EVALUATION OF WIND POWER PREDICTION USING STATISTICAL OR PHYSICAL APPROACHES

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Summary

Wind power was predicted for two wind turbines of a wind farm situated near Emden (northwest-Germany), using a statistical and a physical model. Prediction errors, dependant on wind direction, are shown. In addition, measured wind speeds (by nacelle anemometer) were compared to forecasted wind speeds (ECMWF).
These forecasts show good agreement with mean measured wind data, but large deviations among individual wind turbines. The results of the power predictions demonstrate the advantage of the Neural Network leading to the lowest forecast errors. The errors of each model depend on the wind direction and show the same characteristics as the errors of forecasted wind speeds. Therefore is seems worth improving the quality of used wind speed forecasts for single situations and conditions.

1. Introduction

Wind power prediction of high accuracy is essential to allow an appropriate integration of wind power into the grid. Predictions of small units as wind farms or even single wind turbines become interesting as contribution to a Decentralized Energy Management System (DEMS, EWE AG).
A physical and a statistical model were applied to predict the wind power of two single wind turbines of a wind farm near Emden (Wybelsum), comprising 17 turbines (Fig. 1). Emden is located on the north-western border of Lower Saxony, Germany. The errors of the predictions were compared to evaluate which model performs better.
Furthermore, wind speeds measured by nacelle anemometers (Scada) were available, so predicted and measured wind speeds were compared in order to assess the influence of the errors of the Numerical Weather Prediction (NWP) on the wind power prediction.
The study comprises the time span May 2005 to April 2006.

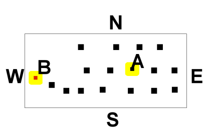

Fig. 1: Sketch of the wind farm with wind turbines A and B. N-north, E-east, S-south, W-west.

2. Physical and Statistical Approach

2.1 Model configurations

The physical and the statistical model differ by the power curves they use to deduce power output from wind speed forecasts (NWP). The physical model uses manufacturers' power curves to relate forecasted wind speed to produced power.
In contrast, the statistical model uses a neural network [2] to determine this linkage. This allows local conditions being captured by evaluating historical data. The algorithm is updated every 14 days and takes the predicted wind components and measured power data of the past 120 days as input.
The power output of the physical model is bias-corrected by Model Output Statistics (MOS). In the present case the mean of the power production of the past 120 days is subtracted. This correction term is updated every 14 days.

2.2 Wind speed

Forecasted wind speeds (3-72h) from the European Centre for Medium-Range Weather Forecasts (ECMWF) serve as input. For both models high level wind speeds were used and interpolated to hub height. In addition, wind speeds which were derived from 10 m wind speeds were used in the physical model. To derive wind speeds at hub height, Monin-Obukhov Theory was used with forecasted temperature at 2 m and 40 m height as input ([4],[3],[1]).
A stability function Ψ is added to the logarithmic wind profile and serves as correction term. The wind speed u in height z is then

$$u(z)=\frac{u_*}{\kappa}\ln\left(\frac{z}{z_0}-\Psi\left(\frac{z}{L}\right)\right)$$

with: u wind speed, u_* friction velocity, κ von Karman constant, z height and z_0 roughness length, Ψ stability function and L Obukhov length.

3. Comparision of predicted and measured wind speeds

Scada wind speed data, measured by nacelle anemometers at every single wind turbine, were analysed. Mean values show a diurnal pattern varying around 6.3 m/s with a range of 0.5 m/s (Fig. 2). During the day, when thermal stratification is frequently unstable, mean wind speeds rise. This pattern is in accordance with the predicted wind speeds of ECMWF (not shown). At this time the standard deviation of the wind speeds is highest, so the wind speeds of all 17 turbines are very much scattered.

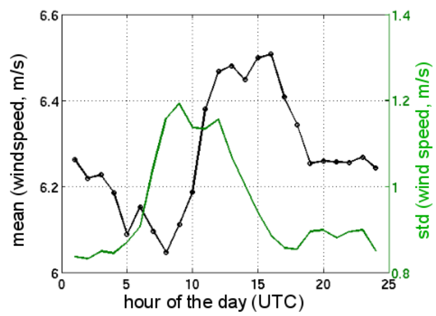

Fig. 2: Diurnal cycle of the mean (with dots) and the standard deviation (without dots) of the measured wind speed (m/s) at the 17 turbines.

The measured wind speeds were compared with predicted wind speeds from the European Centre for Medium-Range Weather Forecasts (ECWMF), 0 UTC run (Fig. 3).

The forecasted wind speeds have low systematic errors (bias = mean(pred) – mean(meas), stdbias = std(pred) – std(meas), with: pred: predicted, meas: measured, std: standard deviation). They range between -0.2 and 0.2 m/s, if compared to the mean measured wind speeds (black line). Though, the errors of the single wind turbines vary a lot among each other (coloured lines), so the internal variance of the wind farm is relative large.

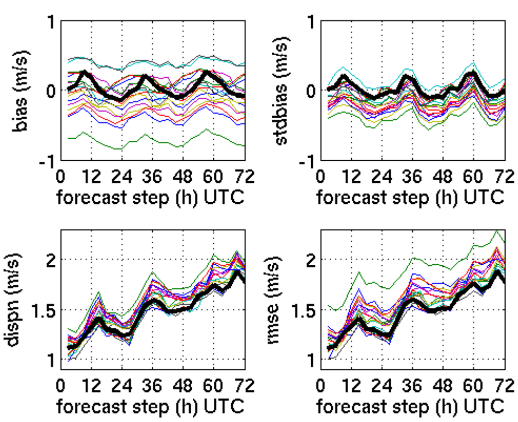

Fig. 3: Errors of wind speed for forecast steps 3 to 72 hours (m/s). Coloured/thin: predicted - measured of 17 single wind turbines. Black/thick: predicted - mean measured wind speeds.

In contrast to bias and stdbias, dispersion is much higher, with values up to 1.8 m/s. This parameter describes the phase error between two time series, based on correlation coefficients. The root mean square error is dominated by the dispersion.

A diurnal pattern with higher errors at the afternoon indicates that forecast values are less exact during unstable situations. Especially the dispersion shows that the numerical weather models (NWP) have problems to hit the truth in time in unstable situations.

4. Wind power predictions – prediction errors

Wind power predictions for turbine A and B (Fig. 1) were calculated. The errors in % of the installed capacity are shown in Fig. 4.

The root mean square errors (rmse) of the wind power predictions as a result of the statistical model (Neural Network, NN) are smaller than the errors of the physical model. In case of the physical model, the use of high level wind speeds give better results than the use of 10 m wind speeds transformed to hub height by using vertical temperature gradients (Monin-Obukhov).

The values range between 10 and 18 %.

In contrast to this, error smoothing leads to lower errors when predicting the total wind farm (Fig. 5). Here the rmse decreases for about 2%.

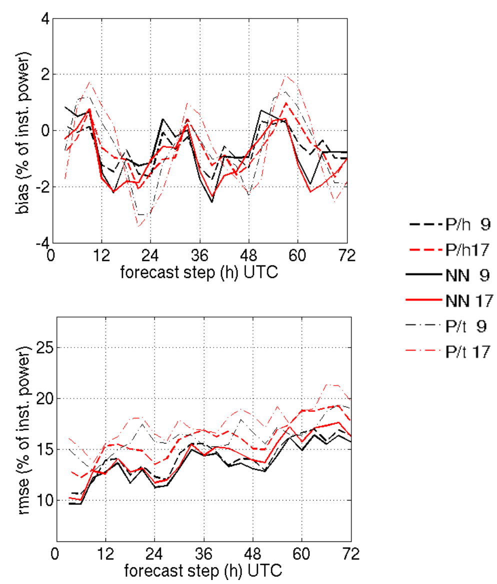

Fig. 4: Bias and root mean square error (rmse) of wind power predictions (predicted-measured) for the power plants A and B (% of the installed capacity). Models are: NN - Neural Network, P/h and P/t - Physical model using high level or transformed 10 m wind speeds.

In both cases the errors are characterized by diurnal fluctuations which are already obvious in the error variation of the predicted wind speeds.

This shows, that although the mean error of the predicted wind speed alone is low, the characteristic of the wind speed errors remains, dispersion having a great influence.
Also the pronounced higher errors for wind power plant B are to a large part consequence of the errors in predicted wind speeds.

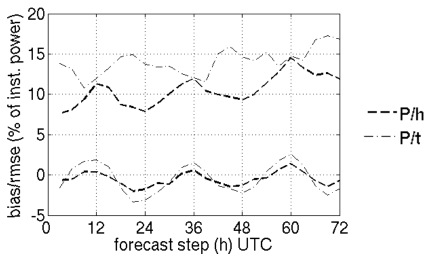

Fig. 5: Bias and root mean square error (rmse) of wind power predictions (predicted-measured) for the total wind farm (% of the installed capacity). P/h and P/t - Physical model using high level or transformed 10 m wind speeds.

Errors which occur in times of different wind directions are shown in Fig. 6. This separation reveals that forecast errors of all models depend on the wind direction. This is also true for the Neural Network, although it deals with direction dependent power curves. This minimizes the errors which occur using constant power curves.

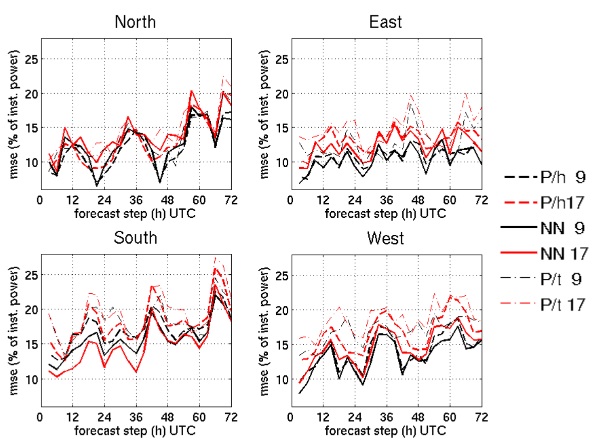

Fig. 6: Root mean square errors (rmse) of wind power predictions (predicted-measured) for the power plants A and B (% of the installed capacity). Models are: NN - Neural Network, P/h and P/t - Physical model using high level or transformed 10 m wind speeds, separated by wind directions.

Stable weather situations with frequently east wind and low wind speeds are characterized by lower and less variable power prediction errors. In contrast to this, in case of other wind directions, errors rise significantly with increasing forecast step as it is typical for numerical weather predictions (NWP).

This shows that the performance of the NWP seems to strongly influence the results of the wind power predictions.

5. Conclusions

We performed wind power predictions for two single power plants of a small wind farm, using a statistical and a physical model. The Neural Network shows better results in both cases.
Although the errors of the wind speeds of the Numerical Weather Prediction (NWP) compared to the mean measured wind speeds are moderate, the power prediction errors are dominated by the wind speed forecast errors.
Further steps should therefore concentrate on improving and adapting wind speed forecasts for different conditions.

6. Acknowledgement

The work is funded by EWE AG and the Federal Ministry for Science and Culture of Lower Saxony. The European Centre for Medium-Range Weather Forecasts and EWE AG kindly provided meteorological and wind power production data.

7. References

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