PO.0110

Using Bayesian Model Averaging for wind farm group forecasts

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

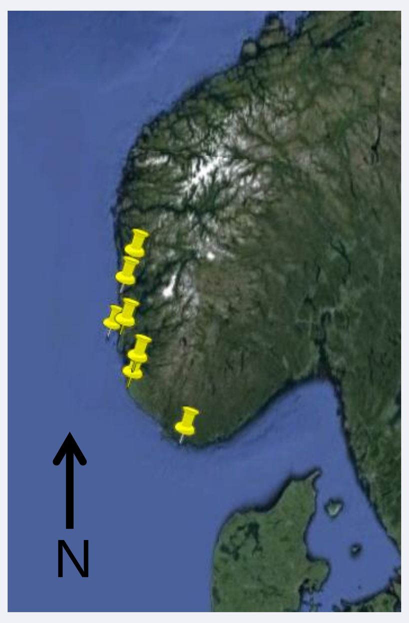
UNIVERSITY OF AGDER

Abstract

In this poster we explore the possibilities of producing probability density functions for the future group mean wind speed and the future group lumped power output through the use of an implementation of Bayesian Model Averaging. Single site wind speed measurements are used as input data. The method is found to work well for predicting wind speeds. For predicting power output further model development is needed.

Objectives and data

Bayesian Model Averaging (BMA) (see e.g. [1],[2],[3]) is a statistical technique for ensemble learning that has been successfully used for post-processing of NWP-ensemble forecasts for a wide variety of meteorological applications (wind speed, wind direction, visibility, temperature etc.). Raftery et al. [2] show how BMA can be used to produce probability density functions (PDFs) of future weather quantities. In this poster we explore the possibilities of using BMA based on single site measurements to produce PDFs of average wind speed of groups of sites and of lumped power output of groups of wind farms. As this is intended as an initial exploration, the procedure outlied in [3] is followed closely.



Hourly wind measurements from 8 weather stations in southern Norway and Hirlam 4*4 km forecasts for forecast horizons 12h and 24 h covering the time-period 01.01.2009 – 17.12.2011, kindly made available by the Norwegian meteorological service Met.no, are used as input to the BMA and to compute wind power forecasts using a generic wind turbine model (2.3 MW). Both the measured and forecasted wind speeds are initially given for 10 meter above ground level (a.g.l.). For the wind power forecasts a height transformation to 80 meter a.g.l. is performed using a logarithmic profile with approximate roughness lengths taken from aerial photos.

Methods

The BMA predictive PDF of the future mean wind speed of a group of sites is a weighted average of the single-site PDFs, where the weights can be interpreted as posterior probabilities and reflect the single site forecasts' contribution to overall group forecasting skill over a training period. Single site PDFs of wind speed is modeled as gamma distributions. The parameter estimation is based on forecast-observation pairs from a training period of *N* days. Training periods of 15, 30 and 45 days length are tested.

In BMA for group forecasts each group member f_k is associated with a component PDF, $g_k(y|f_k)$. The BMA predictive PDF for a future quantity is then $p(y|f_1,\ldots,f_K) = \sum_{k=1}^{K} w_k g_k(y|f_k)$, where the BMA weight w_k is based on forecast k's relative performance over a training period. The w_k's are probabilities, hence they are non-negative and add up to 1. K is the number of group members. The component PDFs of wind power production is modeled as a gamma distribution with shape parameters α_k and scale parameter β_k. This gives the PDF $g_k(y|f_k) = \frac{1}{\beta_k^{\alpha_k}\Gamma(\alpha_k)} y^{\alpha_k - 1}\exp(-\frac{y}{\beta_k})$ for $y \geq 0$, and $g(y) = 0$ for $y < 0$. The parameters of the gamma distribution is assumed to depend on the group member forecast, f_k, through the relationships $\mu_k = b_{0k} + b_{1k} f_k$ and $\sigma_k = c_0 + c_1 f_k$, where $\mu_k = \alpha_k \beta_k$ is the mean of the distribution, and $\sigma_k = \sqrt{\alpha_k}\beta_k$ is its standard deviation. The standard deviation parameters are assumed constant across all group members to reduce the number of parameters to be estimated and increase the solidity of the model. A thorough description of the method is found in [3].

The training period is a sliding window, and the parameters re-estimated for each period. The mean parameters, b_{0k} and b_{1k}, are estimated by linear regression for each ensemble member. The remaining parameters, $w_1,\ldots,w_k$, c_0 and c_1, is estimated by maximum likelihood from the training data. The log-likelihood function for the BMA model is $\ell(w_1,\ldots,w_K; c_0; c_1) = \sum_{s,t} \log p\,(y_{s,t}|f_{1st},\ldots,f_{Kst})$, where the sum covers all locations and times in the training data. The log-likelihood function is maximized numerically using the ECME algorithm.[3][4]

Forecasted PDFs and estimates of the lumped power output of a group of wind farms is made by converting the wind speed results into power through the transformations described above. The method and different lengths of training periods are evaluated by whether the share of outliers for a given confidence level is in line with expectation.

Results and conclusions

- BMA is able to produce fairly accurate PDFs for the future mean wind speed of a group of sites from the single sites wind speeds. (See Tab. 1 and Fig. 1)
- For the longest training periods the probabilities for coverage of the true measurements are a little high indicating a bit too wide confidence intervals (CIs). It should however be noted that the sample data set is somewhat limited. (See Tab. 1)
- The simple method that here is tested to transform the group mean wind speed CIs into CIs for lumped group power output underestimates the group power output and gives very unsatisfactory results. An important reason for these problems are the flat upper part of the power curve and the upper cut-out limit that this transformation is unable to reflect.
- Attempts were made to apply the same implementation of BMA to wind speed data in advance transformed into power output, but for this to work larger changes needs to be made to the parameter estimation and the assumptions. The main challenge is how to deal with longer consecutive periods of no production or of full production. This will be the subject of further studies.
- The possibilities for using the BMA weights w_k to identify sample sites giving a good representation of a larger group will be investigated.

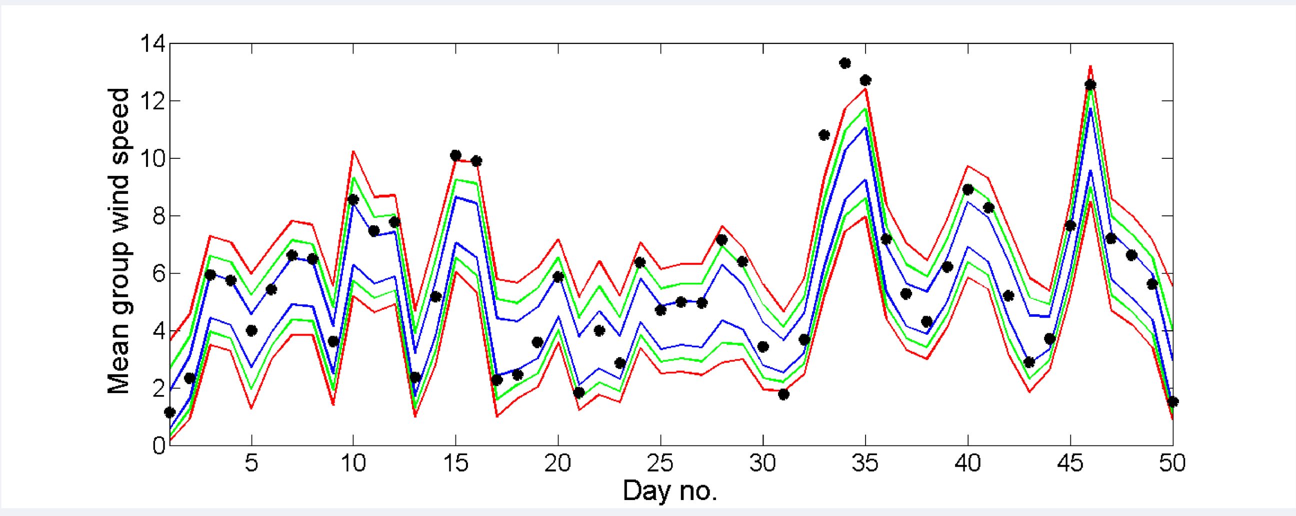


Fig. 1 – Example of group mean wind speed confidence levels. Red lines = 90%, green lines = 75%, blue lines 50% and black dots actual observations. 30 days training period.

Conf. level	12 hour forecast horizon			24 hour forecast horizon		
	15 days	30 days	45 days	15 days	30 days	45 days
50 %	44 %	51 %	54 %	51 %	63 %	64 %
75 %	70 %	77 %	79 %	72 %	85 %	87 %
90 %	86 %	91 %	90 %	86 %	93 %	95 %

Tab. 1 - Probability that a BMA-based forecast confidence interval for group mean wind speed based on a certain number of training days covers the true group mean wind speed. (N ≈ 400)

References

[1] Hoeting, J. A., et al. (1999), *"Bayesian Model Averaging: A Tutorial"*, Statistical Science, Vol. 14, No. 4, 382-417
[2] Raftery, A. E., et al. (2005), *"Using Bayesian Model Averaging to Calibrate Forecast Ensembles"*, Monthly Weather Review, 133, 1155-1174.
[3] Sloughter, J. M., T. Gneiting and A. E. Raftery (2010), *"Probabilistic Wind Speed Forecasting Using Ensembles and Bayesian Model Averaging"*, Journal of the American Statistical Association, Vol. 105, No. 489, 25-35
[4] Liu, C., and D. B: Rubin (1994), *"The ECME Algorithm: A Simple Extension of EM and ECM With Faster Monotone Convergence"*, Biometrica, 81, 633-648.