Offshore ramp forecasting using offsite data

Pål Preede Revheim, Hans Georg Beyer, Department of Engineering, University of Agder, Grimstad, Norway

DeepWind'2014, Trondheim, 22-24 Jan. 2014

UNIVERSITY OF AGDER

Objectives

The increasing use of wind power as an energy source poses new challenges for the management of electrical grids. One of the major challenges is dealing with sudden large changes in wind power production, normally referred to as wind power ramp events. The sooner and more accurate ramp events can be predicted, the smoother and more efficiently they can be dealt with. As a result of the large size of future offshore wind farms, and thus also large capacity, ramp forecasts will be of particular importance. At the same time the offshore location will pose additional challenges since the possibilities of using wind speed measurements from surrounding sites as early warnings will either be limited or costly.

Here on-site NWP wind forecasts and already available historical offsite wind measurements are used as input to forecast whether the next hour falls into one of the three categories "no ramp", "up ramp" or "down ramp". For doing this, the techniques random forests (RanFor) [1] and multinomial logistic regression (MLR) [2] are evaluated .

Case and data

The data used are wind speeds from three sources – the nacelle of Hywind, met-stations at 6 oil-platforms in the North sea (see map in Fig. 1) and Hirlam 4*4 km forecasts run by the Norwegian Meteorological Institute. Hywind serves as the site of interest, While the oil-platforms are used as off-sites. From Hywind the wind speeds are given as 500 second averages, From the oil-platforms at 10 minute averages measured once every 6 hours and from Hirlam as hourly forecasts rerun every 24 hours. All wind speeds are transformed to an uniform height by the use of a logarithmic profile, and computed into wind power using a generic wind turbine model. The data covers the time-period 01.01.2009 – 17.12.2011, in total 982 observations.

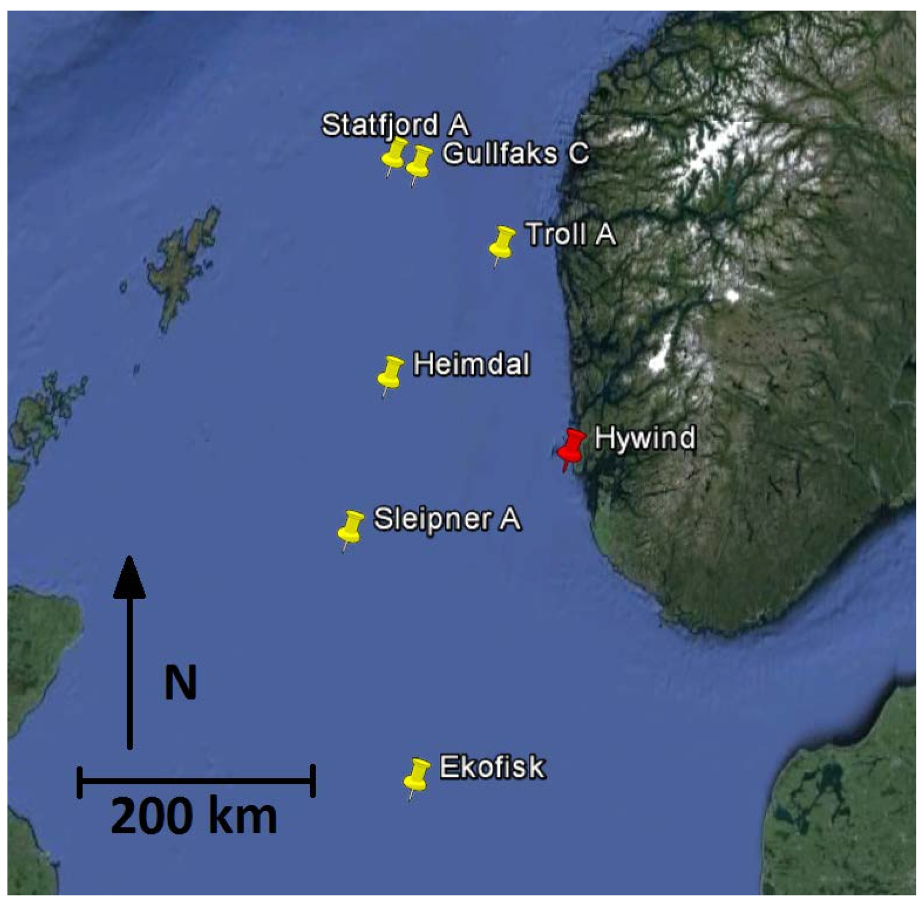

Fig. 1 – Map of locations (Google Earth)

The ramp forecasts are performed in three stages. First the ramp events are identified, then the datasets used for the random forest and MLR scheme s is constructed, and finally the forecast models are fitted.

For Hywind it is assumed that the forecast for the next hour and the measurements from a number of previous hours contain information about the probability of a ramp. For the off-sites it is assumed that there is a high probability of the ramp event one wants to predict occurred at a upwind site at an earlier time, hence that the ramps are subject to spatial propagation from upwind sites to downwind sites. Similarly to for Hywind this is included through information about the forecast for the next hour together with measurements from a previous hour. Because of the 6 hour interval between the off-site measurements only one hour at a time is included for these. This gives a dataset of 11 columns and 982 rows.

Wind power ramps

A main challenge of ramp forecasting is how to define a ramp event. In the literature there is no consensus about a standard formal definition of a ramp [3]. A part of the reason for this is that a ramp is described primarily by the function it has, and that this will vary depending on the location and size of the wind farm, the flexibility of the grid, other energy sources connected to the grid etc. There are good practical reasons for this, so the lack of consensus about a definition cannot be considered a problem in itself.

Here, the ramps are identified using the following definition:

$$P(t+\Delta_t)-P(t)>P_{val}, \quad (1)$$

where Δ_t is a pre-defined time increment set to 3 hours and P_{val} is a threshold value set to 0.3, i.e. is a change in wind power production of more than 30% within 3 hours considered a ramp. The result of the ramp identification process is that 852 of the observations are identified as no-ramp, 62 as up-ramps and 63 as down-ramps.

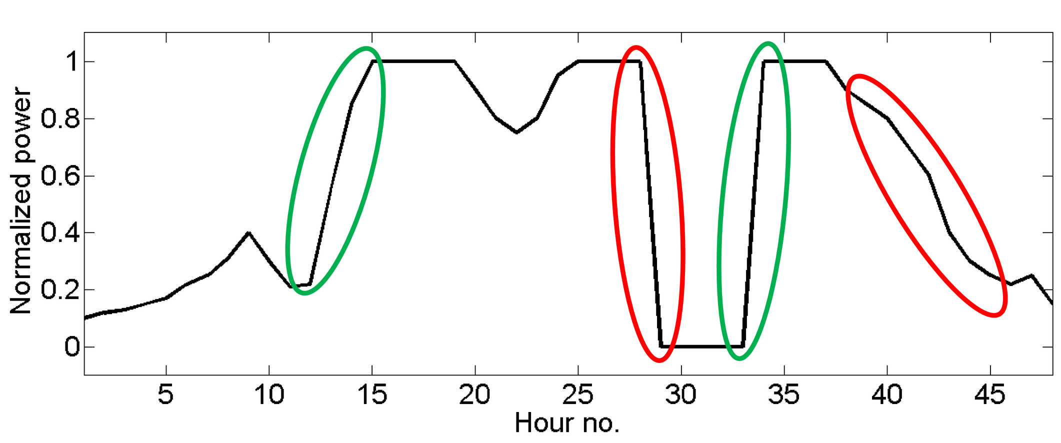

Fig. 2 – Example of normalized wind power production over 48 hours. Up-ramps (according to the definition in (1)) indicated with green cirkles and down-ramps indicated with red cirkles.

Methods

RanFor (Fig. 3) is an ensemble learning method for classifications that operate by constructing a large collection of de-correlated decision trees, and then predicts a class through a majority vote. Decision trees are able to capture complex structures in the data while at the same time having a relatively low bias, but they are notoriously noisy and hence tend to have a high variance. Averaging over *B* de-correlated and identically distributed trees, as is done when building a RF, reduces the variance by *1/B*. A thorough description of RanFor is found in [1].

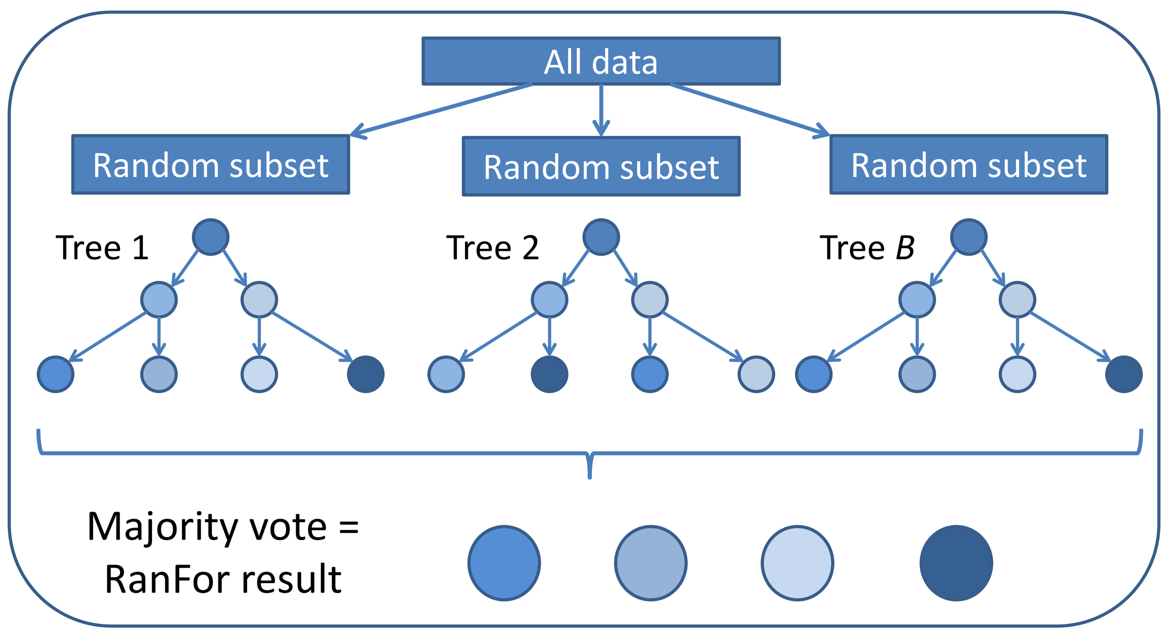

Fig. 3 – Visualization of random forest procedure

MLR is a generalization of logistic regression that allows more than two discrete outcomes, and is widely used for a variety of applications . Instead of directly providing a category as the output the MLR gives the probabilities that each observation belongs to each of the categories. The predicted category can then be found by selecting the outcome with the highest probability. A thorough description of MLR is found in [2].

Results

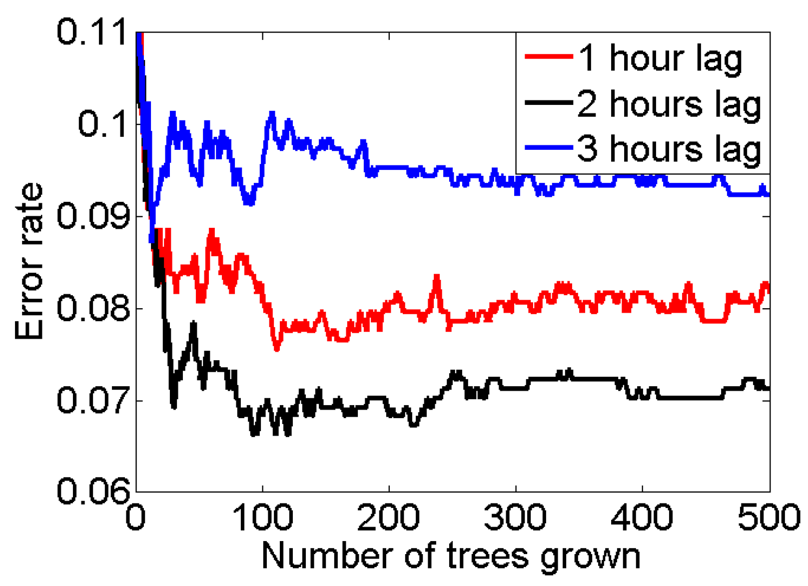

Fig. 4 – Error rates (fraction of wrong classification) for time-lags 1-3 hours for random forests of up to 500 trees.

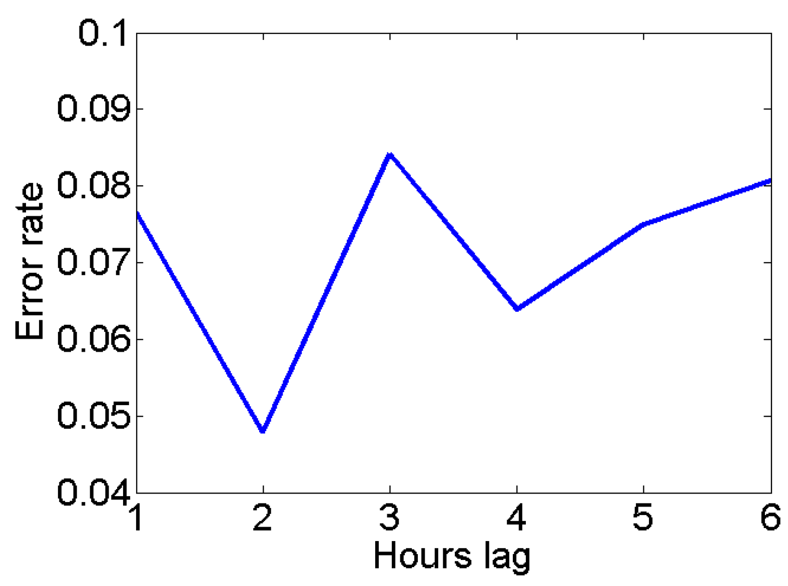

Fig. 5 – Error rate for time lags 1-6 hours for multinomial logistic regression

Figure 4 shows that the error rates of the RanFor stabilize from approx. 300 trees and that including additional trees after this does not give improved results. Figures 4 and 5 show the error rates for RanFor and MLR for different time-lags from the measurements at the off-sites. Both models give the lowest error rates for ramp forecasts based on measurements made two hours earlier. The decline in error rate from hour 3 to hour 4 that is found for MLR is not present for RanFor (graph not shown). It should be noted that as a result of the very low update rate of the measurements (6 hours) these results are the subject of large uncertainties.

Tab. 1 – Confusion matrix for random forest, multinomial logistic regression and unprocessed numerical weather prediction. Correct forecasts on the diagonal. Forecast errors off the diagonal.

Random forest/ Multinomial logistic regression/ Numerical weather prediction		Forecasted		
		No ramp	Up ramp	Down ramp
Observed	No ramp	845/ 843/ 778	6/ 8/ 42	6/ 6/ 37
	Up ramp	30/ 20/ 48	32/ 42/ 13	0/ 0/ 1
	Down ramp	28/ 13/ 48	0/ 0/ 1	35/ 50/ 19

Table 1 shows the confusion matrix (classification/misclassification) for RanFor and MLR as well as for a ramp forecast made from the NWP forecast without any post-processing (for comparison). From the table it is obvious that both RanFor and MLR has a much higher number of correct classifications (and thus also forecasts) than the raw NWP. Ranfor is slightly more conservative than MLR, predicting 25 more observations as no-ramps. This gives MLR slightly better results than RanFor, but the differences are small.

Conclusions

- Measurements from upwind off-sites can give positive contributions to the precision of wind power ramp forecasts.
- Off site measurements made only once every six hours gives very large uncertainties and is not well suited for the purpose of ramp forecasting.
- Both random forests and multinomial logistic regression gives large improvements in the number of correctly predicted ramps compared to an unprocessed NWP forecast.

References

[1] Breiman, Leo (2001). Random Forests. Machine learning, 45, 5-32.
[2] Agresti, Alan (2013). Categorical Data Analysis, 3rd Edition. Wiley.
[3] Ferreira, C. et al. (2010). A Survey on Wind Power Ramp Forecasting. ANL/DIS-10-13, Argonne Nat. Lab.