Optimal Linkage of NWP Models with Neural Networks for Offshore Wind Power Predictions

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***Abstract*—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 four Numerical Weather Predictions for the Danish offshore wind farm Middelgrunden. The approach is divided into three independent steps: It starts with the fit of the overall wind farm power output to the nacelle wind speed. In a second step wind sector dependent Model Output Statistics (MOS) using a Neural Network are used to fit the forecasted winds to the site of Middelgrunden. In a third step MOS corrected wind speeds from four different predictions are combined and finally applied to the power curve that had been computed in the first step.

The forecast error at day 2 can be reduced from 18 % to 15%.

***Index Terms*—wind power predictions, offshore, combination, Numerical Weather Prediction, neural network**

I. 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.

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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 in the following steps local wind power from large-scale wind forecasts (typically between 7 to 40km horizontal resolution): 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].

The use of Neural Networks (NN) in statistical algorithm development is very common, i.e. satellite meteorology [4, 5] and also wind power forecasting [6]. Differences exist in i) used input data, i.e. different NWP data and number of variables, but also ii) in application, e.g. regional forecasts [7] or single site forecast [8].

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 [9]. In case ensembles of several models are used, the terminology is multi-model ensembles.

The application of multi-model techniques in short-term prediction is not very developed. However, first studies for wind power forecasting are done [10, 11]. More work was already done with single model ensembles [11], [12] and [13]. Not multi-model, but multi-scheme ensemble prediction is suspected to overcome the underestimation of spread for wind power forecasting in single-model ensemble [14].

The two investigated approaches to increase the forecast skill in wind power forecasting with up to four 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.

II. SITE AND WIND DATA DESCRIPTION

A. *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.

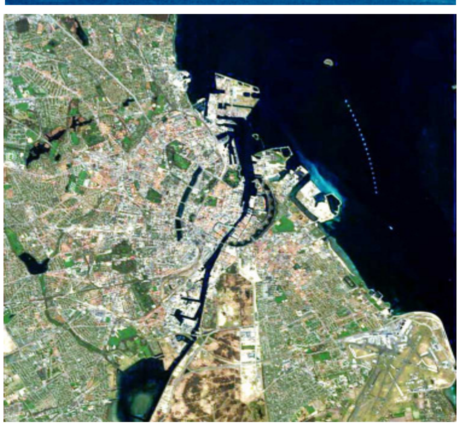

Fig. 1. Wind farm Middelgrunden 2km east of Copenhagen.

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. 2 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.

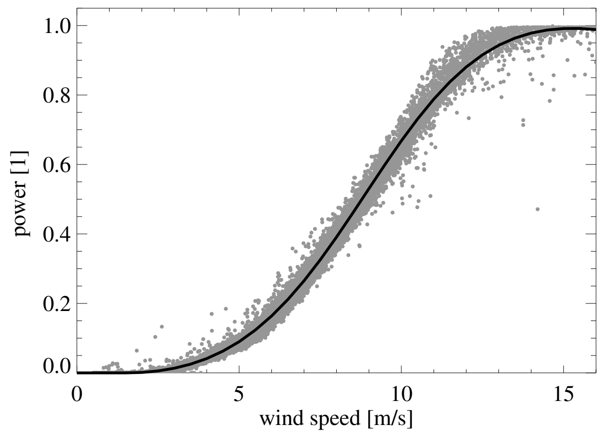

Fig. 2. Normalized power curve for the wind farm Middelgrunden as fitted with the Neural Network (solid line) and observed in the years 2001 and 2002. The data is averaged over one hour and the power data is normalized with the rated capacity of 40MW.

B. *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).

As forecasts are available twice daily, we use two model runs as a kind of ‘poor man’s ensemble’, resulting in four model runs that can be combined.

III. 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). 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 to 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.

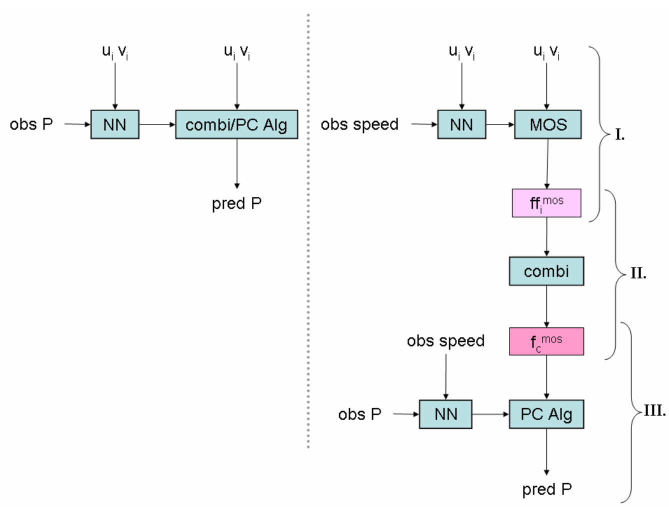

Fig. 3. Overview of the two investigated approaches: Direct combination of wind components u_i, v_i (left) and combination of MOS wind speeds ff_c^{mos}.

B. Combination of MOS wind speeds

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

I.) In the first step the transfer function between the mean observed nacelle wind speed and the mean power production on hourly averaged values is derived, i.e. fitting the power curve for the entire wind farm with the Neural Network. Two hidden neurons are used. The derived algorithm is drawn as a solid line in Fig. 2 together with all observed data pairs.

Fig. 4 shows the verification how good the non-linear power curve is represented by the nacelle wind speed. In the independent test data set the root mean square (RMS) difference between parameterized/estimated power output (ordinate) and produced power (abscissae) is only 1.7 % of the nominal power. The systematic error (bias) is less than 1% and the correlation is with 99.8% very high. It can be therefore suspected that the transformation of a predicted wind speed in hub-height into power output is only introducing a marginal additional error.

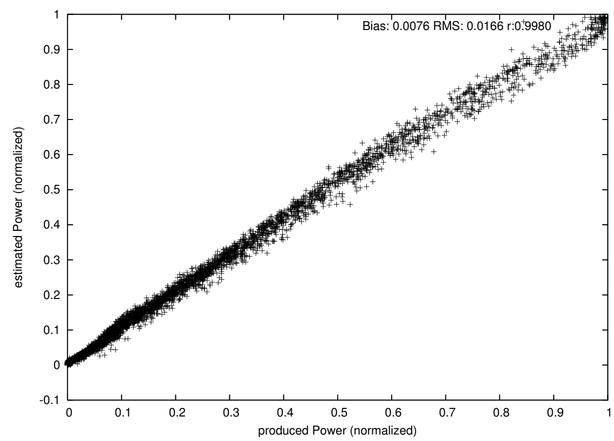

Fig. 4. Verification of the parameterized wind farm power curve (normalized) for the wind farm Middelgrunden with independent observations, that had not been used in the training of the Neural Network.

II.) The second 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. 4.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.

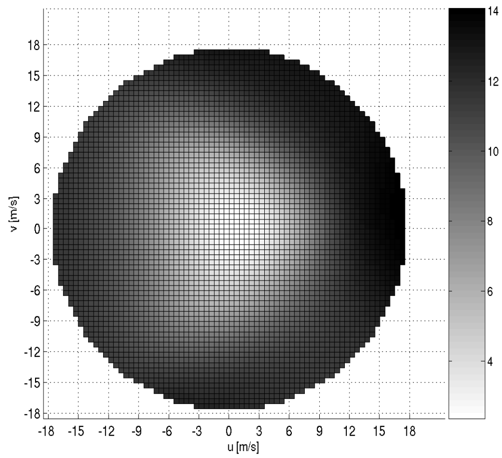

Fig. 5. Sectoral MOS (Model Output Statistics) for the observed wind speed [m/s] at the wind farm Middelgrunden as calculated for wind components (u, v) forecasted by ECMWF. The city of Copenhagen is located westwards of the wind farm.

III). The linear combination of MOS wind speeds is done in step III. The weighting coefficients of each individual forecast member depend on the quality of the individual forecast to the observed wind speed. A common measure is the root mean square error between the predicted wind speed and the observation [15]. The weight w_i for forecast i is calculated as

$$\frac{1}{RMSE_i \sum_{i=1}^{N} \frac{1}{RMSE_i}} \qquad (1)$$

and N denotes the number of available forecasts. In our case N is either 2 or 4. As the relative performance of one NWP to another one can be better for short look-ahead times but worse on longer forecast steps, the weighting is a function of forecast step. The calculation of w_i is repeated every 12 hours of the forecast range.

Table I gives an overview of the conducted combination experiments.

Symbol	***N***	***Model***	***Forecast run***
◊	2	HIRLAM	00,12 UTC
×	2	HIRLAM,ECMWF	00 UTC
Δ	2	ECMWF	00,12 UTC
□	**4**	HIRLAM,ECMWF	00,12 UTC

Table I. Conducted wind speed combination experiments

IV. 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 weightings of 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).

Fig. 5 compares the two investigated approaches (A, B). As a reference the result for only one NWP model run (*) is shown, where u and v of the 00UTC ECMWF run are the only predictors (input) into the NN. The additional use of the 12UTC ECMWF run (◊) gives slight improvements, in particular at day 2 where the mean error is decreased from 18 % to 17.3%. There is no improvement at day 1, i.e. the combination of forecasts has no benefit on very short timescales. The impact of analysis errors is marginal on these timescales and becomes only crucial in the medium-range [16, 17]. As a consequence the benefit of combination of forecasts pays off much more at forecast steps beyond day 1. At forecast day 1 model errors in the physical parameterizations are predominate and are responsible for discrepancies between forecast and observation.

A more considerable improvement at day 2 is obtained with approach B (Δ) that uses also ECMWF run 00 and 12 UTC. The average prediction error at day 2 is 15.8% and has to be compared to the mentioned 17.3% that were obtained with the first approach but the same input data. It is much more worthwhile to combine the MOS wind speeds in a separate step, than to give this task to the Neural Network. Apparently the NN has problems in approach A to fulfill the three steps of approach B in one go: transferring wind components to the local site (MOS), combination of forecasts and representation of the wind farm power curve.

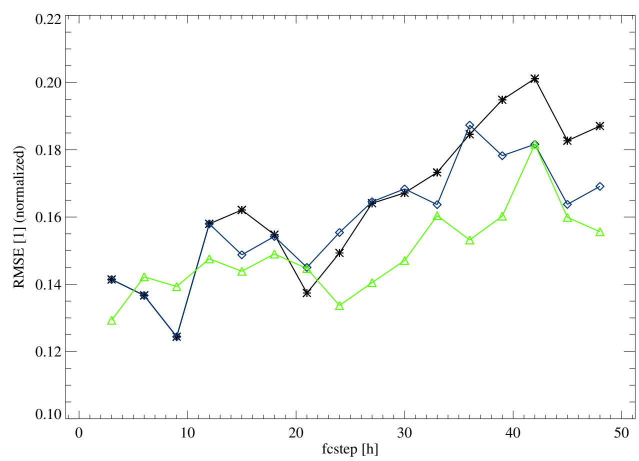

Fig. 6. Root mean square error (RMSE) of wind power forecast (normalized with the rated capacity) against look-ahead time. Three different algorithms are used: (*) u, v wind components from ECMWF 00UTC, (◊) u, v from ECMWF 00UTC and 12 UTC are used as predictors in the Neural Network. A better result (Δ) is obtained by first applying a local wind speed MOS to ECMWF 00UTC and 12UTC separately and then combining the resulted wind speeds. Finally the derived wind farm power curve (Fig. 2) is applied.

The impact of different combinations of forecasts using approach B is shown in the following part. Four combination experiments have been conducted (Tab. I). Fig. 7 shows the results in RMSE of the combined forecasted wind speed to the observation. It can be seen that the combination of both HIRLAM forecasts has the lowest skill with an average RMSE of 1.9 m/s at day 2. Compared to this the combination of HIRLAM and ECMWF 00UTC forecasts is slightly performing better, although the difference was expected to be larger, as two independent models are combined.
The best performance shows the combinations of all four model runs with a RMSE in wind speed of 1.7 m/s. The result is slightly better than two ECMWF runs alone.

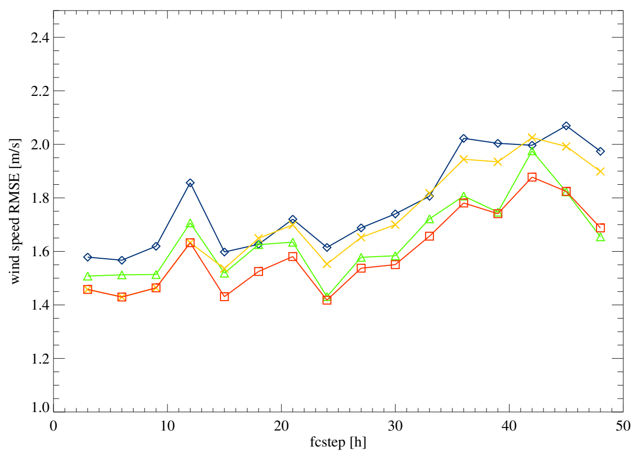

Fig. 7. Root mean square error (RMSE) of forecasted wind speed at Middelgrunden wind farm against look-ahead time. Four different combinations of MOS wind speeds predicted by several NWP models are shown: ◊ HIRLAM 00UTC and 12 UTC forecast, × HIRLAM and ECMWF 00UTC forecasts, Δ ECMWF 00UTC and 12 UTC forecasts and (□) forecasts from all mentioned NWP models and runs.

According to step III of approach B (Fig. 3, right) the combined wind speed is used in the power curve algorithm (Fig. 2) to calculate the wind power prediction.
For reference purposes the result with the ECMWF 00UTC run in approach A is also depicted (*). Following the similar performance of two HIRLAM (◊) forecasts and the combination of HIRLAM with ECMWF 00UTC (×) with respect to wind speed, the results in RMSE of predicted wind power are very close.

The best result is obtained when combing all available forecast runs (□). The RMSE is on average 15 % at day 2, which is a considerable improvement compared to the reference forecast (18 % RMSE).
The combination of the two ECMWF forecast runs (Δ) is by far the best choice when only two forecasts are considered and shows that the ECMWF forecasts are in particular superior to the HIRLAM forecasts. However, the HIRLAM forecasts are carrying information that is useful to increase the quality of the combined forecast.

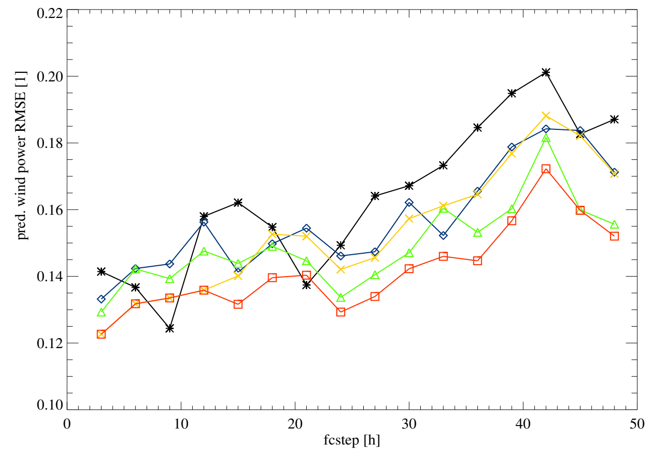

Fig. 8. Root mean square error (RMSE) of wind power forecast (normalized with the rated capacity) against look-ahead time. Five different algorithms are shown: u and v wind components by one (*) NWP model and different combinations of several MOS wind speeds predicted by several NWP models: ◊ HIRLAM 00UTC and 12 UTC forecast, × HIRLAM and ECMWF 00UTC forecasts, Δ ECMWF 00UTC and 12 UTC forecasts and (□) all available forecasts.

V. CONCLUSIONS

We showed in this study that the use of several NWP models (multi-model) is beneficial for wind power forecasting. The RMSE forecast error for the offshore wind farm Middelgrunden is about 20% lower when four wind forecasts are used as input compared to a single forecast. In particular, ECMWF forecasts added big value to the combination results as they are superior to the available HIRLAM forecasts.

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 (Bayesian approach [18]) will be tested and probalistic forecasts will be studied.

VI. ACKNOWLEDGMENTS

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