Anemos.Rulez: Extreme and ramp event alarming to support stability of energy grids

Hans-Peter (Igor) Waldl, Philipp Brandt
Overspeed GmbH & Co. KG, Oldenburg, Germany, igor@overspeed.de

Summary

In this paper, we discuss the need to predict and alarm upcoming extreme events, such as a sharp increase in wind power production or cut-off events, as a complement to daily operational wind power predictions. As there is no universal definition for extreme events, we describe important parameters for their definition and factors that influence these parameters. A tool for extreme event predictions, *Anemos.Rulez*, will be presented, including evaluation results from an application test case.

1. Motivation

The worldwide increase of wind power installations is leading to the high penetration of electrical grids with fluctuating wind energy. In countries like Germany, a rise up to 25% (2020) of the total electrical energy production is expected during the next years [1]. Due to the unscheduled fluctuations of wind power production, this increasing share represents a major challenge to ensuring grid stability. In recent years, this challenge has been tackled partly by the development of tools for accurate wind power prediction (WPP) e.g. [2]. The focus of this work was to forecast the power production with a minimized average statistical error (e.g. RMSE).

Under high penetration conditions, achieving a low average prediction error is not sufficient to ensure grid stability. Single extreme events, such as a ramp event caused by a rapid increase in the average wind speed due to a weather front, can temporarily lead to very high prediction errors. As the probability of their occurrence and the exact timing of these events is sometimes hard to predict, they can severely endanger the grid stability. An increasing share of wind power in the grid also increases the frequency of these events significantly. Today, therefore, the prediction of extreme events has to be given attention to ensure grid stability with high wind power penetration.

2. Ramp events

Ramp events are characterized by significant changes in the total power production of a wind farm or a region within a relatively short period, 'rising' if the power production increases, 'falling' for a decreasing production. A dip in the production is also classified as a ramp. Figure 1 and Figure 2 show two examples of typical ramp events.
The causes for ramp events can be different, but, as expected, in most cases they are related to a change in weather conditions which have a significant influence on the wind speed. Very high wind speeds close to or above the cut-out wind speed of the turbines can also cause ramp events. In addition, other environmental conditions such as extreme high or low temperatures and icing could lead to fast shut-down of wind farms.

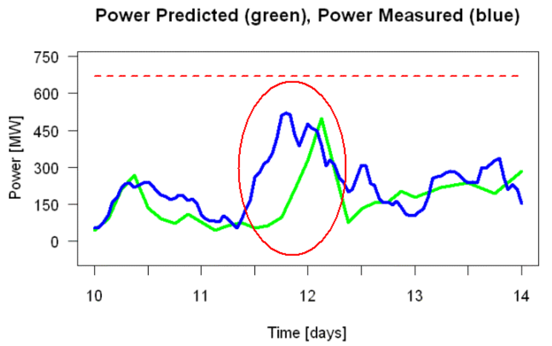

Figure 1: Ramp event example with significant phase error in the forecast. Predicted (green) and measured (blue) power over time in days (dotted line: installed capacity).

Figure 1 shows a rising ramp with a power increase of about 500 MW (~ 75% of installed capacity) within 12h, where the occurrence in time is wrongly predicted with a time shift of about 8-10 hours. This leads to a large instantaneous error of up to 500 MW.

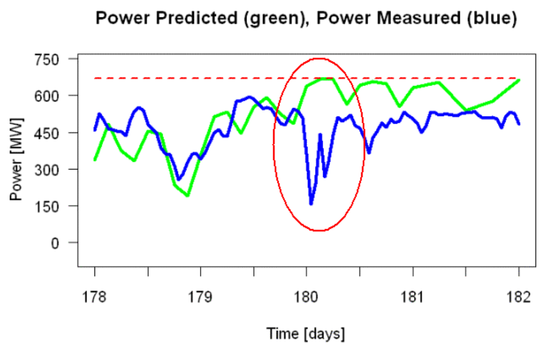

Figure 2: Ramp events caused by cut-offs due to very high wind speeds. Predicted (green) and measured (blue) power over time in days (dotted line: installed capacity).

The second example in Figure 2 shows a ramp event due to multiple cut-offs. Instead of an increase of the power production, it drops significantly likewise causing an error of up to 500 MW.

Due to the system critical nature of these events system operators should not only receive information on the expected power production, but extreme events should be notified as well by specific alarms which, for example, may be included in the control room routines.

3. Definition of ramp events

Figure 3 includes some typical properties that can be assigned to a time series with regard to extremes: amplitude, maximum gradient, sign, maximum change in a given time window, etc. Naturally, the amplitude together with the time frame is an important property of a ramp. But also the maximum gradient, the uncertainty of the timing and the sign of the predicted power change are of importance for the TSO in order to facilitate the maintenance of grid stability.
Most will agree that the events depicted in Figure 1 and Figure 2 are to be classified as ramp events. However, this might not be the case for all type of events and environments. For some TSOs, predicted power changes from day 10 in Figure 1 might be a ramp, but for others possibly not. Therefore, it will be difficult to find general values for these ramp parameters that define a ramp. Figure 3 illustrates the interdependency between parameters defining a ramp and the technical and the business environment of a TSO, leading to individually tailored definitions. In practical applications, the exact definition of a significant extreme event depends on the characteristics of the transmission system.

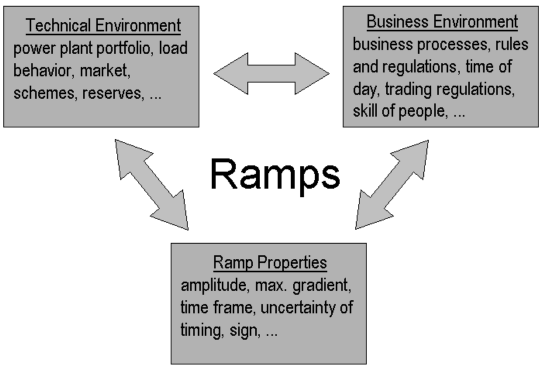

Figure 3: Dependencies of a suitable ramp specification for a TSO

The less flexible the system is, the higher is the impact of ramps on grid stability. Aspects of the technical environment are the availability of power reserves, start-up times, transport capacity, wind power penetration, conventional power plant capacity, power plant portfolio, etc. An additional influence stems from load characteristics. If load shifting is possible, this would, of course, facilitate the handling of ramp events.
From a business environment point of view, ramp definitions are to take business processes such as plant scheduling, reserve planning, storage optimisation and load management into account to ensure the stability of the grid and to compensate possible differences between load and production. This also includes the regulations for trading and, of course, the skill of the staff to react to ramp events.
In total, the technical and the business environment determine the procedures and parameters to define an extreme event. A general definition and thus a general handling of extreme events will never be applicable to all TSOs.

4. Ramp detection with Anemos.Rulez

4.1 Anemos.Rulez

With *Anemos.Rulez*, we developed a flexible and extensible software product in order to tackle this challenge of detecting extreme events of virtually any kind. *Anemos.Rulez*, is a highly configurable tool that can easily be adapted to customer needs. It detects extreme events and issues alarms for upcoming events. Figure 4 shows the structure of the extreme event prediction system with *Anemos.Rulez*.
Based on the latest weather predictions, wind farm information (e.g. number, type and layout of wind turbines, orography), measured SCADA data and other data (e.g. load forecasts, prices) predictions are calculated with a WPP model specialised for extreme events. This prediction data is analysed by *Anemos.Rulez* and, if applicable, an alarm is issued.

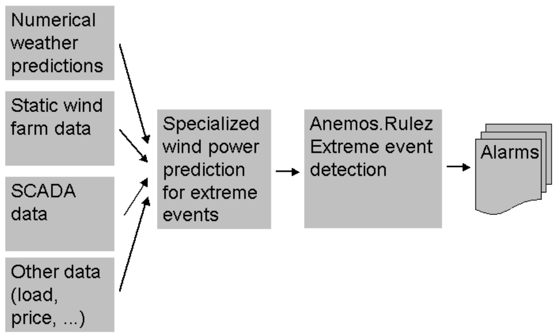

Figure 4: Structure of a extreme event prediction system with Anemos.Rulez

In order to cover all possible cases and write a piece of software which is developed and tested under quality management conditions, we separated the tool in two parts: the module core and the configuration via rules. The module core is implemented as a Java executable with basic detection algorithms such as gradients, thresholds, maximum change in a time interval, and the alarming functionalities. This part of *Anemos.Rulez* is generic and can be tested in detail independently of the specific customer.
The exact definitions and parameters of ramp detections are implemented as Groovy scripts, which are run from the *Anemos.Rulez* Java executable. These rules offer a set of methods specific for the domain of extreme event detection. A rule specifies the parameters of the events that should be detected, which input data should be used and the parameter for the alarm management

(e.g. how and when alarms will be issued). For example, such a definition may consist of a combination of gradients and thresholds of power and a minimum electrical load. The rules and the respective parameters can be defined on farm or regional level and are developed for and together with each customer.

4.2 Specialized wind power predictions for extreme events

For the optimization and evaluation of wind power prediction models measures like the NMEA or the NRMSE are commonly used [3]. A statistical optimization based on these error criteria lead to a prediction characteristic, where especially extreme events are predicted poorly.

Figure 5 shows a ramp event and the according WPP of a statistical WPP model. The model tends to limit the predicted power values at high and low wind speeds in order to achieve an optimal RMSE. This behavior automatically limits the amplitude of predicted ramps and therefore the number of predicted extreme events.

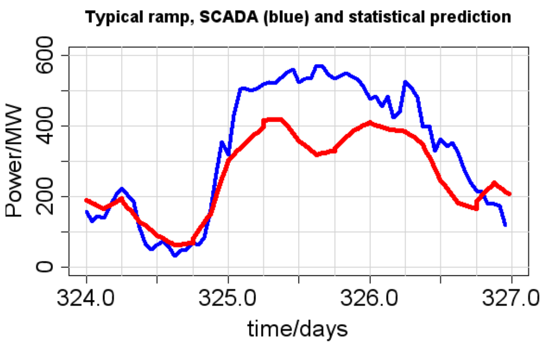

Figure 5: Typical behavior of a statistical prediction model

A comparison of the number of predicted ramps of a statistically optimized model with a basic physical, where "just" the power curve is used for the predictions, is shown in Figure 6. In this case, for the physical model the number of predicted ramps is much closer to the number of ramps in the measured SCADA data, especially for high gradients.

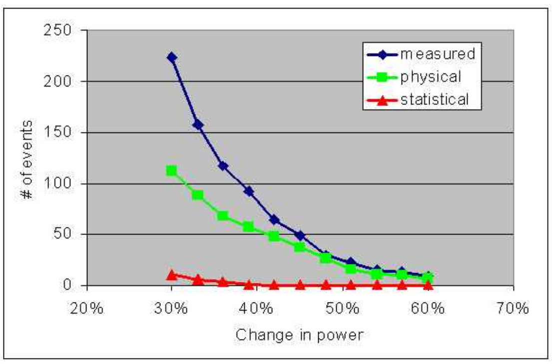

Figure 6: Ramps in measured SCADA data compared to a physical and a statistical prediction model depending on the maximum power change in a given time period.

This shows that for extreme event prediction different optimisation procedures have to be applied to the WPP models.

4.3 Extreme event detection

For the detection of extreme events *Anemos.Rulez* analyses the latest WPP time series. Figure 7 illustrates the approach for the ramp detection which is used for the following investigation. Within a sliding time window min-max values of the time series are determined and the expected change is checked against the specified ramp threshold. If the threshold is exceeded, an alarm will be issued.

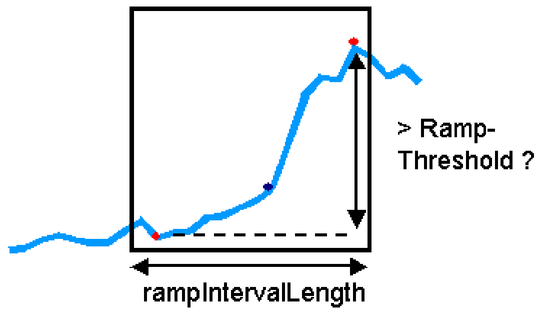

Figure 7: Example of a ramp event detected by Anemos.Rulez. The parameters applied for the detection are a minimum change of power (=RampThreshold) within a given time frame (=rampIntervalLength).

5. Results

The extreme event detection with *Anemos.Rulez* has been applied to different scenarios. The results for a test case at Northern Ireland are shown in Table 1.

Wpp Model	Nwp model	Hits	Misses	False forecasts
Model1	Skiron	19	12	10
Model2	BMO	11	20	22
Model3	BMO	12	19	16

Table 1: Evaluation of extreme event prediction for Northern Ireland with different WPP models

The evaluation was done with one year of data for three different WPP models, which were based on to different NWP models. The investigated prediction horizon was 12-36 hours and the installed wind power capacity of the region was 335 MW.

A ramp that was detected within the prediction data and in the measured data with the same type (falling or rising) and with a difference of the timing of not more than 12 hours, is considered a *hit*. Ramps that are only detected within the measured data are called *misses*. *False forecasts* are ramps that are only detected within the prediction data but did not occur in reality.

The results are very different for the three WPP models with Model1 showing the best results.

Approximately 2 out of three predicted ramps are correct forecasts for this model.
A comparison of the results of Table 1 with the average prediction accuracy of the models in Table 2 show that a WPP model with a low average error does not necessarily show good results for the extreme event prediction or vice versa.

Wpp Model	NMAE [%]		RMSE [%]	
	1 day	3 days	1 day	3 days
Model1	9.68	12.4	12.1	16.4
Model2	20.7	26.5	27.4	34.9
Model3	10.7	16.7	15.1	23.7

Table 2: Average accuracy of the of prediction models used for the extreme event prediction for Northern Ireland

Results of previous evaluations have shown that besides the WPP model itself the accuracy of the extreme event prediction is also dependant on the NWP model. I.e. like for WPP in general the same prediction model has a different accuracy of the extreme event prediction for different NWP models. However the share of the influence of the NWP model on the accuracy of extreme event prediction has not been studied yet.

6. Conclusion and Future Challenges

In order to ensure grid stability, the increasing share of wind energy in modern power production leads to a need for the prediction of extreme events as a complement to the daily wind power prediction.
In practice, the exact definition of critical extreme events is heavily depending on the technical and business environment of each specific TSO. In addition, we emphasized the need of selecting a specialized wind power prediction model for the purpose of extreme event detection.
Our extreme event prediction tool *Anemos.Rulez* presented here is a highly configurable software that offers a variety of different algorithms for extreme event prediction. By using a special purpose language to describe the detection algorithms and their parameters in Groovy, it can easily be adapted to the individual needs of any customer. For a test case in Northern Ireland, 19 out of 31 ramp events have been predicted correctly, which is a very good result compared to other publications. Nevertheless, there is need for an improvement of the prediction and detection process.

Future work will focus on two main points:
(1) Evaluation of additional ramp detection methods and add other methods for the detection and characterisation of extreme events to *Anemos.Rulez*.
(2) Further development of prediction models which are specialized for extreme event prediction.

7. References

[1] Bundesverband Erneuerbare Energien e.V.: “Stromversorgung 2020 – Wege in eine moderne Energiewirtschaft“, 2009.

[2] Kariniotakis G., et al, "ANEMOS: Development of a Next Generation Wind Power Forecasting System for the Large-Scale Integration of Onshore & Offshore Wind Farms", EWEC 2003, Spain, 2003.

[3] Madsen, H., et al. "A Protocol for Standardising the Performance Evaluation of Short-Term Wind Power Prediction Models", Global WindPower, USA, 2004.