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Comparison of the economic impact of different wind power forecast systems for producers

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Abstract. Deterministic forecasts of wind production for the next 72 h at a single wind farm or at the regional level are among the main end-users requirement. However, for an optimal management of wind power production and distribution it is important to provide, together with a deterministic prediction, a probabilistic one. A deterministic forecast consists of a single value for each time in the future for the variable to be predicted, while probabilistic forecasting informs on probabilities for potential future events. This means providing information about uncertainty (i.e. a forecast of the PDF of power) in addition to the commonly provided single-valued power prediction. A significant probabilistic application is related to the trading of energy in day-ahead electricity markets. It has been shown that, when trading future wind energy production, using probabilistic wind power predictions can lead to higher benefits than those obtained by using deterministic forecasts alone. In fact, by using probabilistic forecasting it is possible to solve economic model equations trying to optimize the revenue for the producer depending, for example, on the specific penalties for forecast errors valid in that market. In this work we have applied a probabilistic wind power forecast systems based on the "analog ensemble" method for bidding wind energy during the day-ahead market in the case of a wind farm located in Italy. The actual hourly income for the plant is computed considering the actual selling energy prices and penalties proportional to the unbalancing, defined as the difference between the day-ahead offered energy and the actual production. The economic benefit of using a probabilistic approach for the day-ahead energy bidding are evaluated, resulting in an increase of 23 % of the annual income for a wind farm owner in the case of knowing "a priori" the future energy prices. The uncertainty on price forecasting partly reduces the economic benefit gained by using a probabilistic energy forecast system.

1 Introduction

Among the limiting factors to the penetration of wind energy is the variable nature and limits to predictability of wind speed. Electricity is distributed over a region via a grid, and in a deregulated market it is crucial for the utility companies that provide electricity to be able to deliver the committed energy to the grid. In this sense wind energy is at a disadvantage when compared to other types of energy sources because of its intrinsic limited predictability. For this reason, in the past wind energy producers have often been exempted from penalties for failing to deliver the day-ahead planned energy. However, with the increasing penetration of the wind energy

in the energy market, in many European countries (e.g., Germany, Denmark and Italy) the requirement of an accurate energy forecast has been introduced, along with penalties proportional to the forecast errors. Wind power predictions can be categorized in two main groups: deterministic and probabilistic. A deterministic forecast consists in a single value for each time in the future for wind power. Probabilistic forecasting provides probability density functions (PDF) from which probabilities of future outcomes of events can be estimated. The value of probabilistic power predictions and the usefulness of uncertainty quantification that results from it have been explored (Roulston et al., 2003; Zugno et al., 2013). A significant application is when renewable energy is traded

in day-ahead electricity markets. Trading future wind energy production using probabilistic wind power predictions can lead to higher economic benefits than those obtained by using deterministic forecasts alone. In fact, the maximum income for a producer is obtained by offering in the day-ahead market an amount of energy that can be different from the mean value of the forecasted PDF (see Roulston et al., 2003; Zugno et al., 2013). Indeed, it can be analytically shown that under the conditions imposed by the day-ahead energy market, the optimal day-ahead market bid for a wind energy producer is a certain quantile of the distribution of forecasted wind power (Bremnes, 2004; Linnet, 2005; Pinson et al., 2007). This optimal quantile is a function of the day-ahead and the imbalance prices, which are not known apriori and change on hourly basis. The optimal bids might significantly differ from the point forecasts of wind power production. A theoretical discussion about quantile forecasts being optimal bids in electricity markets can be found in Gneiting (2011).

In this work we prove, for the first time on a real case application of an Italian wind farm, that it is possible to limit the economic loss (caused by penalties regulation) by using a probabilistic forecast that choses the optimal quantile for bidding wind energy in the day-ahead market.

2 Site and power data description

The case study is based in one wind farm located in a complex-terrain mountainous area of Southern Italy, whose total installed power is about 8 MW. An hourly time series power data is available for the period November 2010–May 2012. The power data have been filtered and quality controlled following Alessandrini et al. (2013).

3 The probabilistic power forecast

The probabilistic wind power forecast has been obtained by using a deterministic meteorological model's simulation, performed by applying the non-hydrostatic model RAMS (Pielke et al., 1992) and the analog ensemble technique (AnEn) (Delle Monache et al., 2012, 2013).

RAMS has been run using the ECMWF (European Centre for Medium range Weather Forecast) analysis as initial conditions and 6-hourly ECMWF deterministic forecast fields as boundary conditions. The simulation set up consists of 2 nested grids with a horizontal grid spacing of 12 and 4 km and 30 vertical levels. A set of 59 h long forecast simulations have been run, starting at 12:00 UTC of every day of the two-year period 2011–2012.

The AnEn technique provides a set of likely power predictions (i.e., an ensemble that is a Monte Carlo approximation of the PDF associated with future power production) using a historical dataset of observations and deterministic model predictions. For each forecast lead time the ensemble set of forecasts of a certain variable is constituted by a set of its

measurements from the past. These measurements (in this case wind power data) are those concurrent to past forecasts at the same lead time, chosen across the past runs most similar to the current forecast. The metric used to rank past forecasts' similarity to the current forecast is defined as follows (Delle Monache et al., 2012, 2013).

$$\|F_t, A_{t'}\| = \sum_{i=1}^{N_v} \frac{w_i}{\sigma_{f_i}} \sqrt{\sum_{j=-\tilde{t}}^{\tilde{t}} \left(F_{i,t-j} - A_{i,t'+j}\right)^2} \tag{1}$$

where F_t is the current forecast for the lead time t at a certain location, $A_{t'}$ is an analog forecast for the same lead time t' before F_t was issued and at the same location, N_v and w_i are the number of physical variables and their weights, respectively, σ_{f_i} is the standard deviation of the time series of the past forecast of a given variable at the same location, $\tilde{t}$ is an integer equal to half width of the time window over which the metric is computed (e.g., if $\tilde{t} = 1$ h, the distance will be computed over the 3 forecast lead times corresponding to $t - 1$ h, t, $t + 1$ h), and $A_{i,t'+j}$ and $F_{i,t-j}$ are the values of the analog and the forecast in the time window for a given variable. The goal is to find past forecasts of the meteorological variables (chosen among the ones with the highest correlation with the quantity to be predicted, wind power in this case) that were predicting similar values and temporal trend (a similar behaviour as a function of time along the time interval defined by $\tilde{t}$) compared to the current forecast. In the current application the number of the ensemble member has been kept constant and equal to 20.

In this study, wind speed and wind direction have been extracted at the wind farm location at the hub height, equal to 50 m above the ground, and are used as predictors for the AnEn's algorithm. Year 2011 has been chosen as the training period, while probabilistic wind power forecast are issued along year 2012. The hourly probabilistic forecasts in the interval between lead times equal to 36 and 59 h are retained for the economic computation, assuming they are used for the day-ahead market bids.

4 Economic model

In this section the economic impact of a probabilistic wind power forecast is evaluated introducing a very a simple model of an electricity market. This model mimic the real situation of some nations where penalties must be paid by the producers of the energy market on the unbalancing, which is computed as the difference between the hourly promised (a day-ahead) energy and the delivered one. The penalties are usually related to the day-ahead and spot market energy prices (the day-ahead market occurs once a day usually ending around 09:00 a.m. local time and defines the hourly energy production for the day after, while the spot market occurs every hour to balance the energy production with the real demand). In this kind of mechanism, Roulston et al. (2003) showed that the maximum income can be achieved

by promising an hourly energy production that is not nec-essarily the mean value of the forecasted energy PDF (de-pending on the day-ahead and spot market prices). While the market model used here is a simplified version of real condi-tions and may not replicate all current situations of different nations, the wind power data are related to a real wind farm located in Italy. The market model simulates the mechanism by which producers promise a target amount of electricity, E_c, for a particular hour of the day-ahead. The producer is paid a fixed unit price, P_c, for the promised electricity. If at that particular hour the wind production is not sufficient to satisfy the contract, then the generator must satisfy the con-tract by purchasing the shortfall on the spot market at a cost of P_s per unit usually greater than P_c. If, in the opposite case, the real production exceeds the promised energy the excess of production is paid at a price P_{s1} usually lower than P_c. In this latter case there will be some other energy producers (usually from conventional sources) who must be reimbursed by the amount of energy they are not able to deliver in to the grid. Indicating E_a as the real generated energy, the hourly income I for the producer can be computed as follows:

$$I = \begin{cases} E_c P_c + (E_a - E_c) P_{s1} & \text{if } E_a \geq E_c \\ E_c P_c - (E_c - E_a) P_s & \text{if } E_a < E_c \end{cases} \quad (2)$$

In this model the penalties faced by the producers are asym-metric. It can be shown (see Roulston et al., 2003; Zugno et al., 2013) that under the conditions described by Eq. (2) the optimal day-ahead market bid for a wind energy producer is a certain quantile of the distribution of forecasted wind power. The optimal value of E_c is such that the marginal income from an additional unit of promised electricity is exactly bal-anced by the expected penalty from failing to meet E_c for that unit. This balance occurs when:

$$P_c - P_{s1} = P(E_c)(P_s - P_{s1}) \quad (3)$$

or,

$$P(E_c) = \frac{P_c - P_{s1}}{P_s - P_{s1}} \quad (4)$$

where the function $P(E)$ is the probability that the actual pro-duced energy E_a is lower than any critical value E (i.e., the cumulative function of the distribution of the expected pro-duced energy). Since P_s is greater than P_c, and P_{s1} is gener-ally lower than P_c, the ratio at the right hand side in Eq. (4) is always between 0 and 1. The optimal quantile obtained by solving Eq. (4) is dynamic since P_s, P_c, and P_{s1} are not known a priori at the time of the bid and change every hour, while the cumulative function $P(E)$ can be obtained as an output of a probabilistic power forecast system and depends on the time too. The optimal bid E_c might significantly differ from the point forecasts of wind power production, which of-ten is considered as the value of the energy with the expected highest probability of occurrence.
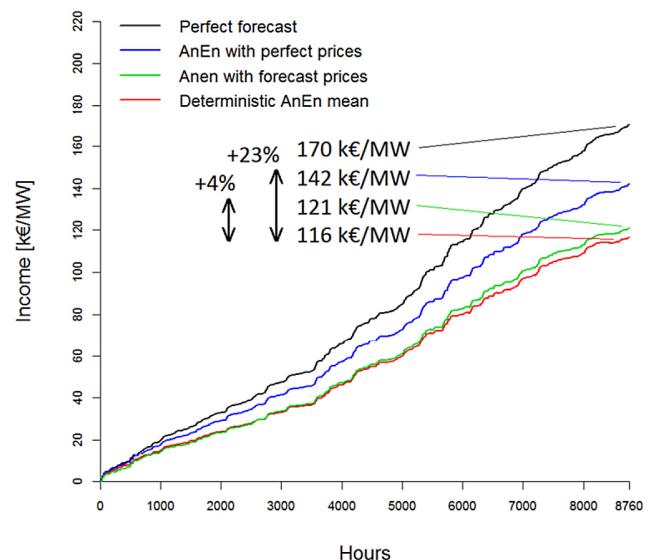

Figure 1. Cumulative income obtainable per 1 MW of installed ca-pacity by a wind farm located in the south of Italy as a function of the hours of the year 2011. The different lines refer to the different approaches in bidding the wind energy in the day-market.

5   Results

In Fig. 1 the cumulative income of the studied wind farm is plotted as a function of the hours of one year. The hourly income is computed following Eq. (2) with P_s, P_{s1} and P_c being respectively the real occurred buy and selling prices of spot market and the spot prices of the day-ahead market. The black line refers to the income obtainable per 1 MW of in-stalled capacity and a perfect forecast (the promised energy in the day-ahead market is exactly equal to the produced en-ergy). The red line refers to the income achievable by selling during the day-ahead market an amount of energy obtained by a deterministic (or spot) wind power forecast (the mean of the 20 members used for the probabilistic forecast) that doesn't consider any economic optimization model. The blue line indicates the case when the amount of energy sold in the day-ahead market is set by solving Eq. (4). Since P_s, P_c, and P_{s1} are not known a priori at the time of the bid they would need to be forecasted as the cumulate function $P(E)$. In this case, the real prices are assumed known in advance. The next simulation (green line) has been carried out under the real-istic condition of not knowing the market prices at the time of the bidding. A simple method for forecasting the market prices has been adopted. For each day of the test period the forecasted price for a given lead time is the average of the 7 prices occurred during the previous 7-day long period at the same lead time. The analog ensemble method is used to forecast the cumulative function $P(E)$ of Eqs. (3) and (4). The economic benefit of a probabilistic approach compared to a deterministic one corresponds to a potential increment of 23 % on the total annual income (blue line compared to

2011/05/15 00.00 - 2011/05/15 23.00
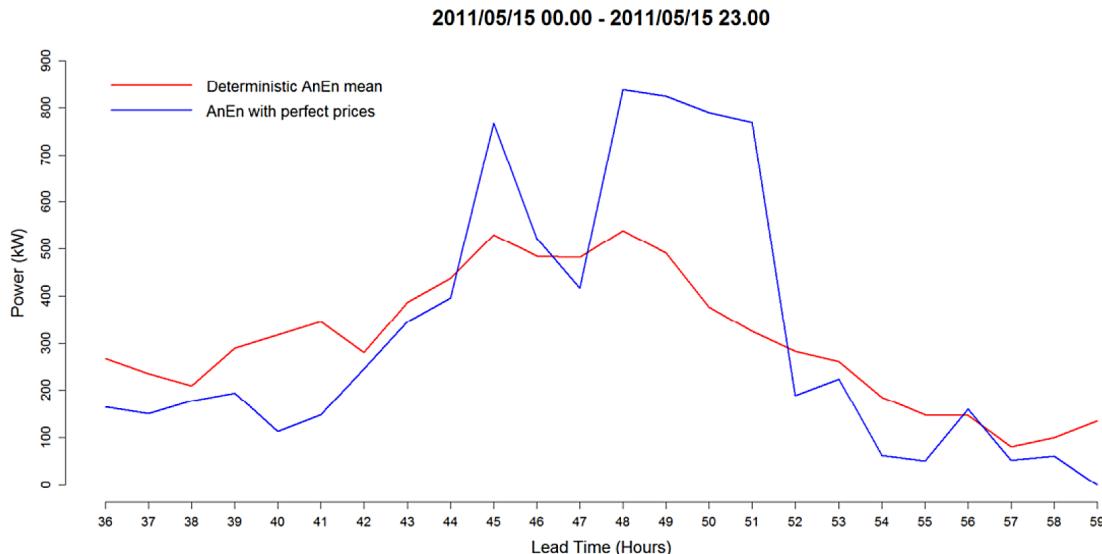
Figure 2. Hourly time-series as a function of forecast lead time of the deterministic forecast provided by AnEn mean (red), and optimal quantile forecast (blue) chosen, in the case of perfect prices forecast, by using the PDF of AnEn in the Eq. (4).

red line). The uncertainty of price forecasting significantly reduces this increment even if a greater annual income, compared to the deterministic approach, is still achieved.

In Fig. 2 an example of two bidding approaches are shown. A strategic bidding based on the choice of the optimal quantile (blue line) can lead to significantly different values from those of a deterministic approach (red line).

6 Conclusions

In this work, a practical application of probabilistic wind power forecast for selling wind energy in the day-ahead energy market has been shown. The energy corresponding to an optimal quantile of the forecasted distribution has been used for bidding in the day-ahead market. The economic benefit compared to a deterministic approach has been examined. This benefit corresponds to a potential increment of 23 % on the total annual income, under the hypothesis of knowing a priori the actual market prices that will occur during the day-ahead. The uncertainty in forecasting the market prices reduces the efficacy of the model in increasing the annual income. In fact, it has been shown that if the market prices are also predicted, the economic benefit achieved by choosing the "optimal quantile" approach is considerably reduced. Further investigations will consider the use of more accurate price forecasting techniques and different economic rules.

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