How to avoid Biases in Offshore Wind Power Forecasting

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Abstract

Large-scale offshore wind farms need to be operated as power plants for renewable energy in the near future. The dependency of energy production on highly fluctuating weather systems is inherent but will become manageable due to accurate wind power forecasting. The quality of statistical wind power forecasting algorithms can be optimized by proper selection of appropriate weather parameters and consideration of their natural characteristics like spatial-temporal evolution, uncertainty and error correlation.

We investigate in this study whether the uncertainty in Numerical Weather Prediction shall be included in the algorithm development. We found that Neural Networks are perfect to retrieve smooth wind power forecasting algorithms from noisy input data. It is shown that algorithms developed with wind speeds from weather analysis or predicted wind speeds are equivalent. Special attention must be paid to systematic differences in wind speeds used for training and application, as different wind statistics are responsible for systematic forecast errors. This problem can be solved by an adaptive system approach.

1. Introduction

The accuracy of short-term (72 hours) wind power forecasts will trigger the economic success of large-scale on- and offshore wind farms in a liberalized electricity market. High accuracy on estimated power production is needed for the efficient integration of large scale wind power into the UTCE grid in terms of reliability and stability but also with respect to energy trading. The demand for valuable regulative power must be kept to an absolute minimum, in particular when challenging scenarios (e.g. 12% of Europe's electricity production from wind power by 2020 [1]) shall be met.

High-Resolution Numerical Weather Predictions (NWP) of wind play the key role for excellent wind power forecast [2] and are issued from several NWP Centers worldwide. In general, deficiencies in the predicted wind power are supposed to be related to the uncertainty in NWP. But also wind power algorithms themselves (either physical or statistical) that are used to predict the wind power at a single site contribute to the observed discrepancies between forecasted and produced power. Further-more unconsidered outages of single turbines reflect a higher forecast error than expected from NWP.

Wind power algorithms are responsible for the following steps to transfer large-scale wind forecasts into local wind power predictions at an individual wind farm site: i) spatial refinement (e.g. horizontal interpolation), ii) calculation of the wind speed at hub height (e.g. extrapolation of 10m surface wind considering thermal stability or use of high level NWP model fields), iii) consideration of orography effects and iv) surface roughness, v) losses due to turbine wakes in the wind park and vi) accounting the availability of turbines with respect to damages, maintenance or cut-off at high wind speeds.

The key advantage of statistical algorithms is that at least three of the above mentioned important impacts on power production do not require any physical modeling, i.e. orography effect, surface roughness and turbine wakes. In general, these effects can be accounted as wind directional dependent effects on the power curve of the entire wind farm.

The use of Neural Networks in statistical algorithm development is very common, i.e. satellite

meteorology [3, 4] and also wind power forecasting [5]. Differences exist in i) used input data, i.e. different NWP data and number of variables, but also ii) in application, e.g. regional forecasts [5] or single site forecast [6, 7].

This study investigates the impact of input (training) data for single wind farm sites using Neural Networks. In particular, we study the effect of uncertain weather data in the algorithm development phase. This approach will be explained in the following section. Section 3 and 4 describe data and the Neural Network approach, respectively. A new way to visualize wind power curves is presented. Results are shown in Section 5, while Section 6 discus the problem of systematic forecast errors. Conclusions are given in Section 7.

2. Approach to integrate uncertainty from Numerical Weather Prediction

Three different kinds of wind speeds can be used for the development of statistical wind power algorithms: i) Measured wind speeds at hub height, ii) wind speeds from weather analysis and iii) wind speeds from weather forecasts. While measured and analysed wind speeds have a very strong relation with produced power of the wind turbine, large scatter exists between predicted wind speeds and measured wind power, because of the uncertainty in the Numerical Weather Prediction (NWP uncertainty).

The algorithm developed with predicted wind speeds is called a 'non-sharp' algorithm because it copes with uncertain wind data, i.e. uncertainty was integrated during the development phase. On the other hand we call the algorithm retrieved from analysed/measured wind speed 'sharp', as it represents the best relation between wind speed and wind power. This is comparable to the classical power curve of a wind turbine or wind farm retrieved from measurements.

In order to answer the question which of these algorithms is superior and if the integration of NWP uncertainty is possible or worthwhile, they are applied to independent wind speed forecasts. Measured wind power output from single wind farms is used as validation.

Obviously the "sharp" and "non-sharp" algorithms will be different when systematic differences between analysed and forecasted exist. In general, a Neural Network is determined to remove any bias from the result for the training data. Consequently a systematic error will occur when the new input data is biased against the training input data or the distributions are different. Furthermore it is crucial that no biases or shifts in distribution occur between wind speeds in the training and application study period. We will address this problem in Section 6.

The predominant uncertainty in current NWP models in the time scales of interest (24-72h) are driven by upstream initial condition errors at the start of the model integration [8,9]. These errors in the analysis of the state of the atmosphere influence the phase and intensity of synoptic fronts to a much larger extent than local conditions. The later are important at time scales up to 24 hours and horizontal scales of less than 10 km and can be accounted by mesoscale modeling that different NWP centers do (e.g. [10]). As already mentioned our technique is able to overcome effects on the wind field by local conditions, i.e. large scale winds are the ideal input.

3. Data for the Algorithm Development

The proposed approach for integrating NWP uncertainties is investigated for two test cases (wind farms) in North-West Germany. One case can be considered as an in-land case while the other is near-shore. The original wind power production data has a time resolution of 15 minutes, but was smoothed with a linear kernel to 1h resolution. All wind power data is normalized with the rated power, respectively.

Operational forecast and weather analysis data of the European Centre for Medium-Range Weather Forecasts is used. Model fields are interpolated using directional Bessel Interpolation to the required wind park position. Wind components are available approximately at 30, 60, 90 and 120 m height and are interpolated to hub height of about 80m.

In case of wind analysis data all available synoptic times at 0, 6, 12, 18 UTC are considered. Forecast data for the 0 and 12 UTC forecast run are taken with forecast steps ranging from 3 to 72 hours ahead. The time resolution is 3 hours.

Data of the year 2004 serves as training in the development phase, while Jan-Mar 2005 is available for independent validation with production data.

4. Neural Network Approach and 3-dimensional Power Curves

The used Neural Network was developed at the Institute for Physics of the University Kiel [11] and belongs to the group of fully interconnected Networks. The minimization is done using a variable metric method in combination with the Davidon-Fletcher-Powell technique, i.e. to account the information of second derivatives in the cost function in order to accelerate the convergence.

The meridional and zonal wind components in turbine hub height are used as input variables. The normalized produced wind power is the output.

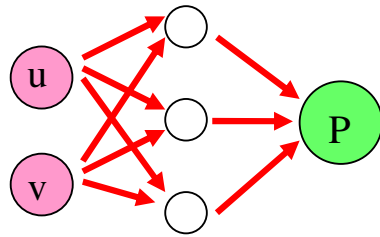Three hidden neurons serve as connectors between input and output with certain weights (Fig. 1).

Figure 1: Architecture of the Neural Network with two input neurons (wind components), three hidden neurons and a single output neuron (normalized wind power).

Starting from the linear solution two additional combinations of initial weights are considered to avoid trapping into local minima.
The two data sets containing analysed and forecasted winds merged with wind power, respectively, are randomly split into training and generalization data sets with same size. Generalization data is absolutely necessary to prevent the Neural Network to learn the training pairs by heart. Otherwise any data not presented before, would immediately overcharge the retrieved algorithm as no generalization is possible. In our case training is stopped, whenever results for the generalization data set get worse than in the previous iteration step.
The generalization data set is not suited for evaluating the performance of the Neural Network. A concluding validation is only possible with completely independent data, e.g. from another time period. We use January to March 2005 to do so.

As a retrieved Neural Network algorithm is a linear combination of weighted input variables, a hypercurve (Fig. 2) of wind power for the whole wind farm can be drawn.
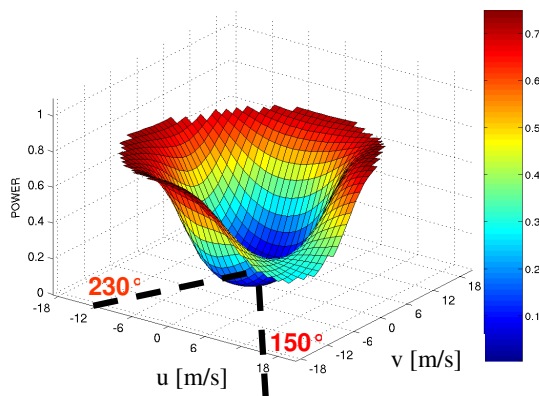

Figure 2: 3-dimensional wind farm power curve (in-land test case) retrieved by a Neural network algorithm depending from u and v wind component. Values are normalized with the installed capacity.

This wind power can be depicted as a surface in a 3-dimensional plot and represents the power curve (Fig. 2) that is depending on u wind component and v wind component. It is possible to adjust the plot in a north-south direction with the wind park in the middle of the plot. Together with a topography map, and a map of indicated obstacles it is straight forward to identify and explain regions of suboptimal flow and performance of the wind farm. Even turbine wake effects can be checked and explained by comparing the wind park power curve with the wind farm layout.
In our case a flattening of performance in the wind farm power curve can be seen at around 150°. This will be addressed in more detail in the next section.

5. Results

The training pairs of wind power and wind speeds are normally visualized in two dimensional scatter plots. In Figure 3 this is done for the wind direction sectors 230° and 150°. Much more training pairs are available for forecasted wind speeds as in total 24
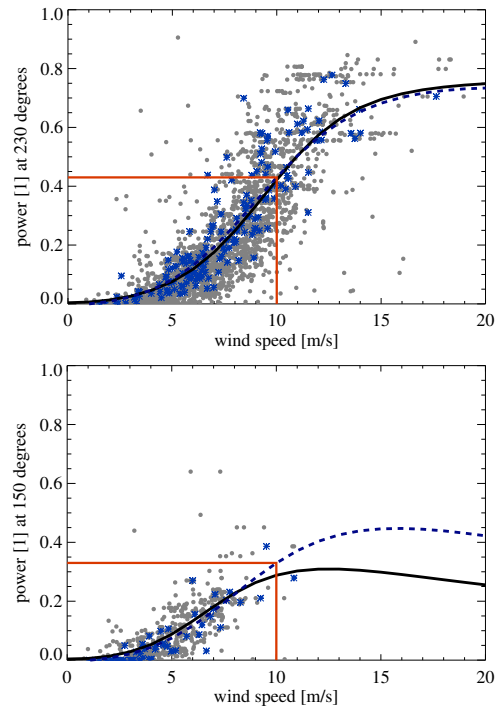

Figure 3: Cross section through a 3-d wind farm power curve (in-land test case) for wind directions 230° (top) and 150° (bottom). Gray bullets represent training pairs with forecasted wind speeds while blue stars mark analysed wind speeds. The retrieved Neural Network algorithm with forecasted winds ("non-sharp") is shown in black (solid line), using analysed wind speeds ("sharp") in blue (dashed line). Sector width is 20°.

forecast steps had been used per forecast run. As expected, their scatter is much larger than for analysed wind speeds as the wind forecasts have a certain degree of uncertainty. Nevertheless the two algorithms that were retrieved by the Neural Network are very similar in the 230° wind direction sector (Figure 3, top).

The wind park has poorer performance in the 150° wind sector (Figure 3, bottom). On one hand no wind speeds higher than 11 m/s occur, but furthermore the power output for 10 m/s is considerably lower compared to the 230° sector, as indicated by the red lines. The deviation between the "non-sharp" and the "sharp" algorithm for speeds larger than 11 m/s is not critically as no wind observations exist.

As it can be already guessed from Fig. 3 the "sharp" and the "non-sharp" algorithm look in a 3-d power curve plot very similar. In order to decide which of the two algorithms performs better, they are applied to forecasted wind in the training period and validated with produced wind power. The root mean square error is shown against forecast time (Fig. 4).

In 2004 the „non-sharp" algorithm (black solid line in Fig. 4), that integrated NWP uncertainty in the training phase, is slightly better than the "sharp" algorithm that was retrieved with analysed winds.

In the independent study period Jan-Mar 2005 the "sharp" algorithm (blue dashed line) has little advantages. Both algorithms got affected by a strong diurnal cycle, which repeats every 12 hours as two forecast runs are used per day.

We believe that the pronounced diurnal cycle is an effect of the different periods in time, i.e. the algorithm has adopted to characteristics in the wind speed distribution that is representative for the entire year 2004, but are not presentative for the first three month of 2005. The problem of representativeness of training and testing data period will be studied in the next chapter, e.g. the effect of systematic wind speed differences.

6. Effect of systematic wind speed differences

Figure 5 shows the wind power forecast error for the near-shore test case. The forecast error is split into
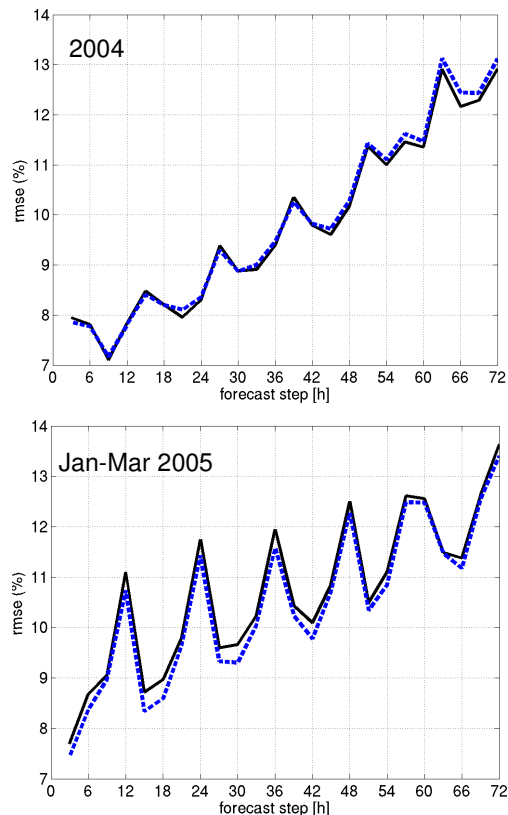

Figure 4: Root mean square error of predicted wind power for the **in-land** test case for the training period (year 2004, top figure) and test period (Jan-Mar 2005, lower figure). "Non-sharp" algorithm in black (solid) and the "sharp" in blue (dashed). The error is normalized with the installed capacity.
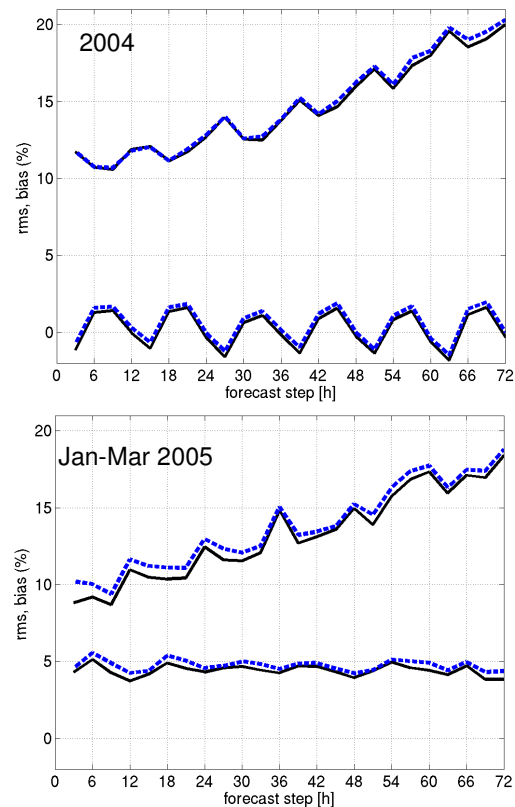

Figure 5: Standard deviation (rms, upper lines) and systematic difference (bias, lower lines) of predicted wind power forecast error for the **near-shore** test case. Training period (year 2004, top figure) and test period (Jan-Mar 2005, lower figure). "Non-sharp" algorithm (black, solid) and "sharp" (blue, dashed).

standard deviation (rms) and systematic difference (bias).

As for the in-land test case no clear difference can be noted for results with the "non-sharp" (black, solid line) and the "sharp" (blue, dashed line) algorithm during the training period (Fig. 5 upper panel). The bias is between ±2% of installed capacity following a diurnal cycle. The overall bias is zero. The forecast error is considerably larger than for the in-land test case (Fig. 4, upper panel), which is a fact of the higher load factor for the near-shore wind farm. The averaged wind power production in the year 2004 was 30?% of the installed capacity at the in-land site, but 60?% at the near-shore site.

For the test period (Jan-Mar 2005) the standard deviation of the forecast error at the near-shore site is less than for the training period (Fig. 5). The algorithm that was retrieved with integrated uncertainty in 2004 slightly outperforms the "sharp" algorithm.

Very notable is the systematic overestimation of wind power of about 5 % (Fig. 5, lower panel) during the test period. As this happens for both types of algorithms the nature is believed to lie in different wind statistics for 2004 and the beginning of 2005.

We also trained a Neural Network with analysed wind speeds for the first three month of 2005 and found an algorithm that has no systematic error. A considerable difference in 3-dimensional power curve for the entire wind farm exists between the algorithm for 2004 and 2005 (Fig. 6). In particular for westerly winds the park performance is higher in 2004 than in 2005 as can be seen by the positive difference.
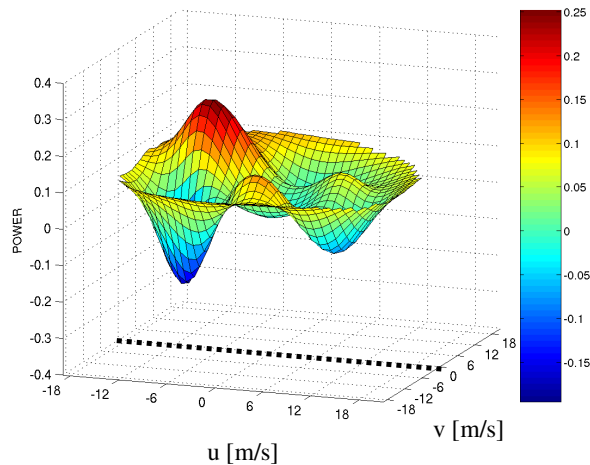

Figure 6: Difference between 3-dimensional power curves for the near-shore test case. Wind park power curve of 2004 minus 2005. The dashed line shows the cross section for a power curve for zonal winds that is depicted in Figure 7.

The wind park power curve for zonal winds is shown in Figure 7 for the period 2004 (top) and Jan-Mar 2005 (bottom).
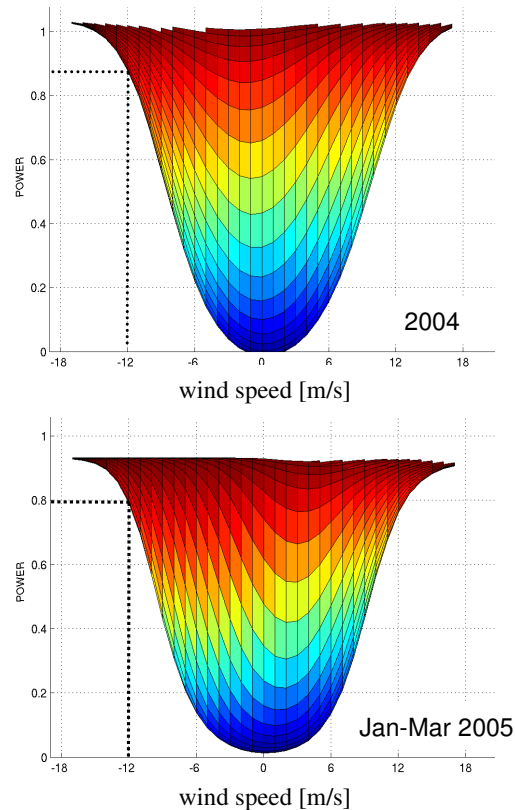

Figure 7: Power curve for the near-shore wind park valid for zonal winds. Analysed wind speeds for 2004 (top) and for Jan-Mar 2005 (bottom) are used for training the Neural Network.

It can be seen that for west wind with 12 m/s the park performance is 0.87 in the year 2004, while it is only 0.8 in the first three months of 2005 as indicated by the dotted lines, i.e. the same wind speed leads to about 10 % more wind power as if the algorithm developed for 2005 is used. It is obvious that if in the beginning of the year 2005 considerably higher wind speeds prevail than on average in 2004, a significant overestimation occurs.

Figure 8 that shows wind speed distributions, confirms this hypothesis in a way that more moderate to strong (> 8m/s) wind speeds in Jan-Mar 2005 than in 2004 occur at the near-shore test site. The reason is natural variability. However, as a result the forecasted wind power in the first three months of 2005 is overestimated by about 5 % as mentioned earlier (Fig. 5, bottom).

Just by the fact that the wind speed distributions in 2004 and in the beginning of 2005 are not equivalent, it can not be explained why the 3-

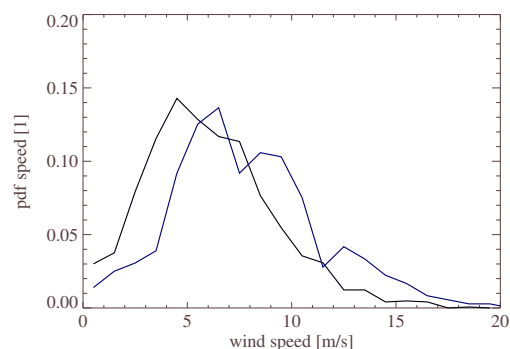dimensional wind park power curves are different for the two time periods (Fig. 6, 7).

Figure 8: Distribution of wind speeds for the year 2004 (black line) and Jan-Mar 2005 (blue) in hub height at the near-shore test site.

As a first step it is essential to check whether time or seasonal dependent systematic forecast errors exist in 2004. The low pass filtered wind power forecast error for the near-shore test site is shown in Figure 9 for the whole year 2004. A very pronounced seasonal dependency can be seen, i.e. about the first half of 2004 the wind power is always underestimated while in the second half of the year 2004 strong overestimations occur in three cycles. It can be already seen that under- and overestimation are very much balanced, i.e. the overall bias for the whole year is zero (Fig. 5, top).
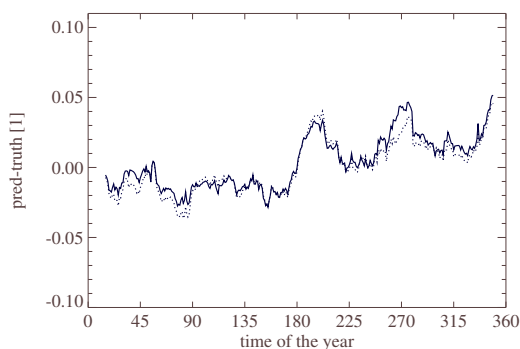

Figure 9: Low pass filtered error in forecasted wind power for 2004 using the "sharp" algorithm (solid) and the "non-sharp" (dotted) Neural Network algorithm.

The solution to the problem can be time dependent power curves. In our case the power curve underestimation (day 1-180) could be alleviated by a power curve that has higher performance, i.e. gives higher wind power at a certain wind level. While for day 181-360) the retrieved power curve is too steep and needs to be broadened. Apparently the same effect as in the beginning of 2005 happens, i.e.

higher wind speeds than on average during 2004 occur. This means on the other hand that during day 1-180 lower wind speeds occurred compared to the whole year 2004.

7. Conclusions

The motivation for this study was the question whether wind power forecasting can be improved by integrating the uncertainty in forecasted wind speeds in the algorithm. For two single wind farms a Neural Network was trained with u and v wind components in hub height as input and historic produced wind power data as output. We found that it is equivalent if analysed or forecasted wind speeds are used for the training as long as no biases or differences in distribution exist. However, the larger scatter in forecasted wind speeds related to produced power is smoothed very well by the Neural Network.
Directional power curve modelling can be done very efficiently and is useful to visualize orographic effects on the large scale flow and to determine turbine wake effects in the wind farm.

In general, the entire algorithm development approach using Neural Networks is hampered by the problem of systematic wind power forecast errors that can occur for time periods outside the training period. This is equivalent to be fact that retrieved power curves can change from time to time. On the other hand the overall results with retrieved wind power algorithms for single sites are very good ranging between 10% and 20% of installed power for forecast day 1 and day 3, respectively.
So far we found one explanation for the bias problem that is inherent for algorithms that are based on Neural Networks: the distribution of input variables to the Neural Network must stay constant as otherwise the training data looses its representativeness. Biases in input data between training and application time are very severe. We believe that time dependent power curve can be the solution to this problem. Test will show how often re-training is necessary and how much historic data is useful in such an adaptive algorithm/system.

It is definitely necessary to investigate if there is a physical explanation to time dependent power curves. Therefore the behaviour of two wind data sets from different seasons that have the same distribution in speed and direction have to tested carefully with the Neural Network. Possible findings are that despite similar winds in hub height the performance of the whole park differs by season because of different thermal stratification or different turbulence intensity. If this is the case additional input variables for the Neural Network algorithms are needed.

Acknowledgements

References

[1] van Hulle, F., and others. *Large Scale Integration of Wind Energy in the European Power Supply: analysis, issues and recommendations.* EWEA Report, December 2005

[2] Tambke, J., C. Poppinga, L. von Bremen, L. Claveri, M. Lange, U. Focken, J. A. T. Bye, J.-O. Wolff. *Advanced Forecast Models for the Grid Integration of 25 GW Wind Power in German.* Proc. of European Wind Energy Conference, Athens, March 2006.

[3] von Bremen, L., *Mikrowellenfernerkundung bei inhomogener Bewölkung.* PhD Thesis at the Christian-Albrechts University of Kiel, Germany. 137 p, 2001.

[4] Jung, T., E. Ruprecht, F. Wagner, 1998: *Determination of Cloud Liquid Water Path over the Oceans from Special Sensor Microwave/Imager (SSM/I) Data suing Neural Networks.* J. Appl. Meteor., **37**, 832-844.

[5] Pinson, P., Siebert, N., Kariniotakis, G., *"Forecasting of Regional Wind Generation by a Dynamic Fuzzy-Neural Networks Based Upscaling Approach."*, CD-Rom Proceedings of the European Wind Energy Conference & Exhibition EWEC 2003, Madrid, Spain, June 16-19, 2003.

[6] Marti, I., San Isidro, M.J., Cabezón, D., Loureiro, Y., Villanueva, J., Cantero, E., Pérez, I., *"Wind Power Prediction in Complex Terrain: From the Synoptic Scale to the Local Scale",* CD-Rom Proceedings of the Conference: The Science of making Torque from Wind, Delft, The Netherlands, April 19-21, 2004

[7] Giebel, G., G. Kariniotakis and R. Brownsword. *The State-Of-The-Art in Short-Term Prediction of Wind power. A literature overview.* Deliverable 1.1 of Anemos Project, July 2003. http://anemos.cma.fr

[8] Downton, R. A., & Bell, R. S., 1988: *The impact of analysis differences on a medium-range forecast.* Meteorol. Mag., 117, 279-285.

[9] Simmons, A. J., Mureau, R., & Petroliagis, T., 1995*: Error growth and predictability estimates for the ECMWF forecasting system.* Q. J. R. Meteorol. Soc., 121, 1739-1771.

[10] Wilson, C., S. Cusack, B. Chalcraft, M. Goeber, J. Bornemann, B. Macpherson, R. Renshaw, A. Maycock, N. Robertson. *Implmentation of New Dynamics in the UK mesoscale model.* Numerical Modelling report No. 434, UK Met Office, 2005.

[11] Wagner, F. *Manual for netfit, version 1.1.* Tech. Rep. Institut für Theoretische Physik an Christian-Albrechts Universität Kiel, Germany. 1996.