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Minimizing asymmetric loss in medium-term wind power forecasting

Carsten Croonenbroeck [a,*], Georg Stadtmann [b,1]

[a] European University Viadrina, Chair of Economics and Economic Theory (Macroeconomics), Post Box 1786, 15207 Frankfurt (Oder), Germany
[b] University of Southern Denmark, Department of Business and Economics, Campusvej 55, 5230 Odense M, Denmark

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ABSTRACT

In this article we propose a new wind power forecasting model that does not focus on providing the most precise forecasts, but minimizes the financial loss of forecasting impreciseness. We show that the loss function is asymmetric and therefore account for asymmetry during the estimation stage of our model. The new model's forecasts are compared to two state-of-the-Art models and we are able to show that the new model can increase the financial profit for power producers, power traders and/or network operators by a severe degree.

1. Introduction

Many electricity pools such as NASDAQ OMX Commodities (formerly Nord Pool OMX Commodities), APX, EEX or UKPX feature rather similar rules on energy trading: Traders (sellers as well as buyers) first place daily bids on their respective desired quantities. At a certain point in time, these bids are automatically matched and contracted (clearing). Afterwards, the seller is obligated to deliver the contracted energy amount. Though there are slight differences in the details on power trading from pool to pool, spot market mechanisms are comparable. [1] provide more details on the respective rules of different spot market trading places.

As there is a time frame of up to 36 h between bidding and contracting, both market sides require forecasts of the energy that is to be traded. These forecasts provide only limited precision, so uncertainty exists: Energy is consumed at that point in time at which it is produced, there are hardly any methods to save the energy and consume it later. From the sellers' perspective, this results in a loss from the forecasting impreciseness: If the seller produces and delivers less energy than contracted (i.e. the forecast imposed an overestimation), the buyer needs to cover his demand from the intraday market. If there was an underestimation (i.e. the actual amount of energy produced is larger than forecasted), the producer needs to sell the non-contracted power at the intraday market.

In times of unexpectedly low power production (i.e. whenever the seller fails to deliver the full contracted amount of energy), the producer has to refund the fraction of contracted power that is not delivered, sometimes in addition to a fine. Also, buying power from the intraday market and delivering it to the contract partner is not an option in most of these times because prices at the intraday market are likely to be up, then. As a consequence, there is a real economic loss to the seller. In times of unexpectedly high power production however, the seller needs to sell the non-contracted fraction of produced power at the intraday market. Prices there are likely to be low at these times, much lower than the contract price. So there is an imputed loss: If the forecast had been more precise (i.e. if the seller had known the true amount of produced power), that power could have been contracted and the profit for the seller would have been larger.

The economic impact of these two-sided losses is asymmetric. [2] define a piecewise linear loss function with weight $\gamma \in [0,1]$ for underestimation and $1-\gamma$ for overestimation. They find an empirical value of $\gamma = 0.73$, stating that underestimation is to be emphasized. [3] concur and find similar orders of magnitude for their asymmetry measures. Also, [4] defines a comparable type of asymmetry in his static model.

* Corresponding author. Tel.: +49 (0)335 5534 2701; fax: +49 (0)335 5534 72701.
E-mail addresses: croonenbroeck@europa-uni.de (C. Croonenbroeck), geo@sam.sdu.dk (G. Stadtmann).
[1] Tel.: +45 65 50 44 79; fax: +45 65 50 32 37.

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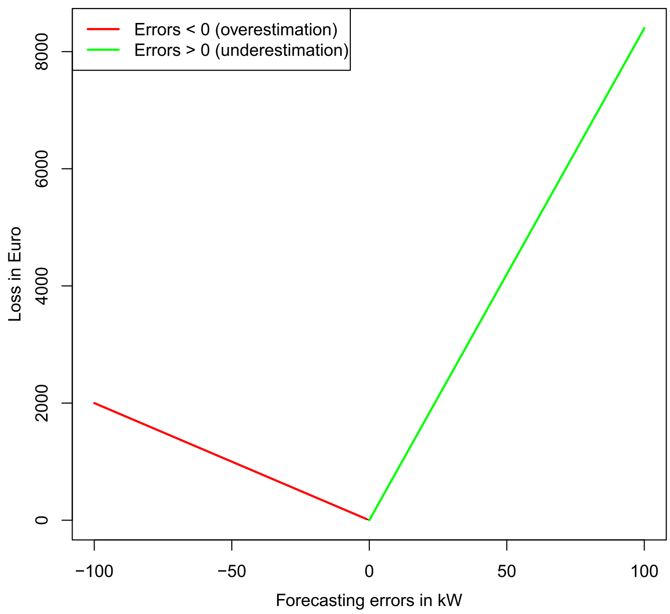

Fig. 1. Theoretical asymmetry of loss. Losses increase more steeply in the positive area of errors, i.e. for underestimation forecasts.

Table 1
Descriptive statistics for Turbines A to D, time frame October 31, 2010 to November 06, 2012.

	Wind speed (m/s)	Power (kW)	Wind direction (°)
Turbine A			
Min	0.4	−19.0	5.0
Median	4.9	123.0	205.0
Mean	5.1	217.8	184.4
Max	18.0	1532.0	353.0
Variance	5.89	74998.72	–
Turbine B			
Min	0.4	−19.0	2.0
Median	5.2	124.0	218.0
Mean	5.3	231.3	194.2
Max	18.6	1493.0	355.0
Variance	6.46	85909.22	–
Turbine C			
Min	0.4	−18.0	5.0
Median	5.2	127.0	213.0
Mean	5.3	230.6	192.5
Max	19.0	1542.0	355.0
Variance	6.22	85466.88	–
Turbine D			
Min	0.4	−18.0	3.0
Median	5.1	124.0	199.0
Mean	5.2	225.0	183.4
Max	19.3	1515.0	357.0
Variance	5.96	82676.63	–

Longer term forecasting (24 h and beyond) is usually performed by physics/meteorology based models as discussed by, e.g., [5]. However, for short to medium term forecasting, stochastic models have prevailed. Literature holds a wide range of stochastic forecasting models. There are point forecasting models, probabilistic forecasting models and even density forecasting models. [6] provide an overview, also see the references therein. One of the most acknowledged models is the Wind Power Prediction Tool (WPPT) by Ref. [7]. The basic idea is to map numerical weather predictions (NWP), i.e. wind speed forecasts, to power production. The model captures diurnal periodicity via a Fourier series, but has its shortcomings because it is a linear model, does not utilize wind direction (which has proven to be an important predictor) as an explanatory variable and does not take seasonality into account. Several approaches to generalize the model have been proposed, for instance, [8] suggest the nonlinear generalized WPPT model (GWPPT) model that exploits wind direction and also utilizes both-sided censoring of the data range, since there is a pre-determined power interval known for each turbine. [9] provide a thorough comparative study on GWPPT. [10] pursues a similar approach at modeling both-sided censored data.

However, all of these models focus on the most precise forecast, i.e. seek for the lowest prediction error as measured by, e.g., RMSE or MAE (Root Mean Squared Error, Mean Absolute Error, cf. [11]). During the prediction stage, asymmetric losses are ignored. [12] account for asymmetry during wind speed prediction, but not during the second stage, the wind power forecast. So far, no research had been carried out trying to respect asymmetric losses during wind power prediction directly. We take GWPPT and expand the estimation by an asymmetric penalty term to acquire forecasts that are not necessarily the most precise ones per se. That is, we do not minimize forecasting errors, but we maximize the economic profit that comes out of these forecasts. This leads to an intentional systematic bias in the forecasts that represents the asymmetry. We are able to show that these maximum-profit-forecasts generate significantly larger profits than their unbiased and consistent benchmark counterparts (GWPPT).

The paper is structured as follows: Section 2 presents the proposed model. In Section 3 we discuss in-sample properties, run a sensitivity analysis and evaluate the statistical features of the model. Section 4 sheds light on out-of-sample results and measures the financial gain of our model. Section 5 concludes.

2. Model proposition

GWPPT forecasts power k periods ahead using the model specification

$$\begin{aligned} p_t^* &= m + a_1 \cdot p_{t-k} + a_2 \cdot p_{t-(k+1)} + b_1 \cdot w_{t|t-k} + b_2 \cdot \left(w_{t|t-k}\right)^2 \\ &\quad + c_1 \cdot v_{t|t-k} + d_1^c \cdot \cos\left(\frac{2\pi d_t}{144}\right) + d_2^c \cdot \cos\left(\frac{4\pi d_t}{144}\right) \\ &\quad + d_1^s \cdot \sin\left(\frac{2\pi d_t}{144}\right) + d_2^s \cdot \sin\left(\frac{4\pi d_t}{144}\right) + \varepsilon_t, \end{aligned} \tag{1}$$

where p_t^* is power produced at time t, $w_{t|t-k}$ is wind speed at time t given at time $t-k$, v_t is wind direction at time t, and d_t is time of day for observation t. The Fourier series captures diurnal periodicity, as data is provided at a frequency of ten minutes (=144 observations per day). p_t^* is modeled as a both-sided censored feature, i.e.

$$p_t = \begin{cases} l, & p_t^* \le l \\ p_t^*, & p_t^* \in (l, u) \\ u, & p_t^* \ge u. \end{cases} \tag{2}$$

l and u are the lower and upper censoring points, i.e. they determine the ex ante known power range of the turbine investigated. The model's parameters are then estimated using the maximum likelihood (ML) based generalized Tobit model by Ref. [13].[4] observes actual trading at Nord Pool OMX Commodities and, basically, constructs the loss function

$$L_t(P_C, P_I, P_P, \varepsilon_t) = \begin{cases} (P_C - P_I) \cdot \varepsilon_t, & \varepsilon_t \ge 0 \\ P_P \cdot |\varepsilon_t|, & \varepsilon_t < 0, \end{cases} \tag{3}$$