Confidence in Large-scale offshore wind farming: Wind Power Predictability and stable Grid Integration of 25 GW German Wind Power

Lueder von Bremen, Jens Tambke, Nadja Saleck and Detlev Heinemann[1]

ForWind – Center for Wind Energy Research, University of Oldenburg, Germany

Abstract— **The integration of large shares of wind power from large-scale offshore wind farms is very challenging and economically important. In particular, the German 25 GW offshore wind power scenario is very ambitious to this respect. In our study we address the aspect of wind power predictability using state-of-the-art meteorological data from the European Centre for Medium-Range Weather Forecasts (ECMWF). Weather analysis and forecasted wind speeds in high resolution are analyzed for the years 2001-2005 to show anticipated forecast performance. The aggregation of wind power from regional distributed offshore wind farms is the key factor to reduce the anticipated forecast error significantly. The overall RMSE forecast error is 15% for day-ahead and 21 % for the two-day-ahead. Error smoothing is in particular high in strong wind situations up to forecast step +36h.**

Very low shares of wind power can be forecasted with a considerably higher skill than intermediate wind power production. This is related to the nominal speed of the turbines power curve that uncorrelated to a certain extent the wind power forecast error from the wind forecast error.

The variability of load factors for the planned German offshore wind farms are given for the 5 years that had been analyzed. The average is 48.7 % which corresponds to 106 TWh per year.

Index Terms—**wind power, prediction, forecast, offshore, grid integration, scenario**

I. INTRODUCTION

CONFIDENCE in reliable and save grid integration of large-scale offshore wind power is of primary importance to push the ambitious German offshore plans forward. The challenge of the goal of 25GW wind power capacity in the German Bight by 2030 [1] that was proposed by the German government is a typical scaling problem. At the moment the wind power industry and investors are facing many problems and concerns with respect to technology of offshore foundations, turbines, grid connection, financial risk management and wind resources. Without putting down these problems we believe that they can be addressed and solved on a case by case basis. In contrast to this, the grid integration of large-scale offshore wind power is not at all a case by case problem, it is an integrated problem that increases whenever new offshore wind farms are connected. However, there is no doubt that the integration of high shares of fluctuating wind power will be doable while ensuring stable grid operation. But care must be taken that the costs for required reserve power and regulative power do not render offshore wind power uneconomic for individual stakeholders or the entire domestic economy. With reserve power we mean the share of generation capacity that can not be substituted by wind power. The amount of power generation capacity that can be substituted by wind power relative to the rated wind power capacity is called capacity credit. The capacity credit for onshore wind power in Germany was 7.5 % in 2003 and is expected to drop to 6 % in 2015 with 26 GW onshore and 10 GW offshore wind power [2]. It is in the nature of the capacity factor that it will get lower the higher the wind power capacity gets, because of the even large-scale spatial correlation of wind patterns.

The questions that arise from this integrated look at the German 25 GW offshore scenario are very complex with respect to the requirement on available reserve and regulative power and can be roughly grouped into two categories that need scientific investigation. These categories are *capacity credit* and *predictability* of offshore wind power. In this early stage the type of reserve power is uninteresting, i.e. it may be conventional power production or from other renewable energies or both. When it comes to the point to integrate and combine the answers of the two categories, it will be complex engineering work to decide on appropriate reserve power and storage systems.

Concerning the *capacity credit* of offshore wind farming the fundamental questions are: what is the maximum of required reserve power and for which maximal time period it is needed? What is the frequency of events (minimal return period) that maximal reserves are needed? The answer to these questions will determine the capacity of alternative power generation and the time to refill storage systems. A comparison of approaches to estimate the capacity credit of wind power is given in [3]. Ensslin et al. [3] favors the use of wind time series, local refinement of wind conditions and comparison of wind power

[1] This work was in part funded by the German Federal Ministry for Cultural Affairs, Education and Sciences of Lower Saxony, Germany.

Lueder von Bremen, Jens Tambke, Nadja Saleck and Detlev Heinemann are with ForWind – Center for Wind Energy Research at the University of Oldenburg, Marie-Curie-Strasse 1, 26129 Oldenburg, Germany (e-mail: lbremen@gmx.de).

generation with historic load. In principle his model can be also used to calculate the maximal duration of critical events, e.g. extraordinary low wind power production in high pressure systems, can only be given when looking at historic time series. The minimal return period can be estimated if very long historic time series of wind are available.

The *predictability* of offshore wind power using Numerical Weather Predictions (NWP) is in the focus of this paper. The predictability determines the amount and respond time of regulative power that is maximal required to balance deviations between actual wind power production and forecasted wind power. Although it is not foreseeable how the German and European electricity market will be organized at the time that large offshore wind power penetration are available, it seems to be doubtless that the better wind power predictions can get, costs of integrating wind power will be reduced, which helps wind power to become more and more competitive.

The skill of offshore wind power predictions reflects mainly the skill of wind forecasts issued by various meteorological services worldwide. The downscaling of forecasted wind speeds from large scale wind fields to single wind farm sites is less problematic than onshore, provided no coastal influences are present, since the local conditions are more homogenous. Local effects like locally generated turbulence and distorted air flow due to orographie, obstacles, spatial changes in surface roughness or induced heat fluxes can be disregarded. However, the accurate modeling of the vertical wind profile gains importance as in general much higher wind speeds prevail over sea (typically 10 m/s at 100m height) than over land (7-8 m/s). Simple error analysis using a simple power curve and assuming a fixed absolute error of 0.5 m/s leads to higher absolute wind power forecast errors.

Spatial forecast error smoothing is well-known for onshore regional wind power forecasting [Lange] and helps to reduce the day-ahead forecast (root mean square) error for Germany to 6-8% of the installed capacity (18 GW in 2005) [5].

Tambke et al. [6] started to investigate the anticipated offshore forecast error in the German Bight for the German 25 GW scenario. The analysis was done for the year 2004 and a smoothing factor of 0.73 was calculated. The smoothing factor is the ratio between the regional forecast error and the forecast error assuming the whole capacity is concentrated in one point, i.e. all turbines are at the same site.

In this paper the study period of offshore wind power predictability in the German Bight is extended to the years 2001 to 2005 and empathize is given to the anticipated predictability in extreme situations, i.e. situations with very low and very high wind power concentration. In a first step the probability distribution of anticipated wind power is analyzed to discriminate wind power penetration (Section III). The predictability up to 72h ahead is shown in Section IV and spatial smoothing factors are presented. Section V concludes results and points to future work how to improve current achievable forecast skills. Section II starts to describe the methodology and the used data.

II. Methodology

The predictability of wind power in the German Bight is simulated using wind forecast data of the European Centre for Medium-Range Weather Forecasts (ECMWF). Wind speeds from vertical high resolved model fields are interpolated to a unified height of 100m. 00UTC and 12 UTC model runs are used up to forecast step 72h.

The simulation of wind power is carried out for 22 planned wind farm projects in the German Bight (Fig. 1) and wind speeds are horizontally interpolated to these sites. The original resolution is 1x1° which corresponds to 44km in meridional and 27km in zonal direction at 53°N. The study period is 2001 to July 2005.

For the transformation of wind speeds to wind power a typical multi megawatt power curve is used. The cut-in speed is set to 2.5 m/s, nominal power is reached at 14 m/s and the cut-off wind speed is 25 m/s. It should be mentioned here that in the entire study wind power (production) is used as a dimensionless number that refers to the rated capacity. All results can be therefore immediately multiplied with the (appropriate) rated capacity to get absolute values.

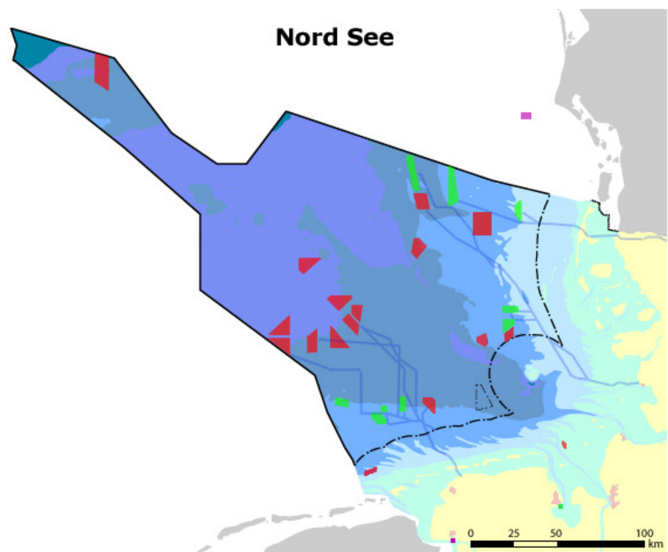

Fig. 1. Offshore wind power project in the German Bight. Green areas mark approved projects by BSH (Federal Maritime and Hydrographic Agency). Red areas mark projects that are subject to approval. Source: BSH.

The validation of predicted wind power is done with ECMWF analysis data that is available every 6 hours on a 39x39km grid. The same interpolations as for the forecast data are applied to these model fields. Wind analysis from operational NWP is a good representation of the true state of the atmosphere according to Tambke et al. [6] who showed the good agreement between FINO1 [7] wind observations in 100m height and wind analyses from the German Weather Service (DWD). The use of ECMWF wind speed analyses in the development of statistical wind power algorithms was shown by von Bremen et al. [8].

The correlation for the year 2004 between FINO1 wind observations in 100m height and ECMWF analyzed wind speeds is 0.95. The root mean square error is 1.55 m/s. FINO1 are only considered at the synoptic hours of 00, 06, 12 and 18 UTC. Furthermore the speeds are linear averaged over 80 minutes around the synoptic hours to take into account that the wind speed in the ECMWF analyses represents a spatial average for a size of 39x39km². Therefore the variability of the FINO1 observations must be downgraded for a fair comparison. To calculate the appropriate averaging time we estimate the time that air parcels in the grid cell needs to pass the sensor (anemometer at FINO1). The effective distance that air parcels have to travel can be approximated with the diameter of a circle that has the same size as the grid cell. The effective distance is therefore about 44km. Assuming an average wind speed of 10m/s, results in a traveling time of t=80min, that corresponds to the appropriate averaging time. The temporal averaging makes the variance of FINO1 as a point measurement comparable to the ECMWF analyses. The variances are 22.3 m^2/s^2 and 21.7 m^2/s^2, respectively. Apparently, FINO1's variance is still too high, or it is better to say that the variance of the analysis is too low. Without temporal averaging FINO1's variance is 22.7 m^2/s^2.

III. Historic Wind Power Production in the German Bight

In this section the wind power production for the 22 wind park projects in the German Bight are estimated according to wind speed analyses January 2001 to July 2005.

Fig. 2 shows the cumulative distribution of anticipated (normalized) wind power production. More than 10% of the time nominal power is produced. And about 20% of the time 95% of nominal power is reached. Another 20% of the time the power yield is less than 10.2 %.

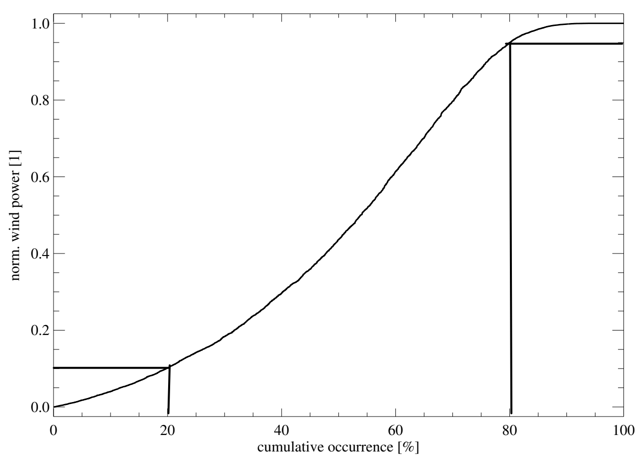

Fig. 2. Cumulative occurrence of anticipated wind power production in the German Bight for Jan 2001-July 2005. The two enveloping lines indicate the standard deviations among the 22 considered wind parks. The power production is normalized with the rated capacity. The vertical bars indicate the 20% and 80% percentile, that are used to divide the data set in low, intermediate and high wind power production.

The annual variability of anticipated wind power production is shown in Fig. 3. The smaller the area under the cumulative distribution functions the lower the produced wind power. The year 2003 shows a particular low yield of wind energy. The other years have about the same performance with respect to occurrence of wind power production less than 0.8. Year 2001 has considerably less strong winds that correspond to power production values between 0.8 and 0.95. Note the dent of the black (solid) line.

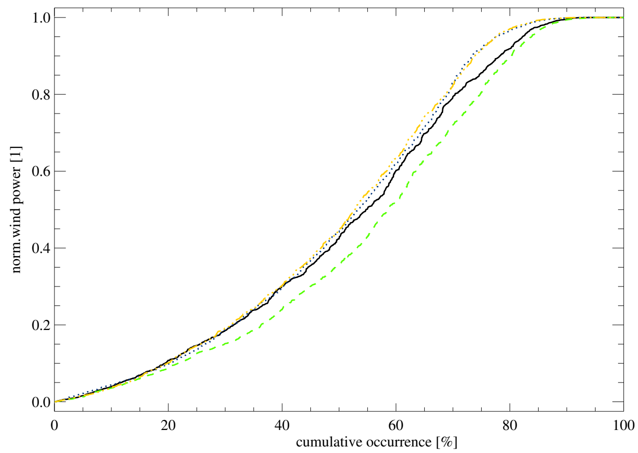

Fig. 3. Individual cumulative occurrence of anticipated wind power production in the German Bight for the years 2001 (black, —), 2002 (blue, ···), 2003 (green, - -) and 2004 (orange, – ··).

The average load factor for the planned wind projects in the German Bight is calculated with ECMWF wind analyses and is 48.7% of the rated capacity. This leads to an anticipated average annual wind power yield of 106 TWh for the 25 GW scenario.

Fig. 4 shows the intra-annual and inter-annual variability of the load factor. Seasonal differences dominate the variability. The highest power yield is expected in March while the weakest season is the end of summer (August, September). The strongest seasonal signal occurred in 2001, where the beginning of the year started with high yields of almost 54% of rated capacity. However, in August 2001 the lowest load factor in the whole study period occurred (43.5%). As already mentioned above the wind year 2003 was very poor. In all months of 2003 the load factor is lower than the 4½ year average.

The enveloping red lines show the standard deviation that exists between the individual wind farms. The spatial difference in wind resources does not show a seasonal dependency, i.e. the standard deviation is constant in time. The load factor of some wind parks is always higher than the average of 48.7 % for all parks.

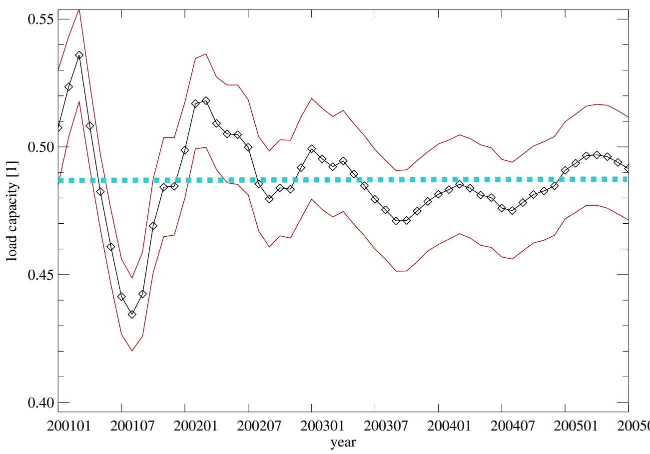

Fig. 4. Monthly load factor for the 25 GW German Wind Power scenario from 2001 to mid 2005 as anticipated from ECMWF wind speed analyses. The enveloping lines represent the standard deviation among the 22 wind farms. The straight line marks the average load factor of 48.7 %.

IV. Predictability

In this section the anticipated skill for wind power forecasts for the planned wind parks in the German Bight is studied. The validation is focused on the normalized RMSE error, which is depicted every six hours against the forecast step (Fig. 5). The forecast error is shown for all 22 wind parks individually. The average forecast error is the bold solid line (yellow with ●). The skill of an aggregated forecast (green line with ×) is considerably higher as forecast errors are balancing each other (spatial error smoothing). The RMSE ranges from 7% at forecast step +6h to 23.5% at forecast step +72h.
The beneficial effect of spatial error smoothing is expressed by the smoothing factor that is defined and discussed in more detail at the end of this section.

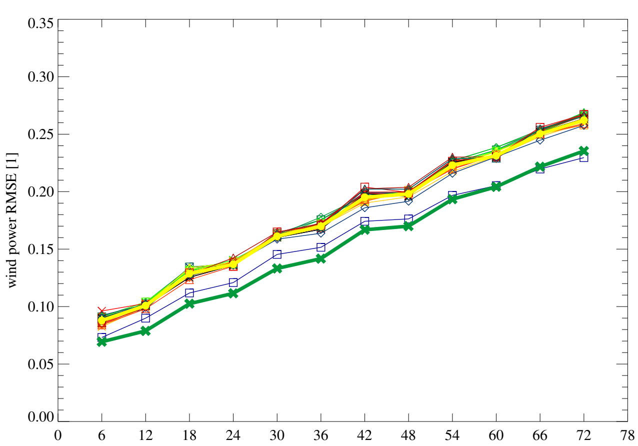

Fig. 5. Root mean square wind power forecast error (RMSE) for the German offshore wind park scenario calculated for the period April 2001-July 2005 with ECMWF data. All thin lines represent the performance for the individual parks and the yellow (solid with ●) the average performance. The lower green line (solid with ×) is the spatially smoothed prediction.

A. *Low and high wind power production*

It is of interest for the integration of wind power to know the skill of wind power forecast in the lower and upper limits of possible wind power penetration. Therefore it may give confidence to a transmission system operator (TSO) to know that the occurrence of low wind power penetration is better predictable than other situations. In this case he will calculate with lower uncertainties when buying the (large) shares of conventional power to substitute the (missing) wind power.
The same is true when wind power penetration is high. The TSO would react more conservative when knowing that the expected forecast error is high compared to less conservative when he believes that the forecast error will be small.

The complete data set is divided into classes of expected (forecasted) wind power production. The bins of the classes are defined by the occurrence of wind power production. Data with total (all parks) power production of less than 10.2% of nominal power are put into the first class. They represent the 20% percentile of the cumulative occurrence (Fig. 2). The second class is the 20% to 80% percentile and the third class holds events that have wind power production larger than 95% (80% percentile). For each class the forecast skill (RMSE) is shown (Fig. 6). The interpretation will focus on the performance of the aggregated (regional) forecast.

In fact, it can be seen that the forecast error is much smaller than for the complete data set. The RMSE is 3% (7%) at forecast step 6 and increases to 19.5% (23.5%) at forecast step 72h. The forecast error for all data is given in brackets.
The forecast error is larger for intermediate wind power production (Fig. 6, middle). They increase from 8.5 to 26 %, respectively. For very high wind power productions the forecast error is about the same as for low wind power production. The later means full power production can be better forecasted than half power production. This is understandable as wind forecasts in the range of 14 to 25 m/s (dependant on the power curve) correspond to the same wind power forecast, i.e. nominal power, i.e. wind power and wind forecast error are in this range uncorrelated.
In this context it must be mentioned that storm cut-off of offshore wind parks is or will be a serious issue with respect to massive power losses and therefore stable grid operation. Within minutes several hundred megawatts of a single wind farm might be shut off, when the cut-off wind speeds is exceeded. As the area where the German wind park will be build is relatively small (about 180km in diameter), it is very likely that various wind farms will be subject to storm cut-off.
In the study period of 4 ½ years the wind speed of 25 m/s was exceeded several times for individual wind farms, in both forecast and analysis. Table I shows the validation how good the storm cut-off forecast is expressed as hit/false alarm rate. A storm cut-off occurred without being forecasted in 0.078 % of all cases. A storm cut-off was forecasted but did not happen in 0.043 % of all cases. In 0.056 % of all cases a storm cut-off was forecasted correctly. Evidently the number of storm cut-offs is very much dependant on the cut-off wind speed that may vary with the turbine type.

	Hit	False
Hit	**0.056%**	0.043%
False	0.078%	**99.82%**

Table I. Hit/false alarm rate in percentage for prediction of storm cut-off. Predicted events are given in the rows and anticipated, i.e. events in the columns.

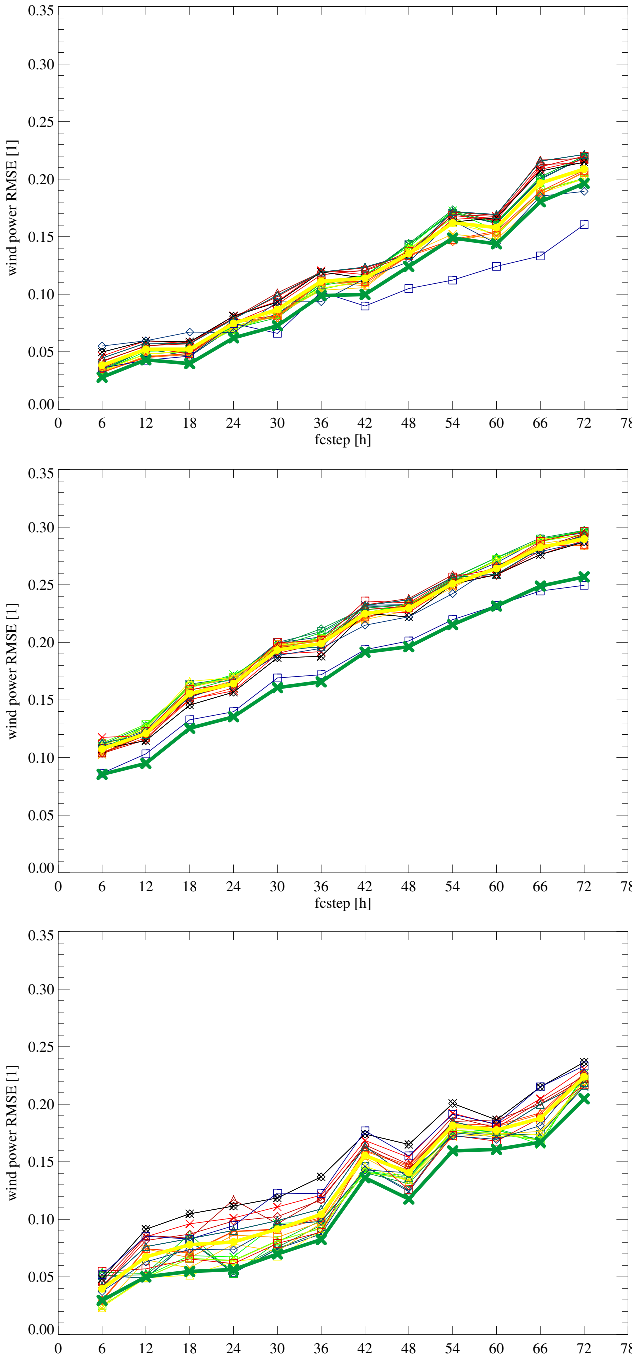

Fig. 6. Same as Fig. 6, but the validation of the forecast error is divided into forecasted wind power production classes (0-8.75% (20% percentile, top), 8.75-99.1%, (20-80% percentile, middle) and >99.1% (80% percentile, bottom)). The average forecast error is marked in yellow (solid line with ●). The lower green line (solid with ×) is the spatially smoothed forecast error.

B. Spatial forecast error smoothing

The beneficial effect of spatial error smoothing is expressed with the smoothing factor. It is defined as the ratio between the regional forecast error and the forecast error assuming the whole capacity is concentrated in one point, i.e. all turbines are at the same site.

The regional smoothing factor (ratio between the lower green line (solid with ×) and the thick yellow (solid with ●) in Fig. 6) is calculated for each of the three defined power production classes and is depicted in Fig. 7.

Regional error smoothing has the most positive effect in high wind power conditions (green line with ×) up to forecast step +36h. The regional forecast error is only 72% (at day 1) of the error if all wind power is installed in one place, which is given by the average forecast error of all individual wind parks.

Error smoothing is smallest for low wind power production from forecast step +36h onwards. The smoothing effect is considerably lower (the factor is higher) than for the other two classes with higher wind power production.

The overall smoothing factor (orange, □) ranges from 0.82 at day 1 and day 2 to 0.88 at day 3. Tambke et al. [6] found an average smoothing factor for the first 48hours of 0.73. The difference to their study is the longer study period, Tambke et al. used only year 2004, and secondly that they used the wind speed analyses of the German Weather Service (DWD) for the validation. It is evident that forecast errors gets less correlated, because the DWD analysis is less correlated to the ECMWF forecast than the correlation between ECMWF analysis and the forecast.

The ratio behind the forecast error smoothing is that forecast errors at individual sites are to a certain extent correlated. The more they are correlated, the smaller is the positive (balancing) effect of regional error smoothing. Or the other way round, the more uncorrelated individual forecast errors are, the stronger is the effect of regional smoothing.

For the case of very high wind power production the nominal wind speed of the turbines power curve plays again an important role to understand the high error smoothing up to forecast step +36h. Once the nominal wind speed is reached, the correlation of wind power forecast errors drops automatically to zero. This explains the very strong error smoothing in case of high wind power production. Apparently the prediction of wind speeds that exceeds 14 m/s has a good forecast skill up to +36h ahead.

To explain why the error smoothing effect is weaker for low wind power production, the nature of synoptic systems must be analyzed. The correlation between individual forecast errors gets higher the less the whole synoptic situation is characterized by advection. If forecast errors are more dependent on local conditions or developments, then forecast errors of individual adjacent sites are higher correlated, i.e. once the forecast for a region is wrong and the flow is non-advective, future forecasts will also be wrong (with the same sign).

Synoptic systems with low advection are characterized by low pressure gradients and are often more stable than other situations, e.g. persistent high pressure systems. The low pressure gradient is the link to the calculated low spatial error smoothing for low wind power production.

The benefit of spatial forecast error smoothing is therefore from forecast step +42h onwards highest in advective westerly weather conditions with intermediate wind speeds and wind power production (blue line, Δ in Fig. 7).

Analysis errors are also the explanation why the smoothing factor depends on the forecast step, i.e. the effect of error smoothing declines with the look-ahead time. The relative importance of analysis errors compared to model errors increases with the integration of the forecast model [9,10]. Thus regional forecasts are affected as a whole. This is equivalent to stronger correlation of forecast errors between single sites and therefore less error smoothing.

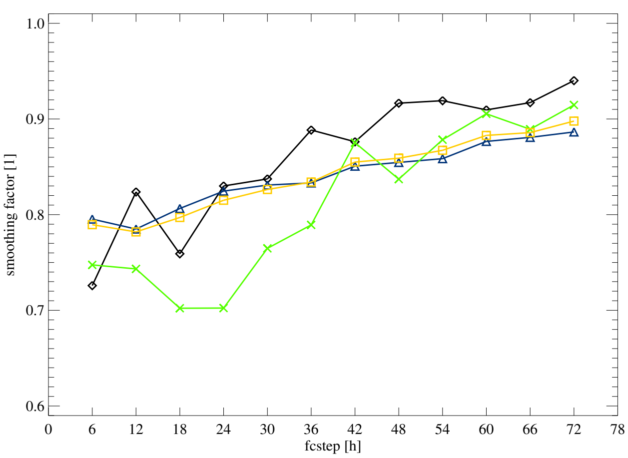

Fig. 7. Spatial smoothing factor for different wind (forecasted) production classes (black, ◊), 20-80% (blue, Δ), >80% (green, ×) and all classes (orange, □) in the German Bight, as calculated with ECMWF forecast and analysis data for April 2001-July 2005.

V. CONCLUSIONS

The German scenario to integrate 25 GW of offshore wind power is a challenge itself. It is of primary importance to know beforehand how good offshore wind power will be predictable with state-of-the-art meteorological data. The knowledge about the predictability of 25 GW will determine grid integration and bid strategies of all stakeholders on the future electricity market.

High resolution weather analysis and forecasted wind speeds from the European Centre for Medium-Range Weather Forecasts (ECMWF) are analyzed for the years 2001-2005 to calculate the anticipated forecast performance on a 6 hourly basis. A standard multi-megawatt power curve was used, that reaches nominal power at 14 m/s.

Preparatory work was done to calculate the power output of the 22 planned German offshore projects in the time from 2001 to July 2005. The load factor was found to be 48.7%. Inter-annual differences can be identified, i.e. 2003 was the weakest wind year. The seasonal variability within a year is well represented and was highest in 2001 with 20 % relative to the average load factor. The average annual wind power yield is 106 TWh for the 25 GW scenario in the German Bight.

The skill score for the predictability of wind power is the normalized RMSE. It increases from 7% at forecast step +6h to 23.5% at forecast step +72h for the regional aggregated wind power forecast. The average RMSE for day-ahead is 15% of the installed capacity.
It was found that the predictability of either low or high wind power production is considerably higher than for all situations. The nominal wind speed of the turbines power curve makes the wind power forecast independent of the wind forecast error and helps to reduce the wind power forecast error.

Spatial forecast error smoothing reduces the regional forecast error to 82% of the error for a single site for the day-ahead. The error smoothing effect is highest for strong wind situations since the wind power forecast error correlation gets minimal when some wind parks reach nominal power. On the other hand error smoothing is minimal for low wind power production for forecast steps larger than 36 hours.
The error smoothing effect declines with increasing look-ahead time as the regional forecast error growth is more and more determined by analysis errors.

When comparing the obtained offshore results with state-of-the –art onshore predictions for Germany, one has to bear in mind that i) the load factor is more than twice as high than over land and that ii) the effect of regional smoothing is considerably smaller. The effective size of the German offshore wind farms is only 180km in diameter, whereas the effective size of the German onshore wind power is larger by a factor of about 3.

Future work will show if the usage of an independent analysis will increase the effect of error smoothing that can be anticipated. There are still plenty of possibilities to improve the quality of offshore forecasts. NWP models are improving rapidly with increasing horizontal and vertical resolution, better parameterizations and better initial conditions. In the field of wind power forecasting the combination of output different NWP models [11,12,13] or the use of single-model ensembles [14] has great potential. Ensemble forecasts clearly outperform single-model predictions and allow the estimation of forecast uncertainties at given confidence levels. Ensemble techniques are superior to improve the skill of offshore wind power predictions, because NWP analysis uncertainties are the predominant source for offshore wind forecast errors and the initial aim of ensembles is to provide an adequate solution, i.e. relate analysis uncertainties into forecast uncertainties that can be quantified.

VI. ACKNOWLEDGMENTS

The European Centre for Medium-Range Weather Forecasts (ECMWF) gratefully provided wind forecast and analysis data.

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VIII. BIOGRAPHIES

Lueder von Bremen was born in Bremen (Germany) on May 08, 1972. He studied Meteorology at the University of Kiel (Germany). He wrote his PhD on Satellite Meteorology and Remote Sensing of clouds.

He was working for 3½ years as a consultant in the Research Department of the European Centre for Medium-Range Weather Forecasts (ECMWF). In the beginning of 2005 he started his career in wind power forecasting at ForWind (Center of Wind Energy Research at the University of Oldenburg, Germany). In his position as project leader he has developed different wind power forecasts methods for various offshore wind farms. Together with his team he designs a new wind power forecasting tool for Germany with integrated uncertainty prediction.

Jens Tambke graduated at Oldenburg University in 2004 (MSc in Physics). He works on offshore wind power meteorology, especially in atmospheric boundary layer modelling, air-sea interaction and wind power forecasting.

Since 2003 he leads the ANEMOS workpackage for offshore predictions and coordinated the with the wind power forecasting model (PREVIENTO) to the model intercomparison within ANEMOS. Jens Tambke is one of the developers of the new ICWP-model to simulate offshore wind profiles. He is about to finsish his PhD about offshore wind power forecasting.

Nadja Saleck graduated with a MSc in Environmental Sciences from University of Oldenburg in 2002. She worked in the field of climate change at the Leibniz Institute of Marine Sciences (IFM-GEOMAR), University of Kiel, and wrote her PhD in 2005.

Hereafter she is working on wind power forecasting at the Center for Wind Energy Research (ForWind), University of Oldenburg in a project for decentralized energy management. Her main task is to develop forecasting models for the integration of local wind power into the regional grid.

Detlev Heinemann is senior scientist in the Energy and Semiconductor Research Laboratory (EHF) of the Institute of Physics at University of Oldenburg. He received a Diplom degree in Meteorology from Kiel University and holds a PhD degree in Physics from Oldenburg University. He is head of EHF's applied renewable energy group and has managed numerous national and international research projects related to renewable energy systems with emphasiz meteorological aspects. Mr. Heinemann is scientificly responsible for the Center for Wind Energy Research (ForWind) at the universities Oldenburg and Hannover. He is also spokesman of the virtual Institute for Energy Meteorology (vIEM), a joint institution of Oldenburg University and the German Aerospace Center DLR.