Enhanced regional forecasting considering single wind farm distribution for upscaling

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Abstract. With increasing wind power penetration the need for more accurate wind power forecasts increases to raise the market value of wind power. State-of-the-art wind power forecasting tools are considered either statistical or physical. Fundamentally new techniques are rare, thus it is tried to establish a new approach. The spatial decomposition of wind power generation in Germany can be done with principle component analysis to extract the main pattern of variability. They have a physical meaning when linked with typical weather situation. The first four eigenvectors explain about 94 % of the observed variance. The time-evolving principle components are linked with the total wind power feed-in in Germany and are used for its estimation. A new wind power forecasting model has been implemented with this approach and shows very good results that are comparable with state-of-the-art commercial wind power forecast models. The day-ahead forecast error for a common intercomparison period Jan-Jul 2006 is 4.4 %. The suggested approach offers wide ranges for future developments (e.g. several NWP models), because it is computationally very cheap to run.

1. Introduction

Wind power's role in the future worldwide energy supply is increasing. The political will to fight climate change and to become less dependent from importing fossil fuel will boost wind power in the coming years. However, increasing wind power capacities require very good forecasts of wind power to facilitate the integration into the power system maintaining a high level of reliability.

Continuous improvement is essential for all stakeholder on the electricity market regarding save grid integration and operation and successful trading of wind power. [1] have analysed the value of Austrian wind power on the EEX spot and future market and considered the difference between the usage of perfect wind power predictions and state-of-the art prediction accuracy. They found that there is still room for improvements and increased earnings using higher skilled wind power predictions.

In some European countries the penetration of wind power has reached very high shares during low demand periods, i.e. in Denmark occasionally shares of 100 % are reached. The average penetration is 7, 9, 15 % for Germany, Spain and Denmark, respectively. The day-ahead production of wind energy by ten-thousands of wind turbines became predictable with the establishment of "wind power forecasting" as a research subject. The root mean square error of the wind power forecast for Germany is nowadays between 5 and 6 % (normalized with the rated capacity) for the day-ahead (24-48h) [2].

Renewable energy sources (RES) shall reach 20% of the demand in 2020 following political targets. The European Wind Energy Association (EWEA) has announced that European wind energy capacities will increase by a factor 6 until 2030 totalling 300 GW [3]. Consequently it is necessary that wind power forecasts keep on improving over the next years. Better wind forecasts provided from Numerical Weather Prediction (NWP) models will be the key driver. Ensemble Prediction Systems (EPS) are becoming more important to provide reliable probabilistic wind power forecasts [4]. However, the use of EPS may stretch the computational limit of a wind power prediction tool, as computation times may rise be a factor of 50, i.e. when 50 member EPS are used.

This paper presents the first results of a full newly developed wind power forecasting approach that is based on principle component regression. It does not fit in the typical classes of physical [5] or statistical model [6, 7 and 8] as it contains parts of both. The approach to compute eigenvectors is explained in Section 2. Section 3 combines the approach with the total generated wind power in Germany. The skill of the new wind power forecasting tool is presented in Section 4. The last section concludes and gives various perspectives how this new approach can be refined.

2. Principle Component Analysis of Wind Power Generation in Germany

2.1. Data

The overall study period is 1 Oct 2005 to 31 Mar 2007. Verification of results starts 1 Jan 2006. The considered lead time is up to forecast step 72 with a resolution of 3 hours. Only the 00UTC model run is considered. Forecasted model level winds of the forecast model of the European Centre for Medium-Range Weather Forecasts (ECMWF) are interpolated to an universal height of 80m. The considered spatial resolution is 0.5°x0.5° (55 km x 33 km). The forecast model is integrated with a horizontal resolution of about 25x25 km (T799). The standard 10m wind forecast is also used.

Historic wind power generation data in Germany published by the German TSOs and by VDN (Verband der Netzbetreiber, ‘Association of German network operators’) [9] with a delay of one day. The resolution of the data is 15 minutes. However, the verification of wind power forecasts is done on a 3 hourly basis. Observed wind power data has not been low-pass filtered.

The third used data source is the so-called ‘Betreiber-Datenbasis’, a data base that lists almost all German wind turbines [10]. From this database the normalized spatial distribution of wind power capacity over Germany on a 0.5°0.5° grid is computed. Figure 1 (left) shows the distribution with a higher spatial resolution (25x25 km) in absolute numbers for demonstration purposes.

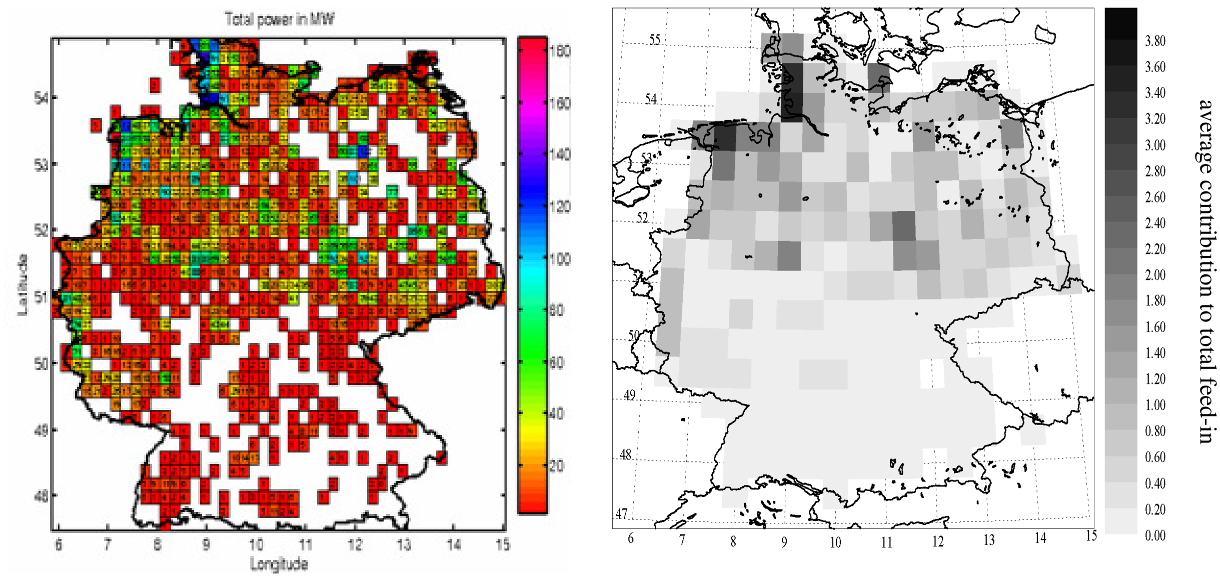

Figure 1: Spatial distribution of wind power capacity [MW] (left) and contribution to total feed-in (right) during 1 Nov - 31 Dec 2005. The rated capacity in Germany is 20.94GW (end March 2007).

In general, the wind power generation of a wind turbine is non-linear related to the wind speed through the powercurve. Wind power is approximately proportional to u^k. The factor k is between 2 and 3. In this study wind speeds over Germany have been squared and multiplied with the normalized spatial distribution of wind power capacity. These wind power weighted squared wind speed maps (ξ) are the input to the principle component analysis of the wind power generation in Germany. The principle component analysis will identify the main patterns that explain the most variance of wind power generation in Germany.

Assuming that wind power generation is hypothetically proportional to u^2, the temporal average of ξ with following normalization provides a map of distributed wind energy generation with the shares quantified in percentage (Fig. 2, right). Obviously, the highest shares are in North Friesland and East Friesland. Both regions have high wind exposure and large installation capacity. There is one region in Sachsen-Anhalt that has got similar high shares than coastal regions.

2.2. Computation of Eigenvectors

Principle Component Analysis is a standard tool to extract linear independent modes from a signal. These modes are called eigenvectors p_j and serve an orthogonal basis to explain with few patterns large shares of the observed variance. Eigenvectors are defined through the eigenvalue equation

$$Cp_j = \alpha_j p_j, j = 1,.., N$$

with C the covariance matrix, N the number of eigenvectors and α the eigenvalues. The number N of eigenvectors and eigenvalus is given by the number of input variables. In this case the wind power weighted squared winds ξ over Germany are given on a grid of 306 cells. Eigenvectors and eigenvalues are time invariant. The variability of ξ is expressed by the principle components c_j that are computed

$$c_j = \frac{1}{\alpha_j} \xi^T p_j, j = 1,..., n \leq N$$

The principle components determine the weight of each eigenvector for a particular state of ξ. When multiplying the principle components to by n≤N eigenvectors, the state ξ can be approximated

$$\xi^* = \overline{\xi} + \sum_{j=1}^{n} c_j p_j$$

The safest (foolproof) way to solve the eigenvalue equation is performed with successive Jacobi rotation. The standard solution is given in [11] but is also available in other numerical libraries.

2.3. Results

The first four eigenvectors for the period 1 Nov to 31 Dec 2005 are shown in Fig. 2. The scale in the legend is arbitrary but is proportional to wind power production.

The first eigenvector (Fig. 2a) explains about 73% of variance and the pattern resembles the map of average production in that time period. By definition the first eigenvector is always a monopole and either lower or increase the average in case of $c_1<0$ or $c_1>0$, respectively.

The second eigenvector (Fig. 2b) has a dipole character and reflects that either the production is high in the South of Germany and low in the northern part or vice versa. The definition of north and south is very relative in this respect. North of Germany means all coastal regions including entire Schleswig-Holstein. The explained variance is 12%. In order to demonstrate that the shown eigenvectors of wind power production are no arbitrary artefacts the following analysis was carried out: The sets of principle components were searched to find cases where all principle components are close to zero but the second pc. A case has been found valid at 16 Apr 2006 12UTC (+57h forecast) with c1=0.11, c2= 3.8, c3=0.18. The surface pressure forecast for Central Europe is shown in Fig 3 (left). A small-scale low pressure system is located in the middle of Germany with a small gradient in the North and stronger gradient in the South. This leads to weak winds in the North. The forecasted wind power in this situation is 23.7% of rated power and the real feed-in was 20.5%.

The third eigenvector (Fig. 2c) is another dipole but separates Germany in a western and eastern part of wind power production. The borderline runs from North-West to South-East. Also for this pattern a very typical situation was found valid at 28 Apr 2006 18UTC (+18h forecast) with c1=0.04, c2=0.1, c3=3.1. It can be seen that the pressure gradients over Eastern Germany is particular low but higher over Western Germany leading to the higher wind production in the West (Fig. 3, right).

The forth eigenvector (Fig. 2d) is a pattern with high production in North-West Germany, Sachsen-Anhalt and Sachsen while the production is low in Southern Lower Saxony. It explains only 2 % of the variance.

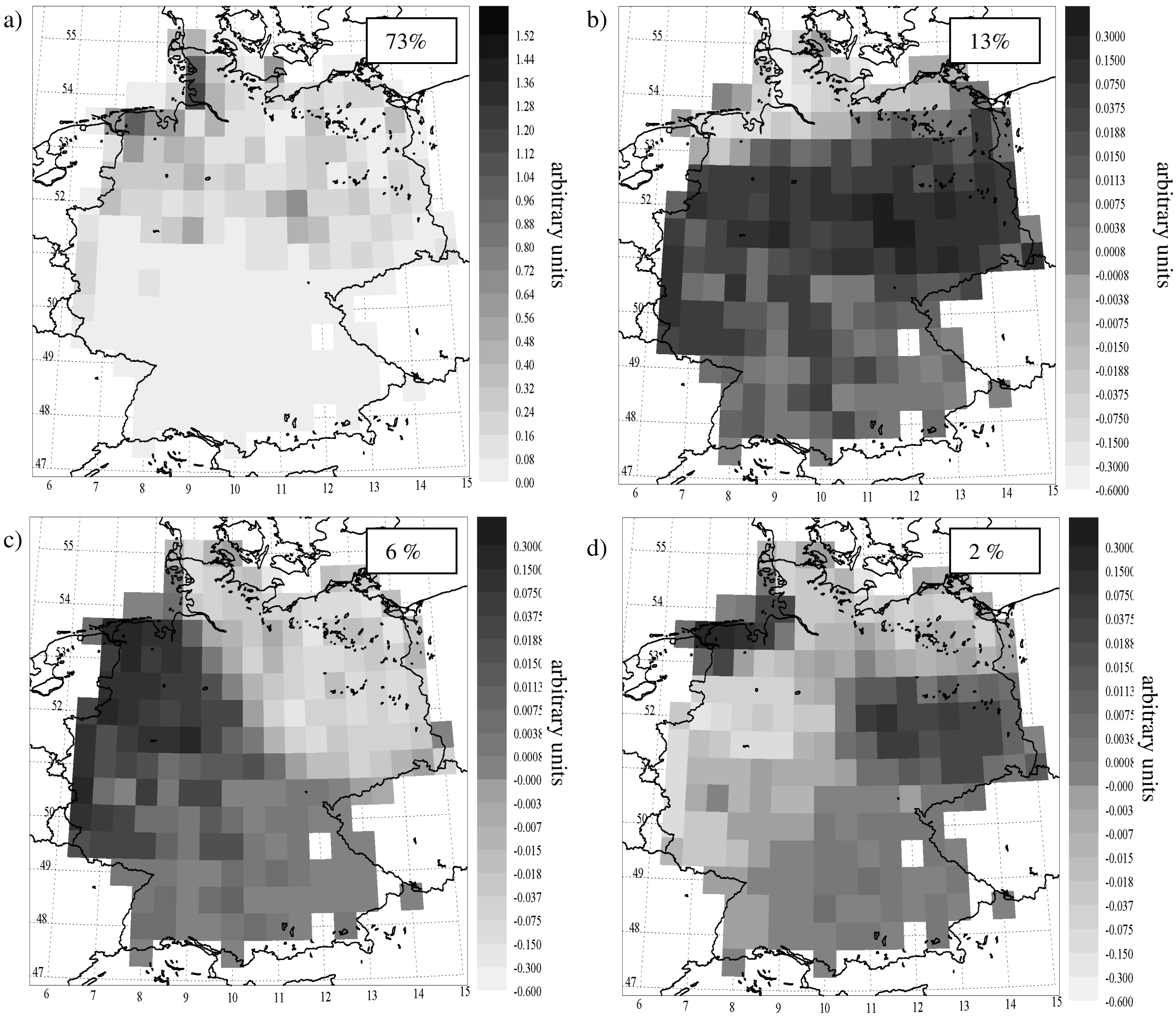

Figure 2: Eigenvectors of forecasted squared wind speeds in 80m height (weighted with the wind power capacity) for 1 Nov - 31 Dec 2005. In a) first, b) second, c) third and d) forth eigenvector. The share of explained variance is given in the upper right corner of each figure.

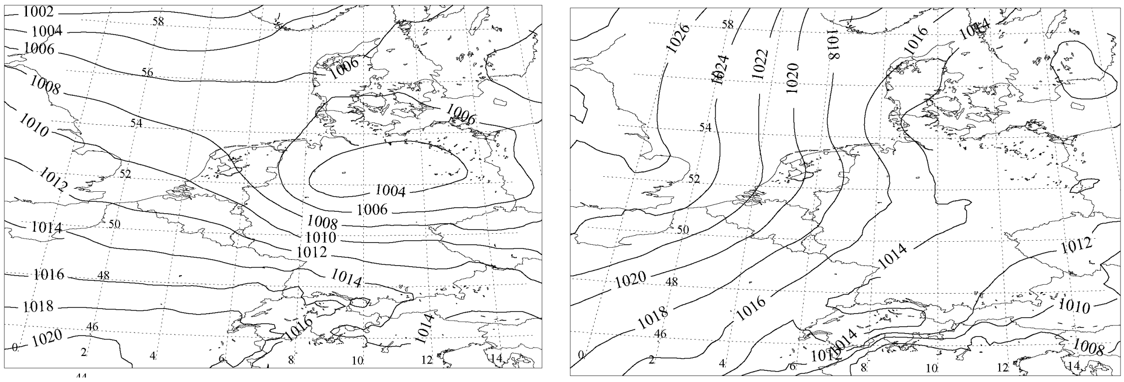

Figure 3: The forecasted surface pressure [hPa] valid at 16 Apr 2006 12UTC (+57h forecast) (left) and at 28 Apr 2006 18UTC (+18h forecast) (right) are typical situations for a strong second (Fig. 2b) and third eigenvector (Fig. 2c) in wind power generation, respectively.

It must be noted that these pattern of wind power generation are solely due to the variability of the wind field over Germany. The weighting with the spatial wind power capacity distribution puts only a constant change (weight). As the first eigenvector is by far the most dominant mode, the interpretation is relatively simple: either the wind field over Germany supports a high wind power at all sites or not.

2.4. Significance of Eigenvectors

It is important to consider if the regarded eigenvectors are significant or if they are a random result. Significance is tested with the simple Farmer-Criteria [12], which rules eigenvectors significant whose eigenvalues are above a straight line when plotted in a logarithmic plot (Fig. 4). It can be seen that at least the 20 eigenvectors are significant.

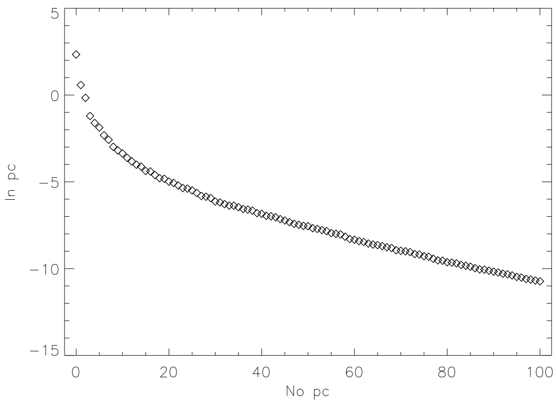

Figure 4: Logarithm of first 100 eigenvalues of forecasted wind power weighted squared wind speeds in 80m height for Germany (1 Nov 2005- 31 Dec 2005).

3. Model setup to predict the total wind power feed-in for Germany

The general approach of the new wind power forecasting model is compute from predicted wind maps ξ^p the principle components and to compute from these the expected total wind power feed-in.

In this section the relationship between the principle components and the total wind power feed-in for Germany is investigated. The principle components of the first eigenvector have the strongest relation to the total feed-in (Fig. 5). In case of virtually zero wind power production the principle component is -1.5. Obviously the relation between the predicted principle component and the total feed-in drops slightly with increasing lead time as the NWP forecasts become more uncertain.

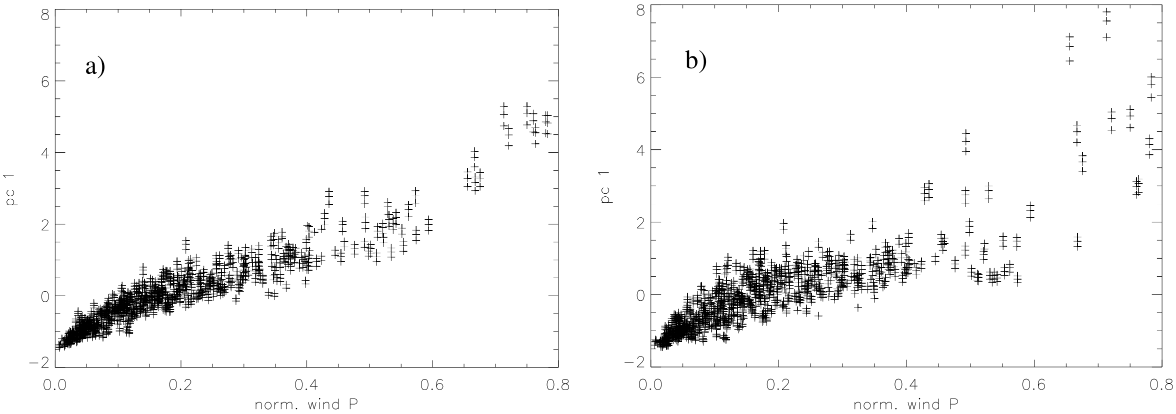

Figure 5: Correlation between the forecasted first principle component of wind power weighted squared wind speed and total wind power production for Germany, a) intra-day and b) two day-ahead.

The new forecasting model consists of the following steps starting from the wind power weighted squared wind speed ξ:

I. Principle component analysis of forecasted ξ using all forecasts (all lead times) of the last 90 days.
II. Computation of principle components c_j corresponding to ξ.
III. Multivariate linear regression analysis between the first six c_j and the (historic) wind power feed-in and storing of regression coefficients.
IV. Calculation of ξ^p from ECMWF forecast
V. Computation of principle components c^p_j that correspond to predicted ξ^p
VI. Application of stored regression coefficients with c^p_j to estimate the total wind power feed-in for Germany

At the moment the regression coefficients are recalculated every 15 days, i.e. the principle component analysis is performed only every 15 days. The consideration of the last 90 days into the principle component analysis it is guaranteed that seasonal changes in the wind field distribution are taken into account.

4. Results

The new wind power forecasting model has been run in two configurations using predicted winds in 80m height and 10m wind speeds. The verification period is from 1 Jan 2006 to 31 Mar 2007. The overall result is given as the root mean square forecast error normalized with the rated capacity (Fig. 6, left) and normalized with the generation (Fig. 6, right). As the rated capacity is increasing rapidly the normalization is not done subsequently but considering the rated capacity valid at the day.

In general, the wind power forecast error shows a strong diurnal variation. In this paragraph the results for 80m height winds are discussed. The peak error can not clearly attributed to a certain time of the day, because it apparently moves from 12/15 UTC in the first half of 2006 (green line, x) to 15/18 UTC for the whole verification period (black line ◊). These effects are attributed to the change of seasons with different characteristics in the daily evolution of the vertical wind profile, i.e. onset of thermal instability during daytime and development of higher wind shear during night.

The usage of 80m height winds is clearly more skilful than 10m winds. The RMSE error is on the average 1 % (relative to the rated capacity) lower.

The forecast error is considerably lower for Jan-Jul 2006 compared to the entire period. This is mainly due the very low load factor of only 14.7 % during this period. The load factor for the entire verification period is 20.8 %. In case the RMSE is normalized with the generation (Fig. 6, right), it becomes obvious that the skill in both periods is similar.

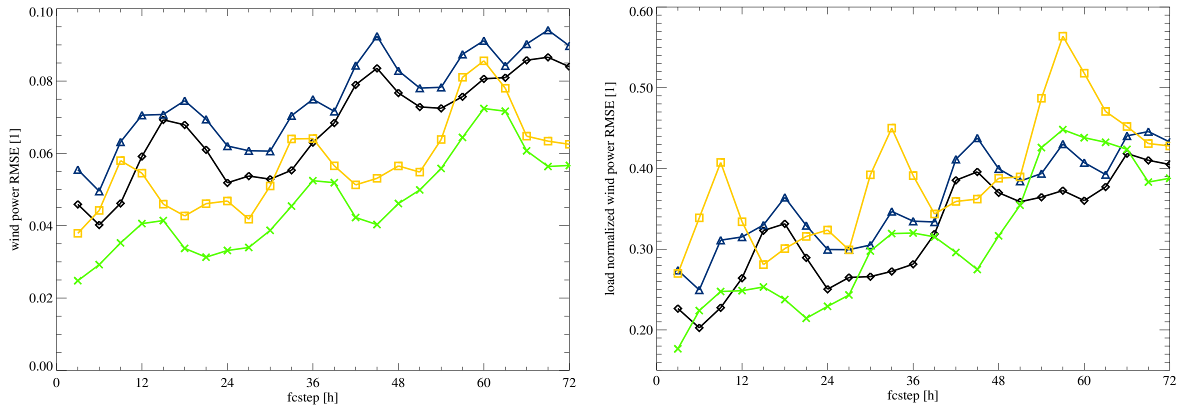

Figure 6: Wind power forecast RMSE normalized with the rated capacity (left) and normalized with the generation (right) for Germany with ECMWF winds in 80m height (black ◊) and 10m wind speeds (blue Δ) for the time period Jan 2006-Mar 2007. The time period Jan-Jul 2006 is shown in green (x) and orange (□) for 80m and 10m height winds, respectively.

The systematic error for 10m winds is very pronounced (Fig. 7, left) and follows a very clear diurnal cycle. During night wind power is severely underestimated as the picking up of the wind in hub height due to thermal stabilization is unrecognized. The overall bias is tuned zero by the method itself, i.e. an overestimation (must) occurs during the day when wind speeds at hub height are lower than suggested (forecasted) due to thermal induced turbulence leading to reduced vertical wind shear.

The standard bias (Fig. 7, right) is slightly negative, which suggests that the forecasted variance of wind power is too low. With increasing lead time the loss for variance (black line ◊) increases which is an obvious problem of any atmospherical modelling.

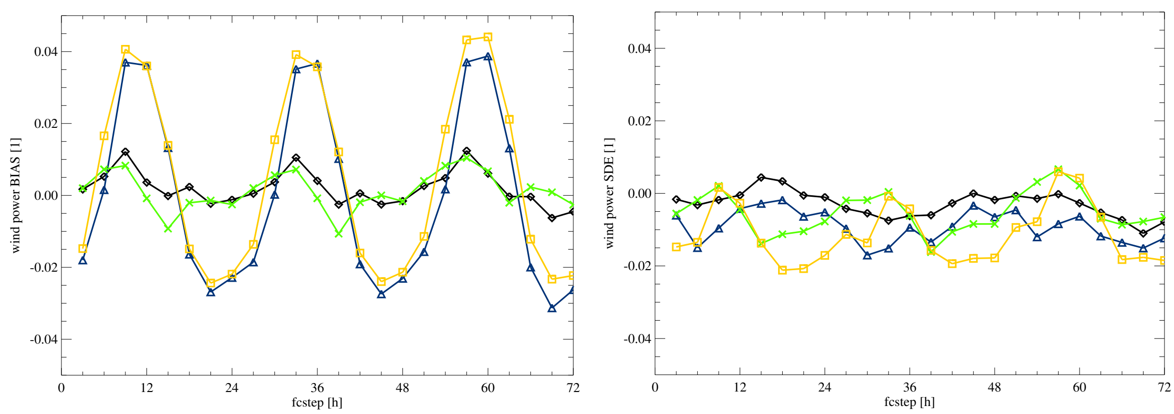

Figure 7: As Fig. 6, but systematic forecast error (bias) (left) and standard bias (right). The standard bias is defined as the difference between the standard deviation of the forecast and the observation.

The results with 80m height winds (Fig. 6, left) are comparable with state-of-the-art commercial wind power forecast models [13, 14]. The day-ahead RMSE forecast error for Jan-Jul 2006 is 4.4 % and 6.1 % for the entire verification period. The two day-ahead RMSE is 6.1 % and 8.0 %, respectively. The model is inexpensive in computational time. The considered 15 months run on a usual single-core PC in about 1 minute. The model is therefore best suited for intense scientific research considering its sensitivity on NWP errors and spatial resolution effects. As Ensemble Forecasting is computationally very demanding to the wind power forecasting tool, the new model can be applied to many test cases and various calibration trials can be carried out to minimize different probabilistic skill scores.

5. Conclusion

We showed that the spatial decomposition of wind power generation in Germany can be done with principle component analysis to extract the main pattern of variability. They have a physical meaning when linked with typical weather situation. The first four eigenvectors explain about 84 % of the observed variance.

The time-evolving principle components are linked with the total wind power feed-in in Germany and are used for its estimation. A new wind power forecasting model has been implemented with this approach and shows very good results that are comparable with state-of-the-art commercial wind power forecast models. The day-ahead forecast error for a common intercomparison period Jan-Jul 2006 is 4.4 %. The suggested approach offers wide ranges for future development. For instance the simple squaring of wind speeds can be refined and linked with a spatial dependency. Furthermore the selected height of the wind forecast can be varied regionally. Most interesting is the breeding of this approach with a multi NWP model setup. Several NWP models can be easily integrated in the principle component analysis.

In a first step it will be necessary to investigate the impact of the used resolution (currently 0.5°x0.5°). It is not obvious that a higher resolution necessarily leads to improvement because eigenvectors are getting noisier which may cause that spatial forecast error smoothing is dropping.

Acknowledgments

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