Development of short-term forecast quality for new offshore wind farms

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Abstract. As the rapid wind power build-out continues, a large number of new wind farms will come online but forecasters and forecasting algorithms have little experience with them. This is a problem for statistical short term forecasts, which must be trained on a long record of historical power production - exactly what is missing for a new farm. Focus of the study was to analyse development of the offshore wind power forecast (WPF) quality from beginning of operation up to one year of operational experience. This paper represents a case study using data of the first German offshore wind farm “alpha ventus” and first German commercial offshore wind farm “Baltic1”. The work was carried out with measured data from meteorological measurement mast FINO1, measured power from wind farms and numerical weather prediction (NWP) from the German Weather Service (DWD). This study facilitates to decide the length of needed time series and selection of forecast method to get a reliable WPF on a weekly time axis. Weekly development of WPF quality for day-ahead WPF via different models is presented. The models are physical model; physical model extended with a statistical correction (MOS) and artificial neural network (ANN) as a pure statistical model. Self-organizing map (SOM) is investigated for a better understanding of uncertainties of forecast error.

1. Introduction

Because of its high potential and innovative developments in wind turbine technologies, the wind energy is considered as one of the most promising renewable energy sources to achieve energy targets of governments and to overcome environmental problems and global warming. Especially the offshore wind power with its higher production capacity, approximately twice more full load hours than onshore [1], is indispensable in the reduction of greenhouse gasses and energy dependency. In Germany, the first offshore wind farm “alpha ventus” with 12 wind turbines and 60MW of total capacity situated in the North Sea was erected in 2009. As to commercial view of offshore wind power market, the first offshore wind farm EnBW Baltic 1 has been put into operation in 2011 in Baltic Sea. Since September 2013, BARD Offshore 1 wind farm supplies with 80 wind turbines a total capacity of 400MW offshore wind energy from the North Sea. The German government aims to install a capacity of 25 GW offshore wind energy in Germany until 2030.

The wind power forecasting (WPF), which predicts the expected power from a wind source, is indispensable to improve the penetration of wind energy in the energy mix. Its accuracy plays a key
role in the grid reliability, need for balancing energy and hence the cost of the wind power integration; shortly to make the wind energy profitable and manageable. This role will become progressively more important in relation to the additional planned German offshore wind farms in the Baltic and North Sea. In the next years the planned 15 GW of offshore wind power requires improvement of the WPF accuracy. Otherwise an increase in reserve requirements will be necessary because of offshore capacity factors of about 40% [2].

As the rapid wind power build-out continues, a large number of new wind farms will come online but forecasters and forecasting algorithms have little experience with them. This is a problem for statistical short term forecasts, which must be trained on a long record of historical power production - exactly what is missing for a new farm. The focus of this study is to facilitate the choice of input data time span and the selection of forecast method to get a reliable WPF on a weekly time range. In this work, the weekly development of WPF quality for day-ahead WPF based on different models is presented.

SOM is one of most used type of artificial neural networks applied for organization and discrete representation of various features of a complex dataset. SOM is used basically to classify the NWP data in frame of this study. This class information is used for a better understanding of uncertainties of forecast error as well as additional input to train ANN in order to perform possible improvement of WPF.

2. Development of wind power forecasting systems

There are different types of wind power predictions systems; mainly we distinguish between physical and statistical models. There is also the learning approach which is considered sometimes as a third approach. The models investigated in this study are physical model; physical model extended with a statistical correction (MOS) and ANN as a pure statistical model.

2.1. Development of a Wake Adjusted Physical Power Model (WAPPM)

The wake adjusted physical power model is based on the individual power curve of installed wind turbines and it predicts the power output of each individual turbine. Considering wake effects, the wind power of the whole wind farm is finally calculated. The physical model does not need historical data but leads often to systematical overestimations of the power output.

The WAPPM is built in following three basic levels:

- The first level is the data acquisition, pre-processing and data conversion. In this first step after validating and correcting wind speed data (if necessary), the wind speed data will be calculated at hub height.
- In the second level, referred to as wind turbine level, the power production of each wind turbine will be calculated. This step considers the turbine wake effects determined by N.O. Jensen “Park” model. [3]
- The last level, referred to as wind farm level, focuses on the calculation of the power production for the entire wind farm. In this step, the production of each wind turbine from second level will be aggregated to calculate the final power production of the whole wind farm by considering wake effects.

Figure 1 illustrates the workflow of the wake adjusted physical power model including the three levels explained above.
2.2. Optimization of the WAPPM with MOS

In the practice, physical models are extended with a statistical correction in order to reduce systematic error of the power output. This extended model needs adequate data to model different weather situations and to correct bias between measured and predicted wind speed (shortest-term) or wind power (day-ahead and shortest-term). In this study historical power predictions and power measurements are used calculate corresponding parameters, which are finally used to correct online power prediction.

Figure 1. Workflow of WAPPM including defined three levels.

2.3. Development of an ANN Model

The reliability of ANN is conditioned to the use of sufficiently large datasets, thus enhancing the determination of a relationship between the wind farm power output and the meteorological input data.

One of the main advantages of ANN compared to other prediction methods is that they learn from experience and generate results, even when their inputs are contradictory or incomplete. ANN has a
great performance if there is enough data available [4]. The figure 3 illustrates the structure of an ANN, which is used to predict wind power.

![Figure 3. Illustration of ANN used to predict wind power.](image)

In this study feed-forward neural network with back-propagation algorithm is used. Because of its black-box structure, it is difficult to analyse its internal structure and with changing start-up initialization the results deviates slightly at each new run. In this study, every training process, which consists the learning the relation between the NWP and the power output of a wind farm, has been repeated 10 times and best network has been selected out based on a validation dataset to predict wind power.

3. Data
This work is based on measured meteorological data from measurement mast FINO1, measured power from alpha ventus and NWP from DWD. FINO1 data was available for the year 2011. The NWP and power data cover approximately 3 years (2010 - 2012) for alpha ventus, 22 months for Baltic1 (2012-2013). 1 year’s data has been used for training with weekly steps and the rest of data has been used for testing.

The research platform FINO1 is located in North Sea very close to alpha ventus wind farm. The data from FINO1 is used for the development of WAPPM and the detection of nominal power of alpha ventus; not for forecasting purposes. Before using this met-mast data, the wind speed measurements has been validated and corrected by using atmospheric stability based on Bulk-Richardson Number (this work has been done in frame of NORSEWiND project). The NWP data has been delivered by DWD twice a day with a forecast schedule of 76 hours. The NWP data, generated with DWD’s COSMO-EU model, has an hourly resolution.

Measured power and also the knowledge of installed capacity of wind farms is one of the necessary information to develop and evaluate the methods, which depict the relationship between NWP and power generation. And surely the correctness of the online power data is indispensable for the operation of the grid, security of supply and market operations of wind power. Similarly, the measured power data also exposes problems with respect to plausibility aspects. Distortions or outliers in the power data lead to inaccurate evaluation of WPF and therefore inaccurate evaluation and adaptation of WPF methods. Hence, the plausibility control of power data is indispensable for both evaluation of WPF and also forecasting method. The outliers are detected by using the newest wind speed predictions and the power measurements.
The installed capacity of the wind farms are used to develop and evaluate the WPF. It is furthermore needed for the integration of wind power generated electricity into the existing energy supply. There are different reasons for the changes of installed capacity. One situation, in which this occurs, is construction phase of a wind farm. In this time period, there are continuous changes of installed capacity depending on the number of newly connected wind turbines. Down or up-scaling, repowering, service and maintenance, failure and extreme weather events are the some other reasons of possible and unexpected capacity changes of wind farms.

These changes are also observed at the alpha ventus wind farm and an algorithm has been developed in order to detect them in availability of the wind speed measurements. Wind speed and direction measurements from FINO 1 were available to perform the detection; results are shown in the following section. As it addressed above, before running the algorithm for the detection of nominal power, the FINO1 data is validated and corrected. Because of the high influence of wind speed in the total wind farm production, its correctness plays a key role in the calculation of the wind power produced.

4. Results

4.1. Detection of nominal power and simulation of power generation of alpha ventus

Figure 4 illustrates the power curves, which are plotted during step by step iterations of installed power detection of alpha ventus. The graduals of measured power, which indicate the changes of installed power, are marked with red circles on the first power curve. It can be well seen from these plots that at each iteration the gradual structure being less. On the final power curve (bottom-right) the graduals are not any more so obvious to recognize.

\[ \text{Figure 4. Detection of nominal power at alpha ventus in availability of met-mast measurements.} \]

Based on wind measurements from FINO1, the power production time series for alpha ventus are simulated. Figure 5 shows an excerpt of this simulated power time series both the corrected (blue) and the uncorrected (green) one, together with power measurements of alpha ventus.
It is observed that the model can approximate the steep gradients of the power generation very well and also reflects the power generation fluctuations of alpha ventus very good. In some cases, it still displays a significant overestimation of the performance. The time delays, defined as the travelling time of an air particle between the mast and the wind farm, affect the agreement between measured and simulated time series. This simulation did not take the time delay of the wind speed between metmast and wind farm into account. This is clearly seen around 15 o’clock on the 23rd on the figure.

![Figure 5. Simulation of power output of the first German offshore wind farm alpha ventus.](image)

**4.2. Wind power prediction results with one year training data**

Table 1 shows nRMSE (normalised root mean square error) of day-ahead WPF done with three applications for both previously described offshore wind farms. With one year training data span, the alpha ventus WAPPM has a prediction error of 18.79%. With a MOS correction, the prediction is slightly improved to an error of 17.82% and ANN has the best result with 17.07% of nRMSE. Prediction error of Baltic1 with WAPPM is approximately 18.96% and with the application of MOS, the prediction error is improved by 2.65%. Similarly to the results of alpha ventus, ANN performs the best with 18.07% nRMSE using one year of training data.

| Wind farm  | WAPPM  | WAPPM +MOS | ANN  |
|------------|--------|------------|------|
| alpha ventus | 18.79% | 17.82%     | 17.07% |
| Baltic1     | 18.96% | 18.46%     | 18.07% |

Table 2 includes results of day-ahead WPF done with ANN. Additional to nRMSE, other statistical results (MAE (mean absolute error) and correlation of the power prediction and the measurement) are listed in this table.

| Wind farm | nRMSE | MAE | Correlation |
|-----------|-------|-----|-------------|
4.3. Improvement of prediction quality with weekly steps
The purpose of this analysis is to investigate the quality of WPF based on the availability of training dataset. Development of the day-ahead WPF is investigated in the weekly steps using the previously described models. The training dataset is extended one week at every new run (1 week training data for the first run, 2 weeks data for the second run …). The following plots illustrate the results of this investigation.

|            | alpha ventus | 17.07%  | 12.26% | 88.55% |
|------------|--------------|---------|--------|--------|
|            | Baltic1      | 18.07%  | 13.01% | 86.84% |

Figure 6. Weekly development of day-ahead WPF for alpha ventus

Figure 7. Weekly improvement of day-ahead WPF for alpha ventus
The results of both offshore wind farms are similar. Extended WAPPM gives better results using 30 weeks of training data. Beyond that period, the ANN model is more performant. The results of WAPPM are not affected by the length of training datasets since it cannot be improve by training. The relative error can be improved slightly after a few weeks by applying MOS to WAPPM. After 27 weeks, the change of prediction error of the ANN is quite less; the highest improvements are considered in this time period.

4.4. Application of SOM in wind power forecasting

This experiment aims to investigate a better understanding of prediction error and a possible improvement of prediction error by using SOM. In this study, the SOM classes are determined based on NWP data. The power predictions have been also split into classes for matching NWP classes. The prediction error of each class is calculated separately. For this investigation a SOM map with size of 6x10 is selected.

It is seen in Figure 10 and 11 that the prediction error varies from one class to another. For example, the class 30 of alpha ventus shows a 10.98% error whereas the class 55 has 24.09% of nRMSE. Baltic1 class 35 is the best class with 6.25% of nRMSE and class 1 is the worst one with 33% of prediction error.

This information can be used to generate probabilistic power forecasts and to have an idea about awaited prediction error.
The classes of meteorological parameters, generated via SOM, are used as additional input to the numerical weather predictions for the training of ANN. Using the SOM class as additional input is degraded the prediction quality for alpha ventus and it was converse for Baltic1 with a slightly improvement.

5. Conclusion
To analyse the weekly development of wind power prediction different methods are investigated. A physical model, based on the Park model, is used to calculate the power production accounting for wind farm wake losses. A statistical correction MOS has been done to remove systematic error at WAPPM forecast. And also ANN is used to predict wind power production of alpha ventus and Baltic1 offshore wind farms.

The results of day-ahead forecast show that ANN does not predict well and is not enough stable with poor data, but after the first 25-30 weeks ANN finally reaches the better results. The WAPPM does not need any historical data for the purpose of learning the relationship between NWP and wind farm power output. The results are showing that if there is not enough data to train ANN, this model can be extended with MOS and used to predict wind power.

Application of SOM in WPF is also investigated in this study and it was noticeable that the error of different classes varies obviously and this information can be used for uncertainties in the WPF. SOM classes as addition inputs for training the ANN model improved the prediction quality for one wind farm but no improvements were observed for the second wind farm.

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