Advanced strategies for wind power trading in short-term electricity markets

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Paper presented in the Brussels EWEC Conference (31^{st} of March – 3^{rd} of April 2008)

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***Abstract*—Independent power producers have the possibility to participate in short-term electricity markets to trade wind power energy in several countries in Europe. Under such market context, penalties may apply for differences between the contracted energy and the produced energy. The limited predictability of the wind resource may thus result to a reduction of the competitiveness of wind power generation. In this paper, we propose a risk-based decision approach for optimizing the benefits of an energy producer who submits energy bids in a day-ahead electricity market. Loss functions are used to model the penalties resulting from imbalances. For achieving this, we use wind power probabilistic forecasts. The benefits from the approach are demonstrated using real-word data for a whole year.**

I. Introduction

WIND power is one of the fastest growing renewable electricity generating technologies. The target for the next decades aims at a high share of electricity generation in Europe coming from wind power. To make such a development possible, one of the challenges is to increase wind power integration in the new European market context. Under such context, Independent Power Producers (IPPs) may participate in short-term electricity markets for trading wind power. However, differences between contracted and produced energy, usually called *imbalances*, may lead to penalties. Such imbalances are mainly due to the variable nature of the wind resource and the limited predictability of wind power production.

Consequently, IPPs participating in electricity markets are faced to a decision-making problem in which they must decide on the amount of energy to bid, based on a given set of decision alternatives. Moreover, the limited predictability of the wind resource implies an *imperfect knowledge* of the future outcome of each alternative. This characteristic renders the decision problem as a decision-making under uncertainty one. In order to manage this kind of problems, the uncertainty related to wind power generation must be modeled, estimated and taken into account in the decision process. For achieving this, one may use advanced wind power forecasting models which not only provide point predictions of the wind power generation, but also information about the uncertainty associated to such predictions. Such uncertainty may be modeled via scenarios, confidence intervals or probability density functions [1].

Decision-making problems under uncertainty have been widely studied in operational research [2]. In contrast to deterministic problems, different attitudes of the decision-maker may lead to different decisions, given the same inputs. In particular, uncertainty associated to wind power generation may lead to an economical risk for the IPP. Different attitudes toward risk may thus lead to different bid decisions.

In this study, we propose a methodology for participating in day-ahead electricity markets considering the economical risks associated to each possible bid due to the uncertainties related to wind power and day-ahead market price forecasts.

In section II, the state of the art on probabilistic wind power forecast models is briefly presented. In section III, we describe the market model adopted in the study. The bidding problem is defined as a decision-making problem in section IV. In subsection IV-C the imbalance penalization is modeled through a dynamic loss function. In section V, we explain the risk-based approach based on the value at risk. Finally, the results obtained via the proposed method are presented in section VI.

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II. Probabibistic wind power forecasts

Wind power forecasts are used as input to the proposed strategic bidding method. Short-term wind power forecasting tools have been in use for more than 15 years. In general, such tools provide the future production of a wind farm for a period ranging from the next hours to the next days, and are based on meteorological predictions, on onsite measurements and on wind farm characteristics. The two mainstream approaches for wind power forecasting are the so-called *physical* approach and the *statistical* one. In the physical approach, the

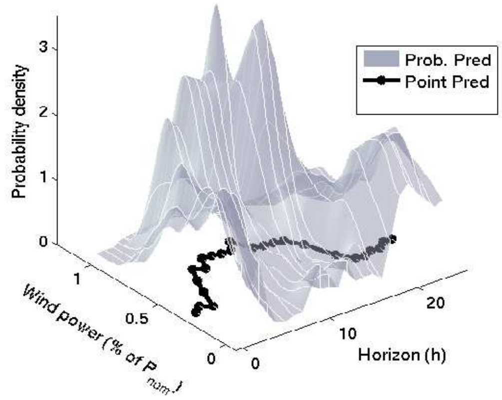

Fig. 1: Probabilistic wind power forecasts from KDE method, for 24 hours.

model chain includes the process of conversion from global to local wind and then to wind power. In the statistical approach past observations and numerical weather predictions are used to statistically determine the future production. A state of the art can be found in [3]. A comparison of performances between various models can be found in [4].

Deterministic wind power forecasting models, provide, for a given horizon, an amount of power corresponding to the prediction. Probabilistic wind power forecasting models provide not only point predictions, but also information about the uncertainty associated to such point predictions. Various probabilistic methods have been proposed in the litterature, such as Kernel Density Estimators (KDE) in [5] and [6], adapted resampling in [7], or spline quantile regression in [8]. In this work, we use forecasts produced with a state of the art KDE wind power forecasting method [5] [6]. Such method provides predictions in the form of probability density functions, which can be used as such or transformed into different subproducts depending on the application (e.g. point prediction, variance, prediction intervals or quantiles). Figure 1 depicts an example of wind power probabilistic forecasts that were obtained by the KDE method for 24 hours ahead as well as the corresponding point predictions. In this paper, hourly probability density functions were used.

III. Market rules model

This section presents the market rules model adopted in this study. This market formulation describes why power imbalance between the contract power and the delivered power may lead to economical risk for the IPP.

Each electricity market has its own rules, defining the way electricity is to be sold or purchased, how electricity prices are settled, and the obligations with which market participants are committed. Different European electricity markets exist [9], each one having its own rules.

When operating under day-ahead electricity markets, IPPs have to bid their power production on day d, usually till noon, but will only start generating the corresponding energy on the first hour of day $d+1$. The time-lag between the day-ahead market clearance (usually referred to a *gate closure time*) and the start of energy production is 12 hours for the first delivery hour and 36 hours for the last delivery hour of day $d+1$. The market system price and volumes are determined for the whole market area by matching purchasing and selling curves. For markets including different regions, regional spot market prices are derived from system prices taking into account transmission bottlenecks.

In this work, the IPPs are considered as price takers: the nominal power of the considered wind farm is considered small enough so that its owner does not possess sufficient market power. Furthermore, the bids from the IPP are considered to be always accepted.

The transmission system operator (TSO) is responsible for maintaining the physical balance between production and consumption. In the case of a direct participation of the IPP to the market, the IPP is taken as a balance responsible actor. Consequentlly, the IPP is paying a market imbalance price for any contribution to the global system imbalance. As a consequence, positive or negative imbalances may lead to regulation costs for the producers, decreasing their individual market income.

Different studies focus on bidding strategies to reduce imbalance cost while trading wind power [10] [11]. The formulation of our problem is similar to the one described in such previous studies and the interested reader may refer to them for formulation details. In general terms, for a given horizon $(t+k)$, the revenue R_{t+k} of a market participant bidding an amount of energy E^c_{t+k} but actually generating E_{t+k} can be formulated as the combination of the income from selling the actual wind generation E_{t+k} at the spot price π^c_{t+k}, minus the costs for regulation:

$$\mathrm{R}_{t+k} = \underbrace{\pi^c_{t+k} \cdot E_{t+k}}_{Revenue\,from\,the\,contract} - \underbrace{T_{t+k}}_{Regulation\,cost} \tag{1}$$

where the imbalance cost T_{t+k} is given as a function g of the imbalance d_{t+k} by:

$$T_{t+k} = g(d_{t+k}) = \begin{cases} \pi^{*,+}_{t+k} \cdot d_{t+k}, & d_{t+k} \geq 0 \\ -\pi^{*,-}_{t+k} \cdot d_{t+k}, & d_{t+k} < 0 \end{cases} \tag{2}$$

$$d_{t+k} = E_{t+k} - E^c_{t+k} \quad (3)$$

where $\pi^{*,+}_{t+k}$ and $\pi^{*,-}_{t+k}$ are, respectively, the regulation unit costs for positive and negative imbalances, and are given by:

$$\pi^{*,+}_{t+k} = \pi^c_{t+k} - \pi^{c,+}_{t+k} \quad (4)$$
$$\pi^{*,-}_{t+k} = \pi^{c,-}_{t+k} - \pi^c_{t+k} \quad (5)$$

with $\pi^{c,+}_{t+k}$ and $\pi^{c,-}_{t+k}$ the imbalance prices for positive and negative imbalances respectively. The determination of the regulation prices varies according to the considered market. In our case (i.e.: NordPool) it is the result of the regulation market, where actors with power reserves place bids for fast production increase or decrease. Furthermore, in the same market, balance responsible actors are only penalized for their imbalance if these are opposite to the regulation measure taken by the TSO. The interested reader may refer to [12] for obtaining further information on NordPool market rules.

Note that the horizon index used in the formulation is $(t+k)$, where t corresponds to the time span between the gate closure time and the first delivery hour and k stands for the horizon inside the delivery day (i.e. k equals the hour of the delivery day being calculated).

IV. Definition of the strategic bidding as a problem of decision-making under uncertainty

A. Sequential decision

In order to participate in the day-ahead market, the IPP has to propose a power production plan, based on a schedule given by the market operator. For every horizon of the market schedule $(t+k)$, the IPP has to make a decision about the amount of energy to bid to the market for the period between the horizon $(t+k)$ and the next one $(t+k+\Delta t)$. The market time unit Δt is thus the difference between two consecutive horizons. Considering the problem from a decision-making viewpoint, the set of alternatives is made of all possible energy bids. For a given horizon $(t+k)$, we define the bid as the contracted power P^C multiplied by the market time unit Δt; we assume that the contract power P^C can be any proportion of the nominal power P_{nom} of the wind farm:

$$E_{t+k} = P^C \cdot \Delta t, \quad P^C \in [0, P_{nom}] \quad (6)$$

There is not a single decision to make, but several sequential decisions about the power production bid for a given period or sequence of horizons. However, for the study, the decision for a given horizon does not depend on the decision for the previous horizons first, and is also independent from that of all remaining horizons. It is important to note that this would not be the case for power systems including storage devices. Energy storage devices can be seen as integrators of imbalance power [13] and the level of storage will depend on former decisions. In [14], an approach based on dynamic programming was developed by the authors to deal with such sequential decision-problems.

B. Objectives

Concerning the market rule model, the formulation of the revenue in Equation 1 distinguishes:

- $\pi^c_{t+k} \cdot E_{t+k}$: the revenue from the contract;
- T_{t+k}: the regulation costs;

where, as previously described, the index $(t+k)$ stands for the $(t+k)$ horizon.

In the *price-taker* hypothesis, π^c_{t+k} is independent from the bid E^c_{t+k} and is considered to be constant. Thus, the revenue from the contract is only dependent from the bid E^c_{t+k}. Regarding revenue in Equation 1, the bid E^c_{t+k} only influences the regulation costs T_{t+k}, and not the revenue from the contract. Consequently, the objective of determining the amount of energy to bid that maximizes the revenue R_{t+k} of the IPP equals that of determining the energy bid that minimizes the regulation costs T_{t+k}.

Here, we propose an approach suitable for building trading strategies based on the minimization of the regulation costs T defined in Equation 2. Two sources of uncertainty have to be taken into account for determining the energy bid that minimizes T:

- the wind power prediction: the uncertainty is expressed through the probability density function (pdf) of wind power for each time step in the future, as depicted in Figure 2;
- $\pi^{*,+}_{pred}$ and $\pi^{*,-}_{pred}$: the prediction of regulation unit costs for positive and negative imbalances;

The probabilistic wind power forecasts, as opposed to deterministic ones, define a range of all possible scenarios for wind production with the associated probability. This results to a distribution of possible values for the energy imbalance d and consequently this implies a distribution of values for the regulation costs T.

The objectives of the proposed approach are the following:

- Estimate the imbalance penalty distribution from a given bid alternative using dynamic loss functions;
- Measure the risk related to this bid alternative;

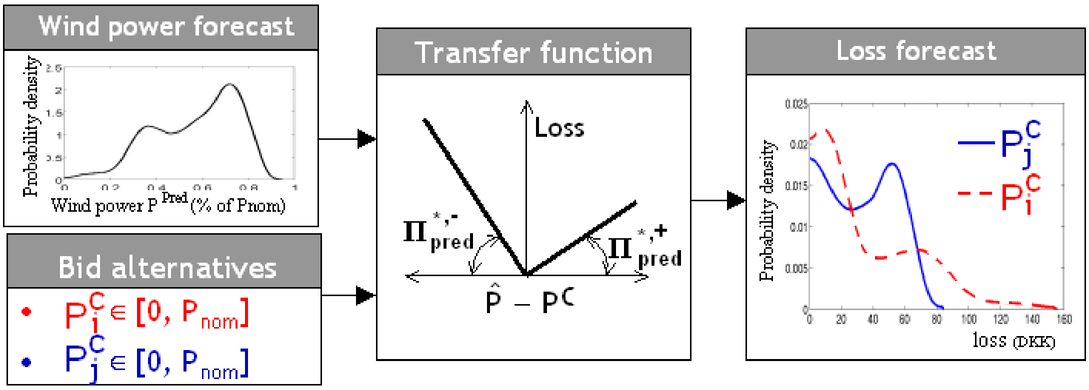

Fig. 2: Use of the loss function to estimate the distribution of the regulation costs.

- Propose a risk-based method that enables to select a bid alternative;
- Evaluate the method for a real case-study;

C. *Dynamic loss functions*

This section focuses on the estimation of the imbalance penalties associated to a given bid alternative, based on wind power and imbalance price forecasts. The method is based on a loss function that gives the estimation of the economic cost or regret associated to each bid alternative. The loss function is taken as a transfer function.

In the market rule model introduced in section III, the function g described by Equation 2 represents the penalization of the realized energy imbalance. In that function, the energy imbalances are penalized by the regulation prices determined by the balancing operator. The goal here is to construct a loss function based on the same penalization rules defined by the function g. We also use predictions of regulation prices for building the loss functions. Such predictions define the slope of the function.

In Figure 2, the followed methodology is described. For the i^{th} bid alternative P_i^C, the loss distribution l corresponding to the regulation costs is calculated from the probabilistic wind power prediction. The methodology for building the loss function is independent from the horizon $(t+k)$, as explained in subsection IV-A. A different loss function is built for each horizon using the price forecasts as parameters that correspond to that horizon. Because the regulation price forecasts may vary through time, the loss function, having such forecasts as parameters, is a dynamic one.

Electricity market prices may be highly variable and hardly predictable [15]. We propose here to analyse the influence of the prediction of the regulation price. For this purpose, different scenarios including *constant prediction*, *perfect prediction* and *naïve prediction* of the regulation prices are analyzed in subsection VI-B.

V. Risk-based decision approach

A. *Uncertainties and risk*

The objective of this section is to integrate the uncertainty related to the wind power forecast and to the regulation price forecast, for developing bidding strategies. A first question arises about the link between uncertainty and risk. Clemen in [2] distinghishes the two notions:

- Uncertainty is related to imperfect knowledge of future outcomes, to the existence of more than one possibility. Measuring uncertainty consists in assigning a set of probabilities to a set of possibilities. Matos in [1] describes the different techniques used to model and measure uncertainty.
- Risk is a state of uncertainty where some of the possibilities involve a loss, catastrophe, or other undesirable outcome. A measurement of risk is defined as a set of possibilities each with both quantified probabilities and quantified losses.

The aim of the risk-based decision approach used here is to integrate the risk in the decision process.

B. *Risk measures: Value at Risk (VaR) and Conditional Value at Risk (CVaR)*

Variance is one of the first types of mathematical definition of risk. It was used in finance by Markowitz [16] to measure the risk associated to each alternative. Much work has been devoted to propose and analyze new risk assessment and management methods, such as in [17]. In particular, the Value at Risk (VaR) and the Conditional Value at Risk (CVaR) are methodologies developed by the financial industry to provide quantification of the exposure to risk of the portfolio of the company

[18]. By definition, with respect to a specified probability level α, the α-VaR of a portfolio is the lowest amount x such that the probability that the loss L exceeds x is not larger than $(1-\alpha)$:

$$VaR_{\alpha} = inf\{x \in \Re : p(L > x) \leq 1 - \alpha\} \quad (7)$$

If F is the cumulative distribution function of the loss, the α-VaR can be written as the α-quantile of the loss distribution:

$$VaR_{\alpha} = inf\{x \in \Re : F_L(x) \geq \alpha\} \quad (8)$$

Although VaR is a very popular measure of risk, it has undesirable mathematical characteristics such as a lack of subadditivity and convexity. The interested reader may refer to [19] for obtaining further information on the limitations about VaR. That is why Rockafellar in [19] proposes the Conditional Value at Risk (CVaR), also named expected shortfall, as an alternative risk measure to the VaR. For a given probability level α, the α-CVaR is defined as the conditional expectation of losses above the α-VaR:

$$CVaR_{\alpha} = \mathbb{E}(x : x \geq VaR_{\alpha}) \quad (9)$$

Figure 3 describes the α-VaR and α-CVaR for a given probability density function.

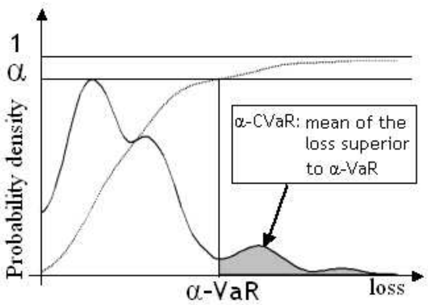

Fig. 3: α-VaR and α-CVaR for a given loss distribution.

C. Spot-Risk Model

Dealing with problems of decision under uncertainty needs the use of approaches different from the ones used to solve deterministic decision problems. Bernouilli [20] in 1738 highlighted the fact that the mathematical expectation was not the right approach to solve decision-making problems under uncertainty. He introduced the notion of utility, taking into account the risk associated to each alternative. Von Neumann and Morgenstern, in 1953, axiomatized the utility theory in [21]. About the same time, Markowitz [16] proposed to take into account the risk while performing portfolio selection by using a mean-variance approach: he quantified portfolio return by the mean, and the risk by the variance, as descibed in subsection V-B. His pioneer work is based on the consideration of both the expected return to be maximized, and the variance, representing the risk of the portfolio to be minimized.

The mean-variance approach corresponds to a risk-management model which provides possibilities for incorporating uncertainty, such as the uncertainty related to wind power generation or uncertainty related to market prices.

In this work we propose to take into account the uncertainty related to the regulation costs through a *mean-CVaR* approach. The risk associated to high regulation costs will be estimated, not by the variance but by the CVaR described in subsection V-B. The decision-making problem consists in determining the energy bid E^* that minimizes a linear combination of the mean and the CVaR of the loss distribution l associated to the regulation costs:

$$E^* = \arg\min_{E}(\mathbb{E}[l] + \beta \cdot CVaR_{\alpha}[l]) \quad (10)$$

where α is a given probability level and β the risk attitude of the decision-maker, determining his sensitivity towards risk. The higher β is, the more sensitive the decision-maker is and, thus, the less risk is taken.

The benefits from risk management approaches using CVaR was already demonstrated in the power system field. For instance in [22], Dahlgren compares different hedging scenarios when participating in a market, and uses CVaR to quantify the economic risk of the considered power portfolio for each scenario. As another example, Wang, in [23], builds a portfolio optimization model with CVaR risk minimization for power producers in electricity markets.

VI. Case-Study

A. Description

A 21 MW wind farm located in the North West of Denmark, for which power production data was available for the years 2000, 2001 and 2002, is considered in this case-study. Numerical weather predictions, including wind speed and direction forecasts for different heights corresponding to the same period and geographical area were used to produce wind power forecasts.

The NordPool electricity market is an international commodity exchange for trading electric power, where Norwegian, Finnish, Swedish and

Danish power producers can sell their production. Hourly contracts for the 24 h of the coming day are traded on the day-ahead market, named Elspot. The market area, West Denmark, corresponding to the wind farm location was selected. The gate closure time is at 12:00 (local time) of the preceding day.

In order to place bids to Elspot before noon, the last available numerical weather predictions data (the ones delivered at 06:00) were used to generate power predictions using a kernel density estimation method, as described in section II. The wind power forecasts are then used to calculate the bids, according to section III, prior to the gate closure time.

The learning and testing of the wind power forecasting model were performed with the data corresponding to the years 2000 and 2001, respectively. The simulation of the market participation was performed with the data and forecasts corresponding to 2002.

B. Results & Analysis

In order to evaluate the performance of the risk-based approach, we analyzed the influence of the risk attitude β on the market revenue. The revenue is normalized by the maximum revenue obtainable, which corresponds to the case in which perfect wind power predictions are used. In that case, there are no power imbalances, and thus the IPP is never penalized.

The α parameter, referring to the probability level for the calculation of the α-CVaR, usually takes values ranging from 0.90 to 0.99 in the financial literature. The following results were obtained with $\alpha = 0.9$; similar results were obtained for higher values of α. Also, it is important to note that the risk term $\beta \cdot CVaR_{\alpha}\left[l\right]$ has to be non-negligible compared to the mean term $\mathbb{E}\left[l\right]$. As a consequence, the decision-maker risk attitude β has to be scaled. The following results were obtained with β varying from 0 to 10.

Figure 4 shows the evolution of the normalized market revenue with the risk attitude of the decision-maker, for different forecasting approaches for the regulation prices. As a reference, we consider the situation where only point wind power forecasts are available. In such case, no information on the uncertainty associated to the power prediction is available. Furthermore, in the reference case, no bidding strategy is used and the energy bid is taken as the wind power point forecast, multiplied by the market time step. That is why the results, for the reference case, are independant from the risk attitude β. The normalized revenue is very high even with the reference approach as it reaches $86.2\,\%$ of the maximum revenue. Then, in *case 1* (see table in Figure 4), we apply the risk-based decision-making methodology, described in this work, considering constant value as a value for the regulation prices. These constants are the average of the regulation prices for the year 2001. The results are plotted in Figure 4, with the red dotted line. As shown in the figure, the method leads to an improvement of the revenue for β values inferior to 7. The improvement is the highest for $\beta = 2$. The case $\beta = 0$ is risk indiferent, and consequently gives the same results as the reference case.

Then, in order to analyse the influence of using regulation price forecasts, we applied the method with perfect predictions of the regulation prices for the second case. The results are shown in Figure 4 with the blue square dotted line. As shown in the figure, the revenue is really close to the maximum value for every value of β, even considering imperfect wind power forecasts. This result is due to the fact that the regulation scheme only penalizes imbalances which are opposite to the system regulation state. By having perfect knowledge of the regulation price, the IPP has perfect knowledge of the system regulation state, and is thus able to set the bid so that imbalance penalties are avoided. For instance, when the system is down-regulating, the system will only penalize surplus power. The IPP will thus propose a high bid; the probability to generate more than his bid, which would be penalized, is then very low. This last case demonstrates the importance of the regulation price forecast in the method.

We then applied the method with the naïve predictions of the regulation prices. As a naïve prediction model we took the forecast of the regulation price for a given month in 2002 equal to the average of the regulation prices for the same month in 2001. The results are shown on Figure 4 with the orange diamond dotted line through which we can observe that using these predictions does not improve the revenue, and even decreases it. The reasons for these results are the following:

1) the naïve prediction model has first very poor results in terms of forecasting performance (the normalized mean absolute error (NMAE) is greater than 50 %);
2) an error in the regulation price prediction may reinforce the error associated to the prediction of the system regulation state, which makes the bidding strategy method irrelevant;

These reasons help to explain why the constant prediction for the regulation prices leads to better results.

The energy imbalances, regulation costs and revenues for the different market price forecast cases

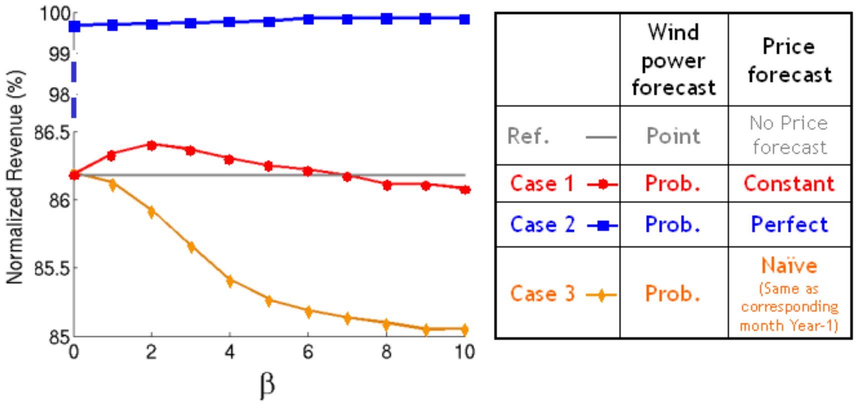

Fig. 4: Evolution of the market revenue with the decision-maker risk attitude, for different regulation price forecasting approaches

	Ref	**Case 1**	**Case 2**	**Case 3**
Imbalance (GWh)	20.51	20.03	58.66	22.34
Regulation Costs (× 1000 DKK)	962	947	19	981
Revenue (× 1000 DKK)	6008	6022	6950	5988

TABLE I: Energy imbalances, regulation costs and revenue for the different market price forecast cases. The results were obtained with $\beta = 2$

are presented in Table I. The results were obtained with $\beta = 2$, which is the value for which we obtained the best improvement in case 1.

- Regarding **Case 1**, the use of the risk-based method permited to decrease both the energy imbalances and the regulation costs, relatively to the reference case. The revenue was thus improved. More precisely, the imbalances were reduced by 2.3 % and the regulation costs were reduced by 1.6 %. These reductions of imbalances and regulation costs are of the same order of magnitude.
- In **Case 2**, the energy imbalances were highly increased whereas the regulation costs were dramatically decreased. This was due to the use of perfect knowledge of the regulation prices, which enabled the IPP to set the bid so that imbalance penalties were avoided.
- Finally, in **Case 3**, both the energy imbalances and the regulation costs were greater than in the reference case, which decreased the revenue.

VII. Conclusions and Further Work

In this study, a novel risk-based decision-making method was developed. Such method permited an efficient participation of wind farm operators into short-term electricity markets. The proposed method is based on the integration of the uncertainty associated to the wind power and market regulation price forecasts.

Regarding wind power predictions, the probabilistic forecast value has been confirmed: the market revenue is improved by minimizing the economic risks associated to wind power forecast uncertainty. A revenue improvement of 0.24 % of the maximum revenue was obtained with a simple constant-value based price prediction. Even if the 0.24 % improvement may seem negligible, it represents for the case study, around 23 000 DKK (Danish currency). We also demonstrated that perfect price prediction can increase the revenue to nearly 100 % independently of the wind power forecast uncertainty for the considered market.

This study clearly showed the distinction between the energy imbalances and the regulation costs. Particularly, case 2 demonstrated that it was possible to nearly avoid regulation costs, but this led to high energy imbalances. In a way, the objective of maximizing the revenue was acheived, using the hypothesis of perfect knowledge of the regulation prices; however, the high resulting energy imbalances may cause issues for network management.

The results obtained demonstrated a high sensibility of the results to price forecasts. Therefore, further improvements on regulation price forecasting models would be of great importance. Future work is going to extend also to other markets.

Acknowledgments

This work was performed in the frame of the project ANEMOS.plus (contract no 038692) funded in part by the European Commission under the 6th RTD Framework Programme. The authors would like to thank NordPool for having supplied historical data about NordPool prices.

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