Optimizing Benefits from Wind Power Participation in Electricity Markets using Advanced Tools for Wind Power Forecasting and Uncertainty Assessment

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Abstract

Short-term wind power forecasting tools are required to support a competitive participation of wind power in electricity markets against conventional energy sources. Certain tools integrate appropriate methodologies to estimate or to predict uncertainties. Then it is possible to use this information to develop bidding strategies for participation in the market that minimize financial risks and penalties in cases of low predictability of wind power. The rules of the market play an important role on the competitiveness of wind power. The paper proposes the use of strategies based on wind power forecasting and uncertainty estimation techniques. The strategies account for the asymmetry that is observed in imbalance prices. The benefits are quantified by simulating the participation of wind farms in the market of Netherlands. The paper shows the increase in revenues that can be achieved and how such strategies might have an impact to the balancing mechanism.

Keywords:* *Wind power, short-term forecasting, uncertainty management, confidence intervals, electricity markets.

1 Introduction

NOWADAYS, wind farm installations in Europe have reached 30 GW. Motivated by the Kyoto Protocol, the European Commission has set the target of doubling the share of renewables in gross energy consumption from 6% in 1997 to 12% in 2010 [1]. This directive targets 22,1% indicative share of electricity produced from renewable energy sources in total Community electricity consumption by 2010. To achieve this share, installed wind power capacity in the Member States should increase to 45-60 GW. In 2003, the European Renewable Energy Council (EREC) revised upwards the 2010 target to 75 GW [2]. Such a large-scale integration of wind generation causes several difficulties in the management of a power system. Often, a high level of spinning reserve is allocated to account for the intermittent profile of wind production, thus reducing the benefits from the use of wind energy. Predictions of wind power production up to 48 hours ahead contribute to a secure and economic power system operation. Also, as electricity markets are gaining importance, wind power predictions are helpful for wind energy producers who have to propose their bids on the market on a day-ahead (or a few-hour-ahead) basis. Increasing the value of wind generation through the improvement of prediction systems' performance is identified as one of the priorities in wind energy research needs for the coming years [3].

Apart from spot forecasts of the wind farms output in the next hours, of major importance is to provide tools for assessing on-line the accuracy of these forecasts. Such tools for on-line evaluation of the prediction risk are expected to play a major role in trading wind power in a liberalized electricity market since they can prevent or reduce penalties in situations of poor prediction accuracy.

So far, several studies concerning the participation of wind energy in electricity markets have been carried out, considering different market mechanisms and various prediction methodologies. For instance, Usaola et al. [4] focus on the Spanish electricity market and try to draw a relation between the wind power prediction tool accuracy and the income. Holttinen et al. [5] describe the participation of Eltra and Elkraft (the independent system operator for western and eastern Denmark) in the Nord Pool and evaluate the cost of forecasting errors for these market players. Roulston et al. [6] envisage the use of ensemble weather forecasts for better seizing the forecasting uncertainty and enhancing the position of wind generation in electricity markets. Bathurst et al. [7] concentrate on the uncertainty of wind generation and the resulting imbalance costs under the New Electricity Trading Arrangement. From the use of probabilistic expected wind generation tables, they define several bidding strategies accounting for the imbalance price asymmetry and the relative difference between imbalances and contract prices. However, the authors express the difficulties for generating the expected energy tables.

The aim of this paper is to evaluate different bidding strategies on a real-world day-ahead electricity market. These strategies are based either on the use of advanced wind power forecasting models or on the use of innovative methods that consider the wind power forecasting uncertainty and imbalance price estimates. The chosen short-term exchange market is the Dutch APX electricity market, which is associated to the regulation market ran by the Transmission System Operator (TSO) TenneT in Netherlands.

Initially, the various European market mechanisms are described and it is explained why wind power may be penalized in comparison with easily dispatchable generation. Then, we consider the participation of wind energy producers in the Dutch electricity market with bidding strategies directly based on wind power forecasts obtained from reference and advanced models. A new approach for defining bidding strategies is presented. Indeed, we will show that even if a wind power prediction obtained from an advanced model is the most accurate guess, it is not necessarily the best bid one may propose on the market. Concluding remarks will follow.

2 Trading wind generation in electricity markets

At every moment, the total amount of produced electricity should meet the consumption. This balance is usually guaranteed by two different mechanisms: *(i)* production/consumption programs established in advance guarantee an a priori overall balance; *(ii)* a real-time balancing mechanism that allows the Transmission System Operator (TSO) to compensate any deviations (imbalances) in the production/consumption programs. Electricity markets may be considered as a solution for that scheduling, since they permit a cost-effective match between supply and demand bids.

Wind is a highly variable energy production source, which can be seen as non-dispatchable. Dispatchability can be improved if wind is coupled with storage, however, state-of-the-art storage options are onerous for supporting large-scale wind integration. Wind forecasting is a cost-effective solution, but it appears obvious that there will always be a deviation between predictions and actual power output. This is why wind power producers have to consider their revenue on the electricity markets as the combination of the income from the power exchange market (spot market) and of the cost of imbalances.

Each electricity pool has its own rules and regulations that determine the way power is to be sold or purchased, how the prices must be calculated, and the obligations that the participants (producers or consumers) are committed to. In order to stimulate the development of renewables, some pools have special rules supporting wind generation, such as guaranteed prices, no program responsibility, etc. In Spain, wind generation is included in a special regime, with different ways of payment for the energy injected in the grid [4]. In Denmark, wind generation may be covered or not by prioritized dispatch (power balance handled by the TSO) depending on the turbines age [8]. At the inverse, in UK all energy producers participating in the market are considered as equal [7]. An overview of the European electricity markets is given in [9].

In this study, we consider that all energy producers participate in the electricity market under the same rules, i.e. they have to propose their bids on the spot market (no fixed price), and they are then financially responsible of their deviations from schedule. The costs of keeping the balance are charged to the participants, proportionally to their imbalance.

Our first aim is to show how the use of an advanced wind power prediction tool can substantially increase the wind power producer's income, by reducing the amount of imbalance. The rules and regulations of the considered market evidently affect the results, and this is taken into account in the analysis of the simulations. However, a roughly similar architecture between these rules and regulations can be found, so that the conclusions may be generalized (with cautiousness) to other electricity pools.

The Dutch case we consider here consists in a day-ahead spot market (APX - Amsterdam Power Exchange), a regulation market ran by the transmission system operator TenneT, and more recently in an adjustment market that we will not deal with in this paper.

The day-ahead APX spot market enables the participants to buy and sell electricity for any of the 24 hours of a day one day in advance. Every day, APX participants electronically send before 10:30 their buy/sell bids for each hour between 00:00 and 24:00 of the next day. This means that wind power producers must base their bids on 14-38 hours ahead wind generation forecasts. APX runs the algorithm that matches demand and supply for determining the hourly marginal price (spot price) and the E-program of each participant, specifying the amount of energy a participant is committed to produce/consume each hour for the following day. Producers are paid by APX the spot price for the quantity of energy specified in the E-program, independently of their actual production.

Every producer supplying power to the Dutch power grid is responsible for the balance of its E-program (balance between E-program and actual production). Energy in excess can be sold on the TenneT imbalance market at the spill price, and lack of energy has to be bought at the top-up price. APX spot market and TenneT imbalance market are independent and there is no constraint on the sign or the magnitude of the imbalance prices. However, imbalance is mainly penalizing: spill price is usually lower and top-up price usually higher than the spot price. For more details and analyses of TenneT imbalance prices, we refer to [10].

For intermittent generation, i.e. by a wind farm, APX spot revenues will globally be reduced by the imbalance costs due to forecasting errors. Moreover, because these prices are determined for every 15 minutes and are dependent on the actual grid imbalance, they are very volatile, almost unpredictable, and they can reach very high levels. If combined with a large prediction error, high imbalance prices expose wind power producers to excessive imbalance costs on a short-term basis, even if on a long-term basis low and high-level imbalance penalties may balance. Therefore, the participation for wind power producers in this market appears risky. This paper aims to show how the prediction uncertainty estimation can help to attenuate these risky situations and minimize imbalance costs on a long-term basis.

3 Evaluation of basic participation strategies on an electricity market - The test-case of the Netherlands

Participating in an electricity market means proposing quantities of energy for every Program Time Unit (PTU) for the following period. For the case of wind power, forecast of future generation are a must for bidding in a day-ahead market. The case of bids from a single wind farm is considered. This is on the pessimist side since prediction errors are expected to be higher than the case of multiple wind farms where aggregation smoothes errors. Firstly, the way wind power predictions are computed is presented, along with the level of performance of the forecasting method. Then, we describe the assumptions and the problem formulation related to the study. Comments on participation strategies follow the computational results.

3.1 Prediction of the wind power output

Wind power forecasting has been an active field of research in the last decade. There are nowadays several prediction models either commercially available or developed for research purposes. For an overview of the main and up-to-date forecasting methodologies, we refer to [11].

In this study, we consider the Armines Wind Power Prediction System (AWPPS) developed by Kariniotakis [12]. This prediction tool accommodates both on-line production data and Numerical Weather Predictions (NWPs) and gives an estimate of future wind power generation typically for the following 0-48 hours. At the moment of update, the most recent available NWPs are used as input to the model together with measurements of wind power. On-line production data are usually provided via a Supervisory Control and Data Acquisition (SCADA) system and allows one to account for the persistent behaviour of the wind. The consideration of NWPs improves considerably the performance [12]. Especially for "longer-term" horizons (up to 48 hours ahead), they are indispensable since they represent weather dynamics that cannot be modelled using only recent on-line data. In an online environment, the models uses self-adaptation schemes for fine-tuning its parameters to account for variations in the environment of the application, changes in the NWP model, etc. AWPPS has already been adapted and evaluated for several onshore wind farms, for instance in Ireland [13], as well as for offshore conditions [14].

In order to illustrate the level of performance of AWPPS, we focus on one of the wind farms considered in this study. The available time-series cover a period of almost two years from which 6600 hours were used for training (learning set), 1000 hours for cross-validation and one year for testing the performance of the model. They include hourly wind generation data for the whole park, as well as Hirlam NWPs of wind speed and direction at 10 meters and at 3 atmospheric pressure levels. The NWPs have a spatial resolution of around 0.15°. They are provided 4 times per day and at the level of the wind farm as interpolated values.

An evaluation protocol for wind power forecasting models has recently been proposed [15]. Here, we concentrate on the Normalized Mean Absolute Error (NMAE) criterion, as well as on prediction error distributions to give a broad view of the model performance for that particular wind farm. The normalization of the prediction error is done by using the installed capacity P_n. The NMAE allows one to give the average deviation (in absolute value) from the power measures over the whole period, while distributions give more insight on the frequency of occurrence of small and large errors. For this test case, the prediction bias is almost null: the model does not tend to under- or over-predict the wind generation.

Figure 1 depicts both Persistence and the advanced model performance described by the NMAE. Persistence is a simple model, considered as a reference, which states that power output in the following hours should be the same as the last measured value. Such benchmark model is hard to beat for the first horizons (0-6 hours). One can notice that here AWPPS always outperforms Persistence even for the short-term. For further horizons, the improvement proposed by the advanced approach is highly significant. For instance, if we focus on the 24-hour lead time the NMAE is around 14% of the wind farm nominal power while the NMAE is around 27% for Persistence.

Moreover, when forecasting 24-hour ahead, the error is less than 7.5% of the installed capacity 37% of the times, while large errors (larger than 27.5% of nominal power) occur only 18% of the times. Such information is given by the error distribution depicted in Figure 2. Note that this level of performance is for that particular wind farm and may be different for wind farms situated in complex terrain or in offshore conditions. It is recognized that wind power prediction models perform differently depending on the site conditions, on the period of the year, on the used NWPs [16], etc. Also, the level of error would be notably lower if we were considering an aggregation of wind farms, or a complete region, thanks to smoothing effects [17].

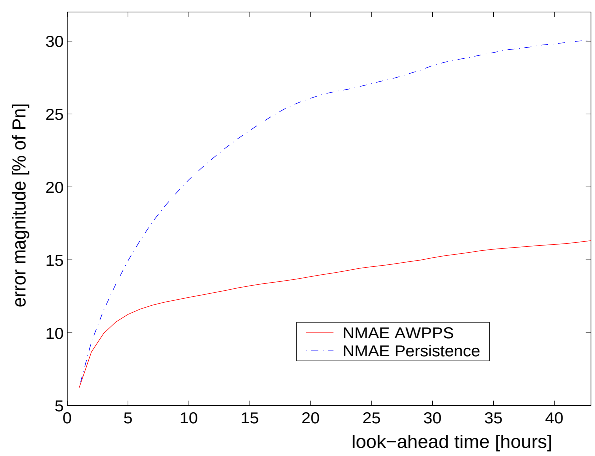

FIGURE 1: Comparison of Persistence and AWPPS performance using the NMAE criterion.

3.2 Assumptions

In order to simulate the participation of wind energy in an electricity market, we use series of wind power forecasts over a one-year period (from January 1st to December 31st). Regarding the electricity market, we consider the APX spot market and TenneT regulation price data over 2002.

Today, it is not really stated if a high share of wind in the

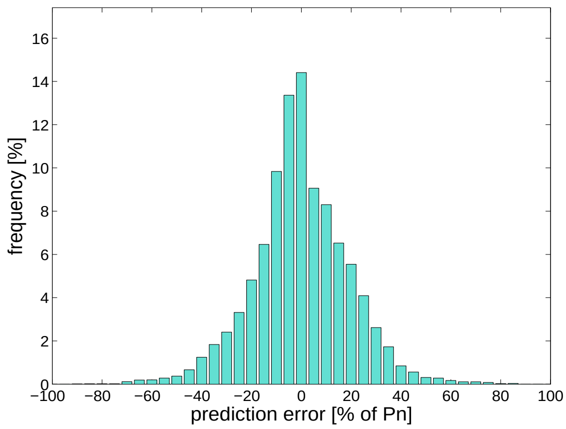

FIGURE 2: Prediction error distribution for the 24-hour ahead horizon. Errors are sorted by bins representing 5% of installed capacity P_n.

total electricity generation has a real influence on the market prices. For the case of the Nord Pool, which is a market highly penetrated by wind generation, several studies have been carried in order to determine the real influence of wind power on the market price behaviour. Kristoffersen et al. [18] developed a market simulation model at Eltra (the system operator for western Denmark), and simulated the market consequences of large-scale integration of wind power. One of the main conclusions is that wind power affects market prices. Besides, Morthorst [8] in an analysis of the market data over the years 2001 and 2002 observed there was a tendency that more wind power in the system leads to relatively lower spot prices (and vice versa), but no strong relation is established. In the case of the present study, which concerns a market that is not highly penetrated by wind generation, we assume that we can neglect this effect anyways.

To set up the present study, we have also made the following assumptions:

- wind power producers act in the electricity market as conventional producers and do not benefit of derogatory rules such as guaranteed price, no program responsibility, or premiums for nature-friendly electricity generation. However, due to stochastic and intermittent nature of wind, we have considered that they do not make any bids for regulation and reserve power supply and that they do not participate in the adjustment market.

- the only control wind power producers have on their production is binary: supplying or not supplying the energy to the grid. This means they do not have possibilities to down-regulate the wind generation, or to couple that power output with conventional generation means, or even to use energy storage devices.

- the price limit in the bids sent to APX will be set to the minimum so that all of the predicted energy is sold. By doing this, the wind power producer determines its E-program. The producer will be paid the hourly system marginal price (spot price) for the corresponding amount of energy stipulated in the E-program.

- normally, it is possible to make changes in the E-programs. Here, we have considered that energy producers make only one bid a day, at 10:30 for the following day. Thus, the 10:00 wind power prediction is used.

- any participant in the APX market have to pay an entrance and yearly fees, which may be prohibitive for small capacity generators. These fees are not taken into account in our study.

3.3 Problem formulation

The revenue of a participant in the Dutch electricity market proposing an amount of energy E_i^c and actually generating E_i^* can be formulated as follows, for a given PTU i:

$$R_i = p_i^c E_i^c + \begin{cases} p_i^+ d_i & , \ d_i \geq 0 \\ p_i^- d_i & , \ d_i < 0 \end{cases} , \tag{1}$$

with:

- $d_i = (E_i^* - E_i^c)$ the deviation from contract,
- p_i^c the spot price,
- p_i^+ the down-regulation price,
- p_i^- the up-regulation price.

This revenue is composed by the income on the spot market and by the cost of imbalances. Note that TenneT regulation prices may be either positive or negative. Thus, it might be possible to be rewarded for an imbalance, if this imbalance is convenient for the system operator.

Because we do not want to see the E_i^c term of (1) appearing in both the contract revenue and the imbalance costs, we reformulate (1) such that the revenue is composed by the income from the actual production plus the cost for eventual deviations from perfect prediction:

$$R_i = p_i^c E_i^* - \begin{cases} w_i^+ d_i & , \ E_i^* \geq E_i^c \\ w_i^- d_i & , \ E_i^* < E_i^c \end{cases} , \tag{2}$$

where

$$\begin{cases} w_i^+ &= p_i^c - p_i^+ , \\ w_i^- &= p_i^c - p_i^- . \end{cases} \tag{3}$$

The coefficients w_i^+ and w_i^- can therefore be seen as the penalties for repectively positive and negative deviations from perfect prediction.

The daily revenue of a market participant is obtained by summing the income for each PTU.

3.4 Results

Table 1 summarizes some of the Dutch market characteristics for 2002 and 2003. Note that the cost for positive and negative deviation from perfect prediction are not the same: a positive prediction error costs in average almost three times more than a negative prediction error for this year for 2002.

This ratio is slightly higher than the one observed for 2003 or for instance by Morthorst [8] for the Nord Pool over 2002. There is a general tendency that penalties for downward regulation are higher than those for upward regulation.

Moreover, one can notice the average spot price is significantly higher in 2003 than in 2002, while penalties for deviations stay at a similar level. The market is more severe in 2002: the cost of prediction errors is relatively higher.

TABLE 1: Market characteristics for 2002 and 2003: average spot price and penalties for upward and downward regulation.

year	$\bar{p}_i^c$ (€/MWh)	$\bar{w}_i^-$ (€/MWh)	$\bar{w}_i^+$ (€/MWh)
2002	29.99	4.03	10.93
2003	46.47	8.93	11.39

Results from the simulation of the market participation of the considered wind farm are gathered in Table 2. Results for other wind farms we have considered in the study are similar and thus not presented here. The main conclusions are that:

- the use of an advanced prediction method contributes to reduce significantly the volume of energy in imbalance. This means that wind power producers are then less concerned by penalties and thus by financial risks,
- the net income obtained with the advanced prediction approach is obviously better than the one obtained with Persistence. The maximum revenue (that would be obtained with perfect predictions) is reduced by more than 20% if using Persistence while it is reduced by only 13% if using AWPPS.

TABLE 2: Simulation results over 2002 with predictions given by both Persistence and the advanced forecasting approach. The *part of imbalance* represents the volume of energy in imbalance. The *performance ratio* represents the revenue obtained with the prediction model in comparison with the revenue one would have obtained with perfect predictions.

	Persistence	Advanced model
Part of imbalance (% of contracted energy)	73.6	40.6
Performance ratio (%)	79.1	87.0

4 Definition and evaluation of advanced bidding strategies

Wind power forecasts cannot be exact. A part of the uncertainty is due to the inaccuracy of the numerical weather forecasts used as input. An uncertainty estimation related to each individual forecast has to be given to end-users, so that they can decide on the risk they should undertake (i.e. level of allocated reserves, trading strategy, etc). Recently, several methodologies have been proposed to provide uncertainty estimates in the form of confidence intervals [19–21] as well as uncertainty estimates depending on meteorological situations [22, 23]. Ideally, probabilistic forecasts would give the whole information on the expected wind generation. In that sense, first methods are developed based either on local quantile regression [24], or on ensemble forecasts [25].

In this section, we describe a generic method that allows a wind power producer to define its optimal bid on an electricity market from a wind power forecast associated with uncertainty information in the form of a probabilistic distribution of expected wind generation.

4.1 A method accounting for the uncertainty assessment

In previous part of the paper, we showed the benefits from the use of an advanced prediction approach for bidding in an electricity market. Such prediction tools are designed for giving forecasts as accurate as possible. For defining the accuracy (or the level of performance) of those prediction tools, several criteria are available. The consideration of different criteria (minimization of errors in absolute values, of squared errors, etc.) may lead to different appreciations of the model interest for decision makers [26].

When considering electricity markets, the best model is not necessarily the one that provides the most accurate predictions, but the one that permits to define an optimal bidding strategy (i.e. which maximizes the expected revenue). In [24], it is shown how to choose the quantile of a probabilistic wind power forecast for that purpose. This quantile is a function of the upward and downward regulation prices only. Here, we describe a method for defining the best contract level by minimizing the imbalance cost.

4.1.1 Cost of deviations

Let us define a function f that gives the cost of a deviation from contract (previously defined as d). Such deviation from contract may be the prediction error if the contracted level of energy is set to the forecast generation value. The cost function f should reflect the cost of the deviation for the wind power producer. If an electricity market such as the Dutch one is considered, the f function can be defined as an asymmetric linear function of the deviations

$$f : d \rightarrow \begin{cases} \alpha^+ d & , d \geq 0 \\ \alpha^- d & , d < 0 \end{cases} , \tag{4}$$

where α^+ and α^- are estimates of the expected imbalance costs for positive and negative deviations:

$$\alpha^+ = \hat{w}^+, \; \alpha^- = \hat{w}^-.$$

Note that one can build their own cost function for better reflecting proper sensitivity to deviation costs (use of an asymmetric quadratic function, combination of quadratic and linear functions, introduction of non-linearities, etc.).

4.1.2 Definition of bidding strategies

Given the probabilistic distribution of expected wind generation for the PTU i, and given the deviation cost function f, there are various ways to determine the optimal contract level. Here, two policies based on Probabilistic Choice (PC) or Risk Analysis (RA) based on definitions by [27] are introduced: the former aims at minimizing the expected imbalance cost, while the latter intends to minimize the cost of the worst case. This means that the PC strategy will lead to a maximized income on a long-term basis, without avoiding large losses on some days. At the inverse, the RA strategy tries to minimize losses in risky situations though it cannot insure optimal revenue on the long-term.

Both strategies can be formulated as follows

- *Probabilistic Choice:*

$$h_{PC}(E_i) = \sum_k \left(\mathrm{P}(E_i^{*,k}).f(E_i - E_i^{*,k})\right), \qquad (5)$$

- *Risk Analysis:*

$$h_{RA}(E_i) = \max_k \left(\mathrm{P}(E_i^{*,k}).f(E_i - E_i^{*,k})\right), \qquad (6)$$

where E_i is the possible contract level at PTU i and $\mathrm{P}(E_i^{*,k})$ is the probability of the event $E_i^{*,k}$ occurring at same PTU. By minimizing h_{PC} and h_{RA}, the optimal bids under the PC and RA strategies are obtained.

4.2 Application to a real-world case study

The case study of the participation of a wind farm in the electricity market in the Netherlands is further investigated here, by applying the PC strategy. Data for the whole year 2002 are used and the aim is to maximise revenues over this period.

Firstly, it is needed to build the probabilistic distribution of expected generation for each PTU. Figure 3 gives the example of a 43-hour ahead wind power forecast (given by AWPPS) accompanied by confidence intervals for several confidence levels. The interval bounds, provided by the adapted resampling method described in [28], are the quantiles of the probabilistic distribution of expected wind power output.

Then, we use (4) for defining the deviation cost function. The α^+ and α^- values are determined by using averages of imbalance costs for spill and top-up generation. It is assumed that it is possible to estimate average imbalance costs over a year or a season (3-month periods). This assumption follows [10], in which a thorough analysis of imbalance price system and data in the Netherlands has shown that it may be possible to roughly forecast imbalance prices. These two ways of estimating imbalance costs (over 2002) lead to two PC strategies denoted hereafter as PC strategy 1 and 2 respectively.

The results of these strategies are compared with the ones from the basic participation strategy based on spot forecasts only (Table 3). One can notice that the consideration of uncertainty information on wind power forecasts and estimates of imbalance costs allows one to increase the market participant revenue. Also, it appears more interesting to have seasonal than annual estimates of the imbalance costs. Indeed, energy production and consumption behaviours may vary significantly from one season to another, leading to different regulation needs. However, one has to note that the income is not increased by diminishing the quantity of imbalances. The optimization process only focuses on the income and the amount of imbalance and is not integrated or considered as a constraint.

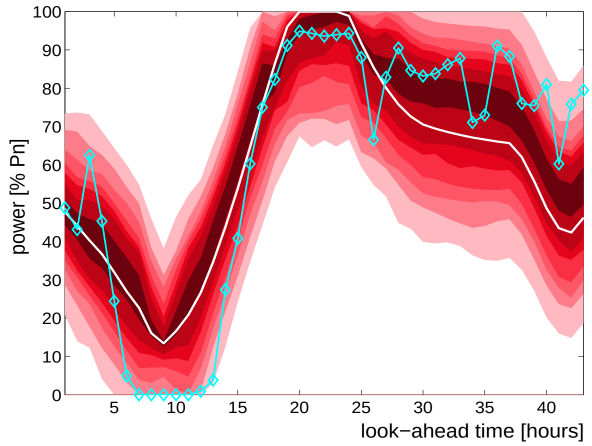

FIGURE 3: Wind power prediction with uncertainty information. The solid line is the wind power prediction and the solid line with squares the measured power output. Different confidence intervals for several confidence levels are used to build the probabilistic distribution of expected generation.

TABLE 3: Simulation results over 2002 with predictions given by both AWPPS and two different PC strategies (1: annual estimate of average imbalance costs - 2: seasonal estimates). The *part of imbalance* represents the volume of energy in imbalance. The *performance ratio* represents the revenue obtained with the prediction model in comparison with the revenue one would have obtained with perfect predictions.

	AWPPS	PC strategy 1	PC strategy 2
Part of imbalance (% of contracted energy)	40.6	45.7	84.7
Performance ratio (%)	87.0	89.1	96.2

5 Conclusions

Wind power forecasting has an interest for wind power producers aiming to participate in electricity markets. We have shown in this paper that the use of advanced wind power prediction techniques (based on fuzzy-neural networks on this case) significantly increases the income of wind producers , by decreasing the amount of energy negotiated in imbalance. Regarding the wind power prediction uncertainty assessment, several methods are available or under development today. Here, we have used an adapted resampling approach developed by the authors in previous work and validated on several case studies.

Because wind power forecasts contain a part of uncertainty, there will always be an imbalance cost related to forecasting errors. In this paper, we have developed a method that takes into account the forecast uncertainty and estimates of imbalance costs in order to define optimal bidding strategies. This method is flexible in the sense that the deviation cost function can be defined according to the producer's sensitivity to revenue losses related to imbalances. Also, it allows one to consider a maximization of the revenue on a long-term basis (Probabilistic Choice strategy) or a minimization of the risk of losses on a short-term basis by concentrating on the worst scenario (Risk Analysis strategy).

Results have been presented for the real-world case study of the participation of a wind farm at the electricity market of the Netherlands over the year 2002. Focus has been given to the amount of energy produced in imbalance and to the wind power producer revenue compared to the one he would have obtained if using perfect predictions. We have shown that bidding strategies based on advanced techniques (PC strategy) permit to augment the producer income. However, estimates of imbalance costs are needed to define the deviation cost function. Here, we have proposed to use annual or seasonal estimates that may be easy to determine. It would be of particular interest to further investigate on methods for estimating/forecasting imbalance prices. Further work in the area is on-going for simulating the participation of wind energy in other European Electricity Markets.

Regarding the wind power prediction uncertainty assessment, several methods are available or under development today. Yet, as we benchmark and compare forecasting models, focus should be given to the performance of these uncertainty assessment methods, in terms of reliability, resolution (situation-dependant uncertainty estimation), etc.

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References

[1] Official Journal of the European Commission, "Directive 2001/77/EC of the European Parliament and of the Council, on the promotion of electricity produced from renewable energy sources in the internal electricity market." Sept. 2001.

[2] A. Zervos, "Developing wind energy to meet the Kyoto targets in the European Union," *Wind Energy*, vol. 6, pp. 309–319, July-September 2003.

[3] S.-E. Thor and P. Weis-Taylor, "Long-term research and development needs for wind energy for the time frame 2000-2020," *Wind Energy*, vol. 5, pp. 73–75, April-June 2003.

[4] J. Usaola, O. Ravelo, G. Gonzalez, F. Soto, C. Davila, and B. Diaz-Guerra, "Benefits for wind energy in electricity markets from using short term wind power prediction tools; a simulation study," *Wind Engineering*, vol. 28, no. 1, pp. 119–128, 2004.

[5] H. Holttinen, "Optimal electricity market for wind power," *Energy Policy*, 2004. available online at *sciencedirect.com*.

[6] M. S. Roulston, D. T. Kaplan, J. Hardenberg, and L. A. Smith, "Using medium-range weather forecasts to improve the value of wind energy production," *Renewable Energy*, vol. 28, pp. 585–602, 2003.

[7] G. Bathurst, J. Weatherhill, and G. Strbac, "Trading wind generation in short-term energy markets," *IEEE Trans. Power Syst.*, vol. 17, pp. 782–789, Aug. 2002.

[8] P. E. Morthorst, "Wind power and the conditions at a liberalized power market," *Wind Energy*, vol. 6, pp. 297–308, July-September 2003.

[9] R. Madlener and M. Kaufmann, "Power exchange spot market trading in europe: theoretical considerations and empirical evidence." OSCOGEN (Optimisation of Cogeneration Systems in a Competitive Market Environment)- Project Deliverable 5.1b, March 2002.

[10] Y.-M. Saint Drenant, "Wind power predictions analysis - Part 1: TenneT imbalance price system. Development of a model for TenneT imbalance price system." ECN report - ECN-I-02-010, Aug. 2002.

[11] G. Giebel, L. Landberg, J. Badger, K. Sattler, H. Feddersen, T. S. Nielsen, H. A. Nielsen, and H. Madsen, "Using ensemble forecasting for wind power," in *CD-Proceedings of the 2003 European Wind Energy Association Conference, EWEC'03, Madrid, Spain*, June 2003.

[12] G. Kariniotakis and D. Mayer, "An advanced on-line wind resource prediction system for the optimal management of wind parks," in *CD-Proceedings of the MedPower Conference, Athens, Greece*, Nov. 2002.

[13] G. Kariniotakis and P. Pinson, "Evaluation of the MORE-CARE wind power prediction platform. Performance of the fuzzy logic based models," in *CD-Proceedings of the 2003 European Wind Energy Association Conference, EWEC'03, Madrid, Spain*, June 2003.

[14] P. Pinson, T. Ranchin, and G. Kariniotakis, "Short-term wind power prediction for offshore wind farms - Evaluation of fuzzy-neural network based models," in *CD-Proceedings of the 2004 Global Windpower Conference, Chicago, U.S.*, March 2004.

[15] H. Madsen, H. A. Nielsen, T. S. Nielsen, G. Kariniotakis, and P. Pinson, "A protocol for standardizing the performance evaluation of short-term wind power prediction models," in *CD-Proceedings of the 2004 Global Windpower Conference, Chicago, U.S.*, March 2004.

[16] G. Kariniotakis and the Anemos team, "What performance can be expected by short-term wind power prediction models depending on site characteristics," in *CD-Proceedings of the 2004 European Wind Energy Association Conference, EWEC'04, London, UK*, Nov. 2004.

[17] U. Focken, M. Lange, and H.-P. Waldl, "Previento : a wind power prediction system with an innovative upscaling algorithm," in *Proc. of the 2001 European Wind Energy Association Conference, EWEC'01, Copenhagen, Denmark*, pp. 826–829, June 2001.

[18] B. B. Kristoffersen, B. Donslun, and P. B. Eriksen, "Impacts of large-scale wind power on the power market," in *Proc. of the Fourth International Workshop on Large-Scale Integration of Wind Power and Transmission Networks for Offshore Wind Farms, Billund, Denmark*, Oct. 2003.

[19] A. Luig, Bofinger, and H. G. Beyer, "Analysis of confidence intervals for the prediction of regional wind power output," in *Proc. of the 2001 European Wind Energy Association Conference, EWEC'01, Copenhagen, Denmark*, pp. 725–728, June 2001.

[20] M. Lange, "On the uncertainty of wind power predictions," in *Proc. of the 2004 EAWE Conference, 'The science of making torque from wind', Delft, The Netherlands,* April 2004.

[21] P. Pinson and G. Kariniotakis, "On-line assessment of prediction risk for wind power production forecasts," *Wind Energy*, vol. 7, pp. 119–132, April-June 2004.

[22] M. Lange and D. Heinemann, "Relating the uncertainty of short-term wind speed prediction to meterological situations with methods from synoptic climatology," in *CD-Proceedings of the 2003 European Wind Energy Association Conference, EWEC'03, Madrid, Spain*, June 2003.

[23] P. Pinson, G. Kariniotakis, and D. Mayer, "Uncertainty and prediction risk assessment of short-term wind power forecasts," in *Proc. of the 2004 EAWE Conference, 'The science of making torque from wind', Delft, The Netherlands*, April 2004.

[24] J. B. Bremnes, "Probabilistic wind power forecasts using local quantile regression," *Wind Energy*, vol. 7, pp. 47–54, January-March 2004.

[25] H. A. Nielsen, T. S. Nielsen, H. Madsen, J. Badger, G. Giebel, H. Feddersen, and K. Sattler, "Wind power ensemble forecasting," in *CD-Proceedings of the 2004 Global Windpower Conference, Chicago, U.S.*, March 2004.

[26] C. S. Nielsen and H. F. Ravn, "Criteria in short-term wind power prognosis," in *CD-Proceedings of the 2003 European Wind Energy Association Conference, EWEC'03, Madrid, Spain*, June 2003.

[27] V. Miranda and L. M. Proenca, "Probabilistic choice vs. risk analysis - Conflicts and synthesis in power system planning," *IEEE Trans. Power Syst.*, vol. 13, no. 3, pp. 1038–1043, 1998.

[28] P. Pinson and G. Kariniotakis, "On-line adaptation of confidence intervals based on weather stability for wind power forecasting," in *CD-Proceedings of the 2004 Global Windpower Conference, Chicago, U.S.*, March 2004.