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Abstract: This report describes the advantages for short-term wind power forecasts obtained by changes to the ensemble prediction system (EPS) at the European Centre for Medium-Range Weather Forecasts (ECMWF) within the SafeWind project. The development of ensemble winds in 100 m height can be regarded as a major boost to improve the skill of probabilistic wind power forecasts. Compared to the 10 m ensemble the raw 100 m ensemble is quite well calibrated and shows high reliability and ensemble spread. Probabilistic wind power forecasts for Germany are improved by 50 %. In general, it can be stated that the provision of information on the vertical wind profile for ensemble winds is essential to enhance short-term wind power forecasts and justifies additional data storage costs.

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Content

1. Introduction

For many years wind power capacities in Europe have been strongly increasing which requires accurate short-term forecasts of wind power to facilitate the save integration of wind power into the European power supply system. Most of the existing wind power prediction (WPP) methods provide the end users (e.g. wind farm operators and energy traders) with point forecasts computed from deterministic forecasts. Probabilistic forecasts obtained from multiple simulations of numerical weather prediction models are carried out by ensemble prediction systems (EPS). They can provide end-users also with e.g. forecast uncertainty and confidence intervals of the expected wind power production since the ensemble forecasts take uncertainties in initial conditions into account. An overview of ensemble forecasting and developments in ensemble forecasting is given in [1].

Studies have shown that ensemble forecasts should be regarded as raw output from numerical weather prediction models which need calibration to improve the statistical properties of the ensemble [2, 3, 4, 5]. Within the SafeWind project 10 m winds of the ensemble prediction system (EPS) run at the European Centre for Medium-Range Weather Forecasts (ECWMF) have been calibrated with respect to the analysis. The overall benefits are shown in [6] and partly these calibrated 10 m winds have been used in this report to demonstrate the advantages for probabilistic wind power forecasts. The SafeWind Deliverable Dp.5.8 describes the benefits of the calibrated 10 m ensemble winds in more detail. Validations have been made for wind observations and short-term wind power forecasts. These calibration results that are considered as post-processing of the raw EPS are not repeated in this report because this report focus on changes in the EPS and forecasting system itself.

Since years deterministic wind power forecasts are not using 10 m winds anymore. Wind speeds on model levels of the atmospheric forecasting model are used instead. Thus, the wind speed on hub height of modern wind turbines can be computed more precisely as no extrapolation errors using the neutral or non-neutral logarithmic wind profile will occur. Until recently, only 10 m ensemble wind forecasts were used for probabilistic wind power predictions since ECMWF-EPS wind forecasts were only available for the 10 m height. As not all required forecast parameters are archived for the EPS to compute the stability of the atmosphere, the neutral logarithmic wind profile had to be used to compute ensemble winds at hub height. The archiving of all EPS model levels is far too expensive in terms of data storage and ECMWF decided to develop a new wind product, i.e. ensemble winds in 100 m height. This product was introduced at 26 January 2010 and is regarded as the most important achievement to enhance the quality of ensemble wind power forecasts.

The advantages of 100 m ensemble winds over 10 m ensemble winds are shown in this study for German wind power forecasts. Unfortunately, no calibration of 100 m ensemble winds was carried out to demonstrate the need for calibration. Furthermore, the calibration of 10 m ensemble winds was stopped in 2009. Consequently, no direct comparison of calibrated 10 m winds and uncalibrated 100 m winds can be done. However, an overlap of calibrated 10 m winds that are available for 2008 and 2009 exists with some EPS model level winds. In section 3 of this report it is investigated if the provision of better vertical wind profile information in the EPS or calibrated 10 m ensemble winds is beneficial. A wind park in the North of France is studied for this purpose.

2. Enhanced regional probabilistic wind power forecasts with 100 m ensemble winds

2.1 100 m wind product of ECMWF

Since years wind power forecasters have been correcting the effect of atmospheric stability on winds in hub height. Without stability correction hub height winds are underestimated (overestimated) in stable (non-stable) atmospheric conditions when logarithmically extrapolated from surface winds (10 m height). Deterministic forecasts provide the required data for the stability correction. Furthermore, forecasts on model levels are available for deterministic forecasts and can be used to interpolate wind speeds on adjacent model levels to required hub heights. Due to very high data volumes there had been major concerns to archive model levels for Ensemble Prediction Systems. Ensemble forecast data to extrapolate surface winds with stability information to hub heights, i.e. surface fluxes, friction velocity or vertical temperature gradients in the atmospheric boundary layer had not been archived as the requirements for wind power forecasting were unknown.
Within the SafeWind project ECMWF introduced winds in 100 m height as a new product tailored for the wind energy industry in the analysis, deterministic and ensemble forecasting suite at 26 January 2010 (12 UTC run).

2.2 Wind power forecast model

The wind power forecast model used in this study is intentionally kept very simple to enable the efficient computation of German wind power forecasts with 50+1 ensemble members. The wind forecast at each model point of the ECMWF forecast model is used provided that any wind turbines are located in a 0.25°x0.25° grid cell around this grid point.

In a pre-processing the mean characteristics of wind turbines in each 0.25°x0.25° grid cell over Germany are determined utilizing a data base [7] that holds the information about regional distribution and capacity of wind power deployment in Germany. All wind turbines in Germany including the installed capacity, rated power, date of commissioning and geographical information are listed in this data base and are mapped to the 0.25°x0.25° grid cells. The number of model grid cells populated with wind power is around 770.The data base is evaluated on a monthly basis.
The distribution of wind power in Germany is rather inhomogeneous (Fig. 2-1). The majority of wind

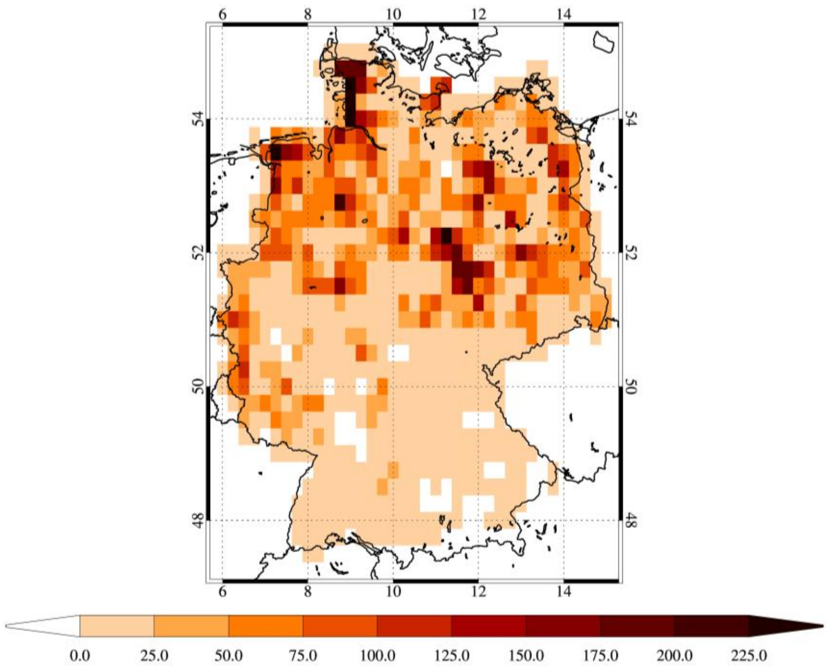

Fig. 2-1: Wind power capacity [MW] for grid cells of 0.25°x0.25° in Germany (end of January 2010).

power is located in the North-West of Germany and high concentrations can be found in the Federal State of Saxony-Anhalt. The hub height for each grid cell is computed as a weighted average of all wind turbines in the grid cell and the power of the wind turbine, respectively. As modern and more efficient turbines have larger hub heights, the average (weighted) hub height per grid cell is increased. Average hub heights in North-West of Germany are in January below 70 m while average hub heights in others regions are up to 50 m higher (Fig. 2-2).

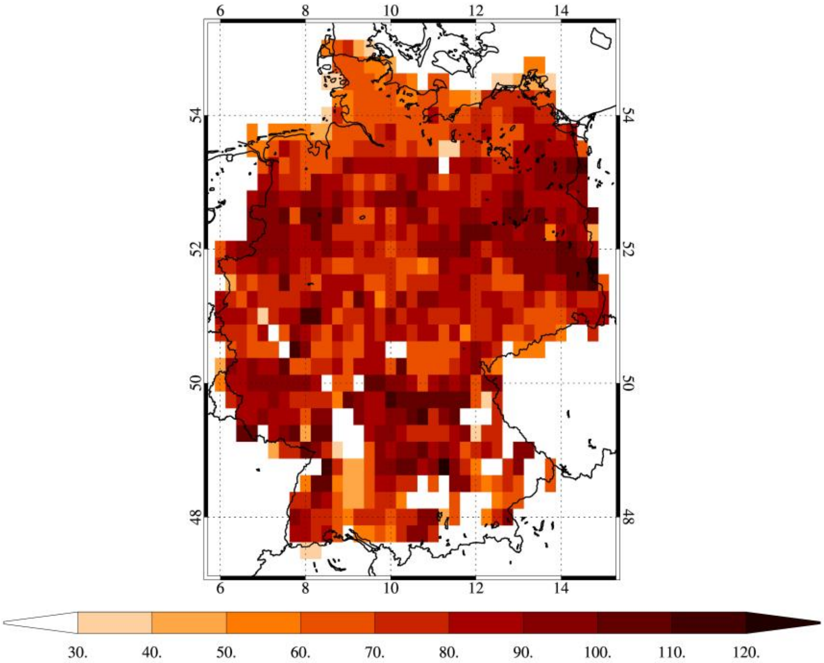

Fig. 2-2: Hub height [m] of wind turbines for grid cells of 0.25°x0.25° in Germany (end of January 2010).The hub height in a region is computed as a weighted average of all turbines in a region with respect to the nominal power of each turbine.

When computing winds in hub height from surface winds the surface roughness z_0 is needed. In the current configuration information about sub-grid cell surface roughness of the COSMO [8] mesoscale model is used. In each 0.25° grid cell around 23 roughness lenghts are given as the resolution of COSMO is 7x4.2 km. As wind turbines are rather sited in smooth terrain the lowest 20 % quantil of surface roughness lenghts is used to in the 0.25° grid cell of the wind power model. The corresponding z_0 distribution can be seen in Fig. 2-3.

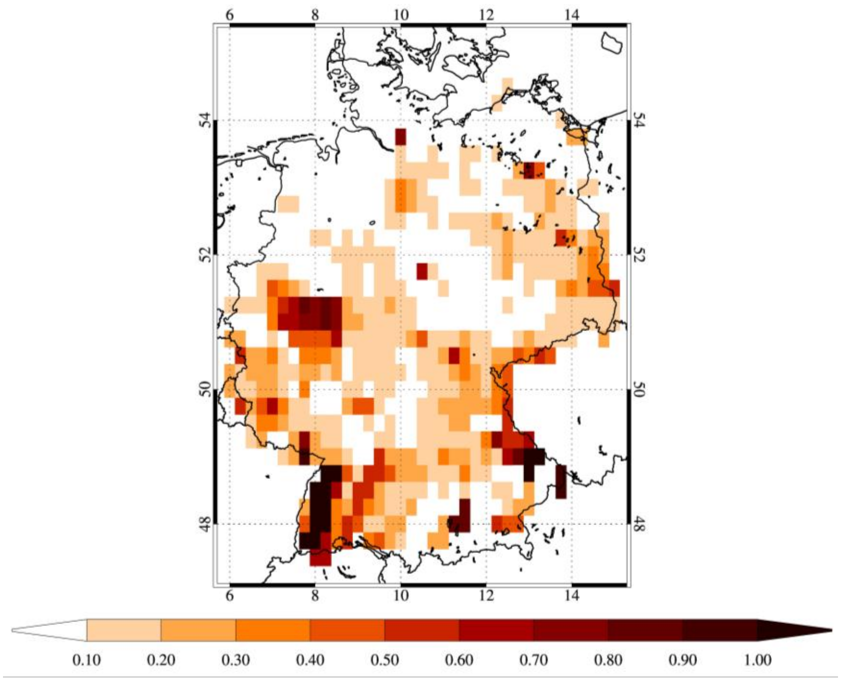

Fig. 2-3: Surface roughness length z_0 [m] used in the wind power forecast model with 0.25° resolution.

The extrapolation of 10 m winds to hub height with the neutral logarithmic wind profile is done utilizing these z_0 values. In the next step the wind speed in hub height is converted for each grid cell to normalized wind power using a regional power curve (Fig. 2-4) from the TradeWind Project [9]. Note, that the normalized wind power is multiplied with the rated wind power in this grid cell (Fig. 2-1). Finally, the wind power forecasts of grid cells are totalled for each control zone, individually. The 10 m wind speed forecasts are used as a reference case to determine the improvement when 100 m winds are used.

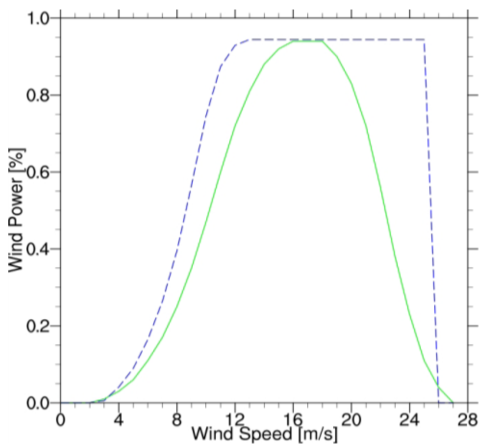

Fig. 2-4: Regional power curve from the TradeWind Project (green) and manufacturer's onshore power curve (blue) for a multi-megawatt wind turbine.

The computation of wind power forecasts with 100 m winds is very similar as described above for 10 m winds. The sole difference is the determination of the wind speed in hub height of the grid cell. Here a linear interpolation of the 10 m wind speed forecast and 100 m wind speed forecast to the required hub height is performed. In such a way some crude information about the wind profile is considered. In case the hub height of the grid cell exceeds 100 m an extrapolation is done. In the following the terminology "100 m winds" is used for simplicity, although 10 m and 100 m winds have been used.

2.3 Results

Wind power forecasts have been computed for each of the four control zones in Germany individually. The study period is limited by the availability of the new 100 m EPS winds. Thus, the study period is from 26 Jan 2010 until 30 April 2011 utilizing 00 und 12 UTC model runs. In a post-processing step a bias-correction is applied to the wind power forecasts to account for diurnal biases. This is in particular useful for 10 m winds since thermal stability effects have been dismissed when extrapolating 10 m wind speeds to hub height. The wind power bias correction is done for each control zone individually utilizing the observed wind power time series. The observed wind power time series is publically available at the websites of the involved transmission system operators (TSO). Furthermore the four time series are aggregated to the German wind power production, thus large scale spatial smoothing of variability occurs. This time series of the total German wind power production is finally averaged to hourly values from 15 min resolution. As the ensemble forecast time series has only a temporal resolution of 3 hours, only one third of the German wind power time series is used to verify the ensemble wind power forecasts.

Fig. 2-5 shows the root mean square error (RMSE) for German wind power forecasts dependent on the forecast horizon. The bias correction for wind power forecasts with 10 m winds leads to a major improvement (compare green and red (solid) curves) and reduces the dependency on the diurnal cycle considerably. A bias correction for 100 m winds does not improve the RMSE and is therefore not depicted in Fig. 2-5. However, the forecast accuracy of 100 m winds is much better than using 10 m winds. At forecast day+2 the ensemble mean outperforms a single forecast (control forecast). Fig. 2-5 reveals that the ensemble wind power forecast is very underdispersive as the ensemble spread (dotted line) is much lower than the RMSE. The ensemble spread is defined as the standard deviation of the ensemble members around the ensemble mean.

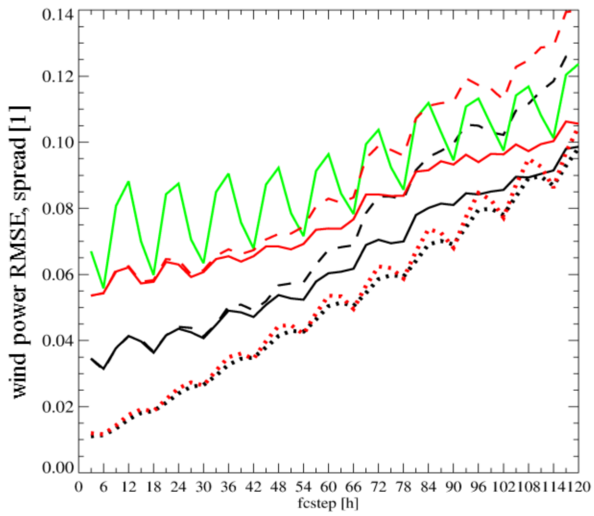

Fig. 2-5: RMSE of wind power forecast normalized with installed capacity for Germany utilizing 100 m (black) and 10 m bias corrected (red) ensemble winds (black). The ensemble mean (solid line) clearly outperforms the deterministic forecast (dashed) at forecast day+3. 10 m ensemble mean forecast without bias correction (green) and ensemble spread (dotted) is also shown.

Talagrand Rank Histograms confirm that the spread of the wind power forecast members are too small (Fig. 2.6). In particular, utilizing 10 m ensemble winds the Talagrand Rank Histogram is strongly U-shaped as very often low and high wind power events fall outside the ensemble range. The application of a wind power bias correction does not improve the spread. For 10 m ensemble winds the population of the outer ranks even increases (Fig. 2.6, top right). Compared to 10 m winds the Talagrand Rank Histogram for 100 m winds looks very much improved, i.e. the spread of 100 m wind power forecast members is considerably better (Fig, 2-6, bottom).

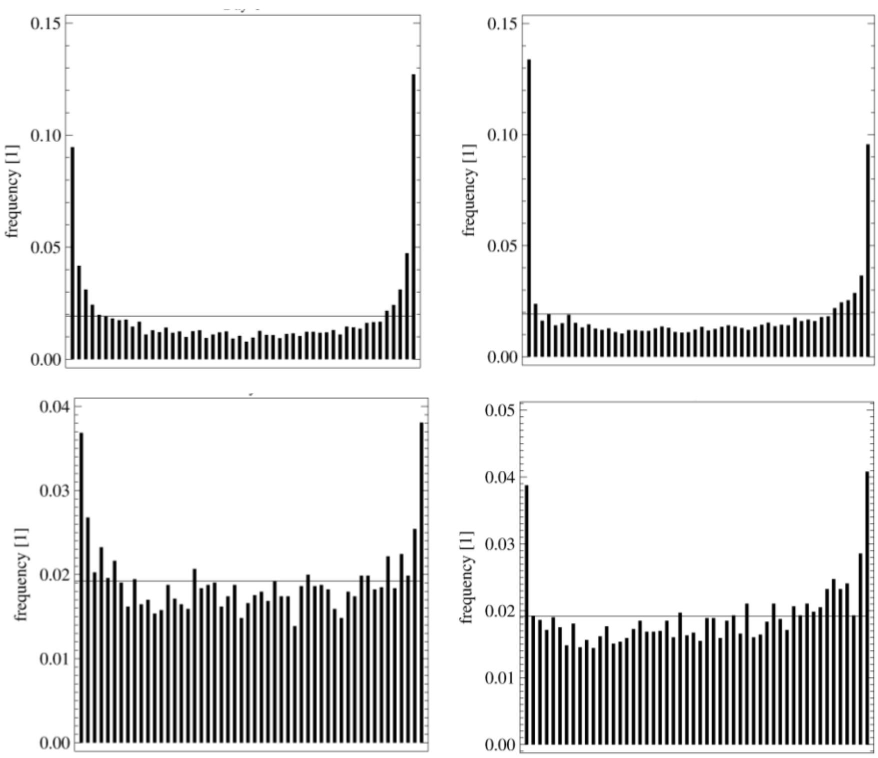

Fig. 2-6: Talagrand Rank Histogram for German wind power at forecast Day+3 with 10 m winds (top) and 100 m winds (bottom). Left: Not post-processed wind power forecasts. Right: Wind power bias-correction depending on the time of the day is applied.

The reliability of wind power forecasts for Germany at forecast day+3 are shown in Fig. 2.7 for the event of exeeding 30 % of installed wind power. Left: No wind power bias correction applied and right with wind power bias correction. The reliability is shown for 10 m winds (red dashed line) and 100 m winds (black solid line). 100 m wind power forecasts have a much better reliabilty than 10 m wind power forecast with and without wind power bias correction. The wind power bias correction improves the reliability of 100 m winds only marginally while an improvement can be noted for 10 m winds.

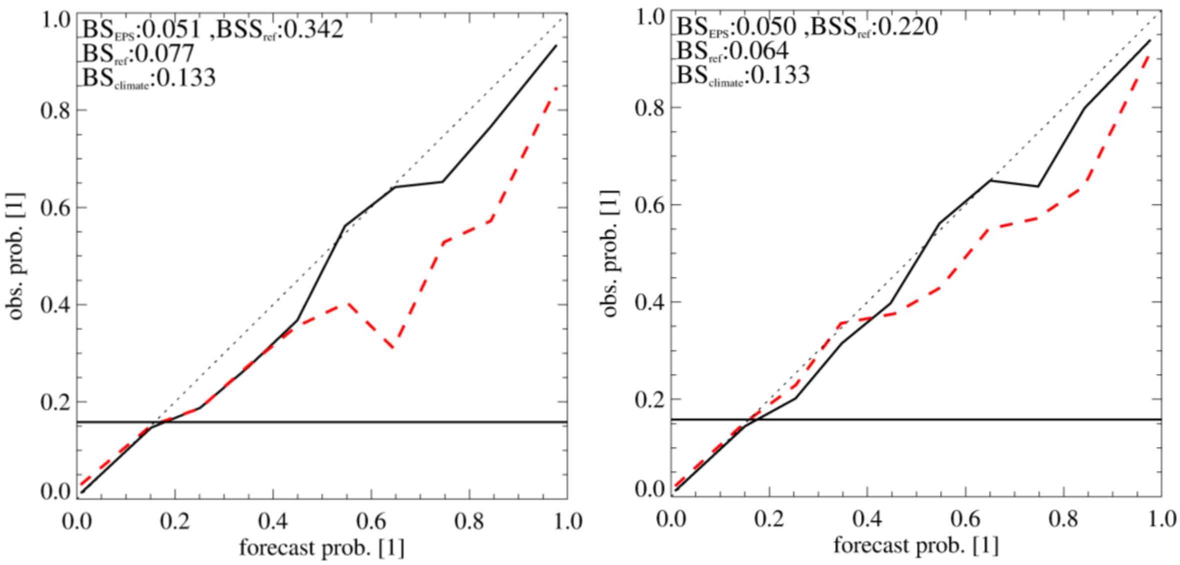

Fig. 2-7: Reliability diagram for German wind power at forecast day+3 exceeding 30 % of installed wind power without (left) and with (right) wind power bias correction. Wind power forecasts with 100 m winds in black and 10 m winds in red (dashed).

The criteria reliability, sharpness and resolution for a skilful probabilistic forecast are combined in the Continuous Ranked Probability Score (CRPS). The comparison with a reference probabilistic forecast system leads to the Continuous Ranked Probability Skill Score (CRPSS). The reference system is outperformed whenever the CRPSS is larger than zero. The superiority of 100 m over 10 m ensemble is shown in Fig. 2-7 and the CRPSS is 50 % at forecast day+1. The CRPSS decreases with forecast step and is 15 % at forecast day+5. The improvement for the control zone of 50Hertz is slightly higher than for Germany.

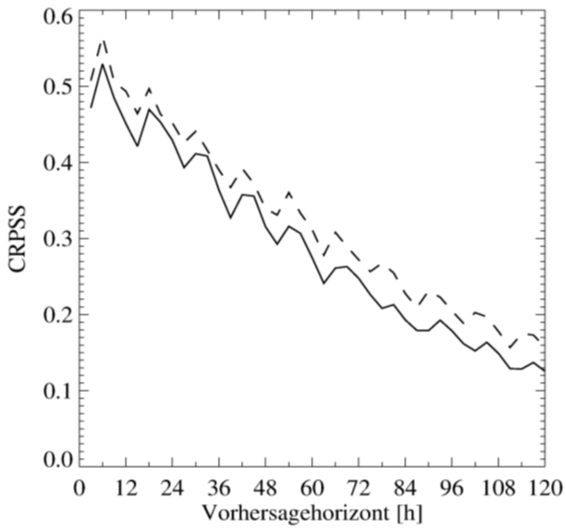

Fig. 2-8: Improvement in skill (CRPSS) for an ensemble wind power prediction system for Germany (full line) and 50Hertz control zone (dashed line) utilizing 100 m ensemble winds. The reference ensemble system uses 10 m ensemble winds and the 10 m wind power forecast is bias corrected. The time period is Feb 2010 to Apr 2011.

3. Enhanced single site probabilistic wind power forecasts using model level winds

In the previous section the improvement of using the 100 m ECMWF-EPS winds were compared to the usage of the raw 10 m ensemble winds for probabilistic wind power predictions (WPP) for Germany. The usage of raw 10 m winds clearly constrains the quality of the ensemble forecast due to large extrapolation errors. Since hub heights of wind turbines are still often below 100 m, the usage of model level winds closer to hub height might further improve probabilistic wind power forecasts. [10] analysed wind speed measurements at heights crucial for wind energy for various sites and compared the measurements to short-term forecasts (0-9 h) of the deterministic ECMWF model. They found that highest forecast accuracy is achieved with winds from neighbouring model levels as well as by linearly interpolated wind from model levels closest to hub height. In this case study, the benefit of using ECMWF-EPS ensemble model level wind forecasts closer to hub height than the 10 m wind forecasts will be evaluated in detail for one wind farm in the North of France.

3.1 Data and Methods

The wind farm with an installed capacity of around 10 MW and a hub height of 78 m is located in the North of France in flat terrain. For fitting the power curve and for the evaluation of the ensemble wind power predictions, timeseries of total wind power production are used with a time resolution of 1 h for the period May 2005 to October 2008. Wind speed and wind direction measurements at a nearby measurement mast are available in 61.6 m und 57 m for the same period and time resolution. The wind power production data is normalized to the installed capacity of the entire wind farm and the wind speed measurements are vertically extrapolated to hub height via the neutral logarithmic wind profile.

The power measurements are filtered against the wind measurements by first cutting out periods of curtailments. Curtailments are detected by searching for periods where power fluctuations are smaller than 2 % of rated power for 12 consecutive steps (which correspond to a period of 12 hours). The filter is applied for normalized wind power between 0.05 and 0.95. Second, data which scatters more than two standard deviations around the mean power curve is filtered. The dataset is then splitted into two periods: The training period (May 2005-December 2007) is used for fitting the power curve with a Neural Network (NN) and the test period (January 2008–October 2008) for the evaluation of the probabilistic wind power forecasts. Fig. 3-1 shows the scatter of wind power over wind speed measurements for the training and test period. The low scatter of wind power against wind speed indicates a good quality of the power data after applying the above mentioned filtering routines.

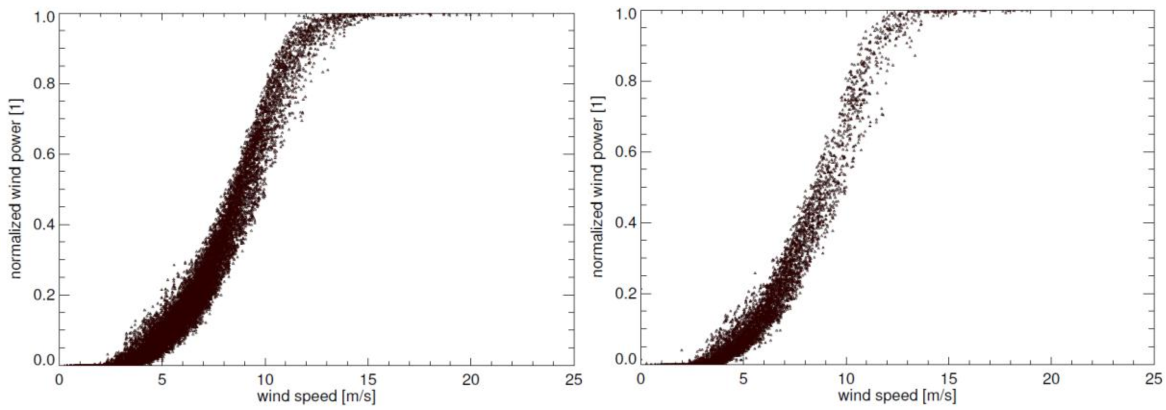

Fig. 3-1: *Normalized wind power [1] over wind speed measurements [m/s] for a wind farm in the North of France (left) for the training period May 2005-December 2007 and (right) for the test period January 2008-October 2008.*

The training data set is used for the derivation of the Neural Network algorithm. The NN is derived with two input neurons (the measured wind components), one output neuron (measured wind power) and

one layer of hidden neurons to find the algorithm (weights) that relate the wind components to wind power by minimizing a cost function [11]. The algorithm is optimized using three hidden neurons and three random searches in weight space. The derived algorithm is then applied to the independent test data set. Parameters such as the bias, the correlation and the root mean squared error (RMSE) between measured wind power and the wind power calculated with the derived algorithm are calculated for the test data set to check quality of the Neural Network algorithm. The RMSE of the wind farm data set is 4%, the bias is less than 0.5 % and the correlation is 0.99.

The aim of this case study is to evaluate the benefit of ECMWF-EPS wind forecasts at different model levels over the usage of 10 m ensemble wind forecasts for the application in probabilistic WPP. For the test period the ECMWF-EPS forecasts with resolution 0.5°x0.5° are horizontally interpolated to the location of the wind farm with a bilinear interpolation algorithm. The 0 UTC ECMWF-EPS forecasts consist of 51 ensemble members with forecast steps of 6 h up 120 h ahead. Wind predictions are available for model level 59 (approx. 110 m), 60 (approx. 67 m) and 61 (approx. 35 m) as well as for 10 m. To calculate the wind speed in hub height of the turbines, the neutral logarithmic wind profile is applied using a roughness length of 0.01 m which corresponds to the flat, agricultural land nearby the wind farm. Since no information is available about the vertical stability of each ECMWF-EPS forecast, neutral conditions have to be assumed during extrapolation despite extrapolation errors. The winds are extrapolated to hub height using winds in model level 59 (*eps_extpol_ml59*), 60 (*eps_extpol_ml60*), 61 (*eps_extpol_61*) and 10 m (*eps_extpol_10m*). Furthermore, a linear interpolation algorithm is applied between winds in model level 59 and 61 (*eps_intpol_lin*).

Another topic which will be addressed in this case study is the calibration of the ensemble wind forecast. For the test period January 2008 to October 2008 ensemble forecasts of the 10 m wind components which were calibrated with the related model analysis are available. Since the model analysis is only available every 6 hours, calibrated forecast are only available for 6 hourly forecast steps. A possible benefit of calibrating the 10 m wind for wind power predictions (*eps_extpol_10m_cal*) will be compared with WPP obtained with the raw 10 m forecasts. The calibration methodology which is detailed in [6] is developed in a multivariate Gaussian framework with the idea of correcting the first and second order moment properties of the ensemble forecast. The wind components are jointly considered instead of focusing on wind speed and wind direction separately and the output of the models are ensemble trajectories instead of predictive densities.

3.2 Results

The evaluation period of the ECMWF-EPS forecasts is January 2008-October 2008 which corresponds to the test data period. Ensemble wind power forecasts are computed applying the NN algorithm to the ECMWF-EPS forecasts extrapolated or interpolated to hub height. Furthermore, the bias is removed by applying a bias correction for the test data period. The bias correction method accounts for the daily non-stationarity of the bias.

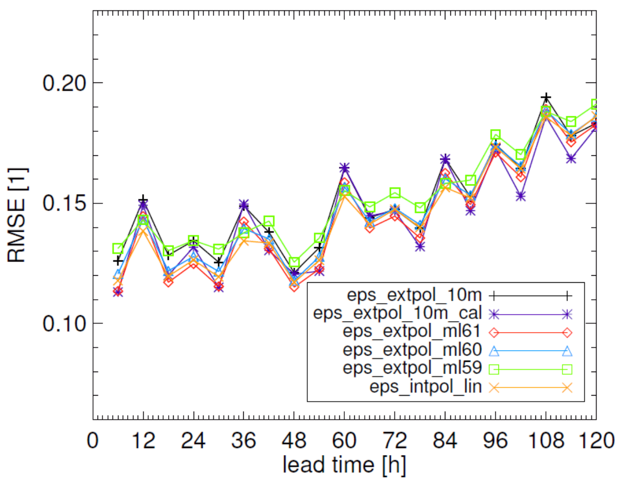

Fig. 3-2: *Root mean squared error (RMSE) [1] of normalized wind power for all forecasted lead times.*

A comprehensive picture of the forecast quality is given with deterministic (RMSE) and probabilistic scores (reliability diagram, verification rank histogram and continuous ranked probability skill score). The RMSE of the normalized wind power ensemble mean is shown in Fig. 3-2. Even after applying the bias correction all experiments show a distinctive daily cycle of the RMSE with higher errors during daytime and lower RMSEs during nighttime. As can be expected the RMSE is increasing with forecast lead time from 11-13 % at lead time 6 h to 18-19 % at lead time 120 h. Extrapolation of the wind components from 10 m and model level 59 to hub height leads to highest RMSEs while extrapolation from model level 60 and 61 winds and from calibrated 10 m winds to hub height as well as linear interpolation between model levels yield lowest RMSEs.

The reliability diagrams of the wind power forecasts are calculated for normalized wind power exceeding 20 % (Fig. 3-3). Using higher threshholds for the calculation of the reliability curve leads to a strong reduction of the sample which might then be unrepresentative for calculating statistical properties of the data set. The forecasts are validated at lead times 30-48 h which corresponds to the day-ahead forecast horizon which is important for end-users of wind power predictions. The vertical bars are consistency bars calculated with a resampling method which is related to bootstrap resampling and accounts for limited counting statistics [12]. The extent to which the ensemble forecast is reliable is reflected by where the observed relative frequencies fall within the consistency bars [12]. However, one has to note that the range of potentially observed proportions for a perfectly reliable forecast might be slightly underestimated since the consistency resampling method does not account for serial correlation [13].

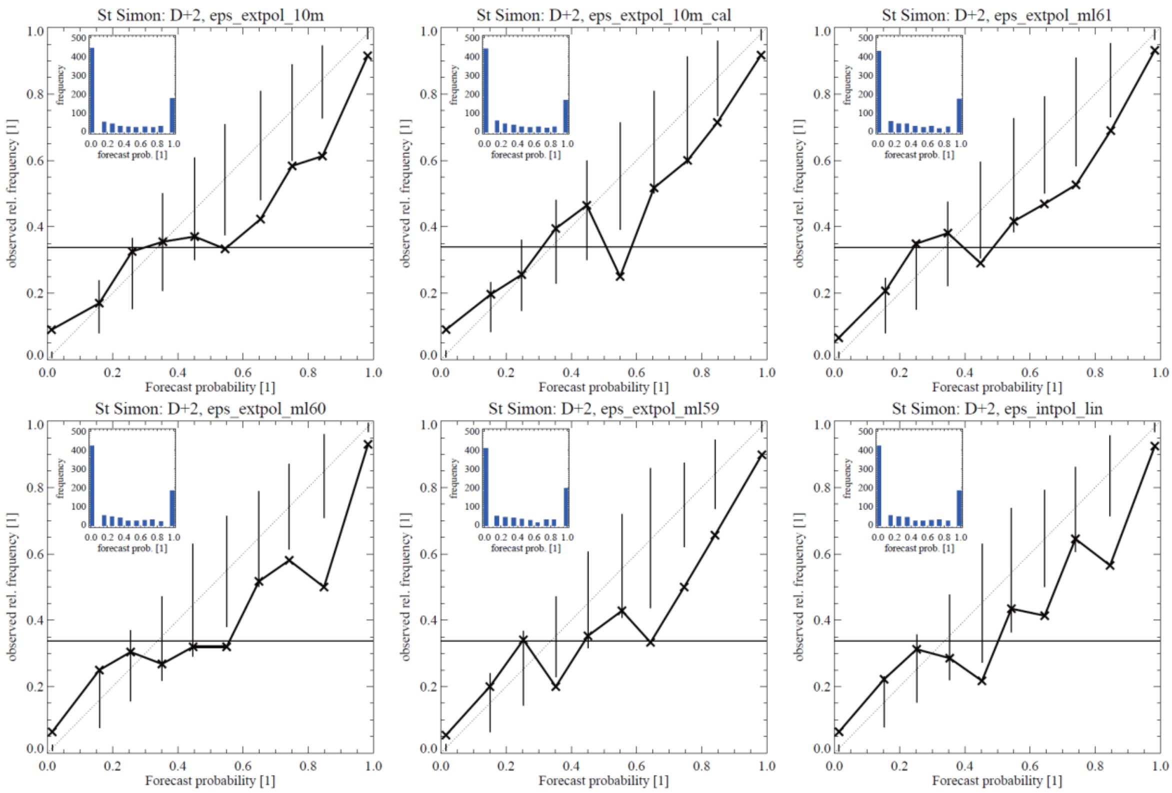

Fig. 3-3: *Reliability diagram for the second forecast day (30-48 h) and for wind power events greater than 20%. Shown are the results for the experiments eps_extpol_10m (top left), eps_extpol_10m_cal (top middle), eps_extpol_ml61 (top right), eps_extpol_ml60 (bottom left), eps_extpol_ml59 (bottom middle) and eps_intpol_lin (bottom right).*

Both the WPP obtained from raw and calibrated 10 m winds lead to underforecasting for very low forecast probabilities (<0.1) and overforecasting for higher forecast probabilities (0.5-0.6) since the reliability curve falls outside the consistency bars. However, the 10 m calibrated wind ensemble leads to slightly higher reliability for low forecast probabilities (0.1-0.4) and high forecast probabilities (0.7-

0.9). The WPP obtained from extrapolation of model levels to hub height as well as linearly interpolating model levels leads to a higher reliability for very low forecast probabilities (<0.1) while winds from model level 61 seem to have the overall highest reliability. However, one has to note that differences in the reliability in the WPP between extrapolation from calibrated 10 m winds and model levels to hub height as well as the linear interpolation between model levels are only small for the day-ahead forecast horizon.

An appropriate tool for the evaluation of the evolution of the forecast skill with increasing lead time is the Continuous Ranked Probability Skill Score (CRPSS). The reference experiment for the skill score is chosen to be the WPP calculated from the raw 10 m wind ensemble forecast (*eps_extpol_10m*). This allows identifying possible benefits of using model level winds over the usage of 10 m winds in probabilistic WPP (Fig. 3.4).

The intra-day (6-24 h) and day-ahead (30-48 h) forecast horizon are of primary interest for end-users of wind power predictions. For the intra-day forecast horizon, the 10 m calibrated wind ensemble leads to a slightly improved wind power prediction (up to +7 %). The CRPSS of the calibrated day-ahead ensemble forecast decreases for longer lead times. The linear interpolation method and the extrapolation from model level 61 lead to the best improvements of the WPP of up 11-14 % for the intra-day forecast horizon. However, the improvement for level 61 is less oscillating with lead time compared to the linear interpolation method. The ensemble wind from model level 60 (which is closest to hub height) also indicates an improvement over the WPP from the 10 m raw wind ensemble up to 10 %. The CRPSS calculated from WPP of model level 59 (~110 m) winds shows clear improvements (up to 10 %) during daytime forecast horizons and strong degradations of the CRPSS (up -16 %) during nighttime. The latter might reflect overestimations of the wind power during nighttime since effects of nocturnal low-level jets are extrapolated down into the hub height layer.

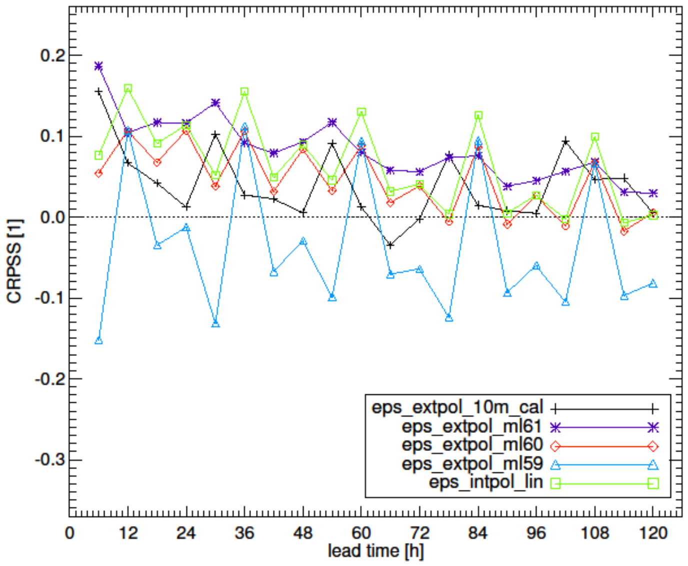

Fig. 3-4: *Continuous Ranked Probability Skill Score (CRPSS) [1] for all forecast steps with eps_extpol_10m as the reference experiment.*

Another common approach to evaluate errors in the mean and spread of an ensemble forecast is the construction of verification rank histograms (Talagrand Rank Histrogram). The rank histograms calculated for the experiments carried out in this case study show that there is a strong deviation from rank uniformity – even for the WPP from the 10 m calibrated winds (not shown here). This means that the wind power ensembles are still underdispersive and need further post-processing in order to produce forecasts with statistical properties comparable to observations. Future work should thus concentrate on calibrating ensemble wind forecast in different model heights (i.e. model level 61, 60 and 59 and 100 m).

In conclusion, uncalibrated WPP from winds in model levels 61 and 60 and WPP calculated from linearly interpolating between model level winds lead to highest forecast skill for the intra-day and day-ahead forecast horizon. The calibration of the 10 m winds leads to an slightly improved CRPS for intra-day and day-ahead forecast. One has to note that the calibration of the 10 m ensemble wind forecasts was carried out with the related ECMWF analyses. Repeating the calibration methodology with actual observations for single test cases might improve the calibrated 10 m wind forecast significantly. For hub heights well below the 100 m, winds from model level 59 do not necessarily lead to improved ensemble forecast skill since the CRPSS strongly oscillates between positive and negative skill scores. It would be interesting to repeat this study for a wind farm having hub heights near model level 59. In general, it would be useful to support the findings of this case study by applying the methods to other wind farms where high quality timeseries of power production and wind power measurements are available. It would be of particular interest to accomplish this for wind farms located within areas of terrain types (i.e. complex terrain, offshore etc.).

4. Conclusions

It has been demonstrated that the new EPS product of ECMWF to archive and disseminate winds at 100 m height is a major achievement for probabilistic wind power forecasting. In this report results for regional and single site wind power forecasts are presented.

In the case of Germany as a regional wind power forecast, no wind power bias correction is necessary to correct for thermal stability effects in the atmosphere as 100 m winds can be directly interpolated to the hub height of modern wind turbines. Note, that the wind speed in 10 m height is also used for this interpolation. The wind power RMSE (for Germany) is decreased by 50 % using the 100 m ensemble mean compared to the 10 m ensemble mean. It is shown that the wind power RMSE for the ensemble mean is less than 8 % of the German wind power capacity at forecast day+3.
The strong superiority of 100 m ensemble winds over 10 m winds is also demonstrated for probabilistic scores: The CRPSS for Germany is about 0.50 in the short-range and decreases to 0.12 at the end of forecast day+5. Compared to the 10 m wind ensemble the spread and reliability of 100 m winds is substantially increased.

The case study for the wind farm in the North of France (single site) focused on the assessment of probabilistic wind power forecasts using ensemble wind forecasts from the ECMWF-EPS at different model heights. The benefits from using ensemble wind forecasts from model levels near hub height over the usage of 10 m winds were evaluated. Since the ECMWF-EPS forecast data does not contain any information about vertical stability, extrapolation to hub height is done using the logarithmic wind profile for neutral conditions. This can lead to large extrapolation errors for model levels that are far off the hub height. The usage of ensemble forecasts in model level 60 and 61 as well as linearly interpolated forecasts from model levels exhibit strongly positive CRPSS for the intra-ahead and day-ahead forecast horizon. The calibration of the 10 m wind does not lead to strong improvements over the raw 10 m winds which might be caused due to using the related ECMWF analyses to calibrate the 10 m ensemble forecast. Using actual observations instead of analyses could improve the skill scores of the calibrated ensemble.

For future probabilistic wind power forecasts it would be beneficial to have access to ensemble wind forecasts in different model levels and to have information about the vertical stability in the planetary boundary layer to avoid large extrapolation errors. The new 100 m product of the ECMWF is already one important step towards this goal. In addition, the evaluation of verification rank histograms has shown that the ensemble wind power forecasts are under dispersive independent of the model level winds used for generating the wind power forecast. Future studies should thus focus on the calibration of wind power ensemble forecasts to generate an ensemble with reliable statistical properties. Thus, the usage of model levels winds, the calibration of the ensemble wind power forecasts (optimally with observations instead of analyses) and vertical stability information could significantly improve wind power forecasts.

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