ACCURACY OF SHORT TERM WIND POWER PREDICTIONS
DEPENDING ON METEOROLOGICAL CONDITIONS

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Short term wind power predictions should provide two types of information: The expected power output of wind turbines and the expected uncertainty of this prediction. So far, the uncertainty is commonly given by annual averages such as the root mean square error. But the prediction error depends on the complexity of the prevailing meteorological situation and, therefore, should be newly assessed for each individual prediction. We investigate the impact of meteorological conditions on the prediction accuracy. As a first approach we consider the wind speed and find that the uncertainty of the wind speed prediction does only weakly depend on the magnitude of the predicted wind speed. Moreover, we derive a method to model the uncertainty of a specific power prediction in terms of the power curve and the mean error of the underlying wind speed prediction. Using an existing weather classification scheme we relate the prediction error of the wind speed to the overall weather situation. While for a number of sites the prediction uncertainty is significantly lower in weather conditions dominated by high pressure than in low pressure situations other sites do not show this effect.

1 Introduction

The efficient integration of wind energy into electrical grids requires knowledge of the expected energy production from wind farms. While conventional power plants are operated according to fixed scheduling schemes the availability of wind energy is determined by meteorological conditions. In recent years wind power prediction tools based on numerical weather forecasts have been developed for operational use to provide utilities, grid operators or energy brokers with information concerning the upcoming amount of this renewable energy 48 hours in advance [1 - 6].

Knowing the uncertainty of a wind power prediction enables users to assess the risk of relying on the prediction which, e.g., helps energy brokers to decide on making a bid on the spot market. Therefore, prediction tools should provide two types of information: the forecast itself and the expected uncertainty of this forecast. The accuracy of the wind power prediction is commonly given by statistical measures based on annual averages of the deviations between prediction and measurements like the well-known root mean square error (rmse). Such a statistical approach gives a single value of the uncertainty for all predictions disregarding the complexity of the current weather situation.

The approach followed in this work is to relate the prediction error to the prevailing meteorological situation. The investigation is based on historical weather prediction data as well as measured wind speed and power output from 30 wind farms in Germany. In particular, we concentrate on the role of the wind speed and its impact on the power prediction error. Moreover, the overall weather situation is described according to an existing classification scheme and the prediction error for the most frequent weather situations is calculated. The aim is to establish criteria which describe the uncertainty of an individual prediction depending on the current weather situation.

numerical weather prediction

$\Downarrow$

local wind speed

$\Downarrow$

wind turbine's power curve

$\Downarrow$

local prediction of power output

Figure 1: Principle of the prediction system Previento *with a spatial refinement of the numerical weather prediction leading to a local prediction of power output at one site.*

2 Forecasting method and verification

The power predictions are made with *Previento* which is based on a spatial refinement of the output of the numerical weather forecast provided by the German weather service. The prediction method we use and its performance are described in detail in [1,2,4]. The principle scheme of the prediction system *Previento* can be seen in figure 1. As input the result of an operational numerical weather prediction model is used. Our calculations are based on the wind speed and direction forecasts up to 48 hours. The resolution of the data is 14×14 km^2, i.e. rather sparse, so a spatial refinement is necessary to predict the wind power at a specific site. We calculate the wind speed at hub height under consideration of roughness, atmospheric stability, orography and farm effects.

For verification purposes measured data from about 30 German wind farms for 4 years is available. Measured wind speed and power output are used to assess the respective prediction errors which are expressed by the standard deviation of the difference between prediction and measurement, i.e.

$$\sigma = \sqrt{\frac{1}{M}\sum_{i=1}^{M}[(x_{\mathrm{pred},i} - x_{\mathrm{meas},i}) - (\overline{x_{\mathrm{pred}}} - \overline{x_{\mathrm{meas}}})]^2} \tag{1}$$

where x_{pred} is the predicted timeseries, x_{meas} the corresponding measurement and M the number of datapoints. The crucial point is that we use this error measure for subsets of timeseries which are chosen according to common meteorological conditions or certain ranges of wind speed.

3 Accuracy of wind speed prediction

The wind speed from the numerical weather prediction (NWP) is the main input to the power prediction system. Thus, prior to looking at the power prediction error we first investigate the accuracy of the underlying wind speed prediction. The general accuracy of the wind speed in 10 m height is published by the German weather service on a regular basis, e.g. [7]. It is measured by the rmse and typically of the order 1 to 2.5 m/s. We find about the same values if we compare DWD's wind speed prediction with our measurement data.

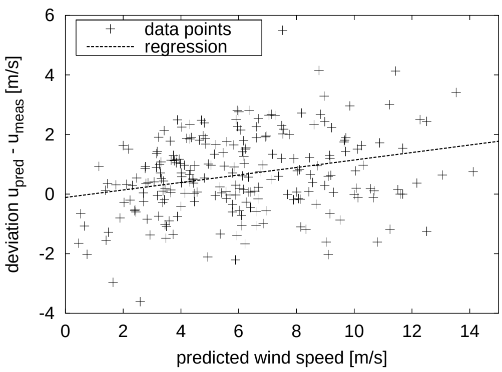

Figure 2: Deviations of predicted and measured wind speed in 10 m height versus the predicted wind speed. Each data point represents a 6 h prediction of the year 1996. A trend towards larger differences for increasing wind speed can be observed. Linear regression gives a slope of about 0.13. The scatter of the data points around the regression line seems to be independent of the wind speed.

One major question is: Does the accuracy of the wind speed prediction depend on the magnitude of the wind speed? In order to answer this we consider the deviations between predicted, u_{pred}, and measured wind speed, u_{meas}, for different wind speeds. Each data point in fig. 2 represents the difference $u_{pred} - u_{meas}$ versus the predicted wind speed u_{pred} in 10 m height for the 6 h predictions of the year 1996. Two observations strike the eye: The differences are on average increasing with increasing wind speed and the scatter of the data points does not change much over the whole range of wind speeds. Linear regression reveals that the trend of the deviations is about 0.13, i.e. at 12 m/s the average deviation is 1.3 m/s larger than at 2 m/s. This linear trend in the prediction is normally related to systematic errors in the local refinement of the prediction, e.g. a general underestimation of the surface roughness. It can easily be eliminated by model output statistics (MOS) applied to the wind speed. Thus, what is more important to assess the accuracy of the prediction is the scatter of the differences around the line of regression (fig. 2).

We investigate the scatter, i.e. the variation of the deviations, in more detail. The magnitude of the variations of $u_{pred} - u_{meas}$ are not influenced by MOS and express the inherent uncertainty of the wind speed prediction. We calculate the binwise standard deviation (eq. 1) with intervals of 1 m/s width. Note that the mean value in each bin and, therefore, the trend is removed. Fig. 3 and 4 show that the prediction uncertainty does practically not depend on the wind speed (for relevant wind speeds larger 2 m/s). Within the 95%-confidence interval indicated by the errorbars the accuracy of the predicted wind speed is nearly constant. This applies for most stations and almost all prediction times.

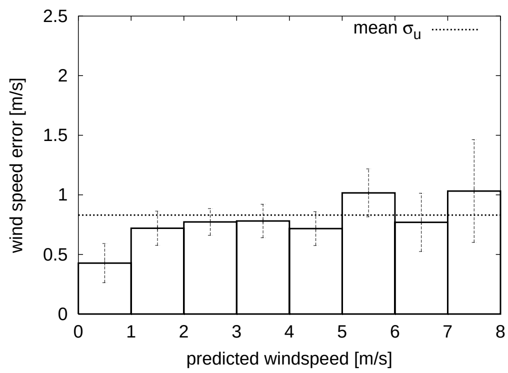

Figure 3: Binwise error of wind speed prediction expressed by the standard deviation at one site for a prediction horizon of 6 hours. Within the 95%-confidence interval indicated by the errorbars the uncertainty of the wind speed prediction does not depend on the magnitude of the wind speed. The dashed line is the mean standard deviation averaged over bins with wind speeds exceeding 2 m/s.

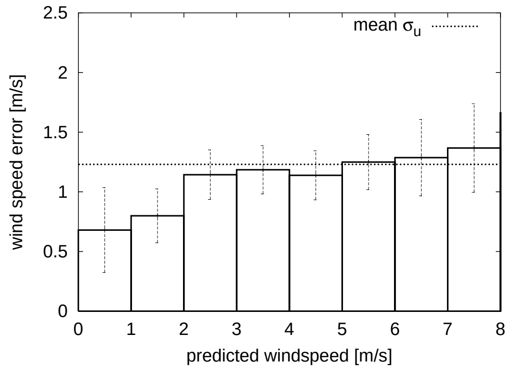

Figure 4: Same as fig. 3 but for a forecast time of 36 hours.

4 Modelling the power prediction error

It is a well-known fact that the nonlinear power curve amplifies initial errors in the wind speed according to its slope leading to a very pronounced increase of the power prediction error for medium wind speeds. Fig. 5 shows a typical power curve of a wind turbine. As shown in fig. 6, for wind speeds in the interval with steepest slope the resulting power bias, i.e. difference between predicted and measured power output, is considerably larger than for low or high wind speeds. This indicates that the uncertainty of the power prediction is proportional to the slope of the power curve and the accuracy of the underlying wind speed prediction.

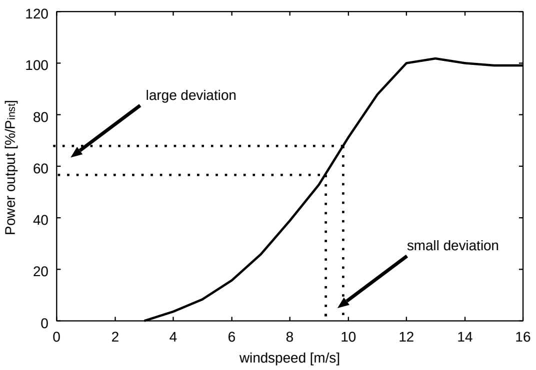

Figure 5: Power curve of wind turbine (stall machine). Due to the large slope for medium wind speeds small errors in the wind speed prediction are magnified.

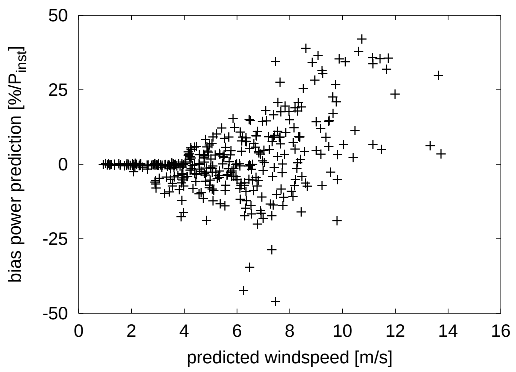

Figure 6: Bias of power prediction, each data point represents the differences between predicted and measured power output at one point of time. In the interval with steepest slope of power curve (fig. 5) the bias increases.

In mathematical terms the relation between the slope of the power curve and the uncertainty of the power prediction can be approximated as

$$\sigma_P(u) = \left|\frac{dP}{du}(u)\right| \overline{\sigma_u} \tag{2}$$

where σ_P is the standard deviation representing the current power prediction error, $|dP/du|(u)$ the absolute value of the derivative of the power curve at u and $\overline{\sigma_u}$ the annual mean of the wind speed prediction error. Note that this formula is also valid if the wind speed prediction error is not constant and depends on the predicted wind speed.

Fig. 7 shows the binwise power prediction error versus the predicted wind speed at hub height for the 12 hours prediction. Obviously, the behaviour of this error is rather precisely modelled by the curve calculated according to eqn. 2 (dashed line). Within the errorbars the calculated uncertainty of the power prediction describes the measured one. For larger prediction times (e.g. 36 h in fig. 8) the prediction error is generally higher but still covered well by our model. Thus, it is now possible to assign an individual uncertainty to each power prediction according to the predicted wind speed. A possible way of doing so is shown in the timeseries in fig. 9 where the shaded area indicates the uncertainty of the power prediction. The shaded area is calculated using eqn. 2. Obviously, the uncertainty is considerably smaller for low power output than for medium power output. The measured power output shown for comparison lies inside the uncertainty bounds for most of the time. However, on day 44 the prediction was far too high. This error was presumably caused by a wrongly predicted low pressure system. This type of event is not covered by our model.

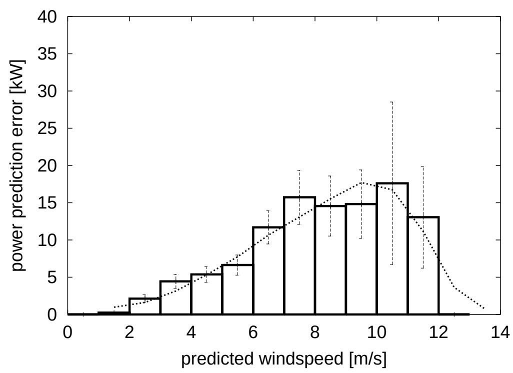

Figure 7: Binwise error of power prediction calculated with standard deviation from measured power output. Same site as before (bars) with prediction time 12 hours. The dashed curve shows the calculated prediction error according to eqn. 2. It describes the power prediction error very well.

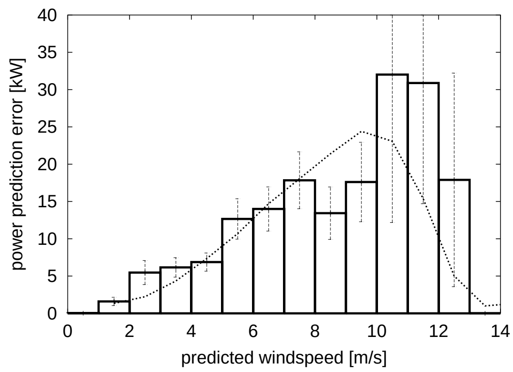

Figure 8: Same as in fig. 7 but for 36 hours prediction time. The overall error level is higher but is still rather well covered by the calculated prediction error.

5 Impact of overall weather situation

The overall weather situation in Central Europe can be defined by the configuration of low and high pressure systems at the surface and 500 hPa pressure level (approx. 5.5 km

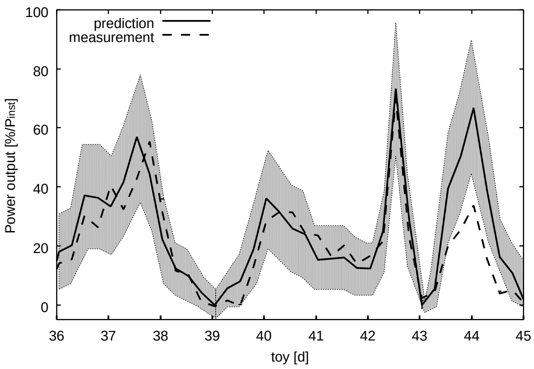

Figure 9: Timeseries of power output at one site. The solid curve is the prediction where the shaded area indicates the uncertainty of the individual prediction. Obviously, the uncertainty varies considerably depending on the underlying wind speed prediction according to eqn. 2. The dashed line shows the measured power output which is inside the shaded for most of the time. The large error on day 44 is caused by an event not covered by the modelling procedure.

height) and the position of the jetstream. The weather map in fig. 10 shows a typical high pressure bridge over Central Europe which is one of the most frequent weather situations. Another typical condition is low pressure with frontal zones crossing Europe from the west. Using these criteria a classification of the daily weather situations has been recorded since 1881 in [8]. We use the results of this classification scheme to see if for some weather conditions the wind speed prediction is more accurate than for others. In particular, we expect a difference in the prediction uncertainty between low pressure situations, where fast moving frontal zones with complicated wind patterns cross the domain of interest, and high pressure situations with rather stable wind conditions.

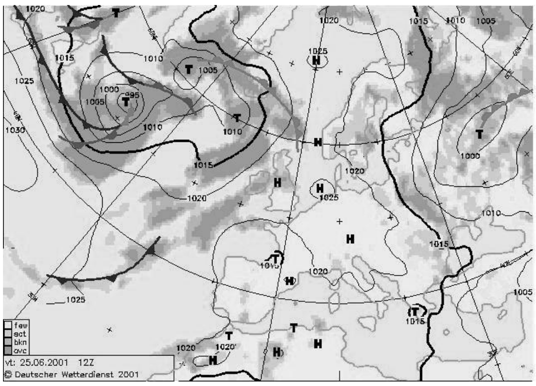

Figure 10: Typical high pressure situation over Europe illustrated by the surface pressure with additional frontal zones. Weather situations can be classified according to the configuration of low (T) and high pressure (H) areas and the position of the jetstream.

Fig. 11 shows the uncertainty of the wind speed prediction for two of the most frequent weather situations for an inland site. For all prediction times the prediction error is much larger for the low pressure situation (WZ) than for the high pressure bridge (BM) which is similar to fig. 10. This indicates that the accuracy of the wind speed prediction is indeed dependent on the overall weather situation and as expected the low pressure situation which is assumed to be harder to predict leads to a larger prediction error. But unfortunately, not all sites show this behaviour as can be seen in fig. 12 where the difference between the two weather types is not significant. This might be due to the local conditions at the site but it is not clear yet why there is an effect for some sites and not for others.

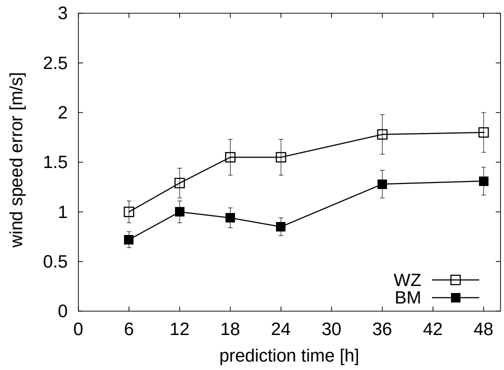

Figure 11: Wind speed prediction error at inland site for the two most frequent weather situations for various prediction times. WZ is a low pressure situation with mainly westerly wind direction whereas BM is a high pressure bridge over Europe similar to the one shown in fig. 10. For this site the prediction error is significantly lower for BM than for WZ.

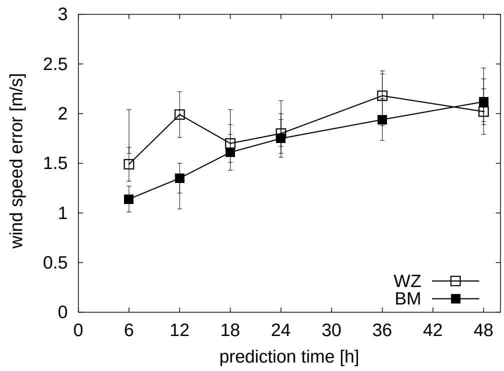

Figure 12: Same as in fig. 11 but for a different site at the coast of the Baltic sea showing no significant differences between the two weather situations.

6 Resume

In a first approach to assess the uncertainty of wind power prediction with regard to the meteorological situation we find that the uncertainty of wind speed prediction does practically not depend on the magnitude of the predicted wind speed, i.e. low wind speeds are predicted with almost the same accuracy as high wind speeds. The wind speed is used as input for our prediction system where the nonlinear power curve leads to an amplification of the error. Due to the slope of the power curve small errors in the prediction of the wind speed might result in large errors in the power prediction. We show that this behaviour can be modelled very well using the fact that the uncertainty of the power prediction is proportional to the slope of the power curve and the average uncertainty of the underlying wind speed prediction. Thus, it is now possible to assign a specific uncertainty to each prediction in contrast to having only one value averaged over one year.

Concerning a classification of the prediction error depending on the overall weather situation we obtain first results indicating that for some sites the uncertainty of the predicted wind speed significantly varies for different weather types. As expected the error is larger for low pressure situations with frontal zones crossing. But on the other hand some sites do not show these differences and it is so far an open question why. The overall weather classification of Central Europe might be too global to be a reliable indicator of the expected prediction uncertainty. Thus, further research following this approach will focus on smaller scales and will also consider local meteorological conditions. For this purpose data provided by synoptic stations will be investigated to classify the prediction error, e.g. temporal pressure gradients, wind direction or vorticity. In particular, the passage of frontal zones is of special interest with regard to the prediction error as the wind fields in their vicinity are hard to predict.

In this work the focus lies on investigating the uncertainty of the prediction for single sites, i.e. single wind farms. In [9] the statistical smoothing effects of the prediction uncertainty that arise if a wind power forecast is made for a region with spatially distributed wind turbines was considered. It was shown that depending on the size of the region the prediction of the aggregated power output has a smaller error compared to a single site. Generally, the same holds for the uncertainty due to the meteorological situation as discussed above. For an aggregated power prediction the uncertainties for individual predictions reduce roughly by a factor that is determined by the size of the region. If there are different regimes of meteorological conditions inside the region this must be taken into account.

Acknowledgements

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