Combination of Deterministic and Probabilistic Meteorological Models to enhance Wind Farm Power Forecasts

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Abstract. Large-scale wind farms will play an important role in the future worldwide energy supply. However, with increasing wind power penetration all stakeholders on the electricity market will ask for more skilful wind power predictions regarding save grid integration and to increase the economic value of wind power. A Neural Network is used to calculate Model Output Statistics (MOS) for each individual forecast model (ECMWF and HIRLAM) and to model the aggregated power curve of the Middelgrunden offshore wind farm. We showed that the combination of two NWP models clearly outperforms the better single model. The normalized day-ahead RMSE forecast error for Middelgrunden can be reduced by 1 % compared to single ECMWF. This is a relative improvement of 6 %. For lead times >24h it is worthwhile to use a more sophisticated model combination approach than simple linear weighting. The investigated principle component regression is able to extract the uncorrelated information from two NWP forecasts. The spread of Ensemble Predictions is related to the skill of wind power forecasts. Simple contingency diagrams show that low spread corresponds is more often related to low forecast errors and high spread to large forecast errors.

1. Introduction

The accuracy of short-term wind power forecasts is very important to facilitate the integration of very large-scale offshore wind power into the grid. Obviously, the integration of high shares of wind power is not a given pre-requisite 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 [1].

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 regulative power must decrease in order to increase the economic value of wind power, in particular when challenging scenarios (e.g. 22% of Europe's electricity production from wind power by 2030 [2]) shall be met. However, day-to-day trading of offshore wind power at the spot market will attract energy traders and wind farm operators. The monetary benefits of short-term wind power forecasts are highlighted for Spain and the UK in [3].

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

Physical wind power algorithms compute local wind power from large-scale wind forecasts (typically between 7 to 40km horizontal resolution) as follows: i) spatial refinement (e.g. horizontal interpolation), ii) calculation of the wind speed at hub height (e.g. extrapolation of 10m surface wind considering thermal stability or use of high level NWP model fields), iii) consideration of orography effects and iv) surface roughness, v) losses due to turbine wakes in the wind park and vi) accounting the availability of turbines with respect to damages, maintenance or cut-off at high wind speeds.

In statistical algorithms at least three of the above mentioned aspects of wind power prediction do not necessarily require physical modeling, i.e. orography effect, surface roughness and turbine wakes. These effects can be accounted and derived during the learning period as wind directional dependent (sectoral) effects on the power curve of an entire wind farm [4]. However, these effects can be modeled physically and the results are used in a statistical wind power prediction scheme.

This study compares two approaches to combine two wind speed forecasts to predict the wind power for the Danish wind farm Middelgrunden up to two days ahead. Recently, projects to combine various European NWP models have started. The strategy in [5] is to discriminate model performance by weather situation and to combine models accordingly. A more general approach is the use of single model ensembles [6] and [7]. Multi-scheme ensemble prediction [8] is suspected to overcome the observed underestimation of spread in wind power forecasts using single model ensemble.

The investigated approach to combine two NWP models is explained in Section 3 together with the application of Neural Networks to i) perform Model Output Statistics (MOS) between forecasted wind speeds from NWP and observation and ii) to model the aggregated wind farm power curve. In Section 2 the site, observational data and available wind forecasts are described. Section 4 discusses the relation between wind power forecast skill and the spread of ensemble predictions. Conclusions are given in Section 5.

2. Site and Wind Data Description

2.1. Wind Farm Middelgrunden

The Danish wind farm Middelgrunden is located 2km east of Copenhagen (Fig. 1) and was built in 2000. Twenty BONUS (now Siemens Wind Power) SWT-2.0-76 turbines each 2MW nominal power

Fig. 1. Wind farm Middelgrunden 2km east of Copenhagen.

were rated with a hub height of 64m. The park geometry is a slight concave line in north-south direction. Commissioning started early 2001 and gradually more and more turbines became available. 10min averages of Scada data (power production) are used from January 2001 to October 2002. These data and also the 10-minute averages of nacelle anemometer wind speeds are available for each individual turbine. This allows an intrinsic quality control, i.e. to account for situations when individual turbines are down regulated.

Mean values of wind speed and power have been calculated for the entire find farm. The power is normalized with the instantaneous available capacity, e.g. to account for outages of individual turbines. In a last step wind speeds and power data are averaged to hourly values in order to make the variance of forecasted wind speeds (3 hourly) and observed wind speeds (and power) comparable. Figure 5 shows the observed mean wind speeds versus the wind production data for the entire wind farm. We therefore call this curve the wind farm power curve.

The direction of the observed wind (approximated from the yaw angel of the turbines) is not considered in this study as the scatter between wind speed and power is very little and indicates that the directional dependence between wind speed and generated wind power is marginal.

2.2. Wind Forecast Data

Wind forecast data (u, v component) is used as point predictions from two Weather Services. The original horizontal grid resolution is 40 km for ECMWF forecasts. ECMWF is the European Centre for Medium-Range Weather Forecasts in Reading (U.K.) and provides two forecasts per day (00UTC and 12UTC). Wind speeds have been interpolated to the turbine hub height of 64m and were taken from the original model level fields of wind. The height of these model levels is approximately 10, 33, 60, 90 meters above ground.

HIRLAM forecasts from the Danish Meteorological Institute (DMI) are also available twice per day. The original horizontal resolution (16km) is considerably higher than for ECMWF. Winds from the model level 30 are used. Forecasts from both models are available till forecast step 48h, i.e. our study focus on wind power predictions for the day-ahead (forecast day 2).

3. Combination of deterministic Forecasts in Wind Power Prediction

The combination is done in three steps that are described in the following subsections. The sketch in Figure 2 gives an overview how the different steps are linked.

3.1. Non-linear Model Output Statistic

The first step is a sectoral MOS system that is derived for each NWP model. With the help of the Neural Network the predicted wind components are related to the observed nacelle wind speed using three hidden Neurons. 90 days of historic data are used and the training was repeated every 15 days. To take diurnal changes in the atmospheric flow at the wind farm into account the MOS was done for different hours of the day. Four groups are pooled that are characterized by roughly the same local wind behavior at the site. The group 0, 6 UTC is characterized by less turbulent flow as radiative cooling of the sea surface and near-surface layers occur. Consequently the stratification of the atmosphere is getting on average more stable during night and wind shear increases. One other important group is 12 and 15 UTC where radiative heating is strongest and the wind shear is smallest. Land-sear circulation is possible. Two intermediate groups 18, 21 UTC and 6, 9UTC are formed.

As an example the sectoral MOS for Jul–Oct 2002 (0,3 UTC) is visualized in Fig. 3.The rim of the circle represent the 18 m/s wind speed as it comes from the NWP model. It is related two 14 m/s observed wind speed for easterly directions. Two minima can be seen for SW and NW winds, when the local wind speeds drops to about 11m/s. It is inevitable to say that the city of Copenhagen has a significant impact on the MOS.

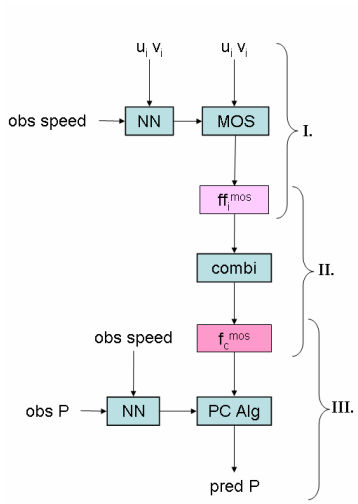

Figure 2.Sketch of the proposed approach: I. Model Output Statistic (MOS) applied to forecasted wind components u_i, v_i; II. combination of MOS wind speeds ff_c^{mos}; III. Power curve modelling.

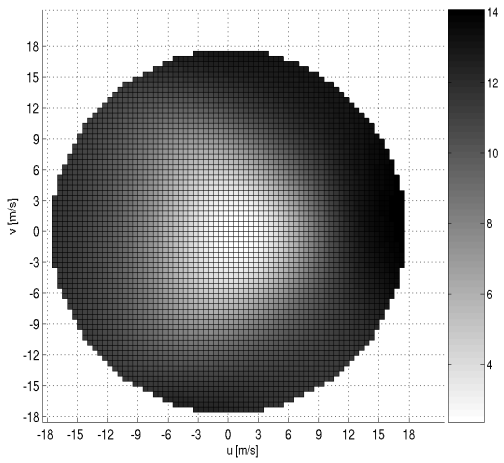

Figure 3. Sectoral Model Output Statistics (MOS) for the observed wind speed [m/s] at the wind farm Middelgrunden as calculated for wind components (u, v) forecasted by ECMWF. The city of Copenhagen is located westwards of the wind farm.

3.2. Combination of Wind Speeds

The correlation between ECMWF's and HIRLAM's forecast error (prediction minus observation) can reveal the potential for the combination of forecasts (Fig. 4, left). For this analysis forecasted wind speeds that are corrected by MOS are used. The error correlation is smallest in the two summer periods and 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 different forecasts which are less correlated; a feature that is wanted for the combination of forecasts.

Two different combination approaches are applied: i) linear average of both forecasts, i.e. equal weighting and ii) principle component regression. The later technique has the advantage that the uncorrelated information in the two forecasts is extracted and usable. In case of principle component regression two eigenvectors of the two wind speeds forecasts (after the MOS) are computed for the last 150 days. It is assumed that the two eigenvectors are indifferent for the forthcoming 15 days. The two time dependant principle components are regressed (least-square fit) to the observed nacelle wind speed and the regression coefficients are stored. In the application period two principle components are calculated using the formerly derived eigenvectors. Multiplying those principle components with the stored linear regression coefficients leads to the estimation of the nacelle wind speed.

ECMWF wind speed forecast (after applying the MOS) outperforms HIRLAM by about 0.2 m/s in terms of RMSE (Fig. 4, right). The combination of both forecasts with equal weighting shows considerable improvements compared with the individual forecasts. The skill of the combination has a seasonal dependency, i.e. in winter the combination forecast is worse than ECMWF alone. As discussed before the error correlation between ECMWF and HIRLAM is highest in winter and the averaging effect of forecast errors gets comparable lower. In periods of low error correlation (spring/summer) the improvement of the combination with respect to ECMWF is highest. The combination with principle component regression has small but notable advantages against the simpler equal weighting combination approach. It seems to be worthwhile to extract the information from the two wind speeds by building an orthogonal basis as provided by the eigenvectors.

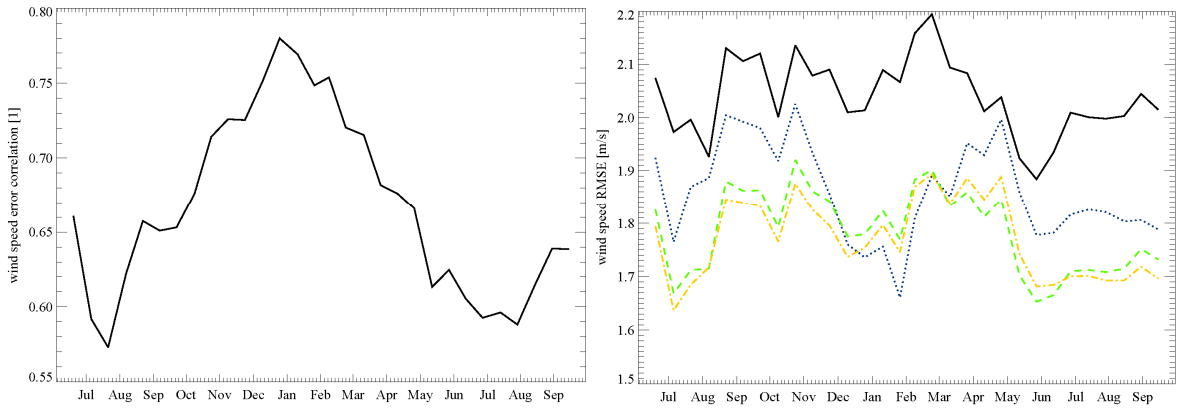

Figure 4. Correlation (left) between HIRLAM and ECMWF wind forecast errors (forecast step 25-48h) for Middelgrunden wind farm from Jul 2001 to Sept 2002. The RMSE of wind speed for HIRLAM (black, solid) and ECMWF (blue, dotted) is shown in the right figure. The RMSE of the equal weighting combination is shown in green (dashed) and the principle component regression combination in orange (dashed dotted). In both figures a 90 days low-pass filter is applied.

3.3. Modelling the Wind Farm Power Curve

In the last step the wind farm power curve is applied. It was modeled at an earlier stage for the entire wind farm. A Neural Network with two hidden neurons is used to find the algorithm that relates observed wind speed to measured wind power by minimizing a cost function that measures the difference between modeled wind power and measured wind power. The derived algorithm is drawn as a solid line in Fig. 5 together with all data pairs (observed wind power vs. observed wind speed).

In an independent test data set the root mean square (RMS) difference between wind power that is calculated with the derived algorithm from observed nacelle wind speeds and truly observed wind power is only 1.7 % (normalized with nominal power). The systematic error (bias) is less than 1% and the correlation is 99.8%. It can be therefore suspected that the transformation itself of a (forecasted) wind speed in hub-height into wind power is only introducing a marginal additional error.

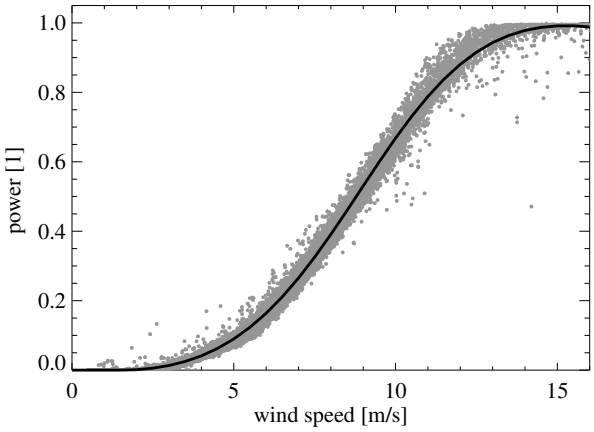

Figure 5. Normalized wind farm power curve for Middelgrunden fitted with the Neural Network (solid line) and data pairs of observed wind power vs. observed nacelle wind speed for the years 2001 and 2002. Wind power and wind speed are averaged over one hour.

3.4. Results

The validation period is July 2001 to mid of October 2002. The months before July 2001 are excluded as they have been used i) in the first training cycles of the NN to derive the wind speed MOS and ii) in

the principle component regression to combine ECMWF and HIRLAM forecasts. Wind power forecasts are computed with the wind farm power curve as described in the previous subsection.

Figure 6 shows the low-pass filtered time series of the wind power forecast error (normalized RMSE) for HIRLAM, ECMWF and the combinations of both. As for wind speeds (Fig. 4, right) day-ahead wind power predictions using ECMWF are clearly better, in particular in winter (Fig. 6). Both combination approaches add notable value to the wind power forecasts compared to the individual ECMWF forecast. Only in winter individual ECMWF forecasts are better than the combination. Apparently HIRLAM deteriorates the combination during that time.

A more comprehensive view on the combination result is obtained from Fig. 7. At all lead times the principle component regression combination equals or outperforms the equal weighting combination in terms of RMSE for wind speed (Fig. 7, left) and wind power (Fig. 7, right). The RMSE is normalized with the nominal capacity (40 MW). The average day-ahead forecast error is 16.8 % for ECMWF and is reduced to 15.8 % for the principle component regression combination.

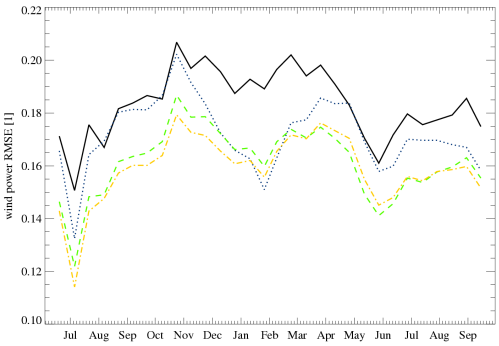

Figure 6. Normalized RMSE of day-ahead (+25-48h) wind power predictions with HIRLAM (black, solid) and ECMWF (blue, dotted). Equal weighting combination is green (dashed) and principle component regression combination is orange (dashed dotted). A 90 days low-pass filter is used.

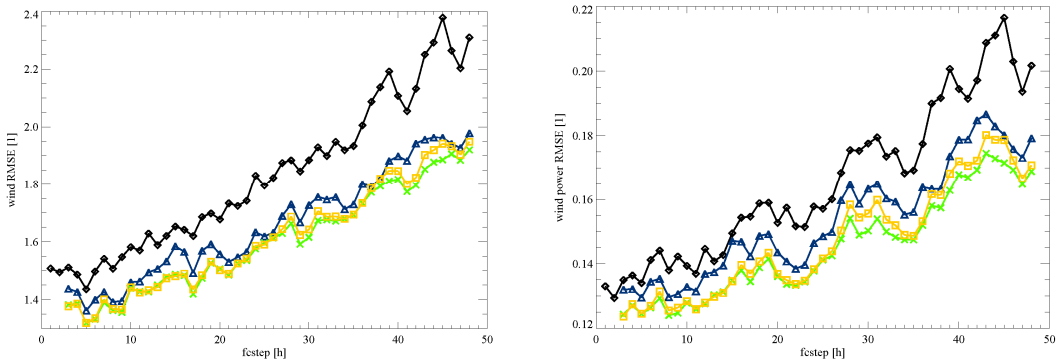

Figure 7. Normalized RMSE of wind (left) and wind power (right) forecast for Middelgrunden using HIRLAM (black ◊) and ECMWF (blue Δ) forecasts. The combination of both with principle component regression and equal weighting is shown in green (x) and orange (□), respectively.

In general, the RMSE vs. lead time graphs in Fig. 7 for wind speed and wind power prediction look very similar. But it is worth to note that the blue curve (ECMWF) is much more rippled in wind power space than in wind speed. It is believed that they occur due to better predictability of various hours of the day than others. Note, that 00UTC and 12UTC model runs are used. Furthermore it is interesting to see that at forecast day 1 both combination approaches are almost equivalent while at day 2, when both models gets more independent, the use of the principle component regression approach tends to give better results.

4. Forecast error and ensemble spread relation

One of the principle uses of an ensemble forecast is to provide an estimate of the confidence in a prediction; the larger the ensemble dispersion, the less reliable is the forecast, because initial condition (analysis) errors had been large. In our case we investigate the use of ECMWF's Ensemble Prediction System (EPS) to classify whether the (deterministic) wind power prediction is skilful or not. ECMWF's EPS consists of 50 ensemble members [9]. As a measure of the ensemble dispersion or ensemble spread, it is common to use the standard deviation between the ensemble members and the control forecast. As a meteorological parameter relevant to the surface wind field the 1000hPa geopotential height has been chosen and is interpolated to Middelgrunden.

Figure 8 shows the scatter diagrams of forecast skill (RMSE forecast error) and spread as occurred in autumn 2001 for lead times of +24 (left) and +48h (right). For each diagram, the distribution is divided by the median value, and the number of elements in each quadrant is shown in the figure. These give a 2x2 contingency tables for high/low, high/low skill cases. Note that by using the median to define the categories, the contingency table is necessarily symmetric.

The diagonal entries are notably more populated than the off-diagonal entries, i.e. low spread of the ensemble is more often related to low forecast errors (lower left quadrant) than to large forecast errors (upper left quadrant). Conclusively for this case, large spread is more often related to large forecast errors (upper right quadrant) than to low forecast errors (lower right quadrant). Comparing the two lead times shown in Fig. 8, it can be seen that the forecast error to spread relation gets slightly worse for +48h. The spread increases and the maximal forecast error is now 0.53 higher than the median. The median is about 0.08 for +24h and +48h.

Further studies will focus on improved relationship between forecast skill and spread. The spread shall be characterised by the spread in wind power forecasts or at least by the spread in forecasted wind speeds by the individual ensemble members.

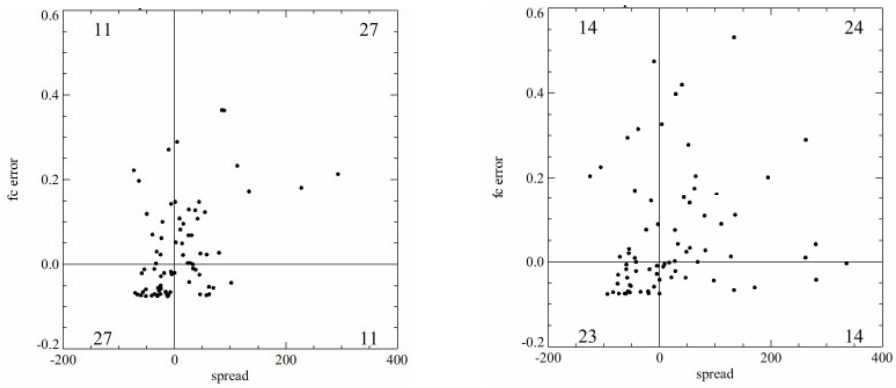

Figure 8. Scatter diagram between ECMWF wind power forecast error (normalized RMSE) and ensemble spread for lead time +24h (left) and +48h (right) in Sept-Nov 2001, 12UTC model run. The ensemble spread is expressed as the standard deviation between the ensemble members and the control forecast of 1000hPa geopotential height at Middelgrunden. Data are plotted as deviations from the median value.

5. Conclusion

We showed that the use of several NWP models (multi-model) is beneficial for wind power forecasting compared to single models. In the superior of the two combination approaches, the normalized day-ahead RMSE forecast error for the offshore wind farm Middelgrunden is 1 % smaller than the ECMWF forecast. This is a relative improvement of about 6 %.

With increasing lead times (>24h) a more sophisticated NWP model combination turns out to be the better choice than simple linear weighting of model results. Principle component regression is able to extract also the uncorrelated information out of two NWP forecasts.

It is inevitable that along with historic wind power production data complementary wind speed measurements are available. This is required to model the entire wind farm power curve and to develop an exact Model Output Statistic (MOS) between NWP forecast and measurement. We believe that wind observations behind the rotor (nacelle anemometer) are of sufficient quality to facilitate and to improve short-term wind power forecasts; i.e. NWP errors are an order of magnitude higher than (slightly distorted) wind speed measurements behind the rotor.

Future work will focus on the forecast range beyond day 2 and the comparison of single-model ensembles against combination of different NWP models.

Acknowledgments
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