ASSESSING THE UNCERTAINTY OF WIND POWER PREDICTIONS
WITH REGARD TO SPECIFIC WEATHER SITUATIONS

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The uncertainty of a short term wind power prediction is commonly given by statistical measures such as the root mean square error having the same value for every prediction. In order to provide a more detailed assessment of the current prediction uncertainty we investigate the impact of meteorological conditions on the prediction error. As a first approach we consider the wind speed and find that the uncertainty of the wind speed prediction is independent of the magnitude of the predicted wind speed. Moreover, we show that the uncertainty of a specific power prediction can be described quantitatively in terms of the power curve and the mean error of the underlying wind speed prediction. Using existing weather classification schemes the impact of the overall weather situation on the prediction error is investigated. 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.
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1 Introduction

The growing share of wind energy in electrical grids demands new strategies to improve the integration of this fluctuating renewable resource into existing power supply systems. In recent years wind power prediction tools based on numerical weather forecasts have been developed for operational use to provide grid operators and energy brokers with information concerning the wind energy to be expected 48 hours in advance [1 - 6].

In general, a wind power prediction has to provide two types of information: the forecast itself and a measure of the uncertainty of the forecast. Knowing the uncertainty enables users to assess the risk of trusting in the prediction which, e.g., helps energy brokers to decide on making a bid on the spot market. The quality 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.

Our approach here is to investigate the correlation between the meteorological situation and the corresponding prediction error using historical weather predictions 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 existing classification schemes and the prediction error for the most frequent weather situations is investigated. The aim is to establish criteria which describe the uncertainty of an individual prediction depending on the current weather situation.

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 forecast 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.

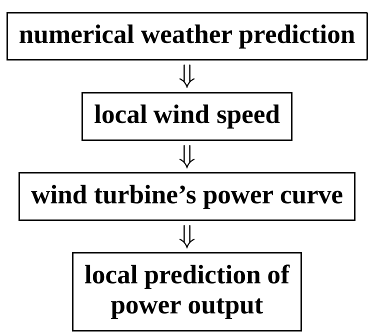

Figure 1: Principle of Previento *with a spatial refinement of the numerical weather prediction leading to a local prediction of power output at one site.*

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.

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 calculate the binwise standard deviation (eq. 1) with intervals of 1 m/s width. Fig. 2 and 3 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.

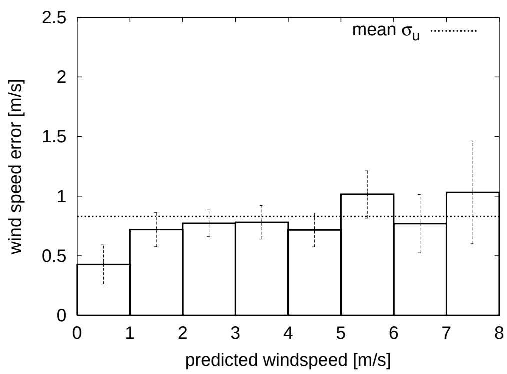

Figure 2: Binwise error of wind speed prediction calculated with standard deviation at one site for a prediction horizon of 6 hours. Within the 95%-confidence interval indicated by the errorbars the uncertainty of the wind speed prediction does not depend on the magnitude of the wind speed. The dashed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

4 Error amplification by power curve

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

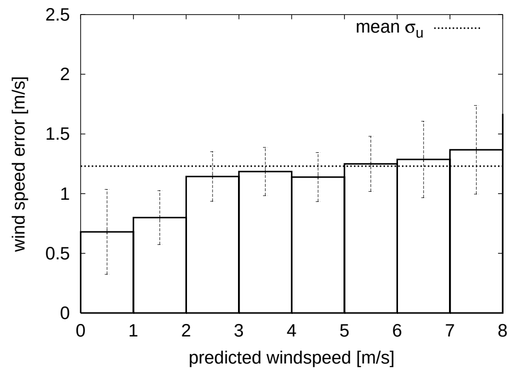

Figure 3: Same as fig. 2 but for a forecast time of 36 hours.

wind speeds. Fig. 4 shows a typical power curve of a wind turbine. As shown in fig. 5, 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.

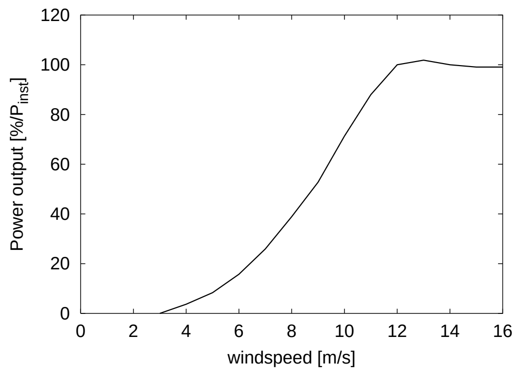

Figure 4: Power curve of wind turbine (stall machine). Due to the large slope for medium wind speeds small errors in the wind speed prediction are magnified.

5 Modelling the power prediction error

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.

Fig. 6 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. 7) the prediction error is generally higher but still covered well by our model.

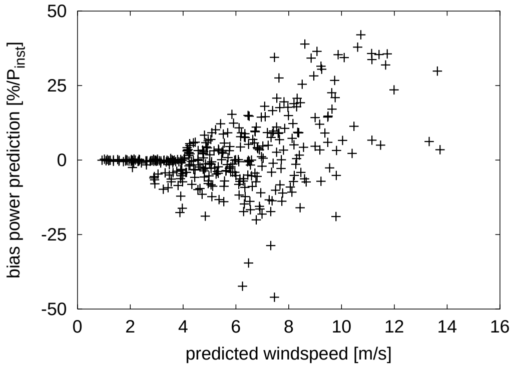

Figure 5: Bias of power prediction, each data point represents the differences between predicted and measured power output at one point of time. In the interval with steepest slope of power curve (fig. 4) the bias increases.

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 time-series in fig. 8 where the errorbars indicate the uncertainty of the power prediction. The errorbars are calculated using eqn. 2 and are considerably smaller for low power output than for medium power output.

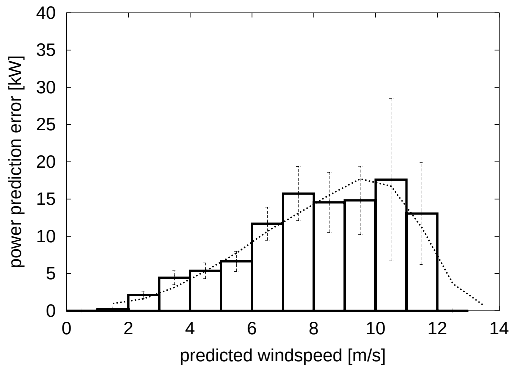

Figure 6: Binwise error of power prediction calculated with standard deviation from measured power output. Same site as before (bars) with prediction time 12 hours. The dashed curve shows the calculated prediction error according to eqn. 2. It describes the power prediction error very well.

6 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 height) and the position of the jetstream. The weather map in fig. 9 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

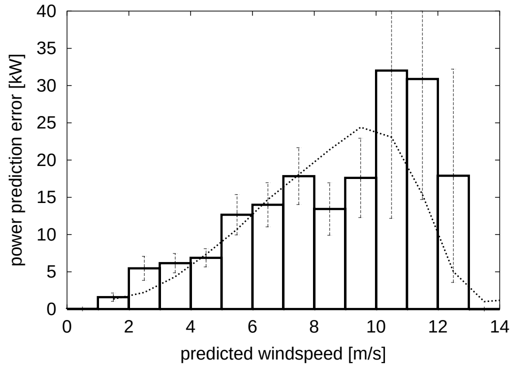

Figure 7: Same as in fig. 6 but for 36 hours prediction time. The overall error level is higher but is still rather well covered by the calculated prediction error.

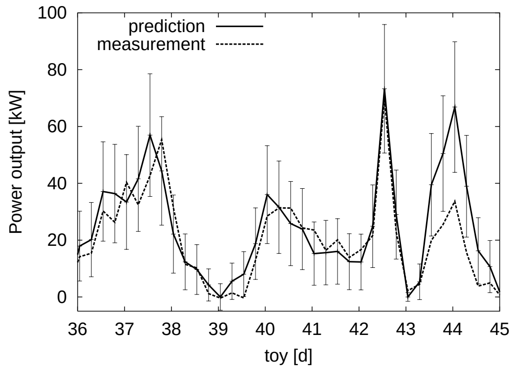

Figure 8: Timeseries of power output at one site. The solid curve is the prediction where the errorbars indicate the uncertainty of the individual prediction. The size of the errorbars varies considerably depending on the underlying wind speed prediction according eqn. 2. The dashed line shows the measured power output.

frontal zones with complicated wind patterns cross the domain of interest, and high pressure situations with rather stable wind conditions.

Fig. 10 shows the error of the wind speed prediction for two of the most frequent weather situations for an inland site. The prediction error for all prediction times is much larger for the low pressure situation (WZ) than for the high pressure bridge (BM) which is similar to fig. 9. 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. 11 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.

7 Resume

In a first approach to assess the uncertainty of wind power prediction with regard to the meteorological situation we find that the accuracy of wind speed prediction does practically not depend on the magnitude of the predicted wind speed, i.e. low wind speeds are as good predicted as high

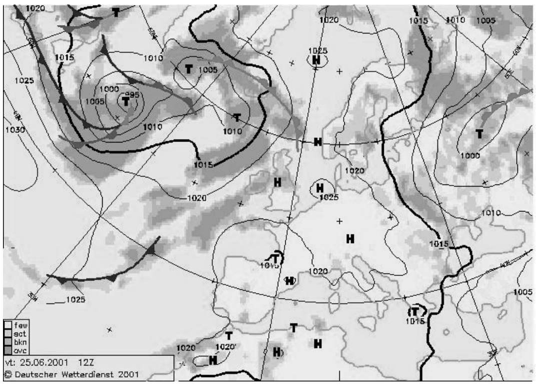

Figure 9: Typical high pressure situation over Europe illustrated by the surface pressure with additional frontal zones. Weather situations can be classified according to the configuration of low (T) and high pressure (H) areas and the position of the jetstream.

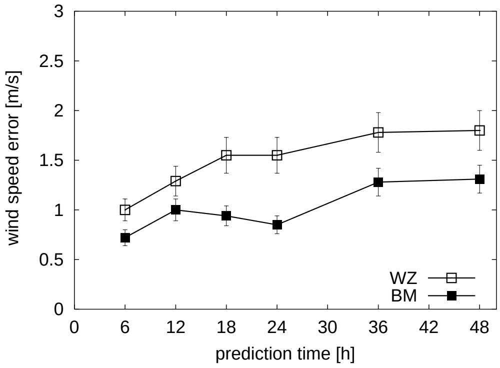

Figure 10: Wind speed prediction error at inland site for the two most frequent weather situations for various prediction times. WZ is a low pressure situation with mainly westerly wind direction whereas BM is a high pressure bridge over Europe similar to the one shown in fig. 9. For this site the prediction error is significantly lower for BM than for WZ.

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 a value averaged over one year.

Concerning a classification of the prediction error depending on the overall weather situation we obtain promising first results. For some sites the uncertainty of the predicted wind speed significantly differs 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.

Further research following this approach will include more meteorological variables to classify the prediction error, e.g. pressure gradients, wind direction or vorticity. In particular,

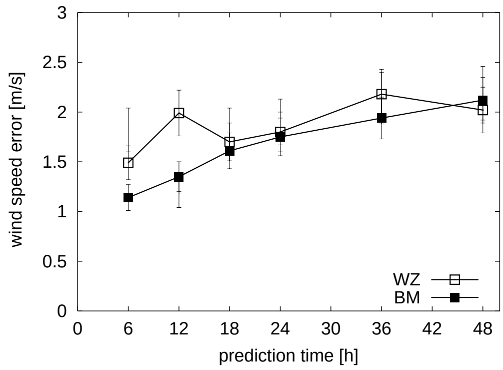

Figure 11: Same as in fig. 10 but for a different site at the coast of the Baltic sea. Here there is no significant differences between the prediction errors.

the passage of frontal zones is of special interest with regard to the prediction error as the wind fields in the vicinity are hard to predict.

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