Using forecast information for storm ride-through control

Barahona Garzón, Braulio; Trombe, Pierre-Julien; Vincent, Claire Louise; Pinson, Pierre; Giebel, Gregor; Cutululis, Nicolaos Antonio

Published in:
Proceedings of EWEA 2013

Publication date:
2013

Citation (APA):
Using forecast information for storm ride-through control

Braulio Barahona\textsuperscript{1,*}, Pierre-Julien Trombe\textsuperscript{2,**}, Claire L. Vincent\textsuperscript{1}, Pierre Pinson\textsuperscript{2}, Gregor Giebel\textsuperscript{1} and Nicolaos A. Cutululis\textsuperscript{1}

\textsuperscript{1}DTU Wind Energy, Frederiksborgvej 399, 4000 Roskilde, Denmark
\textsuperscript{2}DTU Informatics, Asmussens Alle, 2800 Lyngby, Denmark
\textsuperscript{*}brab@dtu.dk, \textsuperscript{**}pmtr@dtu.dk

Abstract

Using probabilistic forecast information in control algorithms can improve the performance of wind farms during periods of extreme winds. This work presents a wind farm supervisor control concept that uses probabilistic forecast information to ride-through a storm with softer ramps of power. Wind speed forecasts are generated with a statistical approach (i.e., time series models). The supervisor control is based on a set of logical rules that consider point forecasts and predictive densities to ramp-down the power of the wind farm before the storm hits. The potential of this supervisor control is illustrated with data from the Horns Rev 1 wind farm, located in the North Sea. To conclude, an overview of ongoing and future research in the Radar@Sea experiment is given. This experiment aims at improving offshore wind power predictability and controllability through the increased use of meteorological information, and particularly weather radar images.

1 Offshore wind power in critical weather

Offshore wind power fluctuations in the North Sea increase the complexity of the transmission system operator (TSO) tasks for managing the power grid \cite{1, 2}. Fluctuations in wind power are driven by meteorological phenomena \cite{3}, both through fluctuations in the wind speed itself and through strong wind speeds leading to cut-off events in the wind farm. Depending on the time and length scales of the relevant meteorological features, wind power fluctuations may be enhanced by the concentration of large wind farms in a given area \cite{4} and by the design and control of wind turbines. Wind speed fluctuations and the precise timing of the onset of strong wind speeds are difficult to forecast in a deterministic sense \cite{1, 2}, which means that the problem is an obvious target for the application of probabilistic forecasts \cite{1}. Furthermore, probabilistic forecasts could help TSO’s and wind power plant owners to find an optimal compromise between energy loss and a safe operation of the power system. For example, a planned wind farm shutdown that reduces the power gradually before the storm hits without wasting too much power \cite{2}.

Here we use data collected at the Horns Rev 1 wind farm (HR1) to study control concepts at the wind farm level (i.e., supervisor control-modes) that use forecast information to regulate the power output of a wind farm during stormy weather (i.e., storm ride-through) in order to achieve softer ramps of power. By stormy weather we mean periods of high wind fluctuations and/or high wind speeds that can lead to large and sudden wind power fluctuations. For example, in some cases high wind speeds can reach extreme values that will typically force wind turbines to immediately shutdown causing a sudden drop of wind power. In other cases high wind variability will make wind turbines go from full power to nearly zero as the wind speed suddenly drops. Such wind conditions can refer to cases of extreme events listed in \cite{5}.

The Radar@Sea experiment collected information from weather radars with the objective of improving the understanding of meteorological phenomena that influence fluctuations of wind speed in time and space. The goal is to show that the predictability and controllability of large offshore wind farms can be improved through an increased use of meteorological information, particularly real-time observations from weather radars. Weather radars are very powerful tools for monitoring weather conditions at high spatio-temporal resolutions. For example, weather phenomena such as open cellular convection which have been shown to be associated with large wind fluctuations at (HR1) \cite{6}, are often marked by precipitation from cell walls that can
clearly be seen in radar images [7]. Furthermore, the approach of weather fronts and the associated strong wind speeds and high variability that may lead to wind farm shutdown events can be observed in real-time using weather radar data. One potential approach consists of using the precipitation characteristics extracted from the weather radar images to explain and predict wind speed fluctuations [8]. Finally, the weather radar is a useful tool for gaining insights into the types of weather phenomena that drive wind speed and power fluctuations over time.

Operating offshore wind farms during extreme weather means that wind fluctuations must be monitored at temporal resolutions of a few minutes [9]. Therefore the control concepts and the forecast methods used here are illustrated using data sampled every 10 minutes; they are described in Section 2 and 3 respectively. Simulation results that show the improved performance of the wind farm combining such concepts are shown in Section 4. Radar images and wind farm measurements during a summer storm are discussed in Section 5. Finally we discuss future research works in Section 6.

2 Wind farm control using probabilistic forecast

As part of the objectives of the project we developed control concepts at the wind farm level (i.e. supervisor control-modes) that use statistical forecasts to improve wind farm power controllability. Namely, to reduce power fluctuations and to ride-through storms with softer power ramps. Supervisor control-modes that give wind farms power regulation capabilities similar to those of conventional power plants have been demonstrated in HR1 [9]. Analysis of such wind farm capabilities and control design has been shown in [10] by numerical simulations with dynamic models. However, the automated use of forecast information in wind farm controls has not been investigated, here we use wind farm measurements at 10-minute resolution to qualitatively evaluate its potential.

Mainly two kinds of wind farm supervisor control-modes were developed in this project depending on the forecast method and control objective: regime-based and rule-based. The regime-based controls use regime probabilities and point forecasts from MSAR model (Markov-Switching AutoRegressive forecast [11]) and are aimed at reducing power fluctuations. In this work we focus on extreme wind conditions, we present a ruled-based supervisor control-mode aimed at storm ride-through. It uses point forecast and predictive densities with lead time up to 2 hours in order to achieve softer ramps of power. Let us first introduce the typical control of wind turbine during a storm and thereby describe the wind farm response.

2.1 Typical control of wind power during storm

Wind turbine control consists essentially on controlling the speed of the wind turbine rotor and the power output of the electrical generator. During high wind speeds, wind turbines are controlled to shutdown in order to avoid extreme mechanical loads. Although from the early days it was proposed to have soft cut-out strategies [12], what has prevailed is a storm control that will trigger a fast–but gentle–wind turbine shutdown upon values exceeding thresholds for wind gusts (measured every few seconds), average values of wind speed (30-second and 10-minute for example) or other signals such as blade pitch angle activity [12]. Such typical storm control is illustrated in the wind turbine power curve in Figure 1a, where blue circles correspond to measurements (i.e. 10-minute average values) collected over a period of nearly 3 years at a wind turbine in HR1. The red dotted line is the typical theoretical power curve of a wind turbine that shuts down at a given cut-off wind speed (i.e. a given threshold for 10-minute average wind speed, usually 25 m s$^{-1}$). Once shutdown it remains off until the wind speed is back to a lower value (i.e. 20 m s$^{-1}$), it then starts up again.

The aggregated response of the wind turbines shows spatio-temporal smoothing effects, which depend on the correlation of the wind speeds sensed by the wind turbines over the wind farm. The aggregated response (i.e. average of wind speed and wind power of individual wind turbines) of Horns Rev 1 is shown with blue circles in Figure 1b. A slope on the wind farm power as the wind speed reaches the wind turbine cut-off wind speed is observed. Since wind speed and wind turbulence at the individual wind turbines are not exactly the same all over the wind farm due to wake and shield effects, they shut down at different time. Similarly, wind turbines do not start up all at once, therefore there is also a slope on the power as the wind farm starts to produce again when the wind speed is lower.
2.2 Rule-based probabilistic supervisor control-mode

The rule-based supervisor uses probabilistic forecast information to calculate a set-point for the individual wind turbines. The objective is to start a ramp-down of the wind farm when the forecast indicates that a wind farm shutdown or a sudden loss of power is likely to happen. Thereby achieving a softer ramp of power that would allow some of the load to be picked up by the secondary control of central power plants while power reserves are dispatched. The control rules use historical data of wind speed, wind power and statistical forecast of wind speed at 10-minute resolution. First, a wind category is defined based on measured wind speed averaged over the wind farm. Then point forecast and the corresponding predictive densities, together with possible power are used to derive the wind turbine power set-point. The rules can be summarized as follows

1. A **High wind** category and a **Low wind** category are defined according to wind speed measurements $V_{10\text{min}}$, when $V_{10\text{min}}$ is above a given threshold $V_{\text{high}} = 11 \text{ m s}^{-1}$ the category is **High wind**, otherwise it is **Low wind**

2. In **Low wind** keep maximum power tracking mode
   (a) if possible power $P_{\text{possible}}$ is different that actual power output $P_{\text{out}}$, then start to ramp $P_{\text{out}}$ up (at a ramp factor $R_{\text{up1}} = 1.1$) to reach maximum power  
   (b) else keep maximum power

3. In **High wind** use probabilistic forecast and possible power to estimate a power set-point.
   (a) If wind speed point forecast $\hat{v}$, within a prediction interval $I$, up to a given lead time $\hat{t}$, yields wind speed above an extreme-wind threshold $T_{\text{extreme}} = 23 \text{ m s}^{-1}$ then start to ramp power down (at a ramp factor $R_{\text{down1}} = 0.90$)  
   (b) If wind speed point forecast $\hat{v}$, up to a given lead time $\hat{t}$, yields wind speed below a rated-wind speed threshold $T_{\text{rated}} = 12 \text{ m s}^{-1}$ then start to ramp power down (at a ramp factor $R_{\text{down2}} = 0.95$)  
   (c) Otherwise keep maximum power  
      i. if possible power $P_{\text{possible}}$ is different that actual power output $P_{\text{out}}$, then start to ramp $P_{\text{out}}$ up (at a ramp factor $R_{\text{up1}}$) to reach maximum power  
      ii. else keep maximum power

where $I$, is selected to 90 % and the 95th quantile is compared to $T_{\text{extreme}}$, $\hat{t}$ is selected to 2 hours ahead or 10 minutes ahead for two different episodes as described in Section 4. Ramp down conditions 3.a and 3.b are over ruled if $P_{\text{out}}$ is nearly zero and $P_{\text{possible}}$ increases, in order to allow the supervisor to start-up the wind farm when the wind is high.
3 Statistical forecast method

Forecasts at different time-scales are used by TSOs to estimate wind power production and take the necessary actions to secure the operation of the power system and meet the energy demand. Meteorological forecasts are used to see days ahead. Statistical forecast are applied for shorter time-scales (i.e. days, hours). In the case of Energinet.dk meteorological forecast are updated every 6 hours and statistical forecasts of wind power every 5 minutes [1]. However, forecasting up to 2 hours ahead with time steps of few minutes is quite difficult in a deterministic sense. Moreover forecasting extremes is by nature a difficult task, because by definition extremes rarely occur and therefore do not have clear identifiable patterns. Furthermore, because definition of these extremes is very much influenced by our background and activities. For instance, meteorologists consider as extremes events which largely deviate from climatology, power system operators give more importance to events which threaten the secure operation of power systems (e.g., large power fluctuations of renewable power plants, supply shortage), while forecaster’s interest on extremes is focused on large forecast errors [5].

Our goal here was to generate wind speed forecasts to be used as inputs for the supervisor controller. The temporal resolution and lead times of these forecasts were to match those required by the supervisor controller:

- temporal resolution: 10 minutes,
- lead times: from 10 minutes to 2 hours ahead,

These requirements called for the use of statistical, time series type of models. In the very short-term, a prominent feature of offshore winds is their time-varying variability [13, 8]. Therefore, the forecast method applied accounts for changes in the variability of the wind. Namely, it describes the stochastic nature of the wind speed with an AutoRegressive model with time-varying variance. The autoregressive part of the model is described in (1) and the conditional variance is estimated as in (2)

\[ y_t = \theta_0 + \sum_{i=1}^{r} \theta_i y_{t-i} + \sigma_t \varepsilon_t \]  
\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \]  

where \( y_t \) is the observed wind speed at time \( t \), \( r \) in the autoregressive (AR) order, \( \sigma_t^2 \) is the conditional variance at time \( t \) which is defined as an ARMA process of orders \( p \) and \( q \), \( \varepsilon_t \) is a sequence of independent and identically distributed random variable following a Normal \( \mathcal{N}(0, 1) \) distribution. Parameters were estimated by Maximum Likelihood Estimation. The optimal values for \( r \), \( p \) and \( q \) were obtained by cross-validation. An early application of AR-GARCH (AutoRegressive-General AutoRegressive Conditional Heteroskedasticity) models for capturing wind speed dynamics can be found in [14].

Decision-making problems such as the one presented in this study call for the use of probabilistic forecasts rather than the sole point forecasts [15]. In wind energy, the integration of this type of forecasts into operational applications remain a challenge, and the prevalence of point forecasts is still strong because they are easier to interpret [16]. Here, we generate probabilistic forecasts in the form of predictive densities in order to fully describe the potential distribution of the wind speed in the very short-term. In particular, with these predictive densities it is straightforward to compute the probability of the wind speed exceeding the threshold over which cut-off events may occur. To accommodate the natural truncation of the wind speed in 0, predictive densities are Truncated Normal so that \( Y_{k|t} \sim N^+(\mu, \sigma^2), k = 1, \ldots, 12 \) with the location parameter \( \mu \) given by (1) and the dispersion parameter \( \sigma \) given by (2).

We use wind speed measurements collected from the nacelle anemometry and SCADA systems at a temporal resolution of 10 minutes to derive forecasts. Figure 2 shows the measured wind speed and the corresponding point forecasts and predictive intervals at a given time with lead time up to 2 hours. Each prediction interval is computed by selecting two quantiles (extracted from the predictive densities) as lower and upper bound. For instance, the prediction interval with a coverage rate of 90% is defined with the 95th and 5th quantiles as bounds. Wider prediction intervals reflect higher uncertainty of the point forecast.
4 Simulation results

Two episodes of critical weather conditions were selected to illustrate the performance of the supervisor control-mode described in Section 2. One corresponds to a summer storm where wind speeds exceed the typical wind turbine cut-off wind speed $V_{\text{cut-off}}$, this is described in Section 4.1. The second episode is described in Section 4.2, it corresponds to a period with high wind speeds and extreme variability observed during the autumn. This episode is further discussed in Section 5.

4.1 Episode of extreme winds during the summer

A summer day storm is illustrated in Figure 3, where the top plot shows measured wind speed and the bottom plot wind farm power output. Wind speed is above rated wind speed (i.e. 12 m s$^{-1}$) nearly all the time, except for about 20 minutes at around 15:30 hrs when the wind speed drops down to $V_{\text{high}}$. Immediately afterwards, wind starts to increase for the next 4 hours going above $T_{\text{extreme}}$ and shortly after above $V_{\text{cut-off}}$. Therefore, wind turbines shutdown and the wind farm power output falls down with a maximum rate at 19:30 of nearly 0.3 p.u./10-minutes when the power is 0.7 p.u., as it can be seen on the measured power (i.e. blue line). The average rate at which the power falls is 0.23 p.u./10-minutes between 19:10 and 19:50. The response of the wind farm using the ruled-based probabilistic supervisor (RBPS) with $t = 2$ hr, is shown with the red line. Observe that around 50 minutes before the extreme wind shuts the wind turbines down, the control starts ramping down the power of the wind farm. The power ramps down at an average of around 0.1 p.u./10-minutes from 18:20 to 19:50. The maximum rate at which the power drops in this case is nearly 0.28 p.u./10-minutes, when the power is down to 0.4 p.u. Later as the wind speed drops below $V_{\text{cut-off}}$ again, wind turbines start up and power starts to increase. Wind farm with RBPS starts up slower because the wind speed is still high. Towards the end of the time series a down regulation event took place as it can be observed from the measured power.

4.2 Episode of extreme wind variability and high winds during the autumn

In this case we look at an episode of extreme wind variability with high wind speeds shown in Figure 4. In such cases forecasting is difficult because the dynamic regimes of the wind change abruptly (as it can also be observed from Figure 2 and 6). We use the RBPS with $t = 10$ min, red line in bottom plot, Figure 4. Observe that when the wind speed is increasing and approaching $V_{\text{cut-off}}$ (just after 12:00) RPBS starts to ramp the power down for one or two time steps and then...
ramps up again. Later wind speed drops while showing high variability, in the very beginning RBPS reduces the sharp ramps while in High wind and later while in Low wind.

Figure 4: Episode of extreme wind variability and high winds in the autumn (25.10.2010). Top: measured wind speed. Bottom: wind farm power output (obs=measured power, ctrl=power output with rule-based supervisor).
5 Perspective for the use of weather radar observations

In the previous section an episode of high winds and extreme variability was studied. These extreme changes in variability can be associated with specific weather conditions that the radar may detect. These concepts can be illustrated by the conditions on 25 October 2010, when a cold, unstable North-Westerly flow influenced the North Sea region. Early in the day, open cellular convection dominated the region around the Horn Rev wind farm, and associated wind fluctuations between about 8 and 17 m s\(^{-1}\) were observed. At around 1200UTC, an embedded low pressure system approached western Denmark, and a sudden episode of strong wind speeds was observed at the Horns Rev wind farm. The event is depicted in Figure 5, where contours of radar reflectivity are superimposed on a satellite image, showing the embedded low pressure circulation and the fragments of open cellular convection approaching the wind farm.

In this case, the satellite images are clearly mirrored by the precipitation patterns seen by the radar, although the meteorological features leading to wind power fluctuations are not always marked by precipitation, which places a limitation on the strategy of using weather radars to predict such events. Furthermore, there is an interesting interplay between the propagation speed of weather systems and the wind speed itself; in general, weather systems do not propagate as a result of advection by the near-surface wind, although there may be cases where this is a reasonable approximation. For example, recent work [8] shows that it is possible to automatically detect wind speed regimes from weather radar images, in cases where precipitation is present. Therefore, although the weather radar data is a rich source of forecasting information, there are several interesting challenges to overcome for its automated use as a forecasting tool.

Figure 5: Visual satellite image from the AQUA satellite and contours of radar reflectivity. The satellite data is from the MODIS AQUA satellite, downloaded from http://ladsweb.nascom.nasa.gov. The radar reflectivity data was generously provided by the Danish Meteorological Agency.

6 Summary and future work

There is potential in the use of probabilistic forecasts to improve wind power controllability. The supervisor controls developed, use probabilistic forecasts to regulate wind farm power, showing qualitatively that there is potential for their application. Namely, in this work we presented a rule-based supervisor control-mode which uses point forecast and predictive densities from AR-GARCH model to regulate power output in critical weather conditions that can lead to a sudden and large loss of power. A simulation example showed that softer wind farm cut-off can be achieved during extreme winds with the use of forecast with lead time up to 2 hours.

Future work is the evaluation of these control concepts by means of quasi-static models and quantitative indicators to ponder the value to the power system and wind farm operators.
against the risk and energy loss. Then, to verify stability and the impact on wind turbine loads by dynamic simulations.

Finally, the project has provided data, experience and methods for the use of radars for wind power applications. However, it is yet challenging to integrate the information in weather radar observations into prediction systems and therefore into control systems because the relationship between precipitation and wind is complex. The way forward is to use periods of specific weather conditions where radar images can be used for automatic detection of wind regimes to test the value as input to control systems.

Acknowledgments

This work was fully supported by the Danish Public Service Obligation (PSO) fund under the project "Radar@Sea" (contract PSO 2009-1-0226) which is gratefully acknowledged. Vattenfall and DONG Energy are acknowledged for providing data from the Horns Rev 1 wind farm and the weather radar images, respectively. DMI is also acknowledged for providing radar reflectivity data. The contribution of C L Vincent was supported by the Danish Council for Independent Research - Technology and Production (contract number 10-093196).

References


