Wind Power Forecast with Probability Density Estimation: a Tool for the Business

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Abstract

The wind energy industry and power system operators are today mostly accustomed to use single-valued wind power forecasts (or point forecasts). The main reasons are: generally only deterministic formulations of decision making problems are considered and sometimes empirical rules are used; there are several approaches for representing and communicating uncertainty [1]; it is difficult to find a suitable representation to include wind power uncertainty in some decision making problems.

The solution for motivating the industry to include wind power uncertainty in their decision making problems is to develop models that allow a flexible representation of forecast uncertainty. Moreover, in parallel to this, it is also important to rethink the traditional decision problems in order to incorporate information about uncertainty.

Therefore, to be useful for the industry, a tool for wind power uncertainty forecasts should ideally have as requisites: 1) a high flexibility to represent wind power uncertainty, and 2) avoiding an intermediate step to compute deterministic forecasts. In this work, new contributions for the advancement beyond the state-of-the-art in wind power uncertainty forecasting are presented. An algorithm for wind power probability density forecast, which respects the above mentioned requisites, is described. Moreover, suggestions on how to include the forecasting tool output in some decision making problems are presented.

This work is one of the motivations behind the project led by Argonne National Laboratory, together with INESC Porto from Portugal, to develop statistical wind power forecasting algorithms that may serve as a benchmark for other models and improve the current state of the art.

Why Probability Density Forecasts?

The best way to represent uncertainty is determined by end-user requirements and decision-making problems. In general, one cannot talk about better and worse uncertainty representations, only of more or less adequate representations. However, a probability density function (*pdf*) gives the necessary flexibility for several decision-making problems.

The problem of finding "optimal" wind power bids for the electricity market can be formulated with different methods when wind power uncertainty is considered. When the objective is to maximize the expected profit (or minimize the expected cost of imbalances), one approach is to find the optimal forecast quantile to bid into the market. For some electricity markets, the best strategy can be determined from the ratio of positive and negative imbalance prices (or penalties) [2]. Hence, it is possible to extract the optimal quantile from the *pdf* for each hour and, consequently, the "optimal" bid under the expected value paradigm. Botterud et al. [3] presented an approach which considers risk preferences by maximizing the expected utility. For this approach, the *pdf* enables the production of a probability mass function (*pmf*) that can be combined with other stochastic variables (e.g. prices) to compute the expected utility. The aim is to describe the exposure to uncertainty by a set of deterministic risk measures. For this problem, the knowledge of the *pdf* allows the computation of any risk measure. For instance, it is possible to evaluate a trade-off between expected income and risk described by the variance, skewness, or the conditional value at risk (CVaR).

From the system operators perspective, the *pdf* representation is also useful to set the required operating reserve for the current and next days. The *pdf* representation provides the full probability distribution, which allows a complete characterization of the tails. The extreme events represented by the tails of the *pdf* are important to consider to set operating reserve requirements that ensure sufficient reliability of the power system. Another potential application is to use the *pdf* as a starting point to generate wind power scenarios, which can be used as input to a stochastic unit commitment formulation.

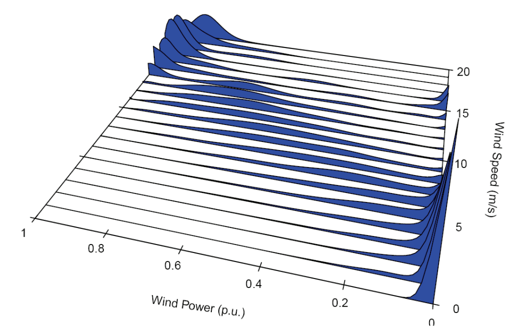

Fig. 1. Stacked conditional plot for wind power and forecasted wind speed.

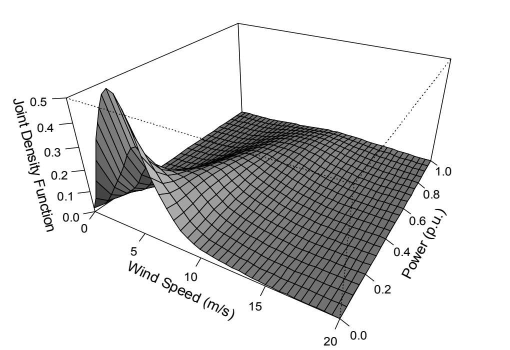

Fig. 2: Joint probability density function of forecasted wind speed and measured wind power.

Kernel Density Forecast Method

The wind power probability density forecast problem can be formulated as: forecast the wind power *pdf* at time step *t* for each look-ahead time step *t+k* of a given time-horizon (e.g. up to 72 hours ahead) knowing a set of explanatory variables (e.g. numerical weather predictions (NWPs), wind power measured values). Translating this sentence to an equation, we have:

$$\hat{f}_{P_{t+k}}\left(p_{t+k} \mid X = x_t\right) = \frac{f_{P,X}\left(p_{t+k}, x_t\right)}{f_X\left(x_t\right)}$$

where p_{t+k} is the wind power forecasted for look-ahead time *t+k*, x_t is a set of explanatory variables available at time step *t*, $f_{P,x}$ is the joint density function of the forecasted wind power and explanatory variables, f_X is the density function of the set of explanatory variables, and is the forecasted wind power density function for look-ahead time step *t+k*.

An idea of the forecasting tool output is given by the stacked conditional plot depicted in Fig. 1. In this case, the forecasted wind speed is the explanatory variable. For instance, if the forecasted wind speed is 15 m/s, the *pdf* of the forecasted wind power corresponds to the distribution in the 15 m/s line of Fig. 1. Moreover, this plot allows seeing the changes in the wind power density function for different values of wind speed (ranging from 0 to 20 m/s). The conditional densities for intermediate values of wind speed are very broad, and we may also detect a higher concentration of density in the tails for lower and higher values of wind speed.

From an information theory perspective, the *pdf* contains all the information associated to a random variable. For instance, it enables the computation of the moments of the forecasted distribution. Therefore, the *pdf* representation is generic and can be transformed to several uncertainty forms, such as quantiles, standard deviation, and skewness.

Nadaraya-Watson (NW) Estimator

The Kernel Density Forecast (KDF) tool uses the Nadaraya-Watson (NW) estimator for producing the conditional density estimator. The estimator is as follows:

$$\hat{f}\left(p \mid X = x\right) = \sum_{i=1}^{N} K_{h_p}\left(p - P_i\right) \cdot w_i\left(x\right)$$

where

$$w_i\left(x\right) = \frac{K_{h_x}\left(x - X_i\right)}{\sum_{i=1}^{N} K_{h_x}\left(x - X_i\right)}$$

and *N* is the number of samples, *K* is a Kernel function and h the bandwidth parameter.

In the wind power problem, the variable *P* is the wind power, and the explanatory variables *X* are for instance: NWP (wind speed, wind direction, pressure), wind power point forecast, measured wind power.

The choice of Kernel functions are important for the quality of the forecasts. Since the wind power generation is bounded between 0 and nominal power a beta kernel is used:

$$\hat{f}_P\left(p\right) = \frac{1}{N}\sum_{i=1}^{N} K_{p/h+1,(1-p)/h+1}\left(P_i\right)$$

where *Kg,q* is the density function of a *Beta(g,q)* random variable with *g* and *q* as the two positive shape parameters, and h being the bandwidth parameter.

For the wind speed, bounded between 0 and Inf, a gamma kernel is used:

$$\hat{f}_X\left(x\right) = \frac{1}{N}\sum_{i=1}^{N} K_{x/h+1,h}\left(X_i\right)$$

where *h* is the bandwidth parameter of *Kg,q*, which is the density function of a *Gamma(g,q)* random variable with *g* as the shape parameter and *q* as the scale parameter.

Fig. 2 depicts the joint *pdf* computed for data from a real wind farm. This *pdf* represents the probability density associated to each point plotted in the wind speed vs wind power scatter of Fig. 3. The region with highest density in Fig. 2 matches the zones with highest concentration of points in Fig. 3.

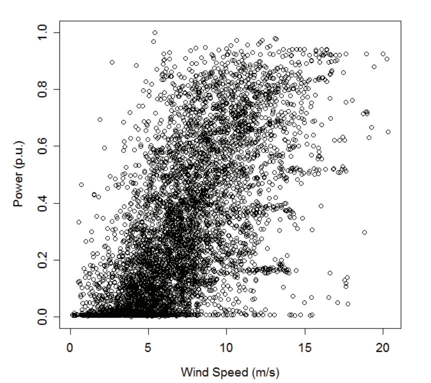

Fig. 3: Scatter plot of forecasted wind speed versus measured wind power.

Results

We present a small selection of results for a large wind farm located in flat terrain in the U.S. Midwest. The complete dataset (SCADA and NWP) correspond to the period between January 1st 2009 and February 20th 2010. The NWP data was generated with the Weather Research and Forecasting (WRF) model by Argonne National Laboratory. The temporal horizon is between t+6 up to t+48 hours, and with the temporal resolution of one hour.

Fig. 4 depicts the calibration obtained with NW and splines quantile regression (QR). The best calibration performance is from the NW estimator, as the deviation between empirical and nominal quantiles is smallest for this method. Due to the trade-off between calibration and sharpness, it is expected from the splines QR a better sharpness performance, as depicted in Fig. 5.

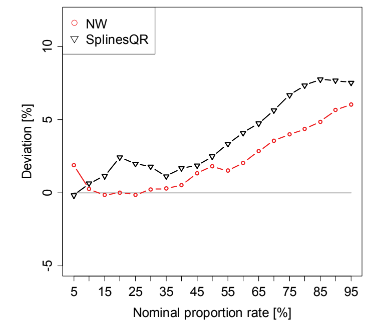

Fig. 4: Calibration diagram for a Midwest wind farm with NW and splines QR estimators.

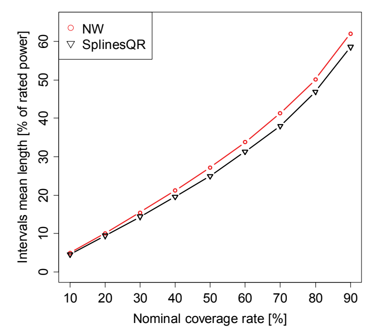

Fig. 5: Sharpness diagram for the Midwest wind farm with NW and splines QR estimators.

Conclusions

The main contribution to the state of the art from this model consists of using the classic NW estimator and selecting the adequate Kernel for modeling the different variables in the wind power forecast problem.

Based on the case study results, it is possible to derive the following main conclusions:

- KDF methods have a tendency to present a better performance in terms of calibration
- QR methods have a tendency to present a better performance in terms of sharpness

Overall, the proposed model is simple, and it can be used by system operators, forecast providers, and generation companies. Moreover, the model provides a high level of flexibility and can therefore be included into several important decision making problems for the wind energy and power industries.

References

[1] C. Monteiro, R. Bessa, V. Miranda, A. Botterud, J. Wang, and G. Conzelmann, "Wind power forecasting: state-of-the-art 2009," Report ANL/DIS-10-1, Argonne National Laboratory, 2009.

[2] R.J. Bessa, V. Miranda, A. Botterud, J. Wang, "'Good' or 'bad' wind power forecasts: a relative concept," *Wind Energy*, In Press, 2011.

[3] A. Botterud, J. Wang, R. Bessa, H. Keko, and V. Miranda, "Risk management and optimal bidding for a wind power producer," in *Proc. of the IEEE PES General Meeting*, Minneapolis, USA, 2010.

Research on wind power forecasting and electricity markets at Argonne:
http://www.dis.anl.gov/projects/windpowerforecasting.html

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