The impact of electricity market schemes on predictability being a decision factor in the wind farm investment phase

Fiona Foucault, Robin Girard, Georges Kariniotakis

The impact of electricity market schemes on predictability being a decision factor in the wind farm investment phase

F. Foucault*[1] R. Girard†[1] G. Kariniotakis‡[1]

[1]MINES-ParisTech, PERSEE: Center for Processes, Renewable Energies & Energy Systems, 1 rue Claude Daunesse, 06904 Sophia Antipolis Cedex, France.

2 July 2013

1 Summary

Wind power production forecasts over the next hours to days ahead are a prerequisite for the secure and economic operation of power systems with high wind power penetration. For wind power producers who participate in a day-ahead electricity market, low predictability of wind production results in imbalance costs. This influences the revenue, and in turn, the pay back of the investment. The aim of this work is to evaluate the role of wind power predictability versus the traditional used criterion of capacity factor on the investment phase of a wind farm and on spatial planning in an electricity market context. The study cases of OMEL and PJM markets are considered to generalize the results of the West Denmark (DK1) case study (also presented here) in order to quantify the impact of predictability. In the three studies, we find that the role of capacity factor in explaining the revenue is greatly more important than the predictability (more than 99% in comparison with 0.05% for predictability in OMEL, 0.04% in NordPool and, in average, 0.001% for PJM).

2 Introduction

The share of renewable energy sources in the energy mix of several countries worldwide is rapidly increasing. As regards the European Union (EU-27), the European Commission has set the target of having 20% of EU-27´ s energy consumption coming from renewable sources. Wind energy is anticipated to be a major contributor to this target with an installed capacity that is expected to extend from 74.7 GW by end of 2010 in EU-27, to 230 GW by 2020 according to EWEA projections (see [1]).

Such large-scale integration of wind energy raises several challenges in operating and managing power systems, as they are a great deal more subject to variability. An yet, the electricity being a non-storable product, the balance between production and consumption must be maintained. Therefore, it is now recognized that accurate short-term forecasts of wind farms´ power output over the next few hours to days are important factors for the secure and economic operation of power systems with high wind power penetration [2]. Today, significant R and D efforts are being undertaken to improve the performance of wind power prediction models and related weather

[1]PhD Student, e-mail:fiona.foucault@mines-paristech.fr Tel.: + 33 4 93 95 74 45

[2]Research fellow, e-mail : robin.girard@mines-paristech.fr, Tel: +33 4 93 67 89 64 , Fax: +33 4 93 95 75 35

[3]Head of Renewable Energies & SmartGrids Group, Senior Scientist, e-mail: georges.kariniotakis@mines-paristech.fr, Tel: +33 4 93 95 75 01, Fax: +33 4 93 95 75 35

forecast models. Increased overall wind power predictability is expected to be beneficial for several actors, such as transmission or distribution system operators, to efficiently perform functions such as estimating reserves, unit commitment, and congestion management.

Furthermore, this growth of the share of renewables in the generation mix calls for an adaptation of the incentive policies. Accordingly, a means to protect the grid from imbalances is to adapt the economical mechanisms governing this production. This corresponds to the introduction of renewable production in the traditional electricity markets, where deviations of the produced energy from the contracted energy (imbalance) due to forecast errors are exchanged at a different price called the imbalance price. Indeed, with growing integration of renewables, countries tend to shift from a feed-in tariff policy difficult to sustain in the long-run (given the fixed remuneration per kW.h, predictability does not play any role in decision-making for producers), to a management of imbalances with imbalance prices so that variablity is regulated by prices whose design can be adapted.This direct translation of wind power forecast errors into a financial cost, as well as strategies for the reduction of this cost, have already been studied (see e.g. in [3, 4, 5, 6]), and yet it is still difficult to quantify the economic benefit of increasing predictability. The direct consequence of this is the difficulty in devising clear economic incentives aiming at greater predictability.

From the producer or the investor´ s point of view, this change of paradigm questions the usual decision-making process concerning the choice of location of wind farms. Usually based on well-established "resource assessment" study based on capacity factor, the costs incurred from forecast errors could damage benefits, all the more as the more wind farms are installed the less the choice among sites is large and the more complex the sites´ terrains are. Indeed, previous works like the benchmarking exercise performed in [7] have shown to what extent predictability is dependent on terrain complexity; the higher the complexity, the lower the predictability. It was shown also in [8] that predictability tends to decrease when wind speeds increase.

The aim of this paper is to quantitatively assess the role of predictability versus the role of capacity factor, with real market data and real wind farm production data. The actors concerned could be independent power producers, wind farm developers, aggregators or virtual power plant operators who need to decide where to install a new wind farm, or how to compose an optimal portfolio of wind farms to participate in an electricity market. In addition, penalties paid by producers who deviate from the day-ahead contract are settled by the transmission system operator and market operator, who will thus be concerned by the results of this paper.

This paper and the article [9] study the new questions which are increasingly being asked by end-users: Can a compromise between resource potential and predictability be beneficial when choosing among two sites where to install a wind farm? Is some compromise to be found when choosing among two sites, let us say one with high potential but low predictability (i.e. a complex terrain site) and one with lower potential but higher predictability (i.e. a flat terrain site), so that such a compromise might lead to choosing the site with lower potential if the loss in revenue can be compensated by lower penalties? Taking this reasoning one step further, one might study how to optimally extend a portfolio of wind farms by adding new wind farms so that the ensemble has an optimal performance in the market.

To sum up, this paper may present an interest for investors and producers in order to help them choose the optimal strategy to maximize their revenue, but it also presents an interest for the power system and market operators, who may want to incite wind farm operators to adopt practices which increase predictability so that wind production is the source of less imbalances. In this paper we propose a methodology to study the above questions, and carry out the study for three real-world markets : Nordpool, OMEL and PJM. In section 3 we present a general market model, the data which was used in this study, and the methodology used on approximately 200 wind farms in Denmark. In Section 4, the results obtained with this methodology are shown before concluding in section 5.

3 Case studies methodology

3.1 The generic market model

We consider producers selling their forecasted production in a day-ahead market. A producer´ s revenue can be decomposed in two terms : the product of sales, given by the amount of energy actually sold times the spot price and the imbalance cost, which can be positive or negative and is determined by the amount of error between the forecasted (and therefore bid) and the actual amount of energy delivered. This can be expressed by

$$Revenue = f^1\left(\pi^c, E^*\right) + f^2\left(\pi^c, \pi^{c+}, \pi^{c-}, d^*\right)$$

where
π^c is the spot price,
E^* is the energy actually delivered,
π^{c+} is the imbalance price for a positive deviation from the bid,
π^{c-} is the imbalance price for a negative deviation from the bid,
$d^* = E^* - E^c$ is the error between the actual energy delivered and the bid, with E^c the contracted energy. Indeed,

$$f^1\left(\pi^c, E^*\right) = \pi^c \times E^*$$

and

$$f^2\left(\pi^c, \pi^{c+}, \pi^{c-}, d^*\right) = \begin{cases} d^{*+} \times \pi^{*+} = d^{*+} \times \left(\pi^c - \pi^{c+}\right) \\ d^{*-} \times \pi^{*-} = d^{*-} \times \left(\pi^{c-} - \pi^c\right) \end{cases} \tag{1}$$

where d^{*+} is the positive amount of imbalance and d^{*-} is the negative amount of imbalance. Low predictability is reflected through imbalance costs in the second term of the revenue expression. The impact of this term can be influenced by two factors:

- The market mechanism can fix different imbalance prices to favor or penalize the balance responsible party according to the system´ s state (up or down regulation), and the imbalance direction of the producer.
- The magnitude of the regulation prices which are used to distribute the balancing costs among participants may be high or low compared to the spot price according to the system.

Indeed, apart from market mechanisms, market participants may be penalized by the level of regulation prices as they impact on participants which are not balanced with respect to their bid. Therefore, the magnitude of regulation prices should also be compared to spot prices to measure the impact of imbalances on revenues earned with sales on the spot market.

There are several potential factors which may influence this ratio:

→ The availability of interconnections with the exterior which brings flexibility to the system (storage is also another flexibility mean);

→ The availability of low-cost balancing power such as hydropower;

→ The share of renewable energy in the generation mix : a priori, all else being equal, the larger the share the bigger the imbalances and the costs of regulation;

→ The size of the area or the level of aggregation: variability can be smoothened by compensating shortages in one area by the production in another.

3.2 The wind data

In this study, we analyse the impact of capacity factor and predictability on the revenue of wind farms. This calculation is based on data collected from November 2007 to October 2009 on approximately 200 wind farms from West Denmark. For each of them, the capacity factor and the predictability were calculated. To measure predictability, normalized average mean absolute error was used:

$$NMAE = \frac{1}{T}\sum_{t=1}^{T} NMAE_t^X$$

with

$$NMAE_t^X = \frac{1}{24}\sum_{h=13}^{H=36} \left| Err_{t+h|t}^X \right|$$

where $Err_{t+h|t}^X$ is the normalized forecast error:

$$Err_{t+h|t}^X = \left(P_{t+h}^X - \widehat{P}_{t+h|t}^X \right) / P_{nom}^X \times 100$$

where P_{nom}^X is the nominal power of a wind farm X in the set of wind farms, P_{t+h}^X is the actual power delivered at horizon h and $\widehat{P}_{t+h|t}^X$ is the forecast production at the horizon h at time t.
The forecast and actual energy delivered data were collected for each farm.

3.3 The market data

Three real-world markets were studied : NordPool, OMEL and PJM. For each market, the spot and imbalance prices were collected. Here is a brief description of their mechanisms:

In NordPool, the imbalance price equals the spot price when the producer´ s imbalance direction is opposite to the system´ s imbalance. Otherwise it is based on the price of regulation. This market is decomposed into several price zones, but only West Denmark (DK1) was studied.

In OMEL, the same market mechanism is applied with an additional control on the energy prices. This market is regional and covers Spain.

In PJM, the imbalance prices are the real-time Locational Marginal Prices (LMP). Indeed, this market, located in the United States, is a nodal one, where the region is split into small areas, for which local prices are determined. The study is carried out for each of the 98 nodes identified.

3.4 The methodology

For each market, the revenue for each wind farm was calculated. Then, a regression according to each wind farm´ s capacity factor was carried out. The residue of this regression was analysed through another regression according to each wind farm´ s NMAE (characterizing predictability). Figure 1 illustrates this process:

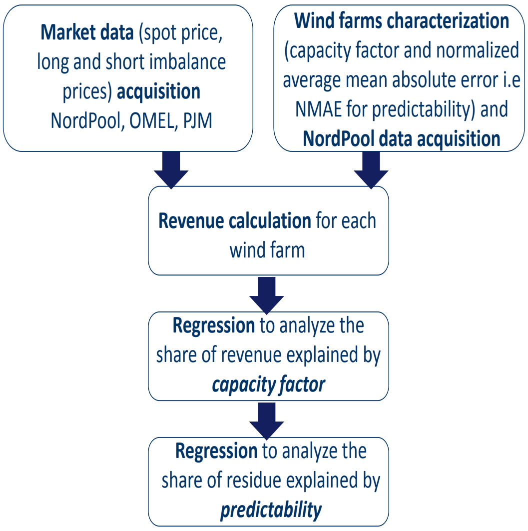

Figure 1: Methodological process

4 Results

In this section, we show the results determining the share of predictability and capacity factor in explaining the revenue. They were obtained by carrying out a regression on the revenue according to the capacity factor of wind farms. Then, the residue from this regression (the share of revenue which was not explained by revenue) underwent a regression according to the NMAE of wind farms.

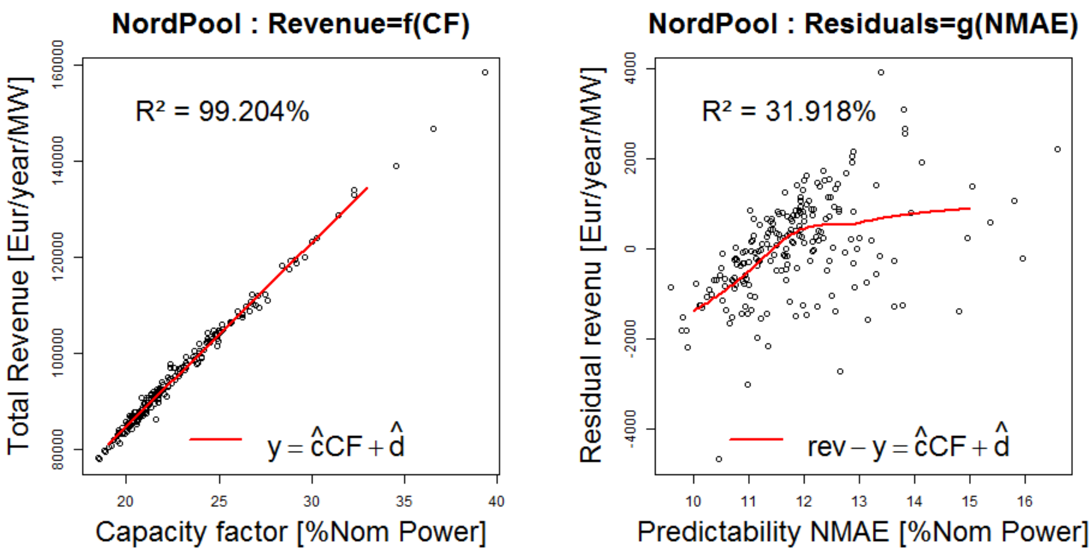

Figure 2: Results for the NordPool (DK1) market

We can see that the results for NordPool and OMEL are very similar.

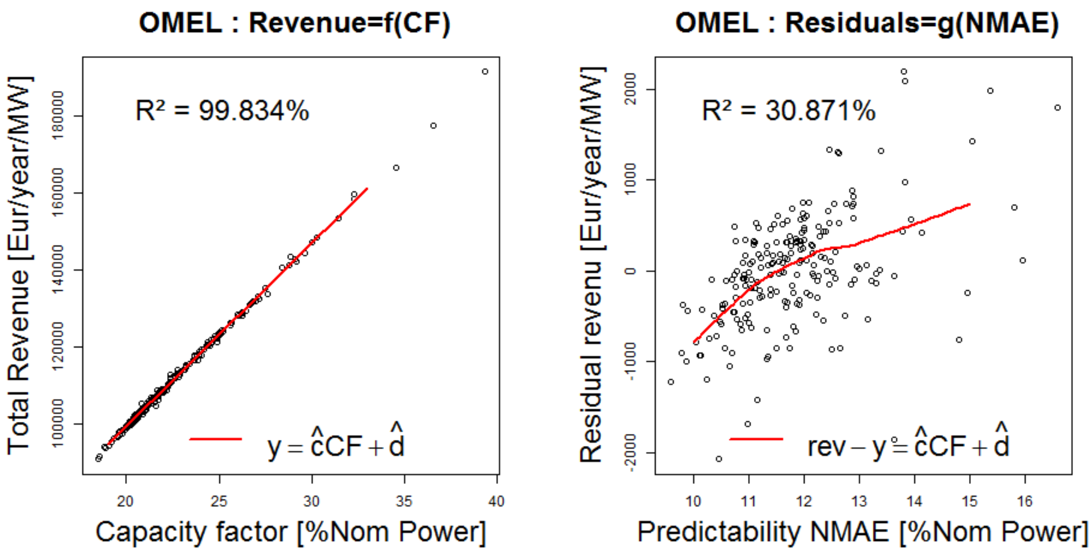

Figure 3: Results for the OMEL market

For PJM, we carried out the regressions for each of the 98 nodes of our inventory. In the following, we kept the values of percentages representing the share of revenue explained by capacity factor, and the share of the residue from this first regression explained by predictability. These values are shown in two histograms:

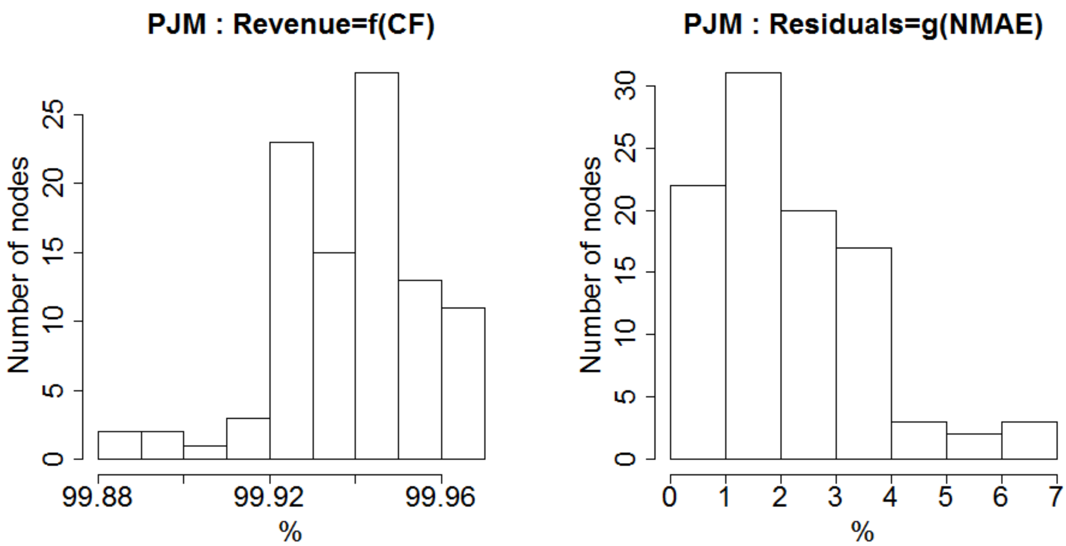

Figure 4: Results for the PJM market

The results for PJM go in the same direction as for NordPool and OMEL. For the three markets, we have a very high share of revenue explained by capacity factor, and a minor to low share of the residue of revenue explained by predictability, which results in an overall very low share of revenue explained by predictability.

5 Conclusion and perspectives

Our work studied the impact of predictability on a producer´ s revenue for three real-world market mechanisms: NordPool (West Denmark DK1 region), OMEL (Spain) and PJM (United States). For OMEL, we obtained that the predictability accounted for 0.05% and for NordPool it accounted for 0.3% of the revenue. For PJM, in average, the predictability accounted for 0.001% of the revenue. In opposition to this, for the three markets, the capacity factor explained the major share of revenue. From these results, we can conclude that for these markets, the capacity factor remains the most important factor in the determination of a producer´ s revenue, as opposed to the predictability.

These results may be explained by low regulation (low level of imbalance costs). In NordPool for instance, strong interconnections with neighboring countries and the existence of low-cost balancing power such as hydro provides more flexibilities, enabling the prices of regulation to decrease.

These results may also be explained by the strong positive correlation which exists between prediction errors and the capacity factor. Ultimately, this implies that in any resource assessment phase, lower predictability will go hand in hand with a high associated capacity factor. This makes predictability almost irrelevant in the resource assessment phase, at least from a wind power producer´ s point of view.

Note that there is a difference between considering predictability in the resource assessment phase and considering predictability for a given installed wind farm. In the second case, not treated in this paper, the capacity factor is fixed and the role of predictability is much stronger. Market imbalance cost reduction is not the only benefit a wind power producer can obtain from predictability. Within the O and M cost breakdown, predictability can play a more important role, especially for offshore wind farms, where the lack of predictability leads not only to market imbalance costs but also to loss of availability due to downtime periods (turbines not accessible due to bad weather that was not well predicted in the maintenance strategy). Still, apart from specific rules in tenders for wind power installation projects, market imbalance costs constitute the only incentive for producers toward achieving more predictability.

Finally the results of this paper do not quantify the benefit of predictability from the system´ s point of view. Indeed, the effectiveness of the market measure does not necessarily coincide with the value of predictability with respect to the electric system, and might miss the benefits and costs brought about by longer-term investment. Further work should contain a systemic analysis in the spirit of the capacity value [10], in order to reveal the intrinsic value of increasing predictability for a given system at a given level of predictability.

Further developments of this work could include the application of the methodology to systems with other characteristics (share of renewable, available interconnections...) influencing the magnitude of regulation compared to the spot price, as this factor could have more influence on the revenue than the mere choice of a particular market mechanism.

6 Acknowledgments

The authors thank the European Commission for partially funding the FP7 project Safe wind (http://www.safewind.eu) in the frame of which part of this work was performed. We also thank the ANR for partially funding the Winpower project.

References

[1] A report by the European Wind Energy Association EWEA. Pure power wind energy targets for 2020 and 2030. Technical report, July 2011.

[2] Arturs Purvins, Alyona Zubaryeva, Maria Llorente, Evangelos Tzimas, and Arnaud Mercier. Challenges and options for a large wind power uptake by the european electricity system. *Applied Energy*, 88(5):1461 – 1469, 2011.

[3] P. Pinson, C. Chevallier, and G.N. Kariniotakis. Trading wind generation from short-term probabilistic forecasts of wind power. *Power Systems, IEEE Transactions on*, 22(3):1148–1156, 2007.

[4] Bourry F. *Management of uncertainties related to renewable generation participation in electricity market*. PhD thesis, Ecole des Mines de Paris, Center for Energy and Processes, Rue Claude Daunesse, Sophia Antipolis, 2009.

[5] Vincenzo Marano, Gianfranco Rizzo, and Francesco Antonio Tiano. Application of dynamic programming to the optimal management of a hybrid power plant with wind turbines, photovoltaic panels and compressed air energy storage. *Applied Energy*, 97(0):849 – 859, 2012. Energy Solutions for a Sustainable World - Proceedings of the Third International Conference on Applied Energy, May 16-18, 2011 - Perugia, Italy.

[6] J.M. Morales, A.J. Conejo, and J. Perez-Ruiz. Short-term trading for a wind power producer. *Power Systems, IEEE Transactions on*, 25(1):554 –564, feb. 2010.

[7] Marti I et al. Europ. What performance can be expected by short-term wind power prediction models depending on site characteristics? Wind Energy Conf EWEC.

[8] Pierre Pinson. *Estimation of the uncertainty in wind power forecasting*. PhD thesis, Ecole des Mines de Paris, 2006.

[9] R. Girard, K. Laquaine, and G. Kariniotakis. Assessment of wind power predictability as a decision factor in the investment phase of wind farms. *Applied Energy*, 101(0):609 – 617, 2013. Sustainable Development of Energy, Water and Environment Systems.

[10] A. Keane, M. Milligan, C.J. Dent, B. Hasche, C. D'Annunzio, K. Dragoon, H. Holttinen, N. Samaan, L. Soder, and M. O'Malley. Capacity value of wind power. *Power Systems, IEEE Transactions on*, 26(2):564 –572, may 2011.

[11] L. von Bremen (ForWind) J. Sanz Rodrigo (CENER) L. Frías Paredes, N. Stoffels. Safewind project - statistical analysis of wind power and prediction errors for selected test areas. Technical report, CENER,ForWind, 2012.

[12] Erik Holmgren Nils Siebert Georgios Kariniotakis Robin Girard (ARMINES) P. McSharry, L. von Bremen. Safewind project - predictability measure and communication of information on uncertainty to forecast users. Technical report, University of Oxford, OLDENBERG, ARMINES, 2012.

[13] Georgios Anastasiades Arthur Bossavy Robin Girard, Patrick McSharry. Safewind project - forecast combination conditioned to a predictability information, and benefits for controlling forecast error. Technical report, ARMINES and Oxford, 2012.01.04.