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Wind power forecast error smoothing within a wind farm

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Abstract.

Smoothing of wind power forecast errors is well-known for large areas. Comparable effects within a wind farm are investigated in this paper. A Neural Network was taken to predict the power output of a wind farm in north-western Germany comprising 17 turbines. A comparison was done between an algorithm that fits mean wind and mean power data of the wind farm and a second algorithm that fits wind and power data individually for each turbine. The evaluation of root mean square errors (RMSE) shows that relative small smoothing effects occur. However, it can be shown for this wind farm that individual calculations have the advantage that only a few turbines are needed to give better results than the use of mean data. Furthermore different results occurred if predicted wind speeds are directly fitted to observed wind power or if predicted wind speeds are first fitted to observed wind speeds and then applied to a power curve. The first approach gives slightly better RMSE values, the bias improves considerably.

1. Introduction

Smoothing of the wind power forecast error due to balancing effects between various wind farms is a very well-known and established fact. It requires low correlations of forecast errors of evenly distributed wind parks in large-scale areas [1]. This leads to a very small forecasting error of only 5% in the day-ahead wind power forecast for entire Germany as achieved by several commercial service providers.

An increasing interest is shown by different stakeholders in the wind energy market to enhance the development of more precise predictions for single wind farms. The wind farm operator needs the forecast for his successful bidding at the spot market and the scheduling of maintenance whereas the Distribution System Operator (DSO) is interested to feed the information on the forecasted wind power production of a specific wind farm in his Decentralized Energy Management System (DEMS).

The state-of-the-art statistical wind power forecast tools for single wind farms treat the entire wind farm as one system that needs to be described or fitted by a mathematical relation (algorithm), [2] [3] [4]. As the development of statistical wind power algorithms with Neural Networks is getting less time consuming with increasing computing power it becomes possible to derive statistical algorithms for each single turbine within a wind farm.

In this study smoothing effects within a wind farm are studied. As the area is very small smoothing is not generated by the wind forecasts but arise from the slight difference in the wind power algorithms. Study site and data will be described in the next section, the used

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algorithms follow in sec. 3. Forecast errors for the different approaches are compared (sec. 4) and a conclusion is given (sec. 5).

2. Study site and data description

2.1. Wind farm description

Investigations focus on a single wind farm near Emden (Wybelsum), comprising 17 turbines (Fig. 1). Emden is located near the north-western border of Lower Saxony, Germany. The Dollart (bay) connecting the river Ems and the North Sea is situated directly south of the wind park providing a smooth roughness environment in this direction. Towards the other directions there is a flat environment with mainly grass or fields and some obstacles like other turbines, bushes and remote small villages.

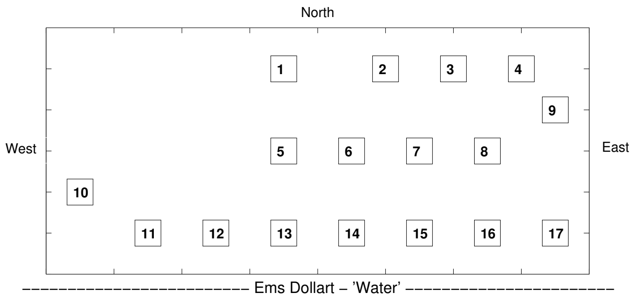

Figure 1. Sketch of the approximate arrangement of the 17 turbines within the wind farm Wybelsum.

2.2. On site data

Measured wind data are an essential source for statistical tools to refine the forecast wind data of a Weather Service to local conditions. Thus the availability of such data sets is of very high value. In the described wind park a SCADA system (Supervisory Control And Data Acquisition) is recording wind speeds observed behind the rotor of each turbine (nacelle anemometer). In addition corresponding produced wind power data is available. The original data comprises January 2005 to April 2006 with a time resolution of 15 minutes. For the analyses the values are smoothed to an hourly resolution.

The wind data show diurnal variations (Fig. 2) with rising values during the day, ranging from 5.9 to 6.4 ms^{-1}. The scatter of the wind speed between single turbines increases in the afternoon to be highest around midnight, standard deviation reaching values up to 0.74 ms^{-1}. These variations are highly dependent on the season, with rather constant values in winter and a pronounced diurnal variation in spring.

2.3. Wind forecast data

Wind forecast data is used as point predictions from the European Centre for Medium-Range Weather Forecast (ECMWF T511). It was made available with a horizontal resolution of 39 km. ECMWF provides two forecasts per day (00 UTC and 12 UTC) for forecast steps up to 72 hours, with a time resolution of 3 hours. Wind components u and v were taken from the original model level fields of wind and interpolated to hub height. Data from one grid point were used for all turbines.

2.4. Influence of park layout and positioning

Knowledge of the park layout helps to understand the different observed values at a time within a wind park because observed wind speeds sometimes strongly depend on the wind direction. This also arises in forecast errors since such regional effects cannot be taken into account in the wind forecast of Weather Services.

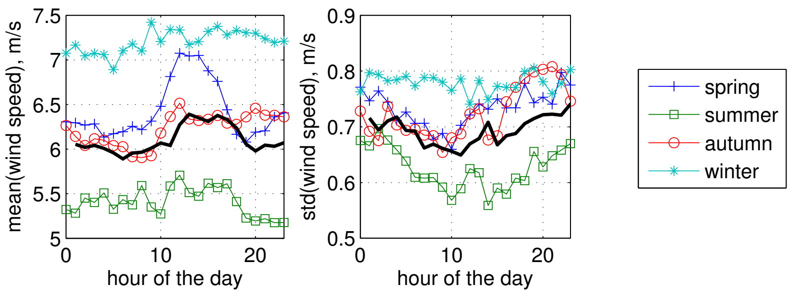

Figure 2. Diurnal cycle of the mean (left) and the standard deviation (right) over the wind speeds at the 17 turbines (ms^{-1}). Data are shown for the whole time span May 2005 to April 2006 (——), as well as separated by seasons: spring (+), summer (□), autumn (○), winter (⋆). Only forecast steps ≤ 24 h are taken. Hour of the day is shown in UTC.

As the bias of the mean data (Fig. 3, gray background) shows, the errors of the predicted wind speed are dependent on the wind direction. For winds coming from southern directions an underestimation of the predicted data (negative bias) indicates real wind conditions with comparably large values like pronounced for flat terrain. This pattern, positive errors for northern, negative for southern directions, is also characteristic for all turbines located directly at the water to the south (e.g. turbines 12 and 15 (Fig 3), positioning see Fig. 1).

The more north the turbines stand the less obvious is this dependency on the north-south direction. For those turbines it is possible that influences like wind park effects dominate. Turbines surrounded by others (e.g. turbine 8) reveal a comparably large overestimation of the predicted wind speed (positive errors, Fig. 3), which means reduced wind speeds in reality. This wind park effect can also be seen for turbines 2, 3, 4 and 9 with their high positive errors for south-westerly wind directions.

This characteristic direction dependency of the bias can be seen in all seasons (Fig. 3).

3. Methods

One state-of-the-art statistical tool for wind power forecasting is a Neural Network which derives forecast data with help of historical data. It learns the relation which is immanent in historical data and transfers it to situations in the future. This approach showed a slightly better performance in comparison to a physical model for the described wind farm [5]. The used Neuronal Net was developed at the Institute for Physics at the University of Kiel. It is implemented using the Davidson-Fletcher-Powell algorithm as minimization method (netfit, [6]). One hidden layer with two or three hidden neurons were used, depending on the application (see sections 3.1 and 3.2). Input data to the Neural Network were randomly split into training and generalization data sets with same size. Generalization is necessary to prevent overfitting. Training is stopped whenever results for the generalization data set get worse than in the previous iteration step.

Forecasted wind speed from ECMWF as well as produced wind power as observed by the SCADA System (normalised with rated power) serve as input data. Wind power forecasts for the whole wind park are the wanted results.

In a first approach this is derived with the mean wind speed of the whole park as input to the Neural Net. In a second approach the wind speeds measured at the individual turbines serve as inputs. This guarantees that the existing information is used in detail, combination is done afterwards. With the comparison of these two methods, smoothing effects within a wind farm can be studied.

The implementation of these two approaches was done using two different algorithms:

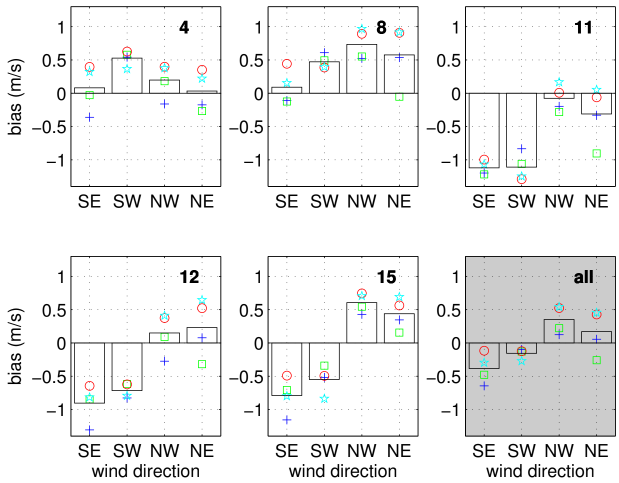

Figure 3. Bias (mean error, ms^{-1}) of the predicted wind speed in comparison to the observed wind speed, depending on the wind directions southeast (SE), southwest (SW), northwest (NW) and northeast (NE), all comprising 90°. Errors are shown separately for the turbines 4, 8, 11, 12 and 15 and for the entire wind farm (gray background). Data are shown for the whole time span May 2005 to April 2006 (bars) as well as separated by seasons: spring (+), summer (□), autumn (○), winter (⋆). Only forecast steps ≤ 24 h are taken.

(i) stepwise algorithm: fitting of predicted wind speed (ECMWF) to observed wind speed (SCADA), then fitting of corrected predicted wind speed to observed wind power (SCADA).

(ii) direct algorithm: direct fitting of predicted wind speed to observed wind power.

Both are explained in detail in the following.

3.1. Stepwise algorithm

Model output statistics (MOS) of wind speeds

Wind predictions from ECMWF are adjusted to observed wind speed using the described Neural Network with three hidden neurons. Predicted wind components u and v and 10 m wind speeds were related to observed nacelle wind data. Both were interpolated to hourly values. Fitting was done for the last 120 days, updating every 15 days, so data of the time period 1st May 2005 to 30th April 2006 remain from the original data set. This time dependent training assures that training data does not loose its representativeness. The algorithm was applied to each forecast day separately. The weights were taken to convert predicted wind speeds into corrected wind speeds. This was done for every single turbine and also for the mean value of the whole park.

This method takes the wind direction into account, so errors which occur because of roughness differences nearby or wind park effects can be corrected. The result of the correction is shown for the wind speeds of 5 turbines and for the mean wind speed of all 17 turbines, for times of south westerly wind directions (Fig. 4). The model output statistics (MOS) causes a reduction of the predicted wind speed from ECMWF for turbines 4 and 8, which are at the south eastern corner of the wind park, thus subjected to wind farm effects in these wind situations. In contrast, it comes to an amplification for turbines 11, 12 and 15 which are directly exposed to the wind. The subfigure 'all' (Fig. 4) reveals the comparison of mean wind speeds, which is much more balanced.

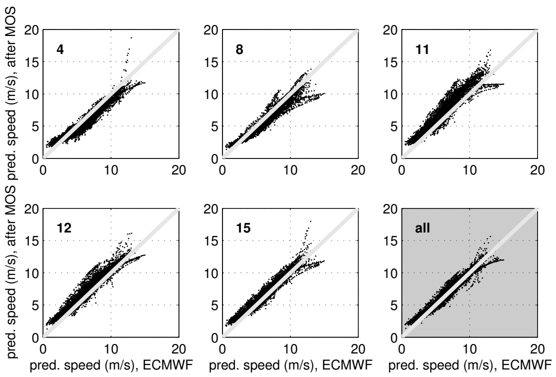

Figure 4. Predicted wind speed after MOS correction plotted against predicted wind speed as given by ECMWF (ms^{-1}), for wind turbines 4, 8, 11, 12 and 15 and for the entire wind farm (gray background). Only times with southwesterly wind direction were taken into account.

Power curve fitting
The corrected (MOS) wind speeds have to be transformed into wind power. For this a Neural Network constructs wind power curves (Fig. 5). Input data are observed wind speeds, which are related to observed wind power. Tests showed that only two hidden neurons are sufficient for this kind of application with only one input parameter. The dataset for the time period 1. Jan. 2005 to 30. April 2006 was used. The power curve is independent of the forecast day, because only observed values are involved. In a next step resulting weights could be applied to the corrected (MOS) wind speeds in order to get wind power forecasts. The derivation of the power curve was done for all turbines separately and also for mean values of observed wind speed and power.

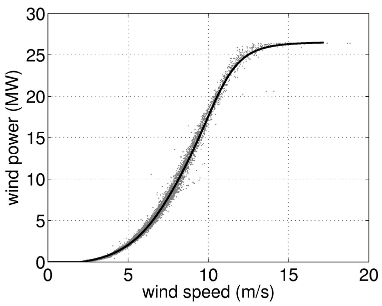

Figure 5. Produced wind power (MW) of the whole wind park dependent on the measured wind speed (ms^{-1}) (dots) and the fitted power curve provided by the Neural Net (line).

3.2. Direct algorithm
This algorithm uses the direct way to calculate wind power forecasts. That means predicted wind components (u and v) and 10 m wind speeds were directly fitted to observed wind power, without the need of observed wind speed. The Neural Net was applied using three hidden neurons, taking the last 120 days as reference for the next 15 days, as described in section 3.1. A power curve constructed by observed data is not needed, so the algorithm for the conversion into wind power is dependent on the wind direction and on forecast days. Fitting weights then serve to convert forecasted wind velocities into wind power predictions.

4. Results
4.1. Forecast errors
The aim of the study was to compare the results of Neural Networks applied to single turbines within a farm and to the farm as a whole. Forecast errors (predicted minus observed) show the quality of both approaches. Bias (mean error) and root mean square errors (RMSE), in % of installed capacity, are depicted as a function of forecast steps (Fig. 6). Stepwise and direct algorithm are included.

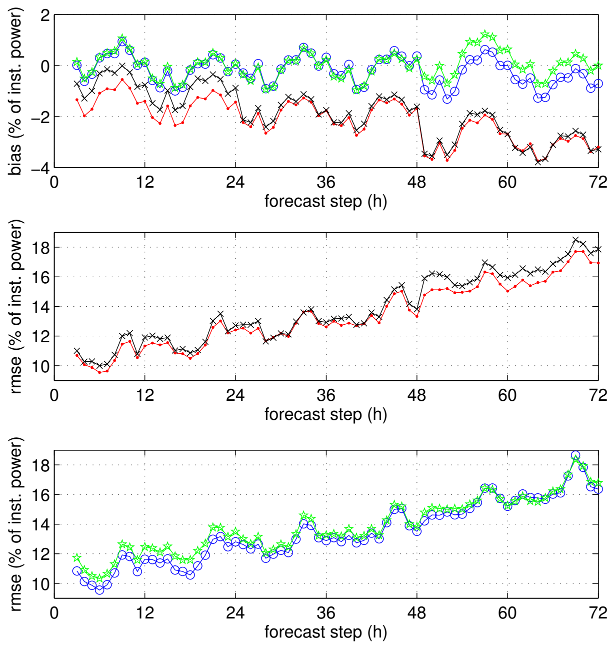

Figure 6. Bias (mean error, top) and root mean square error (RMSE, middle and bottom) of wind power predictions (predicted-measured) as a function of the forecast step. ECMWF wind forecasts with both basetimes, 00UTC and 12UTC, were used. Stepwise algorithm: mean data fitting (×, black), individual data fitting (· , red). Direct algorithm: mean data fitting (⋆, green), individual data fitting (○ , blue).

The differences in the bias are very pronounced. The use of the direct algorithm results in a bias fluctuating around zero whereas the stepwise algorithms leads to a negative bias that increases with the forecast step (0 to -3.5 %). This will be investigated in detail later.

The RMSE of the different approaches and algorithms show only small differences. It is hardly influenced by the bias, because the bias free root mean square errors (RMS, standard deviation of the error) already reveal values almost as large as the RMSE (not shown). The daily means of the RMSE range from 11.5 % and 13.2 % to 16.6 % (1. to 3. forecast day) for the stepwise algorithm and from 12.1 % and 13.5 % to 16.0 % (1. to 3. forecast day) for the direct algorithm. The approach of applying the Neural Net for individual turbines show root mean square errors lying only marginally about 3 % to 4.5 % lower (Fig. 6). In case of the stepwise algorithm this method is advantageous especially for greater forecast steps. However, errors resulting from the direct algorithm already lie in this region, without the need of an individual calculation. For this range of high forecast steps it is beneficial for the nonlinear conversion to wind power to vary with forecast day. In the case of stepwise calculation the constant power curve increases the forecast errors in wind to a greater extent. This effect is not seen for low forecast steps for which forecast errors in wind are lower.

The bias strongly increases with forecast step when using stepwise algorithms, as seen above. A closer inspection of the standard deviation of different wind parameters helps for interpretation. The mean is constant and almost identical for all wind parameters over the forecast horizon (Fig 7). Also constant are the standard deviations of forecasted (ECMWF) and observed wind speeds (SCADA). MOS correction of wind speed in contrast creates data with decreasing standard deviation for later forecast days. This is a characteristic of Neural Nets which reduces deviations from the mean in case of higher deviations from the truth.

Data with standard deviations lower than those of the observed values lead to systematic errors when applied to (nonlinear) power curves. This is confirmed by test data with equal mean but different standard deviation which was randomly generated and applied to a standard power curve.

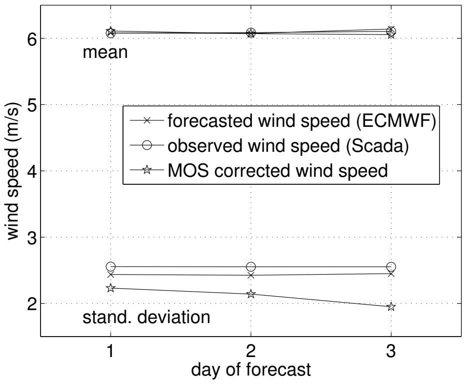

Figure 7. . Mean (top) and standard deviation (bottom) (ms^{-1}) of the forecasted wind speed (ECMWF, $\times$), the observed wind speed (SCADA, ○) and MOS corrected forecasted wind speeds ($\star$), dependent on the forecast day.

4.2. Forecasts using subgroups of turbines

Forecast errors can be decreased if applying the Neural Net individually to data of each turbine and then combining the results, as shown in section 4.1. Furthermore the number of turbines can be determined which is necessary to reach the level of the errors of the method using mean data. This knowledge is useful if only a fraction of turbine data is available.

Subgroups of the 17 wind turbines were selected covering all possible subgroup sizes (1 to 17 turbines). For each size 50 combinations were randomly chosen. Wind power forecasts derived from the stepwise algorithm were investigated. Forecasts for the whole wind park were received by combining the selected turbines in each subgroup taking the installed power into account. Mean values and the standard deviation of the RMSE as a function of the size of the subgroups are depicted in Fig. 8. Mean values of three days ahead are shown. Additionally the RMSE as result of fitting the power by mean values is included as gray lines.

The RMSE converges with increasing size of the taken subgroup (Fig. 8). Already a size of 4 to 6 turbines is enough to fall below the RMSE of the 'mean method'. For sizes greater than 9 turbines the RMSE reaches a stable level.

These are average considerations. For individual calculations this number depends on the choice of turbines. These should then be evenly distributed which can be important especially in times of strong winds from one direction like west wind conditions.

5. Conclusions

In this work forecast error smoothing within a single wind farm was studied. Only small differences in root mean square errors were found for several different approaches which were designed to forecast wind power of the whole farm. Compared to the approach 'mean to mean fitting', individual algorithms for each wind turbines with subsequent combination show only slightly lower root mean square errors (RMSE). Usage of the mean wind speed smoothens already a lot.

However, calculations with subgroups of the wind farm indicate that the use of only half of the turbines in the farm on average is sufficient to receive an output with stable errors lying below the errors of the 'mean to mean fitting'. This could also be valid for other wind farms but could be dependent on the location and the farm layout so has to be checked carefully.

Furthermore, better results with lower RMSE are obtained if predicted wind speeds are directly fitted to observed wind power in contrast to a stepwise fitting with adaptation of wind speeds first and successive application of a power curve. The second also leads to a bias increasing with forecast step. In this sense observed wind data is not essential for a Neural Net to produce wind power forecasts. However, wind data remain important to provide the possibility of error control.

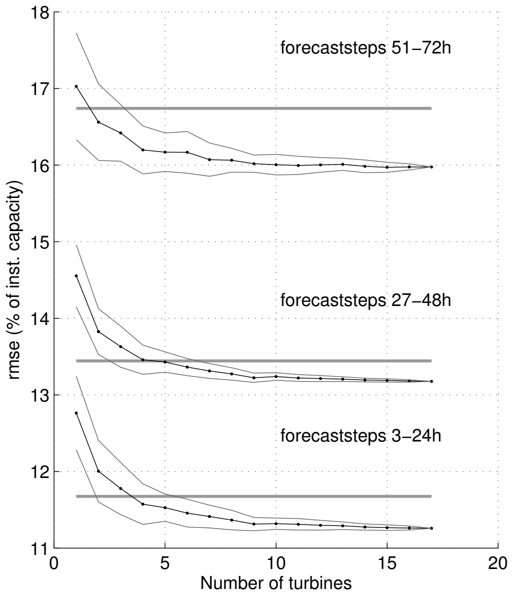

Figure 8. Root mean square errors (RMSE, % of the installed capacity) as a function of numbers of turbines used for prediction, considered forecast steps: 3,6,9,...,72 h. Mean errors for three look-ahead days (forecast steps: bottom: 3-24h, middle: 27-48h, top: 51-72h) were calculated. Depicted are the mean and standard deviation of 50 randomly chosen combinations of turbines. The RMSE as result of fitting the power by mean values is included as a gray line.

In addition the results show that the variance of the input data to the power curve has a great influence on the results. So it is advisable to use power curves trained with forecasted wind speeds (i.e. dependent on the forecast day) in order to avoid a high bias for high forecast steps.

6. Acknowledgments

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7. Bibliography

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