E.ON Energy Research Center
FCN | Institute for Future Energy Consumer Needs and Behavior

FCN Working Paper No. 2/2014

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February 2014

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School of Business and Economics / E.ON ERC

RWTH AACHEN UNIVERSITY

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February 2014

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Abstract

Forecasting the production of photovoltaic (PV) and wind power systems inevitably implies inaccuracies. Therefore, sales made based on forecasts almost always require the vendor to make balancing efforts. In the absence of resources available within their own portfolios, operators can turn towards the intraday market in order to avoid an engagement in the imbalance market with the resulting surcharges and regulatory penalties. In this paper, we combine a novel trade value concept with options valuation and dynamic programming to optimize volume and timing decisions of an individual operator without market power when compensating PV or wind power forecast errors in the market. The model employs a multi-dimensional binomial lattice, with trade value maximized at every node to help formulating bids in view of correlated, uncertain production forecast and price patterns. Inspired by the German electricity market's characteristics, we test the sensitivity of the model's output – namely trade timing and trade volume – to changing uncertainty and transaction cost parameters in 50 different setups. It shows that the model effectively outbalances price against volumetric risks. Trades are executed early and with large batch sizes in the case of price volatility. In contrast, increasing forecast error uncertainty leads to trade delays. High transaction costs trigger batch size reductions and ultimately further trade delays. Running 10,000 simulations across ten scenarios, we find that the model translates its flexible trade execution into a competitive advantage vis-à-vis static bidding strategy alternatives.

Keywords: Bidding strategy; Production forecast; Renewable energy; Options; Intraday market

JEL classification: Q42; Q47; G12;

1 Introduction

While progress has been made in recent years regarding renewable energy production forecasting quality (Giebel *et al.*, 2011; Kraas *et al.*, 2013; Lorenz *et al.*, 2011; Pelland *et al.*, 2013), actual PV and wind power production is far from being perfectly foreseeable. For instance, Giebel *et al.* (2011) find the six-hour wind power root mean square error (RMSE) for a Danish wind farm to range between roughly 12% and 22% of installed capacity, depending on the methodology applied. Apart from methodology, the forecasting accuracy for specific sites or areas depends on forecasting horizons, power system characteristics and geographical conditions. Generally, aggregated forecasts for multiple sites are more accurate than single-site forecasts due to netting effects. For instance, Borggrefe and Neuhoff (2011) illustrate RMSE as low as 4% when considering the aggregated German transmission zones. In any case, forecast errors remain significant. As a result, their management strongly impacts the market value of renewable energy. Von Roon (2011) calculates overall costs incurred by the German transmission system operators (TSOs) in order to balance deviations from day-ahead forecasts of wind and PV power in Germany between March and October 2010. She finds average adjustment costs of 2.2 €/MWh, in addition to 2.2 €/MWh of missed rents from volumes that, due to forecasting inaccuracies, were sold at lower prices intraday instead of day-ahead. A large share of these costs can be attributed to operations in the imbalance market. Apart from forecasting quality[2], then, two major factors appear as drivers for intraday balancing costs.

The first is *market liquidity*. The more liquid and competitive the intraday market is, the more efficient it is to balance forecast errors intra-daily. With increasing liquidity, transaction costs decline and abundant trade partners become available at any time. In fact, however, the German and many other European intraday markets do not seem to be liquid. Weber (2010) investigates the liquidity of the German intraday market in 2006 and 2007. He finds that it levels well below what would be required to accommodate wind power forecast errors, load deviations, and conventional power plant outages. He argues that this deficit cannot be sufficiently explained by the netting that market actors conduct either internally or over-the-counter. Hagemann and Weber (2013) conduct a detailed empirical analysis of liquidity in the German intraday market in 2010 and 2011. They find various indications for limited liquidity. Notably, they can show that wind and PV forecast errors at the TSO level are

[2] Numerous forecasting methods and commercial tools are available to operators. Obviously, the quality of forecasts in terms of both speed and accuracy hugely influence the economic value of PV or wind power production before any balancing activities are even necessary. However, the assessment of different forecasting methods and their economic impact are beyond the scope of this paper.

correlated with price variance in the intraday markets. Further, they calculate a bid-ask spread significantly higher than in the day-ahead market. Interestingly, they also suggest that intraday price variance is higher for those delivery hours that have previously been traded at unusually high or low day-ahead prices.

As a second factor, operators of PV or wind power systems need to formulate efficient *bidding strategies*. Since trading is possible continuously, operators have significant leeway regarding both timing and volumes of trades. The impact on value can be substantial. Möhrlen *et al.* (2012) investigate forecasting methods as well as short-term trading strategies to optimally deal with forecast inaccuracies for wind (and PV) power production in the German intraday market. They define an efficient trading strategy based on probabilistic forecasts, attempting to avoid double trading[3] by accounting for the remaining uncertainty in updated forecasts. The strategy presented by Möhrlen *et al.* (2012) strongly focuses on the volumetric uncertainty caused by forecast error uncertainty. It does, however, not account for intraday price and liquidity dynamics.

Usaola and Angarita (2007) suggest a method to optimize revenues across day-ahead, intraday and imbalance markets for a Spanish wind power plant. Comparing different bidding strategies, they show that accounting for forecasting uncertainty in the bidding strategy yields the greatest value in most cases. For some instances, they find that not participating in the intraday market at all may be even more beneficial. However, similarly to Möhrlen *et al.* (2012), they do not account for intraday price uncertainty, since they assume price predictability.

In contrast, Morales *et al.* (2010) include both forecasting and price uncertainty in their wind power bidding model across day-ahead, intraday, and imbalance markets. More specifically, they simulate an auction-based intraday market with a single clearing process rather than a continuous-trade market. As a result of the auction design, fluctuations regarding prices and forecast error assumptions only occur across markets.

Going one step further, Henriot (2014) investigates bidding strategies to manage wind power forecast errors in a continuous-trade intraday market, approximated by a market model with several subsequent trade windows. Both price and forecast-error uncertainties are accounted for. He assumes wind power to be managed by a central entity – similarly to the wind and PV power marketing responsibility of the German TSOs today – and compares three different bidding strategies: avoiding the intraday market and purely using the imbalance market,

[3] Double trade refers to a trade required in order to sell (buy) volumes which were previously bought (sold) during intraday trading in a balancing trade based on an overestimation of the forecast error due to an inaccurate forecast update.

actively balancing based on forecast updates whenever available, and deciding at every new trade window whether to trade or not. Henriot (2014) finds that participation in the intraday market for the wind player is far from granted; it strongly depends on the forecast uncertainty (reduction over time) and on the penalties that late trading imply. He argues that there is no simple measure to increase both intraday market liquidity (through more participation) and overall balancing cost efficiency. Two important properties of the model of Henriot (2014) need to be mentioned: the wind player can only either trade exactly the forecast error or nothing. In other words, he does not have the possibility to apply a mixed strategy by setting the trade volume below or above the current forecast error estimate. Second, tapping the imbalance market is considered to be a legitimate component of a bidding strategy. In some markets, for instance Germany, regulators insist that the imbalance market has a mere back-up function and that its systematic use as part of a trading strategy over time will be penalized (Schultz, 2013).

While the studies mentioned have provided important insights about strategies for wind (or PV) power plant operators to manage intraday dynamics, there is still much room for investigation. Our approach is distinct and contributes to the literature in several ways.

First, both price and forecast error uncertainties are accounted for in the context of a continuous-trade market. Opposed to the more analytical approach in Henriot (2014), we translate these uncertainties into stochastic processes, whose properties can be flexibly adjusted to reflect specific intraday markets or points in time. Apart from generating insights at the market level, the ultimate goal is to provide a tool that can be practically applied to guide trading decisions.

Second, the operator in our setting can set trade volumes freely and pick any available intraday trade window for execution, thus reflecting the actual degrees of freedom an operator faces, and needs to take advantage of, more realistically.

Third, this research builds on the perspective of a small- to mid-sized operator of PV and wind power units. This viewpoint reflects the increasing fragmentation of supply due to the expansion of distributed generation. It also reflects the fact that the German TSOs (and similar entities in other markets) will increasingly shift back responsibility for PV and wind power marketing to owners and intermediate operators, supported by corresponding regulatory changes[4]. A limitation of this perspective is that it treats long-term impacts on

[4] For instance, recently planned amendments to the renewable energy law ("EEG") in Germany require operators of PV and wind power assets to self-market their outputs (even in the case of fairly small asset capacities).

market prices and liquidity as exogenous, making it less applicable to players with market power (e.g., TSOs) unless game-theoretic considerations are added to the model.

Fourth, the model in our effort excludes the opportunity to use the imbalance market as a strategic optimization resource. While this may not reflect today's reality in the German and some other European power markets, it does reflect the intentions of the regulator. With a growing share of PV and wind operators in the market, enforcement of this intention will likely be tightened in the future.

This paper proceeds as follows. In section 2, the model for optimizing the trade value under uncertain price and production forecast error processes is introduced. In section 3, a numerical simulation is conducted and the results discussed. Finally, section 4 presents the implications and limitations of our approach.

2 Model formulation

2.1 Starting point

In the following, we formulate an intraday bidding strategy to maximize the trade value under price and production forecast error uncertainty. The entire description in this section refers to a trade activity aimed at balancing the forecast error for one particular delivery slot t. The intraday trading period preceding slot t is dissected into trade windows $w = \{1, \dots, W\}$. These will be set such that a new trade window begins whenever a forecast update is received. In practice, the optimization procedure would be repeated for every delivery slot and at any trade window to fully cover intraday operations.

We assume an operator of weather-dependent renewable assets (wind or PV) who sold a forecast-based amount X_{da} in the day-ahead market due for delivery at time t. The operator must attempt to provide exactly the amount previously sold without making use of the imbalance market[5]. This implies that any forecast error must be compensated by the end of the intraday trading at window W.

[5] The exclusion of the imbalance market from the analysis is justified by two arguments. First, the German regulator legally requires balancing-responsible parties to minimize their use of the imbalance market to the largest possible degree. Violations are penalized, with the regulator planning to more stringently enforce penalization in the future (Schultz, 2013). Second, in the case of a short (long) transmission zone balance, the prices in the imbalance market must, by regulation, be as high (low) as or higher (lower) than intraday prices. The only advantage in using the imbalance market might lie in eliminated costs of double trades, i.e. first selling (buying) and then re-buying (re-selling) the same volumes due to oscillating forecast errors. However, since our

At the beginning of any intraday trade window w, the operator receives an updated production forecast X_w. He can then compare the updated projection with the amount sold day-ahead, and derive an estimate for the forecast error $F_w = (X_{\mathrm{da}} - X_w)$ he will have to balance prior to delivery. At W, X_W equals actual production. Thus, F_W provides the actual forecast error between day-ahead sale and actual delivery.

2.2 Value of an immediate trade

Given F_w at the current trade window w, the operator generally has two options:

(1) immediately trade $I_w \neq 0$ in the market with $I_w \in \mathbb{R}$, or

(2) trade nothing, $I_w = 0$, and wait for the next trade window and forecast update X_{w+1}.

In order to make an appropriate choice between these options, and in order to optimally choose I_w in the case of option 1, the operator has to evaluate the trade-off between an immediate and a postponed trade to balance the forecast error.

The *disadvantage of postponing a trade* is that it exposes the operator to market risks associated with late intraday trading. Shortly before delivery, many operators of PV or wind assets try to balance their (remaining) forecast errors. Meanwhile, resources for balancing, i.e. thermal power plants and flexible demand, become scarcer due to finite availability and long ramp-up times. Average marginal costs of available resources are high. Thus, the market tightens up considerably.

One result is that the available trade prices in the market could worsen from the viewpoint of an individual operator with a balancing need. Postponement implies the absorption of this price change. Furthermore, spreads for available trade positions are likely to widen, entailing another cost source related to postponement. A third result is that postponed trades imply the risk of not finding a trade counterparty at all. In that case, the unmatched volume will have to be balanced in the imbalance market. Based on these consequences, unit costs C_{b} of postponing a trade necessary for balancing can be formulated as

$$C_{\mathrm{b}} = (1 - \varphi_{\mathrm{e}}) \cdot \left(\Delta P + \frac{\Delta c_{\mathrm{s}}}{2} \cdot \frac{F_w}{|F_w|} \right) + \varphi_{\mathrm{e}} \cdot (c_{\mathrm{ime}} - P_w), \tag{1}$$

optimization process accounts for that risk, and due to the penalty argument, we do not consider the explicit use of the imbalance market to be a viable alternative.

where φ_{e} denotes the counterparty risk[6], ΔP reflects the price change, Δc_{s} refers to the change in the spreads between the current trade window and later trade windows, and c_{ime} specifies the cost of balancing an untraded forecast error in the imbalance market. The term $\frac{F_w}{|F_w|}$ helps to adjust the spread growth costs for the trade sign: whether we deal with a short position (positive sign) or a long position (negative sign), the change in spread always increases postponement costs. The product of spread costs and trade position thus needs to be positive.

The *disadvantage of trading immediately* is that it increases the exposure to volumetric risks. The probability that forecasts long before delivery will be updated again is high. Thus, trading based on early forecasts entails the risk of trading either insufficiently or excessively. Trading insufficiently is equivalent to a postponed trade regarding the omitted volumes, at cost C_b. Trading excessively triggers double trades. Double trades imply three (potential) cost sources. First, the full bid-ask spread and other transaction costs are incurred for superfluous volumes, with half the spread incurred in the late trade market. Second, the change in price between purchasing (selling) and reselling (repurchasing) is absorbed. Third, there might be a risk of not finding a counterparty for reselling (repurchasing) shortly before delivery, meaning that the unmatched volume may have to be balanced in the imbalance market. The costs of double trading for every unit traded in excess, C_{d}, can thus be formulated as:

$$C_{\mathrm{d}} = \left(TC + \frac{c_{\mathrm{s}}}{2}\right) \cdot \frac{F_w}{|F_w|} + (1 - \varphi_{\mathrm{o}}) \cdot \left[(-\Delta P) + \left(TC + \frac{(c_{\mathrm{s}} + \Delta c_{\mathrm{s}})}{2}\right) \cdot \frac{F_w}{|F_w|}\right] + \varphi_{\mathrm{o}} \cdot (P_w - c_{\mathrm{imo}}), \qquad (2)$$

where c_{s} describes the spread, φ_{o} denotes the counterparty risk for a double trade, TC denotes transaction costs (clearing), and c_{imo} specifies the costs of balancing an overestimated forecast error in the imbalance market.

In order to evaluate a specific immediate trade with volume I_w, both C_{b} and C_{d} need to be considered. Note that, on the one hand, the total of C_{b} avoided thanks to immediately and correctly traded volumes constitutes the value of an immediate trade. On the other hand, the total of C_{d} incurred due to excessively traded volumes makes up the cost of an immediate trade. The total value of trading immediately for a short position (forecast error with positive sign) equals:

[6] From here on this term refers to the risk of not finding a counterparty for an intended trade.

$$V_{\mathrm{s}}(I_w) = \sum_{1}^{\min(I_w, F_W)} C_{\mathrm{b}} \left(-\sum_{F_W}^{I_w} C_{\mathrm{d}} \middle| I_w > F_W \right). \tag{3}$$

Analogously, the total value of trading immediately for a long position (forecast error with negative sign) equals:

$$V_l(I_w) = \sum_{\max(I_w, F_W)}^{-1} C_b \left(-\sum_{I_w}^{F_W} C_d \middle| I_w < F_W \right). \tag{4}$$

2.3 Forecast error and intraday price as correlated stochastic processes

If the forecast error and the intraday price level were perfectly predictable, deciding upon the immediate trade volume I_w would be quite simple. $V(I_w)$ could be maximized by trading the final forecast error volume at times when the prices are most favorable. However, both error volume and intraday price follow stochastic processes that require the operator to optimize his trading strategy under uncertainty.

Hence two issues arise that need to be dealt with. First, the actual forecast error F_W will not be known until the final update is provided at W. Given the remaining forecast uncertainty at any stage prior to W, F_w for $w < W$ is the mean of a normal probability distribution with volatility expressed in absolute terms between w and W. In order to discretize the stochastic path of F into steps that match the trade windows, and thereby the forecast updates, we approximate the normal distribution with an Arithmetic Brownian Motion (ABM). The change in value between two trade windows is described in its most general form by

$$dF(w) = \alpha_F \cdot dw + \sigma_F \cdot dZ_F, \tag{5}$$

where dZ_F is the increment of a Wiener Process and σ_F describes the volatility of the forecast error in absolute terms. Since the forecast error estimate is expected to not over- or understate production systematically, no drift is assumed ($\alpha_F = 0$).

Second, intraday prices fluctuate as well. The degree of fluctuation is driven by limited liquidity and strong correlation between PV or wind operators' trade behavior in the case of changing weather conditions. Given the ramp-up times of many thermal power plants and other balancing resources, prices in the market tend to worsen from the PV or wind operators' perspective when approaching delivery slot t. In order to account for both price fluctuations and worsening trade prices, and in order to discretize the stochastic process along the above-defined trade windows, we approximate the intraday price path with a Geometric Brownian Motion (GBM), meaning that the logarithm of the change in price follows a stochastic process of the form

$$\frac{dP(w)}{P(w)} = \alpha_P \cdot dw + \sigma_P \cdot dZ_P, \tag{6}$$

where α_P describes the expected price drift, σ_P is the volatility of prices and dZ_P is the increment of a Wiener Process. The degree and sign of α_P depends on the market situation at the beginning of intraday trading: if most traders are long (e.g., due to negative PV or wind power production forecast errors), $\alpha_P < 0$. Conversely, if traders are short, $\alpha_P > 0$.

Correlations add to the complexity of the stochastic processes. This is due to the fact that the forecast error of the PV or wind power plant operator, being correlated with the forecast errors of other PV or wind operators in the market, will be accompanied by increased balancing trade activity, which in turn impacts prices.

We account for this by enforcing correlation in the Wiener processes of both stochastic paths, such that $[dZ_F Z_P] = \rho_{FP} dw, \quad F \neq P$, and where ρ_{FP} denotes the correlation between process F and process P.

2.4 Unfolding the correlated stochastic processes as a multi-dimensional lattice

We base our options analysis on the binomial lattice method originally presented by Cox *et al.* (1979). The idea is that continuous stochastic processes are displayed binomially in discrete time steps with either up or down increments. The actual probability distribution is approximated fairly accurately in an intuitive fashion: by fixing the size and adjusting the probabilities of up and down increments, and by ensuring a sufficient number of time steps. Further, the method allows creating a recombining tree, meaning that an up (down) movement followed by a down (up) movement eventually leads to a return to the initial value. However, the construction of a recombining lattice in our case must account for three added complications:

(1) there are two dimensions of uncertainty instead of one, error volume and price;

(2) only the price path follows a GBM as in Cox *et al.* (1979), while the uncertainty of the forecast error is described by an ABM;

(3) these processes are correlated such that up and down movements and / or probabilities in one process must relate to the other.

With stochastic processes given, the construction of a lattice primarily depends on the determination of up and down increments and probabilities between two time steps for both processes. The main complication arises from the correlation between them.

The traditional approaches, i.e. Cox *et al.* (1979) for one stochastic process and Boyle *et al.* (1989) for multiple stochastic processes, fix the up and down increments in order to determine the matching probabilities. A throwback of this approach is that the resulting discretization does not reflect the underlying probability distributions well in case of highly correlated processes. Rohlfs and Madlener (2013) therefore suggest a method extending from Rubinstein (1994). Rather than fixing up and down increments, up and down probabilities are equalized and the up and down factors skewed such that the stochastic paths – i.e., the grids of the tree – account for the correlation of the two processes. For a more detailed technical explanation, we refer to Rohlfs and Madlener (2013). In our analysis, we adjust their method slightly, in order to be able to accommodate both the GBM of the intraday price, and the ABM of the forecast error. As a result of this approach, we are able to create a tree where each node leads to four different correlated nodes in the next time step, with equal probability $p = 0.25$ of arriving at any one of them, i.e.:

$$p_{uu} = 0.25 \text{ that } F_{w+1} = F_w \cdot u \wedge P_{w+1} = P_w \cdot u \tag{7}$$

$$p_{ud} = 0.25 \text{ that } F_{w+1} = F_w \cdot u \wedge P_{w+1} = P_w \cdot d \tag{8}$$

$$p_{du} = 0.25 \text{ that } F_{w+1} = F_w \cdot d \wedge P_{w+1} = P_w \cdot u \tag{9}$$

$$p_{dd} = 0.25 \text{ that } F_{w+1} = F_w \cdot d \wedge P_{w+1} = P_w \cdot d \tag{10}$$

2.5 Options-based trade optimization

In the optimization process, the lattice is used simultaneously for two purposes. First, we want to identify the optimal volume for an immediate trade, in view of the current forecast error estimate and the remaining uncertainties regarding price and production forecast development. Second, analogously to an option to wait, we want to analyze whether there is value in not trading at the current stage at all, due to too much uncertainty in the remaining process and too little value inherent in an immediate trade. This would imply that $I_w = 0$.

In the following, we exercise the required optimization steps for a short position. As shown in eq. (4), the steps for a long position require slightly adjusted formulas but follow the same principles.

The analysis starts at the end nodes of the lattice. These nodes represent the possible price-production forecast error combinations at the end of intraday trading at stage W. At that stage, the final forecast error is exactly known, thus $I_W = F_W$. Likewise, the realizable prices are the last available intraday prices. Based on these parameters, double trade costs C_{d} can be avoided. Recalling the formula for C_{b} and given that W is the last available intraday trade window, the value of trading equals the difference between the current intraday price and the expected imbalance market price for the required balancing volumes, for the case that a trade partner can be found, i.e.

$$V(I_W^*) = (1 - \varphi_{\mathrm{e}}) \cdot \left(\sum_{1}^{I_W} (c_{\mathrm{ime}} - p_w) \right). \tag{11}$$

Moving one time step backwards, the optimal volume for an immediate trade at $w = W - 1$ and the corresponding value at each node must be identified by solving for the value-maximizing trade volume I_w^* in view of the four price-production forecast error combinations $F_W, P_W, p_{uu}, p_{ud}, p_{du}, p_{dd}$ that may occur at W. More generally, the volume and corresponding value of trading immediately prior to W is optimized by maximizing C_b and minimizing C_{d} across the range of probability-weighted price-production forecast error combinations $(F_W, P_W)_m$, $m = 1, \dots, M$, that can be reached at the last stage W from the current price-production forecast error combination at w. The following illustration exemplifies this logic for a specific node at $w = W - 2$.

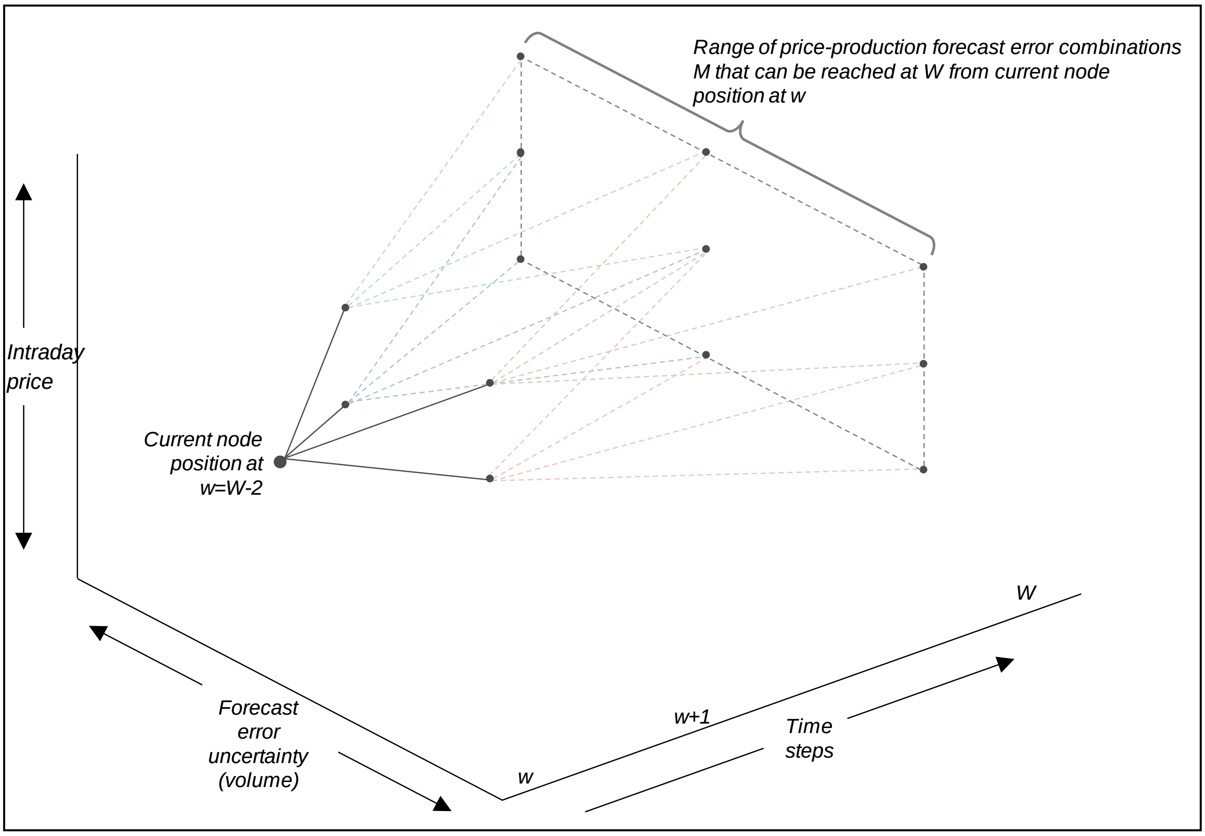


Figure 1: possible developments of intraday price and production forecast error between the current trade window and the final stage, given the current price-production forecast error combination.

Dynamic programming can be applied to find the I_w^* that maximizes the trade value $V(I_w^*)$ in view of the M possible price-production forecast error combinations with their respective probabilities of occurrence, p_m.

$$V(I_w^*) = \max_{0 \le I_w} \sum_{m=1}^{\mathrm{M}} \left[\left(\sum_{1}^{\min(I_w, F_W)} C_{\mathrm{b}} \left(-\sum_{F_W}^{I_w} C_{\mathrm{d}} \middle| I_w > F_W \right) \right) \cdot p_m \right]. \tag{12}$$

The value of immediately trading the value-maximizing volume I_w^* must then be compared to the discounted sum of the four probability-weighted values of holding on to the option to trade until the next trade window. At the last stage, this comparison is trivial, since the trade must be initiated; otherwise, the error volume could no longer be traded in the intraday market at all. The value-maximizing option is thus to trade immediately at W, i.e.

$$O(I_W^*) = \max(V(I_W^*), 0) = V(I_W^*). \tag{13}$$

For preceding stages, making the comparison involves some more calculations. The higher of the immediate trade value $V(I_w^*)$ and the discounted sum of probability-weighted expected values of delaying the trade needs to be chosen. The latter depends on the possible trajectories of price and forecast error from the current price-production forecast error combination.

$$O(I^*{}_w) = \max\left[V(I_w^*), \frac{p_{uu} \cdot O(I_{w+1}^*)_{uu} + p_{ud} \cdot O(I_{w+1}^*)_{ud} + p_{du} \cdot O(I_{w+1}^*)_{du} + p_{dd} \cdot O(I_{w+1}^*)_{dd}}{1+\tau}\right]. \tag{14}$$

Recalling that the probabilities are equalized ($p = 0.25$), allows simplifying to

$$O(I_w^*) = \max\left[V(I_w^*), \frac{\left(\frac{O(I_{w+1}^*)_{uu} + O(I_{w+1}^*)_{ud} + O(I_{w+1}^*)_{du} + O(I_{w+1}^*)_{dd}}{4}\right)}{1+\tau}\right]. \tag{15}$$

Here, the discount rate τ requires some explanation. In conventional discrete-time options models, τ reflects the risk associated with delaying cash flows and the resulting value discount on postponed cash flows. Given the short time span covered by our intraday trade model, loss in cash value in this traditional sense does not apply. However, delaying a trade implies another risk, more specifically the mounting risk of not finding a trade counterparty due to a tightening market. With any postponement, this risk increases and approaches its ultimate value as defined for the end of intraday trading in eq. (1). Therefore, τ is set to reflect the increase in counterparty risk between the current and the next trade window. As a result, the value of waiting must not only be higher than the value of an immediate trade; it also needs to compensate for the augmented risk of not finding a counterparty when trading in the next stage.

3 Bidding simulation

This section serves two purposes:

(1) to analyze the sensitivity of the model's executed bidding strategy to changes in market and forecast parameters, and

(2) to assess the performance of the executed strategy vis-à-vis alternative approaches.

The intention is to account for changing market states and validate the model's robustness. Thus, we refrain from in-depth derivation of static parameter values, but rather test different parameter scenarios and run numerous simulations. The key parameter (range) estimates are explained in the following, while a comprehensive overview is provided in the appendix.

3.1 Setup

We assume a random early afternoon delivery slot t. From EPEX intraday trade data, we see that afternoon slots are rarely traded more than six hours in advance[7]. The exemplary optimization thus begins at $t-6$, with every trade window $w=\{1,\dots,W\}$ covering one half hour. Trading closes 45 minutes prior to delivery, implying a total of eleven trade windows being simulated with the last window lasting only 15 minutes.

A set of small-scale wind power assets is considered. The intraday price level at $w=1$ is assumed to be 60 €/MWh, while the forecast error provided by the available forecast update at that time amounts to 20 MWh for the hour slot. This basic setting can now be combined with changing market parameter values in the simulation runs.

We simulate the time period from the current trade window till the end of trading at W by randomly drawing the change in price and forecast error between any two trade windows based on the alternative paths and probabilities provided by the multi-dimensional binomial lattice. Note that counterparty risk is included into the simulation as well: at every stage a probability-based random draw is conducted to determine whether any intended trade will be matched with a counterparty or not. Both the counterparty risk and the spread are assumed to double at each stage, such that they reach the predefined final trade window parameter value for a given scenario at the last stage W. This procedure is repeated with 50 different parameter settings to understand how the model responds to varying conditions. We then investigate the resulting performance in more detail for ten scenarios, by running 1000 simulation loops each.

At any trade window, the bidding model runs an optimization process by first creating a new binomial lattice for the remaining trading windows and then making a trade decision based on the calculated maximum immediate trade value. Once the model has executed a trade, the position is locked in and held on to. At the very last stage, the remaining open position (due

[7] Share of number of trades executed more than 6 hours in advance for slots beginning between noon and 5 PM range between 2.1% and 3.5% for three randomly selected months in 2012.

to either further changes in the forecast error volume after trading, or no trade having previously occurred) is closed through a final trade.

3.2 Input parameters

A number of intraday parameters are required as input factors for our analysis. To our knowledge, not all of them are readily available from existing research. They can, however, mostly be derived or at least inferred from available data. We base our parameter range estimates for price behavior on EPEX intraday transactions data for Germany, containing all intraday transactions made through the exchange including volume, trade price, timing of trade, and delivery slot. Randomly selecting three different months out of 2012, we analyze the growth and volatility of intraday prices for particular delivery slots[8]. Insights on bid-ask spreads are taken from existing empirical research, most importantly the German intraday market analysis provided by Hagemann and Weber (2013). The imbalance surcharge, i.e. the difference between (closing) intraday price and imbalance fees for forecast violations, are inferred from 2012 TSO data. It indicates that imbalance prices, in times of a short balancing area portfolio with intraday prices of 60 €/MWh (as in our scenario) or more, exceeded average intraday prices roughly by 76%. We conservatively set our base case at 70% on top of the final intraday trade price.

Regarding the forecast error, an overall volatility parameter is required to construct the trade volume dimension of the binomial lattice. When assuming only wind power or only PV power either from a single site or few highly correlated sites, matching data can be drawn from recent forecasting research or reports where forecasting tools have been developed or analyzed. When assuming a geographically dispersed portfolio or a portfolio with both PV and wind power sites, further efforts (e.g., by means of Monte Carlo simulation) are necessary in order to understand how the various individual volatility parameters interact and what the resulting aggregate volatility is. Generally, combining sites lowers overall volatility.

[8] Our analysis looks at changes in transaction price levels throughout trading periods for specific delivery (hour) slots in three months of 2012. Controlling for the preceding day-ahead price and the size of the forecast error (based on the TSO forecast and actual production data), we find that prices usually increase throughout the trading period if PV or wind operators in the market are short. Values range between 0% and more than 4% for the growth between two hourly trade windows, depending on the day-ahead and forecast error limits set to draw a sample. The effect is clearly stronger for delivery slots whose day-ahead prices were already high and the supply situation likely tight. In our base case, we set the growth value between the half-hourly trade windows conservatively at 0.5%. Regarding price variance, our analysis again indicates varying standard deviation values, typically in the range of 5% to 10% between two hourly windows. Based on these insights, we opt for a base case volatility estimate of 5% between the half-hourly windows.

For the sake of simplicity and transparency, we refrain from a complicated setting and concentrate on a set of few, perfectly correlated small-scale wind power sites. In Sideratos and Hatziargyriou (2007), a forecasting model is applied to a wind farm and yields a forecasting error distribution curve in which more than 90% of the six-hour forecasts are within the 20% boundary. Factoring in advances in forecasting accuracy made since their effort, we choose 20% as our base case forecast error volatility for a six-hour period. An important assumption that we make is that the forecast error between the current point in time and the end of intraday trading can be dissected into symmetric, discrete time steps. Forecast error uncertainties for most wind sites typically exhibit a less linear trajectory; in the final hours before delivery, uncertainty is more drastically reduced than in the earlier hours (Borggrefe & Neuhoff, 2011). We consider the deferring effect of this assumption to be minor for our purposes.

The rate τ applied to discount the value of waiting is set to reflect the increasing counterparty risk between the current and the next stage. Through this measure, the model appropriately accounts for the fact that the value of waiting is diminished by execution risks. Consequently, τ is dynamic and coupled to the behavior of the counterparty risk. Table A.1 in the appendix summarizes the value ranges considered for all relevant input parameters.

3.3 Simulation

In the following, we assess the strategy and impact of our bidding model under different scenarios. We focus on the model's execution adjustments to changing conditions and afterwards on the resulting performance vis-à-vis alternative approaches. A base case is defined[9], based on which different parameter dimensions are tuned individually and in combination to create more than 50 scenarios. For ten of these alternatives, we run 1000 simulation runs each to gain insights into the model's relative efficiency. Across scenarios, the model responds very actively to changing market conditions by tailoring the bidding execution. This applies to both changes in the devised batch size I_w^* and changes in timing.

[9] *Base case:* Forecast volume at $w = 1$, $X_1 = 20$; Price $P_1 = 60$; Forecast volatility $\sigma_F = 0.4$; Price volatility $\sigma_P = 0.05$; Price growth $\alpha_P = 0.005$; Correlation $\rho_{FP} = 0.3$; Counterparty risk market trades $\varphi_e = 0.3$ (value at last stage, value doubles in preceding stages to reach φ_{e} at W) ; Counterparty risk counter trades $\varphi_{\mathrm{o}} = 0$; Imbalance market surcharge market trade $c_{\mathrm{ime}} = 1.7$; Imbalance market surcharge counter trade $c_{\mathrm{imo}} = 1$; Bid-ask spread $c_{\mathrm{s}} = 0.05$; Spread growth of bid-ask spread $\Delta c_{\mathrm{s}} = 0.25$ (the growth value refers to the difference between w and W; the growth factor doubles between stages); $TC = 0.1$; Discount rate $\tau = \varphi_{\mathrm{e}}$, dynamically adjusting.

The kind and extent of adjustments depend on the parameter changes made and their interaction.

In the base case, the model trades aggressively, with a trade being executed in the very first stage with a batch size equal to the maximum forecast error volume within the range of possible outcomes provided by the lattice ($I_1 = 24$). The primary reason for this aggressive behavior is the expected (moderate) price growth ($\alpha_P = 0.005$ between two stages). Given the growth and the exponential stochastic process of the price, the model anticipates a great price risk and likely higher prices in the later stages of trading. Accordingly, the risk of incurring higher transaction costs due to double trades is accepted for the sake of minimized exposure to price risks. A reduction in expected price growth leads to smaller batch sizes (at $\alpha_P = 0$, $I_1 = 21.6$). However, the model still executes trades with volumes greater than the expected forecast error. Once both price growth and price volatility σ_P are minimized, trading becomes much more conservative. Assuming zero price growth, reductions in price volatility σ_F lead to both delays in trade executions and further reductions of the batch size.

The price impact on the model dominates the impact of changes in the forecast error uncertainty. As long as price growth is assumed, trading remains aggressive despite high forecast error uncertainty (even for 50% error uncertainty, i.e. $\sigma_F = 1$). Note that, once price growth is nullified, an increase in forecast error uncertainty leads to delays in trade execution and more cautious trading behavior. The model first lowers batch sizes (up to $\sigma_F = 0.8$), then additionally delays execution into trade windows four to seven (at $\sigma_F = 1$). However, the traded batch size remains slightly above the expected forecast error, despite the delays and relative reduction. The correlation between prices and forecast errors has an impact as well. If $\alpha_P = 0$, increasing the correlation from 0.3 to 0.5 triggers a reduction in batch size ($I_1 = 21.6$); a further increase to 0.7 leads to a trade delay into the sixth trade window with batch sizes set more conservatively ($I_6 = X_6 + 1.2$).

The impact of changing transaction costs on trade behavior varies. On the one hand, actual exchange market clearing costs have a low impact, given the limited relevance for overall costs. Further, they are fixed by the market operator, making variation less realistic in practice. The bid-ask spread (c_S), on the other hand, plays a noticeable role for the trade strategy of the model. Even small changes in the price-relative spread charge (from $c_s = 0.05 \cdot P$ to $c_s = 0.075 \cdot P$) leads to a reduction in batch size (I_1=21.6 instead of $I_1 = 24$ for $X_1 = 20$). However, a change in spread does not trigger any delays in trading.

Turning to late trade cost surcharges, the model responds to both changes in spread growth rate and counterparty risk by increasing the batch size. However, this effect is generally minor and only leads to changes in trade behavior if price volatility is set low and forecast error uncertainty high. If price volatility is high, the model trades early anyhow.

Figure 2 contrasts the strategy adjustments initiated by the model in view of changing conditions.

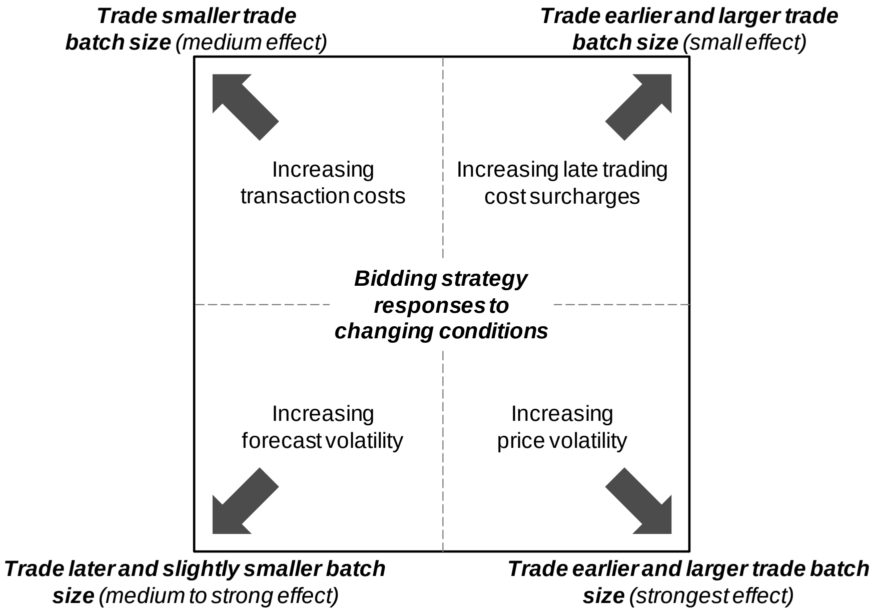


Figure 2: bidding strategy responses of the model to parameter changes.

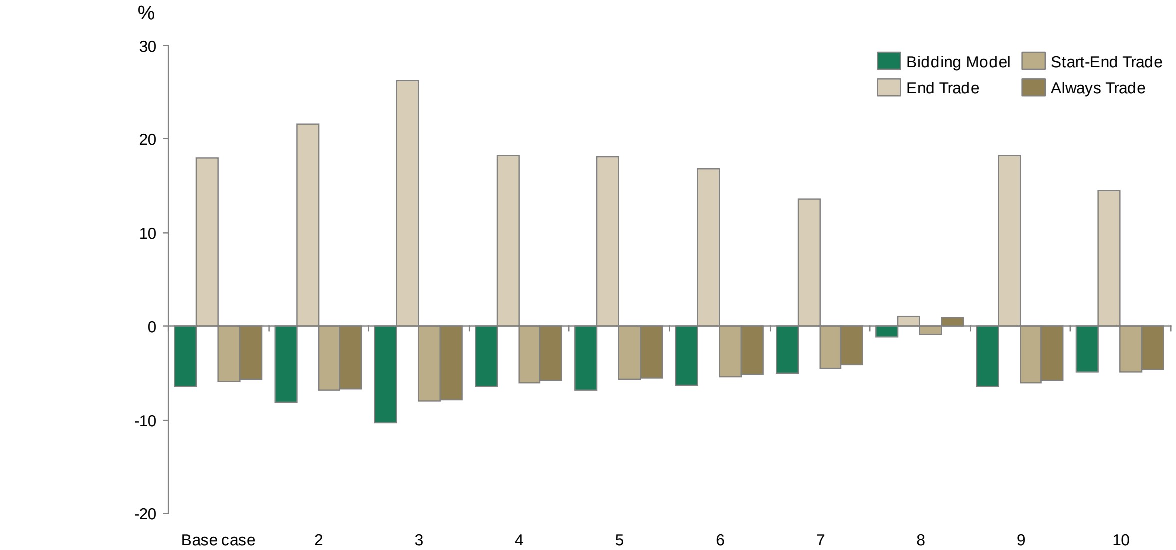
The ultimate goal when applying a specific bidding strategy from an operator's viewpoint is to minimize average trade costs. In order to quantify the degree to which the model achieves this goal, we review its performance against three static bidding strategies similarly used for comparison in other previous works on intraday trading of forecast errors (Henriot, 2014; Möhrlen *et al.*, 2012):

(1) trade open positions at any stage based on the latest forecast update ("Always trade"),

(2) trade now and correct any remaining deviation at the final stage ("Start-end trade"), or

(3) only trade at the final stage based on the final price and forecast error ("End trade").

In every tested scenario, the model operates more efficiently than the most efficient alternative (around 1% average trade cost savings overall). In comparison to the aggregate average performance of all strategies across scenarios, the efficiency benefit amounts to more than 6%. Noticeably, the performance advantage grows when introducing more volatile price conditions than in the base case. For instance, in a scenario with price growth $\alpha_P = 0.01$ and volatility $\sigma_P = 0.1$ between time steps, the bidding model saves 2.5% compared to the second-most efficient alternative and 10.3% compared to the aggregate average. The efficiency gain achieved in the base case amounts to 6.5% in relation to the average; the most competitive alternative strategy trails by 0.6%. Across scenarios, the "Start-end trade" strategy presents the second-most competitive alternative, while the "End trade" strategy trails behind all others.



	Base case	2	3	4	5	6	7	8	9	10
Price	-	Vola. up	Vola. up Growth up	Vola. up Growth 0	-	Vola. up Growth 0	Growth 0	Growth 0	-	Growth 0
Forecast	-	-	-	-	Up	Up	High up	High up	-	-
Transaction costs	-	-	-	-	-	-	-	Spread up	Up	-
Late trade costs	-	-	-	-	-	-	-	Down	-	Up

Figure 3: performance of the individual bidding strategies compared to their aggregated average performance per scenario, for all ten tested scenarios (in %). Changes of parameters compared to the base case are described in the table below the chart (details on results and scenarios can be found in the appendix).

Regarding absolute rather than relative trading costs, the main contributors to higher average cost levels are transaction costs and increasing forecast error uncertainty. With trades being delayed due to forecast error uncertainty, cost surcharges for late trading are incurred and efficiency is reduced. However, the differences in average cost levels between scenarios are moderate: while the costs in the base case amount to roughly 1,233 for the bidding model, they rise to about 1,261 (+2.3%) in the case of high forecast error uncertainty and high bid-ask spreads ($\sigma_F = 1$, and $c_s = 0.1 \cdot P$). On the other hand, average costs go down to about 1,210 in a scenario with high price growth and volatility compared to the base case ($\alpha_P = 0.01$, and $\sigma_P = 0.1$). Here, trades are executed early and aggressively.

Nevertheless, the variance of trade costs incurred per scenario and between simulation loops varies greatly. Depending on the scenario, variances for the developed bidding model range from around 6,000 to around 55,000. It shows that variance is strongly driven by the production forecast error uncertainty. Price uncertainty increases performance variance as well, but to a lesser degree. Compared to alternative strategies, the developed bidding model leads to a much greater variance in the results in scenarios with significant price growth and volatility. For instance, variance equals 16,070 for the model compared to 10,788 for the "Start-end trade" strategy and 7,441 for the "Always trade" strategy in a scenario with price growth $\alpha_P = 0.01$ and volatility $\sigma_P = 0.1$. Interestingly, this is precisely the kind of setting in which the model yields exceptionally high average efficiency gains. In scenarios with less extreme price volatility, the variance in results is comparable to the variance in results when applying the most efficient alternative strategy ("Start-end trade").

3.4 Discussion

The trade-off between early, aggressive execution and trade delay made by the bidding model depends on the market parameters and their interaction. Volatile prices trigger early execution and large batch sizes; volatile forecast error volumes and high transaction costs induce more conservative trading. These simulation results suggest that different intraday market conditions require different bidding strategies to minimize the costs of trading, at least in continuous-trade intraday markets. This may seem trivial but stands in contrast with suggested strategies focusing on forecast errors mainly while dealing with intraday prices as given, or as average values in auction-like settings (Möhrlen *et al.*, 2012; Morales *et al.*, 2010).

It further shows that volatility increases the relevance of bidding strategies. The more volatile prices and production forecast errors are, the more inefficient static or one-dimensional trading approaches become. Unsurprisingly, our model yields the largest relative efficiency gains in environments of high price volatility or both high price and production forecast error volatility. It may appear striking that price parameters seem to have a stronger impact on trade execution than production forecast error parameters. This, however, can be traced back to the underlying types of stochastic processes assumed. The intraday price is modeled as a GBM, implying a log-normal rather than a normal process. As a consequence, the intraday price is more likely to become worse than to become favorable from the viewpoint of a PV or wind operator. The production forecast error follows a normally distributed process and is thus equally likely to either increase or decrease.

Investigating the average efficiencies of the alternative strategies, it becomes obvious that permanently delaying trades ("End trade" strategy) leads to poor performance. The best alternative performance is achieved by the "Start-end trade" strategy. This, again, can be explained by the underlying stochastic processes, implying that prices tend to be worse when trading at the final trade window. As explicated earlier, we do find support for this notion when looking at EPEX intraday transactions data for 2012. While we have not conducted empirical investigations, it seems that prices are more extreme in the final hours before delivery. Consequently, choosing the "End trade" strategy presents a significant threat to profitability in markets with price volatility and diminishing balancing resource availability towards delivery. A similar point is made from an analytical perspective by Henriot (2014). Interestingly, this logic is in stark contrast to the relevance on late trading observed in intraday transactions data for 2012. Trading activity increases dramatically when approaching delivery, indicating a wait-and-see behavior by operators.

The absolute trade cost levels are primarily negatively impacted by the production forecast error uncertainty, not by price uncertainty. On the one hand, when production forecast errors are volatile, trades need to be delayed to minimize volumetric risk exposure. This in turn leads to higher transaction costs and late trade surcharges incurred. On the other hand, price uncertainty triggers early trades with aggressive batch sizes. The result is that no late trade surcharges are absorbed and the overall cost levels reduced. However, transferring such aggressive trading to settings with great forecast error uncertainty would not be appropriate – as can be seen by the inferior results of the "Start-end trade" strategy compared to our bidding model in such scenarios. Put differently, the avoidance of late trade costs can simply not compensate for the exposure to volumetric risks.

4 Conclusion

In this paper, we have formulated and tested a model to optimize trade execution aimed at balancing forecast errors for wind or PV power production. The model features options valuation methodology and dynamic programming to identify the perfect timing and batch size under market and production forecast uncertainty. It determines the possible paths of intraday prices and production forecast errors with their respective probabilities, and derives the optimal trade execution for each path at each step. Depending on the actually realized path, trades are either executed or delayed.

Across scenarios, the bidding model outperforms the most efficient alternative by values up to more than 2.5% and the aggregate average by more than 6%. This may seem moderate, but in fact implies significant absolute return improvements in very competitive markets such as the power wholesale market in Germany. If we had considered scenarios with higher price volatility, even greater efficiency gains would have occurred. However, the real benefit of the model lies in its flexibility. The intraday market is fairly illiquid, subject to frequent changes (e.g. growing market shares of PV and wind power) and far from extensively researched. Bidding models thus need to be able to quickly adapt and embrace volatility along multiple dimensions. Fixed strategies, or strategies purely focused on the magnitude of the forecast error, cannot provide sufficient flexibility.

At this point, it is essential to discuss the limitations of our approach and the scope for further research. Most notably, our simulation runs are based on value ranges that have not been empirically tested. While we deem them realistic and have relied on existing research and own analyses to calibrate the model, further research is needed to draw a more detailed and robust picture of relevant intraday market conditions in continuous-trade intraday markets like the German intraday market. This refers particularly to the patterns of bid-ask spreads, prices, and counterparty risk. In fact, transparency on these market parameters would allow for better trade calibration and help operators increase their efficiency in balancing production forecast errors. It could therefore present a major contribution to the successful integration of small- to mid-scale renewable power assets into competitive energy markets.

As a further limitation, it should be noted that we have taken on the perspective of an individual operator with no market power. Therefore, we have assumed a perfectly competitive market. In fact, if a significant share of operators or large-scale operators (e.g., the TSOs in Germany) were to adopt the same bidding model, prices would very likely respond and thus game-theoretic effects would have to be included into the model to account for strategic bidding and to assure optimal results.

Turning towards further research scope and opportunities, we consider it appealing to investigate trading behavior and intraday market dynamics from a macro rather than a micro perspective. As already pointed out by Weber (2010), much balancing happens over-the-counter or within the portfolios of large operators. In fact, the value of avoiding intraday market trading is likely significant, especially when considering the counterparty risks and price uncertainties. This may have two implications. First, it amplifies the problem of tight markets and resulting risks by lurking actors and their resources away from the market. Second, it creates a competitive disadvantage for small operators who usually have no internal resources for balancing. As a result, small operators may increasingly get crowded out from competition as market exposure rises. This undermines the idea of a landscape which is increasingly shaped by distributed generation and should thus be thoroughly analyzed.

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Appendix

Table A.1 Input parameter value ranges and explanations

Parameter	Range	Estimation method	Pparameter change impact
Forecast error volatility	20-50%[10]	· Error estimate uncertainty distribution between current trade window and delivery, input from research papers[11] · 20% overall volatility, i.e. 2% volatility between two windows in base case (in absolute terms, since ABM)	· Greater forecast volatility leads to trade postponement · Medium to strong impact
Bid-ask spread	0-10%	· Indications from research, e.g. Hagemann and Weber (2013) and EPEX data[12] · 5% spread assumed in base case	· Spread makes trading of each volume more costly · With larger spread, batch sizes are reduced · Medium impact
Development bid-ask spread	0-50%	· No empirical research available so far · 50% total spread growth applied in base case	· Spread increase enhances relative attractiveness of early trades and larger batches · Small impact
Price drift	0-10%	· 2012 EPEX intraday data shows varying growth patterns, depending on sample and shortness of market · 0.5% price drift between windows in base case (i.e., 5% overall)	· Price growth triggers earlier trades and larger batch sizes, due to higher relative attractiveness · Strong impact
Price volatility (under GBM)	0-10%	· 2012 EPEX intraday data show varying variances, depending on sample and shortness of market · Standard deviation mostly between 5% and 10% between hourly trade windows · 5% volatility between half-hour	· Volatility drives uncertainty and implies growth expectation (due to exponential function) · Higher volatility triggers earlier and larger trades, due to higher relative attractiveness · Strong impact

[10] Translated into absolute values, since the forecast error is modeled as an Arithmetic Brownian Motion.

[11] For instance, Sideratos and Hatziargyriou (2007), Giebel *et al.* (2011), Borggrefe and Neuhoff (2011). Generally diverse values, depending on site, forecasting methodology, and time horizon.

[12] Hagemann and Weber (2013) find average intraday bid-ask spreads of around 3 €/MWh in 2010 and 2011. As we find EPEX intraday prices in 2001 to average roughly €51, we conservatively choose 5% in the base case.

		windows in base case	
Price-production forecast error correlation	0-50%	· Indications from research, e.g. (Hagemann and Weber (2013))[13] · 30% in base case	· Correlation increase leads to batch size reduction and eventually delay as well · Small to medium impact
Imbalance price surcharge	>50%	· 2012 TSO data indicating imbalance prices around 76% above average intraday price for short balancing zone and prices of 60 €/MWh and more · 70% assumed in base case	· Higher surcharge decreases relative attractiveness of later trades, due to higher risk of incurring imbalance fees when postponing trades · Medium impact
Counterparty risk (market-reflective position / counter-position)	30% / 0%	· No empirical research available so far; Möhrlen *et al.* (2012) mention significant risk, but do not quantify it · 30% for market-reflective position in base case; 0% for counter position (counter position likely to find match due to need for balance by operators being short)	· Higher risk increases costs of postponement, since exposure to imbalance fee surcharge augmented · For counter market position, assumption that risk is 0 (since counterparty is very likely found, and in order to not incentivize arbitrage) · Medium impact
Transaction costs	0.1 €/MWh	· EPEX Spot information, reflecting transaction costs incl. ECC clearing · 0.1 €/MWh in base case	· Higher transaction costs make trading generally less attractive · Thus trading behavior becomes more volume-sensitive, leading to postponement and conservative trade volumes · Very small impact
Risk-free rate	Dynamic	· In model setting, the risk-free rate dynamically reflects increasing counterparty risk between two stages, to discount value of waiting	· Higher rate induces earlier trades, since value of waiting is diminished by strong increase in counterparty risk · Small to medium impact

[13] Hagemann and Weber (2013) investigate the correlation between the magnitude of the wind or PV power production forecast error and intraday parameters. They find that increasing (wind) forecast errors significantly increase intraday price variance. However, the applicability of their research to the setting in our paper is limited, since their empirical research takes on a static perspective with average intraday values instead of timing-specific transactions prices. Still, their findings support the notion that balancing activities of PV or wind operators in the market noticeably increase trading activity and affect prices.

Table A.2 Simulation setup and results

Setup	Setup explanation	Model trade costs (€)	Cost vs. average (%)	Cost vs. best other (%)
Base case	$\sigma_F = 0.4$, $\sigma_P = 0.05$, $\alpha_P = 0.005$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.25$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1232,7	-6,5%	-0,6%
2	$\sigma_F = 0.4$, $\sigma_P = 0.1$, $\alpha_P = 0.005$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.25$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1218,7	-8,1%	-1,3%
3	$\sigma_F = 0.4$, $\sigma_P = 0.1$, $\alpha_P = 0.01$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.25$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1210,4	-10,3%	-2,5%
4	$\sigma_F = 0.4$, $\sigma_P = 0.1$, $\alpha_P = 0$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.25$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1235,4	-6,5%	-0,5%
5	$\sigma_F = 0.8$, $\sigma_P = 0.05$, $\alpha_P = 0.005$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.25$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1240,4	-6,9%	-1,3%
6	$\sigma_F = 0.8$, $\sigma_P = 0.1$, $\alpha_P = 0$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.25$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1236,9	-6,3%	-1,0%
7	$\sigma_F = 1$, $\sigma_P = 0.05$, $\alpha_P = 0$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.25$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1247,5	-5,0%	-0,6%
8	$\sigma_F = 1$, $\sigma_P = 0.05$, $\alpha_P = 0$, $\rho_{FP} = 0.3$, $\varphi_e = 0.1$, $\varphi_o = 0$, $c_{ime} = 1.2$, $c_{imo} = 1$, $c_s = 0.1$, $\Delta c_s = 0.1$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1260,8	-1,1%	-0,2%
9	$\sigma_F = 0.4$, $\sigma_P = 0.05$, $\alpha_P = 0.005$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.075$, $\Delta c_s = 0.25$, $TC = 0.2$, $\tau = \varphi_e$, dynamically adjusting	1252,7	-6,4%	-0,4%
10	$\sigma_F = 0.4$, $\sigma_P = 0.05$, $\alpha_P = 0$, $\rho_{FP} = 0.3$, $\varphi_e = 0.3$, $\varphi_o = 0$, $c_{ime} = 1.7$, $c_{imo} = 1$, $c_s = 0.05$, $\Delta c_s = 0.5$, $TC = 0.1$, $\tau = \varphi_e$, dynamically adjusting	1233,7	-4,9%	-0,1%
	Average	**1236,9**	**-6,2%**	**-0,8%**

Acknowledgments

The authors gratefully acknowledge the helpful comments received from Wilko Rohlfs regarding the technical implementation of the binomial tree with two different underlying stochastic processes. Further, we would like to thank the participants of the 8th World Congress of the Bachelier Finance Society 2014 (June 2-6, Brussels) for their valuable questions and comments.

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