k,qh}^{\text{IDM, gen,bid}} \tag{3}$$

$$x_{i,j,k,qh}^{\text{IDM,long,trade}} = \sum_{lid=1}^{LID} \left(1 - \beta_{lid,j,k,qh}^{\text{IDM}}\right) x_{lid,i,j,k,qh}^{\text{IDM, long,bid}} \tag{4}$$

$$x_{i,j,k,qh}^{\text{IDM,short,trade}} = \sum_{lid=1}^{LID} \beta_{lid,j,k,qh}^{\text{IDM}} x_{lid,i,j,k,qh}^{\text{IDM,short,bid}} \tag{5}$$

We model the realised price in the IDM endogenously across different scenarios $y_{j,k,qh}^{IDM}$, whereby j and k indicate the path through the scenario tree, namely the realisation of the DAM and IDM. The revenue $\rho_{i,j,k}^{\text{IDM}}$ can be calculated as the product of the traded volume $x_{i,j,k,qh}^{IDM,trade}$ with the uniform clearing price $y_{j,k,qh}^{\text{IDM}}$ and the respective probabilities of the scenarios in the IDM (pr_k) and DAM (pr_j) of those prices summed up over all quarter hours qh (7).[3]

$$x_{i,j,k,qh}^{\text{IDM,trade}} = x_{i,j,k,qh}^{\text{IDM,gen,trade}} + x_{i,j,k,qh}^{\text{IDM,short,trade}} - x_{i,j,k,qh}^{\text{IDM},long,\text{trade}} \tag{6}$$

$$\mathbb{E}_{(i,j,k)\in\Omega}\left(\rho_{i,j,k}^{\text{IDM}}\right) = \sum_{i=1}^{I} pr_i \sum_{j=1}^{J} pr_j \sum_{k=1}^{K} pr_k \sum_{qh\in QH} \left(y_{j,k,qh}^{\text{IDM}} x_{i,j,k,qh}^{\text{IDM, trade}}\right). \tag{7}$$

3.1.4. Self-dispatch

After the IDM clearing, all market commitments are known, and the dispatch of the portfolio must be formulated. This consolidates all preceding stages, ensuring that market commitments in aFRR, DAM, and IDM are met while accounting for all technical constraints of the power plants. Most notably, the open positions between the DAM and IDM must be closed. Otherwise, the market participant faces imbalances. In the current market design in Germany, imbalances are penalised with an imbalance price. Theoretically, speculating on this price is possible but forbidden in the German market. Hence, we penalise imbalances with a sufficiently high factor, ensuring the optimised solution entirely avoids them.

For the technical constraints, we distinguish between renewable energy power plants $res \in RES$ and conventional power plants $u \in U$. For example, we enforce maximum and minimum capacity constraints limiting the dispatch. In the case of a renewable plant res, the maximum capacity is constrained by the available renewable infeed. To ensure the market participant can fulfil the aFRR commitment, the power plant must be able to ramp up within minutes. Since the start-up time is longer, the power plant must already be running. Furthermore, the maximum ramping capabilities must accommodate the changes from the IDM, DAM and traded aFRR products. Most notably, the potential activation of the reserved aFRR capacity still needs to be technically feasible. In summary, self-dispatch is subject to a variety of constraints. These constraints are detailed in Appendix B.

3.2. Determination of bidding strategies

A power plant operator typically aims to maximise expected profits across all markets, considering all potential scenarios $(i, j, k) \in \Omega$. Thus, the objective is to maximise the contribution margins, denoted as $\pi_{i,j,k}$, comprising the profits ρ_i^{aFRR}, $\rho_{i,j}^{\text{DAM}}$, and $\rho_{i,j,k}^{\text{IDM}}$ as introduced before as well as the respective imbalance and dispatch costs $\kappa_{i,j,k}^{\text{Imb}}$, and $\kappa_{i,j,k}^{\text{var}}$, for each of the three modelled auctions. The methods for solving this optimisation problem differ based on the extent of foresight used when making bidding decisions—specifically, how many future stages are taken into account. In the following section, we describe two distinct approaches.

3.2.1. Myopic bidding heuristic

The first approach for defining a bidding strategy in sequential electricity markets is a myopic heuristic. In this approach, decisions are made with limited foresight, often neglecting future revenue streams or only partially considering them. One widely used myopic heuristic, implemented by Plazas et al. (2005), Kongelf et al. (2019), Klæboe et al. (2022), and Löhndorf and Wozabal (2022), is sequential bidding. This method is characterised by a greedy optimisation process, which maximises immediate rewards by considering scenarios from only one stage at a time. Other notable approaches include a deterministic benchmark, as presented by Plazas et al. (2005), or models assuming perfect foresight, such as those by Ottesen et al. (2018) and Keles and

[3] The probability of the aFRR scenario is not included here since scenarios at stage i and j are independent from each other (cf. Section 3.1.1).

Dehler-Holland (2022). We follow the literature by implementing a sequential approach, dividing the model into three separate optimisations. At each stage, only the contribution margin from the market being cleared is included in the objective function, and the subsequent markets are not considered.

For the first cleared market in stage i, this approach would cause solely adding up the revenue ($\rho_i^{\text{aFRRpos}}, rho_i^{\text{aFRRpos}}$) of the positive and negative aFRR. However, this modelling needs to be adjusted regarding the first stage. Capacity reservation is only feasible if the power plant is dispatched in the spot market (cf. Section 3.1.4). Thus, a heuristic must combine the immediate revenue maximisation with some indication of the spot market in the first stage. To address this, we adopt a combination of the sequential bidding approach with the expected spot market prices ($y_{i,h}^{\text{DAM}} = \mathbb{E}_{(j)\in\Omega} y_{j,h}^{\text{DAM}}$), following the deterministic solution proposed by Plazas et al. (2005), as shown in (8). Consequently, both the revenue ρ_i^{DAM} and the bid $x_{lda,i,h}^{\text{DAM,gen,bid}}$ from the DAM are included in the first-stage objective.[4] It is important to note that such a heuristic represents a lower bound for bidding strategies.

$$\text{stage 1:}\ \max \mathbb{E}_{(i)\in\Omega}\left(\pi_i\right) = \mathbb{E}_{(i)\in\Omega}\left(\rho_i^{\text{aFRR}} + \rho_i^{\text{DAM}} - \kappa_i^{\text{var}}\right). \tag{8}$$

The second optimisation takes the aFRR bids $x_{lp,i,ts}^{\text{aFRRpos,trade}}$ and their corresponding acceptance as given, and optimises the day-ahead bids $x_{i,j,h}^{\text{DAM,trade}}$ for all day-ahead scenarios, without considering the IDM (see (9)).

$$\text{stage 2:}\ \max \mathbb{E}_{(i,j)\in\Omega}\left(\pi_{i,j}\right) = \mathbb{E}_{(i,j)\in\Omega}\left(\rho_{i,j}^{\text{DAM}} - \kappa_{i,j}^{\text{var}} - \kappa_{i,j}^{\text{Imb}}\right). \tag{9}$$

In the final optimisation stage, both the aFRR and day-ahead dispatches are treated as fixed input parameters, and the IDM bids $x_{i,j,k,qh}^{\text{IDM,trade}}$ are optimised accordingly. The objective function for this stage focuses solely on maximising intraday profits (see (10)).

$$\text{stage 3:}\ \max \mathbb{E}_{(i,j,k)\in\Omega}\left(\pi_{i,j,k}\right) = \mathbb{E}_{(i,j,k)\in\Omega}\left(\rho_{i,j,k}^{\text{IDM}} - \kappa_{i,i,k}^{\text{var}} - \kappa_{i,j,k}^{\text{Imb}}\right). \tag{10}$$

3.2.2. Coordinated bidding

In contrast to the myopic approach, coordinated bidding takes into account the entire time horizon of auctions within a single day, aiming to maximise the expected contribution margin across all stages. This is shown in (11).

$$\begin{aligned}&\max \mathbb{E}_{(i,j,k)\in\Omega}\left(\pi_{i,j,k}\right)\\ &= \mathbb{E}_{(i,j,k)\in\Omega}\left(\rho_i^{aFRR} + \rho_{i,j}^{DAM} + \rho_{i,j,k}^{IDM} - \kappa_{i,j,k}^{\text{var}} - \kappa_{i,j,k}^{\text{Imb}}\right).\end{aligned} \tag{11}$$

This objective function now encompasses all stages, eliminating the need for sequential execution at each stage. However, to find meaningful bidding strategies that represent realistic information availability, decisions must remain consistent across consecutive stages. To ensure this consistency, non-anticipativity constraints are incorporated into the model formulation according to the information relations. Therefore, (12) and (13) are defined to ensure consistency for the aFRR bids throughout all $i \in I$, as well as for the bids on the DAM ($j \in J$). $Ord(.)$ is defined as the ordinal number of an element in its set and $|.|$ as the cardinality of the set.

$$.x_{lp,i,ts}^{\text{aFRRpos,bid}} = x_{lp,i+1,ts}^{\text{aFRRpos,bid}} \quad \forall lp, \{i|\,\text{Ord}(i) < |I\,|\},\ \text{ts} \tag{12}$$

$$x_{lda,i,j,h}^{\text{DAM,bid}} = x_{lda,i,j+1,h}^{\text{DAM,bid}} \quad \forall lda, i, \{j|\,\text{Ord}(j) < |J\,|\}, h. \tag{13}$$

In addition, we calculate the outcomes for a purely financial trader employing a coordinated bidding strategy. In this case, instead of optimising the operation of the power plant itself, we focus solely on bid strategies for long and short trades in the two spot markets, namely the IDM and the DAM. From a modelling perspective, this approach sets the capacity constraints P_u^{U} and P_{res}^{RES} to zero while still allowing $x_{lid,i,j,k,qh}^{\text{IDM,long,bid}}$ and $x_{lid,i,j,k,qh}^{\text{IDM,short,bid}}$ to represent $q^{\text{short/long}}$ percentage of the non-zero capacities (cf. Section 3). Please note that for the myopic heuristic, there is no need to evaluate a financial trader, as the stage-wise optimisation provides no incentives for utilising short or long positions.

3.3. Relaxation of price-taker assumption

A price impact, also referred to as market impact or price-making effect, occurs when the execution of a large order affects the price of the underlying asset. In contrast, for a price-taker, the offer volume is assumed to be so small relative to the overall market volume that it does not influence the price level (Almgren and Chriss, 2001; Gatheral and Schied, 2013). Assuming price-taking overestimates the contribution margin, particularly in markets with limited liquidity (Narajewski and Ziel, 2022). We incorporate a price impact into our model to assess how it would affect the gains from coordinated bidding.

In the context of stochastic optimisation problems in electricity markets, Vardanyan (2016) distinguishes between models with endogenous and exogenous price formation. The former naturally includes a price impact as they use, for example, a residual demand model like Baringo and Conejo (2016) for depicting the market clearing process. Building on the market modelling previously described, the methods available for specifying price impacts are limited to those that treat price formation exogenously. In line with the literature (cf. Section 2), we implement a linear representation of the price impact. Although this is a simplification, Narajewski and Ziel (2022) demonstrate that it still improves the modelling of bidding strategies in markets.

The price-taker assumption is valid for highly liquid markets where many participants exist and individual bidders have low market shares (Klæboe and Fosso, 2013; Boomsma et al., 2014). Therefore, integrating the price impact in less liquid markets with fewer participants is a more reasonable assumption, as the influence of a single bidder is expected to be higher. Only a modest volume is typically offered in the balancing market and for aFRR due to the high technical restrictions for participation and the relatively low potential revenue (Kraft et al., 2023). However, the relative share of balancing revenues compared to spot market revenues does not justify extensive modelling of the price impact for aFRR. Moreover, the price impact for the balancing market can hardly be captured with a linear impact approach and deserves a separate study (Kath and Ziel, 2020). Instead, we focus on modelling the price impact in the spot markets. Nowadays, more than three times the energy is traded in the DAM compared to the IDM in SE (2022a). Thus, considering the price impact in the IDM is expected to have a greater effect than in the DAM. Nonetheless, Narajewski and Ziel (2022) show that the price impact in the DAM is also important for higher volumes. Since both auctions are modelled as uniform price auctions, implementing the price impact is similar for both. Here, we present the formulation for the IDM.

Following the chosen method, we present an implementation of the impact of bids on the realised market price in the spot markets. Rather than considering only $y_{j,k,qh}^{\text{IDM}}$ in the revenue equation, the linear price impact must be subtracted. The new revenue from the IDM is specified

[4] Due to the variation of the potential generation of renewables over the day-ahead scenarios described in Section 3.1.1, the potential to offer renewables to provide aFRR to zero. Otherwise, infeasibilities occur when the aFRR dispatch is planned with their average potential and a scenario with a lower one is realised at the second stage.

in (14), where the impact factor b_{qh} is considered.[5]

$$\mathbb{E}_{(i,j,k)\in\Omega}\left(\rho^{\mathrm{IDM}}_{i,j,k}\right) = \sum_{i=1}^{I} pr_i \sum_{j=1}^{J} pr_j \sum_{k=1}^{K} pr_k \sum_{qh=1}^{QH}\left(y^{\mathrm{IDM}}_{j,k,qh} - b_{qh} x^{\mathrm{IDM,trade}}_{i,j,k,qh}\right) x^{\mathrm{IDM,trade}}_{i,j,k,qh}. \quad (14)$$

The formulation in Eq. (14) results in a quadratic function. To limit the calculation time, the need for linearisation arises. In accordance with Plazas et al. (2005) this function is linearised without using binary variables. The respective equations and visualisation can be found in Appendix C.

4. Case study

The chosen market setup is representative for the typical market structure in most European countries. A specific country, namely Germany, is selected for the exact lead times and products, because of the high availability of data. The following sections present the constructed case study based on the outlined method.

4.1. Data and implications

To parameterise the model, both the scenario tree must be constructed, and the price impact factors must be estimated. The former is based on the work of Kraft et al. (2023), who derived scenarios using German market data from July 2019 to March 2020. This period was chosen due to the stability of the balancing reserve market rules. Price data for the balancing reserve market are published by regelleistung.net (2022), while IDM and DAM prices are available from the EEX group (2018) and are used to parameterise the price risk. Additionally, the renewable energy forecast and its updates, along with historical load profiles are sourced from ENTSO-E (2022). The portfolio analysed in this study comprises one biomass and one PV power plant, each with a capacity of 100 MW. The technical characteristics of the portfolio are listed in Appendix B. These two technologies were chosen for three main reasons. First, their variable costs fall within the range of observed market prices; thus, the plant changes from being inframarginal to marginal and extra-marginal, depending on the realised scenario. Second, the combination of one controllable and one intermittent electricity source allows us to assess the impact of both price and quantity risks, which are modelled here. Finally, the portfolio can provide up- and downward regulation for aFRR.

4.2. Quantification of the price impact

The price impact factors are derived following the modelling approach outlined in Section 3.3. Linear impact factors, b_{qh} for the IDM and b_h for the DAM, are estimated from historical time series data. The time horizon spans from July 2019 to March 2020, consistent with the period used for the uncertainty specification. To derive the impact factors, all bids in the respective auctions (DAM and IDM) are ranked in ascending order by price. As elaborated in Section 3.3, we do not model the price impact for aFRR. A linear function is then fitted to the ordered bid data, and the slope is determined using linear regression with ordinary least squares.

Day-ahead Auction. In this auction, the historic prices used for the regression correspond to a subset of all offers made in the day-ahead auction. The historic prices cover a wide range from −500 EUR/MWh to 3000 EUR/MWh. In contrast, the discrete bid levels $lda \in LDA$, defined for the different type days, only range between 0 EUR/MWh and 63 EUR/MWh. Including all submitted bids would significantly distort the expected price impact within the actual bidding range lda. Moreover, in pay-as-cleared auctions, bidders generally have an incentive to bid in line with their marginal costs. For the portfolio under consideration, these costs fall within the aforementioned range. Therefore, the regression is performed only on bids within the interval defined by the minimal and maximal discrete bidding levels (0 EUR/MWh to 63 EUR/MWh). Based on these prices, we perform the linear regression to derive b_h. All determined coefficients are significant at a significance level of 0.01. However, the average price impact is small, namely below 0.01 EUR/MWh/MWh. This price impact is contextualised with results from Kraft et al. (2023). For instance, for one type day, the bid volume in the DAM is around 60 MW, leading to a price difference of 0.6 EUR/MWh. This corresponds to a percentage difference of 1.5% of the average DAM price, which we argue is negligible. Therefore, to avoid an unnecessarily high computational burden, we focus on the price impact in the IDM and do not account for price-making effects in the DAM within this case study.

Intraday Auction. As stated before, we model the IDM as one uniform price auction where the ID3 price for quarter-hourly products is realised. In line with this assumption, only historical bids contributing to the ID3 price index are considered when deriving the impact factor. It should be noted that this only includes offers that successfully found a counterparty. A similar assumption is made by Löhndorf and Wozabal (2022). Contrary to the consideration of the DAM, all bids are considered here. Firstly, all the historic bids are close to the discrete bid levels. Secondly, in a pay-as-bid auction, the bidder tries to anticipate the bid of the highest successful offer, which levers out the argumentation of restricting the bids. With this historic price data, we perform the linear regression to derive b_{qh}. Of the 26,000 performed regressions, all determined b_{qh}, but four are significant (p-value below 0.01). Further analysis of subsets did not reveal substantial differences in the slopes for distinct type days and the quarter hours within one hour. However, as illustrated in Fig. 3, the slopes vary substantially across delivery hours. To account for this intra-daily variability, we consider 24 different coefficients, using the mean values of all identified coefficients. These are visualised with red triangles in Fig. 3.

5. Results

This section presents the results of the previously described case study. The problem is formulated in GAMS and solved using the CPLEX MILP solver. The solver settings include a parallel mode with 36 threads and a relative optimality criterion of 0.01. The computations are performed on a machine equipped with an Intel Xeon Gold 6248R processor and 64 GB of RAM. Depending on the type day, the optimisation for the portfolio setup is completed within two to four hours. We start the presentation of the results with a comparison between the myopic and coordinated bidding consideration, which defines the gain of coordinated bidding (Section 5.1 and is illustrated in Fig. 4(a)). Following this, the price impact is introduced, demonstrating how its exclusion tends to overestimate the gains from coordinated bidding strongly (see Section 5.2 and Fig. 4(b)). The results are all presented for one modelled type day, namely a weekday in the transition season with a medium residual load. This type day is chosen because it has a prominent trade-off between different markets and is, hence, especially suitable for visualising the effects of the modelling approaches. Finally, the found gain of coordination is reported for additional type days, and the influence of considering purely financial trades is discussed.

5.1. Bidding strategies under coordinated and myopic approaches

First, the bidding strategies without considering the price impact are analysed, as visualised in Fig. 4(a). On the one hand, the figure shows the empirical cumulative distribution of the contribution margins achieved across all markets (black line). The modelled scenarios are sorted by their overall contribution margin and displayed

[5] This modelling assumes that the market participant is new in the market, as the bid is not yet accounted for in the modelled price $y^{IDM}_{j,k,qh}$ from the historical setting. For an alternative approach, see Narajewski and Ziel (2022).

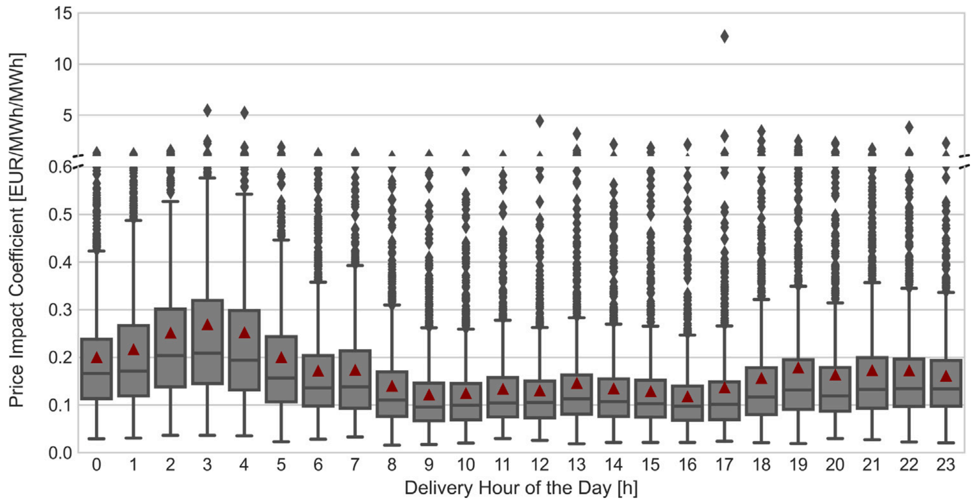


Fig. 3. Boxplots of the derived coefficients for price impact, distinguished by the delivery hour, with the average impact factor shown as a red triangle. The impact coefficient is highest during the night hours and lowest during the midday peak.

according to their cumulative occurrence probability. The black dotted lines summarise the empirical cumulative distribution by showing the average contribution margin over all scenarios. On the other hand, the respective individual realisations of the contribution margin in each market, which collectively sum to the overall contribution margin, are plotted as coloured points. The strategies determined through the use of coordinated and myopic bidding differ strongly. The head and tail of the distribution of the contribution margin overall markets in Fig. 4(a) covers a considerably lower range in myopic bidding compared to coordinated bidding. While myopic bidding maximises the contribution margin in the early auctions, coordinated bidding takes open positions in the DAM and speculates on higher prices in the IDM. This behaviour can be explained by focusing on the markets individually.

Spot Markets. The extraordinarily high and low contribution margins in the coordinated bidding case (4(a), right graph) are caused by building up a long position in the DAM (buying electricity) in expectation of particularly high prices in the IDM. Hence, the optimised bidding strategy often leads to a negative contribution margin in the DAM (green points) because energy is bought. Hence, the strategy for the IDM (red points) includes selling energy at almost any price to close the position, generating high profits or losses. In contrast, such behaviour cannot be observed in the myopic bidding case (4(a), left graph). Since the individual contribution margin is maximised at each stage, no taking of long or short positions can be observed. Consequently, the contribution margin in the DAM is higher and relatively stable compared to the coordinated case. This, however, leads to less revenue opportunities in the IDM when using the heuristic. In most scenarios, the contribution margin achieved in the IDM falls within the range of the positive aFRR market. In a few cases, it exceeds the DAM's contribution margin, which shapes the upper end of the distribution.

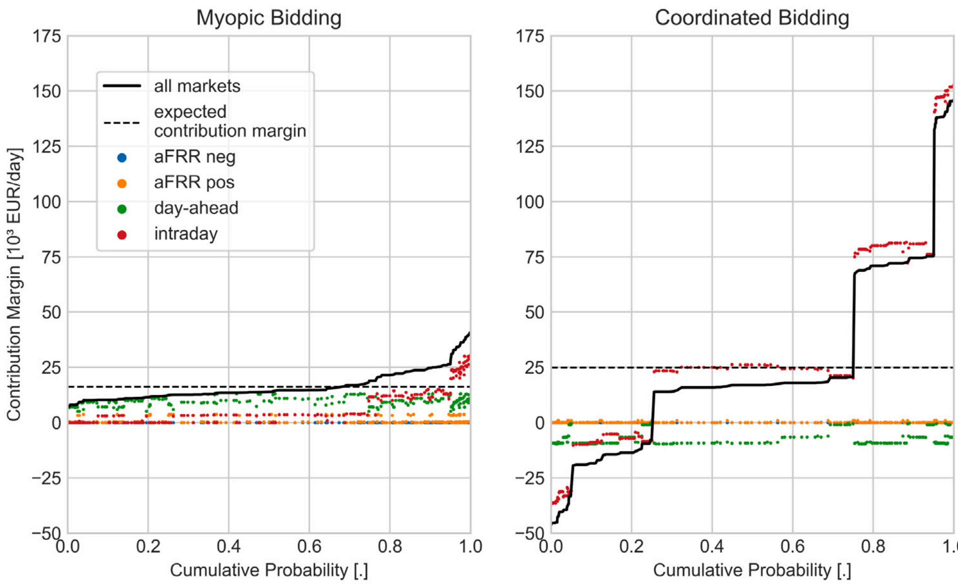
Reserve Markets. Furthermore, the contribution margin generated by the aFRR bids (orange and blue points) is barely visible in Fig. 4(a) and contributes little to the overall contribution margin compared to the spot markets. Considering them in the market setup is nevertheless vital, as they may impose technical restrictions on spot market bidding. In the bidding strategy of the myopic heuristic, a difference between positive and negative aFRR bidding can be observed. Positive aFRR bids directly compete with revenue opportunities in the spot markets. Since the achievable contribution margin on the spot markets is often similar or higher, only bids for very high price levels (i.e., bids with low acceptance probability) are placed for positive aFRR. In the case of an (unlikely) acceptance, they yield a high contribution margin, as visible in the few isolated points deviating from zero. Offering negative aFRR does not compete with selling that electricity on the spot markets. As a result, bids for negative aFRR are more evenly distributed across price levels, leading to a more flattened and less significant contribution margin. In the coordinated case, however, it becomes evident that the achievable contribution margin in the aFRR markets is overshadowed by revenue opportunities in the spot markets, leading to fewer bids and a smaller contribution margin in the aFRR reserve markets.

These differences in the distributions also influence the average contribution margin over all scenarios that can be achieved in the markets, which is illustrated by the black, dotted, horizontal line in Fig. 4(a). The coordinated bidding approach yields a contribution margin of 24,930 EUR/day on the depicted type day, whereas the myopic bidding strategy only achieves an average contribution margin of 16,230 EUR/day. This results in a percentage increase of 35%. Compared to the coordinated approach, the myopic strategy simplifies the trading problem and fails to exploit all revenue opportunities. As a result, the coordinated bidding approach proves to be highly beneficial. This comparison visualises the high revenue opportunities the IDM presents and the speculation on it compared to the DAM. However, the coordinated approach carries greater risk, as seen in the distribution function's shape.

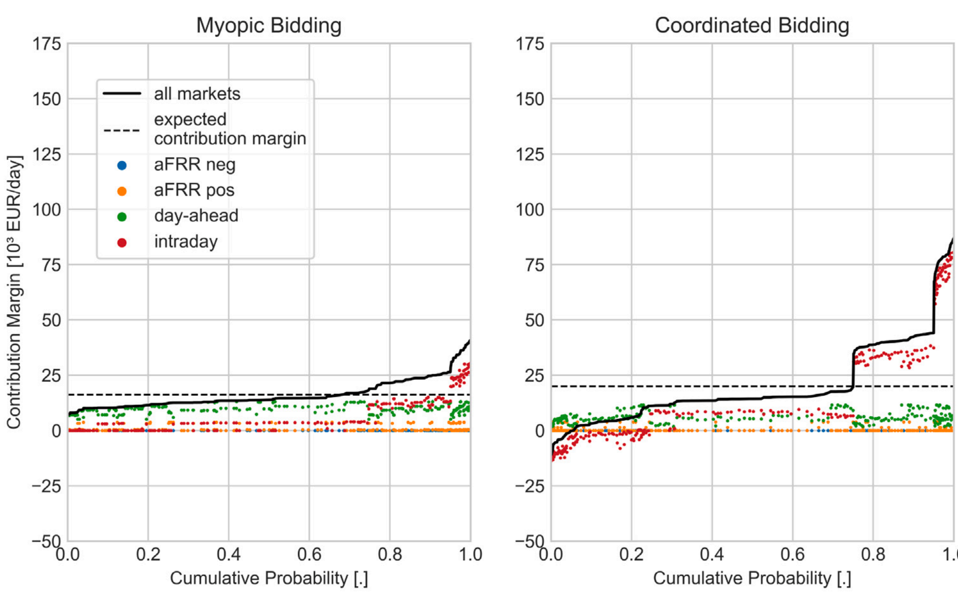
5.2. Relaxation of the price-taker assumption

The difference between coordinated and myopic bidding presented in the previous subsection is likely overestimated, as a high portion of the generation volume is bid into the IDM. Consideration of the price impact in the IDM should dampen the benefits of speculative behaviour, thereby putting the results into perspective. Fig. 4(b) illustrates the effect of considering price-making. The comparison of the myopic bidding heuristic without (Fig. 4(a)) and with (Fig. 4(b)) a price impact shows that it only has a modest impact on the myopic bidding strategy. Under this bidding strategy, a significant portion of the contribution margin is generated in the DAM, which remains unaffected by the price impact modelling. Only the profits in the IDM are affected, slightly reducing the average contribution margin made in this market.

In contrast, considering the price impact has a sound effect on the resulting profits in the coordinated bidding case, as illustrated in the right graph in Figs. 4(b) and 4(a). It becomes apparent that the extreme cases are less pronounced when the price impact is considered, and the individual realisations are more dispersed. The trader anticipates the price impact on the IDM, which reduces the attractiveness of speculating on IDM prices. Hence, the trader offers more volume in the DAM. However, open positions in the DAM and subsequent selling in the IDM are still observed as a trading strategy. Yet, not to an extent where



(a) Price Taking.



(b) Price Making.

Fig. 4. Empirical cumulative distribution function of the contribution margin of all markets and their sum for the developed myopic bidding heuristic (left) and the coordinated bidding approach (right).

it overshadows the revenue from selling in the DAM. Moreover, the reduced attractiveness of the IDM leads to more bidding for aFRR than in the coordinated case without a price impact consideration. The share of expected contribution margin achieved with aFRR in comparison to the overall expected contribution margin increases from less than 0.5% to 2.8%, respectively.

Thus, including price-making reduces the differences between myopic and coordinated bidding strategies. The coordinated strategy still benefits from some speculation in the IDM, resulting in a more pronounced head and tail of the distribution. These differences are apparent in a lower overall expected contribution margin of 20,230 EUR/day (black horizontal line). The gain equals a profitability increase of 21%, which is much lower than in the price-taking case, underscoring the importance of accounting for price-making.[6] As sensitivity runs show, the difference between coordinated and myopic bidding would be further reduced for a bigger portfolio with a consequently even higher price impact.

5.3. Gain of coordination and its seasonal dependency

The previous section explained the different bidding strategies and their underlying mechanisms for a specific type day. In this section, we present the gain of coordination for all type days with a medium residual load level. Table 2 presents the average contribution margin

[6] These results are also presented in the Table 2 in Section 5.3.

Table 2
Quantification of the Contribution Margin (CM) and the gain of coordinated bidding for all type days with a medium residual load scenario and a consideration of the price impact.

Season	Residual load level	Day of week	Average CM myopic bidding [EUR/day]	Average CM coordinated bidding [EUR/day]	Gain of coordination [EUR]	Gain of coordination [.]	Gain of financial coordination [.]
Summer	Medium	Weekday	32,072	35,094	3022	0.09	0.01
Summer	Medium	Weekend	13,701	16,685	2983	0.18	0.01
Transition	Medium	Weekday	15,962	20,151	4189	0.21	0.03
Transition	Medium	Weekend	n/a	n/a	n/a	n/a	n/a[a]
Winter	Medium	Weekday	8341	14,805	6464	0.44	0.05
Winter	Medium	Weekend	7887	12,153	4265	0.35	0.01

[a] These values are denoted n/a as the technical restrictions of the biomass power plant lead to an unprofitable dispatch.

achieved with both the coordinated and myopic bidding strategies, taking the price impact into account. We further present the ratio from the gain of coordination that is also achieved by a purely financial trader without an underlying asset.

It should be noted that the general contribution margin achieved by the evaluated portfolio varies strongly depending on the type day. With the coordinated bidding strategies, revenues of up to 35,000 EUR/day can be achieved. However, on some days, the price level is so low that no profitable dispatch is possible, like on a weekend in the transition season. These differences originate from the different demand and renewable generation patterns during the seasons. For example, on a weekend day in summer, the considered portfolio is more often infra-marginal on the spot markets. Therefore, the described rationale for the aFRR bids intensifies so that no bids for positive aFRR are made due to the competition with spot market revenues. However, since a profitable dispatch on the spot market is often possible, many successful bids on negative aFRR are placed. In comparison, on a weekday in winter, we observe a similar pattern as on the in-depth analysed transition season weekday for the aFRR market. Yet, we observe less successful long bids on the DAM.

The gain of coordination is then calculated as the difference between the average contribution margin achieved with the coordinated and myopic bidding strategy. Contrary to the average contribution margin, the calculated absolute gain of coordination across all seasons is comparably stable. It is around 3500 EUR/day and stems from the difference described in the trading strategies. This indicates that the benefit of the coordination, like exploiting the differences between the IDM and DAM, is relatively constant overall type days as well. Consequently, the relative gain of coordinated bidding is lower for days in which the overall contribution margin is high compared to the average one overall type days. Considering the probability of each of the considered type days, the overall relative gain of coordinated bidding in this case study with 18 type days lies at 18%.[7]

Furthermore, the coordination gain achieved by a financial trader without an underlying asset is quantified in relation to the average contribution margin in the coordinated bidding case. Compared to the average contribution margin of coordinated bidding with the entire portfolio, the gain of coordination yielded by the financial trader alone is relatively low. It reaches a maximum of just 5% of the contribution margin on a winter, medium-load weekday. On this particular type day, the total coordination gain reaches 44%, leaving at least 39% attributed to the coordination of the underlying portfolio. The financial trader, as discussed in Section 3.2, can only take financial long and short positions, limiting participation to the spot markets and excluding aFRR. The relatively small contribution margin from the financial trader suggests that exploiting price differences in the spot markets contributes less to the overall gain of coordination than the actual coordination of the underlying portfolio.

[7] The probabilities for the occurrence of each season and day can be calculated straight forward from the days. The different residual load levels are equally probable according to the scenario derivation in Russo et al. (2022).

6. Discussion

Overall, the results show a strong impact of coordinated bidding compared to myopic heuristics, extending beyond the mere financial exploitation of spot market price differences. We show how market interdependencies and the inherent uncertainty of a portfolio with a high share of renewables influence the chosen bidding strategy. Consequently, this introduces new challenges and roles for the bidding of market participants. The commitments taken in the early stages of the market increase the risk of imbalances due to diverging renewable generation forecasts. Especially given the limited liquidity of the IDM, the price impact of the own bid is not negligible. This results in a shift towards earlier market stages, despite the poorer availability of information. Even with the current level of liquidity in the IDM, price expectation differences across market stages can still be strategically exploited. While this can increase profits, it also inherently carries a higher level of risk. Our analysis demonstrates that this potential for exploitation will increase with IDM liquidity, opening the door to new bidding strategies in the future. These analyses shed light on the upcoming dynamics in bidding and how they might shift in light of increased IDM liquidity.

Against the background of the efficient market theorem, our finding regarding exploiting price expectations is not intuitive. For instance, Narajewski and Ziel (2022) conclude that there is limited profit potential for trading between the DAM and IDM. However, our results, along with findings from other studies on coordinated bidding, show that the information discrepancy between market segments exists and can indeed be exploited (Löhndorf and Wozabal, 2022). When considering unevenly distributed information and physical production characteristics, such as start-up costs, markets are not always perfectly efficient, thereby leaving room for portfolio optimisation (Fleten et al., 2018).

While the model aims to reflect the current market design as realistically as possible, and the methodological improvements in this work further serve that purpose, some simplifications remain. As mentioned, our approach necessitates collapsing continuous intraday trading into a single hypothetical auction. By doing so, this work cannot capture the repositioning throughout continuous trading and hence does not reflect the complete profit potential of the IDM. Therefore, the gain of coordination might be even higher if this profit is depicted and could be successfully anticipated one day ahead. In our analysis, we focus exclusively on quarter-hourly products within the IDM. The quarter-hourly products allow for adapting the hourly DAM commitments to the power plants' modelled ramping. Further imbalances are also calculated in 15-min intervals, which makes balancing the generation and market commitments in this interval necessary. However, it is important to note that the IDM also provides hourly and half-hourly products. Incorporating the hourly and half-hourly products into our model would likely result in a mixture of products on the IDM. Analysing portfolios with different cost structures would provide further insights into the gain of coordination. It is expected to be lower for portfolios with substantially smaller or larger costs than market prices. The technology compositions of this study were explicitly chosen to inherit a trade-off between the markets as their marginal costs lie close to the market prices. As the importance of real-time trading and, hence, of the IDM increases, the price impact may decrease in the future. Similarly, the increase in renewable energy leads to higher volume and, consequently, price uncertainties. These future developments should be further analysed, but they play into the strengths of coordinated bidding.

7. Conclusion and outlook

Market participants are confronted with an increasingly complex market design, necessitating more sophisticated bidding strategies. To perform well in the current electricity market setting, a bidding strategy for a power plant portfolio must account for all available revenue opportunities and their associated uncertainty. This type of bidding behaviour is referred to as stochastic coordinated bidding. Despite its relevance, the electricity trading literature often focuses on sequential and deterministic strategies.

Building on a previous study and its preliminary findings, this study illustrates coordinated bidding under uncertainty in a three-stage market setting and compares it to myopic heuristics. This contributes to informing power plant owners about whether to pursue coordinated bidding in common European electricity markets, considering the dynamics of intraday trading liquidity as well as price and quantity uncertainty. In this study, we analyse one balancing reserve market with separate products for positive and negative reserve followed by two sequential spot markets: the day-ahead and intraday market. A three-stage scenario tree is used to represent the uncertainty of market prices, renewable infeed and demand. In line with the literature, this work includes a price-maker effect to model the liquidity of the intraday market (Finnah et al., 2022).

The analysis suggests that assuming a high intraday market liquidity, modelled as neglecting the potential price impact of one's own bids, leads to a high attractiveness of the intraday market relative to the day-ahead market. A coordinated bidding approach exploits revenue opportunities between the day-ahead and the intraday market by taking open positions in the day-ahead market. In contrast, the bidding strategies found by the myopic heuristic shift electricity offers to earlier market stages, particularly from the intraday to the day-ahead market. While accounting for price-making reduces the gain of coordinated bidding, it still strongly increases revenue. The majority of the gain can be accounted to the coordination of the actual asset, as an analysis of the share of the gain of coordinated bidding that can be achieved with a purely financial trader shows. Given the expansion of renewable generation, which leads to heightened uncertainty and more liquid intraday markets, coordinated bidding is expected to become increasingly important in the future.

Based on the proposed methods, conclusions regarding the dependencies of coordinated bidding for market participants evaluating their individual portfolios can be derived. However, the relative gain strongly depends on the portfolio composition, particularly its cost structure, compared to market price levels. Future research should analyse these findings for different portfolios and under various market circumstances to shed more light on the gain of coordinated bidding and enable generalised conclusions.

Nomenclature

Symbol	Description	Unit
i, j, k	Stages of decision-making under uncertainty	–
$i_l \in I = \{i_1, \dots, i_L\}$	Discrete scenario realisations for stage i	–
$j_m \in J = \{j_1, \dots, j_M\}$	Discrete scenario realisations for stage j	–
$k_n \in K = \{k_1, \dots, k_N\}$	Discrete scenario realisations for stage k	–
Ω	Finite probability space combining all scenarios across stages i, j, k	–
$u \in U$	Set of modelled conventional units	–
$res \in RES$	Set of modelled renewable energy source units	–
$lp \in LP, ln \in LN$	Discrete price levels for positive and negative aFRR bids	–
$lda \in LDA$	Discrete price levels for DAM bids	–
$lid \in LID$	Discrete price levels for IDM bids	–
$ts \in TS$	Four-hourly time slices	–
$h \in H$	Hourly time slices	–
$qh \in QH$	Quarter-hourly time slices	–
B	Number of linearisation intervals	–
$m \in [0, 1, 2, \dots, B]$	Set of position in piecewise linearisation	–
$\pi_{i,j,k}$	Overall contribution margin in all markets	EUR
pr_i	Probability of scenario i	–
pr_j	Probability of scenario j	–
pr_k	Probability of scenario k	–
$\phi^{\mathrm{DAM}}_{qh,res}$	Renewable availability factor for DAM	–
$\phi^{\mathrm{IDM}}_{k,qh,res}$	Renewable availability factor for IDM	–
short/long	Maximum ratio of short and long position in relation to the portfolio's capacity	–
P^{U}_u	Installed capacity of conventional unit u	MW
P^{RES}_{res}	Installed capacity of renewable unit res	MW
ΔP^{U}_u	Maximum load change of biomass unit	MW
$\Delta P^{\mathrm{RES}}_{res}$	Maximum load change of PV within five minutes	MW
$v^{\mathrm{min/max}}_u$	Minimum and maximum daily generation of biomass	–
b_{qh}	Price impact factor in IDM	EUR/MW
$T^{\max}$	Maximum bid amount (generation capacity)	MW
$\rho^{\mathrm{aFRRpos}}_i$	Expected revenue from positive aFRR bids	EUR
$\rho^{\mathrm{IDM}}_{i,j,k}$	Revenue from IDM trades	EUR
$\rho^{\mathrm{DAM}}_{i,j}$	Revenue from DAM trades	EUR
$\kappa^{\mathrm{var}}_{i,j,k}$	Variable costs resulting from the dispatch of the portfolio	EUR
$\kappa^{\mathrm{imb}}_{i,j,k}$	Imbalance costs resulting from open positions of the portfolio	EUR
κ^{var}_u	Variable costs of conventional generation	EUR/MWh
$y^{DAM}_{j,h}$	Uniform price in the DAM for hourly resolution	EUR/MW
$y^{IDM}_{j,k,qh}$	Uniform price in the IDM for quarter-hourly resolution	EUR/MW

$y^{\text{aFRRpos}}_{i,ts}$	Positive aFRR price scenario for stage i	EUR/MW
$y^{\text{aFRRneg}}_{i,ts}$	Negative aFRR price scenario for stage i	EUR/MW
$y^{\text{aFRRpos,bid}}_{lp,i,ts}$	Positive aFRR bid price at discrete price level lp	EUR/MW
$y^{\text{aFRRneg,bid}}_{ln,i,ts}$	Negative aFRR bid price at discrete price level ln	EUR/MW
$x^{\text{aFRRpos,bid}}_{lp,i,ts}$	Positive aFRR bid volume at discrete price level lp	MW
$x^{\text{aFRRneg,bid}}_{ln,i,ts}$	Negative aFRR bid volume at discrete price level ln	MW
$x^{\text{IDM,gen,bid}}_{lid,i,j,k,qh}$	IDM bid volume at discrete price level lid	MW
$x^{\text{IDM,long,bid}}_{lid,i,j,k,qh}$	IDM long position volume	MW
$x^{\text{IDM,short,bid}}_{lid,i,j,k,qh}$	IDM short position volume	MW
$x^{\text{DAM,gen,bid}}_{lid,i,j,h}$	DAM bid volume at discrete price level lid	MW
$x^{\text{DAM,long,bid}}_{lid,i,j,h}$	DAM long position volume	MW
$x^{\text{DAM,short,bid}}_{lid,i,j,h}$	DAM short position volume	MW
$\beta^{DAM}_{lid,j,h}$	Binary variable indicating DAM bid acceptance	–
$\beta^{\text{aFRRpos,bid}}_{i,lp,ts}$	Binary variable indicating aFRR bid acceptance for positive bids	–
$\beta^{IDM}_{lid,j,k,qh}$	Binary variable indicating IDM bid acceptance	–
$x^{\text{IDM,gen,trade}}_{lid,i,j,k,qh}$	IDM accepted bid volume at discrete price level lid	MW
$x^{\text{IDM,long,trade}}_{lid,i,j,k,qh}$	IDM accepted long position volume	MW
$x^{\text{IDM,short,trade}}_{lid,i,j,k,qh}$	IDM accepted short position volume	MW
$x^{\text{IDM,trade}}_{i,j,k,qh}$	Total traded IDM volume (generation, short, and long)	MW
$x^{\text{IDM,lin}}_{i,j,k,m,qh}$	IDM bid volume in linearised interval m	MW
$x^{\text{DAM,gen,trade}}_{lid,i,j,h}$	DAM accepted bid volume at discrete price level lid	MW
$x^{\text{DAM,long,trade}}_{lid,i,j,h}$	DAM accepted long position volume	MW
$x^{\text{DAM,short,trade}}_{lid,i,j,h}$	DAM accepted short position volume	MW
$x^{\text{DAM,trade}}_{i,j,h}$	Total traded DAM volume (generation, short, and long)	MW
$x^{\text{DAM,dispatch,U}}_{i,j,h,u}$	Day-ahead dispatch volume for unit u	MW
$x^{\text{DAM,dispatch,RES}}_{i,j,h,res}$	Day-ahead dispatch volume for renewable unit res	MW
$x^{\text{IDM,dispatch,U}}_{i,j,k,qh,u}$	Intraday dispatch volume for unit u	MW
$x^{\text{IDM,dispatch,RES}}_{i,j,k,qh,res}$	Intraday dispatch volume for renewable unit res	MW
$x^{\text{dispatch,U}}_{i,j,k,qh,u}$	Total dispatch volume for unit u	MW
$\triangle x^{\text{aFRRpos,U,}-}_{i,qh,u}$	Negative load change due to positive aFRR bid volume for unit u	MW
$\triangle x^{\text{aFRRneg,U,}-}_{i,qh,u}$	Negative load change due to negative aFRR bid volume for unit u	MW
$\triangle x^{\text{spot,U,}-}_{i,j,k,qh,u}$	Negative load change due to Spot market commitment for unit u	MW
$\triangle x^{\text{spot,U,}+}_{i,j,k,qh,u}$	Positive load change due to Spot market commitment for unit u	MW

CRediT authorship contribution statement

Kim K. Miskiw: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Emil Kraft:** Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing, Investigation. **Stein-Erik Fleten:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing.

Declaration of generative AI and AI-assisted technologies in the writing process

The original manuscript was written without the help of generative AI and AI-assisted technologies. After the submission during the revision of this work the authors used Grammarly and ChatGPT 4o for language refinement, grammar correction, and to receive feedback on the structure of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Acknowledgements

Kim K. Miskiw thanks the German Federal Ministry for Economic Affairs and Climate Action (BMWK) for its support within the ASSUME project. Emil Kraft gratefully acknowledges funding from the German Federal Ministry of Education and Research (BMBF) for the Kopernikus Project ENSURE ‘New ENergy grid StructURes for the German Energiewende’. Moreover, Emil Kraft gratefully acknowledges funding through a Research Travel Grant by the Karlsruhe House of Young Scientists (KHYS) for his research stay at NTNU. Stein-Erik Fleten acknowledges support from the Research Council of Norway through grants 296205 and 320789.

Appendix A. Day-ahead market specification

$$\mathbb{E}_{(i,j)\in\Omega}\left(\rho^{\text{DAM}}_{i,j}\right) = \sum_{i=1}^{I} pr_i \sum_{j=1}^{J} pr_j \sum_{h\in H}\left(y^{\text{DAM}}_{j,h} x^{\text{DAM, trade}}_{i,j,h}\right) \tag{A.1}$$

$$x^{\text{DAM,trade}}_{i,j,h} = x^{\text{DAM,gen,trade}}_{i,j,h} + x^{\text{DAM,short,trade}}_{i,j,h} - x^{\text{DAM,long,trade}}_{i,j,h} \tag{A.2}$$

$$x^{\text{DAM,gen,trade}}_{i,j,h} = \sum_{lda=1}^{LDA} \beta^{\text{DAM}}_{lda,j,h} x^{\text{DAM, gen,bid}}_{lda,i,j,h} \tag{A.3}$$

$$x^{\text{DAM,long,trade}}_{i,j,h} = \sum_{lda=1}^{LDA}\left(1-\beta^{\text{DAM}}_{lda,j,h}\right) * x^{\text{DAM,long,bid}}_{lda,i,j,h} \tag{A.4}$$

$$x^{\text{DAM,short,trade}}_{i,j,h} = \sum_{lda=1}^{LDA} \beta^{\text{DAM}}_{lda,j,h} x^{\text{DAM,short,bid}}_{lda,i,j,h}. \tag{A.5}$$

Appendix B. Modelling of technical constraints

The chosen power plant portfolio is modelled with the technical characteristics listed in Table B.4. We summarise the equations that model the power plants' technical and further market constraints in the following sections.

Imbalances from open positions in the spot markets are penalised in the optimisation. The imbalances are calculated in (B.1), and are the not fulfilled spot market commitments. The penalty is chosen so high that imbalances are avoided by the model. The absolute amount of long or short bids is limited to 10% of the portfolios capacity to limit speculative behaviour. Moreover, in one market and at one price level,

Table B.4
Technical parameters of the considered portfolio.

Parameter	Symbol	Unit	Value
Installed capacity PV generation	P^{RES}_{res1}	[MW]	100
Maximum load change of PV within five minutes, as a share of P^{RES}_{res1}	ΔP^{RES}_{res1}	[–]	1.00
Installed capacity of biomass generation	P^{U}_{u1}	[MW]	100
Minimum load requirement of biomass, as a share of P^{U}_{u1}	P^{min}_{u1}	[–]	0.20
Minimum daily generation of biomass, as a share of P^{U}_{u1}	v^{min}_{u1}	[–]	0.50
Maximum daily generation of biomass, as a share of P^{U}_{u1}	v^{max}_{u1}	[–]	0.95
Variable costs of biomass	κ^{var}_{u1}	[EUR/MWh]	40
Maximum load change of biomass within five minutes, as a share of P^{U}_{u1}	ΔP^{U}_{u1}	[–]	0.5

one is only allowed to place either a short or long bid, not both at once. The temporal resolutions between the IDM and DAM need to be accounted for by using $qh(h)$, which denotes the mapping of individual hours to the respective quarter-hour interval qh (e.g., for $h = 1$ follows $qh(1) = \{1, 2, 3, 4\}$).

$$x^{\text{DAM,trade}}_{i,j,h} + x^{\text{IDM,trade}}_{i,j,k,qh} + x^{\text{imb}}_{i,j,k,qh} = x^{\text{DAM,gen,trade}}_{i,j,h} + x^{\text{IDM,gen,trade}}_{i,j,k,qh} \quad \forall (i,j,k), h, qh(h). \tag{B.1}$$

In the optimisation model, the dispatch of the power plants $u \in U$ and $res \in RES$ is also planned. For this dispatch, several technical constraints must be met. The commitments from the successfully traded bids can be distributed between different units, as shown in (B.2) exemplarily for the DAM. Similarly, the commitments for the IDM and aFRR can be divided between the units, resulting in $x^{\text{aFRRpos,U}}_{i,qh,u}$ and $x^{\text{aFRRneg,U}}_{i,qh,u}$, respectively. The actually realised dispatch $x^{\text{dispatch,U}}_{i,j,k,qh,u}$ is calculated in (B.3) and is the sum of the day-ahead $x^{\text{DAM,dispatch,U}}_{i,j,h,u}$ and intraday dispatch $x^{\text{IDM,dispatch,U}}_{i,j,k,qh,u}$. The resulting dispatch is constrained by the capacity of the units, as shown in (B.4) to (B.6). $\phi^{\text{DAM}}_{qh,res}$ and $\phi^{\text{IDM}}_{k,qh,res}$ are the availability factors of the renewable unit res in the DAM and IDM, respectively.

$$x^{\text{DAM,gen,trade}}_{i,j,h} = \sum_{u \in U} x^{\text{DAM,dispatch,U}}_{i,j,h,u} + \sum_{res \in RES} x^{\text{DAM,dispatch,RES}}_{i,j,h,res} \quad \forall (i,j), h \tag{B.2}$$

$$x^{\text{dispatch,U}}_{i,j,k,qh,u} = x^{\text{DAM,dispatch,U}}_{i,j,h,u} + x^{\text{IDM,dispatch,U}}_{i,j,k,qh,u} \quad \forall (i,j,k), h, qh(h), u \tag{B.3}$$

$$x^{\text{aFRRpos,U}}_{i,qh,u} + x^{\text{DAM,dispatch,U}}_{i,j,h,u} + x^{\text{IDM,dispatch,U}}_{i,j,k,qh,u} \leq P^{\text{U}}_{u} \quad \forall i,j,k,h,qh(h),u \tag{B.4}$$

$$x^{\text{aFRRpos,RES}}_{i,qh,res} + x^{\text{DAM,dispatch,RES}}_{i,j,res,h} \leq P^{\text{RES}}_{res} \phi^{\text{DAM}}_{qh,res} \quad \forall (i,j), h, qh(h), res \tag{B.5}$$

$$x^{\text{aFRRpos,RES}}_{i,qh,res} + x^{\text{DAM,dispatch,RES}}_{i,j,h,res} + x^{\text{IDM,dispatch,RES}}_{i,j,k,qh,res} \leq P^{\text{RES}}_{res} \phi^{\text{IDM}}_{k,qh,res} \quad \forall (i,j,k), h, qh(h), res. \tag{B.6}$$

Further, the fuel storage capability for dispatchable plants is limited, leading to a minimum and maximum daily generation $v^{\text{min/max}}$ of unit u, as in (B.7). Here we use $|.|$ the cardinality of the set QH to calculate the energy output from P^{U}_{u} in MW.

$$|QH| P^{U}_{u} v^{\text{min}}_{u} \leq \sum_{qh \in QH} x^{\text{dispatch,U}}_{i,j,k,qh,u} \leq |QH| P^{U}_{u} v^{\text{max}}_{u} \quad \forall (i,j,k), u. \tag{B.7}$$

Lastly, each unit u is limited in its load change gradient ΔP^{U}_{u} per time step. We further present the ramping constraints for one dispatchable unit u. They are analogous for the renewable unit res and are omitted for brevity. (B.8) shows the calculation of the upwards and downwards load change ($\Delta x^{\text{spot,U,+}}_{i,j,k,qh,u}$, $\Delta x^{\text{spot,U,-}}_{i,j,k,qh,u}$) exemplary for the spot market. They are similarly calculated for the aFRR market, resulting in the necessary upward and downward regulation ($\Delta x^{\text{aFRRpos,U,+}}_{i,qh,u}$, $\Delta x^{\text{aFRRneg,U,+}}_{i,qh,u}$). The maximum change is considered to be the same for upward and downward regulation ΔP^{U}_{u}. To model this load change limit we need to consider three components from which potential load change can arise as seen in (B.9) and (B.10). For the upward ramping they comprise, the positive change in aFRR commitments compared to the preceding interval, the positive spot market ramping ($\Delta x^{\text{spot,U,+}}_{i,j,k,qh,u}$) and the subtraction of negative ramping ($\Delta x^{\text{spot,U,-}}_{i,j,k,qh,u}$). Finally, the third term, $x^{\text{aFRRpos,U}}_{i,qh,u} + x^{\text{aFRRneg,U}}_{i,qh,u}$, ensures sufficient ramping capacity is available to meet the total committed capacity required to be ramped up and down by the transmission system operator.

$$x^{\text{dispatch,U}}_{i,j,k,qh,u} - x^{\text{dispatch,U}}_{i,j,k,qh+1,u} = \Delta x^{\text{spot,U,+}}_{i,j,k,qh,u} - \Delta x^{\text{spot,U,-}}_{i,j,k,qh,u} \quad \forall (i,j,k), qh, u \tag{B.8}$$

$$x^{\text{aFRRpos,U}}_{i,qh,u} + x^{\text{aFRRneg,U}}_{i,qh,u} + \Delta x^{\text{aFRRpos,U,+}}_{i,qh,u} + \Delta x^{\text{aFRRneg,U,+}}_{i,qh,u} + \Delta x^{\text{spot,U,+}}_{i,j,k,qh,u} - \Delta x^{\text{spot,U,-}}_{i,j,k,qh,u} \leq P_u \Delta P^{\text{U}}_{u} \quad \forall (i,j,k), qh, u \tag{B.9}$$

$$x^{\text{aFRRpos,U}}_{i,qh,u} + x^{\text{aFRRneg,U}}_{i,qh,u} + \Delta x^{\text{aFRRpos,U,-}}_{i,qh,u} + \Delta x^{\text{aFRRneg,U,-}}_{i,qh,u} + \Delta x^{\text{spot,U,-}}_{i,j,k,qh,u} - \Delta x^{\text{spot,U,+}}_{i,j,k,qh,u} \leq P_u \Delta P^{\text{U}}_{u} \quad \forall (i,j,k), qh, u. \tag{B.10}$$

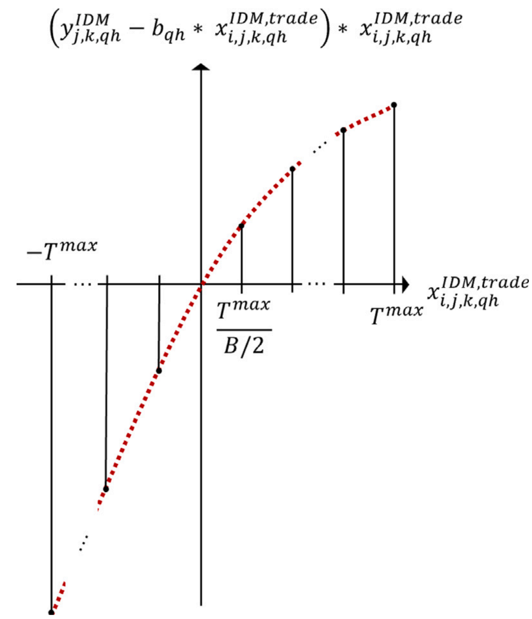


Fig. C.5. Linearisation of quadratic intraday revenue following Plazas et al. (2005).

Appendix C. Linearisation of the price impact implementation

As discussed in Section 3.3, the price impact formulation in the revenue function needs to be linearised. In accordance with Plazas et al. (2005), we perform a stepwise linearisation, as shown in (C.1) to (C.4). We approximate the quadratic function using B linear segments. To achieve this, a new variable, $x^{\text{IDM,lin}}_{i,j,k,m,qh}$, is introduced, representing the position m within the B different intervals. The quadratic function is then approximated as presented in (C.1). T^{max} represents the maximum amount of energy that can be bid, which equals the absolute generation capacity of the portfolio. This is used to limit the newly introduced variable, as shown in (C.2) and (C.3), following the approach outlined in Plazas et al. (2005). Finally, (C.4) shows the aggregation of the linearised bids over the B intervals. We illustrate the linearisation in Fig. C.5.

$$\mathbb{E}_{(i,j,k)\in\Omega}\rho^{\mathrm{IDM}}_{i,j,k} = \sum_{i=1}^{I} pr_i \sum_{j=1}^{J} pr_j \sum_{k=1}^{K} pr_k \sum_{qh=1}^{QH} \sum_{m=1}^{B} (y^{\mathrm{IDM}}_{j,k,qh} - b_{qh} \frac{2T^{\max}(2m-(B+1))}{B}) x^{\mathrm{IDM,lin}}_{i,j,k,m,qh} \tag{C.1}$$

$$\frac{-2T^{\max}}{B} \leq x^{\mathrm{IDM,\ lin}}_{i,j,k,m,qh} \leq 0, \forall qh, \forall k, \forall i, \forall j, \forall m \leq \frac{B}{2} \tag{C.2}$$

$$\frac{2T^{\max}}{B} \geq x^{\mathrm{IDM,lin}}_{i,j,k,m,qh} \geq 0, \forall qh, \forall k, \forall i, \forall j, \forall m > \frac{B}{2} \tag{C.3}$$

$$x^{\mathrm{IDM,\ trade}}_{i,j,k,qh} = \sum_{m=1}^{B} x^{\mathrm{IDM},lin}_{i,j,k,m,qh}, \forall qh, \forall k, \forall i, \forall j. \tag{C.4}$$

References

Aasgård, E.K., 2022. The value of coordinated hydropower bidding in the nordic day-ahead and balancing market. Energy Syst. 13 (1), 53–77. http://dx.doi.org/10.1007/s12667-020-00388-7.

Almgren, R., Chriss, N., 2001. Optimal execution of portfolio transactions. J. Risk 3 (2), 5–39. http://dx.doi.org/10.21314/JOR.2001.041.

Ayón, X., Moreno, M., Usaola, J., 2017. Aggregators' optimal bidding strategy in sequential day-ahead and intraday electricity spot markets. Energies 10 (4), 450. http://dx.doi.org/10.3390/en10040450.

Baringo, L., Conejo, A.J., 2016. Offering strategy of wind-power producer: A multi-stage risk-constrained approach. IEEE Trans. Power Syst. 31 (2), 1420–1429. http://dx.doi.org/10.1109/TPWRS.2015.2411332.

Boomsma, T.K., Juul, N., Fleten, S.-E., 2014. Bidding in sequential electricity markets: The nordic case. European J. Oper. Res. 238 (3), 797–809. http://dx.doi.org/10.1016/j.ejor.2014.04.027.

Castillo, A., Flicker, J., Hansen, C.W., Watson, J.-P., Johnson, J., 2015. Stochastic optimization with risk aversion for virtual power plant operations: A rolling horizon control. IET Res. J. 13 (11), http://dx.doi.org/10.1049/iet-gtd.2018.5834.

EEX group, 2018. EEX group webshop. URL https://webshop.eex-group.com/.

ENTSO-E, 2022. ENTSO-E transperency platform. URL https://transparency.entsoe.eu/.

Finnah, B., Gönsch, J., Ziel, F., 2022. Integrated day-ahead and intraday self-schedule bidding for energy storage systems using approximate dynamic programming. European J. Oper. Res. 301 (2), 726–746. http://dx.doi.org/10.1016/j.ejor.2021.11.010.

Fleten, S.-E., Midthun, K.T., Bjorkvoll, T., Werner, A., Fodstad, M., 2018. The portfolio perspective in electricity generation and market operations. In: 2018 15th International Conference on the European Energy Market. EEM, IEEE, pp. 1–5. http://dx.doi.org/10.1109/EEM.2018.8469857.

Gatheral, J., Schied, A., 2013. Dynamical models of market impact and algorithms for order execution. Handb. Syst. Risk http://dx.doi.org/10.1017/CBO9781139151184.030.

Heredia, F.-J., Cuadrado, M.D., Corchero, C., 2018. On optimal participation in the electricity markets of wind power plants with battery energy storage systems. Comput. Oper. Res. 96, 316–329. http://dx.doi.org/10.1016/j.cor.2018.03.004.

Kath, C., Ziel, F., 2020. Optimal order execution in intraday markets: Minimizing costs in trade trajectories. URL http://arxiv.org/pdf/2009.07892v2.

Keles, D., Dehler-Holland, J., 2022. Evaluation of photovoltaic storage systems on energy markets under uncertainty using stochastic dynamic programming. Energy Econ. 106, 105800. http://dx.doi.org/10.1016/j.eneco.2021.105800.

Keles, D., Genoese, M., Möst, D., Fichtner, W., 2012. Comparison of extended mean-reversion and time series models for electricity spot price simulation considering negative prices. Energy Econ. 34 (4), 1012–1032. http://dx.doi.org/10.1016/j.eneco.2011.08.012.

Klæboe, G., Braathen, J., Eriksrud, A., Fleten, S.-E., 2022. Day-ahead market bidding taking the balancing power market into account. TOP 30, 683–703. http://dx.doi.org/10.1007/s11750-022-00645-1.

Klæboe, G., Fosso, O.B., 2013. Optimal bidding in sequential physical markets – a literature review and framework discussion. In: IEEE Power Tech Conference. pp. 1–6.

Koch, C., Hirth, L., 2019. Short-term electricity trading for system balancing: An empirical analysis of the role of intraday trading in balancing Germany's electricity system. Renew. Sustain. Energy Rev. 113, 109275. http://dx.doi.org/10.1016/j.rser.2019.109275.

Kongelf, H., Overrein, K., Klæboe, G., Fleten, S.-E., 2019. Portfolio size's effects on gains from coordinated bidding in electricity markets. Energy Syst. 10 (3), 567–591. http://dx.doi.org/10.1007/s12667-018-0294-8.

Kraft, E., Russo, M., Keles, D., Bertsch, V., 2023. Stochastic optimization of trading strategies in sequential electricity markets. European J. Oper. Res. 308, 400–421. http://dx.doi.org/10.5445/IR/1000134346.

Löhndorf, N., Wozabal, D., 2022. The value of coordination in multi-market bidding of grid energy storage. Oper. Res. 71 (1), http://dx.doi.org/10.1287/opre.2021.2247.

Mazzi, N., Kazempour, J., Pinson, P., 2018. Price-taker offering strategy in electricity pay-as-bid markets. IEEE Trans. Power Syst. 33 (2), 2175–2183. http://dx.doi.org/10.1109/TPWRS.2017.2737322.

Narajewski, M., Ziel, F., 2022. Optimal bidding in hourly and quarter-hourly electricity price auctions: trading large volumes of power with market impact and transaction costs. Energy Econ. 110 (C), http://dx.doi.org/10.1016/j.eneco.2022.105974, Elsevier.

Ottesen, S.Ø., Tomasgard, A., Fleten, S.-E., 2018. Multi market bidding strategies for demand side flexibility aggregators in electricity markets. Energy 149, 120–134. http://dx.doi.org/10.1016/j.energy.2018.01.187.

Plazas, M.A., Conejo, A.J., Prieto, F.J., 2005. Multimarket optimal bidding for a power producer. IEEE Trans. Power Syst. 20 (4), 2041–2050. http://dx.doi.org/10.1109/TPWRS.2005.856987.

regelleistung.net, 2022. Datacenter. URL https://www.regelleistung.net/ext/tender/.

Russo, M., Kraft, E., Bertsch, V., Keles, D., 2022. Short-term risk management of electricity retailers under rising shares of decentralized solar generation. Energy Econ. 109, 105956. http://dx.doi.org/10.1016/j.eneco.2022.105956.

SE, E.S., 2020. EPEX SPOT annual market review 2019. URL https://www.epexspot.com/en/news/new-trading-record-epex-spot-2019.

SE, E.S., 2022a. Auction price indices. URL https://www.epexspot.com/en/indices.

SE, E.S., 2022b. New record volume traded on EPEX SPOT in 2020. URL https://www.epexspot.com/en/news/new-record-volume-traded-epex-spot-2020.

SE, E.S., 2024. All-time high volumes: Growth in spot markets illustrate trust of trading participants. URL https://www.epexspot.com/en/news/all-time-high-volumes-growth-spot-markets-illustrate-trust-trading-participants.

Steeger, G., Lohmann, T., Rebennack, S., 2018. Strategic bidding for a price-maker hydroelectric producer: Stochastic dual dynamic programming and Lagrangian relaxation. IISE Trans. 50 (11), 929–942. http://dx.doi.org/10.1080/24725854.2018.1461963.

Vardanyan, Y., 2016. Optimal Bidding of a Hydropower Producer in Sequential Power Markets with Risk Assessment: Stochastic Programming Approach (Dissertation). KTH Royal Institute of Technology, Stockholm.

Wozabal, D., Rameseder, G., 2020. Optimal bidding of a virtual power plant on the Spanish day-ahead and intraday market for electricity. European J. Oper. Res. 280 (2), 639–655. http://dx.doi.org/10.1016/j.ejor.2019.07.022.