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A NOVEL METHODOLOGY FOR COMPARISON OF DIFFERENT WIND POWER RAMP CHARACTERIZATION APPROACHES

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ABSTRACT

Wind power forecasting is recognized as a means to facilitate large scale wind power integration into power systems. Recently, focus has been given on developing dedicated short-term forecasting approaches for the case of large and sharp wind power variations, so-called ramps. Accurate forecasts of specific ramp characteristics (e.g. timing, probability of occurrence, etc) are important since the related forecast errors may lead to potentially large power imbalances, with high impact to the power system. Various works about ramps' periodicity or predictability have led to the development of new characterization approaches. The evaluation of these approaches has often been neglected, leading to potentially irrelevant conclusions on ramps characteristics, or ineffective forecasting approaches. In this work, we propose a comprehensive framework for evaluating and comparing different characterization approaches of wind power ramps.

1. INTRODUCTION

Wind power forecasting is recognized as a means to facilitate large scale wind power integration into power systems. Considerable R&D in the last 25 years resulted in the development of numerous approaches (for a literature overview, we refer to [1], [2]). At operational level, the applied models are in general of good accuracy. Shortcomings relate often to challenging and extremes situations, but also to specialized forecasts for the various business processes and their integration into the decision making tools.

Recently, focus has been given on developing dedicated short-term forecasting approaches for the case of large and sharp wind power variations, so-called ramps [3], [4], [5], [6], [7], [8]. Those situations are particularly challenging since the related forecast errors, e.g. errors in the ramps timing (phase errors), may lead to potentially large power imbalances, with high impact to the power system. Often the aim of such approaches is improving forecasts of specific ramp characteristics like the ramps timing or probability of occurrence. In the related literature however, we observe that there is not a standard definition of what is a ramp. Various works about ramps' periodicity or predictability have led to the development of new characterization approaches [3], [7], [9]. The evaluation of these approaches has often been neglected, leading to potentially irrelevant conclusions on ramps characteristics, or ineffective forecasting approaches.

An approach dedicated to the characterization of ramps can be approved only if it is evaluated according to a certain protocol. In the edge detection literature, the development and evaluation of such an approach generally involve an edge[1] model and evaluation criteria (e.g. Canny's criteria [10]). Such a paradigm does not exist in the wind energy literature.

In this work, we propose a comprehensive framework for evaluating and comparing different characterization approaches of wind power ramps. As a first step we introduce a theoretical model of a ramp inspired from the edge detection literature. The proposed model incorporates some important aspects of the wind power

1 In the edge detection literature, the term "edge" is commonly used to denote a sharp and large level change in a signal.

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production process to reflect non-stationarity and bounded aspects of the process, as well as the random nature of ramp occurrences. Then, adequate evaluation criteria from the signal processing and statistical literature are introduced to assess the ability of an approach to reliably estimate ramp characteristics (i.e. timing, intensity). Based on simulations from this model, and using the evaluation criteria, we study the performances of different ramp detection filters and multi-scale characterization approaches.

The paper is organized as follows: in Section 2, we describe the proposed ramp model and the performance criteria which constitute our evaluation framework. In Section 3, we study the performances of state-of-the-art filters and scale selection or combination procedures, in detecting and localizing ramps. Finally, some summary conclusions are given in Section 4.

2. METHODOLOGY

In this section, we describe the proposed evaluation framework, namely the proposed ramp model and the evaluation criteria of a detection approach.

The proposed ramp model

Our model is based on the following decomposition:

$$p_t = R_t + \varepsilon_t$$

where p_t denotes the production at instant t, R_t a ramp profile defining the geometry of ramps to be detected and ε_t a noise.

Ramps are modeled as segments joining constant production episodes. To represent the random nature in the occurrence of wind power ramps, the durations T_i of ramps and in-between ramps are considered random variables. We assume them to be independent truncated exponential variables. The simulation of a ramp profile with N increasing and N decreasing ramps comes from the sampling of duration variables T_i to generate N elementary profiles, which at last are concatenated. An elementary profile $^{el}_{t}$ is defined by:

$$^{el}_{t} = \begin{cases} 0 & \text{if } t \in [0, T_1] \\ /_{T_2}\,(t - T_1) & \text{if } t \in [T_1, T_1+T_2] \\ A & \text{if } t \in [T_1+T_2, T_1+T_2+T_3] \\ -{}^{A}/_{T_4}\,(t - T) & \text{if } t \in [T\text{-}T_4, T] \end{cases}$$

where T=T_1+T_2+T_3+T_4. In the remaining of this paper, we will assume that increasing and decreasing ramp durations T_2 and T_4 are identically distributed, while null production episodes are in average longer than high (i.e. equal to A) production episodes by a factor c, i.e. $E[T_1]=cE[T_3]$, $c \geq 1$.

To reproduce the fastest fluctuations of wind power production, we add white noise ϵ_t with truncated Gaussian distribution to the ramp profile R_t. Wind power is a non-stationary process whose variability increases with the power production level. After some data analysis, we chose to model the standard deviation of noise (i.e. of production) as a piecewise linear function

$$\sigma_{tr,p} = a_1 + a_2 p - a_2(p - p_1)_+$$

where a_1, a_2 > 0, p denotes the power production level represented by the ramp profile R_t, and p_1 the level at which the variability stop increasing and remains constant.

For a full discussion about the model's assumptions and experimental conditions, we refer to [11]. A simulation example from the proposed model can be seen in Figure 1.

Evaluation criteria

A ramp detection approach is based on a measure of wind power variations. From such a measure it is possible to characterize each variation with some parameters, e.g. the variation timing, amplitude, duration, etc.

We consider a characterization of a variation restricted to two parameters: its timing t_I and

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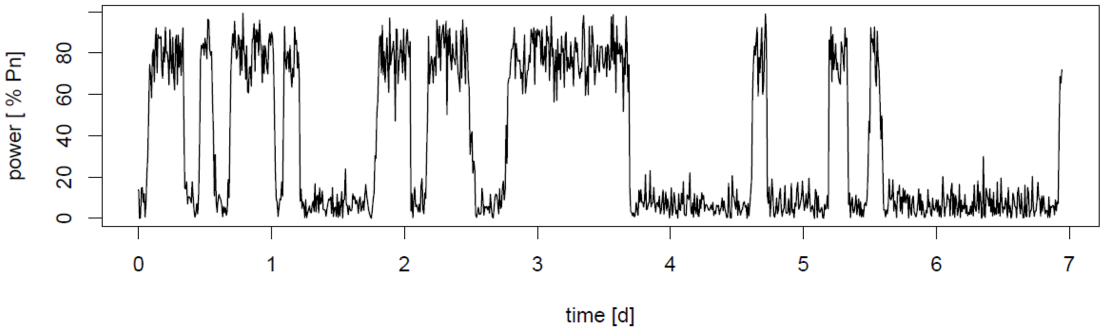

Figure 1 : Simulation example from the proposed ramp model of a 7 days long production episode. The ramps have here an amplitude of A = 80% of the nominal power P_n. *In average*: ramps are 1/2 h long, decreasing ramps are separated from increasing ramps by 12 h, while on the other hand increasing ramps are separated from decreasing ramps by half less time, i.e. $c = 2$. Noise parameters controlling the increase of variability with power production level have been set to the following values: a_1 = 5 %, a_2 = 20 % and p_1 = 25% of P_n (see the text for more details).

intensity I. The latter is a combined measure of the amplitude and sharpness nature of a variation. Both these parameters can be defined from the local maxima in the absolute response of a derivative filter for instance [7]. Truth is whatever the tools a detection approach is based on (e.g. filter, scales combination or selection procedure), and the characterization of variations it assumes, it should be possible to limit such a characterization to the two considered parameters.

Then, evaluating a ramp detection approach easily translates to evaluating a classification problem. To ramps and variations due to noise as simulated from our model, any detection approach should respectively associate high and low absolute intensity values $|I|$. Thus, once a thresholding procedure is introduced, it should constitute a good classifier of variations:

$$f_\tau(I) = \mathbb{1}_{|I| \geq \tau}$$

τ being a threshold set so as to classify high intensity variations as ramps. Because we simulate ramp occurrence from a model, we know exactly which variations of a signal are ramps or not. We are then able to associate to each variation (t_I, I), and to its classification result by a detection approach $f_\tau(I)$, the real class of variation it belongs to: Y = 1 if it is actually a ramp, 0 otherwise.

Of course the detection performance of an approach also relies on its ability to localize well ramps. The right classification of a ramp, based on the associated intensity value, will be so only if the ramp has been localized not too far from its true position.

Finally, besides a measure of the localization error, the evaluation of a detection approach may rely on one of the numerous criteria available in the statistical classication literature. In the following, we shall use the filter's response signal-to-noise ratio (SNR) proposed by Canny [10], which can be interpreted as a classification criterion. We shall also use the area under the ROC curve (AUC). The AUC allows to sum up to one number the whole performance of a detection approach, generally characterized by a tradeoff between the hit (well detected) and false alarm (wrongly detected) ramp rates. For an introduction to the ROC and AUC criteria we refer to [12].

3. RESULTS

In this section, we give some results obtained in the evaluation of different filters and scales combination and selection procedures encountered in the edge detection and wind power ramp literature.

Filters performance

We evaluated the performance of three different filters: the Prewitt filter (DOB, see [7]), the first derivative of a Gaussian (FDG),

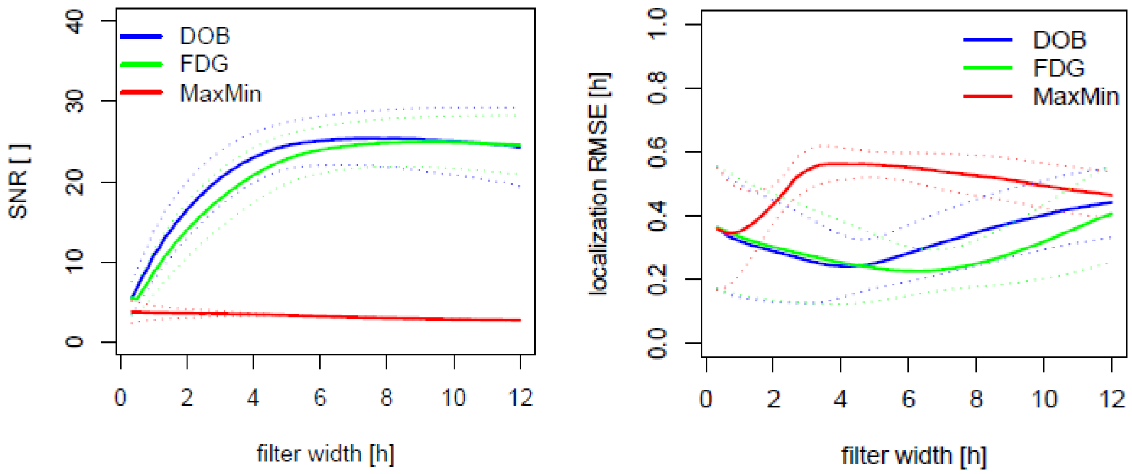

Figure 2: Detection and localization performances of 3 state-of-the-art ramp detection filters: 2 from the signal processing literature (DOB and FDG), and one from the wind energy literature (MaxMin). The absence of smoothing operation in the MaxMin filter makes it sensitive to noise and unable to discriminate of localize well ramps.

and a filter (MaxMin) used in the wind energy community (see [3] and [6]), which measures a signal's variations through computing the difference between its maximum and minimum values in a sliding window.

In Figure 2, one can see the detection and localization performances of the three considered filters depending on their width. Usual derivative filters from the signal processing literature (DOB, FDG) combine a smoothing to the differentiation operation so as to reduce the impact of noise in measuring a signal's variations. Then, the filter width controls a tradeoff between noise reduction and limiting the perturbation due to neighboring elements of a signal (e.g. nearby ramps) in the detection of a ramp. It explains the pattern we can observe in Figure 2 about DOB and FDG performances first increasing before decreasing with the filters width. Because of its adequacy to the geometry of ramps considered in our model, the DOB filter gets slightly better detection performances. On the other hand, the particular shape (with thinner tails) of the FDG filter makes it less sensitive to neighboring ramps, resulting in better localization performances.

The MaxMin filter does not benefit from noise reduction while increasing its width; it just becomes more sensitive to it and neighboring ramps. That explains its stagnating or continuously decreasing performances.

Multi-scale approaches performance

In edge detection, selecting appropriate scales is paramount. The choice of one or several scales is generally made so as to best control the tradeoff between reducing noise and limiting perturbation in detecting neighboring edges. In our work, we studied the performances of three different scale selection and combination procedures: the use of an unique scale (uniscale) for the detection of all ramps in a signal, the (local) selection of a scale maximizing the filter response to a particular ramp as proposed in [13] (here denoted Lindeberg), and finally the use of several scales to define a measure of variations based on the sum of the respective filter responses as in [9] (here denoted Gallego).

Detection and localization performances of the considered scale selection and combination procedures, as a function of the inter-ramp average duration, are shown in Figure 3. One can notice that the scale selection procedures (particularly the local one Lindeberg) get better detection performances than the scales combination procedure Gallego, especially for closely following ramps.

On the other hand, a combination of several

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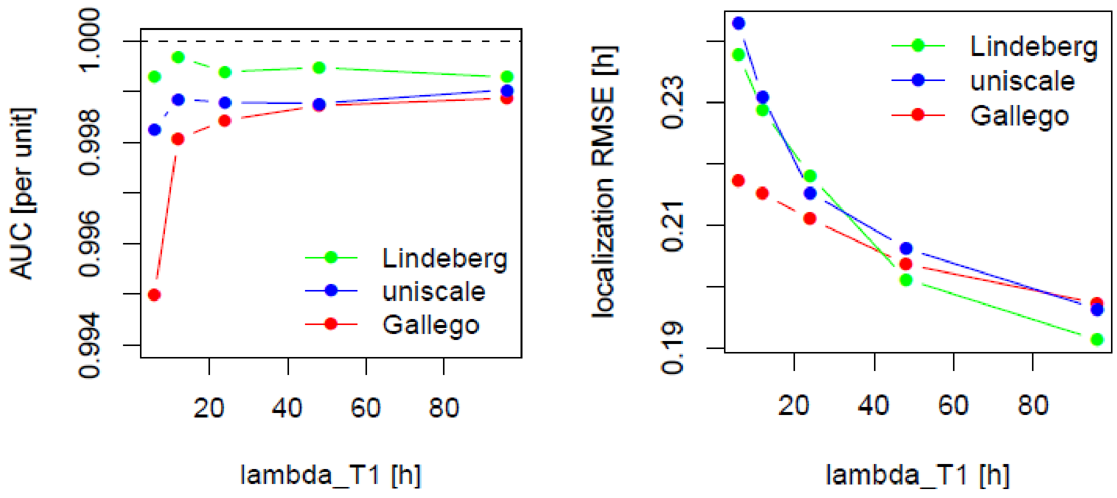

Figure 3: Detection and localization performances of three different scale selection and combination procedures: considering an unique scale (uniscale), with a local selection of a scale (Lindeberg) and with a "sum" of scales (Gallego, see the text for more details). If the selection procedures get better detection performances than the combination one, especially for closely following ramps, the hierarchy is somewhat reversed for the case of localization performances.

scales may offer better localization performances, particularly for such closely following ramps.

Further analysis of the results showed that the better detection performances of scale selection over scales combination procedures were particularly true in case of low signal-to-noise ratio (defined through the joint consideration of different values of ramp amplitude, duration and noise intensity). Again, for a detailed description of the results and more insight about the different approaches, we refer to [11].

4. CONCLUSIONS

The development of dedicated short-term forecasting approaches has undertaken the development of new ramp characterization approaches. However, those approaches have not been yet evaluated and compared to standard procedures like the ones introduced in the edge detection literature. Without a rigorous assessment of those approaches, we cannot ensure they provide reliable information about ramp characteristics.

In this paper, we proposed a framework to evaluate and compare different ramp characterization approaches. The proposed framework is based on a theoretical model of ramps and associated criteria for the evaluation of approaches in the detection of ramps and estimation of the latter characteristics. Within this framework, we evaluated the relevance of some practical choices encountered in the wind energy literature and compared them to those from the signal processing literature. Among other, the results of our work show that the MaxMin filter often used to measure wind power variations performs very poorly when used for ramp detection. Filters derived from the signal processing literature should be preferred. Local scale selection procedures also turned out to be promising in detecting ramps with recurrent, random occurrence.

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