Can Weather Radars Help Monitoring and Forecasting Wind Power Fluctuations at Large Offshore Wind Farms?

Pierre-Julien Trombe, Pierre Pinson, Henrik Madsen, Niels Einar Jensen, Lisbeth Birch Pedersen, Anders Sommer, Nina F. Le

***Abstract*—The substantial impact of wind power fluctuations at large offshore wind farms calls for the development of dedicated monitoring and prediction approaches. Based on recent findings, a Local Area Weather Radar (LAWR) was installed at Horns Rev with the aim of improving predictability, controlability and potentially maintenance planning. Additional images are available from a Doppler radar covering the same area. The parallel analysis of rain events detection and of regime sequences in wind (and power) fluctuations demonstrates the interest of employing weather radars for a better operation and management of offshore wind farms.**

***Index Terms*—Wind Power, Forecasting, Weather Radar, Rainfall, Wind variability, Offshore.**

I. Introduction

The benefits of remote sensing tools have long been acknowledged in hydrological sciences [1] [2], whereas applications of such technologies are relatively new in wind energy, due to its more recent history. For the time being, remotely sensed observations have mainly been used for wind resource assessment purposes [3]. Yet, a new field for potential applications of these technologies has been pointed out by recent advances in wind power meteorology.

Indeed, statistical analysis of high frequency wind power measurements from large offshore wind farms identified several regimes of production, characterized by different volatility levels [4]. At the operational level, this translates into an increased difficulty for grid integration and may lead to large losses of resource. Regarding this problem, one of the noticeable limitations of statistical models is that they are short of adequate meteorological observations to explain the volatile nature of the wind field in the neighborhood of offshore wind farms. Consequently, these models often fails in predicting sudden and extreme meteorological changes affecting the wind farm power production.

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Commonly today, high-frequency measurements (with periods between 1 second and 10 minutes) are available from nacelle anemometry and SCADA systems. Optimal accounting of this information in statistical forecasting techniques for the very short-term was shown to improve forecast accuracy substantially [5]. However, these anemometers provide very local and instantaneous observations, within the area delimited by the wind turbines, and are not informative of upcoming changes in the weather conditions. In that regard, observations at the offshore site of Horns Rev have revealed the presence of convective rain cells as a meteorological indicator for extreme wind variability and suggested the use of weather radars for detecting and tracking such phenomena [6]. Advantages of weather radars are manifold and the meteorological observations they provide can be employed for different applications:

- development of new Graphical User Interfaces for wind power applications,
- rapid update cycle of meteorological models,
- detection of specific patterns of high wind variability and improvement of offshore wind power fluctuation predictability,
- development of dedicated control strategies for offshore wind farms.

As a first step towards the optimal usage of weather radar data, this study presents the results of some exploratory data analysis which gives evidences of the interest of our approach. Section 2 introduces the experimental design of the study. Then, Section 3 presents an applet that allows the combined visualization of radar images and wind data. Section 4 shows two examples of the early detection of rain for the anticipation of episodes of high wind speed/power volatility. Finally, Section 5 delivers concluding remarks and exposes the lines for future work.

II. Experimental design

The main data acquisition system is based on a X-band Local Area Weather Radar (LAWR) which measures rain reflectivity at high spatio temporal resolutions [7]. The system is portable and ideal for remote locations such as offshore wind farms. The LAWR settings can easily be modulated in order to meet the requirement of specific applications. In this experiment, the LAWR is operated with a 60km range and set to generate one image in output every minute, with a pixel resolution of 500m. The LAWR is installed on the transformer platform of the Horns Rev 2 wind farm, off the west coast of Jutland, Denmark. Measurements from the nearby Rømø weather radar (C-Band) are also available. That radar is operated by the Danish Meteorological Institute at a temporal resolution of 10 minutes. Its range is 240 km with a pixel resolution of 2km.

These two weather radars have different scanning procedures due to their respective frequency bands, and their outputs exhibit many significant differences. However, ongoing investigations to combine observations from these 2 devices concluded on their promising complementarity [8]. Their respective location and coverage area are illustrated on Figure 1.

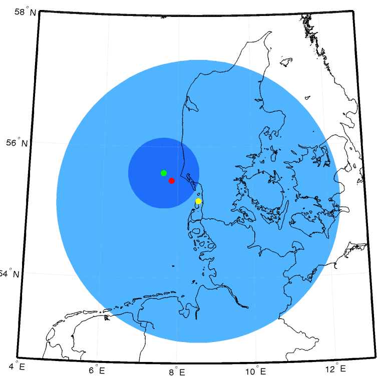

Fig. 1. The red dot indicates the location of the Horns Rev 1 wind farm. The green dot indicates the location the LAWR and the area it covers is shaded in dark blue. The Rømø radar location is depicted by the yellow dot and its area is shaded in light blue.

III. A FIRST STEP - VISUALIZING THE DATA

Weather radars generate tremendous quantities of data, and the complex spatio temporal variability of the rain reflectivity, though captured in 3 dimension, is commonly synthetized into 2 dimensional images. These images constitute a very rich source of information and their potential is best exploited through graphical tools for several purposes.

First, the inspection of the image visual features can reveal (i) to which extent the measurements are contaminated by undesirable targets (ships, planes, wind turbines), (ii) the influence of the surrounding environment (mountains, sea) and (iii) the radar sensitivity to specific weather conditions affecting the propagation of the radar beam. Some of the problems encountered with the images generated by the LAWR are illustrated in [9]. Image post processing turned out to be necessary in order to separate the information linked to rain reflectivity from the other sources cited here above. Noise removal procedures were routinely implemented. There is no measurement available for south westerly directions due to a blockage of the radar beam by an obstruction on the platform hosting it. Measurements within the first 10km were discarded because of the spurious influence of the sea, completely masking the reflectivity from rainfall.

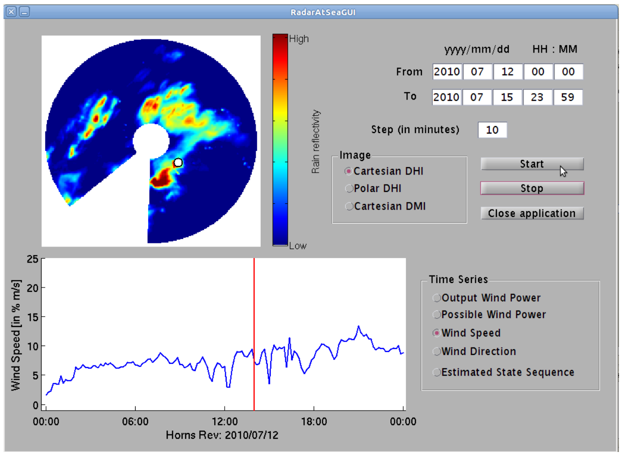

Fig. 2. Example of GUI for simultaneous visualization of weather radar images and wind data.

Second, each image provides a one minute average of the weather conditions nearby the wind farm but remains (i) difficult to interpret if not part of a sequence and (ii) of limited value if not combined with other measurements. For this purpose, a Graphical User Interface was developed and can be seen on Figure 2. Radar images are displayed in the upper window while a time series (i.e. wind speed or power, sequence of regimes) is plotted in the lower window. Besides the type of images and time series to display, the user only sets the time interval of interest defined by 2 dates/times. An extra option consists in defining a time step for the images (i.e. a value of 10 means that one wants to display one image out of every 10 images produced) and works as fast forward control. The red line (in the lower window) automatically scrolls from left to right at the same pace as the images are updated and indicates the corresponding values on the time series. A module for spectral analysis of wind speed time series as in [10] will shortly come to complement this GUI. Advantages of such tool are straightforward and manifold:

- it provides an automatic and user friendly data manipulation system,
- it allows for a more advanced understanding of the spatial structure of the rain as well as its scale and motion,
- it allows to highlight the relationship between the presence of rain and measurements (wind speed and power) from nearby wind farms,

From Figure 2 in the upper window, one can see a rain field of high reflectivity crossing the Horns Rev 1 wind farm (depicted as a white dot) and its neighborhood as observed by the LAWR. In the mean time, in the lower window, the wind speed measured by anemometers at Horns Rev 1 exhibits a growing volatility as the rain front approaches and goes away. Many other similar phenomena can be identified over the entire set of observations, from January 2010 to March 2011. This comes as the first confirmation of the previous observations on the role of rain as a potential indicator for extreme wind variability [6].

IV. Rain: an indicator of high wind speed/power variability?

Moving on from visual observations in the previous section, we propose a simple statistical approach to link the detection of rain and episodes of high volatility of wind speed and wind power. For a more detailed description of the models used in this section, we refer to [11].

First of all, it is worth mentioning that we did not attempt to convert rain reflectivity observations into rain intensity values since this conversion is based on an approximation, the so called Z-R relationship, which requires the raindrop size distribution to be known or assumed [12]. Instead, we prefer working on the original reflectivity values. Based on the common segmentation used in Hydrology and Meteorology, rain reflectivity values are grouped into 5 different classes with respect to their dBZ values (decibel of reflectivity):

- class 1 - no rain (<8 dBZ)
- class 2 - light rain (8-24 dBZ)
- class 3 - moderate rain (25-45 dBZ)
- class 4 - heavy rain to thunderstorms (46-65 dBZ)
- class 5 - extreme thunderstorms (>65 dBZ)

Few events depicting dBZ values of class 5 were observed and after verification, these values were most of the time linked to contaminated pixels. We used images from the Rømø radar for this analysis. A circular area of 60km radius and centered on the Horns Rev 1 wind farm is defined and only pixels within that area are considered. For each image, the rate of pixels falling into one of the 5 classes is computed. That way, we can detect the presence of rain if the cumulated sum of pixels in class 2-4 exceeds a given threshold.

A. *Wind speed variability*

As for modeling the wind speed variability, time series based methodologies in the frequency domain provide a wide range of methods of which some are presented in [13]. In particular, it is shown in [10] that a method based on the Hilbert-Huang transform is able to highlight specific seasonal cycles as key features of wind variability. However, this is beyond the scope of this study and will be investigated at later times. Instead, we use a general approach based on Autoregressive (AR) - Generalized AutoRegressive Conditional Heteroscedastic (GARCH) models. The AR part of the model will capture the mean behavior of the wind speed time series (i.e. the low frequency fluctuations) while the GARCH part will model the dynamics of the squared errors (i.e. the high frequency fluctuations). GARCH models are often applied for time series featuring time-varying variance. For a given time series of wind speed $\{y_t\}$, the model is formulated as follows:

$$y_t = \theta_0 + \sum_{i=1}^{r} \theta_i y_{t-i} + \sqrt{h_t}\varepsilon_t \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{2}$$

with $\{h_t\}$ the estimated conditional variance at time t and $\{\varepsilon_t\}$ a sequence of independently distributed random variables following a Normal distribution $\mathcal{N}(0,1)$.

The time series of wind speed was sampled over 10 minute intervals and all observations for the year 2010 were used to fit the model using Maximum Likelihood Estimation. Figure 3 depicts a 17 day episode of wind speed observed at Horns Rev 1 in July 2010 (top window) along with the estimated conditional variance series $\{h_t\}$ (second window from the top). The observed peaks correspond to periods of high wind speed volatility. The corresponding time series of cumulated coverage rate for classes 3 to 4 (rate of pixels having dBZ values larger than 25) is also plotted and illustrates the sequence of rains fronts detected nearby Horns Rev 1. Interestingly, the 3 periods of highest wind speed volatility correspond to periods where rain fronts with high reflectivity are detected nearby Horns Rev 1. On July 3, the peak of coverage is lagged of a couple of hours when compared to the peak in the conditional variance potentially indicating that strong turbulences in the wind field were experienced as the rain front was approaching. Similar phenomena were also spotted in several other occasions and make us think that the change in the wind speed dynamics may not be perfectly synchronized with the instantaneous detection of rain nearby. Wind turbulences are experienced a few hours before and after the rain front hits the wind farm.

B. *Wind power variability*

The nonlinear conversion from wind to power makes that periods of high wind speed variability do not necessarily translate into periods with high wind power variability. It is therefore important to assess whether the detection of rain can lead to identify episodes of large wind power fluctuations, independently of the wind speed variability.

For this purpose, we want to show whether the detection or rain can be related to different regimes of power production following the definition proposed in [4]. That definition assumes that a wind farm can be modeled as a single system which switches between different states or regimes, given the dynamics of its power fluctuations. For the specific case of Horns Rev 1, it was shown that the mean dynamics were relatively similar across regimes but that the standard deviation levels were significantly different.

We extracted a 3 regime sequence based on a time series of wind power sampled over 10 minute intervals, for the whole year 2010. Given $\sigma^{(i)}$ is the estimated standard deviations in regime i, regimes were ranked with respect to increasing volatility levels so that $\sigma^{(1)} < \sigma^{(2)} < \sigma^{(3)}$ and $\sigma^{(1)} = 3.10^{-4}$, $\sigma^{(2)} = 0.014$, $\sigma^{(3)} = 0.068$. Then, we computed the conditional probabilities of the wind farm being in each of the 3 regimes, given high reflectivity rain (i.e. rain reflectivity of class 3 or 4) was detected the hour before, and given no rain. These results are reported in Table I.

Rain (classes 3 and 4) was detected in 17% of the observations. In both cases, rain and no rain, regime 2 is dominant with the largest conditional probability. As for regime 1, its

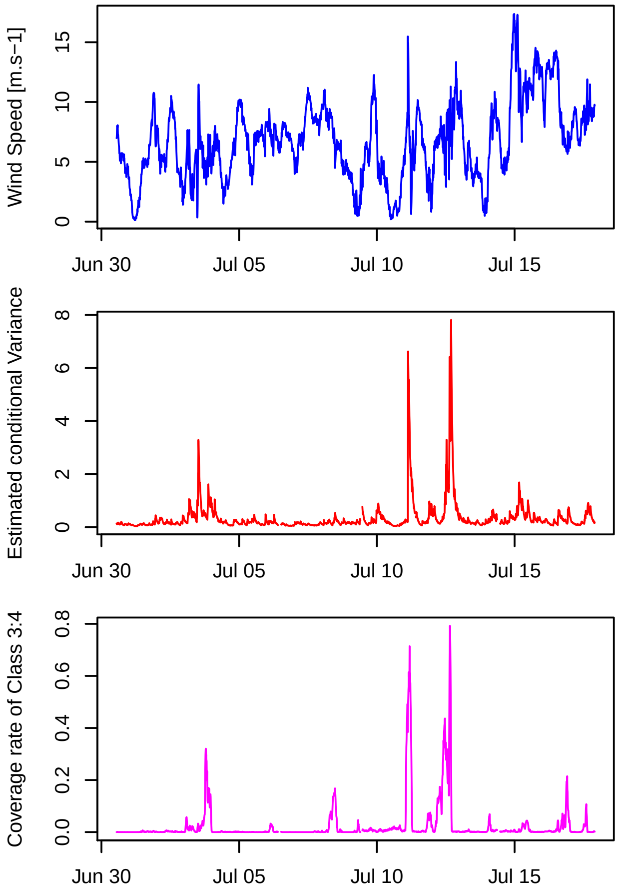

Fig. 3. From top to bottom: (i) Original wind speed time series, (ii) Estimated conditional variance, (iii) Coverage rate of pixels in classes 3 and 4.

TABLE I
CONDITIONAL PROBABILITIES OF WIND POWER PRODUCTION REGIME GIVEN RAIN OR NO RAIN WAS DETECTED. REGIME ARE RANKED BY INCREASING VOLATILITY.

	Reg. 1	Reg. 2	Reg. 3
rain	0.18	0.43	0.39
no rain	0.08	0.64	0.28

conditional probability is higher when rain is detected. Atfer verification this is due to a higher rate of wind speeds above $15m.s^{-1}$ for which the wind power dynamics is smoothed. However, the most noticeable feature revealed by these results is that the conditional probability of the wind farm being in regime 3 (i.e. the regime for which the wind power fluctuations are the most volatile) is 11% larger when rain is detected compared to the no rain case. Interestingly, it is this type of wind power fluctuations that statistical models cannot predict accurately for the moment. It is shown here that the early detection of rain fronts can improve the anticipation of these volatile wind power fluctuations and hence that weather radars are very useful.

V. Conclusion

In this study, we demonstrated that weather radars could be valuable assets for offshore wind power applications. Through a binary approach (rain / no rain), we managed to clearly identify episods of high wind speed variability. In addition, it was shown that it could also improve the anticipation of highly volatile wind power fluctuations for which state-of-the-art forecasts are characterized by large uncertainties. However, it is clear that a more advanced approach is needed for an optimal use of the information contained within the radar images. Improved image segmentation as well as the extraction of dynamic features such as motion speed and direction are expected to give more insights on rain events. An other line of work is to merge the expertise of meteorologists and statisticians to perform a classification of rain events with respect their impact on wind speed/power variability.

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