Forecasting Uncertainty Related to Ramps of Wind Power Production

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***Abstract* - The continuous improvement of the accuracy of wind power forecasts is motivated by the increasing wind power integration. Today forecasters are challenged in providing forecasts able to handle extreme situations. This paper presents two methods focusing on forecasting large and sharp variations in power output of a wind farm called ramps. The first one provides probabilistic forecasts using large temporal scales information about ramps. The second method uses ensembles to generate confidence intervals allowing to better estimate the timing of ramps. The two methods are tested and results are given for a real case study.**

***Key words* : wind power forecast, ramps, phase errors, forecasts ensemble.**

1 Introduction

Most of the existing wind power prediction methods are designed to provide single point forecasts (often called as "deterministic" ones). The parameters of the models involved are commonly obtained with minimum least square estimation, and the provided point forecasts then relate to the conditional expectation of wind power generation for each look ahead time, given the information available up to current time. Two extensive reviews of the state of the art in wind power forecasting are available in [9] and [6].

Recent research works in wind power forecasting have focused on associating uncertainty estimates to these point forecasts. Pinson and Kariniotakis [20] have described two complementary approaches that consist of providing forecast users with skill forecasts (commonly in the form of risk indices [22]) or alternatively with probabilistic forecasts. The present paper focuses on the latter form of uncertainty estimates, which may be either derived from meteorological ensembles [18, 17, 21], based on physical considerations [14], or finally produced from one of the numerous statistical methods that have appeared in the literature, see [3, 10, 15, 13, 16] among others. They may take the form of quantile, interval or density forecasts. If appropriately incorporated in decision-making methods, such forecasts permit to significantly increase the value of wind generation. Recent developments in that direction include among others methods for dynamic reserve quantification [8], for the optimal operation of combined wind-hydro power plants [5, 1], or finally for the design of optimal trading strategies in liberalized electricity pools [19].

One of the main issues that we encounter today, when it comes to the accuracy of wind power forecasts, is to give a forecast able to handle an extreme situation. What can be considered as an extreme is not an obvious task and is highly end-user-dependent. Often for power system operators extreme events are linked to large deviations of power generation with respect to the expected power generation. The severity of the large deviation depends highly on how fast it happens, and on the timing especially if concurrently other events happen (i.e the electricity demand is also highly fluctuating). Nowadays it is a challenge to improve the forecasts for such situations. Two types of solutions, rather complementary can be envisaged:

1. Try to detect early the deviation between the ex-

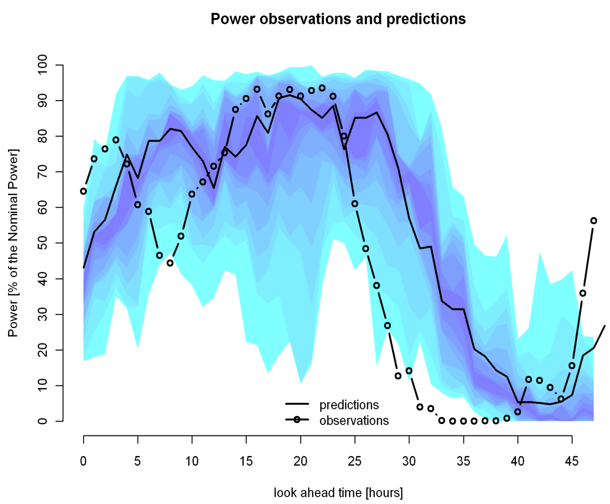

Figure 1: An Example of wind power observations and predictions, with uncertainty estimation provided by centered prediction intervals of nominal coverage rates of 10% to 90% with 10% increment. One can see 8 consecutive observations lying under the 5 percentile estimations between horizons 31 and 38.

pected and the observed power generation and correct the corresponding spot forecast or send an alert to the end-user. This type of solution clearly relies on improving the data assimilation process. It is related to time scales of a few minutes to a few hours.

2. Try to provide uncertainty bounds that indicate the possibility of such deviations to happen or provide risk indices as warnings for such large deviations. This type of solution relies on improving the way we learn the uncertainty from the past. It is related to time scales of a few hours to one week.

In this paper, we try to improve the second type of solutions. The challenge we encounter is the following. We have a probabilistic forecast that is **reliable** in the probabilistic sense: for example there are around 5% of observations that fall under the 5 percentile estimations. But as we see in Figure 1, we can have 8 consecutive observations under them. Mathematically speaking, there are two possible explanations to what we see in Figure 1:

1. We are in a situation where the observations are highly dependent: if one observation falls under the 5 percentile estimation at time t, then it is likely that it will stay under it for some time.

2. We are in a situation where our forecast is not reliable "locally". Note that if the observations are purely independent along time (when the system is really chaotic) the probability that 8 consecutive observations fall under the 5 percentile estimations is around 5^{-8}. Even if this "independence" assumption is weak, we can say that when the system is chaotic the situation we see in Figure 1 should never happen.

However, for a wind power forecaster, Figure 1 is just representative of a so-called phase error, i.e an error on the timing of a ramp. This paper investigates the problem we see in Figure 1. Firstly, in Section 2, we give a forecasting procedure including information about ramps to increase local reliability of a probabilistic forecast. Then, in Section 3, we show how to use ensembles to forecast confidence intervals for the timing of a ramp. Conclusions are given in section 4.

2 Probabilistic forecasts conditional to ramps information

The probabilistic procedures that are commonly used in the literature, for forecasting at time t the distribution of wind generation, use as input weather forecasts available at time t for look ahead time $t+h$. However a ramp event evolutes over several time steps corresponding to several hours within an interval $[\,t+h\,,\,t+h'\,]$. The related uncertainty at the same interval is also correlated and can propagate up to time $t+h'$

In this section, the aim is to extend the prediction model through some additional explanatory variables that contain information about nearby ramp timing and intensity. In the first subsection we explain how to forecast the timing and intensity of a ramp and in the second subsection we explain how to use this information in a probabilistic forecasting process.

2.1 On the definition of ramp events

A ramp event of wind power production is commonly defined as a variation exceeding a minimum percentage V_{min} of the nominal power of a wind farm, within a period less than or equal to a maximum duration T_{max} ([11] [2] and [7]). It is difficult to find a consensus on the value of V_{min} and T_{max}, and it is likely that the adapted values for those parameters might depend on the geographical situation (climate), the complexity of the terrain and the situation with respect to the network. However, a common choice is $V_{min} = 50\%$ of the nominal power and $T_{max} = 5$ hours.

To define a ramp, it seems necessary to introduce a parameter related to time and one to the amount of power (respectively T_{max} and V_{min}). The difficulty to standardize a such definition, comes from the fact that these parameters are arbitrarily fixed, depending on the modeller's appreciation. In this paper, we propose a slightly different definition implying filtering. Let $(p_t)_t$ be a wind power time series and $(p_t^f)_t$ be the associated filtered signal :

$$p_t^f = mean\,\{\,p_{t+h} - p_{t+h-n_{am}};\, h = 1, \ldots, n_{am}\,\} \quad (1)$$

where n_{am} stands for the number of averaged differences of measures. Note that this can be written with a convolution product of the power signal with $f_{n_{am}} = 1/n_{am}\,(\mathbf{1}_{n_{am}}, -\mathbf{1}_{n_{am}})$: $p_t^f = p_t * f_{n_{am}}$. The filtered signal $(p_t^f)_t$ measures the variations of the initial power signal $(p_t)_t$. A ramp event then corresponds to an interval of time at which the absolute value of the filtered signal $(p_t^f)_t$ exceeds a given threshold $\tau > 0$ (see Figure 2). Even if a ramp is not localized in time, it is however useful to associate a particular date to a ramp. We choose to associate to a ramp event the time t for which the filtered signal p_t^f has maximal magnitude. This maximal magnitude defines the intensity of the ramp.

The number of averaged measures n_{am} is the width of the filter $f_{n_{am}}$ and hence can be understood as a smoothing parameter. Small values of n_{am} will make the filtered signal $(p_t^f)_t$ more sensitive to short period

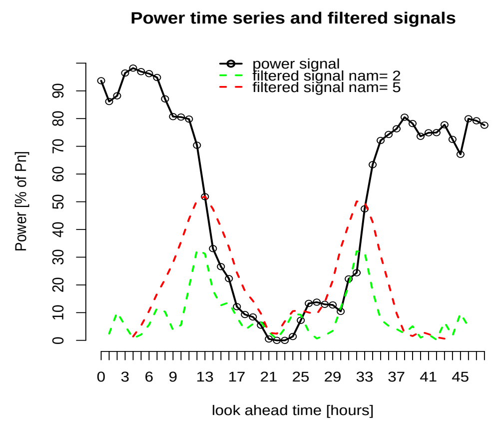

Figure 2: Example of a wind power time series $(p_t)_t$, with absolute value of signals $(p_t^f)_t$ calculated for two values of the n_{am} parameter. The green curve corresponds to a value of n_{am} of 2, and the red one to a value of 5. The timing of ramps coinciding with the local maxima of the red filtered signal are at $t = 13$ and $t = 32$ hours.

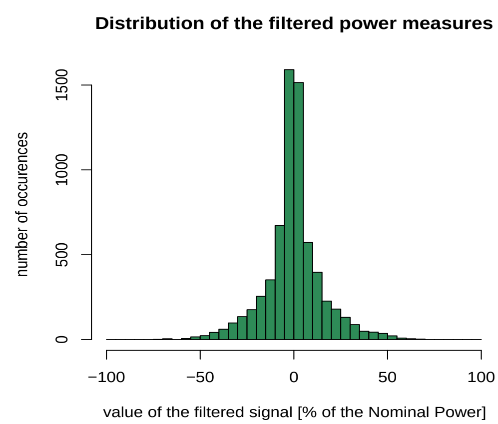

Figure 3: Distribution of the filtered power time series $(p_t^f)_t$, obtained for a parameter value n_{am} of 5. The tails of the distribution correspond to ramp event situations.

variations of the power output $(p_t)_t$ (see figure 2). In our work, we choose a value of $n_{am} = 5$ hours, which is in line with the work of Greaves et al. [11]. The value of τ should be set relying on weather conditions and other criteria such as the terrain complexity. We choose to use $\tau = 25\%$ of the nominal power of the wind farm. This gives around 550 hourly sampled values exceeding the threshold over a period of 6363 hours. Ramp event situations are associated to tails of the filtered power signal distribution (see Figure 3). Such representation makes easier to understand ramp events as extreme events.

2.2 Probabilistic forecasts from predicted ramps information

Let $\hat{p}_{t+h|t}$, $h = 1 \dots h_{max}$, be spot forecasts for the next period. It is now possible to detect forthcoming ramps by filtering the forecasted production: $\hat{p}^f_{t+h|t} = \hat{p}_{t+h|t} * f_{n_{am}}$.

Based on this we design a model that estimates the uncertainty in the forecast, for a given look ahead time h_0, using the following explanatory variables as input:

1. The intensity $I_{t+h_0|t}$ of the nearest ramp. If this nearest ramp is forecasted at time $t + h_1$ this intensity is then $|\hat{p}^f_{t+h_1|t}|$.

2. The time difference $Td_{t+h_0|t} = |h_1 - h_0|$ between the nearest forecasted ramp and the time $t + h_0$.

If $I_{t+h_0|t}$ is high and $Td_{t+h_0|t}$ is small (which means that a ramp of high intensity has been forecasted nearby to time $t + h_0$), the confidence interval should be larger, in order to include the possibility of a translation of the ramp along time.

Forecasting procedure The proposed procedure to produce improved uncertainty forecasts is composed by the following 2 steps.

- Step 1. Make preliminary spot power forecasts and use them to calculate $I_{t+h_0|t}$ and $Td_{t+h_0|t}$.

- Step 2. Make a probabilistic forecast for time $t + h_0$ at time t (for example with the Quantile Regression Forest procedure) using the variables $I_{t+h_0|t}$ and $Td_{t+h_0|t}$ as additional explanatory variables in the model.

Data used for the numerical study included hourly power measures from two European wind farms (one located in Ireland, the other one in Danemark). We used wind speed and direction forecasts, with the *Quantile Regression Forest* method as a basic model to produce quantiles estimations. The forecasted quantiles cover proportions from 5% to 95% with a 5% increment, and were produced respectively four and twice a day for 48 hours ahead. We evaluated our procedure by comparing this basic model, with an advanced one which also included our additional explanatory variables related to ramps.

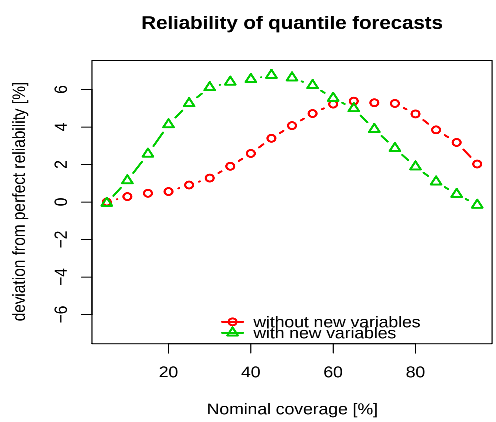

Figure 4: Reliability diagram of $5, \dots, 95$ percentiles estimations made with the *Quantile Regression Forest* procedure, using or not the new explanatory variables related to ramps. Results are for the Danish wind farm.

Figure 4 is a reliability diagram, it shows the deviation from perfect reliability of forecasted quantiles of our two models. The procedure using the new explanatory variables only performs better in the case of high quantiles. Also we could use these additional inputs only to forecast the highest quantiles. However more simulations will be performed to confirm this tendency. The sharpness, measured by the mean size of confidence intervals, is at a good level with similar performance of the basic and advanced models.

Having a reliable probabilistic forecast of the power output is important for an end-user such as a system operator. However, it is also useful to forecast directly the timing of a ramp.

3 Estimating the probability of ramps observation with wind power ensemble forecasts

What could be more difficult to predict than the amplitude of a forthcoming ramp, is the timing of this ramp. Error in the timing results to the so-called phase errors that have a high impact for end users. Current operational state-of-the-art wind power forecasting models do not have dedicated modules for ramp forecasting although first approaches start to appear [12, 23].

In [11], Greaves et al. propose to forecast the probability distribution of the timing of a ramp. The forecasted distribution has a bounded support and it is often observed that ramp events appear outside of this support or do not appear at all. This indicates that in that approach the forecast is not reliable. In addition, their forecast is a climatology: the center of the distribution is forecast with up-to-date information but the distribution itself is the same whatever the conditions. This naturally implies a lack of sharpness in the probabilistic forecast.

Here we propose a method which provides reliable confidence intervals for ramp-timing estimation, from the use of wind power forecasts ensemble. In our numerical study, we used hourly power measures from three wind farms located in France. Data also included meteorological forecasts ensemble of wind speed, consisting of 51 members provided by the EPS model of ECMWF. After an interpolation, we got at each run time (every 12 hours) hourly sampled forecasts up to 80 hours ahead. Each member was used as input to the *Random Forests* procedure, trained with the unperturbed control weather forecast. It results in an ensemble of 51 wind power forecasts.

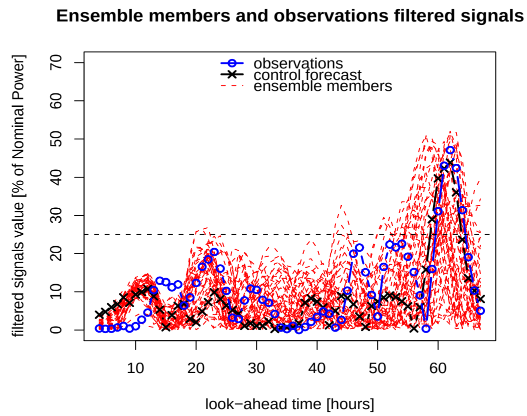

Figure 5: Here is an exemple of absolute value of filtered signals of observations (blue curve) and ensemble members (red curves, black curve is the control forecast). The ramp observed at horizon 63 is predicted by 39 members, which filtered signals cross over the horizontal dashed line representing the threshold τ. The resulting timing estimation $\overline{h}$ is equal to 61.

In a first part, we use the procedure introduced in section 2 to transform the wind power forecasts ensemble into an ensemble of ramp-timing forecasts. Considering a run time t, we first apply the filtering to each member of the wind power forecasts ensemble. We obtain an ensemble of 51 filtered signals (as shown by Figure 5), from which we compute the ensemble of timings of ramps forecasted by each member. For now, it is expected to have different members predicting the same event. So, the set of timings has to be split into several subsets: one for each event. We create N_t^{ramp} subsets focusing on the coherence between filtered signals. We denote by $N_t(i)$ the number of members predicting the event $i \in \{1, \ldots, N_t^{ramp}\}$. Finally we compute a mean timing $\overline{h}_t(i)$ for each ramp event.

In a second part, $N_t(i)$ is used as input to forecast the distribution of the timing of the ramp i. In order to describe this distribution, we choose a set of centered intervals associated to the ramp i:

$$I_t^i(\delta) = [t + \overline{h}_t(i) - \delta, t + \overline{h}_t(i) + \delta] \quad (2)$$

with different sizes $\delta = 2, 4, 6, 8, 10, 12$. We then compute the estimation $\hat{p}_{\delta,n}$ of the probability $p_{\delta,n}$ to have a ramp in $I_t^i(\delta)$, conditionally to $N_t(i) = n$. For each value of δ and each value of $n \in \{0, \ldots, n_{max}\}$, this computation is decomposed into two steps :

1. We determine the set of intervals $I_t^i(\delta)$ with $N_t(i) \in [n - \nu, n + \nu]$ for a fixed $\nu > 0$ (when $n = n_{max}$ find those with $N_t(i) \in [n_{max}, 51]$).
2. Within this subset, we compute $\hat{p}_{\delta,n}$ as the proportion of cases for which a ramp event is observed in $I_t^i(\delta)$.

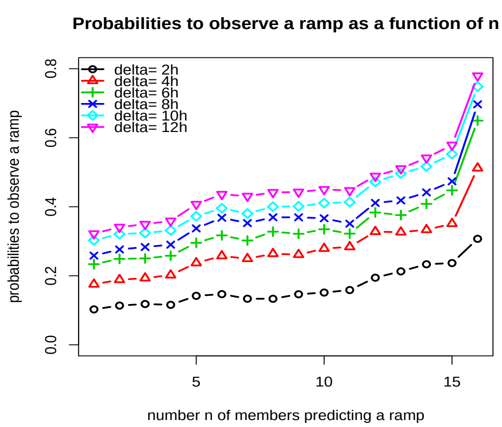

Figure 6: Estimated probabilities $\hat{p}_{\delta,n}$ of ramp observation in intervals I_t^i, as a function of the number n of wind power forecast members predicting the ramp. There is one curve for each interval's radius value δ, measured in hours. Results are for a wind farm located in the south of France.

The parameter ν can be considered as a smoothing parameter to prevent over fitting and hence, $[n-\nu, n+\nu]$ is a smoothing window. In our numerical study we took $\nu = 2$ but a cross validation procedure could be used for automatic selection of the parameter. As the number of cases with $N_t(i) \in [n - \nu, n + \nu]$ tends to

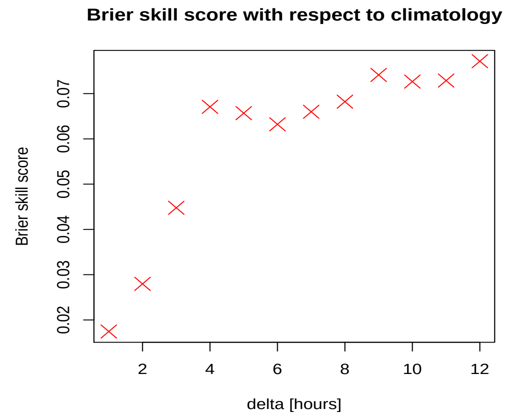

Figure 7: Brier skill score of our procedure, with the climatology as a reference method. Results are given for the different values of δ and the same wind farm as previously.

decrease for $n > 15$, we took $n_{max} = 15$. The learned probabilities are shown in Figure 6.

In this figure, we can see that the probability of observing a ramp in $I_t^i(\delta)$ increases with δ. It also increases with the number of ensemble members predicting it. This indicates that the forecasted probability has more skill than what we could obtain with a climatology. Indeed, in this case, a climatology can be defined by calculating the proportion of observed ramps in the intervals $I_t^t(\delta)$ for differents values of δ (without conditionning with respect to the value of $N_t(i)$). This climatology is used as a reference forecast to compute the Brier skill score: $BSS(\delta) = (BS_{ref} - BS)/BS_{ref}$ (BS_{ref} and BS stand respectively for the Brier score of the climatology and of our procedure. See [4] for a definition). The results (Figure 7) show a better skill of our procedure for the all range of values of δ. Furthermore, we noticed in our case-studies, a sharp increase of the skill score for the first values of δ.

In Figure 8, is associated to observations and control forecast up to 3 days ahead, a plot of confidence intervals defined by our method. While the control forecast only predicted a ramp at the look ahead time 63, some other members predicted ramps at horizons

22, 45 and 55 (respectively 2, 2 and 6 members). This implies the production of confidence intervals taking into account the possible transformation into ramps of some variations in the power observations time series. While the probability of observing such ramps does not exceeds 30% in a radius of 6 hours around the above mentioned horizons, the ramp observed at time 63 was predicted 6 hours around look ahead time 57 by 39 members, which corresponds to a probability of almost 65%.

4 Conclusions

Recent research works in wind power forecasting have focused on associating uncertainty estimates to spot forecasts. A challenge now is to provide forecasts able to handle extreme situations. What can be considered as an extreme situation is not obvious and is highly dependent on the perception of end-users about wind variability or predictability and their impact on decisions related to power system operation. Often Transmission System Operators or other end-users link extremes to large deviations between expected and observed wind power. Such large deviations are often encountered during large and sharp variations in the power output called *ramps*. These ramps are often well-predicted in amplitude, but with a time delay resulting in turn to the so-called *phase error*.

In this paper, we have proposed two methods for forecasting the uncertainty of the power production around ramp events. The first method relies on the use of additional explanatory variables in a state-of-the-art probabilistic forecasting model. As many other conventional short-term prediction approaches, forecasts are made on a per horizons basis. However the introduced inputs contain ramps information for the whole coming forecasting period. As a consequence, they are expected to capture part of the dependence structure in the wind power process, at a lower case the dependence structure related to the development of ramp situations. For each look ahead time, the method is expected to produce more reliable confidence intervals. In our case, the reliability is improved only for the highest quantile, but more experiment are necessary in order to come to a conclusion. The second proposed method uses ensembles to forecast the uncertainty in ramps observation and more precisely in the timing of such ramps. An eval-

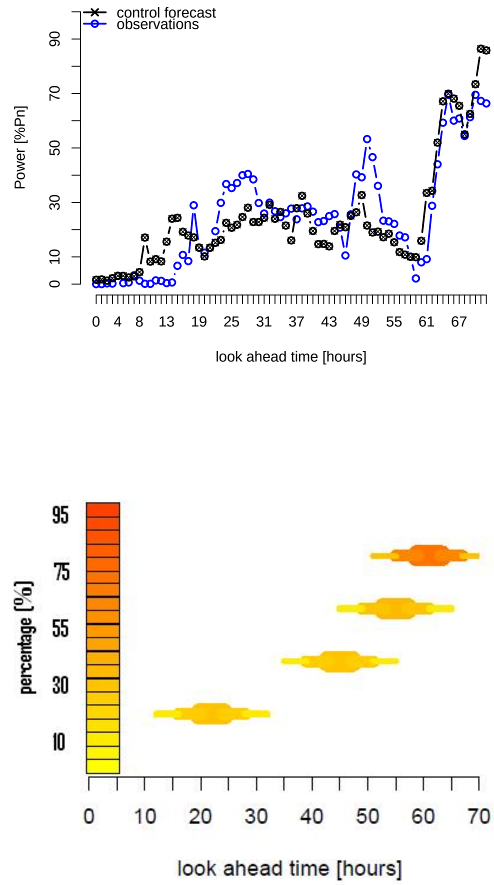

Figure 8: At the top : power observations and control forecast. At the bottom : confidence intervals produced by our method, for ramps predicted by at least one member. The probability to observe such ramps is given by associated colours. See the text for more explanations.

uation carried out on three french wind farms has showed our procedure has more skill than the climatology. In further work the focus will be on improving the tuning of these approaches and also on validation using longer data sets.

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