Reserve forecasting for enhanced Renewable Energy Management

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***Abstract*— As the renewable energy penetration grows we are likely to see that large power generation units will be kept on a stand-by level during periods of high renewable energy production or even stopped completely, because smaller and more flexible power generation units are more competitive. This trend can potentially increase the peak price of reserve and consequently balancing costs and call therefore for hour by hour forecasts of reserve for maximum utilisation of the available capacity. Our focus is how reserve forecasts are produced and how they can be used in the operation of system operators as well as balance responsible parties or traders. This includes the impact of weather uncertainty via ensemble forecasts and stochastic add-on processes to simulate frequently occurring outages. We present a study in a real-time environment with the respective challenges that arise and that need practical solutions in order to generate a benefit for the user. The results of our real-time study are presented and discussed to form a kind of guideline on how to best manage renewable energy imbalances in a market system as well as how to best increase the efficiency of renewable generation and reduce the need for reserves further.**

Keywords-reserve forecasting, ensemble forecasting, renewables, wind power, grid integration

INTRODUCTION

The primary scope of reserve predictions is to reduce balancing costs via dynamic allocation of reserve and if possible with the help of non-fossil fuel capacity. If a system operator (SO) or balance responsible party (BRP) can schedule reserve more dynamic, the costs for imbalances become lower and the energy system more efficient. For lowest operational costs reserve shall be shared rather than bound to specific units or pools. Reserve forecasting is therefore best applied for the full system in question with explicit forecasts of load, wind and solar, while other imbalance sources are simulated as a kind of noise term.

Thus, when forecasting reserve it is important to use aggregated forecasts that have been applied to all weather dependent sources and sinks on the grid. It is also necessary for the generation of reserve forecasts to use ensemble forecasts of these weather dependent sources and sinks, because it is the uncertainty of the weather that generates errors of these sources. And, the more ensemble members, the better, because it is this type of error that is the target of the forecasting process. When aggregating, each source's forecast data is reduced to one time series per ensemble member or model.

A "deterministic" reserve forecast can be defined as the difference between the recent forecast and the forecast used in the market. However, such a single forecast contains a volatile and random signal, while an ensemble of many of such forecasts will be able to provide a more reliable and useful band for allocation of reserve.

Thus, reserve forecasting relies on management of BIG DATA. We will for simplicity not describe in much detail the required processing of all data management for the forecasting process with ensemble data in this study. Nevertheless, it shall be mentioned that highly complex systems in this respect are of for example Germany and Denmark. They have a high dispersion level of wind power, which means that many wind turbines balance each other partially out automatically and the ensemble forecasts shall simulate this kind of inherent self balancing. The average day-ahead RMS error in these countries lies at 3-4% of installed capacity which is only a fraction of the forecast error for a single larger wind farm. Nevertheless, it has to be noted that although the RMS error is very often under 2% it can at times be up to 10% of installed capacity. The peak error occurs in periods, where the error is correlated between wind farms and these are the times, where the cost of balancing is mostly high. Self balancing may be increasing in the future, because a significant amount of the wind capacity operates on pure market terms, the owners can earn as much in the reserve market, than in the spot market. The old wind capacity can in this way compete very well against scheduled capacity on regulating downwards when pooled in reasonably large and flexible pools. This trend is increasing with the age of the wind capacity, because of reduced or discontinued feed-in-tariffs. A large wind pool may therefore potentially self balance in many hours by bidding into the market with a lower percentile. The changes in predictability is caused by changes in the weather and is related to the scale of motion, instability mechanisms and the sensitivity of the physical processes. This is what ensemble forecasts are designed to address. Traditional mean value verification penalizes inevitable phase errors of fast swings. Instead spectral verification techniques can be used to diagnose if a certain time scale is actually forecasted or not. Vincent et al. [1,2] examined multi-hour swings in wind speed forecasts with WEPROG's MSEPS multi-scheme ensemble in a Danish Public Service Obligation funded offshore wind power project "High-Resolution Ensemble for HornsRev"[1].

1 http://hrensemble.weprog.net

They found that the predictability of multi-hour swings was higher than for shorter time scales. This is not a surprising result. The verification method did not penalize phase errors, but only amplitude errors corresponding to the challenges in managing reserve. The results of the study can nevertheless be seen as pioneer work on the utilization of (ensemble) forecasts for reserve. A similar study was carried out in the German Research at Alpha Ventus offshore integration project[2] by von Bremen et al. [3] that confirmed these results.

The conclusion is therefore that even if an operator has enough capacity that is capable of ramping faster than the wind varies and the SO is not bound to market regulations, reserve forecasts will add value for the scheduling.

Fundamentals on the use of ensemble forecasts for reserve predictions

As mentioned in the introduction, the core of a reserve prediction algorithm are the uncertainty forecasts from an appropriate ensemble forecasting method. Appropriate means in this context that the ensemble data needs to have a physical context and requires to generate uncertainty in each forecasting step. To our knowledge there are only two methods that can be used in this context:

These are the so-called multi-model or Poor man's ensemble approach (e.g. [4]) and the multi-scheme approach (e.g. [5]).The multi-model approach simply uses many different NWP models to form an ensemble. The challenge is the time and effort it takes to maintain many NWP models in an operational environment and to keep the output data statistically consistent. The multi-scheme approach uses one core NWP model, where the forecast members are comprised of different sets of equations for certain physical and dynamical processes (so-called "parameterisation schemes"). The difference in the equations leads to different methods of solving these equations and thereby different end results. Because all the equations used are describing the same physical processes, but vary in their assumptions to make them solvable, they in fact describe the physical uncertainty of the weather forecast.

Other approaches based on e.g. singular vectors, breeding method, monte-carlo simulations (e.g. [6],[7],[8]) are not useful in this context, because their target time horizon for the uncertainty of the forecast is in the medium-range of 3 days and longer. The system used in this study, WEPROG's Multi-Scheme Ensemble Prediction System (MSEPS) [9] differs from ensemble techniques and systems provide by NCEP, ECMWF and others using these other methods in two ways.

The MSEPS ensemble is designed to produce uncertainty already from a horizon of +1 hour and it is running in higher spatial resolution of limited areas. These are imperative conditions for the system to be able to generate the hourly uncertainty of the weather development right from the start of the forecast and all along in order to generate weather uncertainty consistent reserve forecasts.

2 http://www.rave-offshore.de

Reserve Forecast description

As seen above, the core of reserve forecasting is lying in the ability of the multi-scheme ensemble approach to simulate weather forecast uncertainty in a weather consistent and responsive manor. This has already been shown by Pahlow et al. [10] and Jørgensen et al. [11].

The reserve predictions generated in this way do not use any standard deviation, correlation or regression over time, because such methods suppress extreme events, which would be against the idea of predicting reserve for system security reasons. Instead, the reserve prediction can be based on MIN/MAX values at the moment of interest with the MSEPS system approach.

In this way, we do not need to use any standard deviation of the ensemble except indirectly for the scaling of the error growth. Additionally, the same approach can be used for the computation of load coverage by wind and solar (i.e. load – wind - solar), or on any subset thereof.

A common challenge in allocating reserve is that the native uncertainty forecast contains too much uncertainty by the time the decision has to be taken, because the lead time is longer than the horizon of the planing of primary power generation. A direct usage of the native ensemble data would therefore result in wasted reserve.

For this reason our reserve prediction algorithm simulates physical need of reserve given the shorter lead time for major and minor adjustments of the primary power planning. Our method uses four time steps:

(t_1) Gate closure for purchase of reserve (assumption: time of forecast generation)
(t_2) Gate closure for major changes of primary power generation (some time next day)
(t_3) Gate closure for minor changes of primary power generation (hours before dispatch)
(t_4) Time of deployment (dispatch)

The need of reserve is evaluated at t_4 from the forecast available at t_1 under consideration of what occurs between t_1 and t_4 in terms of forecast improvement and adjustment of the planned generation.

The reserve forecast uses exclusively the ensemble forecast in the form of a matrix with with dimensions N_{ts} x N_{em}, where N_{ts} is the number of time steps and N_{em} is the number of ensemble members.We consider only 4 rows in the matrix corresponding to time t_1,t_2,t_3 and t_4. Let ROV_n be the row vector at time n, STD_n be the standard deviation of the row vector at time n, MIN_n the minimum of the row vector at time n, AVR_n the average of the row vector at time n, MAX_n the maximum of the row vector at time n. Then, the equation for reserve R consist of two terms:

$$R = (MAX_4 - MIN_4) \cdot (STD_4 - STD_2)/(STD_4 - STD_1) + rsv(ROV_3, ROV_4)((MAX_4 - MIN_4) - (MAX_3 - MIN_3)) \quad (1)$$

The first term represents the uncertainty band error growth between t_2 and t_4 and the second term represent the error growth between time t_3 to t_4 due to special weather variability.

The <rsv> function represent energy on small scales not directly present in the individual ensemble members, but responsible for reduced predictability on the shortest forecast horizon.

On Figure 1 the MIN/MAX range is indicated as a vertical arrow for 3 of the different forecast horizons corresponding to the gate closures. The second darkest gray arrow (right arrow) corresponds to the reserve forecast created at t_1 valid for t_4, which is significantly narrower than the uncertainty predicted at t_1, which is the black arrow. The intervals move up and down with the new forecasts (lighter grey arrows left to the black arrow) corresponding to that the reserve is assumed to not be affected by a change in the primary power generation.

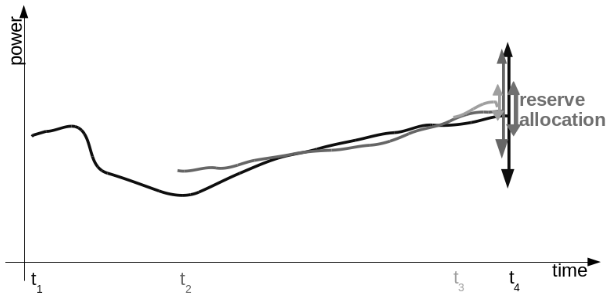

Figure 1: The vertical extend of each arrow indicate the uncertainty for the different time horizons corresponding to the gate closures. The arrow of second darkest gray is the estimated width of the reserve allocation

Note that the STD ratio only gives meaning if the gate closure t_1 is after t_2 and after t_3, i.e. if $t_1 > t_2$ and $t_1 > t_3$.

However, the above formula is mostly applicable for primary reserve, because the positive and negative reserve is not separated. For secondary and tertiary reserve, which is our main objective, a signed split will imply improved competition on offers. We therefore define a positive reserve term R_{pos} and a negative reserve term R_{neg}:

$$R_{pos} = (MAX_4 - AVR_4)\ (STD_4 - STD_2)/(STD_4 - STD_1) + rsv(ROV_3, ROV_4)\ ((MAX_4 - AVR_4) - (MAX_3 - AVR_3)) \quad (2)$$

$$R_{neg} = (MIN_4 - AVR_4)\ (STD_4 - STD_2)/(STD_4 - STD_1) + rsv(ROV_3, ROV_4)\ ((MIN_4 - AVR_4) - (MIN_3 - AVR_3)) \quad (3)$$

The R_{pos} showd generally more variability than R_{neg}, because it is associated with small scale weather phenomena that generates temporally increased power production. R_{neg} on the other hand shows a more volatile behavior during cut-off events. It can sometimes seem convenient to forecast blocks of reserve. However, this may also become a trade-off in costs.

We believe that a native time series of reserve is more useful in an operational environment, so that the decision can be made on the basis of R_{pos} and R_{neg}. This is because short lasting extremes can often be tackled with curtailment more economically, especially if the start-up of the reserve is sufficient expensive. It is also possible to also compute percentiles with a similar formula as above to better illustrate the likelihood of R_{neg} or R_{pos} requirement or how much of the reserve is likely to be used in the given time interval.

What is most characteristic of the above reserve prediction formulation is the ability to tackle that uncertainty is high at the time of allocation and the primary power planning has higher accuracy due to the shorter lead time. Regardless whether the planning horizon is long or short, a useful forecast can be made, which reflects the extreme values in the hour of interest. There are interpretation benefits of looking at the wind generation alone, but also system benefits of looking at the "Load-wind-(solar) generation".

Using reserve predictions in operation: a real-time example application

In the following we present a real-time application of the above described reserve forecast algorithm. The challenge in the real-time environment is in fact that there are many other processes that need to be adopted or suddenly taken into account, while in a development of demonstration phase non-relevant processes are simulated with assumptions or not considered at all. In this case, we additionally include a weather independent term as a function of time of the day to capture noise that is non-weather dependent, but generates a reserve requirement.

Description of the study and control area

Note that for confidentiality reasons, it is not possible to disclose the control area. For the purpose of demonstration of the algorithms and methods, we do not consider this important as long as the setup and corresponding results have a general meaning.

In our sample control area there are approximately 40 wind farms. The permanent allocation of reserves for the control area amounted at the outset to +/-10% and up to +/- 30% of installed capacity of wind dependent on the time of the year, i.e. there are large seasonal reserve allocation differences.

In our example area the wind generation is correlated and strong ramp-rates occur. However, it is seldom to observe that the wind generation ramps down in a dramatic speed. Ramp-ups are faster than ramps down and it is very unlikely that an instant total wind ramp-down to zero can occur in the control area.

Forecasting on the Multi-hour Time Scale

Following the strategy of current and former practices in Denmark and German it makes sense to separate the reserve and to keep the faster reserve set aside for the swings with low predictability. Primary reserve is generally speaking best used solely for the swings, where a forecasting system can at the most predict amplitude and period, while a secondary reserve is suitable for slower swings with limited ramp rate and a minimum predictability. The forecasting method for slower swings is physical while it it almost exclusively statistical for the faster swings. We therefore concentrate in this study on the slower swings. We think this is in fact a smart way of using the reserve forecast, because it takes away the wind ramp from the system balancing and the short-lasting intra-hour variations with less amplitude are then dealt with by the flexible primary reserve system.

For this reason most SO's today have a forecast available with MIN/MAX ranges that reflect the uncertainty in the ramp rate. In the case of a wind ramp-down, the SO must ensure that the contracted reserve provider can sustained ramp down over multiple hours with the MAX ramp rate. Similarly, for a wind ramp up. The reserve forecast values for MIN/MAX hence represent the sustained ramp-rate requirements over multiple hours, targeted for a kind of secondary and tertiary reserve. The values are dynamic and represent the collective uncertainty from wind and load, but without imbalance errors from neighbor control areas.

In our study we represent external imbalances and load forecast errors as a common noise term with time of the day dependence.

Definition of Error Conditions for the Forecast

Fundamental for forecasting is that a criteria for success and error can be defined. Given the fact that certain swings in the data are unrealistic or possibly so extreme that the operational cost of self balancing would be too high, we need to work with probabilities.

One way of doing this is to define that if a forecast value lies within a band, the result is a success and if it lies outside the band, it is false alarm. A constant very wide reserve band would imply 100% success, but would not be affordable. The gain lies in finding a balanced criteria considering the following questions:

- How many failures can be tolerated ?
- What is the allowed maximum error ?
- Which frequency of reserve under-prediction is allowed ?
- What is the cost of spilled reserve ?

These questions are so to speak all related or determined by the SO's operational experience and standards to which the SO must be conform. In the next section we will outline some objective criteria suitable for evaluation of a model result, which relates to operation and present the results of a 3-month test for a specific set of conditions.

Demonstration of the reserve prediction

The following evaluation took place with data from mid of October to end of November 2013. We used 4 forecasts per day with a forecasting horizon of 3-48 hours. This provided us with 5760 hours for the evaluation of the prediction method described above. Table 1 shows the results of the evaluation.

Note, that the column named ***Input forecast*** provides the wind forecast input to the reserve computation. To compute the reserve R, we add the load forecast. The forecast named P10 therefore represents the ramp forecast (rmp) P10 + the load forecast increment (ld). This difference is important, when we use the abbreviations of the input forecasts from the table in the following discussion.

The ***BIAS, MAE*** and ***RMSE*** columns provide a good overview of the plain statistical capabilities of the various forecasts.

TABLE 1: VERIFICATION RESULTS FROM THE EVALUATION PERIOD

Input forecast (rmp+ld)	BIAS [%]	MAE [%]	RMSE [%]	Inside Band [%]	R coverage [%]	Hit rate Total [%]	Hit rate R_{neg} [MW]	Hit rate R_{pos} [MW]	Miss Total [MW]	Spill Total [MW]	Spill R_{neg} [MW]	Spill R_{pos} [MW]
MIN	14	14	21	13	0.18	1	0.00	0.28	0.10	13.00	0.00	12.13
P10	4	4	7	6	0.45	12	0.00	0.68	0.33	3.40	0.00	2.73
P20	2	3	5	5	0.58	23	0.00	0.88	0.45	2.10	0.00	1.50
P30	1	3	4	7	0.65	33	0.00	0.98	0.60	1.35	0.00	0.83
P40	1	2	3	7	0.65	41	0.00	1.00	0.80	0.80	0.00	0.40
P50	0	2	3	9	0.53	36	0.00	0.80	1.05	0.40	0.00	0.15
P60	-1	2	3	8	0.38	26	0.18	0.48	1.08	0.33	0.05	0.08
P70	-1	3	4	5	0.38	23	0.40	0.35	0.85	0.73	0.35	0.05
P80	-2	3	5	5	0.33	16	0.43	0.28	0.70	1.43	0.95	0.03
P90	-4	4	7	14	0.25	8	0.35	0.20	0.55	2.63	2.10	0.03
MAX	-13	14	20	8	0.08	1	0.13	0.05	0.23	12.00	11.33	0.00

The unbiased P50 forecast of course appears as the one with the lowest overall error, while other columns show that other forecasts may be more suitable for decision making.

As can be seen, the number of hours around each percentile band is in the range of 5-15%. This is reflected in column ***Inside Band*** in Table 1. One cannot expect 10% in each band, because we cannot model exactly everything that causes reserve deployment. In fact, we expected a range between 5-15% to be a realisticly achievable coverage given the complexity of the total system of equations.

The column ***R coverage*** indicates how much of the forecasted reserve was actually deployed. The number is an average value over the period. The number is very poor for the lower and higher forecasts, because they score poorly when the deployment is of opposite sign of their bias. This is best explained with an example: during hours of negative reserve deployment (R_{neg}) the forecasts giving only positive reserve deployment (R_{pos}) score a zero. There is no credit given for having forecasted too much either. Thus, only the successful part of the forecast counts. After division with the number of total hours, the average is as low as the table indicates. The next columns in Table 1 are the result of a contingency analysis, in which we have investigated the impact on the different possible strategies of reserve forecasts inside the ensemble spread of possible solutions.

The column ***Hit rate*** indicates the achievable hit rate in percent of the total activated positive (R_{pos}) and negative (R_{neg}) reserve for the various forecast types or strategies. The score is zero in hours, where the actual deployment has opposite sign of the forecast.

The fact that the ***Hit rate*** is normalised with the total allocation of both R_{pos} and R_{neg} means that the highest achievable number would be 50 and not 100. This explains also why the hit rate reduces from the middle forecast P50 to the outer forecasts Min and Max, respectively.

When split into positive reserve deployment R_{pos} and negative reserve deployment R_{neg}, it can be seen that there is no R_{neg} allocation for forecast MIN, P10..P50.

This is because those forecasts always forecast the R_{pos}. Nearly the same arguments count for the R_{pos} forecast. However, there are obviously cases, where all wind power forecasts ramp so strongly down that R_{pos} is indeed fore-casted with high certainty. In the column ***Miss***, we list the average under-predicted reserve requirement (***Miss***) for each hour in the investigated period.

Here, it becomes evident how the allocation from the outer forecasts (towards the MIN and MAX) provide security and reduce the missing predicted allocation to a minimum. However, the next columns, which show the over-predicted reserve requirement (***Spill***) also show that the less missed allocation we have, the higher the amount of unused reserves. The total spill shows the explosive development towards the outer forecast boundaries MIN and MAX. We count spill to both sides. Thus, in case of R_{pos} deployment we calculate all R_{neg} as spill. The spill on top is defined as the unused R_{pos} on top of the deployment. So the spill can be heavy in both directions.

What has to be considered however, is that the optimisation strategy is strongly dependent on the cost and symmetry of allocating R_{neg} and R_{pos}. If, for example the allocation of R_{neg} is significantly cheaper or comprehensive than R_{pos}, a P90 or even MAX may be a more sustainable strategy than a forecasts that is good in average. In the next table, Table 2, we discuss the analysis we carried out to look at the times, where the reserve deployment was outside the forecasted spread.

TABLE 2: ANALYSIS OF THE RESERVE DEPLOYMENT THAT WAS OUTSIDE THE PREDICTED FORECAST SPREAD.

	# of times [%]	RD [% inst.cap]
Rd_{neg} < MIN	8.79	-1.97
RD_{pos} > MAX	7.82	3.57

Table 2 shows that with the current approach the deployed R_{neg} was larger than the predicted maximum R_{neg} close to 9% of the time with an average of close to 2% of installed capacity.

The times, where the R_{pos} deployment was greater than our MAX was close to 8% of the time with an average deployment of close to 3.5% of installed capacity. The cause of these events is unknown.

It can be volatile wind generation not covered by the forecasts, load forecast error or a failure on a scheduled plant. Important is that those events are not R_{pos} > 10%, but something that is within the SO's minimum reserve.

Another way to look at the result of Table 2 is the fact that the real reserve deployment will not be covered two hours per day in average. However, this is at times with deployment less than 10% of installed capacity.

Although 5760 hours of evaluation is not very robust to draw final conclusions and set long-term strategies, it nevertheless provides an indication on that some attention should be given to the question, whether the target would be to get this number to zero or not ?

In this case, the optimisation strategy will have to be tuned and its progress followed closely over some time. Figure 2 shows a 3-day example of such a reserve forecast and illustrates this issue. One method to overcome allocation outside the spread could for example be by adding a statistically relevant amount e.g. a standard deviation, to the MIN and the MAX to move the outer boundaries or possibly to include the previous 75 member ensemble in the ramp calculation.

Our overall conclusion at present is that the P50 forecast is the best average forecast to choose, as it scores best on all error measures. When this is said, we do not take any of the above discussed strategic evaluation and costs into consideration, but consider this recommendation solely from a safety and security aspect.

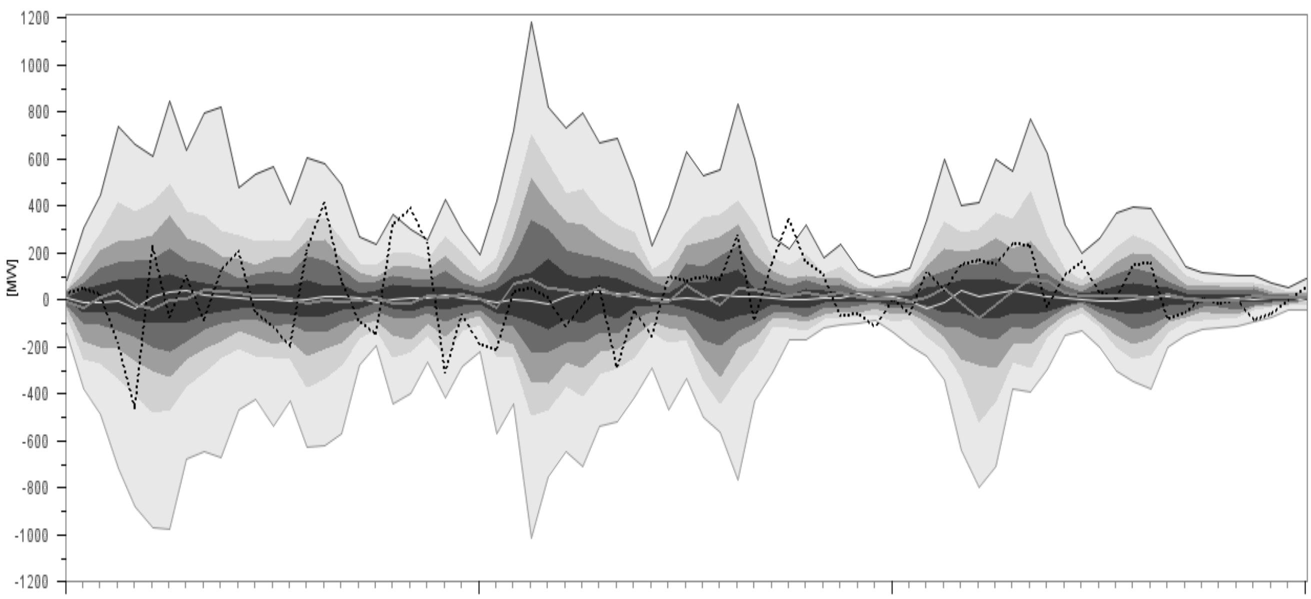

Figure 2: Example Graph of a 3-day Reserve forecast inclusive uncertainty in form of percentiles P10..P90. The black dotted line is the deployed reserve, the white line is the P50 and the gray line is the reserve forecast R.

In that sense, our analysis suggests P50 as the best candidate for a reserve forecast that is reliable in operation.

If a forecast band should be established, the P10/P90 may be a better choice than a MIN/MAX band. The advantage of the P10/P90 choice seems to be less reserve spill.

However, the drawback of using P10/P90 is that there is a higher percentage of values outside the forecast uncertainty band. From Table 1 column 5 we can derive that additionally 21% (8+13) of the hours have actual deployment outside the P10/P90 band. This means there is a trade off that needs to be carefully considered.

Discussion and Conclusions

In this report we have analysed how to best deploy reserve forecasts in a real-time control area environment. Our overall recommendation in a control area with non-specific requirements or as a starting point to gain experience is to use the hourly mean reserve forecast (P50) together with a spread band of MIN/MAX width.

We have outlined how these MIN/MAX bands set requirements for the ramping capabilities of the additional reserve. These values shall be understood as the uncertainty of the hourly mean collective ramp rate of load and wind (and possibly photovoltaic generation).

This is a well defined forecast objective. We have also found out that it is important to keep the time scale hourly, if there is not sufficient information on intra-hourly time scale. This is because the variability on minute scale is much higher than on hourly time scale and the resulting forecast will then not be able to fulfill the quality that is required for the forecast to be valuable. We consider this a future compatible strategy.

A possible next step is then to investigate how to parameterise intra-hour reserve requirements and look closer into the imbalance handling of neighbour control areas. A component in this way will be forecasts for renewable energy and load in these neighbour areas and in that way to generate equations for a wider area than only one SO's control area.

Studies in that direction have already been made in Europe (e.g. [13,14]) to accommodate the plans of the European Network of TSOs for Electricity (ENTSO-E) to harmonise and integrate the entire European grid. Once this is rolled out, forecasting of reserve requirements, especially in congestion areas will be a requisite for a safe grid operation.

Acknowledgment

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5 Online:http://download.weprog.com/pahlow_et_al_2008.pdf

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