Comparison of Probabilistic and Deterministic Approaches for Setting Operating Reserve in Systems with High Penetration of Wind Power

Ricardo J. Bessa and Manuel A. Matos

Abstract—**The increasing levels of wind power penetration motivated a revisitation of methods for setting operating reserve requirements for the next and current day. System Operators (SO) are now moving from deterministic intro probabilistic approaches, and including wind power forecasts in their decision-making problems. In this manuscript, a probabilistic approach that evaluates the consequences of setting each possible reserve level through a set of risk indices is compared with frequently used deterministic rules and a probabilistic rule where wind power uncertainty is described by a Gaussian distribution. The comparison is performed over a period of five months for a realistic power system, using real load and wind power generation data. Results highlight the limitations of deterministic rules, challenge the Gaussian assumption and illustrate the usefulness of risk indices derived from the probabilistic forecast and using a full probabilistic methodology.**

Index Terms-- **Uncertainty; downward reserve; upward reserve, probabilistic forecasts, operating risk, wind power.**

I. Introduction

MAINTAINING the balance between load and generation in a power system is a central requirement for System Operators (SO) in both planning and operation of the power system. The introduction of renewable energy in the power system, in particular wind energy, has motivated a revisitation of methods for long and short-term planning of operating reserve [1] (secondary/spinning and tertiary/non-spinning) and new research to include the uncertainty of wind power forecasting (WPF) in setting the operating reserve requirements [2].

In a recent past, a large number of SO defined the operating reserve requirements based on deterministic methods such as the traditional UCTE (Union for the Coordination of Transmission of Electricity) rule [3] complemented with a percentage of the load and the largest unit in the system; a survey can be found in [4]. In fact, deterministic rules are being used in some countries with a large penetration of wind power. In Portugal the UCTE rule is used for secondary reserve, 2% of the forecasted load and the largest unit for tertiary reserve [5]. In Spain the rules for secondary and tertiary reserve are the same, but an additional reserve is required to deal with forecast errors and units outages [6]. This additional reserve is the sum of the generation shortage due to load forecast errors, wind forecast errors and unscheduled outages.

The short-period to conduct studies and examine alternatives is the main motivation for using deterministic rules, as well their mathematical simplicity. However, some of these deterministic rules depend only on the load level (sometimes on the peak load) and generation units and are insensitive to the level of wind power penetration of the system. Moreover, the rules do not give any indication about the level of risk that the SO is taking, some do not have a clean meaning and others assume that the scenarios are true (e.g. loss of the largest unit).

The recent revision of the UCTE (recently named ENTSO-E, European Network of Transmission System Operators for Electricity) Operational Handbook [7], defined a probabilistic approach for the total reserve (secondary and tertiary) in addition to the deterministic rule from 2004. The approach was called "Probabilistic Risk Management Sizing Approach" and consists in the following: "is based on a requirement to enable the control of the area control error to zero in for example 99.9 % of all hours during the year (that in this case corresponds to accept up to 9 hours of deficits in the reserve expected for a full year). The calculation of the size of the reserve is based on the individual distribution curve of the power imbalance of the control area (statistical data)."

Presently, SO are starting to account WPF errors for setting the operating reserve. For instance, ERCOT (Texas Independent System Operator) defines the monthly non-spinning reserve requirements equal to the percentile 95% of the historical total forecast error [8], and REE (Spanish System Operator) started to study the inclusion of the load and wind forecast error distributions in setting the operating reserve requirements [9].

However, research work is still needed to integrate the WPF systems' output, in particular probabilistic forecasts, in the definition of operating reserve requirements. One example is a simple probabilistic model that computes the square root of the sum of the squares of the standard deviations of hourly wind power and load forecast errors [10]. The reserve is defined to cover all variations contained within $\pm 3\sigma$ of the total system forecast error, which means that 99.74% of variations are covered assuming a Gaussian distribution. Other approach consists in relate the reserve level on the system in each hour with the number of load shedding incidents tolerated per year [11]. Load and wind

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power forecast uncertainties are incorporated in the model as Gaussian errors.

Ortega-Vazquez and Kirschen [12] balance the spinning reserve cost and benefit (expected energy not supplied converted into socioeconomic cost by using the value of loss of load) in an electrical market with unit commitment. The uncertainties are represented by Gaussian distributions and combined using the rule presented in [10].

Due to its mathematical flexibility, the Gaussian distribution is generally used to model WPF uncertainty. However, and as presented by Lange [13], the wind forecast error has a non-Gaussian distribution. An alternative approach is not assuming any distribution for the uncertainty. For instance, Matos and Bessa presented a probabilistic model [2] that uses as input a probabilistic WPF (non-parametric represented by quantiles) and describe the risk of each reserve level by a set of risk/reserve curves. A brief description of this model is presented in section II.

So far, the main concern of SO and researchers, in setting the operating reserve, is the loss of load event. However, with the increasing penetration of wind power the surplus of generation event starts to be also a concern. Normally, during night valley hours the load is lower and wind generation reaches its generation peak, so it will become frequently situations where the renewable generation (or even wind generation solely) will be higher than the load. In this situation, the system operator must waste renewable generation or use storage devices (e.g. hydro pumping storage), or decrease schedule conventional generation.

In a near future the electrical vehicles connected during the night could provide this downward reserve service [14]. It should be noted that this problem is more severe in countries where the renewable generation is supported by feed-in tariffs, since in this scheme all renewable generation must be absorbed by the electrical grid.

Hence, the surplus of generation event must also be considered in the deterministic and probabilistic models that define the downward operating reserve requirements, with particular importance to systems with a high penetration of wind power. Presently the rules used for this type of reserve are generally a percentage of the load of the upward reserve. For instance, in Spain the rule for secondary and tertiary reserve ranges between 40% and 100% of the upward reserve depending on the load variation [6]. It is also considered an additional reserve defined by the sum of load and wind forecast errors.

The main contribution of this paper consists in showing the applicability and additional value of using a probabilistic methodology based on wind power probabilistic forecasts for setting the operating reserve (downward and upward).

The paper is organized in five sections. Section II presents a brief description of the Reserve Management Tool. Section III presents an evaluation of the deterministic and probabilistic load and wind power forecasts. The quality of these forecasts is relevant for the results presented in sections IV and V. Section IV presents the comparison of deterministic and probabilistic approaches for an experiment using a Monte Carlo procedure with probability distributions assumed to represent the true distribution. Section V compares the RMT and a simple probabilistic rule, by using as input probabilistic forecasts obtained with a method from the state-of-the-art. Finally, section VI presents the conclusions.

II. Reserve Management Tool

The Reserve Management Tool (RMT) [2] is a probabilistic approach to build the system generation margin distribution (amount that the available generating capacity exceeds the system load) that results from considering the uncertainties associated to generation (conventional and wind) and load. Risk indices describing the possible consequences of each downward and upward operating reserve level are computed from the system margin distribution. The next step is the determination of the risk/reserve curve, as a basis to the application of decision making methods incorporating the preferences of the Decision Maker (DM) (in this case the System Operator). The output is the downward and upward operating reserve levels determined at a specific time instant for each look-ahead time (e.g. 1 hour) of the next day (or current day).

The term operating reserved used in this manuscript means additional generation capacity (or additional loads) related with the risk of loss of load (or waste renewable generation) due load and wind forecast errors. The reserve due to outages was neglected in this paper without loss of generality (see [2] for the complete model).

This methodology is formulated to an electricity market where the SO is responsible for buying the reserve requirements for the next day (e.g. day-ahead market) and current day (e.g. intraday market). The reserve market is decoupled from the day-ahead market and from the congestion analyses. The chronological order is the following: the day-ahead energy market is the first market to be cleared, and then the SO performs the congestion management analysis, modifying the generation dispatch in order to guarantee a secure operation of the power system. Once the network constraints have been solved, the ancillary services market is launched. This market provides for the 24 hours of the next day the up and down regulation reserves assigned to each agent.

An example of this kind of electricity market is the Iberian market described in [15].

A. Uncertainty Characterization

The uncertainty in wind power is related with the forecast error. Recent research [16] has focused on associating uncertainty estimates with point forecasts, taking the form of probabilistic forecasts, risk indices, or scenarios of short-term wind power generation. Some of these techniques were developed in the framework of the European Project ANEMOS (http://anemos.cma.fr/).

In the Reserve Management Tool (RMT) the wind power forecast uncertainty is modeled through a probabilistic forecast represented by a set of quantiles ranging from 5% to 95% with a 5% increment.

The load uncertainty is characterized through a Gaussian distribution with a given standard deviation and zero mean. The conventional generation uncertainty is characterized by the capacity outage probability table. Note that in the case-study of sections IV and V the conventional generation outages are not considered.

B. System Generation Margin

The approach consists in computing the system generation margin (as M=C+W-L) for each look-ahead time by a convolution between the conventional generation distribution (C), the wind generation distribution (W) and the load distribution (L).

The system generation margin distribution is a discrete probability distribution for each look-ahead time step, represented by its probability mass function (*pmf*); as depicted in Fig. 1 for a situation in the absence of reserve. For a specific level of upward operating reserve R_U, the distribution of $M+R_U$ describes the probability of the reserve being sufficient to cover the shortage of generation. Fig. 2 shows the effect of setting a reserve level of 800 MW in the same situation of Fig. 1. This additional capacity (as reserve) means shifting the Fig. 1 *pmf* to the right by the amount of the reserve (800 MW).

For a specific level of downward reserve the distribution $M-R_D$ describes the probability of the reserve being sufficient to cover the surplus of generation. This reserve means shifting the Fig. 1 *pmf* to the left by the amount of the reserve (500 MW), as depicted in Fig. 3.

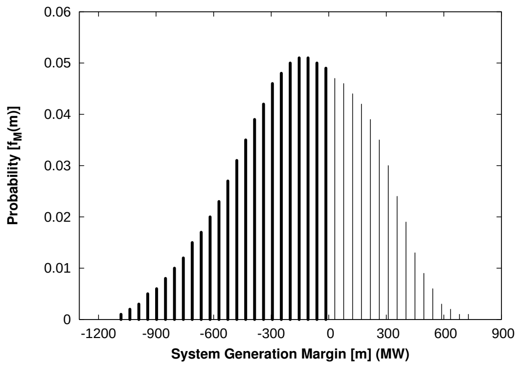

Fig. 1. pmf of the generation margin for a specific look-ahead time step.

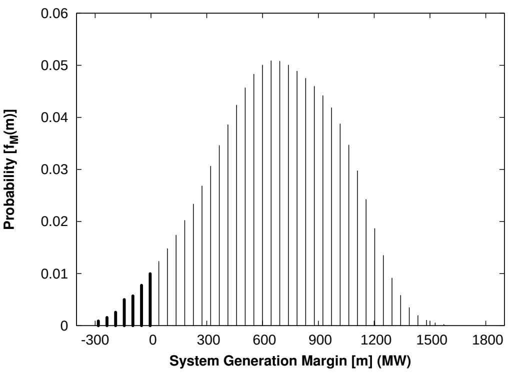

Fig. 2. pmf of the generation margin for a upward operating reserve of 800 MW.

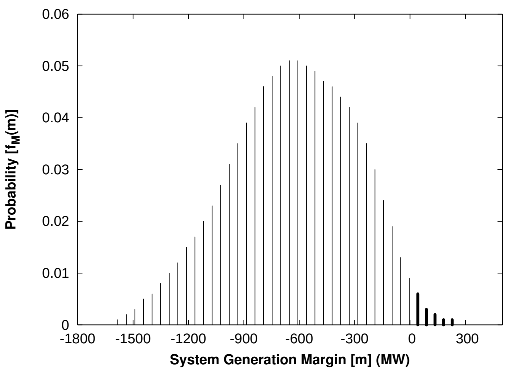

Fig. 3. pmf of the generation margin for a downward operating reserve of 500 MW.

C. *Risk Indices*

Different risk measures meaningful for the SO related to the amount of loss of load and wasted renewable energy can be computed for each value of upward and downward operating reserve.

The classical measures in reliability can be calculated from the system margin distribution, such as the loss of load probability (LOLP), the loss of load expectation (LOLE) or the expected power not supplied (EPNS). For instance, in the situation depicted in Fig. 1 (without any reserve), the risk of loss of load would be described by LOLP=0.64 and EPNS=212.3 MW, but, after adding the 800 MW upward reserve (Fig. 2), EPNS reduces to only 2.82 MW and LOLP to 0.033.

From the positive part of the system generation margin risk measures related with the surplus of generation event can also be computed. These risk measures are analogous to the ones related with the loss of load, for example: probability of wasting renewable energy (PWRE); expected wasted renewable energy (EWRE). For the situation without reserve (Fig. 1) PWRE is 0.36 and EWRE is 78.9 MW; with a downward reserve of 500 MW (Fig. 3), PWRE becomes 0.01 and EWRE reduces to 1.2 MW.

Other risk measures describing operating reserve risk can be found in [17].

D. *Risk/Reserve Curves*

As a result from the exercise depicted in Fig. 1,2 and 3 curves with downward and upward reserve as a function of risk can be obtained. This kind of risk/reserve curves are depicted in Fig. 4 and 5 for the risk measures LOLP and PWRE. Note that the curves are in fact a set of points due to the discrete nature of generation capacity.

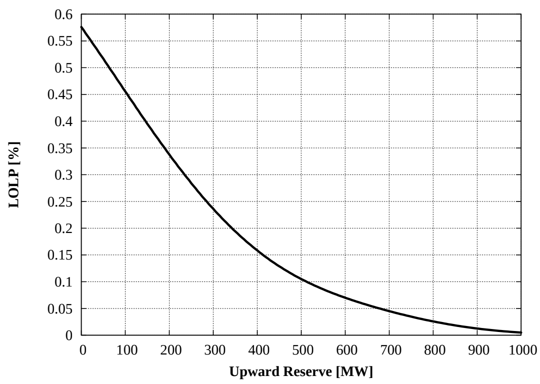

Fig. 4. LOLP against upward reserve curve.

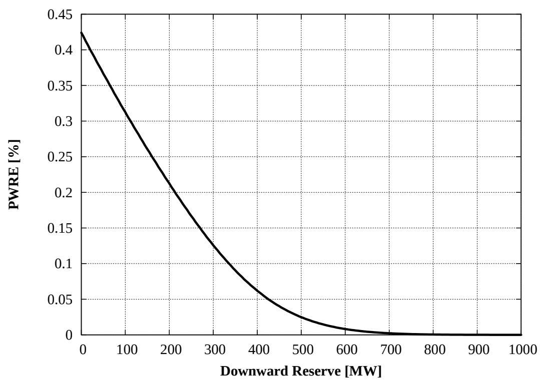

Fig. 5. PWRE against downward reserve curve.

A straightforward decision-making method for this kind of curves consists in setting a reference threshold for the maximum acceptable risk. For instance, in Fig. 4, in order to assure a LOLP not greater than 5%, an upward reserve level of at least 660 MW would be necessary, while for a LOLP of 10% the minimum reserve should be 500 MW. In Fig. 5 a downward reserve of 425 MW is necessary for assure a PWRE of 5%.

More elaborated decision-making methods to balance risk against reserve cost and incorporating more complex structures of the decision maker preferences can be found in [2] and [17].

III. Load and Wind Power Forecast Evaluation

This section evaluates the quality of the load and wind power forecasts that are inputs in the experiments described in sections IV and V. The results of this section are useful for understanding the impact of forecast quality on reserve requirements.

A. Data Description

The wind power data used in this study is from 15 sites (virtual wind farms) in the state of Illinois for year 2006. The data consists on the sum of day-ahead wind power point forecasts and realized generation of each site; the data can be found in [18]. The day-ahead forecasts were generated based on observed forecast errors from four real wind farms (more details can be found in [19]).

The load data used in this study is from MISO (Midwest Independent System Operator) for year 2009. The data consists on day-ahead load forecasts and realized load; this data can be found in the MISO website (www.midwestiso.org).

The peak load for year 2009 was 34.2 GW. The installed wind power is 17 GW, corresponding on average to 29% of the load in the five months, and with a 0% minimum (a day with no wind) and a 103% maximum (a day with more wind generation than load).

B. Deterministic Forecast Quality

The analyses in this section are relevant to understand the statistical properties of the forecast error distributions used in section IV.

1) Wind Power Forecast

The criteria to evaluate the quality of the point (or deterministic) forecasts follow the protocol described in [20]. Here, and due to its relevance for the operating reserve problem, only the skewness and kurtosis of the error (realized minus forecast values) are presented.

The Normalized Mean Absolute Error (NMAE) ranges between 8% and 10.5% of the rated power in the 24 hours.

Fig. 6 depicts the skewness and kurtosis of the forecast error distribution for year 2006. The skewness in each look-ahead time step is always positive, which means that the error distribution is skewed right. Right skewed means that the right tail is long relative to the left tail and, informs on the most likely direction of forecast errors.

In this case, the expected direction is under-forecast (realized wind power above forecast). This represents an impact on the downward reserve requirements, since more wind power will be in the grid than what was predicted.

Kurtosis is a measure of whether the forecast error distribution is peaked or flat relative to a Gaussian distribution. The negative excess kurtosis means "flat" distribution, while positive excess translates to a sharper peak and heavy tails. For year 2006 the excess of kurtosis (w.r.t. to Gaussian distribution) is positive, which means higher probability of errors near the mean and a higher probability of large errors (possible situations with insufficient operating reserve).

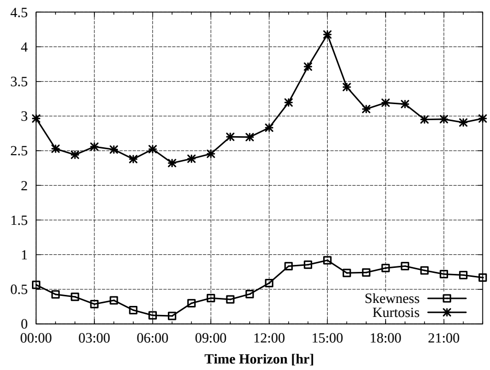

Fig. 6. Skewness and kurtosis of the forecast error distribution for each look-ahead time step.

2) Load Forecast

The Mean Absolute Percentage Error (MAPE) ranges between 2.3% and 3.4%. The skewness ranges between -0.71 and 0.07. Sknewness shows that the most likely direction of expected forecast errors is over-forecast. Moreover, the error bias is negative in all hours indicating systematic error towards over-forecast.

The kurtosis is between 3.32 and 6.06, which indicates higher probability of large forecast errors.

This over-forecast is not a problem for the upward reserve. However, combined with a tendency to under-forecast the wind generation, it may constitute a serious concern regarding downward reserve. In fact, the system operator will face a scenario with less load and more wind levels than the predicted ones.

C. Probabilistic Forecast Quality

These probabilistic forecasts are inputs for the analysis described in section V are produced for each hour of the evaluation period.

1) Wind Power Forecast

The probabilistic forecasts for the RMT were estimated with a B-splines quantile regression [16] with a time-adaptive algorithm [21] that generates new solutions on the basis of old solutions. The wind power data from Jan-Jul was used to train the quantile regression model. The evaluation set consists on quantile forecasts for nominal proportions 5% to 95% and wind power realized values for the period August-December. Only the deterministic forecast was available as explanatory variable.

We followed a framework, presented in [22], to evaluate wind power probabilistic forecasts. Two measures of quality are presented: calibration (also denominated reliability) and sharpness.

Calibration is related with capability of agreement between nominal proportions (forecasted probabilities) and the ones computed from the evaluation sample. In other words, in a quantile the empirical proportion should equal the nominal exactly. For instance, an 85% quantile should contain 85% of the observed values lower or equal to its value.

This difference between empirical and nominal proportions is considered the bias of the probabilistic forecasting method. Calibration diagrams like the one depicted in Fig. 7 are created to give an overview of whether a particular method systematically underestimates or overestimates uncertainty. Fig. 7 depicts the calibration diagram calculated for each quantile nominal proportion and for the whole time horizon; the "ideal" line is the total match between nominal and empirical proportions. Calibration is indicated by the proximity of the plotted curve to the "ideal" diagonal. If the curve lies below the line, this indicates over-forecasting (forecasted probabilities too high); points above the line indicate under-forecasting (forecasted probabilities too low).

Fig. 7 depicts almost perfect calibration. However, the diagram should be conditional to account for the influence of several variables. For instance, in Fig. 8 the calibration diagram is depicted for look-ahead step 15:00 in order to assess the influence of the look-ahead time step. For hour 15:00 an uncertainty over-forecast is detected, nevertheless in other look-ahead steps is the opposite. An over-forecasting means that the forecast informs, for instance, that with a probability of 90% the wind generation will be below this value, but the empirical quantile says that only 80% of the points are below this quantile value. This over-forecasting could represent an underestimation of the downward operating reserve risk. As an example, the quantile 90% means that the probability of having a wind generation above its value is only 10%, however the empirical quantiles estimated from data says that this probability is 20%. This means that the probability of having more wind generation in the system is higher than the predicted one.

Sharpness is the tendency of probability forecasts towards discrete forecasts, measured by the mean size of the forecast intervals (distance between quantiles) [22]. Quantiles are gathered by pairs in order to obtain intervals with different nominal coverage rate. This gives an indication on the level of usefulness, where narrow intervals are desired. This measure does not depend on observations.

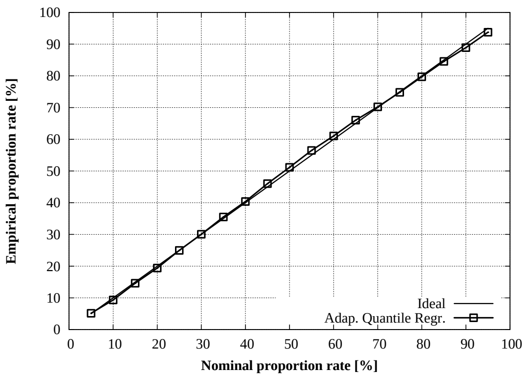

Fig. 7. Calibration diagram for the whole time horizon.

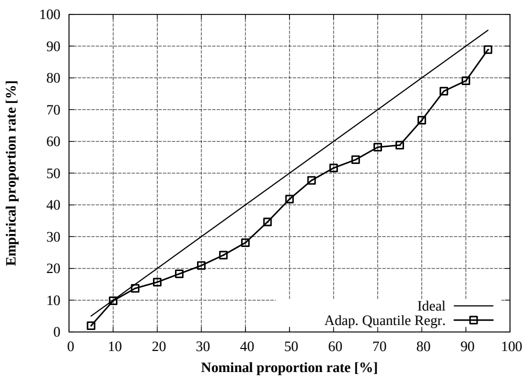

Fig. 8. Calibration diagram for 15:00 look-ahead step.

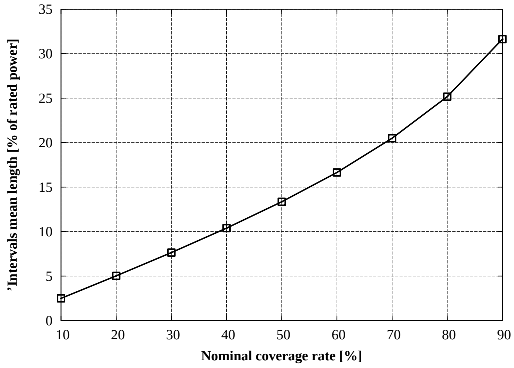

Fig. 9. Sharpness diagram for the whole time horizon.

Fig. 9 depicts the sharpness computed for each interval nominal coverage and for the whole time horizon. In terms of sharpness the forecasted quantiles presented relative narrow amplitude. It is important to note that Juban et al [23] found a trade-off between reliability and sharpness, meaning that improving the reliability will generally degrade the sharpness and vice-versa.

A low sharpness is important for the reserve requirements because it represents a lower "amount of uncertainty" and this has an influence on the amount of required reserve. Consequently, this also represents an impact in the reserve cost, in particular for the situations where there is no loss of load or generation surplus.

2) Load Forecast

The load forecast uncertainty is modeled with a Gaussian distribution where the standard deviation was computed from the MAPE in each hour of year 2009.

Fig. 10 depicts the calibration diagram for the load probabilistic forecasts. The quantiles below 55% are being over-forecasted, while the others are being under-forecasted. The calibration of these forecasts is lower when compared with the one computed for wind power.

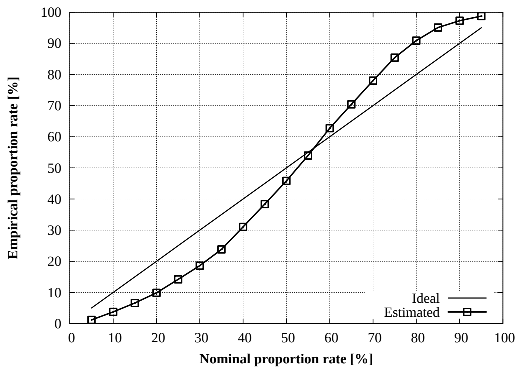

Fig. 10. Calibration diagram for load uncertainty.

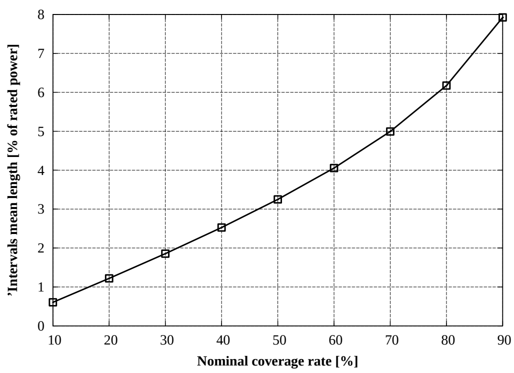

Fig. 11. Sharpness diagram for load uncertainty.

Fig. 11 depicts the sharpness diagram for load uncertainty. The sharpness of the load uncertainty is three times lower compared to wind power. This result is expected because of the lower load forecast error and it shows that wind power uncertainty is the key random variable for setting reserve requirements.

IV. Experiment A: Monte Carlo Simulation with Point Forecast Error Distribution

The aim of this experiment is to show that the RMT approach is more appropriate to hedge the operating reserve risk due to wind and load forecast errors.

For this purpose the distribution of the historical point forecast errors (characterized in section III.B) computed for each hour of the time horizon (24 hours) is assumed to represent perfectly all possible realizations of the random variable. A Monte Carlo procedure is employed to generate samples from the forecast error distribution that represent possible states of the power system in each hour.

A. Experiment Description

1) Assumptions

The distributions of the wind power forecast error were computed for 24 hours using historical forecast error for each day of a six months (Jul-Dec) period.

The standard deviation of the load forecast error was computed from the Mean Absolute Percentage Error (MAPE) (σ=1.4826*MAPE) of the same six months.

It is assumed that the wind energy receives a feed-in tariff and doesn’t go to the market, the market load (conventional generation) is the difference between the deterministic load and wind forecasts.

The units’ outages were neglected for this study since the scope of this paper is focused in the impact of wind power generation. This simplification does not have a significant impact on the conclusions.

2) Rules for Comparison

The RMT is compared with the following deterministic rules:

- rule A: UCTE rule for secondary reserve ($\sqrt{10 \cdot L_{\max} + 150^2} - 150$, L_{max} is the peak load), plus 3.4% of the forecasted load (maximum MAPE). This rule is based on the Portuguese rule [5], however the capacity of the largest unit was not considered in this case. The operating reserve in this rule corresponds to the sum of secondary and tertiary reserve.

- rule B: secondary reserve equal to $6 \cdot \sqrt{L}$ (L is the forecasted hourly load) when the load variation is fast and $3 \cdot \sqrt{L}$ otherwise, tertiary reserve is 3.4% of the forecast hourly load. This rule was previously used in Spain (see [15]), and also the capacity of the largest unit was not considered.

- rule C: the operating reserve is determined by the sum of the load and wind MAPE for each look-ahead time. This rule is based on rule used by REE and described in [6][9].

The RMT is compared with the following probabilistic rule:

- rule D: $\varepsilon \cdot \sqrt{\sigma_L^2 + \sigma_W^2}$, where ε is related with the confidence level and the two σ are the standard deviation of load (L) and wind generation (W). If for instance, the decision maker defines a LOLP of 0.01 the value of ε is defined to cover 98% of all variations assuming a Gaussian distribution, which means equal to 2.33. This value is also the same for having a PWRE equal to 0.01 since the Gaussian distribution is symmetric. This rule can be seen as a probabilistic representation of the deterministic rule C.

B. Evaluation Results

The evaluation procedure consists in a Monte Carlo simulation (40000 random samples from the point forecast error distributions) performed for each hour. Note that this experiment does not intend to mimic the operation of the RMT and rules with probabilistic forecasts, as mentioned before the aim is to show the mathematical accuracy of the approaches under different wind and load states generated by the Monte Carlo sampling procedure.

The number of loss of load situations obtained for each suggested reserve is computed.

Fig. 12 depicts the number of loss of load situations obtained with reserve suggested by rules A, B and C. These three rules are deterministic and therefore the SO does not know the risk that is taking. Nevertheless, in system with a high penetration of wind power rules A and B lead to a high risk because are only functions of the load. Rule C despite using the wind power forecast error, also presents an higher risk, mainly because the average error is taken as worst case and errors greater than the average are assumed to be improbable.

These three rules are only acceptable if the SO is willing to take a higher value for the LOLP and PWRE, which normally is not the case.

The results also show that the rule of adding a reserve equal to the largest unit, besides providing substitution for an unscheduled outage (not addressed in this example), also covers most of the wind power variations.

These deterministic rules are enough for systems with a very lower penetration of wind power. One example is the PJM control area which has only 0.2% of wind power in its generation mix. The rule used by this SO is deterministic, e.g. underforecasted load forecast error based on the 80th percentile of a rolling three year underforecast average plus Forced Outage Rate component [24]. When the wind penetration increases these types of rules are no longer acceptable.

Fig. 13 depicts the results of RMT and rule D for upward reserve and a LOLP threshold of 1%. Since these rules allow the SO to define a risk threshold, the SO knows how much risk is taking. However, the Gaussian assumption of rule D for the WPF error leads to an overestimation of risk and consequently to a higher reserve (which leads to a lower risk but also to a higher reserve cost). The reasons lies in the skewness of the error distribution, since the skewness is positive, the Gaussian distribution will put more weight in the left tail of the error distribution, which leads to an overestimation of the risk of losing load (upward reserve). In other words, the Gaussian assumption increases the probability of having loss of load (or generation deficit). The RMT presents a risk that almost matches the reference threshold.

Fig. 14 depicts the results of RMT and rule D for the downward reserve requirements with a PWRE threshold of 1%. Rule A and B only deal with loss of load situations, while rule C can also be used for downward reserve, but its risk would be much higher.

Also for downward reserve rule D gives a computed risk different from the threshold. In this case during eight hours the risk is below the threshold, while in the rest of the period it is greater that the threshold. In this case, and in particular for the period between 12:00 and 23:00, rule D is making an underestimation of the risk mainly due to the positive skewness in the WPF error distribution; when the skewness of the WPF error is greater than 2.5, rule D tends to underestimate the risk of generation surplus.

RMT on the other hand leads to a risk almost equal to the PWRE threshold.

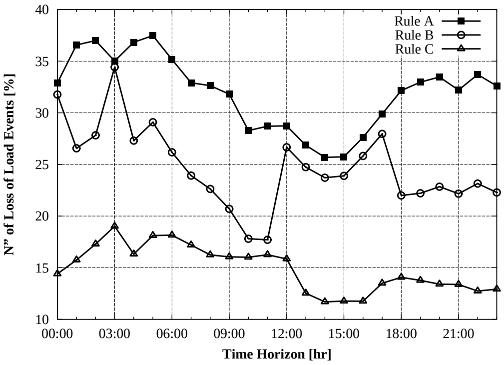

Fig. 12. Number of loss of load events for upward reserve suggested with rules A, B and C.

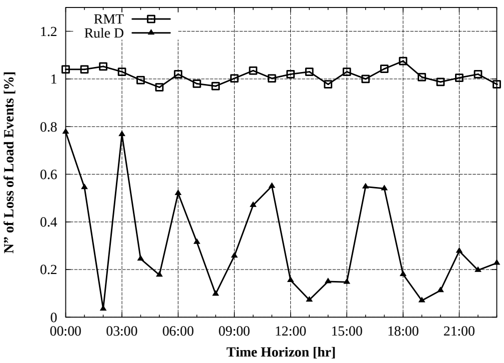

Fig. 13. Number of loss of load events for upward reserve suggested with RMT and rule D.

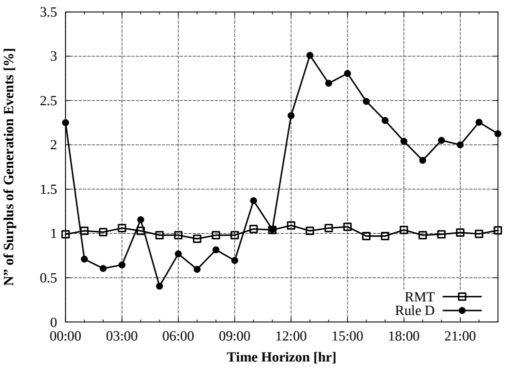

Fig. 14. Number of loss of load events for downward reserve suggested with RMT and rule D.

V. Experiment B: Using Probabilistic Forecasts

The aim of this experiment is to discuss the advantages and limitations of probabilistic approaches when probabilistic forecasts (described in section III.C) are used as input.

This experiment simulates the use of the RMT and rule D by a system operator for setting the operating reserve requirements for the next day. Note that this experiment is not comparable to experiment A because probabilistic forecasts for each hour of each day (five months period) and different from the point forecast error distribution are used. Moreover, the power system state used to evaluate the results corresponds to the realized values of wind and load in each hour and was not to states generated by a Monte Carlo procedure.

A. Experiment Description

The same load and wind data described in section IV is used in this experiment, and the evaluation set is the period from August to December.

The assumptions of section IV for conventional generation (no units' failures) were also adopted in this section.

The wind forecast error standard deviation for rule D is equal to the standard deviation in each hour computed for year 2006.

B. Experiment Results

Only the results of rule D and RMT are compared in this section because only these two allow a definition of a reference value for the risk.

When we define a reference value for the LOLP (or PWRE) we are setting the operating reserve equal to the value of the quantile that corresponds to this risk value. Therefore, the first approach to evaluate the suggested reserve levels is to compute the loss of load (and generation surplus) situations over the evaluation dataset for different reference levels of the risk. The approach is analogous to computing the calibration of the system generation margin (distribution depicted in Fig.1-3). Moreover, the results for LOLP above 1% are simply illustrative because the preferred risk for a SO is normally below 1%.

The results are depicted in Fig. 15 for upward reserve. The ideal curve corresponds to the perfect correspondence between reference LOLP (or PWRE) and the number of situation with loss of load/generation surplus.

Looking at Fig. 15 it is possible to see that if the SO defines a LOLP threshold of 1%, RMT would lead to an empirical LOLP of approximately 1% (during the five months there were 1.17% of hours with loss of load), while rule D would lead to an empirical LOLP of 0.19%. The results for different LOLP thresholds show that rule D has tendency to overestimate the risk which leads to a lower empirical LOLP. Despite the lower LOLP (less than 1%) that results from rule D, this leads to a higher amount of reserve (and consequently to higher reserve cost) when compared with the reserve suggested by RMT.

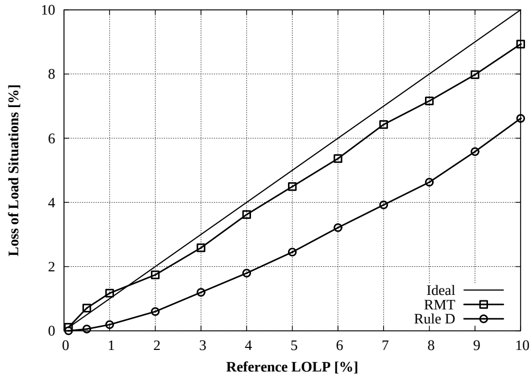

Fig. 15. Loss of load situations against reference LOLP.

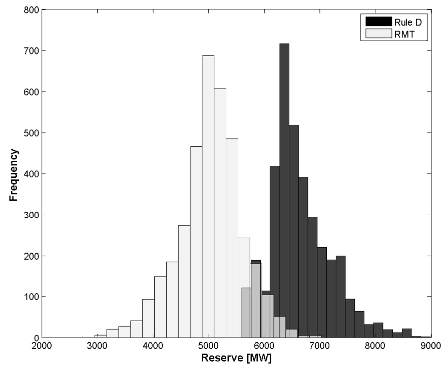

Fig. 16. Histogram with two distributions (in transparent black and grey) of the reserve suggested for a reference LOLP of 0.1%.

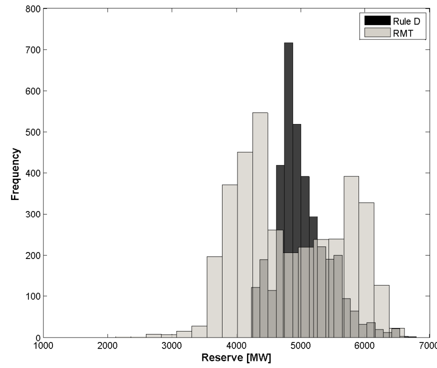

Fig. 18. Histogram with two distributions (in transparent black and grey) of the reserve suggested for a reference PWRE of 1%.

For instance, Fig. 16 depicts the reserve distribution for each hour of the five months obtained considering a reference LOLP of 0.1%. The RMT achieved an empirical LOLP of 0.11% with the reserve distribution depicted in grey, while rule D obtained an empirical LOLP of 0.0% with the reserve distribution depicted in black. Therefore, rule D leads to a situation where there are no loss of load events, but the reserve cost is much higher.

RMT gives a high psychological comfort, since it allows the operator to know how much risk he is taking. Note that this LOLP value is the same recommended by UCTE (99.9 %) and for this value the RMT gives a perfect correspondence.

Fig. 17 depicts match between the defined PWRE threshold and the empirical PWRE. Note that in this case rule D leads to an underestimation of the risk and therefore to an empirical PWRE greater than the threshold. RMT presents good results, in particular for a PWRE below 1%.

By analyzing Fig. 17 we can speculate that, for instance with a PWRE equal to 1%, rule D leads to higher risk (1.5%) but lower reserve cost. However, in Fig. 18 the reserve distribution of both RMT and rule D shows that rule D suggests more reserve in total, 18435.48 GW against 17718.43 GW of RMT, and 5 GW against 4.82 GW on average. This result gives a hint for evaluation of suggested reserve levels: calibration is an important requirement, but the amount of reserve suggested for situations without loss of load is also an important criterion for evaluation.

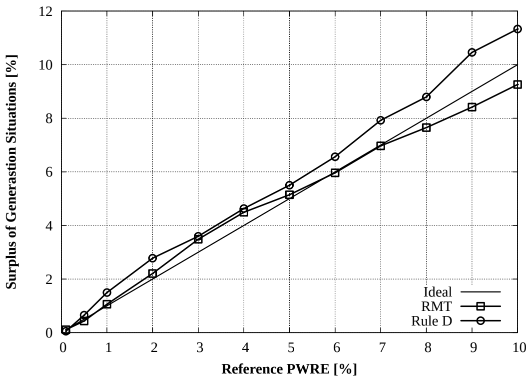

Fig. 17. Surplus of generation situations against reference PWRE.

Finally, the deviations from the ideal of the RMT show the limitation of probabilistic methods, which is its dependency from the quality (e.g. calibration, sharpness) of probabilistic forecasts. Note that the probabilistic approach can represent properly the point forecast errors, however even the probabilistic forecast could have lower quality and this would lead to a unreliable estimation of the risk.

VI. Conclusions

This paper compares different methods and rules for defining the operating reserve requirements. The importance of wind power forecasting is emphasized, in particular the usefulness and limitation of probabilistic forecasts. The results support the idea that it is important to improve uncertainty estimation and also to assess the value of the different probabilistic forecasts. Moreover, heuristic or empirical rules can lead to operational conditions with a higher risk for power system with high penetration of wind power.

The first steps for creating an evaluation framework for the quality of reserve requirements are established. Until know, there was no concerns in evaluating the reserve suggested by empirical rules and probabilistic approaches. However, with the increasing penetration of wind power in the power systems and the use of wind power forecast, it becomes crucial to evaluate the decisions made with this information. Furthermore, probabilistic forecasts also have imperfect information, and a good calibration is not sufficient because the amount of reserve suggested in hours without loss of load is also essential.

A methodology like the Reserve Management Tool can be used to assess the value of probabilistic forecasts defined by Murphy in [25]: "…if the forecast, when employed by one or more users as an input into their decision-making processes, results in incremental economic and/or other benefits".

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VIII. Biographies

Ricardo Bessa received his Licenciado (five years) degree from the Faculty of Engineering of the University of Porto, Portugal (FEUP) in 2006 in Electrical and Computer Engineering. In 2008 he received his Master degree in Data Analysis and Decision Support Systems on the Faculty of Economy of the University of Porto (FEP). Currently, he is a researcher at INESC Porto in its Power Systems Unit and a PhD student of the Doctoral program in Sustainable Energy Systems (MIT Portugal) at FEUP. His research interests include wind power forecasting, data mining, decision-aid methods and electric vehicles.

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