Meteorological Models for Prediction and Simulation of Wind Power

L. von Bremen
N. Saleck
U. Gräwe
J. Tambke
D. Heinemann
ForWind – Center for Wind Energy Research, University of Oldenburg
lueder.vonbremen@forwind.de

Abstract

Numerical Weather Predictions (NWP) can be regarded as the backbone for energy meteorologists when predicting highly fluctuating wind and solar power. While the meteorological forecast models simulate on the world largest supercomputers the passing of high and low pressure systems, including temperatures, clouds, rainfall and many other meteorological parameters, these meteorological parameters are post-processed by energy meteorologists with their own models, e.g. wind power prediction models, to meet end-users' requirements. End-users for wind energy predictions are transmission and distribution system operators (TSOs and DSOs), wind farm operators and energy traders.

Day-ahead RMSE wind power forecast errors for Germany are in the range of 5-6% while single wind farm forecast errors are higher (between 14% and 17% for onshore wind farms and 14-22% for offshore wind farms) due to the missing effect of spatial forecast error smoothing. New methods in wind power prediction are under development and the end-user will benefit from combined NWP forecasts and ensemble predictions that will make forecasts for single wind farms more accurate. These methods will also allow to give reliable measures of uncertainty.

Wind power generation for the German 50 GW wind power scenario (25 GW onshore & 25 GW offshore) is simulated with weather analysis and NWP forecasts. The distributed generation of wind power is favorable in terms of steadiness of wind power and reduction of day-ahead wind power prediction error. The average day-ahead RMSE is simulated to be 4.25 GW. The corresponding onshore RMSE is 5.1 GW, provided that on average the same amount of wind energy is generated, i. e. 121 GW of onshore capacity is needed. The weekly variability of on- and offshore distributed wind power is in its extremes at least a factor two smaller than if the generation would be only onshore. The results of this study support the idea of distributed on- and offshore wind power generation and show that on a larger scale Renewable Energy Sources are less fluctuating than suspected.

Introduction

After decades of hypothesis, warnings and intense climate research, the Intergovernmental Panel on Climate Change (IPCC) [1] makes it undoubtedly clear and constitutes that the currently seen warming of the Earth is related to the extensive release of greenhouse gases and in particular to the burning of fossil fuel that is needed to meet our excessive energy demand. Although climate change has already started to show its face in many regions of the world with the increase in extreme events (heavy precipitation, more intense and longer droughts, more intense tropical cyclone activity in the North Atlantic) and slow transitions (melting glaciers and permafrost, decrease of Arctic sea ice extent), we are far from the climate that correspond to the current (2005) level of 379 ppm (parts per million) carbon dioxide (CO2) in the atmosphere. The lead times are decades.

The current increase of CO_2 in the atmosphere (1.9 ppm per year) is suspected to be higher in the forthcoming years due to the fast industrial growth in many of the emerging nations, but in particular the BRIC countries (Brazil, Russia, Indian, China). The projection for the most positive scenario (B1) with 600 ppm CO_2 in 2100 predicts that the worldwide average temperature will be 1.8 °C higher relative to 1980 to 1999. Currently the Earth is (only) 0.74 °C warmer than hundred years ago.

One of the most regarded reports on the economics of Climate Change is the Stern Review by Sir Nicholas Stern [2] that urges immediate action to avoid the worst impacts of Climate Change. The fight of Climate Change will cost (only) 1% of global GDP when strong actions to reduce greenhouse gas emissions are taken immediately and a stabilisation at 440-480 ppm CO2 can be reached. If no action is taken, the concentration of greenhouse gases could reach double its pre-industrial level as early as 2035, virtually committing to a global average temperature rise of over 2 °C (in 2035). It is estimated that no action will be equivalent to losing at least 5% of global GDP each year, now and forever. In that case climate adoption is likely to become a global social problem concerning the resource of appropriate living conditions for mankind.

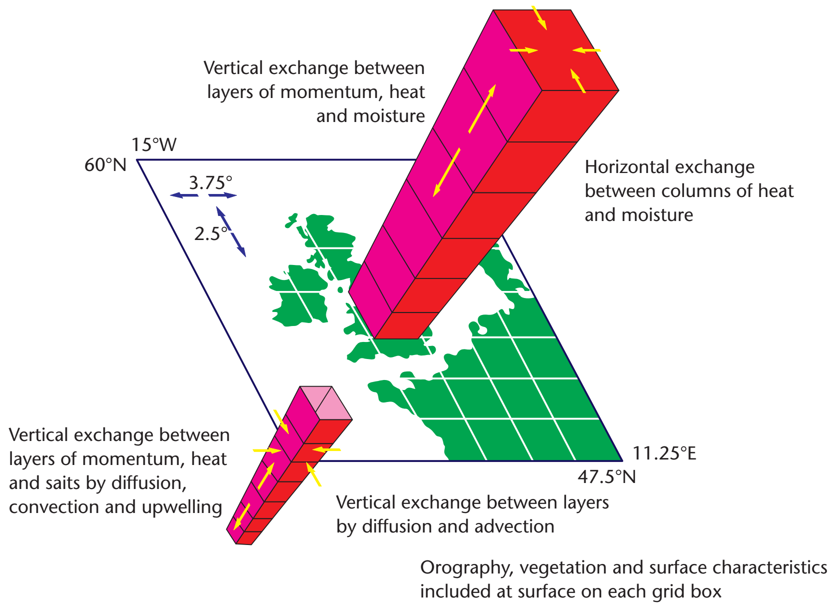
Better later than never politics started to regard Climate Change as a global threat. Most of the western industrial countries take the responsibility and role to lead the discussion of climate protection. Lately the European Union leaders announced plans to slash greenhouse gas emissions by 20% relative to 1990 in 2020. Renewable Energy Sources (RES) shall meet 20% of total energy use. As a side-effect RES will reduce Europe's dependency from natural gas, crude oil imports and will help to phase out the use of nuclear power, which is not favorable for the majority of Europeans [3].

Onshore wind power is the success story of the Renewable Energy Sources worldwide and surpassed already in the end of 2005 the EC White Paper [4] targets of 40 GW in EU-15 that was initially set for 2010. Obviously, the integration of high shares of wind power is not a given prerequisite but experiences in Denmark shows that even very high penetrations (20% on average) of wind power can be managed. Besides technical constraints concerning the transmission network day-ahead predictions of wind power are an essential part of save grid integration. In Germany the integration of about 20 GW of installed wind power is nowadays supported by professional wind power forecasters [5].

High accuracy on estimated wind power production is needed for the efficient integration of large shares of 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. 22% of Europe's electricity production from wind power by 2030 [6]) shall be met.

Although not established yet in Germany, day-to-day trading of offshore wind power at the

Figure 1
Representation of the atmosphere and its physical processes in atmospheric models



spot market is suspected to become an attractive additional part of the earnings for wind park investors besides guaranteed fixed feed-in tariffs. The monetary benefits of short-term wind power forecasts are highlighted for Spain and the UK in [7].

High-Resolution Numerical Weather Predictions (NWP) of wind play the key role for wind power forecast and are issued from several NWP Centers worldwide. Starting from initial conditions that are derived from hundred thousands of observations (radiosondes, aircrafts, satellites), the air flow in the atmosphere is simulated and integrated forward in time with the world largest supercomputers. The underlying weather models are based on the representation of the atmosphere as grid boxes and on the description of the principle laws of physics as mathematical equations *(fig. 1)*. The beginnings of Numerical Weather Predictions can be found in [8], details on modeling are described in [9] and in [10] the 30 years history of the most successful NWP centre, the Centre for Medium-Range Weather Forecasts (ECMWF [11]), can be found.

The spatial scales range from global models to Limited Area Models (LAM) having horizontal resolutions between 25 km and 2.8 km, respectively. The forecast horizon is typically 3 days for LAM and up to 10 days or even longer for global models. Typically the disseminated forecasts have a temporal resolution of 1 h, while the internal forecast step is between 12 minutes for global models and 30 sec for the highest resolved LAM.

The aim of this paper is to give examples of the various usage of modern NWP models in the field of wind power forecasting and grid integration. In chapter “Wind Power Forecasting” the principles and results of wind power forecasts for regions (Germany) are given. Chapter “Wind Power Forecast for Single Wind Farms” focuses on the predictions for single wind farms using the combination of different NWP models and ensemble prediction systems (EPS). In chapter “Simulation of Germany’s 50 GW wind power scenario” data from NWP models is used to estimate the expected wind power forecast accuracy of future large-scale wind farms and to calculate coherence of onshore and offshore wind power generation.

Wind Power Forecasting

Wind power prediction (WPP) models are roughly divided into two groups: statistical models and physical models. A comprehensive overview on models is given in [12].

Physical Wind Power Prediction

Physical WPP models compute local wind power from large-scale NWP wind forecasts as follows: i) spatial refinement (e. g. horizontal interpolation), ii) calculation of the wind speed at hub height (e. g. extrapolation of 10 m surface wind considering thermal stratification or use of high level NWP model fields), iii) consideration of surface roughness changes, iv) losses due to turbine wakes in the wind park and v) accounting the availability of turbines with respect to damages, maintenance or cut-off at high wind speeds. Mostly the later two effects are not modeled explicitly but are adjusted through Model Output Statistics (MOS).

In the last two years a new wind power forecasting tool (Hugin) was developed at ForWind (University of Oldenburg). It can be regarded as the successor of the well-known model Previento that was also developed at the University Oldenburg and is nowadays commercially used by TSOs [13]. Hugin was developed for research, nevertheless semi-operational wind power predictions using NCEP (Nation Centre for Environmental Prediction) forecasts are available at www.forwind.de. The predictions are updated four times a day.

The quality of the forecasts is comparable with other commercial WPP models *(fig. 3,4)*. For day-ahead (24 - 48 h forecast time) Hugin has a normalized root mean square error (RMSE) of 5.2% (4.2%) and for 2 day-ahead (48 – 72 h) a RMSE of 6.5% (5.9 %) using the NCEP 00UTC forecast. The values given in brackets are for ECMWF 00UTC. Both forecasts have a diurnal cycle. Problems in the early afternoon correspond to the uncertainty when and if the thermal stratification of the atmosphere changes from stable to unstable due to heating of the

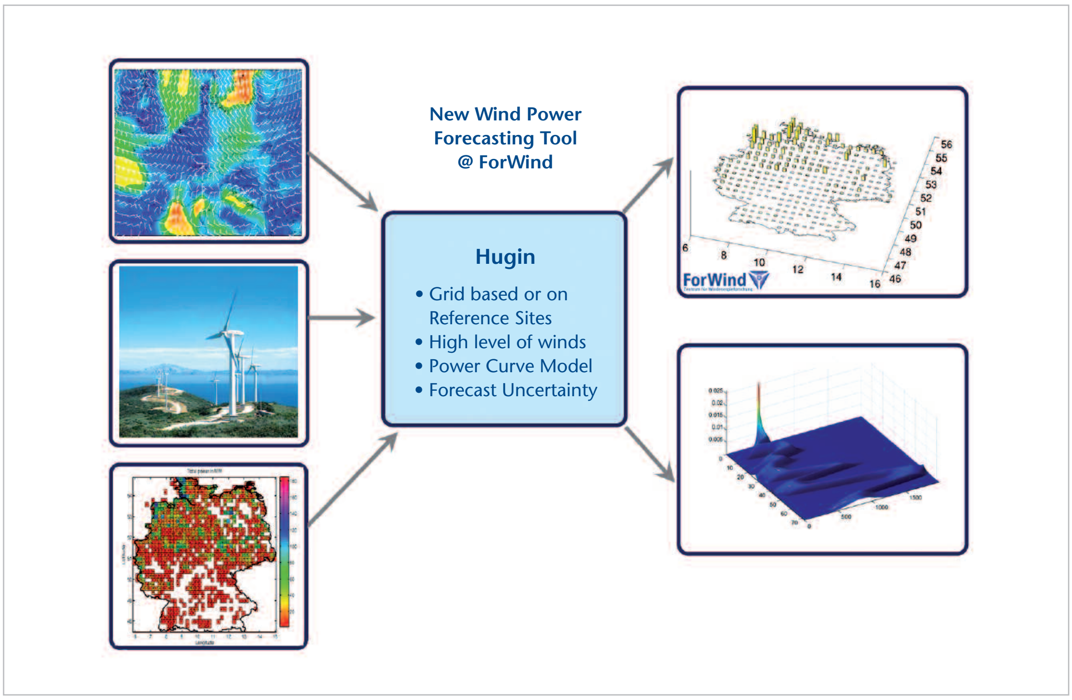


Figure 2
The Wind Power Prediction model Hugin predicts wind power for Germany or subregions.

surface. This possible change from stable to unstable stratification has influence on the vertical wind shear and wind speeds at hub height drop. The use of all four NCEP forecast runs smoothes the error statistic plot *(fig. 3, left)* considerably, but the averages RMSE for day-ahead is in principle unchanged (5.1%). The same is true when both ECMWF forecasts are used.

Predictions with ECMWF are substantially more accurate. This can be attributed to the better initial model conditions. Furthermore ECMWF has a higher horizontal resolution (25 x 25 km) while NCEP has 0.5° x 0.5° that corresponds to 33 x 55 km. It must be mentioned that all shown wind power forecasts errors *(fig. 3,4)* benefit from very weak winds in the first half year of 2006. The load factor for Jan-Jul 2006 is only 14.2%, while in strong wind years 18% can be reached. A load factor of 18% would immediately increase the normalized RMSE of 4.2% (day-ahead) to 5.3%.

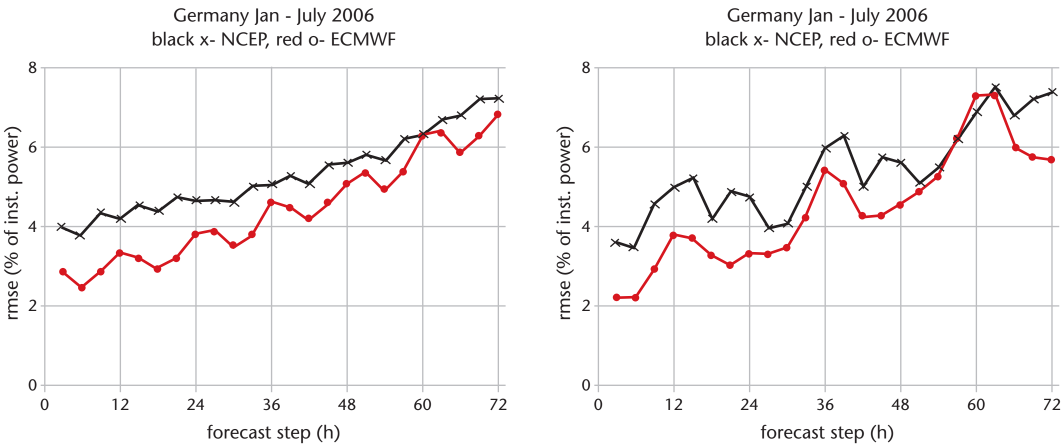


Figure 3
Normalized root mean square error (RMSE) of the wind power forecast for Germany modeled with Hugin. Two different weather models (NCEP black (x) and ECMWF red (o)) are used for the period Jan-Jul 2006. On the left all available forecast runs (four for NCEP and two for ECMWF) are used. The 00UTC forecast run (right) is mostly used for commercial wind power predictions and delivered to end-users. The errors are normalized with the installed wind power capacity in Germany.

Statistical Wind Power Prediction

The key advantage of statistical WPP models is that at least three of the above mentioned important aspects of wind power prediction do not require physical modeling, i. e. interpolation to hub height, consideration of surface roughness and turbine wakes. These effects can be accounted as wind directional dependent effects on the power curve of the entire wind farm [14]. Statistical algorithms are able to account for current generation data of the wind farm, i. e. this ability is very helpful for high accuracy in shortest-term (0-6 h) forecasts.

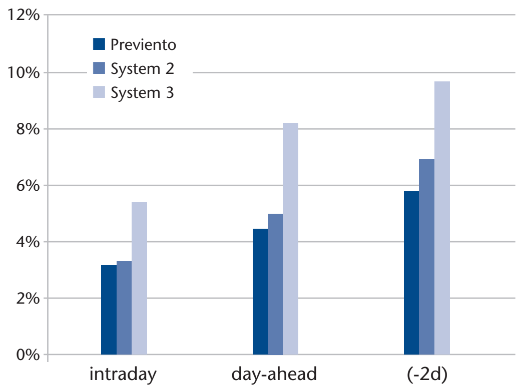


Figure 4
Normalized RMSE of the wind power forecast for Germany calculated by commercial WPP models [13]. The RMSE is normalized with the installed capacity.

Wind Power Forecast for Single Wind Farms

Wind power forecasting of single wind farms does not benefit from spatial forecast error smoothing. Conclusively, the forecast skill is considerably poorer and new ways to achieve good forecast skill must be chosen. In this chapter two approaches are discussed i) ensemble forecasts and ii) the combination of different NWP models.

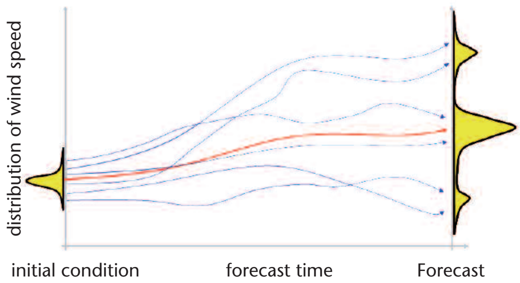


Figure 5
Illustration of trajectories in an Ensemble Prediction System (EPS). The deterministic forecast starting from the best guess (analysis) of the "true" wind is drawn in red.

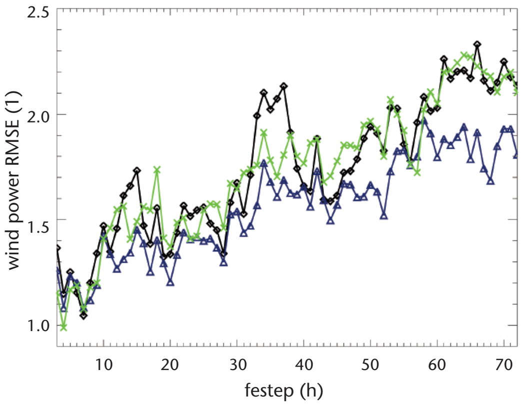
Wind Power Forecasts using an Ensemble Prediction System

The key error source in Numerical Weather Prediction is the error in the initialisation of the forecast model [15], i. e. our knowledge about the state of the atmosphere at the starting point of the model integration is so limited that errors in the future state of the atmosphere amplifies during the temporal integration of the model. In 1992 ECMWF introduced a new forecasting system that helps to alleviate the forecast error that is attributed to the error in the initial conditions (analysis) of the forecast model.

In the Ensemble Prediction System (EPS) 50 forecasts (ensemble members) are computed starting from slightly different initial conditions [16]. Each member leads to a different solution (forecast) after the integration in time. One has to bear in mind that even small changes to the initial conditions can change the result significantly as several processes in the atmosphere are highly non-linear.

For the one-dimensional case *(fig. 5)* the initialising winds can be described with a probability density function (pdf) around the best guess (analysis) of the "true" wind. The forecast model trajectories diverge with increasing forecast step and the forecast result can also be described as a pdf. This pdf can be multi-modal which suggests that different clusters that contain similar forecasts have developed. The 50 ensemble members cover the range of forecasts that are possible due to the uncertainty in the analysis and probabilistic methods can be used to extract the best end-user information from this ensemble of forecast.

A straight forward approach is to consider the mean of all solutions as the best forecast. The ensemble mean of the 10 m wind speed forecast is used to predict the measured nacelle wind speed of the onshore wind farm Wybelsum *(fig. 6, left)*. A least square regression is used to fit wind speeds in hub-height from the 10 m winds. This forecast outperforms the deterministic NCEP and ECMWF forecasts in particular for higher forecast steps when analysis errors



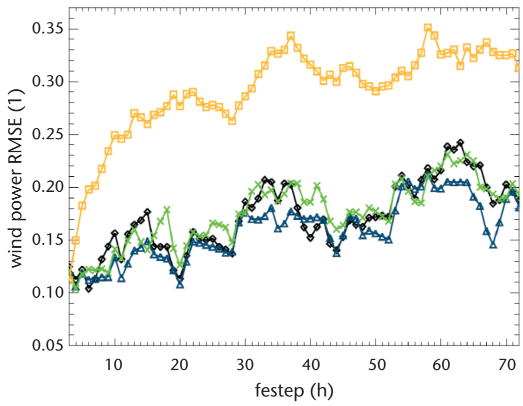


Figure 6
RMSE of wind forecast (left) and wind power forecast (right) error for wind farm Wybelsum in Feb-Apr 2006 against forecast time. 10 m wind speed forecasts are used from ECMWF (black ◊), NCEP (green x) and ECMWF's mean EPS (blue Δ). The persistence wind power forecast error is shown in orange (□).

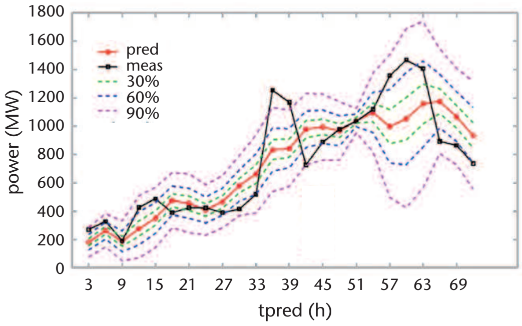


Figure 7
Wind Power Forecast with given 30, 60 and 90% confidence intervals. Taken from [17].

start to deteriorate the deterministic forecast. In a second step the wind power for Wybelsum is predicted with the three different wind forecasts *(fig. 6, right)*. A power curve that was fitted against observed nacelle wind speeds is used as transfer function. While ECMWF and NCEP wind power predictions are very similar, the ensemble mean has some advantages. The persistence forecast shows what errors arise without any wind power prediction.

EPS forecasts are ideal to give information on the uncertainty of a given deterministic forecast, i. e. draw confidence intervals in which the event (wind power generation) will lie. *Fig. 7* gives an example how this type of forecasts looks like [17]. Obviously, the confidence range broadens with increasing forecast time. It is necessary to calibrate the ensemble forecasts properly to ensure that the confidence levels are reliable. Nevertheless the forecast is wanted to be as sharp as possible. More applications of EPS in wind power forecasting can be found in [18].

Combination of Forecasts

The forecasts from various Weather Centers differ due to the forecast model (physics and temporal, spatial resolution). Deviations in the initial condition (analysis) of the model are also responsible that forecasts get different. But it must be considered that the analyses are mainly based on the same observations and therefore highly correlated.

However, as forecast errors are at least partly uncorrelated the combination of two forecasts can cut down overall forecast errors even if one of the models is significant poorer than the other [19].

The application of multi-model techniques in short-term wind power prediction is not very developed. First studies for wind power forecasting are done and achieve improvements in classified weather situations [20] making use out of the weather regime dependent forecast skill of NWP models. As the wind power forecasts are done for Germany, the benefits from inherent spatial smoothing effects of forecast errors are very large.

The approach that is followed here does not discriminate weather situations (regimes) and is applied as a combination of point forecasts, i.e. advantages form spatial error smoothing can not be expected. ECMWF and HIRLAM wind speed forecasts are combined to predict the wind power for the Danish wind farm Middelgrunden *(fig. 8)*. Forecasts in general are very challenging for this site as the wind farm is just 2 km downstream from the city of Copenhagen and NWP models in 2001 were unable to capture this resolution. ECMWF and HIRLAM wind forecasts from high level wind fields are therefore interpolated to the location of the wind farm and then corrected with a Neural Networks to observed nacelle wind speeds. The Neural Network serves as non-linear sectoral dependent Model Output Statistics (MOS). This MOS technique is repeated every 120 days to account seasonal changes in wind statistics and uses always the last 150 historic days for adaptation. Details on this approach are described in [21].

The forecast error correlation from ECMWF and HIRLAM can reveal the potential for the combination of forecasts *(fig. 9, left)*. For this analysis the predicted wind speeds that are corrected by MOS are used. The error correlation is smallest in the two summer periods and is higher during winter. In spring and summer less advective weather regimes prevail and joint analysis errors have less impact on the forecast error than during winter. This means that in more stable weather regimes model difference become more important and lead to forecasts that are less correlated; a feature that is wanted for the combination of forecasts.

Two different combination approaches are applied: i) the linear average of both forecasts is computed, i. e. equal weighting of both forecasts and ii) a principle component regression technique is used. The later technique has the advantage that the uncorrelated information in the two forecasts is emphasized.

In training mode historic forecasts (the last 90 days) are used to compute the two eigenvectors of the two wind speeds forecasts (after the MOS). It is assumed that they are indifferent for the forthcoming 15 days. The two principle components are now regressed linearly to the observed nacelle wind speed and the regression coefficients are stored. In the application mode the two principle components can be calculated from the two forecasted wind speeds and with the stored linear regression coefficients the nacelle wind speed is estimated.

ECMWF wind speed forecast outperforms HIRLAM by about 0.2 m/s in terms of RMSE

Figure 8
Danish offshore wind farm Middelgrunden

(fig. 9, right). The combination of both forecasts with equal weighting shows considerable improvements compared with the individual forecasts. Nevertheless the skill of the combination has a seasonal dependency, i. e. in winter when the error correlation happens to be highest, the combination is worse than the ECMWF alone. In periods of low error correlation the improvement of the combination with respect to ECMWF forecast is highest. The combination with principle component regression has small but notable advantages against the simpler equal weighting combination approach.

Wind power forecasts are computed with a power curve that was fitted from measured wind power generation data and observed nacelle wind speeds. In terms of wind power forecast the gap between HIRLAM and the rest is very wide *(fig. 10)*. Both combination approaches add notable value to the wind power forecasts compared to the individual ECMWF forecast. In the best case (principle component regression) the normalized RMSE error is 11% at forecast step +3 h and 15% at +48 h.

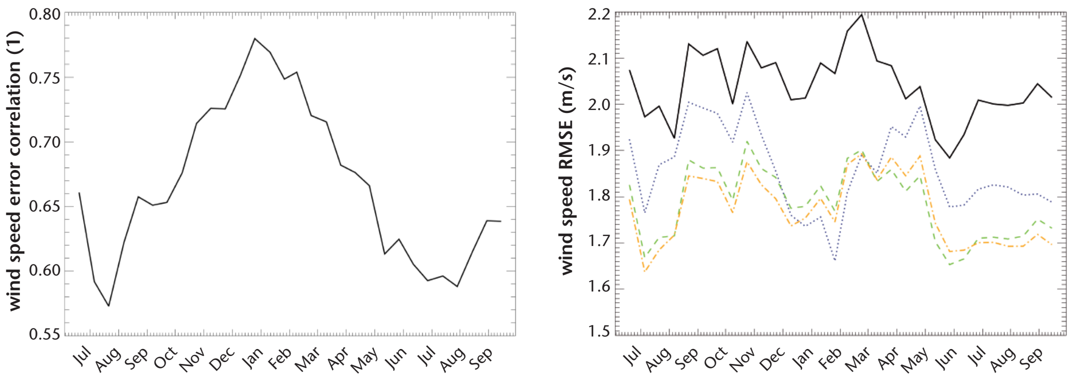


Figure 9
Correlation (left) between HIRLAM and ECMWF wind forecast errors (forecast step 25-48h) for Middelgrunden wind farm from Jul 2001 to Sept 2002. The RMSE of wind speed for HIRLAM (black, solid) and ECMWF (blue, dotted) is shown in the right figure. The RMSE of the equal weighting combination is shown in green (dashed) and the principle component regression combination in orange (dashed dotted). Values are averaged over the last 90 days.

Simulation of Germany's 50 GW wind power scenario

In particular, the *capacity credit* and *predictability* of offshore wind power need to be addressed by energy meteorologists. The work with weather (wind) data is essential to study the variability and coherence of the fluctuating Renewable Energy Sources (RES) like solar and wind on a pan-European level. The combination of these results with load profiles and conventional power generation will give insight into cross-boarder flows, required market rules and the capacity credit of RES.

The estimation of the capacity credit of the planned German offshore wind farm projects in the German Bight requires the analysis of the variability of offshore wind speeds. Basic knowledge is the duration curve of wind power, i. e. the cumulative occurrence of wind power.

Weather analyses of modern NWP systems provide maps of wind speeds every six hours around the globe. Hundred thousands of measurements are processed to calculate these analyses and they provide for meteorologists the best known state of the atmosphere at any time.

The wind power in the German Bight is simulated using wind analysis data from ECMWF. Wind speeds from vertical high resolved model fields are interpolated to a unified height of 100 m. Horizontally the wind field is interpolated to each of the 22 planned wind farm projects in the German Bight *(fig. 11)*. The original resolution is 39 x 39 km. The study period is Jan 2003 to July 2005 and four analyses per day are used. 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.

Wind power generation is always normalized with the rated capacity. As a scenario is looked at, we assume that 25 GW onshore and 25 GW offshore has been already installed in the study period (Jan 2003 to July 2005).

Fig. 12 shows the cumulative distribution of anticipated (normalized) offshore wind power production (green, dashed line). More than 10% of the time nominal power is produced.

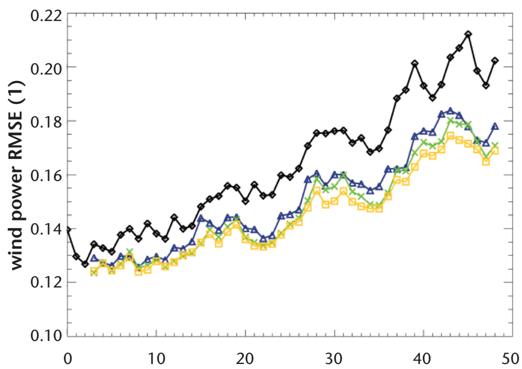


Figure 10
Normalized RMSE of wind power forecast for offshore wind farm Middelgrunden using HIRLAM (black ◊) and ECMWF (blue Δ) forecasts. The combination of both NWP models with principle component regression is shown in (orange □) and (green x) for equal weighting.

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%. The availability of real generated onshore wind power production in Germany (dotted line) is much lower and nominal power (25 GW) is never reached. The aggregation of on & offshore wind power increases the share of considerable wind power very much. Half of the time 28% of the installed capacity (50 GW) is available, while 12% are available from onshore wind power only.

The variability of wind power generation within a week for aggregated on & offshore (50 GW in total) is shown in *fig. 13* (solid line). The fluctuations within a week, that are defined as the standard deviation, are up to 3 GW in summer and 15 GW in winter. The individual variability of on- and offshore (each 25 GW) is shown in thin lines. The variability of offshore wind power is much larger (up to 10 GW) than onshore (up to 7 GW), but one has to bear in mind that the load factor is 50.3% compared to 19.3% onshore, i.e. the average production onshore is only 4.8 GW, which is about 2.6 times smaller than the offshore generation (12.6 GW). The aggregated load factor is the simple average of 50.3 and 19.3% (= 34.8 %) as long as the same installation capacity is distributed equally. The load factor of 34.8% says that the average on & offshore production is 17.4 GW.

Simple scaling says that 3.6 (= 17.4/4.8) times more onshore capacity (25 GW*3.6 = 90.6 GW) is needed to produce the same energy than 50 GW that is distributed equally on- and offshore. 90.6 GW onshore wind power capacity means that the maximal weekly variability is not 7 GW but 3.6 times larger. The time series of this inner-weekly variability is also drawn in *fig. 13* (thick lines) and gives an impression which flexibility in scheduling conventional power plants (fossil or nuclear) is needed. The sharp spikes do not occur when on- and offshore wind power is aggregated. This is a strong argument why distributed wind energy production in Germany is recommendable from the grid integration point of view and helps to operate conventional power plants on a more constant level that is more economical.

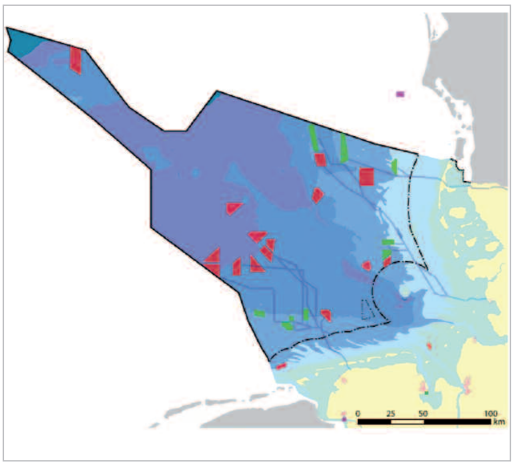


Figure 11
Planned German offshore wind farms in the German Bight. Approved (green) and in approval (red). Source: BSH, Hamburg.

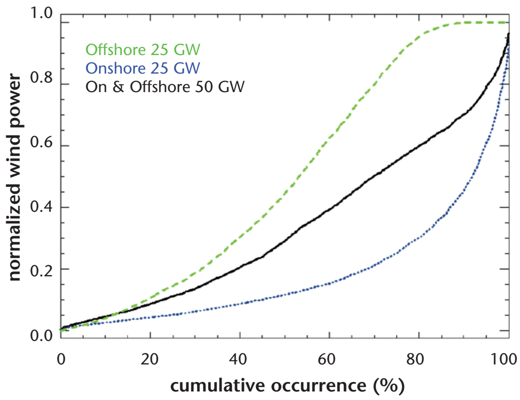
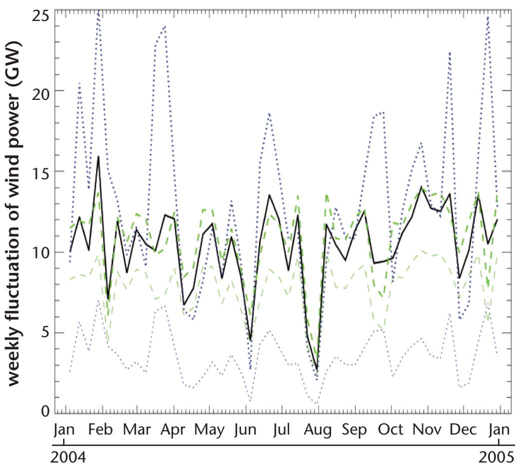


Figure 12
Cumulative occurrence of anticipated offshore wind power production in the German Bight for Jan 2003-July 2005 (green, dashed line), produced onshore wind power (blue, dotted line) and aggregated on & offshore (black, solid line).

In case only offshore wind energy is considered, only a little bit more than 25 GW needs to be installed to meet the average on- and offshore generation of 17.4 GW, i.e. 34.5 GW (= 25 GW *17.4 GW/12.6 GW) are needed). The weekly variability *(fig. 13*, thick dashed line is comparable to the variability in the aggregated case (solid line).

The predictability (skill of a forecast) of large-scale offshore wind power determines the amount and respond time of regulative power that is maximal required to balance deviations between actual wind power production, forecasted wind power and deviations in the load forecast. Spatial forecast error smoothing is known to reduce forecast errors significantly for onshore wind power [22]. As the local concentration of offshore wind power capacity will be much higher than onshore, error smoothing of offshore wind power is discussed in more detail in [23].

Figure 13
Variability of wind power for the German 50 GW scenario within a week simulated for 2004. The thin lines (blue (dotted), green (dashed)) refer to 25 GW onshore and offshore, respectively. The (black) solid line is the aggregated on & offshore wind power. The thick lines are for the separated on- and offshore wind power that is scaled to have the same generation as aggregated on & offshore. The onshore capacity must increase to 90.6 GW.



The aggregation of on & offshore wind power does not only help to limit the variability of wind power generation but also reduces the forecast error dramatically. In a study for 2004 wind power forecasts for the 22 planned German offshore parks are calculated with ECMWF wind speed forecasts using the 00UTC forecast run. The validation was done with wind analyses from the German Weather Service (DWD). Tambke et al [24] has shown that the wind speed analyses from DWD are in good agreement with observations at the FINO1 platform. They are therefore acceptable for forecast validations.

The normalized RMSE of the wind power predictions is shown in *fig. 14* and increases for an individual wind farm from 13% at forecast time +3h to 22% at forecast time +48 h. The aggregation of the offshore wind farms brings the RMSE already down to 9% (+3 h) and 18% (+48 h). This reduction is attributed to smoothing of uncorrelated forecast errors. The average RMSE at day-ahead is 14.5%.

For the same time period the wind power forecasts for Germany were calculated with Hugin using ECMWF forecasts. They are validated against generated power in Germany. In a next step the offshore and onshore forecasts are aggregated.

The aggregation of on & offshore wind power forecasts gives an enormous boost on the achievable accuracy of wind power forecasts for the integration of 50 GW German wind power. The RMSE ranges between 5% and 10%. The average RMSE for day-ahead is 8.5%. However, this appears not to be as good as the currently best onshore forecast for Germany (4.2% in Jan-Jul 2006). But the difference in the load factor must be considered; i. e. the load factor for onshore in the first half year of 2006 was extremely low (= 14.2%). When the onshore forecast is normalized with the actually generated power the RMSE error is 29.6% while the on & offshore forecast has a RMSE error of only 24.4% (8.5%/34.8%). For only offshore generated wind power the day-ahead forecast error normalized with the actual generation is 28.9% (= 14.5%/50.3%) and therefore very similar to the onshore forecast error. This means that the best wind power forecasts can be made for aggregated on & offshore wind power generation, when spatial error smoothing helps to cut down forecast errors.

Summary

We showed in this paper that the use of Numerical Weather Prediction (NWP) models in wind power forecasting and grid integration is manifold and in many aspects essential. As weather centers are very little involved in the application of their forecasts to wind energy and the energy sector in general, atmospheric scientists (energy meteorologists) link modern NWP and the demand of end-users (wind farm and grid operators, energy traders, investors).

Wind power forecasts are required on national, regional and sub-regional level for save grid integration. However, they become most important on single wind farm level. The reasons are twofold. The size of individual wind park projects increases rapidly with larger multi-megawatt turbines; rated capacities of 100 MW and plus are getting common, e.g. USA. This puts pressure on stable grid integration as grids do not expand the same size and speed.

Save and reliable grid integration and operation with large shares of locally concentrated wind power is also the dominate topic for offshore wind power forecasting. Besides grid integration issues, wind farm operators and energy traders show increasing interest in single wind farm forecast in order to sell their wind power at the stock market.

While day-ahead forecast errors for Germany are brought down to 5-6% (depending on the general wind disposal in that year), the day-ahead forecast errors for single wind farms are between 14% and 17% for onshore wind farms and 14-22% for offshore wind farms. The combination of different NWP models offers very good ways to reduce these errors. Ensemble forecasting can be used to determine the forecast uncertainty and confidence can be given to the wind power forecast. A simple approach shows that the ensemble mean has more forecast skill for a single wind farm than the deterministic forecast.

Weather analysis and forecasts from modern NWP systems can be used to simulate time-series of wind power generation for planned offshore wind farm projects to study aspects of expected wind power fluctuation (variability) on time scales of days and weeks. Balancing among various offshore wind farms distributed nationwide in the North Sea and coherency with onshore wind power generation can be investigated.

In this paper the German 50 GW wind power scenario (25 GW onshore & 25 GW offshore) is discussed. The installation of on- and offshore wind power is favorable in terms of steadiness of generated wind power and reduction of day-ahead wind power prediction error. The average day-ahead prediction error is 8.5% of installed capacity. This has to be compared with the state of the art day-ahead forecast error for Germany (onshore) which is around 4.2% for the first half year of 2006. The very low load factor in the first half year of 2006 (= 14.2%) misleads to the assumption that the aggregated on & offshore forecasts is only have as good. When the onshore forecast is normalized with the actually generated power the RMSE error is 29.6% while the on & offshore forecast has a RMSE error of only 24.4%.

Together with less fluctuating wind power this helps to operate conventional power plants at more constant levels that are more economical. The weekly variability of on- and offshore distributed wind power is in its extremes at least a factor two smaller than if the generation would be only onshore providing on average the same amount of energy. The results of this study support the idea of distributed on- and offshore wind power generation. It will be up to the energy meteorologists to study pan-European balancing of all Renewable Energy Sources (wind, solar, hydro, biomass, …) and to demonstrate that RES are one important contribution to protect Earth's climate.

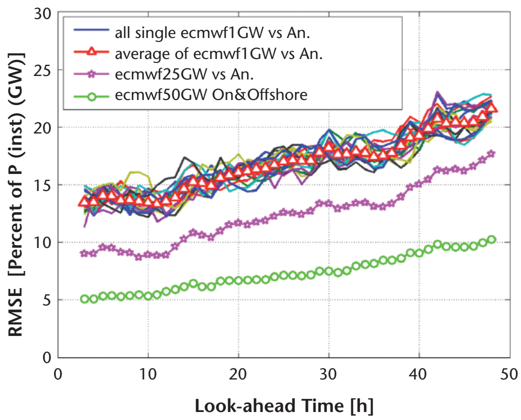


Figure 14
Normalized RMSE wind power forecast error for the planned offshore wind farms in the German Bight against forecast time in the year 2004. Individual wind farm prediction errors (thin lines) are shown and their average values (red triangles). The aggregated forecast error of all wind farms is shown in pink (*). Aggregation with onshore wind power forecasts results in a much higher forecast accuracy (green, o). Taken from [24].

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