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RESEARCH ARTICLE

Trading wind energy on the basis of probabilistic forecasts both of wind generation and of market quantities

M. Zugno[1], T. Jónsson[1,2] and P. Pinson[1]

[1] DTU Informatics, Technical University of Denmark, Richard Petersens Plads, Bld. 305, DK-2800 Kgs. Lyngby, Denmark
[2] ENFOR A/S, Lyngsø Allé 3, DK-2970 Hørsholm, Denmark

ABSTRACT

Wind power is not easily predictable and non-dispatchable. Nevertheless, wind power producers are increasingly urged to participate in electricity market auctions in the same manner as conventional power producers. The aim of this paper is to propose an operational strategy for trading wind energy in liberalized electricity markets and to assess its performance. At first, the so-called optimal quantile strategy is revisited. It is proved that without market power, i.e. under the price-taker assumption, this strategy maximizes expected market revenues. Forecasts of wind power production, of day-ahead and real-time market prices and of the system imbalance are inputs to this strategy. Subsequently, constraining of the bid that maximizes the expected revenues is proposed as a way to overcome the strategy's disregard of practical limitations and, at the same time, of risk. Two constraining techniques are introduced: constraining in the decision space and in the probability space. Finally, the trade of a wind power producer is simulated in a test case for the Eastern Danish (DK-2) price area of the Nordic Power Exchange (Nord Pool) during a 10 month period in 2008. The results of the test case show the financial benefits of the aforementioned strategy as well as the consequent interaction with the electricity market. This study will support a demonstration in the framework of the EU project ANEMOS.plus. Copyright © 2012 John Wiley & Sons, Ltd.

KEYWORDS
electricity markets; probabilistic forecasting; stochastic optimization; decision theory

Correspondence
M. Zugno, DTU Informatics, Technical University of Denmark, Richard Petersens Plads, Bld. 305, DK-2800 Kgs. Lyngby, Denmark.
E-mail: mazu@imm.dtu.dk

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NOMENCLATURE

Main symbols

ρ_k	wind power producer revenues at trading period k
W_k	wind power production at trading period k
π_k	market price at trading period k
C_k	negative wind power producer revenues due to imbalance at trading period k
ψ_k	unit regulation costs for positive and negative imbalances at trading period k
$W^{(\max)}$	installed wind power capacity
r_k	quantile of wind power distribution at trading period k
P_k	probability of imbalance direction at trading period k
a_{v}	parameter determining the width of the bound to the optimal bid in the decision space
a_{p}	parameter determining the width of the bound to the optimal bid in the probability space

Superscripts

$^{(S)}$ referring to the day-ahead market
$^{(\uparrow/\downarrow)}$ referring to the real-time market
$^{(\uparrow)}$ referring to up-regulation in the real-time market
$^{(\downarrow)}$ referring to down-regulation in the real-time market
* optimal
$\tilde{}$ contracted at the day-ahead market
$\hat{}$ forecast

1. INTRODUCTION

In liberalized electricity markets, competition stands as the fundamental mechanism ensuring the efficient operation of the system. Competition is implemented through the establishment of a market (or multiple markets operating under different rules and gate closures) where energy is traded. Bids for sale and purchase are collected by the market operators, which are responsible for optimally scheduling the dispatch of energy and allocating sufficient power reserve. The backbone of most liberalized electricity markets are the day-ahead markets, often referred to as *spot* markets (in Europe) or *forward* markets (in the USA), on which most of the trading takes place. Typically, these markets offer a platform for trading energy to be delivered/withdrawn within a certain period during the upcoming day. The minimum period length is referred to as *trading period* in this paper; every contract covers one or more trading periods.

Although most renewables are not easily predictable and non-dispatchable, renewable power producers are increasingly urged to participate in electricity markets in the same manner as producers of conventional energy. Here, we specifically concentrate on wind energy, which has been the most rapidly growing renewable energy source over the last decade. Our developments and conclusions could however be similarly applied for other types of non-dispatchable renewables, e.g. solar energy.

Wind power generation is the typical example of a stochastic and non-dispatchable renewable energy source. Although the possibility of curtailing power exists, it is not economically sound as long as the electricity price (including potential subsidies) remains positive. As a result, trading wind energy in a day-ahead electricity market requires forecasts of wind power production, which can be performed only with limited accuracy, as discussed in Madsen *et al.*[1] Reviews of the state of the art of wind power forecasting methods and operational tools can be found in Giebel *et al.*,[2] Costa *et al.*[3] and Monteiro *et al.*,[4] while Botterud *et al.*[5] discussed their application in electricity markets.

Differences between contracted and actual energy production (e.g. due to forecasting errors) have to be settled on the intra-day and/or the real-time markets. Because of shorter lead time from gate closure to delivery, these markets might reduce the revenues of producers that cause imbalance, as more flexible market players are called to equilibrate the system—generally at higher costs. Joint operation of wind and hydropower has recently emerged as a way to reduce imbalance costs among other benefits, for instance, see Angarita *et al.*[6] or Montero and Perez.[7] However, this solution is only conceivable for market participants having both energy sources in their portfolio. For other producers, the most practical option for imbalance settlement is to rely on the market. Although it is sometimes possible to adjust contracts through existing intra-day markets, the volumes exchanged there are generally low, as illustrated by Weber[8] for the main European electricity markets. Producers are therefore most often forced to rely on the real-time market, where bids for regulation are activated by the TSO close to real-time, and producers are charged for their imbalances, which are determined post-delivery. Hence, the only way for them to reduce imbalance costs is to bid optimally into the day-ahead market so that the risk of facing losses on the real-time market is minimized. This bid is optimized, conditioned upon the information available at the time of contracting, both in terms of future wind power production and market prices.

The penalties faced by electricity producers in the real-time market are generally asymmetric, in some cases even single sided, i.e. they are only to be paid by the producers that increase the overall imbalance with their own. This incites market participants whose portfolio includes a stochastic component to be more strategic in their approach to bidding.[9] Indeed, it can be analytically shown that under these conditions, the optimal day-ahead market bid for a wind energy producer is a certain quantile of the distribution of wind power generation, for instance, see Bremnes,[10] Linnet[11] and Pinson *et al.*[12] This optimal quantile is a dynamic function of the day-ahead and the imbalance prices, which are not known *a priori*. Market experience shows that such optimal bids might significantly differ from the point forecasts of wind power production (consisting of the conditional expectation for each lead time). In practice, however, point forecasts are still commonly used when contracting wind power in the day-ahead market. A more theoretical discussion about quantile forecasts being optimal bids in electricity markets can be found in Gneiting.[13]

The existing literature has already described and analysed a number of strategies for trading wind power in the day-ahead market, with different approaches with regards to the uncertainty in production and in market prices. As a

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basic approach, some authors consider that traditional point forecasts of wind power generation may be used for analysing the value of wind energy in electricity markets, e.g. Angarita-Márquez *et al.*,[14] Barthelmie *et al.*[15] and Chang *et al.*.[16] Furthermore, Bathurst *et al.*[17] modelled wind generation uncertainty through Markov probability tables and chooses, in a discrete decision space, the bid that minimizes the expected costs. Alternatively, Galloway *et al.*[18] suggested the construction of a utility cost function to model the financial risk of wind power producers participating in the market, using persistence forecasting of wind power and average values as price forecasts. The stochastic optimization algorithm described in the study by Matevosyan and Söder[19] uses scenarios of wind power production as input along with historical imbalance prices. Besides, Pinson *et al.*[12] made use of probabilistic forecasts of wind power and yearly or quarterly average values of imbalance prices in order to determine the optimal quantile bid, in a fashion resembling that of Bremnes.[10] The same strategy is implemented in the study by Gibescu *et al.*,[20] using probabilistic forecasts and measured data for wind speed and yearly averages as estimates of the day-ahead and real-time prices. Finally, Morales *et al.*[21] proposed a linear programming technique for optimizing the trade of wind energy in day-ahead, intra-day and real-time markets. The uncertainty in both wind power production and market prices is modelled through simple autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models. All these works and strategies either only account for uncertainty in wind power generation but disregard uncertainty in the market quantities or include both but make use of simple forecasting methods.

In this work, we revisit the quantile strategy described in Bremnes[10] and Pinson *et al.*[12] and generalize it by considering stochastic rather than deterministic market prices. State-of-the-art probabilistic forecasts both of wind power generation and of market quantities are considered as input. These market quantities include the regulation sign, which can be down-regulation, up-regulation or no regulation, as well as the unit regulation costs. This strategy is formulated in Section 2 as a stochastic optimization problem, which aims at the maximization of the expected revenues (or utility) of the market participant. This approach is hereafter referred to as Expected Utility Maximization (EUM). Having the maximization of the expected value of the revenues as the objective, such an approach directly relates to a long-term optimization of the market performance of the wind power producer. It is also shown through an example that because of the uncertainties involved and the potentially large forecast errors, such a strategy may occasionally lead to severe losses from a single contract. For instance, this might occur when the regulation sign forecast wrongly assigns a high probability to an imbalance direction that is not realized. It is proposed in Section 3 to constrain the EUM bid in terms of deviations from the point forecasts, either in the quantity space or in the probability space. The two constraining methods are proposed with two different ranges of the allowed interval in the decision space. The motivation for this constraining is twofold. From a practical perspective, constraining the bid is beneficial, because system operators are reluctant to allow large deviations from the point forecasts. This is because efficient system planning requires market bids to closely reflect the actual delivery of energy. Moreover, since point forecasts have been used as operational bids since wind energy started to be traded on electricity markets, such point forecasts act as anchors in the mind of the operators. From a different point of view, this work shows that by setting a constraint on the allowed deviation from the point forecast, the trader can reduce the impact of forecasting errors and increase its risk aversion. Next, in Section 4, the participation of a wind power portfolio in the Nord Pool market (Eastern Denmark price area) over a period of 10 months in 2008 is considered in order to evaluate the actual performance of the aforementioned trading strategies. To our knowledge, a test case of such length, combining state-of-the-art forecasts of wind power production, day-ahead and imbalance prices, as well as observed wind production and market data, has never been performed. The results of the exercise show the possibility for wind power producers to significantly reduce their imbalance costs and control the risk of dramatic losses.

The contribution of this paper to the state of the art on the subject is threefold. First of all, the derivation of the optimal quantile strategy is extended to the case where market prices are stochastic. Owing to this formulation, probabilistic forecasts both of wind power production and of market quantities are needed by the decision maker. Secondly, we introduce constraining of the bid as a way to account for issues related to the practical implementability of the strategy and, in parallel, risk aversion. Finally, we present a realistic test case simulating wind power trading, and we assess the market value of state-of-the-art probabilistic forecasts of wind power production and of market quantities.

The derivation of the optimal quantile strategy presented in this paper is valid under the price-taker assumption; i.e. the wind power producer cannot influence market prices with its bid. Therefore, the aim of this work is to propose operational strategies and to assess the market value of forecasts under this hypothesis. In future markets with increasing penetration of wind power, this assumption might not hold, since wind power producers might impact the total system imbalance and therefore influence the price formation mechanisms with their trading strategy. By introducing the constraining of the bid, this issue is partly addressed, since constrained strategies result in lower imbalance and, therefore, limit the impact on prices. The derivations and the results presented in this paper thus constitute a valuable starting point and a reference for further research on the subject, where the dependence structure between wind power production and market prices is taken into account.

The work presented here will support and serve as the basis for a real-world demonstration of stochastic approaches to wind power participation in electricity markets in the framework of the EU project ANEMOS.plus.

2. THE EUM BIDDING STRATEGY

This section is devoted to the introduction of the strategy maximizing the expected utility of a wind power producer participating at both the day-ahead and real-time energy markets. At first, the strategy is derived in Section 2.1. Then, the forecasts needed in order to decide on the optimal bid are described in Section 2.2. Finally, possible shortcomings of the strategy are discussed on the basis of a test case in Section 2.3.

2.1. Derivation of the EUM strategy

In electricity day-ahead markets, power producers have to indicate the amount of energy they are willing to deliver at any trading period through a bid submitted to the market operator. Bids are collected with a certain lead time to the physical delivery of energy. For example, at the Nord Pool day-ahead market, the deadline for submission is at noon on the day prior to delivery. Let $\widetilde{W}_k$ denote the amount of energy contracted in the day-ahead market, and let W_k be the stochastic production of wind energy, both for the kth trading period. The power producer will then have to correct the stochastic imbalance $W_k - \widetilde{W}_k$ on the real-time market. This is because the possibility of trading on the intra-day market is disregarded, because of its general illiquidity. Hence, the total revenues of the generator, ρ_k, can be expressed as the sum of the revenues, $\rho_k^{(S)}$ and $\rho_k^{(\uparrow/\downarrow)}$, obtained at the day-ahead and the real-time market, respectively:

$$\rho_k = \rho_k^{(S)} + \rho_k^{(\uparrow/\downarrow)} \tag{1}$$

The revenues at the day-ahead market can be determined as the multiplication of the contracted energy $\widetilde{W}_k$ with the day-ahead market price $\pi_k^{(S)}$:

$$\rho_k^{(S)} = \pi_k^{(S)} \widetilde{W}_k \tag{2}$$

The real-time market revenues are positive if $W_k > \widetilde{W}_k$ (energy surplus to be sold) and negative if $W_k < \widetilde{W}_k$ (energy deficit to be purchased):

$$\rho_k^{(\uparrow/\downarrow)} = \begin{cases} \pi_k^{(\downarrow)} \left(W_k - \widetilde{W}_k\right), & W_k \geq \widetilde{W}_k \\ \pi_k^{(\uparrow)} \left(W_k - \widetilde{W}_k\right), & W_k < \widetilde{W}_k \end{cases} \tag{3}$$

In this expression, $\pi_k^{(\downarrow)}$ ($\pi_k^{(\uparrow)}$) represents the unit down(up)-regulation price, which is paid to (by) an overproducing (underproducing) generator. At Nord Pool, real-time prices are restricted such that

$$\begin{aligned} \pi_k^{(\downarrow)} &\leq \pi_k^{(S)} \\ \pi_k^{(\uparrow)} &\geq \pi_k^{(S)} \end{aligned} \tag{4}$$

at all times. Then, depending on the total imbalance of the system, the inequality sign is substituted by an equality sign in at least one of the two inequalities in equation (4). More specifically, let the net system imbalance be denoted as

$$(\widetilde{G}_k - G_k) - (\widetilde{L}_k - L_k) \tag{5}$$

where $\widetilde{G}_k$ and G_k denote the total (i.e. summed over all the producers dispatched at the day-ahead market) energy production, contracted and realized, respectively, for the kth trading period. Similarly, $\widetilde{L}_k$ and L_k represent the contracted and realized consumption, respectively, for the consumers and the retailers scheduled at the day-ahead market. Notice that when the quantity in equation (5) is different from zero, real-time bids have to be activated in order to restore energy balance. During hours of power surplus, i.e. when the net system imbalance in equation (5) is <0, the following holds for the prices:

$$\begin{aligned} \pi_k^{(\downarrow)} &\leq \pi_k^{(S)} \\ \pi_k^{(\uparrow)} &= \pi_k^{(S)} \end{aligned} \tag{6}$$

This situation is commonly referred to as down-regulation. Conversely, during hours of power deficit (when the system net imbalance in equation (5) is >0), commonly termed up-regulation, it holds that

$$\begin{aligned} \pi_k^{(\downarrow)} &= \pi_k^{(S)} \\ \pi_k^{(\uparrow)} &\geq \pi_k^{(S)} \end{aligned} \tag{7}$$

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Finally, during hours of perfect balance between load and production, then

$$\pi_k^{(\mathrm{S})} = \pi_k^{(\downarrow)} = \pi_k^{(\uparrow)} \tag{8}$$

In this way, only the producers contributing to the overall system imbalance are being penalized, while the ones acting to reduce it receive the day-ahead price for their realized production, when transactions on both the day-ahead and real-time markets are combined. The rationale behind this choice of market design is that producers should not be allowed to profit from their imbalances. However, it should be pointed out that there are exceptions to this. For instance, the Dutch APX electricity market is just one example of a market where energy imbalance can actually be rewarded.

Now, equation (1) can be reformulated as

$$\rho_k = \pi_k^{(\mathrm{S})} W_k + C_k^{(\uparrow/\downarrow)} \tag{9}$$

Assuming that the wind power producer is a price-taker individually, which is reasonable if it does not hold a significant share of the total production, the term $\pi_k^{(\mathrm{S})} W_k$ in equation (9) is independent of its decision. That is, neither the day-ahead price $\pi_k^{(\mathrm{S})}$ nor the wind power production W_k are influenced by the bidding policy adopted in the day-ahead market. This implies that curtailment is not considered as an option, for the reasons discussed in Section 1. The term $\pi_k^{(\mathrm{S})} W_k$ represents the revenues that the producer could achieve if it had perfect information on its future wind power production (i.e. if contracted power and wind power production are equal: $\widetilde{W}_k = W_k$). The second term in equation (9) can be made explicit as

$$C_k^{(\uparrow/\downarrow)} = \begin{cases} \psi_k^{(\downarrow)} \left(W_k - \widetilde{W}_k \right), & W_k \geq \widetilde{W}_k \\ \psi_k^{(\uparrow)} \left(W_k - \widetilde{W}_k \right), & W_k < \widetilde{W}_k \end{cases} \tag{10}$$

where the variables $\psi_k^{(\downarrow)}$ and $\psi_k^{(\uparrow)}$ represent the unit regulation costs for positive and negative imbalances at the real-time market and are given by

$$\psi_k^{(\downarrow)} = \pi_k^{(\downarrow)} - \pi_k^{(\mathrm{S})} \tag{11}$$

$$\psi_k^{(\uparrow)} = \pi_k^{(\uparrow)} - \pi_k^{(\mathrm{S})} \tag{12}$$

The quantity in equation (10) therefore accounts for negative revenues, which represent the losses for the producer contracting $\widetilde{W}_k$ at the day-ahead market in comparison with the case of perfect information. At Nord Pool, it holds that $C_k^{(\uparrow/\downarrow)} \leq 0$ at all times. Elsewhere (e.g. APX in the Netherlands), $C_k^{(\uparrow/\downarrow)} > 0$ might occur. Regarding the latter case, economists argue that although situations where producers can gain from their imbalance are possible, this cannot be exploited in the sense of strategic bidding. The argument is that the expectation $\mathbb{E}\left\{C_k^{(\uparrow/\downarrow)}|\chi\right\}$ of the losses given the information available at the moment of bidding is negative. As a consequence, the producers are expected to suffer losses from their imbalance in the long run, although in some trading periods they might be able to gain from it. Interested readers are referred to the study by Boogert and Dupont[22] for a detailed discussion.

As one can see from equations (4), (11) and (12), at Nord Pool, $\psi_k^{(\downarrow)} \leq 0$ and $\psi_k^{(\uparrow)} \geq 0$, and they are equal to zero in the cases of up-regulation and down-regulation, respectively. It should also be noted that both the unit regulation costs in equations (11) and (12) are stochastic variables as the day-ahead price and the imbalance prices are not known in advance by the power producer.

It is assumed from now on that the wind power producer is *rational* (e.g. see Binmore[23] for a conceptual introduction) and that its objective is the maximization of the expected value of its total revenues. The set of bids $\widetilde{\mathbf{W}}^*$ maximizing the total revenues is

$$\widetilde{\mathbf{W}}^* = \arg\max_{\widetilde{\mathbf{W}}} \mathbb{E}\left\{ \sum_{k=i_{\mathrm{TP}}}^{f_{\mathrm{TP}}} \rho_k \right\} \tag{13}$$

where i_{TP} and f_{TP} are the shortest and the longest lead times considered in the optimization, respectively. Here, the commonly accepted assumption of independence of decisions for different trading periods is followed. However, it may be argued that market dynamics should be accounted for, for instance, see Alvarado,[24] Liu[25] and Giabardo *et al.*[26] Under the assumption of time-independent decisions over time, the maximization of the sum of the revenues over time is equal to the maximization of the revenues obtained at each single k. The optimal bid at the day-ahead market is then

$$\widetilde{W}_k^* = \underset{\widetilde{W}_k}{\arg\max}\, \mathbb{E}\{\rho_k\} \tag{14}$$

Since the first term in equation (9) is not dependent on the decision on the day-ahead market, the maximization of the expected revenues in equation (14) is equivalent to the maximization of the expectation of the regulation costs, which are non-positive

$$\widetilde{W}_k^* = \underset{\widetilde{W}_k}{\arg\max}\, \mathbb{E}\left\{C_k^{(\uparrow/\downarrow)}\right\} \tag{15}$$

The problem in equation (15) is a variant of the well-known linear terminal loss problem (also called the newsvendor problem), for instance, see Raiffa and Schlaifer,[27] in which the imbalance costs to be borne by the decision maker are stochastic, asymmetric and piecewise linear. Under the assumption that the unit up-regulation and down-regulation costs are independent of the power producer's imbalance, these stochastic costs can be replaced by *certainty equivalents* in the optimization problem. Assuming that the considered wind power producer is relatively small, such a simplification seems quite reasonable as the producer is a price-taker. Nevertheless, it is clear that some variables could influence wind power production and real-time costs at the same time. This could be the case of e.g. weather related variables in a relatively small power system. This issue goes beyond the scope of this article, but it certainly calls for future research in modelling variables influencing both prices and wind power production.

According to the theory of certainty equivalents,[27] the rational decision maker can determine the optimal decision without taking into account the whole distribution function of the unit costs. Instead, an equivalent problem is solved, in which the stochastic unit costs are substituted by certain deterministic functions of the unit costs themselves. It is proved below that maximizing $C_k^{(\uparrow/\downarrow)}$ in equation (10) is equivalent to maximizing the expectation of the following function with deterministic unit costs:

$$\overline{C}_k^{(\uparrow/\downarrow)} = \begin{cases} \widehat{\psi}_k^{(\downarrow)}\left(W_k - \widetilde{W}_k\right), & W_k \geq \widetilde{W}_k \\ \widehat{\psi}_k^{(\uparrow)}\left(W_k - \widetilde{W}_k\right), & W_k < \widetilde{W}_k \end{cases} \tag{16}$$

where $\widehat{\psi}_k^{(\downarrow)}$ and $\widehat{\psi}_k^{(\uparrow)}$ denote the expected values of the unit regulation costs $\psi_k^{(\downarrow)}$ and $\psi_k^{(\uparrow)}$, respectively. The expectation of the imbalance costs in equation (10) can be expanded as

$$\begin{aligned}\mathbb{E}\{C_k^{(\downarrow/\uparrow)}\} = &\int_0^{+\infty}\int_0^{\widetilde{W}_k} \psi_k^{(\uparrow)}\left(W_k - \widetilde{W}_k\right)\mathrm{d}P_{W_k}\,\mathrm{d}P_{\psi_k^{(\uparrow)}} \\ &+ \int_{-\infty}^{0}\int_{\widetilde{W}_k}^{W^{(\max)}} \psi_k^{(\downarrow)}\left(W_k - \widetilde{W}_k\right)\mathrm{d}P_{W_k}\,\mathrm{d}P_{\psi_k^{(\downarrow)}}\end{aligned} \tag{17}$$

where $W^{(\max)}$ is the installed capacity of the wind power producer. Still assuming independence between the unit regulation costs and wind power production, the integrations can be separated so that one arrives to

$$\begin{aligned}\mathbb{E}\{C_k^{(\downarrow/\uparrow)}\} = &\int_0^{+\infty} \psi_k^{(\uparrow)}\mathrm{d}P_{\psi_k^{(\uparrow)}}\int_0^{\widetilde{W}_k}\left(W_k - \widetilde{W}_k\right)\mathrm{d}P_{W_k} \\ &+ \int_{-\infty}^{0} \psi_k^{(\downarrow)}\mathrm{d}P_{\psi_k^{(\downarrow)}}\int_{\widetilde{W}_k}^{W^{(\max)}}\left(W_k - \widetilde{W}_k\right)\mathrm{d}P_{W_k}\end{aligned} \tag{18}$$

This is by definition equal to

$$\begin{aligned}\mathbb{E}\{C_k^{(\downarrow/\uparrow)}\} = &\,\widehat{\psi}_k^{(\uparrow)}\int_0^{\widetilde{W}_k}\left(W_k - \widetilde{W}_k\right)\mathrm{d}P_{W_k} \\ &+ \widehat{\psi}_k^{(\downarrow)}\int_{\widetilde{W}_k}^{W^{(\max)}}\left(W_k - \widetilde{W}_k\right)\mathrm{d}P_{W_k}\end{aligned} \tag{19}$$

which is equal to the expected value of the equivalent loss in equation (16).

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The problem of maximizing the expectation of the utility in equation (16) is a standard linear terminal loss problem, which can then be treated as the general case in Raiffa and Schlaifer.[27] The proof is omitted here, and only the expression for the EUM bid is given:

$$\widetilde{W}_k^* = F_{W_k}^{-1}\left(\frac{\left|\widehat{\psi}_k^{(\downarrow)}\right|}{\widehat{\psi}_k^{(\uparrow)} + \left|\widehat{\psi}_k^{(\downarrow)}\right|}\right) \tag{20}$$

where F_{W_k} is the cumulative distribution function of the wind power production W_k. Therefore, the EUM bid $\widetilde{W}_k$ is a quantile of the distribution of the stochastic variable W_k corresponding to the probability given by the fraction

$$\widetilde{r}_k^* = \frac{\left|\widehat{\psi}_k^{(\downarrow)}\right|}{\widehat{\psi}_k^{(\uparrow)} + \left|\widehat{\psi}_k^{(\downarrow)}\right|} \tag{21}$$

2.2. Input forecasts to the EUM strategy

From the treatment in Section 2.1, it follows that the determination of the optimal bid requires forecasts of both wind power production and imbalance costs.

As far as wind power production is concerned, a probabilistic forecast is needed as the distribution F_{W_k} of the generation W_k appears in equation (20). Here, the non-parametric probabilistic tool described in Pinson[28] and Pinson and Kariniotakis[29] is considered. This tool provides the user with a set of forecast quantiles of the wind power distribution for each trading period. Let us denote the α-quantile of wind power production at time k with $q_{W_k}(\alpha)$ such that

$$F_{W_k}\left(q_{W_k}(\alpha)\right) = \alpha \tag{22}$$

The provided forecasts are then

$$\widehat{q}_{W_k}(\alpha) = \mathbb{E}\left\{q_{W_k}(\alpha)|M, \boldsymbol{\theta}, \chi_t\right\} \tag{23}$$

for different values $\alpha \in [0, 1]$. The expectation on the right side of equation (23) is conditioned on the choice of the model M, on its estimated parameters $\boldsymbol{\theta}$ and on the information χ_t available at the time t when the forecast is issued. It holds trivially that $t < k$. In the example of Nord Pool, t might be 11:00 (1 h before the deadline for bidding), whereas k could be any of the hours in the following day. From now on, the condition on the expectation is discarded in order to lighten the notation. However, the reader should keep this in mind whenever a forecast is defined. An example of quantile forecast can be seen in Figure 1. The complete forecast of the function F_{W_k} can then be obtained from the set of forecast quantiles $\widehat{q}_{W_k}(\alpha)$ by linear interpolation.

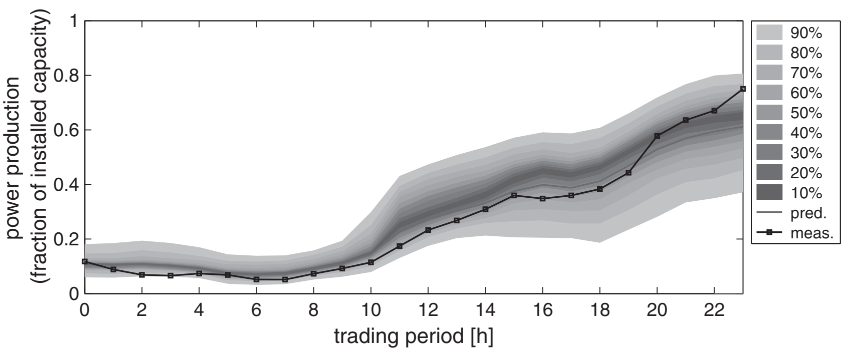

Figure 1. Example of probabilistic forecast of production for a wind power portfolio in Eastern Denmark. The forecast was issued on the previous day at 11:00.

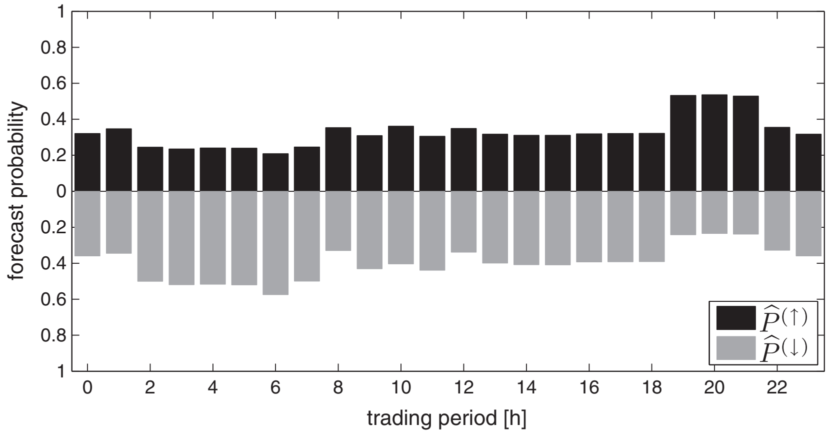

Figure 2. Example of forecast probabilities of up ($\widehat{P}^{(\uparrow)}$) and down ($\widehat{P}^{(\downarrow)}$) regulation in DK-2.

The expected values of the regulation costs $\widehat{\psi}_k^{(\downarrow)}$ and $\widehat{\psi}_k^{(\uparrow)}$ need to be forecast as well. Methods for forecasting the day-ahead market price $\pi_k^{(S)}$, as well as the unit imbalance costs $\psi_k^{(\downarrow)}$ and $\psi_k^{(\uparrow)}$, conditioned upon the regulation sign,* are described in Jónsson.[30] The following forecasts are therefore available:

$$\widehat{\pi}_k^{(S)} = \mathbb{E}\left\{\pi_k^{(S)}\right\} \tag{24}$$

$$\widehat{\psi}^{(\downarrow)}_{k|\psi_k^{(\downarrow)}<0} = \mathbb{E}\left\{\psi_k^{(\downarrow)}|\psi_k^{(\downarrow)} < 0\right\} \tag{25}$$

$$\widehat{\psi}^{(\uparrow)}_{k|\psi_k^{(\uparrow)}>0} = \mathbb{E}\left\{\psi_k^{(\uparrow)}|\psi_k^{(\uparrow)} > 0\right\} \tag{26}$$

Jónsson[30] also presents a method for estimating conditional posterior probabilities of imbalance in each direction being penalized at any given time k, defined as

$$P_k^{(\downarrow)} = P\left\{\psi_k^{(\downarrow)} < 0\right\} \tag{27}$$

$$P_k^{(\uparrow)} = P\left\{\psi_k^{(\uparrow)} > 0\right\} \tag{28}$$

From a pure trading perspective, this is equivalent to predicting the sign of the actual imbalance as the trader is indifferent to imbalances he/she is not penalized for. The models for $\widehat{\psi}^{(\downarrow)}_{k|\psi_k^{(\downarrow)}<0}$, $\widehat{\psi}^{(\uparrow)}_{k|\psi_k^{(\uparrow)}>0}$ and $\widehat{P}_k^{(\uparrow/\downarrow)}$ are all conditional Holt–Winters models with a diurnal seasonality. For the penalty forecasts, the models are conditioned upon the forecast system load and the forecast spot price for the area, whereas the direction probability model is conditioned upon the forecast wind power penetration (i.e. the ratio between the forecast wind power production in the whole system and the forecast system load).

An example of forecasts of the regulation signs is shown in Figure 2. It should be noticed that the two probabilities in the figure do not sum to 1. Indeed, the probability of no regulation $P_k^{(0)}$ might also be positive, and at any time k, it holds that

$$P_k^{(\uparrow)} + P_k^{(\downarrow)} + P_k^{(0)} = 1 \tag{29}$$

The expected values $\widehat{\psi}_k^{(\downarrow)}$ and $\widehat{\psi}_k^{(\uparrow)}$ can then be determined according to the law of total expectation

$$\widehat{\psi}_k^{(\downarrow)} = \widehat{\psi}^{(\downarrow)}_{k|\psi_k^{(\downarrow)}<0}\widehat{P}_k^{(\downarrow)} + \widehat{\psi}^{(\downarrow)}_{k|\psi_k^{(\downarrow)}=0}\left(1-\widehat{P}_k^{(\downarrow)}\right) = \widehat{\psi}^{(\downarrow)}_{k|\psi_k^{(\downarrow)}<0}\widehat{P}_k^{(\downarrow)} \tag{30}$$

$$\widehat{\psi}_k^{(\uparrow)} = \widehat{\psi}^{(\uparrow)}_{k|\psi_k^{(\uparrow)}>0}\widehat{P}_k^{(\uparrow)} + \widehat{\psi}^{(\uparrow)}_{k|\psi_k^{(\uparrow)}=0}\left(1-\widehat{P}_k^{(\uparrow)}\right) = \widehat{\psi}^{(\uparrow)}_{k|\psi_k^{(\uparrow)}>0}\widehat{P}_k^{(\uparrow)} \tag{31}$$

*In Jónsson,[30] a given hour is defined as up-regulation hour if $\psi_k^{(\uparrow)} > 0$ and a down-regulation hour if $\psi_k^{(\downarrow)} < 0$.

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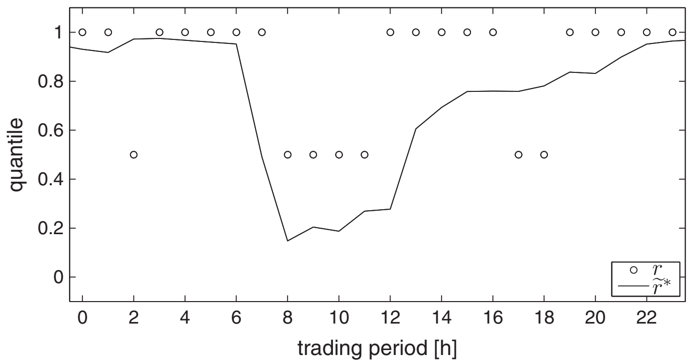

Figure 3. Optimal forecast ($\widetilde{r}^*$) and measured (r) ratios for a wind power portfolio in DK-2 on a selected day.

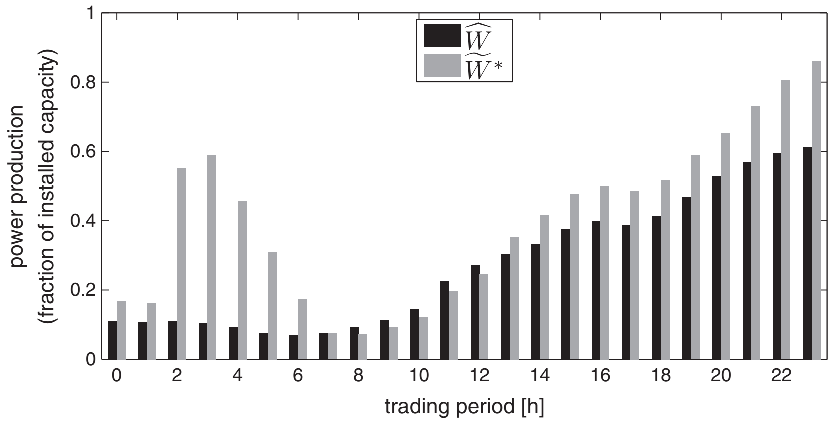

Figure 4. Example of point forecast ($\widehat{W}$) and EUM bid ($\widetilde{W}^*$) for a wind power portfolio in DK-2.

In cases when both $\widehat{\psi}_k^{(\downarrow)}$ and $\widehat{\psi}_k^{(\uparrow)}$ are zero, the ratio in equation (21) is not defined. In these cases, the producer might bid the median, corresponding to the 0.5 quantile, which maximizes the expected market revenues in the general case where the forecast penalties in the two regulation directions are equal. Figure 3 plots an example of forecast, $\widetilde{r}_k^*$, and measured, r_k, ratios in equation (21) for a power producer in Eastern Denmark participating in Nord Pool. The resulting bid maximizing the expected revenues is shown in Figure 4. As one can see from the scale employed on the y-axis of the figure, the bid is shown as a fraction of the total installed capacity. The point forecast, which is currently the reference for wind power producers participating in day-ahead markets, is also shown for comparison.

2.3. Testing the EUM bid

This section presents the setup and the results obtained in a test case simulating energy trading in Nord Pool. Its aim is to assess the performance of the EUM bidding strategy compared with the traditional point forecast bidding. Afterwards, the main drawbacks of the EUM strategy are discussed, along with the reasons motivating the introduction of more risk-averse strategies, which are presented in Section 3.

In this test-case, the DK-2 (Denmark East) market area has been considered as the geographic location of the wind power plants of a virtual power producer. Data and forecast availability motivate the choice of a 10 month period of simulation, spanning from 1 March 2008 to 31 December 2008. The size of the producer is not defined, and all the results are scaled to its installed capacity. It is assumed though that the producer is a price-taker, i.e. that changes in its bidding policy do not influence the market. This implies that its size is small relative to the total installed capacity in the region.

The data set used consists of measured wind power production, point and probabilistic forecasts of wind power production, observed regulation costs and the market forecasts previously described. All data refer to the DK-2 market area and have a temporal resolution of 1 h. On the basis of point forecasts issued by WPPT,[31,32] probabilistic wind power forecasts are obtained by the method described in Pinson and Kariniotakis[29] and Pinson,[28] whereas market forecasts have been obtained as outlined in Jónsson.[30] All observations used are publicly available on www.energinet.dk.

For the sake of performing a realistic test case, the forecasts of wind power production, of day-ahead and real-time market prices and of imbalance direction probabilities used in this study, were issued before 11:00 of the previous day. Because the day-ahead gate closure at Nord Pool is noon, these forecasts are precisely the information available for producers bidding on the day-ahead market.

Table I shows the economic results of the wind power producer in both the cases of point forecast bidding and of EUM bid. The third column represents the reduction in the imbalance costs in equation (10) with respect to the case of point forecast bidding. Imbalance cost reduction is a relevant index for assessing the quality of a bidding strategy for wind power producers. Indeed, there is a 'fatal' part, i.e. which could be achieved no matter how bad a bidding strategy is employed, that is implicitly included in the total producer profits. For example, a producer could at least earn its realized wind power production times the down-regulation price just by never participating at the day-ahead market. On the contrary, imbalance costs represent what the wind power producer can actually improve by employing a more advanced strategy. Furthermore, the imbalance cost reduction with respect to a reference bid, the point forecast in this example, provides with an upper bound for performance improvement, i.e. the 100% reduction that would be achieved by bidding with perfect information. The value of imbalance cost reduction in the first row is trivially 0, while one can notice that the improvement obtained with the EUM is 2.3%.

Figure 5 shows the subtraction of the cumulative revenues obtained with the EUM strategy and the cumulative revenues obtained with the point forecast bid for each trading period in the test case. The difference in revenues is positive overall, meaning that the EUM bid is outperforming the point forecast bid in the long run. On the other hand, the performance of the EUM bid appears to be rather volatile and characterized by steep drops, for instance, around the 1200 and 4500 h in the figure. This suggests that the producer adopting the EUM strategy is exposed to the risk of significant losses stemming from a single contract. It can be shown that the losses are due to inaccurate forecasts of the regulation costs or sign. What the EUM aims at is, essentially, to set the day-ahead market bid on the 'safe' side of the decision space, i.e. on the imbalance direction that will not be penalized at the real-time market and paid at the day-ahead price $\pi_k^{(S)}$. As Figure 3 shows, by doing this, the optimal ratio $\widetilde{r}_k^*$, and therefore the EUM strategy, results in being somewhat 'extreme'. In fact, when the forecasts indicate that one regulation direction is far more likely than another, $\widetilde{r}_k^*$ tends to the extreme values 0 or 1, as shown in the early and late hours of the day in Figure 3. Figure 4 shows that this yields a bid that is significantly different from the point forecast during these hours. Generally situations where the EUM bid is close to the nominal capacity or zero are not rare. Hence, the producer is in the situation of probably having a great imbalance in the forecast 'safe' regulation direction. In the case that the forecasts leading to $\widetilde{r}_k^*$ are correct, the imbalance is paid at the day-ahead price $\pi_k^{(S)}$, with no

Table I. Economic results for the wind power producer in the test case performed from 1 March 2008 to 31 December 2008 with real market data and forecasts issued for the DK-2 market area.

Strategy	Net revenue per installed MW (€ MW^{-1})	Imbalance cost per installed MW (€ MW^{-1})	Imbalance cost reduction (%)	Price per MW h (€ MW^{-1} h^{-1})
Point forecast	94,436.40	4076.51	0.00	54.48
EUM	94,529.96	3982.95	2.30	54.54

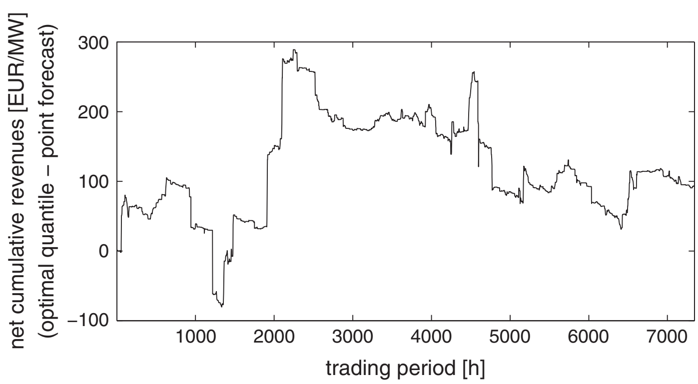

Figure 5. Subtraction of the cumulative revenues per installed MW using the EUM bid and the cumulative revenues using the point forecast. Its positive value signals an improvement in the performance.

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loss for the producer. On the other hand, if the forecast turns out to be incorrect, the producer will have to pay regulation costs for a high amount of energy, resulting in one of the significant losses shown in Figure 5. Furthermore, the wind power producer using the EUM strategy can be expected to incur large imbalances, which are unwanted by the TSO. This casts doubt on the possibility of using the EUM strategy in practice.

3. CONSTRAINING THE EUM BID

As an extension to the EUM strategy, a parameter for constraining the bid is introduced in this section as a way to reduce the expected imbalance level. There are several motivations for doing this. As Section 2 discussed, the EUM bid is often quite far from the point forecast. On the other hand, market authorities require that the energy bid be representative of the actual (or forecast) production of a generator. Hence, an excessive deviation of the bid from the expected production could be seen as a way to take advantage of the market, and thus, it could be penalized. Secondly, a strategy causing high imbalance levels might influence the price formation mechanism, especially with respect to the regulation prices. If this happens, the price-taker assumption is violated, and therefore, the model of the market becomes inconsistent.

As a matter of fact, the point forecast bid is a robust decision when the producer is seeking to minimize the impact on the system imbalance. Indeed, the point forecast commonly minimizes the expectation of the squared deviation from the energy production W_k:

$$\widehat{W}_k = \arg\min_x \mathbb{E}\left\{(x - W_k)^2\right\} \tag{32}$$

It should be pointed out though that different criteria could be employed.[33] The most commonly used least-squares criterion only makes the point forecast optimal in the sense of minimizing imbalance volumes (in squared values), with no economic considerations. Therefore, a compromise between the EUM bid and the point forecast could reconcile revenue maximization with practical implementability of the strategy, with respect both to monitoring of the bid by the TSO and to potential violations of the price-taker assumption. Moreover, seeking a compromise between these two strategies is intuitively related to the reduction of risk. Indeed, as discussed above, the EUM strategy is exposed to the risk of large losses under price-forecasting errors. By trying to render the bid less extreme, i.e. closer to the point forecast, the producer would reduce the amount of regulating power, and therefore losses, in these cases. This will be illustrated in the test case in Section 4. Finally, energy traders are somehow bound to the point forecast, which has traditionally been bid on the day-ahead market and has proved to be reliable over the years. For this reason, it is desirable for an operational strategy not to deviate too much from it.

The main idea in this section is that the bid should somehow be bounded to some values around the point forecast. In this way, extreme bid values—and hence extreme losses—are avoided. Constraints can be imposed in the decision space so that the bid $\widetilde{W}_k^*$ is limited within a certain interval $\left[\underline{W}_k, \overline{W}_k\right]$. The mathematical formulation is described in Section 3.1. As an alternative, the limit can be imposed in the probability space so that the optimal ratio $\widetilde{r}_k^*$ is limited in a similar interval $\left[\underline{r}_k, \overline{r}_k\right]$. This is introduced in Section 3.2.

3.1. Constraints in the decision space

In this section, we propose the determination of the allowed interval for the bid as a function of the expected value of wind power production $\widehat{W}_k$.

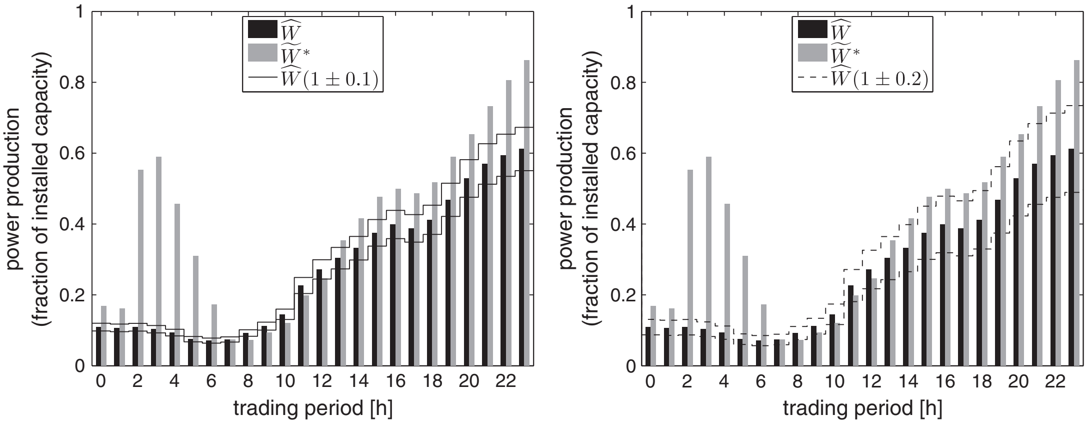
The allowed interval of the decision space is centred around the point forecast

$$\widehat{W}_k = \mathbb{E}\{W_k\} \tag{33}$$

and has radius equal to a certain percentage of this value itself. Two values for the radius are used in the application case study, i.e. 10% and 20% of $\widehat{W}_k$. Naturally, the larger the allowed interval, the more risk-neutral the strategy. The suggested bid in this case can be determined as

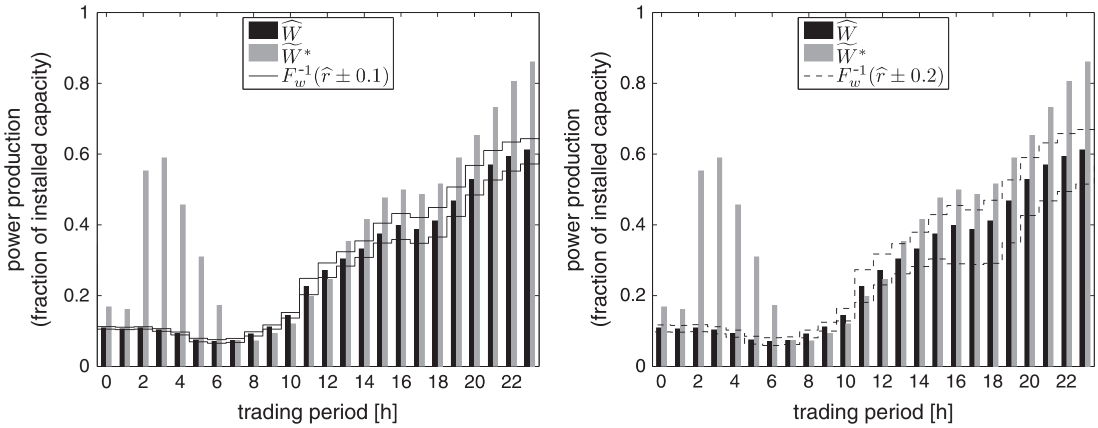
$$\widetilde{W}_k^{\mathrm{v},a_\mathrm{v}} = \min\left\{\max\left\{\widetilde{W}_k^*, \widehat{W}_k \cdot (1 - a_\mathrm{v})\right\}, \widehat{W}_k \cdot (1 + a_\mathrm{v})\right\} \tag{34}$$

where a_v is to be set to either 0.1 or 0.2. Figure 6(a),(b) shows the EUM bid and the point forecast $\widehat{W}_k$ along with the allowed intervals with $a_\mathrm{v} = 0.1$ and $a_\mathrm{v} = 0.2$.



(a) Constraints in value ($a_v = 0.1$) (b) Constraints in value ($a_v = 0.2$)

Figure 6. Point forecast ($\widehat{W}$), EUM bid ($\widetilde{W}^*$) and allowed interval with constraints in the decision space.



(a) Constraints in probability ($a_p = 0.1$) (b) Constraints in probability ($a_p = 0.2$)

Figure 7. Point forecast ($\widehat{W}$), EUM bid ($\widetilde{W}^*$) and allowed interval with constraints in the probability space.

3.2. Constraints in the probability space

In the second method proposed here, the ratio $\widetilde{r}_k^*$ in equation (21) is allowed to span a certain interval in the probability space. This interval is centred around the value of the cumulative distribution at the point forecast $\widehat{W}_k$,

$$\widehat{r}_k = F_{W_k}(\widehat{W}_k) \tag{35}$$

The radius of the interval is then to be set to a certain fraction of the probability space. In this work the radii 0.1 and 0.2 are used. The constrained bid can then be determined as

$$\widetilde{W}_k^{\mathrm{p},a_\mathrm{p}} = F_{W_k}{}^{-1}\left(\min\left\{\max\left\{\widetilde{r}_k^*, \widehat{r}_k - a_\mathrm{p}\right\}, \widehat{r}_k + a_\mathrm{p}\right\}\right) \tag{36}$$

where a_p is to be set to 0.1 or 0.2 according to the desired risk aversion of the bid. Figure 7(a),(b) shows the EUM bid and the point forecast $\widehat{W}_k$ along with the allowed intervals with $a_\mathrm{p} = 0.1$ and $a_\mathrm{p} = 0.2$.

4. TEST CASE RESULTS

In this section we discuss the results of a test case simulating the strategies presented above in a realistic market situation. The setup of the test case is the same as described in Section 2.3. Section 4.1 discusses the performance of the bidding strategies from the point of view of the producer and its economic result, whereas Section 4.2 discusses the implications of the proposed strategies from a system point of view.

4.1. Economic advantage of the strategies

The main economic results for the power producer are shown in Table II. This shows the total revenues of the producer and its imbalance losses per MW of installed capacity, the percentage reduction in imbalance losses obtained by the strategy compared with the case of point forecast bidding and the average price per MW h paid to the producer.

As one can see, the constrained strategies introduced in the previous section produce better results than the plain EUM one. The reduction in imbalance costs amounts to around 6% when the constraint limit is set to 10% (both in value and in probability) and to around 8.5% when it is set to 20%. A slightly better performance is obtained by constraining in value than in probability. As far as the last column of Table II is concerned, it should be mentioned that with perfect information on wind power production, the energy would have been sold at an average price of €56.83 in the considered period.

The improved profits obtained with these strategies, compared with that of using the point forecast bidding, are illustrated in Figure 8. Indeed, this figure displays the difference between the cumulative revenues obtained by using the EUM strategy and its constrained versions and the revenues obtained by bidding the point forecast. All the cumulative revenues in this plot are expressed in € MW^{-1}, i.e. scaled to the installed wind power capacity. It can be seen how the EUM bid ($\widetilde{W}^*$) is the least efficient strategy, apart from the point forecast bidding. The constrained strategies, besides performing better than the EUM, are also less exposed to significant isolated losses.

In view of the results above, there is clearly a relationship between range of the constraint and net revenues. Intuitively, there is also a relationship with risk, since as pointed out in Section 3, an increase in the allowed bid range results in a higher risk of a large imbalance and, therefore, a higher risk of large losses. In principle, the full joint probability distribution of wind power production and market prices should be employed in order to assess risk quantitatively. An *a posteriori* approach is followed here, in which risk is assessed by analysing the realized standard deviation of the hourly imbalance losses.

Figure 9(a),(b) show the imbalance cost reduction obtained in the test case as a function of the parameters a_{v} and a_{p}. The trend is increasing in both cases up to a certain value of the parameter (approximately 0.6 and 0.2 for a_{v} and a_{p}, respectively). Increasing the constraining parameter further beyond these critical values results in less profits. This is

Table II. Economic results for the wind power producer in the test case.

Strategy	Net revenue per installed MW (€ MW^{-1})	Imbalance cost per installed MW (€ MW^{-1})	Imbalance cost reduction (%)	Price per MW h (€ MW^{-1} h^{-1})
Point forecast	94,436.40	4076.51	0.00	54.48
EUM	94,529.96	3982.95	2.30	54.54
Constrained (±10% value)	94,684.18	3828.74	6.08	54.63
Constrained (±20% value)	94,784.27	3728.64	8.53	54.68
Constrained (±10% probability)	94,670.78	3842.13	5.75	54.62
Constrained (±20% probability)	94,768.55	3744.37	8.15	54.67

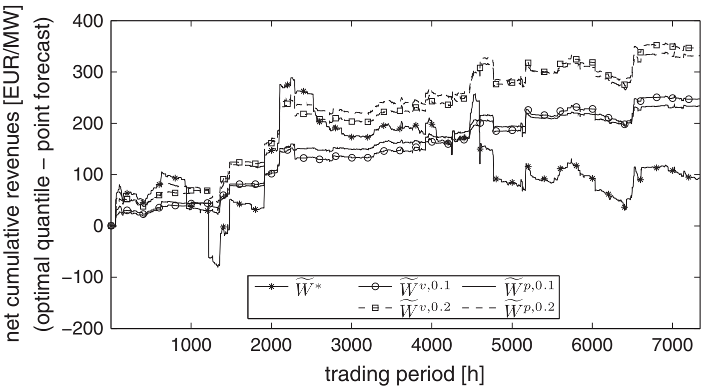
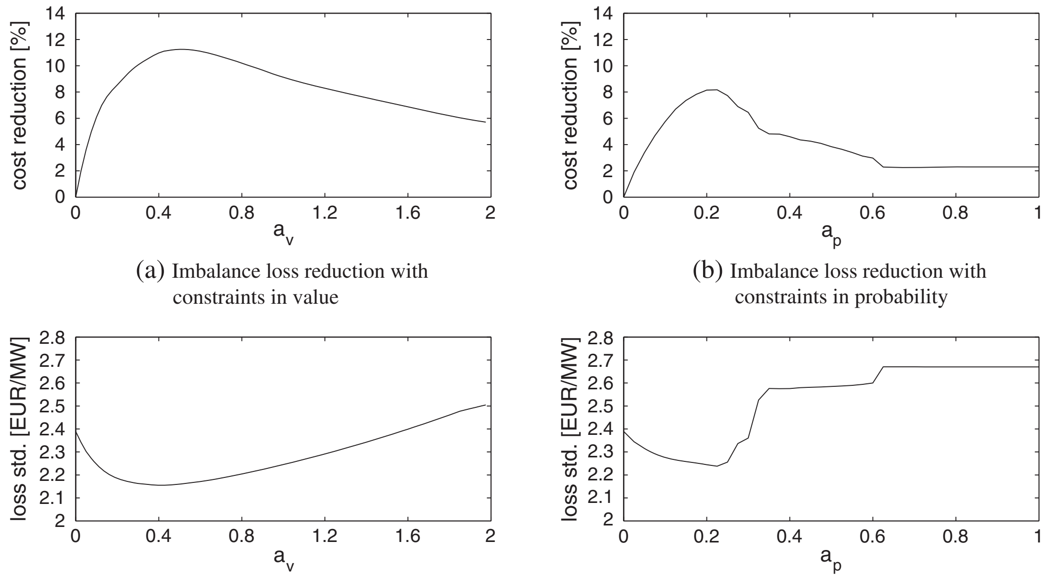


Figure 8. Improvement of the cumulative revenues for the strategies described in Sections 2 and 3 with respect to the point forecast bidding strategy.



(a) Imbalance loss reduction with constraints in value

(b) Imbalance loss reduction with constraints in probability

(c) Imbalance loss standard deviation with constraints in value

(d) Imbalance loss standard deviation with constraints in probability

Figure 9. Producer's imbalance loss reduction and standard deviation in the test case as a function of constraining parameter.

because the distribution of the producer's hourly revenues is bounded on the upper side by $\pi_k^{(S)} W_k$. By allowing larger deviations from the point forecasts, this maximum value of the revenues is reached during more and more trading periods. In this way, the rate of growth of the revenues slows down, as fewer trading periods offer possible improvements. Meanwhile, when forecasts are not perfect, the risk of losses increases. When the critical level of the constraining parameter is reached, the increased losses exceed the revenue growth, resulting in the negative slopes on the right sides of Figure 9(a),(b). This decline is only stopped when the allowed bid interval is large enough to contain the optimal quantiles for all trading periods, as in the flat part of the curve on the right side of Figure 9(b). At that point, the constrained strategy is in practice equal to the original EUM strategy.

The empirical standard deviation of the hourly imbalance losses is plotted in Figure 9(c),(d). As one can see in Figure 9(d), the EUM strategy (to which the constrained strategy converges when the constraining parameter a_{p} is just above 0.6) is the riskiest strategy, since it incurs the highest standard deviation of hourly losses. Strategies with lower values of the constraining parameters are subject to lower risk, but the trend is not monotonic all the way down to the point forecast (achieved with $a_{\mathrm{v}} = a_{\mathrm{p}} = 0$). The latter strategy would in fact be very risk-averse in case of equal penalties for up-regulation and down-regulation. In a realistic case with different penalties, the most risk-averse constrained strategy is obtained for a value a_{v} slightly lower than the one delivering best revenues, whereas the value a_{p} that delivers the highest revenues is to a good approximation the one that is minimizing the standard deviation of the losses.

Furthermore, Table II and Figures 9(a),(b) indicate that the EUM strategy does not achieve the best performance among the considered strategies in the simulated market period. One would expect that a 10 month period is long enough for considering the incidence of isolated losses on the cumulative revenues negligible, so that the EUM strategy achieves the optimal performance. On the contrary, this study seems to suggest that the EUM strategy is not optimal in practice. Indeed, even from a theoretical point of view, the EUM bid is optimal only under the assumption that probabilistic forecasts of wind power production and of market prices are correct. In practice, errors in the probabilistic forecasts might cause the loss of optimality that is observable in this test case. On the other hand, the constrained strategies seem to limit the negative effects of forecast errors both by reducing the risk of losses stemming from single hourly contracts and by achieving a better performance in the long run.

4.2. Interaction with the system

This section sheds some light on the effects of the strategies presented in Sections 2 and 3 in terms of energy imbalance introduced in the system.

Table III shows the simulation results in terms of imbalance direction. The first three columns show the energy imbalance brought to the system by the wind producer in the considered 10 months, in total and divided between positive, i.e.

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Table III. Energy imbalance of the wind power producer in the test case.

Strategy	Energy imbalance (h)			Imbalance hours (%)		Max value (h h^{-1})	
	Total	>0	<0	>0	<0	>0	<0
Point forecast	484.92	235.94	248.98	45.45	54.47	0.54	0.70
EUM	755.29	269.93	485.35	46.28	53.72	0.66	0.89
Constrained (±10% value)	495.91	236.48	259.43	44.26	55.73	0.56	0.68
Constrained (±20% value)	519.70	244.82	274.88	44.06	55.91	0.58	0.68
Constrained (±10% probability)	488.94	237.82	251.12	46.09	53.91	0.57	0.68
Constrained (±20% probability)	514.62	245.98	268.64	46.60	53.40	0.59	0.68

producer being long (second column), and negative imbalance, i.e. producer being short (third column). All the values are expressed in hours of operation at nominal capacity, i.e. they are obtained by dividing the total energy imbalance (MW h) over the simulation by the installed capacity (MW). It can be seen that the more risk-neutral the strategy, the higher the overall energy imbalance. In this sense, the EUM strategy appears to have an extreme behaviour, pushing the total imbalance from less than 500 h of operation, obtained with the point forecast bid, to over 700 h. The four constrained strategies appear to have a limited effect on the overall imbalance. The strategies with tighter bounds ($\pm10\%$ in value and ±0.1 in probability) cause only a negligible increase, whereas when the ones with the less restrictive bounds ($\pm20\%$ in value and ±0.2 in probability) are used, the total imbalance rises by 35 h at most.

Furthermore, an evaluation of the second and third columns shows that generally more advanced strategies tend to bid above the actual production. This means that the producer is more often short rather than long. In fact, one can see that the difference between the values in the second and the third columns, which is almost zero with the point forecast bidding, tends to spread markedly when other strategies are used. This result might at a first sight look counterintuitive, since penalties are on average higher for up-regulation than for down-regulation. Nevertheless, other factors, i.e. skewness of wind power production distribution, have an influence on this. According to expectations, the prevalence of up-regulation power is more evident when less risk-averse strategies are used.

The fourth and the fifth columns of Table III show the percentage of market hours during which the producer is long and short, respectively. It can be seen that the variation in number of regulation hours, despite the significant variation in the imbalance volumes, is at most 1.5%. This indicates that the proposed strategies change the volumes of the energy imbalance but not the general trend in the number of up-regulation or down-regulation periods. Finally, the last two columns show the maximum value of energy imbalance, again expressed in hours of operation at nominal capacity, during a single hour. Interestingly, only the row corresponding to the EUM bid shows a considerable increase, which underlines the fact that constraining the EUM bid is an effective method to limit the maximum value of imbalance.

Table IV looks at the producer's imbalance from a different perspective. This table separates the results for the imbalance into two components: the component opposite to the overall system imbalance, which is paid at the day-ahead market price and is shown in the second and the fourth columns, and the component in the same direction, which is paid at the day-ahead price minus the imbalance cost and is shown in the third and fifth columns. Whereas in the case of the EUM bid the third column shows a significant increase, its values are roughly unchanged with the tighter constraints and slightly increased with the looser ones. In turn, the second column increases by a significant amount in most cases. These two facts indicate that the increase in energy imbalance caused by the use of more advanced strategies, which has been discussed above, actually involves only the direction in which the producer is not penalized, i.e. the one paid at the day-ahead price. There are two implications of this. On one hand, part of the energy imbalance is shifted to the opposite direction with respect to the system imbalance (second column in Table IV), thus contributing to restoring the overall balance—yet on a marginal level because of the price-taker assumption. In other words, the proposed constrained strategies are able to better 'read' the feedback signal sent by the regulation prices and adapt to it, thus reducing the system imbalance. On the other hand,

Table IV. Energy imbalance of the wind power producer in the test case.

Strategy	Energy imbalance (h)			Imbalance hours (%)	
	Total	Day-ahead price	Penalty	Day-ahead price	Penalty
Point forecast	484.92	277.71	207.21	62.81	37.19
EUM	755.29	498.66	256.62	65.14	34.86
Constrained (±10% value)	495.91	286.72	209.19	63.16	36.84
Constrained (±20% value)	519.70	304.85	214.85	63.59	36.41
Constrained (±10% probability)	488.94	281.93	207.00	62.72	37.28
Constrained (±20% probability)	514.62	301.74	212.87	63.39	36.61

the variation in imbalance could become significant if the proposed strategies become common practice for producers. As a result, this could influence the formation of the regulation prices as well as possibly change the direction of the system imbalance. Although it has been shown that the trading behaviour of wind power producers is capable of affecting day-ahead prices at Nord Pool even at the current level of market penetration,[34,35] the relationship with the real-time market penalties, which are the quantities that ultimately determine the optimal bid in equation (20), has not been investigated yet. In the event that the trading strategies presented above become common practice, they might influence the real-time penalties and no longer be optimal and could possibly destabilize the system. Then, the market power of wind power producers should be accounted for if efficient bidding strategies are to be designed for producers with a large total capacity or for combined producers. This can be achieved by modelling energy markets as closed-loop systems, for instance, see Liu[25] and Giabardo *et al.*[26]

5. CONCLUSIONS

In this work, the optimal quantile strategy for trading wind power in liberalized energy market is revisited. It is shown that this strategy maximizes the expected value of the market revenues (utility), under the assumption that the wind power producer is a price-taker, i.e. its market strategy is not capable of influencing price formation. The use of the EUM strategy in practice requires probabilistic forecasts of wind power production and point forecasts of day-ahead and real-time market prices and of the imbalance sign probabilities. All these forecasts can be provided by state-of-the-art forecasting techniques.

An evaluation of the EUM strategy in a realistic test case in Nord Pool highlights both its improved performance and its risk-neutral nature. The former is underlined by a 2.3% reduction of the imbalance costs. As far as the latter is concerned, the test case shows that this strategy is exposed to a number of significant losses that take place in short periods of time. These losses are caused by the use of inaccurate forecasts, which cause the bid to differ significantly from the actual wind power production.

Constraining of the bid is then introduced in two different versions: with constraints in the decision space and in the probability space. The main idea is that bounding the bid to a certain interval around the point forecast can help reduce the distance of the bid from the actual wind power production. This heuristic can solve some issues associated with the control of market authorities of the producer's bid as well as with its influence on the price formation mechanism. Indeed, constrained strategies generally reduce the imbalance introduced by the wind power producer in the system, thus lowering the potential impact on real-time prices and the sub-optimality of the strategy in a price-maker market environment. Moreover, the risk of incurring high regulation costs is also reduced by using constrained strategies.

Furthermore, the test case is extended in order to assess the performance of the constrained strategies. The results of the simulation show that the constrained strategies outperform both the point forecast and the EUM strategies. The latter fact shows that constraining the EUM bid is also an effective way for reducing the impact of forecast errors on long-term revenues. At a second stage in the test case, the interactions between a producer employing this strategy and the overall system are analysed. It is shown that only the EUM bid causes a significant increase in the total energy imbalance compared with the point forecast bid. The constrained strategies increase the amount of regulated energy at most by about 10% in the case of less restrictive bounds, whereas the increase is negligible when the strategies with tighter bounds are adopted. Moreover, it is pointed out that this increase in the regulated power involves only the component in the opposite direction compared with the overall system imbalance. As a result, the constrained strategies might be able to reduce the overall imbalance, thus marginally benefiting the system, at least as long as they do not become common practice.

We underline that the obtained results hold as long as the wind power producer does not own a significant share of the overall production capacity. When this hypothesis is not true, the power producer cannot be considered a price-taker. It is expected that in this case, the performance of the proposed strategies decreases. In addition, the assertion that these strategies may be beneficial to the system by reducing the overall imbalance might prove incorrect. This is because such a large producer—or many smaller producers using the same bidding policy—might change the direction of the system imbalance, thus contributing positively to it rather than reducing it. For these reasons, an interesting future development of this work could be to study the relationship between the bid of a large wind power producer and the formation of the regulation prices in the real-time market. This could then lead to the formulation of optimal bidding strategies of practical use for large wind power producers, as well as more stable from a system point of view.

Similarly, modelling explanatory variables influencing wind power production and energy market prices at the same time is of clear interest for future research. This would account for the situation where a high penetration of wind power in the system is able to influence the prices, although the considered wind power producer is too small to have any sort of market power on its own.

Besides, trading on the intra-day market could also be included in the problem under the assumption of sufficient liquidity of this market. As shown in Morales *et al.*,[21] this trading floor gives market participants further possibilities for reducing the risk of losses. Indeed, producers can employ forecasts with a shorter lead time (typically 1 h) with clear

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advantages in terms of accuracy. Therefore, an assessment of the advantages both for the producers and the system obtained by increasing the liquidity of balancing markets would be particularly interesting.

Finally, another direction for further research could be to account for the dynamic aspects of the market. In this way, the assumption of independence of decisions in different trading periods would be overcome. The dynamic view of the market could include, for instance, modelling competition among producers as well as the market participation of mixed portfolios. In the latter case, a typical situation could be the coupling of wind power with hydropower or energy storage, both of which allow for shifts in the trade of power between different trading periods. This research could lead to the determination of more advanced bidding strategies in competitive market environments, possibly for producers with a diversified portfolio of energy sources.

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