WIND POWER FORECASTING ACCURACY ASSESSMENT FOR MULTIPLE TIMESCALES

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This paper presents a wind power forecasting error accuracy assessment over multiple lead times, as original contribution, for a six-month study period from December 2013 to May 2014. The study was performed on a 2 MW wind turbine generator located near Galați-Romania. The forecast is performed using a specific tool, which is based on a multi-layer neural network method and which receives data from the wind turbine generator SCADA system. The accuracy of the site-specific forecast is determined by comparing the observed/measured power production of the wind turbine generator system with the corresponding power forecast.

Keywords: wind power generation forecast, artificial neural networks

1. Introduction

Short-term prediction of wind power has attracted scientific interest since early '70s, when the wind power made its first mark as a large-scale resource. The first attempts were done with different types of time series analysis models, such as the Kalman filters [1]. Later, during '90s, the Prediktor model, which employs the results of Numerical Weather Prediction (NWP) in conjunction with the Risø wind flow model WAsP, was able to physically parameterize the wind flow in the wind farm and to predict the power output [2].

The ANEMOS project (2002-2006) brought advances in all fields of power forecasting, most notably in the definition of uncertainty, then the subsequent ANEMOS.plus (2008-2011) come with the decision support tools (storage scheduling, power system scheduling, trading, congestion management) which uses the probabilistic forecasts as input [3].

Weather conditions forecast systems were developed in last years especially to help the wind power plant owner to predict the wind power generation. The Integrated Forecast System (IFS) [4] maintained by the European Centre for Medium-Range Weather Forecasts (ECMWF) and the Global Forecast

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System (GFS) [5] provided by the National Centre for Environmental Predictions (NCEP) were developed to provide global meteorological forecasts.

Power forecasts are based on selected forecasted weather parameters in combination with site and turbine specific transfer functions. The weather forecast data are taken from a selection of global and regional numerical weather prediction models, and are employed in the power forecast system presented in this paper, customized for the wind generator system. The models external to the turbine are provided by the Integrated Forecast System [4] and the Global Forecast System [5]. Regional and wind turbine position specific weather forecasts are produced by National Center for Atmospheric Research (NCAR) using the WRF [6] and ETA [7] numerical wind prediction models. The regional data are collected from meteorological stations located around the wind turbine positions, e.g. from Galati and Vaslui counties. Local weather conditions data are measured by the weather stations attached to the wind turbine, i.e. the anemometer.

Artificial neural networks are widely used for various forecasts. A three-layer feed-forward artificial neural network trained by the Levenberg-Marquardt algorithm used for short-term wind power forecasting in Portugal is presented in [8]. In [9], a method based on three types of local recurrent neural networks, i.e. infinite impulse response multilayer perceptron, local activation feedback multilayer network, and diagonal recurrent neural network, to provide more accurate forecast for a wind farm located on the Crete island, in Greece, is presented.

2. Forecast reliability

The accuracy and predictability of weather forecasts varies with geographical location, season, weather patterns, time of day and in general it deteriorates with time. Furthermore, the uncertainty in the weather forecasts is the largest contributor to the power forecast errors [3]. These types of errors can be divided into two groups: level errors and phase errors. For example, consider a storm front passing over a wind farm. The level error misjudges the severity of the storm and the phase error shifts the timing of the storm. Both types of errors will contribute to the wind power forecast error. The aim for any NWP model is to predict the weather several hours to several days in advance. However, the ability of a model to forecast extremes (such as maximum wind gust) with the same frequency as they do occur in the atmosphere is crucial for any model. If the model has a tendency to over or under predicted certain weather elements, their probabilities will be biased. Ideally, the variability in the forecast over time and space should be equal to the observed variability, but typical forecast variability for a single wind farm can vary significantly. The variability is caused by many meteorological phenomena at all scales, including development or movement of large-scale weather systems, thunderstorms, boundary layer processes, including vertical mixing and diurnal heating, complex terrain effects, and thermally forced flows. The NWP models used in Slobozia Conachi Power Forecast are state-of-the-art and stable-performing weather models for which the forecast error increases with the length of the forecast period.

3. The wind power forecast tool

The wind power forecast presented in this paper was performed using a forecast tool attached to the Slobozia-Conachi (Galați) wind turbine generator SCADA system. The forecast model can identify complex connections between the forecasted weather and the historical power production data, and take current weather forecast parameters as input to produce forecasted power output for the wind turbine. The result is an online day ahead power forecast. A short-term forecast correction (intraday power forecast) is calculated by combining the day ahead forecast with near real-time production data using a customized and site-specific model.

The wind generation forecast tool is based on a multi-layer artificial neural network (ML-ANN). The architecture of the ANN is presented in Figure 1. The artificial neural network is trained using a back-propagation algorithm, which was developed by Rumelhart in 1986 [10]. The ANN consists of the input and output layers, and one hidden layer. The number of neurons in the hidden layer can be adjusted in terms of the ANN performance. The input variables are presented to the network as a vector. Each variable x_k have different contribution to the output variables z_j. The contribution of each variable is associated with the weights w_{ki}, then with the weights g_{ij}. These weights are iteratively adjusted using the gradient descent.

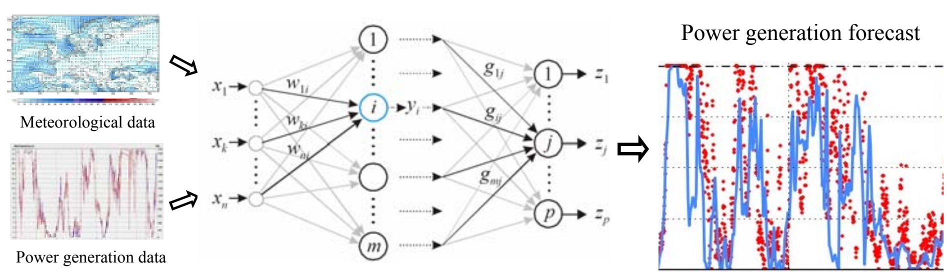

Fig. 1. The architecture of the multi-layer artificial neural network

For the training and validation of the ANN, the inputs are: a) active power generation data, achieved from the wind turbine SCADA system;

b) meteorological data, i.e. wind speed, wind direction, temperature, and air density (calculated in terms of pressure and humidity), all achieved from the wind turbine meteorological station, which are collected also using the wind turbine SCADA system. When the ANN based tool is used for wind power generation forecast, meteorological data are taken from global and regional weather forecast systems.

Since the power forecasts assume that the turbines are producing optimally at all times, the measured production data is filtered to ensure that the objective forecast is met. A filtering tool is employed to remove all instances when production was curtailed, turbines was switched off during start-up and shut-down periods, and when other signals indicated that the turbine was not operating optimally.

A performance function, denoted by E, is used as a stopping criteria of the back-propagation algorithm, calculated in terms of the neural network output errors, e_j.

$$E = E(e_j), \quad \forall j = \overline{1, p} \tag{1}$$

where p is the number of output neurons.

The most used performance function in the multi-layer artificial neural network based wind power generation forecast is the mean square error (MSE), that is

$$MSE = \frac{1}{N}\sum_{j=1}^{N} e_j^2 \tag{2}$$

where e_j is the error between the forecasted power (z_j), which is the neural network output, and the desired power (d_j), which is the measured/observed power and collected from the SCADA system:

$$e_j = d_j - z_j \tag{3}$$

The ANN training problem becomes an optimization problem aiming to minimize the error. In the training of the neural network, the matrix of weights W and G associated to the network are sought so that the performance function has a desired value [10].

4. Forecast error calculation

Wind power generation forecast is critical for energy traders in order to appropriately define their market strategy. The accuracy of the wind power generation forecast performed in the presented application is evaluated using various type of errors provided in Table 1 [3]. Each error indicates particular characteristics of the forecast and are used in the day-ahead market strategy.

Table 1

Statistical errors

Parameter	Description	Formula
Forecast error	The forecast error (prediction error) for a forecast with origin at time t is defined as the difference between forecasted/ predicted power, P_{pred}, and observed power generation, P_{gen}, in percent of the wind farm capacity, P_{cap}.	$\varepsilon(k,t) = \frac{100}{P_{cap}}\left(P_{pred}(t+k) - P_{gen}(t+k)\right)$ where k is lead time from the origin t.
AFB	The average forecast bias (AFB) is the average over all forecasts of the forecast error $\varepsilon(k,t)$. It provides an indication of the general tendency of the forecasts, i.e. if they tend to over- or underestimate the production. A positive AFB value would indicate that the forecasts overestimate the production, whereas a negative AFB value would indicate underestimation. The measure is in percent of wind farm capacity.	$AFB(k) = \frac{1}{\mathbf{T}}\sum_{t\in T}\varepsilon(k,t)$ where T is the set of forecast origins, and $\mathbf{T}$ denotes the number of forecasts in the set.
MAE	The mean absolute error (MAE) is the most commonly used metric to assess forecast accuracy. It is calculated by averaging the absolute value of the forecast errors over all forecasts. The measure is in percent of wind farm capacity.	$MAE(k) = \frac{1}{\mathbf{T}}\sum_{t\in T}\lvert\varepsilon(k,t)\rvert$
RMSE	The root mean squared error (RMSE) is the square-root of the average of the square of the forecast errors. Compared to the MAE, the RMSE is more sensitive to large errors, and not as sensitive to small ones. By comparing the MAE and the RMSE, it is possible to gauge the variation in the size of the errors. A large RMSE compared to the MAE would indicate that there are some large errors in the set. A smaller RMSE would indicate that the set mostly consists of small errors. The measure is in percent of wind farm capacity.	$RMSE(k) = \sqrt{\frac{\sum_{t\in T}\varepsilon(k,t)^2}{\mathbf{T}}}$
Precision	Is the percentage of the errors that are within x% of wind farm capacity. The measure is in percent of the amount of data.	$P_{rec}(x) = 100\frac{\left\lvert\left\{t_{t\in T}, \lvert\varepsilon(k,t)\rvert \le x\right\}\right\rvert}{\mathbf{T}}$
PI	The power index (PI) is the difference between predicted and observed power as a fraction of observed power. The closer this value is to zero, the better the prediction.	$PI = \frac{\sum_{k}\sum_{t\in T}\left(P_{pred}(t+k) - P_{obs}(t+k)\right)}{\sum_{k}\sum_{t\in T}P_{obs}(t+k)}$

5. Numerical results

The optimal configuration of the neural network, which will ensure acceptable errors, depends on the accurate input data and an appropriate experience of the human operator. The weather conditions can change significantly from one day to another, and thus the power forecast is more accurate if the time origin for the forecast calculation is closer to the time for which the forecast is performed. Also, better forecast is achieved by using the most recent weather forecasts. On the other hand, the human operator can improve the ANN architecture in terms of the information he has about the ANN performance on a longer time period.

Table 2 presents the forecast errors obtained on a six-month period with a 24 hours lead-time [11]. The larger amount of data is presented to the ANN in the learning stage, the smaller is the forecast error. Based on personal experience of the authors and literature review, it may be said that the wind power generation forecast can be used with enough confidence for the day ahead market trading strategy after at least 6 month learning period.

Table 2

Error statistics over all lead times for each month

Period	Power Generation [MWh]	AFB [%]	MAE [%]	RMSE [%]	PI [-]	Prec. (± 5%)	Prec. (± 10%)	Prec. (± 15%)
2013-12	466	5	20.3	30.6	0.7	35	48	57
2014-01	676	-0.1	18.8	27.8	0.49	31	45	56
2014-02	423	0.5	20.8	29	0.66	24	40	51
2014-03	808	-1.5	18.6	26.6	0.4	29	44	56
2014-04	574	-3.1	18.3	26.9	0.53	33	46	57
2014-05	429	2.8	18.8	28.3	0.73	33	46	58
All	562	0.6	19.6	28.3	0.56	31	45	56

The sign of the AFB value in Table II indicates whether the power forecast tends to over- or under estimate the wind turbine power generation. It can be seen that in months with high wind speeds and good weather conditions (January, March and April) the forecast tends to underestimate the power generation, whereas in months with bad weather conditions (December, February), such as ice deposits and strong snow, or turbine sensor malfunction caused by wind gust (May), it tends to overestimate the wind turbine power generation.

The difference between the forecasted power generation by the implemented power forecast system (with blue) and the measured power generation at the terminals of the wind generator system (with red) are shown together to provide a visual indication of the forecast accuracy.

Figure 2 illustrates the results achieved for December 2013. In the first half of the month the power generation was under estimated, then after 13th of December, due to the cold weather and ice deposits the forecast overestimated the wind turbine energy generation.

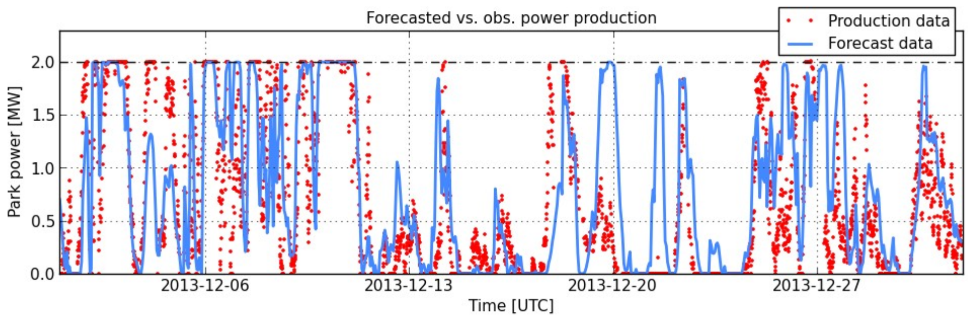

Fig. 2. Forecasted power vs. measured power production during December 2013

The forecast for January 2014 (Fig. 3) was more accurate, the MAE value decreased to 18.8% from 20.3%, and the precision decreased to 0.49 from 0.7. This may reveal that the forecast system started to learn the behavior for winter conditions in the fist part of the month when the wind turbine generation is not over estimated, similar to December 2013.

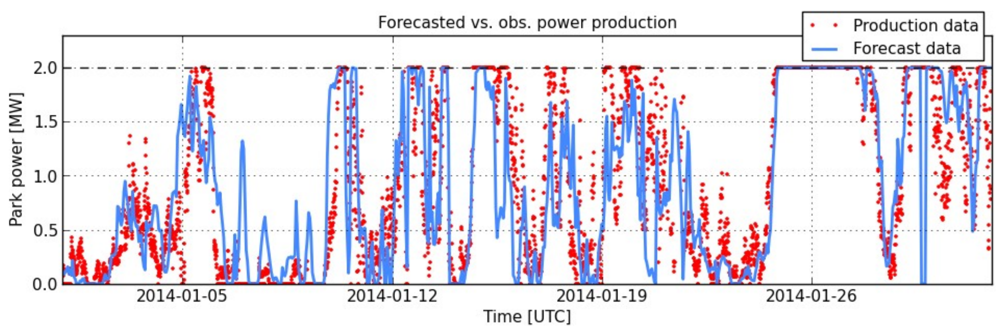

Fig. 3. Forecasted power vs. measured power production during January 2014

February 2014 (Fig. 4) was characterized by extreme snow for a longer period, and the wind turbine energy forecast was affected. The RMSE value indicates that there are again large errors in the set, and the precision decreased to 0.66%. At the end of the month the forecast accuracy was improved, and the reason may be the fact that no unpredictable or fast changing weather conditions occurred.

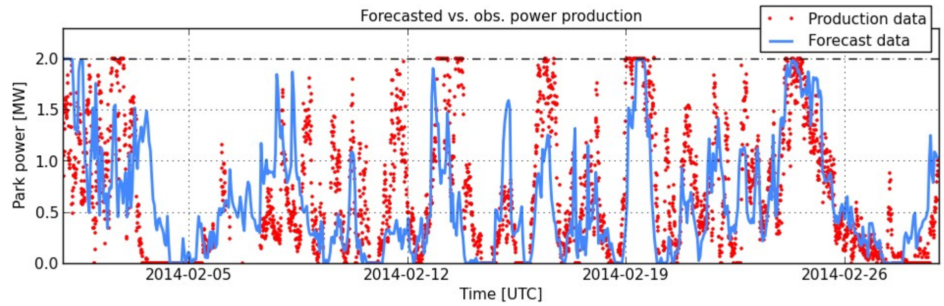

Fig. 4. Forecasted power vs. measured power production during February 2014.

The forecast precision was increased in March 2014, and the RMSE value indicates that very few large errors exists in the set. The AFB value indicates that the forecast system has a better accuracy than in the previous month.

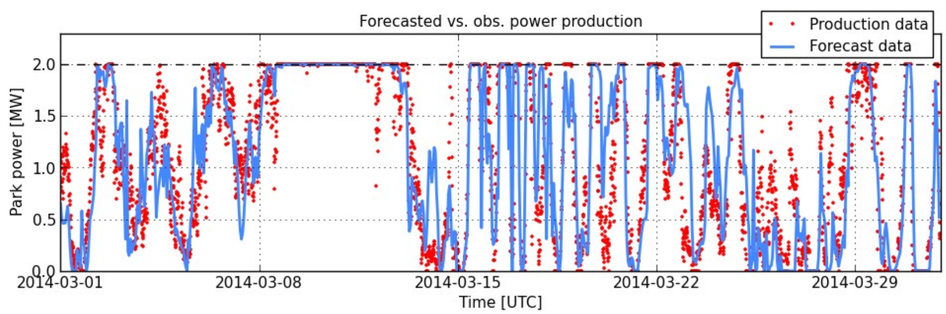

Fig. 5. Forecasted power vs. measured power production during March 2014

The trend observed in March continues in the April 2014 (Fig. 6) when the MAE value decreased to 18.3% and the accuracy of the forecast system was also improved. The forecast tend to underestimate the energy production.

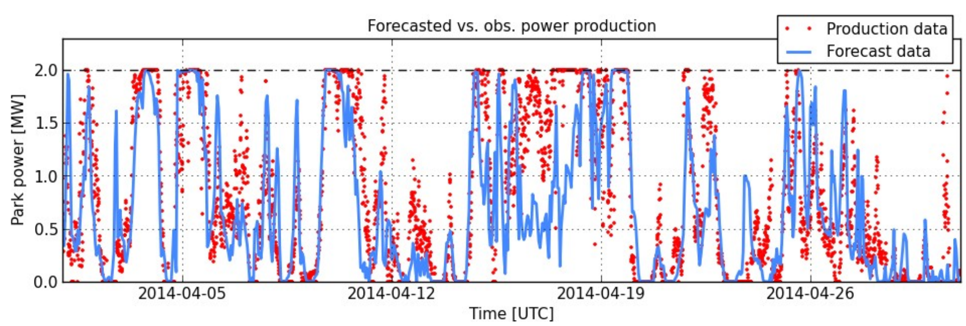

Fig. 6. Forecasted power vs. measured power production during April 2014

In the first half of May 2014 (Fig. 7) two exceptions were recorded, that is the wind turbine power generation was limited to 1.7 MW (as compared to the 2 MW installed power) due to strong winds that induced mechanical vibrations in the tower. For this reason, large errors are again present in the set of forecasted powers, and the RMSE value has increased to 28.8%. In the rest of the time the forecast tool performed much better.

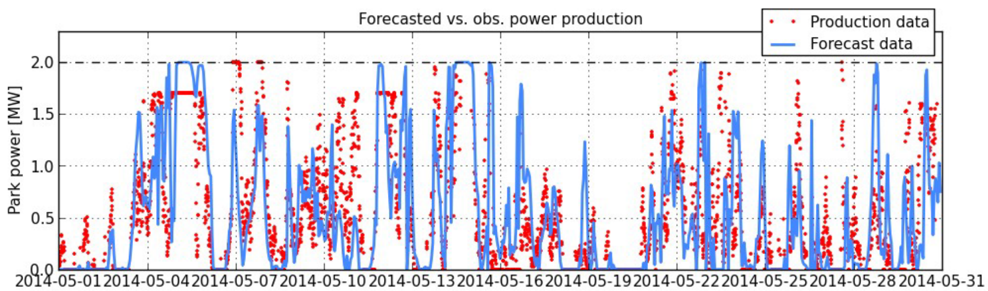

Fig. 7. Forecasted power vs. measured power production during May 2014.

Power forecast errors achieved for five successive time periods, with different lead times, are presented in Table 3. It can be seen that smaller errors are achieved if the forecast time origin is closer to the instant of the forecast calculation. Therefore, the smallest error is achieved for the 0-6 hours forecast period. When the forecast lead time is expanded larger errors are achieved, probably because of the less accurate weather forecast for a longer time period.

Table 3

Summary of the error statistics from December 2013 to May 2014 for different lead times

Error Measure	0-6 hrs	6-24 hrs	24-36 hrs	36-60 hrs	0-60 hrs
AFB	1.1	0.1	0.9	0.7	0.6
MAE	17.2	18.3	19.9	20.8	19.3
RMSE	25.6	26.8	28.9	30.2	28.2
Power Index	0.54	0.52	0.57	0.61	0.56
Precision (±5% capacity)	34	31	30	29	31
Precision (±10% capacity)	48	45	44	43	45
Precision (±15% capacity)	59	57	55	54	56

The plot of forecast errors against different lead times is illustrated in Figure 8. The MAE and RMSE have similar shapes, and both tend to increase as the lead time increases. The histogram of forecast errors (Fig. 9) shows the distribution of the calculated forecast errors with respect to the wind turbine capacity. The dispersion of errors shows that large forecast errors, from 30% to 50%, are achieved in both over- and underestimation directions.

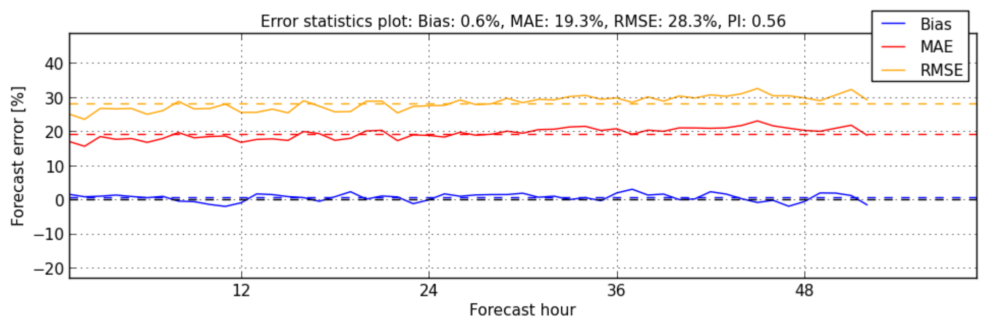

Fig. 8. Errors evolution against the forecast time period.

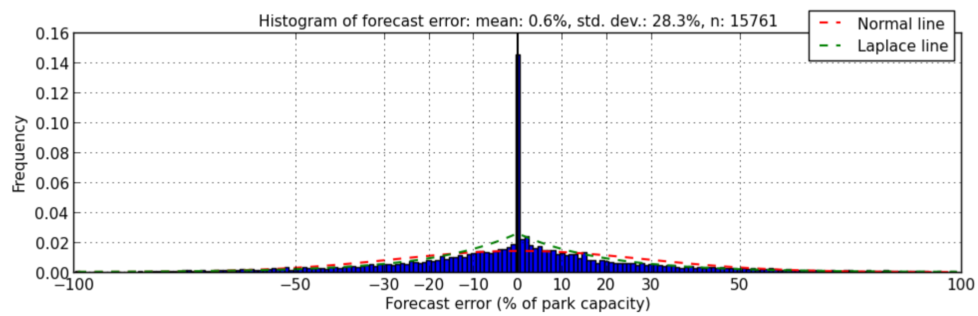

Fig. 9. Histogram of forecast errors.

6. Conclusions

In this paper the results of evaluation of the wind power generation forecast, applied for a 2 MW wind turbine located in Romania, Galați County, were presented. The evaluation study was focused on the methodology for data use rather than on the forecast method characteristics.

The generation forecast analysis was performed for a six month study period, from December 2013 to May 2014. The forecast was performed on a daily basis since forecast results were used to define the day-ahead market strategy. The forecast function is activated every 6 hours, and each time updated weather conditions are used. At each forecast function activation the forecast is performed for a 60 hours window, divided into various lead times, that is 0-6 hrs, 6-24 hrs, 24-36 hrs, 36-60 hrs and 0-60 hrs, starting from same time origin identical with the forecast function activation time.

For the 5 lead times defined, various errors were evaluated. The average forecast bias results shows a tendency to underestimate in month without large changes in the weather conditions, whereas when in month with extreme weather conditions which force the wind turbine automatic systems to limit the power generation the tendency is to overestimate.

The mean absolute error tends to decrease toward the end of the forecast study period, from 20.3% in December 2013 to 18.3% in April 2014, showing that ANN is learning. May 2014 can be seen as exception because of equipment malfunction. In normal conditions, the authors of this study would have expected to reach a MAE value below 18%. The wind power forecast can be used with sufficient accuracy for the day ahead trading after at least 6 months learning period [12].

Analysis of the MAE for the different lead times reveals that the forecast errors increase as the lead time increases. The smallest errors were achieved for the lead time of 0-6 hrs. Thus, for larger lead times the forecasts may give only a direction of the power generation.

The larger errors can be explained by the fact that the forecast study was performed for one turbine only. In case of a wind power plant, consisting of many turbines, the individual errors (positive and negative) can be balanced so that the total error may be lower [13].

The forecast accuracy is very important for the wind turbine owner because the results are used to define the tendering strategy on the day-ahead market. The unbalances produced by a market participant are penalized because ancillary services are called by the power system operator. The penalties for underestimation are greater than the penalties for overestimation because the upward regulation services is more expensive than the downward regulation service. In order to increase the market efficiency, the intra-day market was created, allowing the participants to adjust their bids at least 2 hours before the real-time, which is acceptable for the wind turbines owners, taking also into account that hourly energy is traded instead of constant powers.

The time period for which the forecast was performed was characterized by large and sudden changes, mainly during December 2013 and February 2014. Due to the climate changes, the weather conditions patterns are strongly shifted so that the same month in two successive years may look very different. January 2014 was unexpectedly very calm in Galati, without any snow, and quite high positive temperatures.

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