# Influence of wind power ramp rates in short-time wind power forecast error for highly aggregated capacity

S. Martín Martínez, A. Honrubia Escribano, M. Cañas Carretón and E. Gómez Lázaro
Renewable Energy Research Institute and DIEEAC-EDII-AB.
Universidad de Castilla-La Mancha,
02071 Albacete (SPAIN)
Email: sergio.martin@uclm.es, andres.honrubia@uclm.es, miguel.canas@uclm.es and emilio.gomez@uclm.es

J. P. S. Catalão
Faculty of Engineering of the Univ. of Porto, Porto,
Univ. of Beira Interior, Covilha,
and INESC-ID, Inst. Super. Tecn.,
Univ. of Lisbon, Lisbon (PORTUGAL)
Email: catalao@ubi.pt

***Abstract*—Significant wind power ramps have a remarkable influence on the integration of wind power. Their variability and uncertainty affects to the forecast increasing the error and reducing the reliability in the continued operation of the power system. Ramp events are considered the main source of forecasting error and their study is imperative for an improvement of prediction tools. In this aspect, the first steps to achieve a study of the influence are identifying, grouping and temporal characterizing of the ramp events.**

**This paper develops a methodology for wind power ramp events recognition in order to analyze the relationship between these events and the accuracy of the wind power forecast system according with two criteria: maximum forecast deviation and mean magnitude error. The methodology is validated using real data from the highly aggregated Spanish power system and short time timescale forecasting values.**

***Index Terms*—Wind power forecasting, Variability, Ramp events**

## I. Introduction

Since wind power is almost not dispatchable, wind power forecasts are a very useful tools for the operation and planning in power systems. The importance of wind power forecasting increases considerably when large amounts of wind power are considered and power system interconnection is very limited, e.g. Iberian and Ireland power systems, [1]. According to this, the problem of accurately wind power forecasting has received a great deal of attention in recent years. As an example, a short-term wind power forecasting (between 1 hour and 72 hours) is considerably helpful in power system planning for the unit commitment and economic dispatch process [2].

In spite of the fact that wind forecast models have been improved, in both, short and long term, a considerable amount of error is still registered in custom conditions, reaching higher values at extreme conditions. The wind power forecasting models have to deal with variability and uncertainty. Variability depends on the timescale as wind power presents different prevailing dynamics when it is analyzed for a few milliseconds, for several minutes or for a daily horizon. To sum up, the aggregation level reduces considerably the variability values.

As variability, the wind power forecast error (WPFE) distribution is strongly dependent on the wind power level. For extreme low wind power forecast, the forecasts tend to over-predict the actual wind power produced, whereas when the forecast is for extreme high power levels, the forecast tends to under-predict the actual wind power. Most of the work in this field neglects the influence of wind forecast levels on wind forecast uncertainty and analyses WPFEs as a whole.

With regard to the operation and planning aspects, transmission system operators (TSOs) place primary emphasis on better understanding of the impact of extreme events (e.g., large ramps), which can have significant influence on system economics and reliability. With this criterion, the most important issue is the expected maximum forecast deviation, and not the mean forecast error, as described in [3]. The group's finding is because the extreme deviations may lead to load shedding. Consequently, from a TSO view, a good criterion will be to minimize the expected maximum forecast error. However, this training criterion may be difficult to translate to a function, so the minimum mean square error (MSE) could be an acceptable criterion because it weights the large deviations more heavily, [4]. Secondary concern is focused on uniform wind power forecasting improvements for enhanced planning applications.

Furthermore, to address the challenges in WPFE, it is important to understand the three main sources of error: timing error, magnitude error and ramp error, [5]. A timing error is defined as an event that it is accurately predicted in magnitude, but occurs at the wrong time. This kind of error can achieve a considerable absolute error even when event magnitude has been correctly forecasted. This type of error is usually corrected for short term forecast as event is progressively discovered. A magnitude error is defined as an event that is forecasted to occur approximately at the right time, but with the wrong magnitude. This can occur in two possible ways; the forecast might be in error about the rate of change or might be in error regarding the overall magnitude of the event. A ramp error consists on a ramp event that is forecasted with a different rate of change. This kind of error drives forecast to considerable magnitude errors when wind power reach maximum values. In summary, timing and ramp errors are usually associated with wind power events, like extreme ramps caused by storms or wind power curtailment, while magnitude error is generally a consequence of timing and ramp errors, [6].

For ramp forecasting, the detection and classification of ramp events are an imperative. There are a lot of methods for ramp event pattern recognition. An interesting method consists on the application of swinging door algorithm developed by E. H. Bristol in [7]. This algorithm is used for wind power ramp analysis in [8] and is optimized in [9]. Another example is achieve by R. Sevlian and R. Rajagopal, [10], where optimal ramp detection is introduced to provide empirical statistics of wind ramps.

In this paper, a methodology of ramp event detection and classification is proposed. The purpose of this methodology is the classification of ramps to achieve a comparison of the influence of ramp events in the forecast error. Real measured WPFE are evaluated taking into account ramping rates over multiple timescales. The available data include hourly WPFE and wind power production for the Spanish power system. The considered timescales include short-term forecasting from 1 hour lead time to 24 hours lead time. Ramp Rate Percentage (RRP) is selected for ramp event classification. The final objective is to propose a correction factor in the forecast according with the evolution of the error in the different groups of ramp events.

The contributions of this paper are stated below:

1) An heuristic methodology to measure the accuracy of a WPF system under the influence of ramps, in both criteria: maximum forecast deviation and mean magnitude error;
2) Probabilistic analysis performance to relate events and weather conditions with extreme wind power forecast errors based in their ramp rate and their duration;
3) The proposed methodology could be scaled to individual wind farms and different levels of aggregation as CDF and ramp duration are used in the classification of ramps. To sum up, forecast timescale could also be adapted;
4) A detailed analysis of a case of study in Spain comparing different ramp rates and durations.

The rest of the paper is structured as follow: in section II the methodology is described highlighting its two parts, ramps detection, grouping and classification. The steps are detailed and the main instructions for each step are proposed. Then, the methodology is applied to real data and their results are illustrated in section III. Finally, conclusions are proposed in section IV.

## II. Methodology

The first stage for the analysis of the influence of the ramp events in the forecast error is the recognition of the patterns of the ramp events. Once ramp event pattern is extracted, these events must be grouped according with its severity which has an added difficulty in its forecast. Since this classification divides the variability of the events, their influence can be studied using duration, direction and severity parameters.

The methodology proposed is based on the premises previously named and the search of the computational and structural simplicity. Swinging door algorithm is selected as recognition pattern method for ramp event due to its favorable attributes of robustness and easy implementation, [8]. On the other hand, ramp rate percentage (RRP) is chosen as severity classification of the ramp events. The RRP sorts ramps rates and ramp events using their exact values through cumulative distribution functions (CDF), [11].

This methodology is divided into two sections, the pattern recognition and its classification, and the calculation of ramp rates and parameters for error characterization during ramp events. In this aspect the methodology has a total of five steps developed as follows:

*1) Step 1: Swinging door algorithm:* The swinging door algorithm (SDA) is applied in order to obtain the main pattern of the ramp events. This algorithm contributes to avoid insignificant fluctuations during a ramp event with a marked trend and to combine similar consecutive ramps in the same event with a simple and robust algorithm. This method has a good performance in discerning insignificant changes and filtering. Another advantage of its use is the data compression. The compression rate is controlled by the only tuneable parameter of the algorithm, $\epsilon$. This parameter can vary from 0 to 1 pu. With a value of 0 the resulting data series are the same as the original series, and no compression is achieved. The higher value of $\epsilon$, the higher compression results. more information about the method may be consulted in [8]. In figure 1, a SDA algorithm is applied for a wind power generation time series (red line).

*2) Step 2: Relative extremes detection:* Since SDA produces time series with variable step depending on epsilon value, extreme values could be neglected for some iterations. These extremes are very important for a correct characterization of ramp events. Figure 1 shows some iteration, as hours 5-8, hours 24-27 and hours 36-39, where several relative maximums have been neglected using SDA and must be included in the final series for a proper recognition of the ramp events.

In order to include these extremes in the time series of ramp events, SDA series must be processed to find relative maximums and minimums not included in this series. The process includes the evaluation of the periods of the SDA to distinguish two cases:

- Iterations with their extremes values matching the values at the beginning and at the end of the iteration. In this

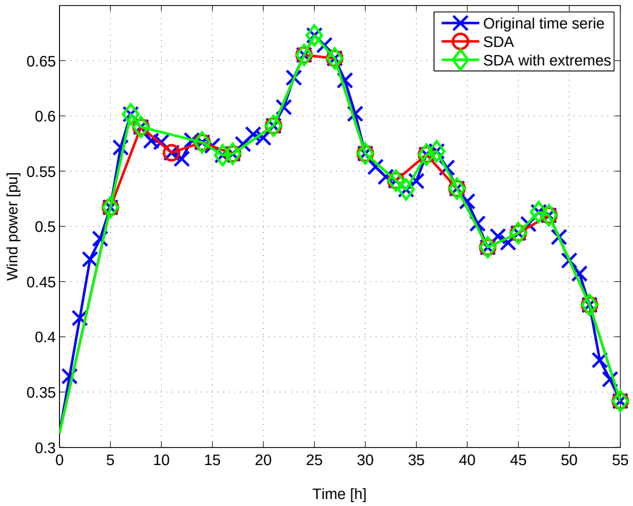



Figure 1. Comparison of original serie, SDA serie and SDA with extreme values.

case there is neither minimum nor maximum to include in the final series. No action is taking place.

- Iterations with one extreme value matching the value at the beginning or at the end of the iteration. In this case the extreme value is included in the series.

Once relative extremes are included in the time series, ramp events are properly characterized for all their duration.

*3) Step 3: Ramp events grouping:* This definition of ramp must include all the aspects of the ramp and is based on the change direction, magnitude, and duration of wind power output. In this aspect, a ramp event could be characterized by some parameters:

- Magnitude. The variation in power produced during the ramp event.
- Duration. Time period during which the ramp event is produced.
- Ramp rate. Defined as the ramp intensity. The ramp rate event value is obtained using equation 1.

$$R_{val} = \frac{P(t+\Delta_t) - P(t)}{\Delta_t} \tag{1}$$

where $P(t)$ is the wind power output at time t; $P(t+\Delta_t)$ is the wind power output at time t+$\Delta_t$; $\Delta_t$ is the duration of the ramp; $R_{val}$ is the defined value of change rate in wind power output.

- Timing. A time instance related to the ramp occurrence.

In this step the consecutive ramp events with the same direction are grouped to obtain the cumulative ramp rate for every event. This cumulative ramp rate value corresponds to the mean ramp during the event. Furthermore, this cumulative ramp events offer a proper delimitation for the study of WPFE in every event.

*4) Step 4: CDF and RRP calculation:* The featured selection technique is based in the CDF curve to identify the severity of the ramp rate. This technique allows a proper scalbility between different cases, for both: amount of data and aggregation level. The RRP values are calculated from the CDF of the ramp values in the ramp events and are defined as the percentage of ramps below this value. 1% RRP and 99% RRP are important values to define in wind power variability as are used to indicates the range of extreme ramps for a case, 1% RRP for positive ramps and 99% for negative ramps,[11]. The selected values of RRP could be defined depending on the case of analysis. In studies with a great amount of data the resolution could be adjusted to 1% or less, while a typical case is the use of decades (10%) resolution.

*5) Step 5: Ramp events influence analysis:* Once ramp events are correctly defined, the error value is studied for every event. In the field of time series prediction in general, the prediction error is defined as the difference between the measured and the predicted value. Therefore, since we consider separately each forecast horizon, the prediction error for the lead time k is defined as

$$e(t+k|t) = P(t+k) - \hat{P}(t+k) \tag{2}$$

It often is convenient to introduce the normalized prediction error as presented in equation 3.

$$\epsilon(t+k|t) = \frac{1}{P_{inst}}(P(t+k) - \hat{P}(t+k)) \tag{3}$$

where $P_{inst}$ is the installed capacity.

According with these definitions of the error and the ramp events characterization, there are some parameters to be considered in order to study the influence of ramps in WPFE. The variation of error, $\Delta e(t|t+k)$ or $\Delta e$, during the ramp event is, for example, an interesting parameter for being analyzed. It represents the change of error, equation 4, and the ramp error as well.

$$\Delta e(t|t+k) = \epsilon(t+k) - \epsilon(t) \tag{4}$$

The study of these parameters could be undertaken in different ways. For a proper analysis of maximum forecast error, a probabilistic analysis is proposed with different ramp rates and duration values. This analysis is performed with the error distribution using boxplots for the ranges of RRP and different duration. Outliners are avoided to represent the main trend of the error with ramp rate and duration.

## III. Results

### A. Data and parameters description

The methodology described in II is evaluated for highly aggregated wind power using data of wind power generation for the Peninsular Spanish power system. These data include wind power generation with and without curtailments, and wind power forecast for timescales from 1 hour lead time to 24 hours lead time from 2010 to 2013. This dataset allows to perform complete study for short-term forecast.

### *B. WPF system accuracy under mean magnitude error criterion*

In order to assess the quality of the WPF under the mean magnitude error criterion for these data we have considered two parameters, recommended in [12] to regard and to compare the performance of a prediction model in a general framework:

- Normalized Mean Absolute Error (NMAE)
- Normalized Mean Squared Error (NMSE)

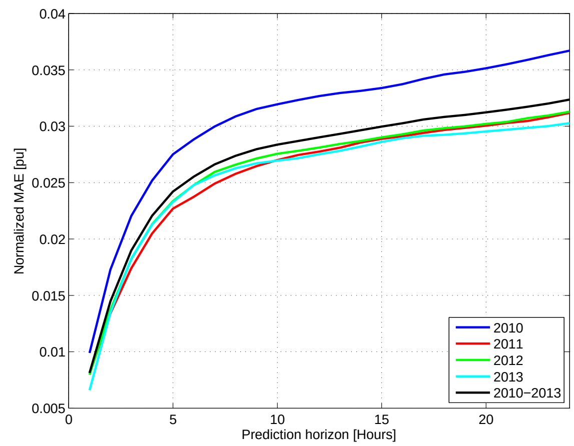
These measures are given per time step and their values are calculated as presented in equations 5 and 6.

$$MAE(k) = \frac{1}{N}\sum_{t=1}^{N}|e(t+k|t)| \tag{5}$$

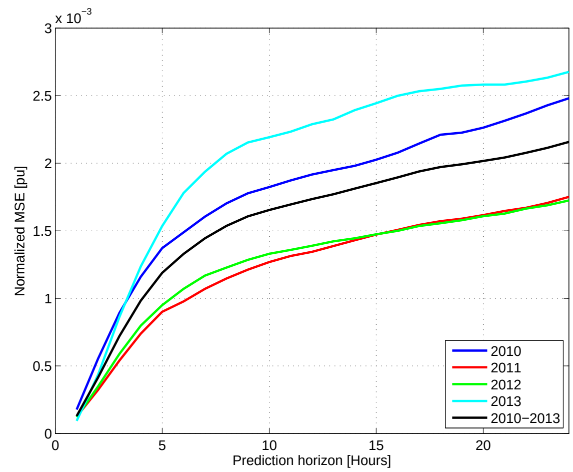
$$MSE(k) = \frac{\sum_{t=1}^{N}(e(t+k|t))^2}{N-p} \tag{6}$$

Statistically, the value of MAE is associated with the first moment of the prediction error, and hence these are measures which are directly related to the produced energy. The values of MSE and RMSE are associated with the second order moment, and consequently to the variance of the prediction error.

Figure 2 shows NMAE and NMSE values for the different timescales in the described data. The forecast quality parameters present an important increase from 1 to 6 hours forecast, and after that the increase is smooth until 24 hours forecast. The changes between years are due to the different variability and the year production.




(a) NMAE




(b) NMSE

Figure 2. Forecasting error parameters in pu

### *C. WPF system accuracy under maximum error criterion and ramp rate influence*

The methodology described in section II is applied to this data. The methodology starts using SDA to the original series. The value of epsilon is fixed at 0.002 pu with a balance between the compression percentage and the details of the events. The compression percentage at the end of step 1 is about $30.3\%$. Then relative extremes are found to improve the characterization of the events. This step increases the percentage of data and the compression percentage rises to $41.4\%$. These remaining data is grouped resulting 6524 ramp events during the 4 years measurement period. In step 4 the events are sorted obtainig its CDF and the ranges of RRP are selected in decades. Finally, ramp error and remaining magnitude error are studied for every RRP range. The results for every parameter in different timescales are described as follows.

Figure 3 shows the probabilistic results of the ramp error for every range of RRP using statistical box-plots, [13] in different timescales, 1 hour, 6 hours, 12 hours and 24 hours. There are remarkable distribution error changes between 1 hour and 6 hours due to the important error increase showed in the NMAE and NMSE. In contrast, the changes between 6, 12 and 24 hours timescales are no relevant. The ramp error during extreme ramp events — RRP 0-10 for upward ramps and 90-100 RRP for downward ramps — have in most of the cases the same direction as ramp rate during the event. Only 5.8 % of the cases in 0-10 RRP and 6.7 % in 90-100 RRP have different direction. For the rest of RRP ranges the error distribution, in both directions, is more symmetrical and extreme errors are restricted to specific cases.

An extensive comparison for extreme ramp events is showed in figures 4 and 5. In these figures, mean and quantile values are showed for every forecast horizon. In the case of extreme upward ramps — figure 4 — the mean values are all positive and for forecast horizons above 6 hours the mean error is constant slightly below 0.02 pu. $25\%$ quantile values are also positive. For downward ramps — figure 5 — results are similar but more symmetrical as $75\%$ quantile values are slightly above 0 pu These facts indicate that, in most of the cases, the forecast system is conservative, especially during extreme events, for both directions, upward and downward ramps. The results also quantify the maximum error deviation according with the extreme ramps. Summarizing, the accuracy of the forecast system for extreme ramps in two criteria: maximum

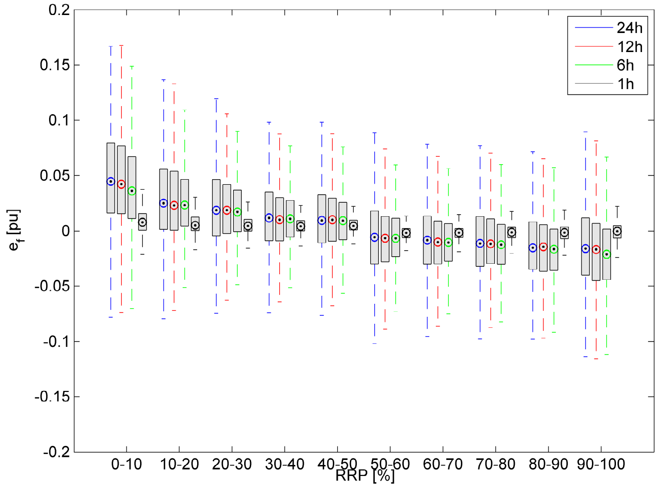



Figure 3. Comparison of error distribution for different timescales.

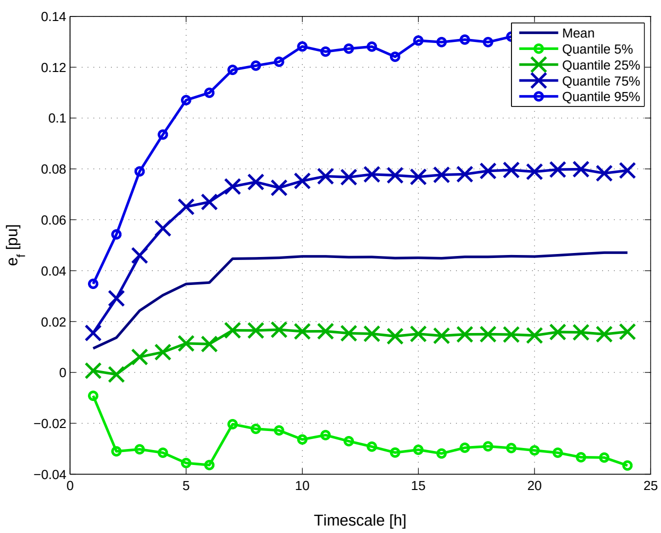



Figure 4. Error distribution with extreme upward ramps (0-10 RRP).

forecast deviation and mean magnitude error.

### *D. Ramp duration influence*

The error distribution for different event durations with 3 hours, 12 hours and 24 hours timescale are showed in the figures 6, 7 and 8, respectively. The duration ranges have been selected to include a similar number of events (aprox. 150-200 events) in every range. The distribution is positively unbalanced for upward ramp events ($< 50RRP$). In contrast, the distribution is almost balanced for downward ramp events ($> 50RRP$). The unbalance increases as ramp event duration increases in most of the cases. Low duration ($< 3hours$) influence is retricted to medium RRP values for all the forecast horizons. In the case of extreme upward ramps ($0 - 10RRP$) the duration has little influence for ramp events with more than 3 hours duration for all timescales. The influence of duration increases as ramp rate reduces.

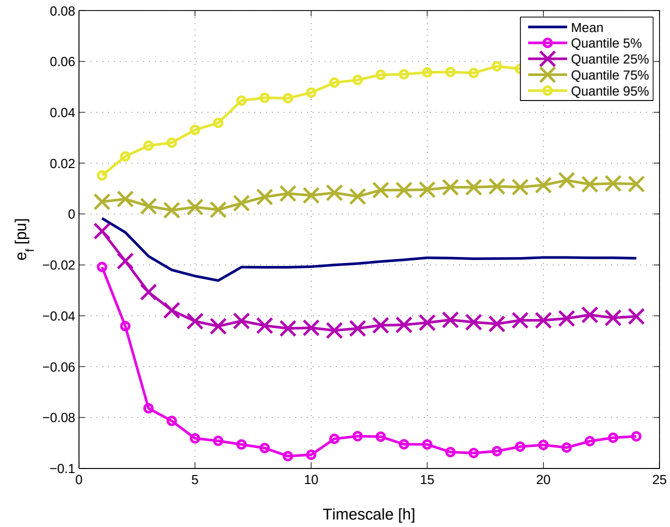



Figure 5. Error distribution with extreme downward ramps (90-100 RRP).

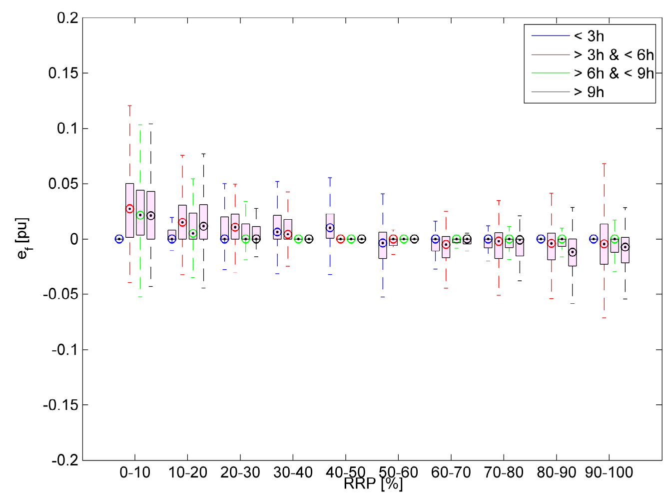



Figure 6. Comparison of error distribution with different RRP and duration for 3h timescale.

To sum up, for ramp duration over 3 hours, its influence in WPFE is restricted to medium RRP for both, upward ($20 - 40RRP$) and downward ($60 - 80RRP$) ramps.

## IV. Conclusions

This paper proposes and studies a methodology for ramp events recognition and classification, and the evaluation of WPFE during these events. The implemented method achieves a considerable compression without loss of desire details in the events. The pattern recognition of the ramp events allows its classification and temporal limitation for the evolution of forecast error in the course of the events. In addition, the accuracy of the forecast could be studied according to maximum forecast error criterion, highlighting these values during extreme ramps which are very important from TSO point of view.

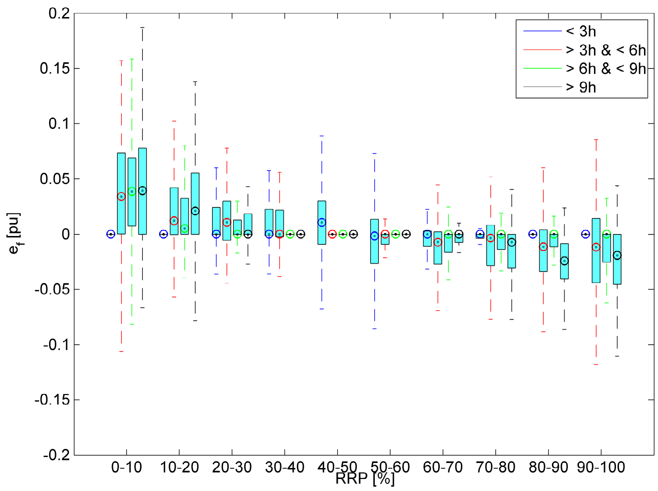



Figure 7. Comparison of error distribution with different RRP and duration for 12h timescale.

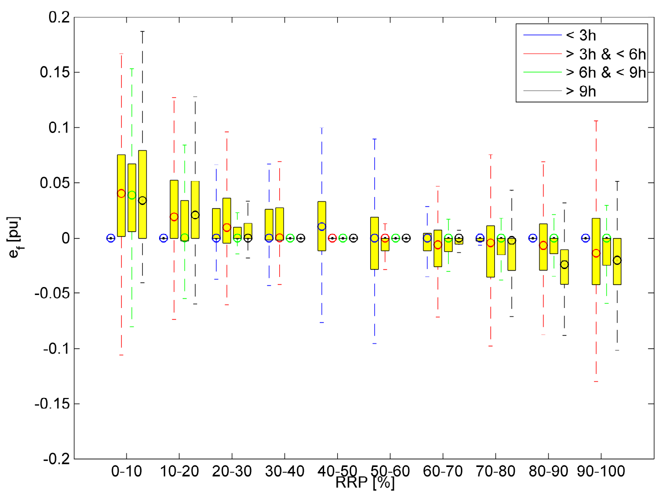



Figure 8. Comparison of error distribution with different RRP and duration for 24h timescale.

The proposed methodology has been applied to real data from a highly aggregated system with detailed short term forecast. The results obtained offer a general overview of ramp influence in forecast error through different cases of ramp rates and ramp event duration. A conservative forecast is observed in the results and specially for extreme upward ramps. The ramp influence results and its error distribution for ramp events could be feedbacked to the forecast system to reduce the WPFE.

## Acknowledgment


The authors would like to thank Ibero-America Santander Grants program for young lecturers and researchers.

This work was supported by 'Ministerio de Economía y Competitividad' and the European Union —ENE2012-34603—

Moreover, J.P.S. Catalão thanks COMPETE and FCT, under FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010) and UID/CEC/50021/2013, and also the EU 7th Framework Programme FP7/2007-2013 under grant agreement no. 309048.


## References


[1] B.-M. Hodge, D. Lew, M. Milligan, E. Gómez-Lázaro, X. Larsén, G. Giebel, J. Dodschinski, H. Holttinen, S. Sillanpää, R. Scharff *et al.*, "Wind power forecasting error distributions," in *11th Annual International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants Coference, November 13-15, 2012, Lissabon, Portugal. National Renewable Energy Laboratory*, 2012.

[2] K. D. Orwig, M. L. Ahlstrom, V. Banunarayanan, J. Sharp, J. M. Wilczak, J. Freedman, S. E. Haupt, J. Cline, O. Bartholomy, H. F. Hamann *et al.*, "Recent trends in variable generation forecasting and its value to the power system," *Sustainable Energy, IEEE Tran*, vol. 6, pp. 924 – 933, 2015.

[3] R. Bessa, V. Miranda, A. Botterud, and J. Wang, "goodor badwind power forecasts: A relative concept," *Wind Energy*, vol. 14, no. 5, pp. 625–636, 2011.

[4] T. Ouyang, X. Zha, L. Qin *et al.*, "A survey of wind power ramp forecasting," *Energy and Power Engineering*, vol. 5, no. 04, p. 368, 2013.

[5] C. W. Potter, E. Grimit, and B. Nijssen, "Potential benefits of a dedicated probabilistic rapid ramp event forecast tool," in *Power Systems Conference and Exposition, 2009. PSCE'09. IEEE/PES*. IEEE, 2009, pp. 1–5.

[6] S. Martin-Martinez, E. Gomez-Lazaro, A. Molina-Garcia, and A. Honrubia-Escribano, "Impact of wind power curtailments on the spanish power system operation," in *PES General Meeting— Conference & Exposition, 2014 IEEE*. IEEE, 2014, pp. 1–5.

[7] E. Bristol, "Swinging door trending: Adaptive trend recording?" in *ISA National Conf. Proc*, 1990, pp. 749–753.

[8] A. Florita, B.-M. Hodge, and K. D. Orwig, "Identifying wind and solar ramping events," in *Green Technologies Conference, 2013 IEEE*. IEEE, 2013, pp. 147–152.

[9] M. Cui, J. Zhang, A. R. Florita, B.-M. Hodge, D. Ke, and Y. Sun, "An optimized swinging door algorithm for wind power ramp event detection," in *Power and Energy Society General Meeting, 2015 IEEE*. Denver (USA): IEEE, 2015, pp. 1–8.

[10] R. Sevlian and R. Rajagopal, "Detection and statistics of wind power ramps," *Power Systems, IEEE Transactions on*, vol. 28, no. 4, pp. 3610–3620, 2013.

[11] S. Martín-Martínez, E. Gómez-Lázaro, A. Vigueras-Rodríguez, J. A. Fuentes-Moreno, and A. Molina-García, "Analysis of positive ramp limitation control strategies for reducing wind power fluctuations," *IET Renewable Power Generation*, vol. 7, no. 6, pp. 593–602, 2013.

[12] H. Madsen, G. Kariniotakis, H. A. Nielsen, T. S. Nielsen, and P. Pinson, "A protocol for standardizing the performance evaluation of short-term wind power prediction models," in *CD-Proceedings of the 2004 Global Windpower Conference, Chicago, US*, 2004.

[13] Mathworks, "Statistical box plots," Tech. Rep., 2015.