FORECASTING WIND POWER IN HIGH WIND PENETRATION MARKETS, USING MULTI-SCHEME ENSEMBLE PREDICTION METHODS

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Summary

Investigations from operational forecasting with a 75-member multi-scheme ensemble prediction system (MSEPS) have been carried out in order to find the various unknown error sources in wind power predictions. Various methods of predicting wind power and an error decomposition was used to identify the model components to further improve. The best of the wind power predictions was based on 300 input weather parameters. Additionally, the ensemble's ability to predict the forecasting error is shown, which can be used to estimate the reserve requirements and thereby lower the costs of balancing wind power, making this energy source more compatible in the liberalised markets. Results are presented for Germany, Denmark , Ireland and Australia.

Introduction

There is a still prevailing opinion in the wind energy community that the wind power prediction error is primarily generated by wrong weather forecasts (e.g. [1],[2]). From a meteorological perspective, this is a statement that may cause misunderstanding, because part of the error is due a complex mixture of weather related errors. The weather forecast process itself can only be blamed for the linear error growth with forecast length. We have therefore conducted an error decomposition in order to quantify the different error sources with a large ensemble of MSEPS weather forecasts.
Traditionally increased spatial weather prediction model resolution has been said to provide better forecasts (e.g. [3], [4]), but the shortest model waves may anti-correlate and cause double punishment in the verification (e.g. [5],[6]) and thereby additional model error.
An ensemble prediction approach is another way to better forecasts with fewer anti correlation hours and the possibility to predict and understand forecast errors.

2. Wind Power Error Decomposition

WEPROG's forecasting system is based on a multi-scheme ensemble prediction method and forecasts the meteorological uncertainty on synoptic scale and resulting forecast errors in weather derived products such as wind power. Weprog uses statistical methods to directly transform raw weather output to derived products and thereby utilize the statistical capabilities of each ensemble forecast.
Our analysis will include forecasts generated in 6 hour frequency. This means that one particular forecast horizon will verify at four different times each day. The forecast error was accumulated in 6 hour bins with centre at 3, 9,.. 45 hour prediction horizon for additional smoothing. This hides the disturbing diurnal cycle arising from verification once per day. Thereby we achieve a linear error growth with prediction horizon. Figure 1.1 shows an error decomposition for a 1-year verification over the forecast length 3-45 hours with data from western Denmark. By generating a decomposition of the forecasting error it can be illustrated, which parts of the error can actually be due to the weather forecast process.
In Figure 2.1, we have split the error into a background error and a prediction system error with a linear error growth. We illustrated the potential improvements from the weather part with ``good forecast'', ``average forecast'' and ``poor forecasts'', which differ to a certain degree. However, when looking at the background error, then the differences between a ``good forecast'' and a ``poor forecast'' is less significant.
The background error is not directly felt by end-users, because online measurements can be extrapolated a few hours ahead to cover the initial error. The light gray line represents a typical pattern of an online forecast.

After some hours, the benefit of adjustments vanishes. This correction, therefore, is only relevant for ultra short-term predictions for up to approximately 8 hours for this particular area.
The linear error growth indicates that the weather forecast is responsible for about 1/3 of the error in the forecast for the next day and the remainder is a background error with different sources. These additional error sources were found to be due to:

1. the initial weather conditions
2. sub grid scale weather activity
3. coordinate transformations
4. the algorithm used to compute the wind power
5. imperfection of turbines and measurement errors

We are still not able to quantify, which fraction of the background error is caused by imperfect initial conditions of the weather forecast and which fraction is due to erroneous wind power parametrisation.
By extrapolating the linear forecast error growth from 9-45 hours down to the 0 hour forecast, the background mean absolute error could be estimated to be just under 4% of installed capacity.

Therefore, we added an additional fixed band of +/-4% of the installed capacity to the native MSEPS ensemble uncertainty to cover for the background error that is additional to the weather forecast generated error. With this band, we achieved that 8120 hours out of 9050 hours or 89.7% of the hours are covered by the predicted uncertainty interval. The remaining 10% have numerically large errors that are only partially covered by the MSEPS uncertainty prediction.

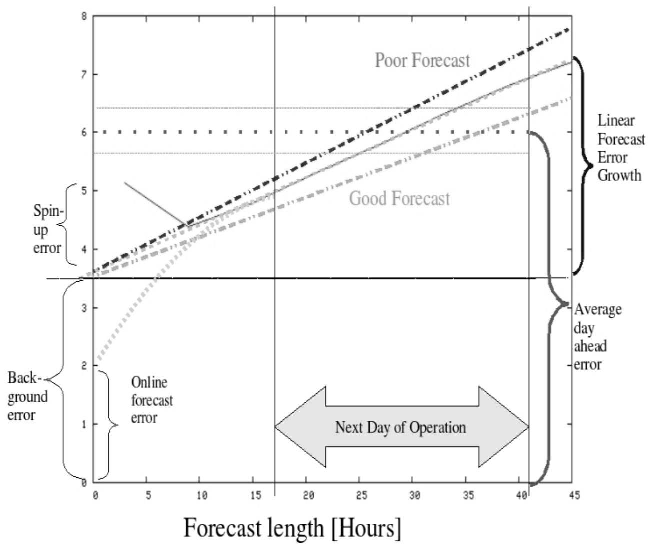

Fig. 2.1: Decomposition of the wind power forecasting error over a period of one year as area aggregated forecast in Denmark. The gray solid line is the error at each forecast length from 3 to 45 hours, the dotted light gray line is the online correction, if online measurements exist, the light gray dashed-dotted line is the error from a ``good'' forecast, the dark gray dashed-dotted line is the error from a ``poor'' forecast, the dark dotted line indicating the average day-ahead error.

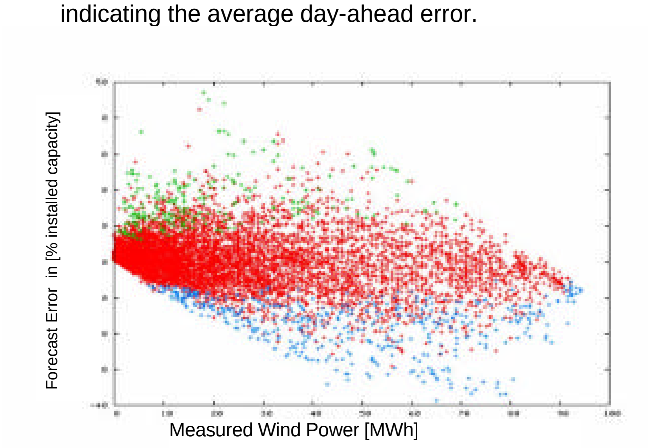

Fig. 2.2: Ability of the MSEPS to cover the uncertainty of the wind power forecast. The red dots indicating that the measurements are within the ensemble spread including the +/- 4% band. The green dots above and blue dots below show the measurements outside the EPS spread.

A 4% constant background error is a poor approximation and probably the explanation behind that 10% of the error events are unpredicted. Part of the background error is due to the computation of the wind power, which will be examined in the next section. The different power prediction methods can be distinguished as follows:

6. method: direction and time independent simple sorting algorithm
7. method: time dependent and direction independent least square algorithm
8. method: direction dependent least square algorithm
9. method: direction dependent least square algorithm using combined forecasts
10. method: same as method 4, but inclusive stability dependent corrections
11. method: 300 member ensemble forecast of method 5 - all farms are handled individually and 6 parameters for each 75 members are used to compute the power

Note, the results are the improvement in % to the mean absolute error for the day-ahead forecasts based on only one daily (00UTC) forecast performed with the basic power prediction (method 1).

12. Advanced versus Simple Prediction Methods

To verify the impact of the conversion from meteorological parameters to wind power on the forecasting error, we used 6 different methods to convert wind and other weather parameters into wind power output. Table 1 shows the results of the different power prediction approaches based on the same weather data. Each result differs only in the level of detail of the statistical computation of wind power.

No	IRL	AUS	DK	GER	E.ON	VE	RWE	EnBW
Cap [GW]	0.5	0.4	1.8	19	7.8	7.5	3.5	0.3
Load [%]	33	30	21	16	16	15	16	14
1	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
2	2,18	3,01	8,52	1,40	1,09	2,11	2,26	5,97
3	9,34	1,51	9,87	7.00	3.93	9.30	14.12	18.81
4	14,44	4,38	12,41	12,32	8,30	12,05	15,44	20,80
5	15,29	6,58	13,60	15,41	11,57	14,80	16,95	24,78
6	17,23	9,18	n/a	n/a	n/a	n/a	n/a	n/a

Tab. 3.1: Results from using different power prediction approaches in 4 countries and the 4 German TSO areas.

The verification for Ireland took place for a period of 1-year (2005) for 51 individual wind farms of a total capacity of 497 MW, The Danish verification of aggregated wind power up-scaled from 160 sites took place for the period 09/2004-10/2005 and in Germany the verification was conducted for total Germany and the individual 4 TSO on a 10-month period with the up-scaled online measurements valid for approximately ~19GW from estimated measurements published by the 4 TSO's (01/2006-10/2006).

Table 3.1 shows that the forecast quality could be improved significantly for all investigated areas from a relatively simple power curve conversion method (1) to a more complex method (5/6), when making use of the additional information from the ensemble. The relatively low improvement in Australia has to be seen in the light of that the background error is higher for only 6 wind farms. Three major results can be drawn from from this investigation:

13. the advanced methods, using many parameters + EPS info are superior to simple methods
14. The forecasting error is dependent to the location, the size and the load of the farms/areas
15. Detailed measurements can significantly reduce the forecast error

4. Prediction of Reserve Requirements

Part of the reserve requirements for wind power has a low marginal cost, because the inertia level of dispersed wind power is high seen in relation to the start-up time of low inertia generation units. This pattern can be exploited with MSEPS reserve prediction in a day-ahead reserve market.
The required reserve for wind power varies with the predictability of the weather. From fig 2.1 and 2.2 we can derive that there is a component that is not predicted by MSEPS, but with inclusion of a background error term of 4% of the installed capacity, then we achieve that 9 out of 10 hours is covered by the predicted reserve. The meso-scale weather contribution to the background error has a frequency and amplitude that is higher than the linear error growth component. It is therefore not optimal to cover this part of the error with a constant 4% allocation as the background varies considerably with time. A stability dependent estimation with a linear regression between forecast error and ensemble spread will give a still simple, but more optimal background error estimate. A practical problem is that the estimation process is dominated by the high density of low prediction error and low generation on fig 2.2. This suggests splitting the regression in at least 3 domains dependent on the predicted load factor.

For the purpose of illustration we have computed samples of the amount of hours that can be covered by the predicted reserve and computed the cost of the pre-allocation in relative wind capacity. The cost model needs prices of passive reserve (P) and activated reserve (A) (regulation) relative to urgent reserve (U). We expect P/U to be around 0.1, because there will always be some generators that may prefer to use their plant as reserve in a market with excess capacity, because their marginal costs of generation may not be competitive. Thus, P should essentially cover the marginal cost of not producing. If the balance responsible of wind power should have an incentive to purchase A, then A/U must be less than 1. We assume 0.6 based on typical amplitudes on the spot market price and the influence of competition on the price. The ensemble spread (S) is computed from:

$$S = c_{extreme}(E_{max} - E_{min}) + c_{stdv}\, SUM_{eps}(E_{eps} - E_{opt})^2 \quad (1)$$

The extreme term should be dominant for a grid security optimised reserve prediction, while the standard deviation term is more suitable for economic decision making, because of its robustness and smoothing effect.
The reserve is computed as:

$$R = C_{scaling} \cdot S + R_{min} \quad (2)$$

Different values of $C_{scaling}$ and R_{min} are used in table 4.1 to illustrate the reserve predictability. The reserve (R) can be interpreted as a cost given in percent of installed capacity and the fraction (F) is the percent of time, where the reserve prediction covered the forecast error.

Additionally, we compute a total cost (T), which can be seen as a total balance costs, but reverted to forecast error. The unit of T is therefore percent error relative to the installed capacity and should in this case be compared to 5.73%, which is the error of the most likely forecast (Err_{real}).

Copti [-]	$C_{scaling}$ [-]	R_{min} [-]	R [%]	F [%]	T [%]
-	0,00	3,00	6,00	42,80	5,40
-	0,00	8,00	15,00	75,30	5,54
Stdv	1,00	1,00	10,20	56,30	5,29
Extr	0,50	0,00	7,90	41,60	5,30
Extr	1,00	0,00	15,70	73,20	5,48
Extr	1,00	4,00	22,87	89,70	5,92
Extr	0,50	4,00	15,49	77,39	5,47
Extr	0,20	4,00	10,88	63,48	5,35
Extr	0,10	4,00	9,33	58,06	5,36

Tab. 4.1 is based on the data-set from section 2. Predicted Reserve (R), Fraction (F) of time where the predicted reserve covered the actual forecast error and the Total estimated forecast error (T), which is sensitive to the ratios P/U and A/U.

To compute the total cost, we assume that:
16. the unpredicted error has a cost of U
17. the predicted error has a cost of A
18. the total allocated reserve has a cost P per unit

Then, we can write:
$T = Err_{with\_reserve} \cdot U + R \cdot P + A \cdot Err_{predicted} < Err_{real} \cdot U$

and devide by U to get:

$$T = Err_{with\_reserve} + R \cdot P/U + A/U \cdot Err_{predicted} < Err_{real}$$
$$= 3.1 + R \cdot 0.1 + 0.6 \cdot Err_{predicted} < 5.7$$

where R and $Err_{predicted}$ are dependent on a scaling optimizer. The results of the optimisation can be seen in Table 4.1.
It can be seen in table 4.1 that we achieve the highest fraction of coverage (89.7%) with the extreme method using a 4% minimum allocation and

giving high weight on the ensemble spread. This is however also the most cost intensive method. When using the standard deviation method, where we have a low minimum allocation and give full weight on the standard deviation as ensemble spread, we achieve a lower balance cost, but also a much lower fraction of hours covered (56.3%).
Without optimisation and a high reserve pre-allocation we can achieve a relative high coverage (75%) for medium costs (5.54%). However, by adding weight of the extreme term (<50%), we have demonstrated (Table 4.1) that we can lower the costs in the range 5.36-5.47% and achieve lower amounts of pre-allocation (9 -15%) and control the number of hours where the reserve can cover the prediction error.

These results hence show that the dynamic computation with the ensemble spread is a promising approach, especially when energy pools are built, where different generating plant are used to balance and provide the reserve. Table 4.1 also demonstrates that the different algorithms of estimating the uncertainty in the weather and wind power production are valuable for different end-user targets. The standard deviation approach, which has an inherent smoothing of the uncertainty is optimal for trading, whereas the minimum and maximum is optimal for grid security.

Predicted Load Factor [%]	Competition on regulation	Forecast choice	Reserve-allocation
0-20	Good on down	EPS minimum	Downward
20-70	Good on up/down	Best Guess	Down and Up
70-100	Good on up	EPS maximum	Upward

Table 4.2 Summary of the optimal use of uncertainty estimation for reserve allocation

The economic value of wind power and the cost of reserve varies with the weather. As the amount of wind power increases, the need to consider skewness in the cost of reserve increases. Periods with high levels of wind power have a high level of competition on up-regulation, because many plant are passive. At low levels of wind generation few plants are passive, but many compete on an attractive down regulation due to unpredicted wind power.

The better wind power forecast is therefore the ensemble maximum at high generation and ensemble minimum at low levels of wind. The reserve allocation can then be computed as a one-way allocation at high and low load and as a combination at medium load. Use of the ensemble minima or maxima should however only be introduced together with a price estimate of the reserve and a security check. These assumptions are summarized in table 4.2.
Further studies are required on the skewness of reserve and regulation costs. However, we believe that we were able to show that a high level of competition on the reserve can be achieved by computing the reserve requirements dynamically, also when the installed capacity reaches the consumption.

5. Conclusions

The presented study of the forecasting error showed that weather ensembles give a useful prediction of the wind power forecast error and that the reserve requirements for wind can be estimated day-ahead with an economic benefit. It has been difficult to find real pricing of reserve dedicated for wind, because wind power is mostly treated together with either all generation or in pools with other generation types. These may fall out unexpected, whereas wind varies smoothly for dispersed wind power and hence would have a much lower marginal regulation cost than other generation types. We have shown that reserve prediction based on the MSEPS has the potential to treat wind power separately with specific reserve pools and thereby reduce the balance costs significantly.

We have additionally identified that only a fraction of the forecast error is generated in the weather forecasting step. This fraction was for the Danish reference data set only 1/3 of the total error (5.7%). The remaining 2/3 of the error are difficult to further analyze, because we we have not yet found means to isolate the error sources. This can be best compared to a black-box containing meso-scale errors, transformation errors between weather prediction and wind power model space, unknown wind turbine behaviour and measurement errors.
We believe that a better understanding of these errors can only be achieved by focusing on the individual wind farms with detailed measurements.

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