Neural Networks to find optimal NWP combinations for Offshore Wind Power Predictions

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Large-scale offshore wind farms need to be operated as power plants for renewable energy. The dependency of energy production on highly fluctuating weather systems is inherent but will become manageable due to accurate wind power forecasting. The performance of statistical wind power forecasting algorithms can be optimized by combination of wind forecasts from different Numerical Weather Prediction (NWP) models.

The use of Neural Networks is superior as a statistical tool to make accurate wind power forecast for single offshore sites. A new approach is presented to combine input data from two Numerical Weather Predictions for the Danish offshore wind farm Middelgrunden. The approach is divided into three independent steps: It starts with a wind sector dependent Model Output Statistics (MOS) using a Neural Network. In this step NWP winds are mapped to observed winds at the site of Middelgrunden to account for local conditions. In a second step MOS corrected wind speeds from two different NWP models are combined with linear regression technique. The resulting wind speed is applied to a wind farm power curve that was derived from observed wind power and nacelle wind speeds. This approach performs better than to leave the combinational work to the Neural Network itself.

The root mean square forecast error is 18 % of the installed capacity at the end of day 2.

1) Introduction

The accuracy of short-term wind power forecasts is besides other factors very important to support large-scale offshore wind farming on its way to repeat the success story of onshore wind power over the last decade. High accuracy on estimated power production is needed for the efficient integration of large scale 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. 12% of Europe's electricity production from wind power by 2020 [1]) shall be met.

Day-to-day trading of offshore wind power at the spot market is suspected to become an attractive additional part of the earnings for wind park investors besides guaranteed fixed feed-in tariffs.

High-Resolution Numerical Weather Predictions (NWP) of wind play the key role for excellent wind power forecast [2]. 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.

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.

The key advantage of statistical algorithms is that at least three of the above mentioned important aspects of wind power prediction do not require physical modeling, i.e. orography effect, surface roughness and turbine wakes. These effects can be accounted as wind directional dependent effects on the power curve of the entire wind farm [3].

This study describes two approaches to combine several wind speed forecasts to predict the wind power for the Danish wind farm Middelgrunden up to two days-ahead. Neural Networks are used at different steps in the computation, e.g. Model Output Statistics (MOS) and combination.

The combination of forecasts is an often applied technique in meteorology to increase the skill of long-term (seasonal and even longer-term) forecasts and is called multi-model approach. In case ensembles of several models are used, the terminology is multi-model ensembles [4].

The application of multi-model techniques in short-term prediction is not very developed. However, first studies for wind power forecasting are done [5]. More work was already done with single model ensembles [6] and [7].

Not multi-model, but multi-scheme ensemble prediction is suspected to overcome the underestimation of spread for wind power forecasting in single-model ensemble [8].

The two investigated approaches to increase the forecast skill in wind power forecasting with two NWP model runs are explained in Section 3. In Section 2 the site, observational data and available wind forecasts are described. Results are shown and discussed in Section 4. Conclusions and an outlook are given in Section 5.

2) Site and Wind Data Description

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 were rated with a hub height of 64m. The park geometry is a slight concave line in north-south direction.

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

The wind farm was in the commissioning phase in early 2001, when gradually more and more turbines became available. Our raw data are the 10-minute averages of Scada data for power production 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 regulated to produce less than their nominal power.
Mean values of wind speed and power have been calculated for the entire find farm. The power values are 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. Fig. 4 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 is marginal.

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) APPROACHES

A. Direct combination of wind components

In the first approach wind components (u, v) interpolated to the site of Middelgrunden are used directly as input to the Neural Network to derive a relation between wind (speed and direction) and the power output of the wind farm. A sketch of this approach is given in Fig. 2 (left, **A.**). The training and application of the Neural Network is done in the following way: historic data pairs of forecasted winds and complementary normalized production data of the last 150 days are divided randomly into two sets. One set is used for the internal minimization of the cost function in the Neural Network, e.g. adjusting the weights related to the neurons, while the second set is used for controlling the solution on generalization. Once a solution for the weight of the three hidden neurons is found by three independent searches (starting points of the minimization), this solution is applied to the wind forecasts issued the following 15 days. After that time the training of the Neural Network is repeated to account for seasonal changes that affect the Numerical Weather Prediction. Earlier studies for the Irish offshore wind farm Arklow Banks showed that even 120 days of historic training data is sufficient and that the same algorithm can be used up to 60 days in the future.
In the simple case of one NWP model, we have two input neurons. In case two NWP models are used, four input variables are fed in the Neural Network, i.e. two u-components and two v-components.

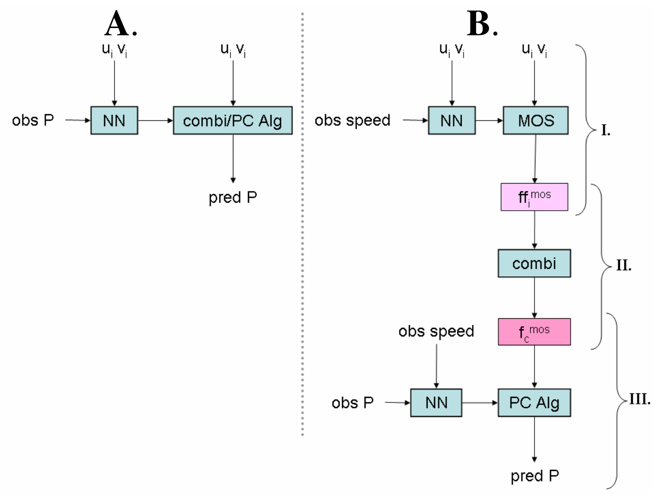

Fig. 2. Overview of the two investigated approaches: Direct combination of wind components u_i, v_i (left) and combination of MOS wind speeds ff_c^{mos}.

B. Combination of MOS wind speeds

This approach comprises three steps as can be seen in Fig. 2 (right, **B.**). Each will be explained in detail.

I.) 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. A local 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.

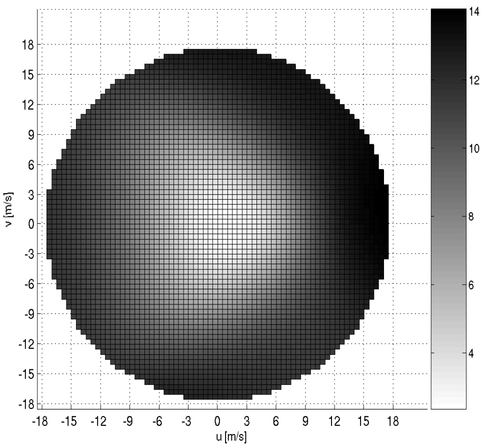

Fig. 3. Sectoral MOS (Model Output Statistics) for the observed wind speed [m/s] at the wind farm Middelgrunden as calculated for wind components (u, v) forecasted by ECMWF. The city of Copenhagen is located westwards of the wind farm.

II). The combination of MOS wind speeds is done in the second step. The weight of each individual forecasted MOS wind speed is determined by linear regression of all cases in the last 150, i.e. a least square fit is done between forecasted MOS wind speeds and observed nacelle wind speed. The coefficients are used in the upcoming 15 days; at day 16 new coefficients are computed to take possible changes in the skill of the NWP models into account.

III.) In the last step the transfer function between the mean observed nacelle wind speed and the mean power production (power curve) is applied. Beforehand the power curve for the entire wind farm is fitted to the observed nacelle wind speed with a Neural Network using two hidden neurons. The derived algorithm is drawn as a solid line in Fig. 4 together with all observed data pairs (observed power production 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 % of the nominal power. The systematic error (bias) is less than 1% and the correlation is 99.8%. It can be therefore suspected that the transformation of a forecasted wind speed in hub-height into wind power using this algorithm is only introducing a marginal additional error. The main power prediction error comes from the inaccurate forecasted wind speed. The relation between wind speeds that are predicted with Approach B. and observed wind power is shown in Fig. 5. The scatter represents the wind power forecasting error. The root mean square error (RMSE) is discussed in the next section.

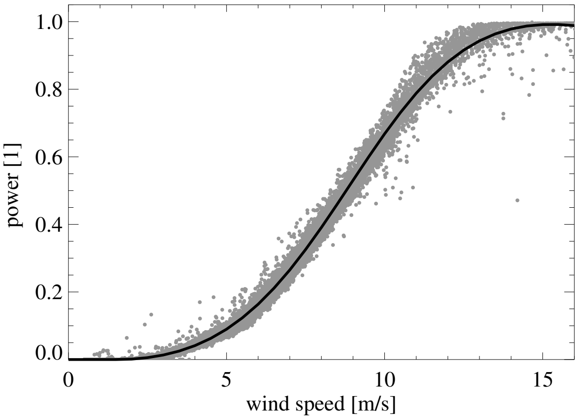

Fig. 4. Normalized power curve for the wind farm Middelgrunden as fitted with the Neural Network (solid line) and observed (observed wind power vs. observed nacelle wind speed) in the years 2001 and 2002. Wind power and wind speed are averaged over one hour.

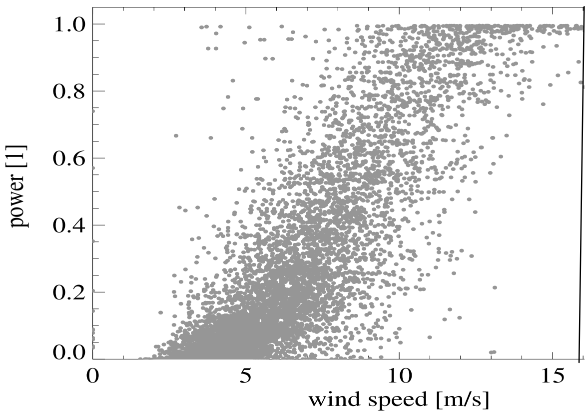

Fig. 5. Normalized power curve for the wind farm Middelgrunden against forecasted and combined MOS wind speeds in hubheight. The wind power data is averaged over one hour.

4) Results

The study period for validation is July 2001 to mid of October 2002. The months before July 2001 have been excluded from validation as they have been used in the first training cycles of the NN and the combination process to find the best set of weighting of the forecasts.
The results are shown as RMSE between predicted wind power and observed wind power against look-ahead time. The RMSE is normalized with the nominal capacity (40 MW).

The results for the two investigated approaches (**A., B.**) are shown in Fig. 6. As references the results for a single NWP model (HIRLAM and ECMWF, respectively) are shown as well. The forecast error is smaller for the combination of HIRLAM and ECMWF compared to a single model. The improvement is about 1.5% in RMSE. The forecast error at the end of day 2 is about 18%.

Approach **B.** gives slightly better results than approach **A.** In principle both approaches have the same input information (two u wind components and two v wind components) for the power forecast. However, MOS and subsequent combination of wind speeds is superior and it is necessary to discuss why the same available input information from the NWP models leads to different results.
A possible explanation is the multiple use of observed nacelle wind speeds in approach **B**. They are used twice for the MOS system, for combination of forecasted wind speeds and for the determination of the wind farm power curve. The nacelle wind speeds can be regarded as an additional observation to account for local effects at the wind farm. This is benefitial for the mapping of coarse resolution NWP wind speeds.

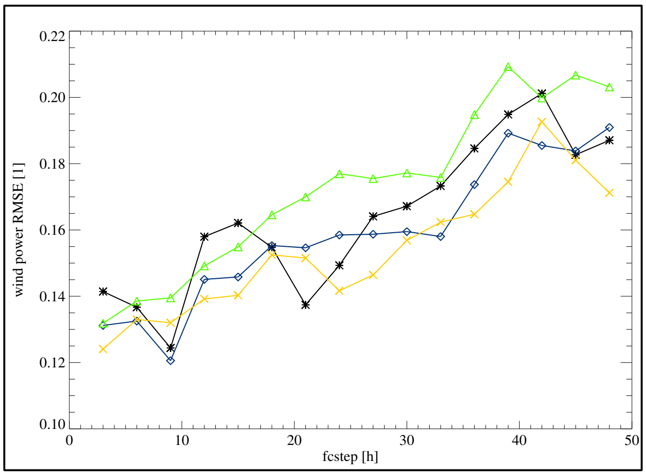

Fig. 6. Root mean square error (RMSE) of wind power forecast (normalized with the rated capacity) against look-ahead time. Four different algorithms are used: HIRLAM (green line, Δ) alone, ECMWF (black line, *) alone, ECMWF and HIRLAM combined with Approach A. (blue line, ◊) and combined with Approach B. (orange line, x)

5) Conclusions

We showed in this study that the use of several NWP models (multi-model) is beneficial for wind power forecasting compared to single models. The RMSE forecast error for the offshore wind farm Middelgrunden is absolute 1.5% reduced. Compared to the forecast error of 18% at the end of day 2 this is an improvement of 8%.

Two different approaches have been tested and we have found that better results are obtained when Model Output Statistics, combination and the modeling of the wind farm power curve are done in separate and consecutive steps.
However, for that approach it is inevitable that along with historic wind power production complementary wind speed measurements are available. This is absolutely necessary to allow the proper modeling of the entire wind farm power curve and the application of exact Model Output Statistics (MOS).

Following our results to model the overall wind farm power curve for Middelgrunden, we believe that the wind observation behind the rotor (nacelle anemometer) is absolutely sufficient to provide good measurements of wind speed and direction.
Future work will focus on the forecast range beyond day 2 and the comparison of single-model ensembles against multi-model use. Different combination techniques [4] will be tested and probalistic forecasts [7] will be studied.

Acknowledgments

The European Centre for Medium-Range Weather Forecasts (ECMWF) is thanked for providing wind forecast data. The HIRLAM forecasts and Middelgrunden wind farm data were provided within the EU project ANEMOS. The main author is funded by the Ministry for the Science and Culture of Lower Saxony, Germany.

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