Minimizing Asymmetric Loss in Medium-Term Wind Power Forecasting

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

[a] European University Viadrina, Chair of Economics and Economic Theory (Macroeconomics), Post Box 1786, 15207 Frankfurt (Oder), Germany, Tel. +49 (0)335 5534 2701, Fax +49 (0)335 5534 72701

[b] University of Southern Denmark, Department of Business and Economics, Campusvej 55, 5230 Odense M, Denmark, Tel. +45 65 50 44 79, Fax +45 65 50 32 37

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.

Keywords: Censored Regression, Wind Energy, Forecasting, Power Trading, Asymmetric Loss

JEL classification: C34, E27, Q47

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

*Corresponding author

Email addresses: croonenbroeck@europa-uni.de (Carsten Croonenbroeck), geo@sam.sdu.dk (Georg Stadtmann)

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 hours 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.

Longer term forecasting (24 hours 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 [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

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

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.

$$p_t = \begin{cases} l, & p_t^* \leq l \\ p_t^*, & p_t^* \in (l, u) \\ u, & p_t^* \geq u. \end{cases} \quad (2)$$

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 [13].

[4] observes actual trading at Nord Pool OMX Commodities and, basically,

constructs the loss function

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

where P_C, P_I and P_P denote contracted prices, intraday prices and a fine for the case of contracted but not delivered energy. Note that this price information is not time dependent, as this is a static model. For his model, [4] states the empirical values of $P_C = 100$ €, $P_I = 16$ € and $P_P = 20$ € per MWh. In fact, the values do vary and the provided actual values are merely averages over time. Given a proper data source however, it is straight forward to model the price information as time-dependent and thus, increase the model's evaluation performance. Still, the approximate values of [4] kept their validity up until today.

Two numerical examples show the asymmetry of losses: In the first case we assume underestimation, i.e. more energy was produced than contracted. Say, $\hat{\varepsilon}_t = 3$ MWh. Then, $L_t = (100 - 16) \cdot \hat{\varepsilon}_t = 252$ €. In the second case we assume overestimation, i.e. $\hat{\varepsilon}_t = -3$ MWh, so $L_t = 20 \cdot 3 = 60$ €. Thus, underestimation is far more costly than overestimation, providing that forecasts are supposed to be biased upward. Fig. 1 shows the piecewise linear asymmetric loss function of the model by [4].

The basic idea now is to integrate the asymmetric loss model as a penalty term into the log-likelihood function that is used to estimate the parameters of the censored model in equation (1). Following [13], the result (GWPPT-Asymmetric Loss, GWPPT-AL) is the function

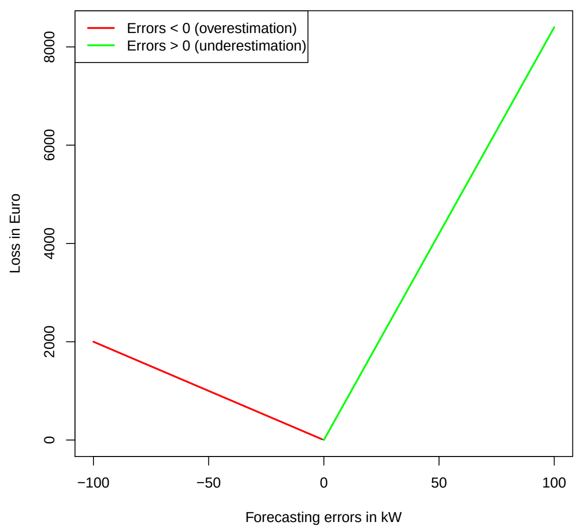

Fig. 1. Theoretical asymmetry of loss. Losses increase more steeply in the positive area of errors, i.e. for underestimation forecasts.

$$\begin{aligned}\log L = I_l \cdot \log\left(\Phi\left(\frac{l - \mathbf{X}\beta}{\sigma}\right)\right) + I_u \cdot \log\left(\Phi\left(\frac{\mathbf{X}\beta - u}{\sigma}\right)\right) \\ + (1 - I_l - I_u) \cdot \left(\log\left(\phi\left(\frac{p_t^* - \mathbf{X}\beta}{\sigma}\right)\right) - \log(\sigma)\right) \\ - \left(\frac{p_t^* - \mathbf{X}\beta}{\sigma} \cdot (P_C - P_I) \cdot I_{pos} + \frac{p_t^* - \mathbf{X}\beta}{\sigma} \cdot (-P_P) \cdot I_{neg}\right), \quad (4)\end{aligned}$$

where Φ and ϕ denote normal cumulative distribution function (CDF) and normal probability density function (PDF), $\mathbf{X}$ is the design matrix of data, β is the parameter vector, $I_l = \mathbf{1}(p_t^* \leq l), I_u = \mathbf{1}(p_t^* \geq u), I_{pos} = \mathbf{1}(p_t^* - \mathbf{X}\beta \geq 0)$ and $I_{neg} = \mathbf{1}(p_t^* - \mathbf{X}\beta < 0)$.

3. In-Sample Properties

We acquired a unique set of sensor data of four Fuhrländer FL MD 77 turbines located in Germany. The turbines have a rated load of 1,500 kW and log

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	–

Table 2
Imputed yearly monetary gain (in-sample) for Turbines A to D, time frame October 31, 2010 to November 06, 2012.

	Turbine A	Turbine B	Turbine C	Turbine D
GWPPT-AL vs. GWPPT in €	18,287.04 €	35,168.53 €	34,812.83 €	29,871.09 €
GWPPT-AL vs. GWPPT in %	29.05 %	57.12 %	66.87 %	62.15 %

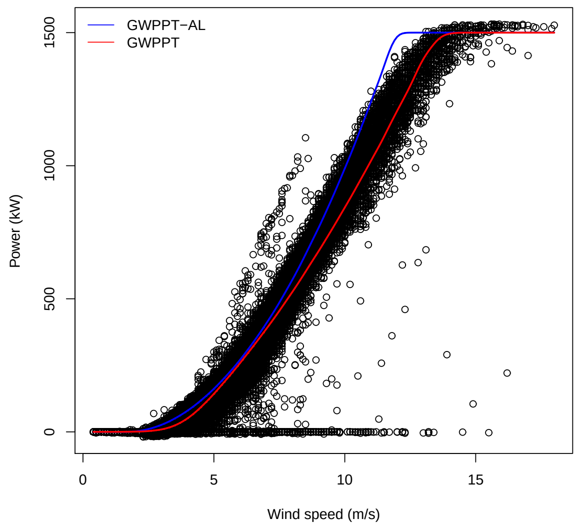

Fig. 2. GWPPT and GWPPT-AL in a power curve (in-sample). Turbine A, time frame October 31, 2010 to November 06, 2012.

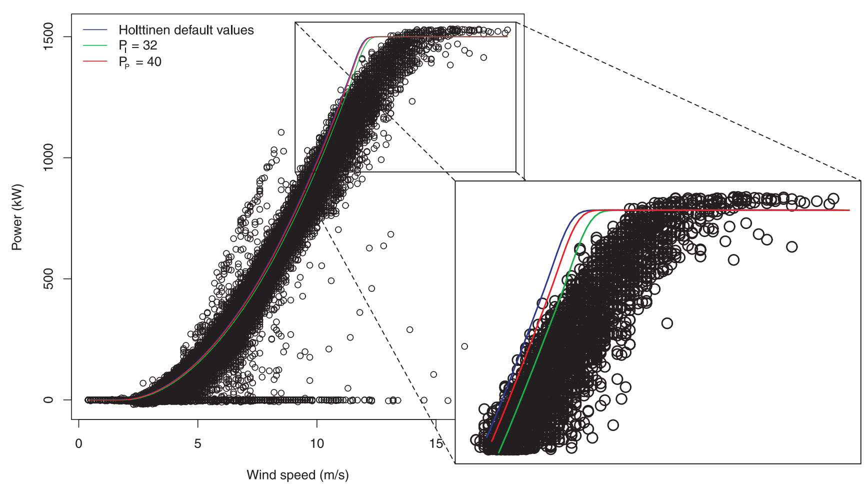

Fig. 3. Sensitivity analysis: Holttinen's default values, $P_P = 40$ and $P_I = 32$ in comparison. Turbine A, time frame October 31, 2010 to November 06, 2012.

their sensor data every ten minutes. Our time frame spans from October 31, 2010 to November 06, 2012, so we have 102,817 observations per turbine. As we are under strict non-disclosure agreement, we cannot reveal detailed information about the four turbines and thus, we denote them “Turbine A” to “Turbine D”. However, all of the four Turbines are located in typical rural surroundings with some afforestation nearby. Table 1 provides descriptive statistics.

Fig. 2 presents the empirical power curve of turbine A during the whole sample period. The red and blue curves show GWPPT and GWPPT-AL estimators in comparison. Both estimators respect the lower and upper bounds of the data range. As it was expected, GWPPT-AL tends to overestimate, while GWPPT is designed to follow the data’s conditional mean (8, go into details on that aspect)[1]. The severity of asymmetry of GWPPT-AL depends on the parameters P_C, P_I and P_P.

The empirical asymmetry in this example amounts to $\gamma_{\text{GWPPT-AL}} = 0.7369$, which means that 73.69 % of all actual values are below the curve. This is very much in line with the value $\gamma_{\text{H\&G}} = 0.73$ found by [2], although the definition of the asymmetric model by [4] is slightly more aggressive. A short sensitivity analysis is performed to investigate this detail.

Doubling parameter P_P (from 20 to 40, i.e. +100 %) puts more weight on underestimation, because the fine for contracted but not delivered power is larger. Thus, overestimation is not as “attractive” anymore. In fact, the asymmetry measure reduces from $\gamma_{\text{GWPPT-AL}} = 0.7369$ to $\gamma_{P_P=40} = 0.7173$ by 1.96 percentage points. Analogously, increasing parameter P_I by 100 % (from 16 to 32) puts more weight on underestimation, because power produced but not contracted can be sold at higher intraday market prices, then. The asymmetry reduces to $\gamma_{P_I=32} = 0.6456$ by 9.13 percentage points. Increasing the contract price P_C has the exact reversed effect of increasing P_I because positive forecasting errors are evaluated by $P_C - P_I$, see equation (3). Fig. 3 presents the estimation curves

[1]Coefficients of determination: $R^2_{\text{WPPT}} = 0.9366, R^2_{\text{GWPPT-AL}} = 0.9424, R^2_{\text{GWPPT}} = 0.9524$.

in comparison.

Coming back to the default values (P_C = 100 €/MWh, P_I = 16 €/MWh, P_P = 20 €/MWh), the model fit of GWPPT-AL is not as good as that of GWPPT: $AIC_{\text{GWPPT}} = 894,227$, while $AIC_{\text{GWPPT-AL}} = 1,443,932$.[2] This was to be expected because, again, it is not the ultimate goal of the GWPPT-AL model to obtain the best fit or the most precise unbiased forecast. Instead, the model produces biased forecasts deliberately, so a poor fit is no surprise here.

We evaluate the respective models' forecasting errors by Holttinen's loss function. That way, we can calculate the yearly monetary gain (or reduction in losses that are due to weighted forecasting impreciseness) of using GWPPT-AL instead of GWPPT per turbine. Table 2 shows these values for turbines A to D. The table should be read as follows: For example for Turbine A, we assume that forecasts are generated by using GWPPT. By switching to GWPPT-AL, the operator could decrease the monetary loss from forecasting errors (or: increase profits) by 18,287.04 € per year. For Turbines B to D, gains are even greater, because wind power data for Turbine A is rather tranquil, so GWPPT produces rather precise forecasts. For Turbines B to D, the data is more noisy (see variance in Table 1), forecasts are less precise, large deviations are more likely and so, asymmetry has an even greater impact. Taking it into account is of greater benefit, then.

As these values are calculated at an in-sample environment, we now switch to a more realistic out-of-sample analysis and investigate the models' actual performances.

4. Out-Of-Sample Properties

Out-of-sample forecasts are calculated based on about half of the total sample set (50,000 observations per turbine) used for fitting the model. Then, 4,000 forecasts are calculated in a rolling window of fixed size for forecasting horizons

[2] Also, $SBC_{\text{GWPPT}} = 894,276$ and $SBC_{\text{GWPPT-AL}} = 1,443,979$, $RMSE_{\text{GWPPT}} = 59.8$ and $RMSE_{\text{GWPPT-AL}} = 71.4$.

of 10 minutes (1 step), 12 hours (72 steps), 24 hours (144 steps) and 36 hours (216 steps) for all turbines, respectively.

Fig. 4 presents the estimations for WPPT, GWPPT and GWPPT-AL, embedded in the empirical power curve (actual values) for Turbine A in a one step (10 minutes) ahead forecasting scenario. Similarly to the in-sample stage, the GWPPT-AL curve shows a strong tendency of overestimation. WPPT and GWPPT fit well and are seemingly unbiased, but WPPT exceeds the Turbine's power range in the lower as well as in the upper limit.

Fig. 5 presents a detailed time series comparison of the models' forecasting errors for Turbine A, one step ahead. All models seem to predict the actual values rather well. Fig. 6 aggregates these comparisons for Turbines A to D. As forecasting horizon expands (Figs. 7 to 9 show comparisons for the forecasting horizons of 12, 24 and 36 hours, respectively), the curves begin to become more volatile. Particularly for the 36 hours ahead forecasts, major fluctuations are being observed. For such rather long forecasting horizons, meteorology based forecasting models provide better performance than stochastic based models, as, e.g., [6] point out. These findings suggest to interpret all further results for the longer forecasting horizons with caution.

Forecasting performance is usually evaluated via Root Mean Squared Error (RMSE) and/or Mean Absolute Error (MAE). Also, these aggregated error measures are usually standardized for better comparison, so we report standardized RMSE and MAE (called sRMSE and sMAE, cf. 6) in Tables 3 and 4. The Tables provide sRMSE and sMAE for all Turbines and all forecasting horizons, separated by calender weeks. Best (i.e. lowest) values are in bold. Table 5 presents the Mean Bias Error as discussed by, e.g., [14]. It provides information on the asymmetry of the forecasts. Furthermore, Table 6 shows results with respect to the Index of Agreement (IA), as developed by [15]. The IA is a standardized measure of the degree of model prediction error and varies between 0 and 1. A value of 1 indicates a perfect match, a value of 0 indicates no agreement at all:

$$d = 1 - \frac{\sum (p_t^* - \hat{p}_t)^2}{\sum \left(\left| \hat{p}_t - \overline{p^*} \right| + \left| p_t^* - \overline{p^*} \right| \right)^2}, \tag{5}$$

where p_t^* denotes actual power values, $\hat{p}_t$ denotes predicted power values and $\overline{p^*}$ determines the mean of actual power values. The index can detect additive and proportional differences in the observed and predicted means and variances; however, it is mostly sensitive to extreme values due to the squared differences, as [16] point out. Thus, IA is rather high for all turbines and models.

GWPPT-AL hardly produces the most precise forecasts: Very few exceptions aside, WPPT and GWPPT perform best, according to sRMSE and sMAE. Investigating the aggregated target time frame (i.e. not separated by weeks), GWPPT-AL occasionally outperforms WPPT. Fig. 10 shows sRMSE values for Turbine A over forecasting horizons up to 216 steps (36 hours). In general, WPPT and GWPPT outperform GWPPT-AL, the accuracy of GWPPT-AL forecasts is limited. The picture looks similar for Turbines B to D, as Fig. 11 reveals.

Table 7 reveals the asymmetry: It presents the percentages of forecasts that are greater than their actual counterparts for all turbines, all models and all forecasting horizons. WPPT and GWPPT forecasts seem empirically unbiased, while GWPPT-AL shows the desired behavior of being strongly biased. GWPPT-AL occasionally exceeds the in-sample-bias of $\gamma = 0.7369$ in the short term scenario (one step ahead). For the longer forecasting horizons, the asymmetry of WPPT/GWPPT and GWPPT-AL levels out, as WPPT and GWPPT become more biased, and GWPPT-AL becomes less biased. That may be due to increasing overall impreciseness of forecasts in the longer horizon scenarios.

After all, the goal of GWPPT-AL is not to produce precise forecasts, but to maximize monetary profit. Therefore, Table 8 presents projected yearly monetary gain of hypothetically switching a) from WPPT to GWPPT and b) from GWPPT to GWPPT-AL. While these gains occasionally become negative in the most imprecise case of 216 steps ahead (36 hours), most of the times the increase in profit is substantial. Looking at the more reliable forecasting horizons 1 step (10 minutes) and 72 steps (12 hours), GWPPT can increase profit over WPPT by up to 14,000 €, just by being the more precise forecasting model. However, GWPPT-AL can gain another up to 67,000 € over GWPPT per Turbine. Additionally, the gain of GWPPT-AL over GWPPT is by far greater than that of GWPPT over WPPT. As GWPPT provides more monetary profit than WPPT and GWPPT-AL more than GWPPT, the comparison WPPT vs. GWPPT-AL is omitted here due to predominant redundancy.

Finally, to check whether the financial difference between the pairwise Holttinen-weighted aggregated forecasting errors is statistically significant, we assume the loss functions to be prediction error evaluation functions in the way [17] describe them. With that we are able to directly use the Diebold-Mariano test (DM test) to analyze the significance of financial differences as reported in Table 8. All positive gains are significant, at least at a level of 5%. As forecasts become somewhat unstable for the longer horizons, the statistical significance declines here in some cases, particularly for the forecasts 36 hours (216 steps) ahead. However, at least for horizons of up to 24 hours, monetary profits are significant and reliable.

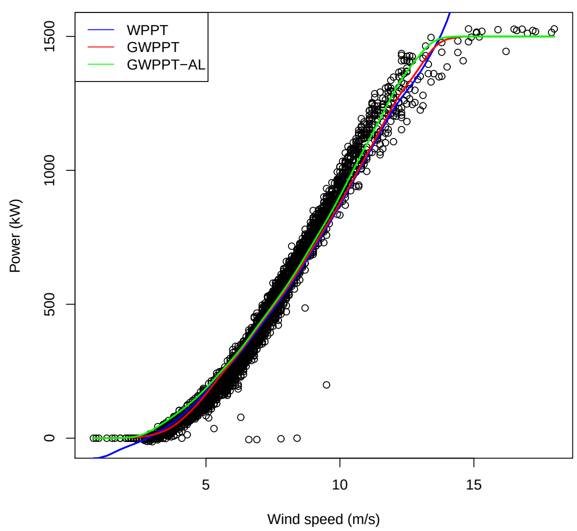

Fig. 4. WPPT, GWPPT and GWPPT-AL in a power curve (out-of-sample, 1 step [10 minutes] ahead). Turbine A, time frame December 08, 2011 to Janury 04, 2012.

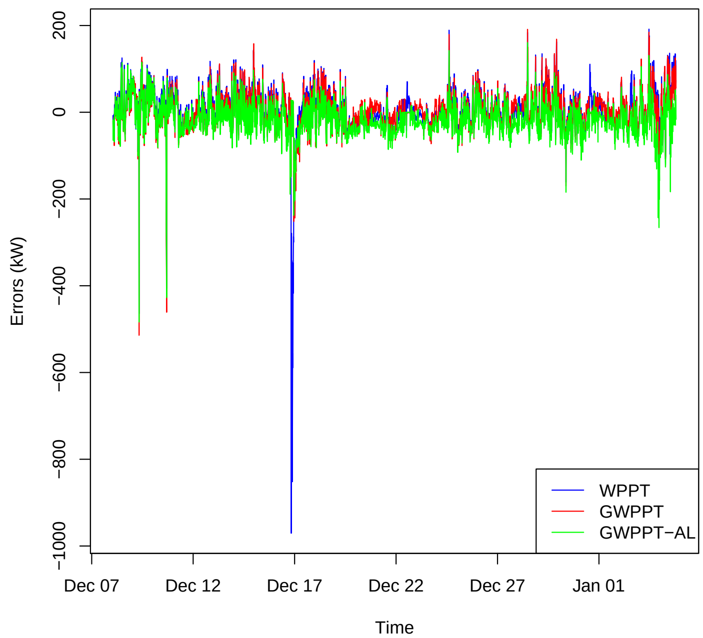

Fig. 5. Errors of WPPT, GWPPT and GWPPT-AL forecasts, time line (out-of-sample, 1 step [10 minutes] ahead). Turbine A, time frame October 31, 2010 to November 06, 2012.

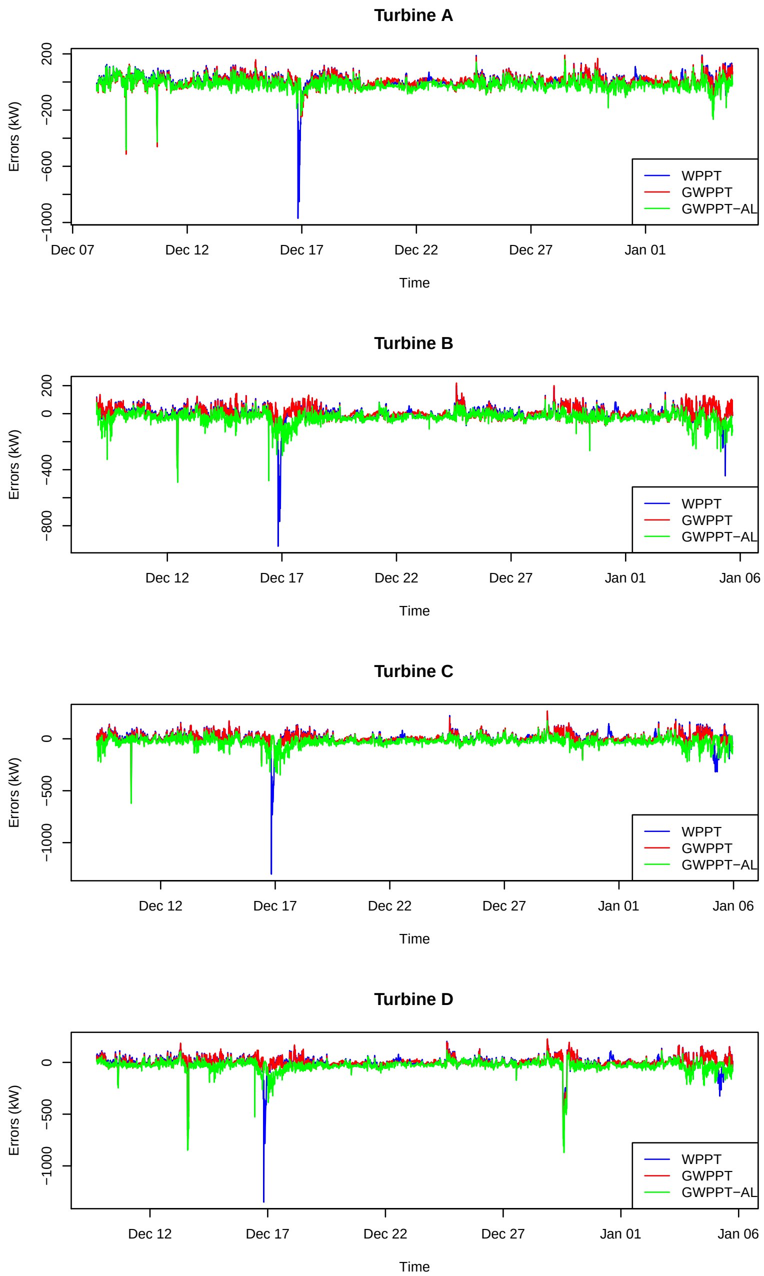

Fig. 6. Errors of WPPT, GWPPT and GWPPT-AL forecasts, time line (out-of-sample, 1 step [10 minutes] ahead). Turbines A to D, time frame October 31, 2010 to November 06, 2012.

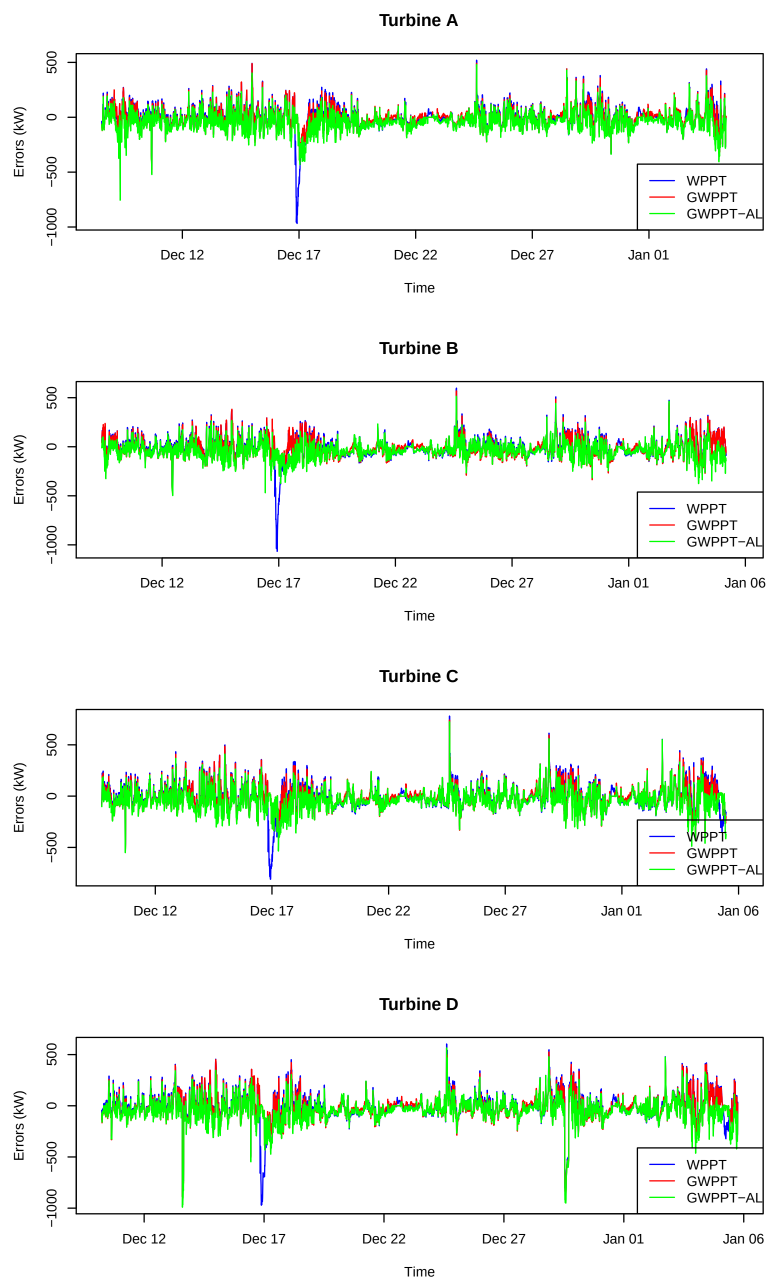

Fig. 7. Errors of WPPT, GWPPT and GWPPT-AL forecasts, time line (out-of-sample, 72 steps [12 hours] ahead). Turbines A to D, time frame October 31, 2010 to November 06, 2012.

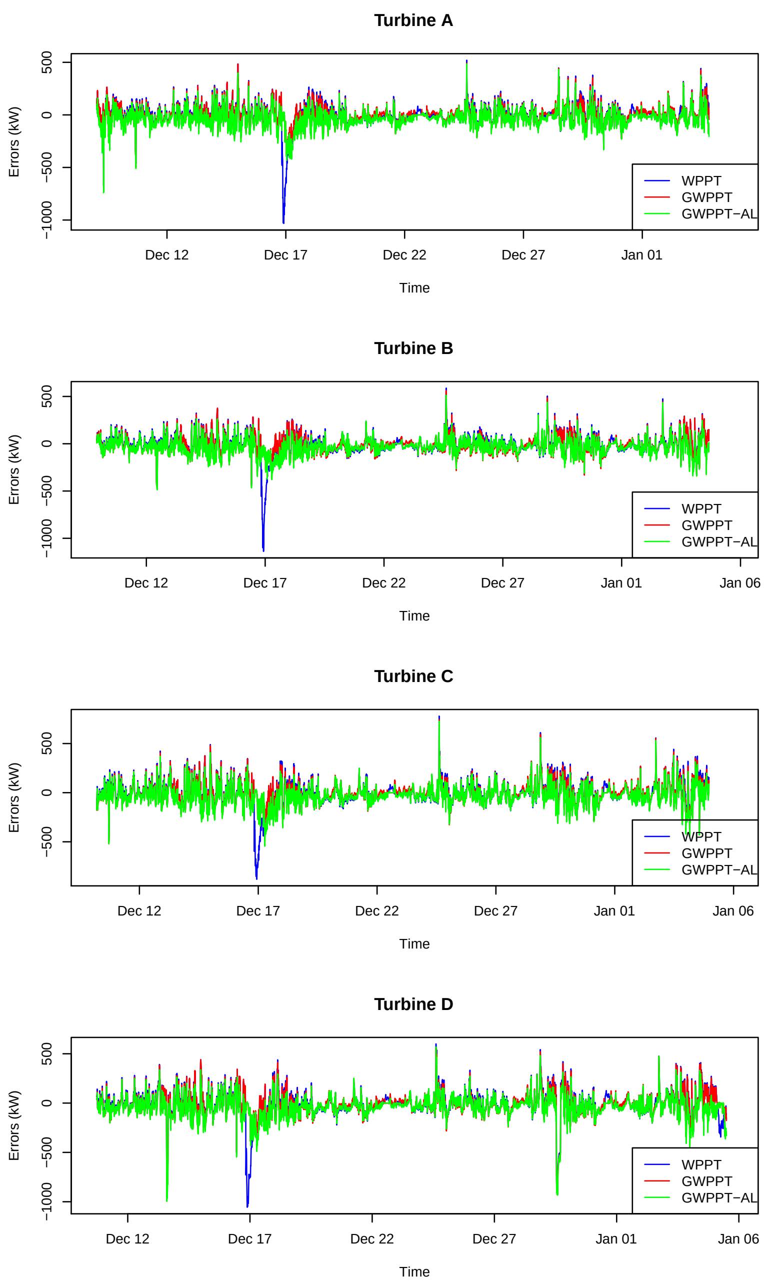

Fig. 8. Errors of WPPT, GWPPT and GWPPT-AL forecasts, time line (out-of-sample, 144 steps [24 hours] ahead). Turbines A to D, time frame October 31, 2010 to November 06, 2012.

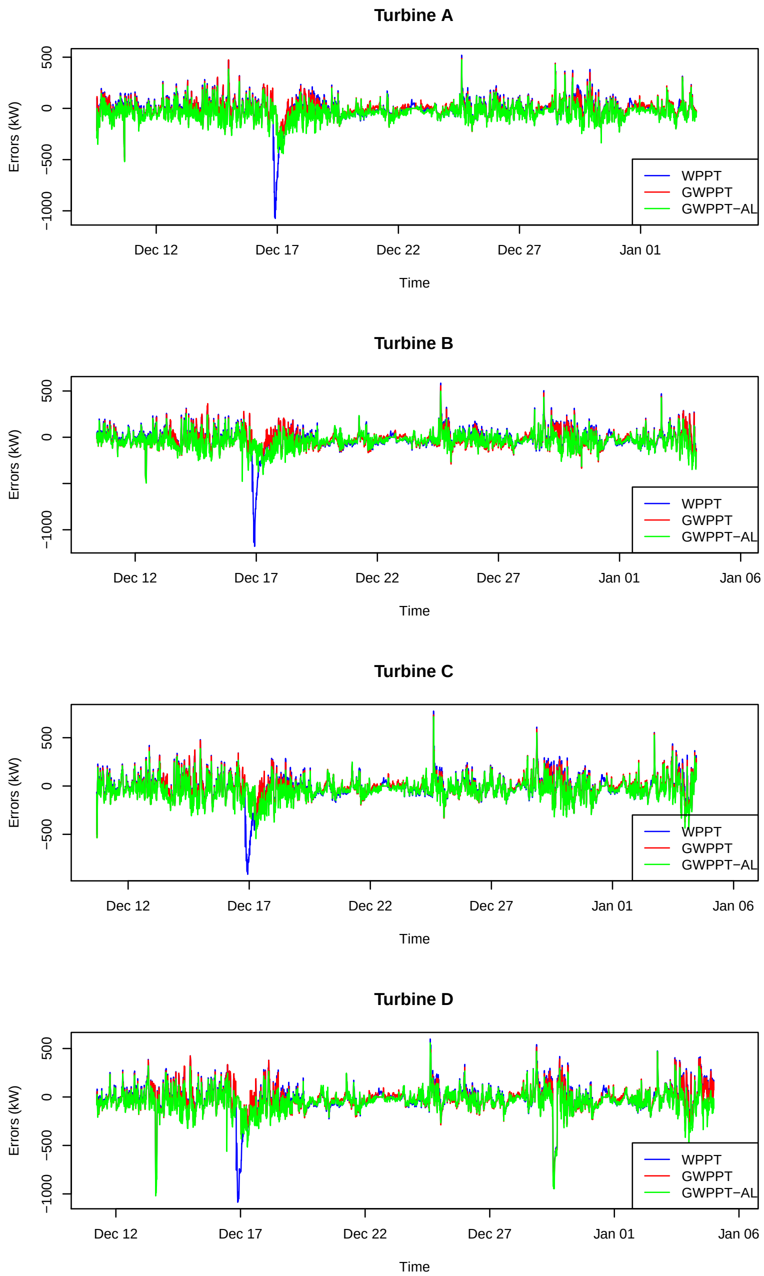

Fig. 9. Errors of WPPT, GWPPT and GWPPT-AL forecasts, time line (out-of-sample, 216 steps [36 hours] ahead). Turbines A to D, time frame October 31, 2010 to November 06, 2012.

Table 3
Standardized RMSE per week, time frame 12/08/2011 to 01/04/2012, all horizons and all turbines.

		Turbine A			Turbine B			Turbine C			Turbine D		
		WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL
1 step	49/2011	0.0809	0.0806	**0.0805**	0.0766	**0.0753**	0.0794	**0.0855**	0.0861	0.0922	**0.0633**	0.0636	0.0651
	50/2011	0.0953	**0.0799**	0.0802	0.1005	**0.0840**	0.0937	0.1030	**0.0879**	0.0966	0.1104	**0.0943**	0.1073
	51/2011	**0.0449**	0.0455	0.0469	0.0494	**0.0491**	0.0499	0.0499	**0.0494**	0.0512	0.0483	**0.0479**	0.0497
	52/2011	**0.0572**	**0.0572**	0.0579	**0.0618**	**0.0618**	0.0637	0.0672	**0.0670**	0.0684	**0.0769**	0.0800	0.0878
	01/2012	0.0857	**0.0856**	0.0878	0.0843	**0.0798**	0.0892	0.0928	**0.0854**	0.0925	0.0937	**0.0885**	0.1010
72 steps	49/2011	0.2630	**0.2612**	0.2776	**0.2274**	0.2279	0.2520	**0.1944**	0.2006	0.2193	**0.1777**	0.1831	0.1921
	50/2011	0.2752	**0.2464**	0.2561	0.2761	**0.2480**	0.2617	0.2856	**0.2618**	0.2732	0.3041	**0.2717**	0.2865
	51/2011	**0.1413**	0.1481	0.1485	**0.1776**	0.1866	0.1865	**0.1658**	0.1736	0.1740	**0.1615**	0.1692	0.1678
	52/2011	**0.1928**	0.1969	0.1998	**0.1984**	0.2046	0.2089	**0.2099**	0.2153	0.2193	**0.2071**	0.2122	0.2150
	01/2012	**0.2973**	0.2992	0.3060	0.2346	**0.2319**	0.2352	0.2667	0.2561	**0.2560**	0.2944	**0.2851**	0.2921
144 steps	49/2011	0.2512	**0.2487**	0.2654	0.2387	**0.2377**	0.2505	**0.2375**	0.2437	0.2490	**0.1605**	0.1682	0.1716
	50/2011	0.3179	**0.2812**	0.2880	0.3480	**0.3126**	0.3259	0.3574	**0.3244**	0.3354	0.3647	**0.3236**	0.3388
	51/2011	**0.1706**	0.1773	0.1844	**0.1867**	0.1937	0.2008	**0.1737**	0.1810	0.1847	**0.1660**	0.1719	0.1705
	52/2011	**0.2510**	0.2563	0.2602	**0.2480**	0.2563	0.2595	**0.2591**	0.2654	0.2684	**0.2576**	0.2640	0.2654
	01/2012	0.3216	0.3215	**0.3136**	0.2933	0.2919	**0.2884**	0.3164	0.3157	**0.3075**	0.3535	0.3410	**0.3384**
216 steps	49/2011	0.2807	**0.2784**	0.3093	0.2700	**0.2682**	0.2887	**0.2559**	0.2626	0.2732	**0.2005**	0.2122	0.2205
	50/2011	0.3163	**0.2831**	0.2899	0.3518	**0.3144**	0.3260	0.3681	**0.3316**	0.3418	0.3576	**0.3194**	0.3349
	51/2011	**0.2182**	0.2259	0.2340	**0.2432**	0.2520	0.2620	**0.2326**	0.2414	0.2495	**0.2159**	0.2268	0.2287
	52/2011	**0.2805**	0.2887	0.2941	**0.2730**	0.2842	0.2903	**0.2910**	0.3009	0.3078	**0.2906**	0.2998	0.3054
	01/2012	0.3466	**0.3456**	0.3361	0.3212	0.3195	**0.3123**	0.3536	0.3529	**0.3424**	0.3570	0.3560	**0.3504**

Table 4
Standardized MAE per week, time frame 12/08/2011 to 01/04/2012, all horizons and all turbines.

		Turbine A			Turbine B			Turbine C			Turbine D		
		WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL
1 step	49/2011	0.0591	**0.0585**	0.0586	0.0560	**0.0554**	0.0586	**0.0605**	0.0610	0.0635	**0.0478**	0.0487	0.0500
	50/2011	0.0672	0.0611	**0.0610**	0.0712	**0.0638**	0.0717	0.0723	**0.0660**	0.0729	0.0755	**0.0685**	0.0778
	51/2011	**0.0319**	**0.0319**	0.0343	0.0338	**0.0326**	0.0349	0.0345	**0.0332**	0.0360	0.0336	**0.0325**	0.0349
	52/2011	0.0411	**0.0404**	0.0413	0.0450	**0.0442**	0.0462	0.0482	**0.0466**	0.0482	0.0501	**0.0495**	0.0530
	01/2012	0.0648	**0.0636**	0.0657	0.0632	**0.0594**	0.0670	0.0686	**0.0598**	0.0637	0.0724	**0.0659**	0.0749
72 steps	49/2011	0.2191	**0.2182**	0.2333	**0.1936**	0.1944	0.2145	**0.1629**	0.1685	0.1865	**0.1469**	0.1509	0.1571
	50/2011	0.2051	**0.1922**	0.1996	0.2137	**0.1974**	0.2086	0.2216	**0.2079**	0.2188	0.2343	**0.2199**	0.2323
	51/2011	**0.1117**	0.1158	0.1173	**0.1375**	0.1452	0.1442	**0.1297**	0.1361	0.1354	**0.1266**	0.1325	0.1305
	52/2011	**0.1527**	0.1560	0.1578	**0.1581**	0.1633	0.1651	**0.1693**	0.1729	0.1739	**0.1657**	0.1687	0.1685
	01/2012	**0.2469**	0.2488	0.2544	0.1937	**0.1912**	0.1936	0.2181	0.2082	**0.2063**	0.2482	0.2385	**0.2378**
144 steps	49/2011	0.2059	**0.2048**	0.2162	**0.1927**	0.1928	0.2015	**0.1901**	0.1956	0.1987	**0.1347**	0.1408	0.1425
	50/2011	0.2376	**0.2224**	0.2298	0.2660	**0.2471**	0.2614	0.2778	**0.2609**	0.2719	0.2740	**0.2570**	0.2728
	51/2011	**0.1355**	0.1405	0.1442	**0.1428**	0.1495	0.1529	**0.1336**	0.1392	0.1415	**0.1296**	0.1337	0.1323
	52/2011	**0.2114**	0.2158	0.2189	**0.2039**	0.2118	0.2145	**0.2153**	0.2208	0.2246	**0.2176**	0.2236	0.2241
	01/2012	0.2464	0.2473	**0.2422**	0.2289	0.2289	**0.2263**	0.2458	**0.2455**	0.2385	0.2813	0.2708	**0.2671**
216 steps	49/2011	**0.2264**	0.2267	0.2511	**0.2187**	0.2190	0.2349	**0.2017**	0.2079	0.2155	**0.1620**	0.1745	0.1800
	50/2011	0.2407	**0.2253**	0.2315	0.2739	**0.2545**	0.2650	0.2863	**0.2679**	0.2769	0.2788	**0.2597**	0.2738
	51/2011	**0.1762**	0.1814	0.1854	**0.1997**	0.2083	0.2121	**0.1903**	0.1971	0.2009	**0.1751**	0.1830	0.1827
	52/2011	**0.2248**	0.2321	0.2373	**0.2193**	0.2303	0.2366	**0.2325**	0.2422	0.2489	**0.2327**	0.2403	0.2438
	01/2012	0.2878	0.2885	**0.2773**	0.2668	**0.2658**	0.2570	0.2929	0.2925	**0.2827**	0.3019	0.3007	**0.2926**

Table 5
MBE per week, time frame 12/08/2011 to 01/04/2012, all horizons and all turbines. "***", "**" and "*" denote significant at levels of 1%, 5% and 10%, according to t-test.

		Turbine A			Turbine B			Turbine C			Turbine D		
		WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL	WPPT	GWPPT	GWPPT-AL
1 step	49/2011	10.9	0.7	0.3	18.4	10.1	-20.1	9.5	-2.8	-25.3	7.2	-6.8	-19.0
	50/2011	2.2	2.7	-11.3	-2.2	1.4	-38.2	0.8	1.9	-35.2	-6.3	-5.0	-45.6
	51/2011	-9.2	-7.2	-23.6	-9.0	-8.4	-19.2	-7.8	-5.7	-21.0	-4.5	-4.0	-18.2
	52/2011	5.8	4.8	-16.3	-1.0	-5.3	-20.6	4.1	3.3	-17.8	-5.0	-8.7	-32.0
	01/2012	19.0	13.4	-20.2	8.0	11.7	-42.5	5.1	10.9	-33.3	8.9	14.7	-51.4
72 steps	49/2011	-29.3	-45.9	-79.7	-106.8	-120.2	-162.0	-127.5	-148.6	-177.2	-52.2	-73.9	-84.4
	50/2011	16.3	21.3	-12.1	7.7	17.1	-20.3	10.6	18.1	-18.7	-26.6	-22.3	-60.0
	51/2011	-37.4	-33.1	-52.8	-37.3	-36.3	-42.6	-33.4	-29.0	-42.4	-14.1	-13.0	-21.7
	52/2011	-13.0	-17.5	-40.4	-22.1	-30.7	-42.5	-11.1	-15.1	-34.7	-33.2	-38.2	-55.7
	01/2012	146.3	142.9	109.7	144.7	140.0	90.8	112.6	117.5	74.8	121.1	124.6	47.2
144 steps	49/2011	-72.8	-86.6	-117.5	-193.5	-202.8	-216.6	-218.8	-236.7	-240.3	-78.4	-100.1	-105.1
	50/2011	36.0	45.6	15.6	17.6	31.9	1.3	22.3	37.5	6.2	-15.2	-3.4	-39.0
	51/2011	-59.2	-57.4	-81.2	-59.4	-59.2	-70.9	-49.8	-47.1	-64.0	-7.4	-6.5	-14.1
	52/2011	-29.4	-36.4	-56.2	-35.1	-47.6	-55.8	-22.9	-29.3	-46.1	-40.8	-48.4	-64.8
	01/2012	287.9	290.3	262.3	272.8	272.7	241.0	284.2	280.8	253.8	223.6	231.0	176.8
216 steps	49/2011	-192.8	-205.0	-246.4	-284.7	-290.9	-315.0	-254.8	-273.0	-283.8	-207.0	-234.2	-241.7
	50/2011	43.1	53.3	24.8	34.0	48.3	22.4	44.5	60.6	32.0	10.5	24.9	-9.7
	51/2011	-79.2	-75.4	-100.2	-83.2	-80.1	-94.5	-77.8	-73.4	-93.7	-42.4	-42.1	-53.9
	52/2011	-69.2	-77.1	-95.9	-79.0	-93.5	-103.4	-65.0	-73.1	-90.3	-58.3	-66.9	-81.3
	01/2012	*424.1	*427.3	*406.0	374.9	376.4	352.6	404.0	403.8	379.4	395.0	390.1	337.8

5. Conclusion

This article presents a new forecasting model that does not focus on returning the most precise predictions, but returns forecasts that aim at minimizing the loss due to forecasting impreciseness. It takes the asymmetry of the loss function into account during the estimation stage and as such, it is deliberately biased. We show that these forecasts cannot compete with sophisticated forecasting models in terms of precision measures, but outperform these models tremendously with respect to their financial impact. Using the new forecasts instead of those generated by a state-of-the-Art model can lead to a statistically significant projected yearly monetary gain of up to 67,000 € per Turbine. Therefore, the proposed model can be very valuable to power producers, utilities and traders.

Table 6
Index of Agreement (IA), time frame 12/08/2011 to 01/04/2012, all horizons and all turbines. A value of 1 denotes a perfect match between actual values and predicted values, a value of 0 denotes no agreement at all.

	WPPT	GWPPT	GWPPT-AL
1 Step			
Turbine A	0.9923	0.9958	0.9959
Turbine B	0.9927	0.9962	0.9950
Turbine C	0.9926	0.9963	0.9950
Turbine D	0.9908	0.9937	0.9905
72 Steps			
Turbine A	0.9686	0.9781	0.9769
Turbine B	0.9698	0.9790	0.9812
Turbine C	0.9665	0.9755	0.9758
Turbine D	0.9601	0.9683	0.9692
144 Steps			
Turbine A	0.9680	0.9792	0.9785
Turbine B	0.9679	0.9791	0.9809
Turbine C	0.9626	0.9737	0.9738
Turbine D	0.9577	0.9681	0.9685
216 Steps			
Turbine A	0.9652	0.9785	0.9768
Turbine B	0.9658	0.9787	0.9795
Turbine C	0.9600	0.9723	0.9718
Turbine D	0.9501	0.9625	0.9634

Table 7
Asymmetry: Percentage of forecasted values that are greater than the respective actual values, time frame 12/08/2011 to 01/04/2012, all horizons and all turbines.

	WPPT	GWPPT	GWPPT-AL
1 Step			
Turbine A	49.50%	50.33%	69.76%
Turbine B	53.20%	57.29%	79.51%
Turbine C	53.65%	54.25%	76.99%
Turbine D	53.90%	56.90%	80.87%
72 Steps			
Turbine A	55.26%	56.25%	71.02%
Turbine B	57.86%	61.09%	71.07%
Turbine C	57.09%	58.01%	67.33%
Turbine D	57.32%	59.51%	70.03%
144 Steps			
Turbine A	58.39%	60.62%	71.34%
Turbine B	56.58%	59.43%	67.08%
Turbine C	54.22%	55.37%	63.92%
Turbine D	55.18%	56.81%	66.23%
216 Steps			
Turbine A	54.85%	55.38%	69.92%
Turbine B	58.76%	61.88%	68.62%
Turbine C	55.49%	56.04%	64.50%
Turbine D	56.94%	57.41%	67.01%

Table 8
Projected yearly monetary gain, time frame 12/08/2011 to 01/04/2012, all horizons and all turbines. "***", "**" and "*" denote significant at levels of 1%, 5% and 10%, according to Diebold-Mariano test.

	GWPPT vs. WPPT	GWPPT-AL vs. GWPPT
1 Step		
Turbine A	***10,804.01 € (5.35%)	***4,102.46 € (1.65%)
Turbine B	***12,821.08 € (6.33%)	***38,987.43 € (17.72%)
Turbine C	***14,130.67 € (6.64%)	***28,477.42 € (12.13%)
Turbine D	***14,396.68 € (6.92%)	***53,903.75 € (23.77%)
72 Steps		
Turbine A	***7,422.73 € (1.05%)	***62,522.08 € (8.76%)
Turbine B	***7,072.69 € (1.00%)	***67,264.95 € (9.44%)
Turbine C	***6,234.42 € (0.86%)	***56,001.37 € (7.67%)
Turbine D	***12,267.44 € (1.69%)	***63,915.36 € (8.63%)
144 Steps		
Turbine A	***6,494.78 € (0.78%)	***20,225.49 € (2.40%)
Turbine B	***4,898.39 € (0.58%)	***37,822.43 € (4.44%)
Turbine C	***2,678.00 € (0.30%)	***7,071.30 € (0.79%)
Turbine D	***10,228.80 € (1.17%)	**1,162.76 € (0.12%)
216 Steps		
Turbine A	***1,457.03 € (0.16%)	***60,521.77 € (6.63%)
Turbine B	**-659.83 € (-0.07%)	**47,570.96 € (4.92%)
Turbine C	*-2,829.87 € (-0.27%)	-23,784.71 € (-2.30%)
Turbine D	2,726.58 € (0.27%)	-16,258.28 € (-1.63%)

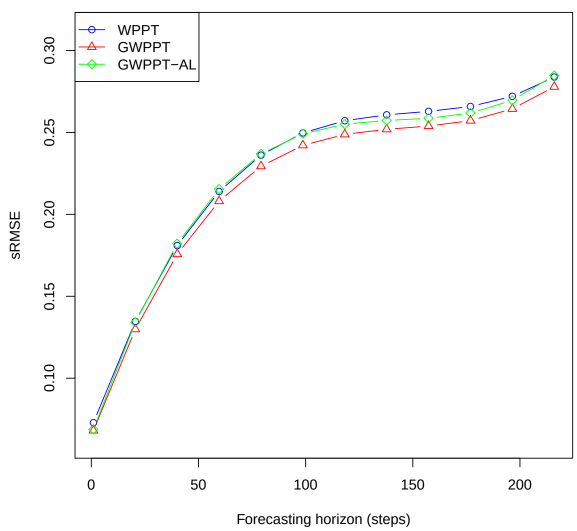

Fig. 10. sRMSE for WPPT, GWPPT and GWPPT-AL for several forecasting horizons. Turbine A, time frame December 08, 2011 to Janury 04, 2012.

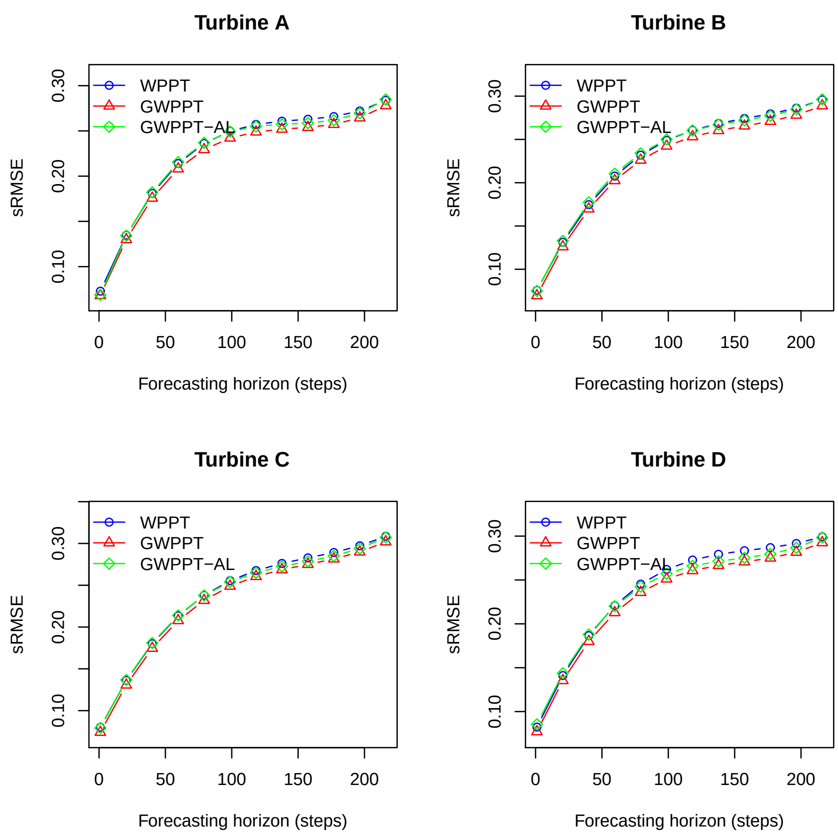

Fig. 11. sRMSE for WPPT, GWPPT and GWPPT-AL for several forecasting horizons. Turbines A to D, time frame December 08, 2011 to Janury 04, 2012.

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