Very short-term probabilistic forecasting of wind power based on dual-Doppler radar measurements in the North Sea

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Abstract. Probabilistic very short-term forecasts of wind farm power can provide valuable information for electricity market participants, especially in power systems with high penetration of wind energy. Recently, the first dual-Doppler radar measurements of an offshore wind farm have become available. A probabilistic very short-term forecasting model of wind power is proposed using observed wind speeds and directions from a dual-Doppler radar system. Predictive wind speed distributions are derived from three-dimensional dual-Doppler observations covering the wind farm and its vicinity. To estimate the power generated by the wind turbines, a power curve constructed with dual-Doppler observations is used. A forecasting horizon of five minutes is evaluated. Results show an improved performance of a deterministic radar-based forecast of power versus the benchmarks persistence and climatology, and also a high potential for a wind power probabilistic forecast.

1. Introduction

With increasing penetration of offshore wind power into the grid, very short-term forecasts of wind power are key to efficiently balancing electricity markets and operating reserves. In some electricity markets, such as France, the Netherlands or Belgium, wind power plant operators can participate in intra-day markets with gate closure times as short as five minutes [1]. In the case of electricity trading, the use of probabilistic forecasts can lead to higher economic benefits than those obtained by using a single forecast [2], since information about the associated uncertainty contributes to making better risk-based decisions. Recently, Xydas et al. [3] showed that using updated probabilistic forecasts of aggregated wind power can reduce the uncertainty in the scheduling of gas-fired generators for balancing the grid and in the expected operational costs of the power system.

In very short-term horizons (less than 30 minutes) probabilistic wind power forecasts are derived from statistical methods, since physical models require a long computation time. Examples of very short-term probabilistic forecasts of wind power using statistical methods can be found in [4] and [5]. These types of probabilistic forecasts are known as predictive distributions or predictive densities.

Today, remote sensing technologies like lidars and radars are able to observe wind speed and direction at ranges up to 30 km [6, 7]. These systems represent a compromise between met-masts
(high temporal resolution/low spatial coverage) and satellites (low temporal resolution/high spatial coverage). As an example, lidars have been used to forecast near-coastal winds with a lead time of five minutes, providing better results than statistical methods [8].

In this contribution, we introduce a methodology that uses fully resolved dual-Doppler (DD) radar observations covering an offshore wind farm area and its surroundings to derive a probabilistic forecast of wind power. With our study, we want: i) to determine the capabilities of DD radar observations used as inputs in a probabilistic wind power forecast framework ii) to verify that a DD radar-based wind power forecasting model can produce a more accurate deterministic forecast than the benchmarks persistence and climatology in a very short-term horizon of five minutes. To our knowledge, this is the first probabilistic forecast framework that uses remote sensing wind speed observations to construct wind power predictive densities. Another innovative aspect of this paper is that it aims to provide a skilful probabilistic forecast of wind power in the very short-term scale of one minute, while previous works found in literature predict temporal scales, i.e. averages, of five minutes.

The remainder of the paper is organised as follows: Section 2 introduces the data used for this analysis. In Section 3 the methodology to create the wind power predictive densities is explained. Results are shown in Section 4. A discussion on the application of radar measurements for deriving probabilistic forecasts is presented in Section 5. Conclusions are drawn in Section 6.

2. Data description
The probabilistic forecast is based on data from the BEACon R&D project by the Danish company Ørsted, where two radar units scan the flow within and surrounding the Westermost Rough offshore wind farm in the North Sea (see Fig. 1). The advanced DD radar system [9, 10] has been configured to obtain volumetric wind field measurements, scanning the entire wind farm with a temporal resolution of 64 seconds. The line-of-sight (radial) velocity measurements from the two radars are used to retrieve the two horizontal wind speed components, after interpolation into a three-dimensional Cartesian grid. The range of the radar measurements is up to 32 km. The two radars are located on the shoreline 8 km from the closest wind turbines (see Fig. 2). The wind farm consists of 35 turbines with a rotor diameter $D$ of 154 m and a hub height of 102 m. The furthest row of turbines is 14 km from the coast. The radars have a spatial resolution of 0.5° in the azimuth, given by the beam width, and an effective 15 m spatial resolution along the beam direction.

For this analysis we investigated a sample of 1134 one-minute periods of DD radar measurements with south-westerly winds (191.7 - 281.7°$^{\circ}$) and wind speeds below 16 m/s. These periods correspond to free-flow conditions for the first row of wind turbines (marked in green in Fig. 2). In the analysis presented, only free-flow sectors are considered to avoid the additional complication of wake losses in this proof of concept analysis. In addition power data from the SCADA system of the wind turbines are used to construct the power curve and to validate the forecast. The power data have a temporal resolution of one minute and are temporally synchronized with the DD data. Power data have been filtered regarding outliers and abnormal performance.

3. Wind power probabilistic forecast methodology
The wind power probabilistic forecast is based on a local Lagrangian persistence technique widely applied in probability forecasts of precipitation using continental-scale radar systems [11]. The proposed prediction model uses the wind data observed by the DD radar system to create a probabilistic forecast of wind speed. Thus, given a DD radar wind field, the model propagates the horizontal wind field vectors with their respective wind speeds and directions. In this model it is considered that during the prediction horizon i) the observed DD radar wind field vectors maintain a constant trajectory ii) vorticity, diffusion and mass conservation are neglected. Thus,
for a point of interest for which a forecast is issued, we consider the wind field vectors that with their current trajectory will reach an area of influence around the point of interest within the prediction horizon.

3.1. Predictive wind speed densities

To create a remote sensing probabilistic forecast (RF) of the power generated by a single wind turbine (WT), we want first to predict the wind speed (ws) distributions. Figure 3 depicts a flow diagram indicating the steps to estimate the predictive power densities.

The wind speed predictive densities are based on DD wind vectors that will reach the wind turbine at the time that the forecast is valid for. A simple approach to generate a probabilistic forecast is to search the predicted values in the neighbourhood of the point of interest. Therefore, we define an area of influence $A_i$ encompassing the objective wind turbine. Only the wind vectors at the wind turbine hub height, that will reach the area of influence in a time window of $\tau=60\text{s}$ centred around the forecast horizon will be considered. Thus, the base of our probabilistic very short-term forecast is the cloud of points or observations that fall inside the defined spatio-temporal window.

Figure 4 (top right) shows an example of the cloud of points that the model predicts that will reach the wind turbine (in red), five minutes after the forecast is issued. The predicted wind speed distribution, together with its mean and the observed DD wind speed 2.5 $D$ upstream of the rotor at the validation time are depicted in the bottom-right plot of Fig. 4.

To consider the velocity reduction due to the induction zone in front of the rotor, we correct our wind speed distributions using Eq. (1), \cite{12}, at the distance of $x=-2.5\ D$ upstream of the
wind turbine. The induction factor $a$ is obtained from the manufacturer’s thrust curve.

$$U = U_\infty \left( 1 - a \left( 1 + \frac{2x}{D} \left( 1 + \left( \frac{2x}{D} \right)^2 \right)^{-\frac{1}{2}} \right) \right)$$ (1)

To optimize the forecasting technique, a sensitivity analysis on the area of influence of the wind turbine is conducted. The area of influence $A_i$ is defined as a circle centred at the wind turbine (see Fig. 4 top right). The optimization criterion is the minimization of the continuous rank probability score (CRPS) of one minute ahead wind speed predictions, after correcting for induction effects. The CRPS evaluates the sharpness of the forecast or the spread of the distributions, and it is the equivalent of the mean absolute error in a deterministic forecast framework [13]. A lower score indicates a better probabilistic forecast. The CRPS is given by:

$$\text{CRPS} = \frac{1}{T} \sum_{i=1}^{T} \int_{0}^{\infty} \left[ F_i(u) - \theta(u - u_{o,i}) \right]^2 du$$ (2)

where $F_i$ is the cumulative distribution function of the probabilistic wind speed forecast $u$ for the time $i$, $\theta$ is the Heaveside or step function which takes the value 1 when $(u \geq u_{o,i})$ and 0 otherwise, and $T$ refers to the number of instances evaluated. To validate our wind speed forecast, we use the DD wind speeds observed 2.5 $D$ upstream of each wind turbine $u_o$.

Figure 5 displays the CRPS for different areas of influence, expressed as number of rotor diameters $D$. We also evaluated the minimum number of observations $N_{\text{min}}$ used to estimate the wind speed densities. From Fig. 5 a decrease in the CRPS value can be observed when increasing the diameter of the area of influence up to 2 $D$. Larger areas of influence show no improvement. Increasing the minimum number of observations used to estimate the wind speed

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**Figure 3.** Flow diagram showing the procedure to construct the wind power remote sensing predictive distributions (RF) for the aggregated wind turbines $i=1,2,...,nt$. 
Figure 4. Wind speed forecasting for the wind turbine marked in red. The left images illustrate the DD flow field at the time at which the forecast is issued at (top) and validated (bottom). The top-right image shows the cloud of vectors used to derive the probabilistic forecast and the area of influence (blue circle). The bottom-right image displays the distribution of wind speeds from the cloud, with $N$ the number of wind vectors, together with the mean of the distribution (blue line) and the observed DD wind speed 2.5 $D$ upstream of the rotor (magenta line).

densities also reduces the CRPS slightly. CRPS for higher minimum number of observations are not included, since there is no improvement. From this analysis, we decided to select a diameter of the area of influence of 2 $D$ and to impose a minimum number of 20 observations to determine the probabilistic wind speed forecast.

In Fig. 6 a comparison of the mean of the wind speeds distributions forecasted five minutes ahead using the selected area of influence versus the DD wind speeds 2.5 $D$ upstream of the wind turbine rotor is shown before and after applying the induction correction. The induction correction slightly reduces the bias between the forecasted and the observed wind speeds. For wind speeds below 6 m/s the DD predicted mean wind speeds exceed the DD wind speed 2.5 $D$ upstream by an average of 0.32 m/s. For wind speeds in the range 6-10 m/s the predicted wind speeds overestimate the DD wind speed 2.5 $D$ upstream by an average of 0.14 m/s. In the range 10-14 m/s this difference is 0.12 m/s. Above 14 m/s the predicted mean wind speeds are on average 1.02 m/s lower than the DD wind speed 2.5 $D$ upstream. Differences between the predicted and the observed wind speeds are attributed, among others, to the radar uncertainty.
Figure 5. CRPS for the one minute ahead predicted wind speed distributions for different areas of influence $A_i$ and minimum number of wind vectors $N_{\text{min}}$. The area of influence is expressed in rotor diameters.

and to the assumption of persistence of the wind field vectors. For higher wind speeds an underestimation of the wind speed can also be related to coastal effects, since the discontinuity between the land and the sea results in a wind speed gradient.

3.2. From wind speed densities to predictive wind power distributions

To compute the predictive wind power distributions, we use the power curve constructed with the 1-min DD $2.5D$ upstream wind speed observations from the wind turbines in the first row, only considering free-flow sectors (see Fig. 7). As it is shown in Fig. 7, the power curve presents a high degree of heteroscedasticity below rated wind speed. To include the uncertainty of the power in our model, we first bin the power data into wind speed bins of 0.5 m/s width. Then,

Figure 6. Scatter plot of the 1-min DD wind speeds $2.5D$ upstream of the wind turbine and the mean of the five minutes ahead wind speeds predictive densities without (left) and with the induction zone velocity correction (right).
we calculate the empirical cumulative distribution function (ecdf) of the power for each wind speed bin. To transform a forecasted wind speed distribution into a power distribution we apply a bootstrap resampling technique. This technique consists of picking randomly \( n \) values out of the original ecdf of the predicted wind speed distributions. With the obtained set of \( n \) wind speed values we enter the binned power curve and pick randomly a power value from the ecdf associated to each wind speed bin. We repeat this procedure for \( n=10000 \). With the set of power values we estimate the predictive power densities of each wind turbine.

![Wind turbine power curve](image)

**Figure 7.** Wind turbine power curve constructed with the DD wind speeds 2.5 \( D \) upstream of the rotor (first row of wind turbines). The line is the binned mean power. The error bars represent the standard deviation in 0.5 m/s wind speed bins.

To forecast the power generated by the first row of wind turbines, the average power is calculated by aggregating the power distributions of the individual wind turbines. To do so, we again apply a bootstrap resampling technique and aggregate 10000 random values of each wind turbine power distribution using its power ecdf. Thus, to evaluate the forecast of the wind power we will refer to the average aggregated power of the \( nt \) wind turbines in the first row as:

\[
P_{\text{row}} = \frac{1}{nt} \sum_{i=1}^{nt} P_i
\]

4. Results
In this section we evaluate both the probabilistic and the deterministic forecasts of the average power from the first row of the wind farm and compare them with the benchmarks persistence and climatology. Here we only include timestamps, where all wind turbines in the first row are operating simultaneously. This reduces our data set to 343 1-min periods. The climatology aggregated wind power distribution is derived gathering all available measurements of average aggregated power. For the deterministic evaluation we consider the mean value of the climatology distribution. For persistence the observed value from the previous time stamp is used to predict the current time stamp. The persistence distribution is determined using the persistence point forecast and the 19 most recent values of the persistence error, following [13].

4.1. Evaluation of single point predictions
Our single point forecast refers to the mean value of the predicted distribution of average wind power of the first row. To assess the forecast skill of the models, we use the root mean square
error (RMSE), the mean absolute error (MAE) and the maximum absolute error (MaxAE) metrics. Table 1 presents the aforementioned metrics for the model RF and the benchmarks.

The RF model exhibits the lowest RMSE and the lowest MaxAE compared to climatology and persistence. The persistence method exhibits a similar MAE than the RF model, since the MAE metric does not penalize higher errors as the RMSE does. As expected, the climatology method has very low skill compared to the other methods.

4.2. Probabilistic forecast evaluation
To evaluate the skill of our probabilistic forecast we use the CRPS, previously defined. The respective results are given in Table 1. The RF model has the lowest CRPS, indicating that the forecast is sharper than the benchmarks persistence and climatology.

| Forecast  | CRPS [kW] | RMSE [kW] | MAE [kW] | MaxAE [kW] |
|-----------|-----------|-----------|-----------|------------|
| RF        | 251.3     | 481.3     | 348.4     | 2019.3     |
| Climatology | 930.6     | 1574.5    | 1380.1    | 2740.7     |
| Persistence | 298.8     | 510.1     | 346.9     | 2526.6     |

Table 1. CRPS, RMSE, MAE and MaxAE for five minutes ahead forecast of 1-min average aggregated power for the first row of wind turbines.

To assess whether our probabilistic forecast is calibrated we use a quantile-quantile reliability diagram [14]. In a reliable probabilistic forecast model x% of the observations should be below the xth percentile of the distributions, as in the reference line in Fig.8. Here we evaluate the predictions from 5% to 95% in steps of 10%. Persistence presents an overall better performance in terms of reliability. However, both methods present some degree of overconfidence since not all values are comprised within the prediction intervals. Thus for the RF model nearly 15% of the observations are below the 5% quantile, while only around 73% of the observations are below the 95% quantile. Although it presents a higher reliability, the persistence method is also overconfident in its predictions, nearly 16% of the observations are below the 5% quantile, while only around 85% of the observations are below the 95% quantile.

5. Discussion
We introduced the use of DD radar observations of wind speed and direction to create a probabilistic very short-term forecasting model of wind power. The five minutes ahead predicted mean wind speeds show a high degree of correlation with the wind speeds measured with the radar 2.5D upstream of the wind turbines. The results indicate that when evaluating a single point forecast of average aggregated power, the RF model shows an improvement of 6% in the RMSE over persistence and of 69% over climatology. Based on our results, a DD radar-based forecasting model is likely to decrease the uncertainty in the prediction of offshore wind power. Since the persistence method shows higher maximum absolute errors than the observations-based model, a DD radar-based forecasting model might have a positive impact on the integration of offshore wind power into the grid.

Regarding the probabilistic forecast, the RF model is sharper than the benchmarks persistence and climatology. However, when evaluating its reliability, the RF model is overconfident in its predictions. Figure 9 presents two episodes where the RF model was used to predict the average aggregated power of the first row of wind turbines.

The figure on the left illustrates an episode of rather high wind speed, where the RF model is overconfident on forecasting the aggregated power of the wind turbines in the first row. The figure on the right presents an episode of low wind speeds, where the probabilistic forecast presents a high skill in predicting the average power. We attribute the differences in the skill
of the RF model during the two analysed periods to the different wind speeds. At lower wind speeds the uncertainty in the predictions is reduced due to larger available radar area and consequently higher data density to construct the predictive densities. The fact that the DD radar measurements were not aimed at measuring the inflow of the wind farm further upstream but the interaction of the flow between the wind turbines, limits the range of velocities that the model can predict or the forecasting horizon.

A higher degree of reliability could be achieved using broader uncertainty intervals in the power curve. The fact that below rated speed the wind turbine power production is characterised by a high level of heteroscedasticity translates into high uncertainty related to wind turbine power production. This is especially enhanced due to the limited amount of data that was available to construct the power curve used in this analysis. The uncertainty associated

![Figure 8](image8.png)

**Figure 8.** Quantile-quantile reliability diagram for the RF and persistence method.

![Figure 9](image9.png)

**Figure 9.** Two Episodes of 60 minutes period of five minutes ahead forecasted average aggregated power for the RF model during high wind speeds (left) and low wind speeds (right). Prediction intervals are shown together with the observed power (black squares).
with the use of short data periods or data sets with missing data is discussed in [15]. The heteroscedastic nature of wind turbine power production is less evident when using 10-min data, as it is the current industry practice [16]. As a result, the final probabilistic forecasts might seem overconfident, mainly due to the high uncertainty of wind turbine power production. This overconfidence could be reduced by improving the power curve modelling technique, more suitable for data of higher resolution.

6. Conclusions

This paper introduces a methodology to derive a wind power probabilistic forecast based on DD radar wind speed and direction observations. In a case study, the proposed methodology was used to produce five minutes ahead probabilistic forecasts of average power of seven turbines in the North Sea, during free-flow conditions. Results indicate that from a deterministic perspective, predicted DD wind speed observations can lead to more skilful forecasts of wind power than the benchmarks persistence and climatology. Despite certain degree of overconfidence, results show that there is a high potential on the use of DD radar wind speed observations for probabilistic forecasting of wind power.

In a future work we will extend our analysis to assess the impact of averaging over different number of wind turbines and time scales, and to evaluate the skill of the forecasting model depending on different levels of power.

Acknowledgements

This project has received funding from the European Unions Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 642108 and from the Ministry of Science and Culture of Lower Saxony to the project ”ventus efficiens” (ZN3024, MWK Hannover). The authors would like to thank Luis Vera Tudela for his valuable comments and suggestions.

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