Operating Reserve Adequacy Evaluation using Uncertainties of Wind Power Forecast

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Abstract--**The integration of large shares of wind generation in power systems requires the development of new algorithms and forecasting tools for making decisions in the operational domain taking into account wind generation forecast uncertainties. One of these decisions regards operating reserve requirements to meet load and wind variations. The aim of this paper is therefore to address this issue from a risk evaluation perspective, showing that it is possible to describe the consequences of each possible reserve level through a set of risk indices useful for decision-making. The new reserve management tool described in this paper is intended to support the Transmission System Operator (TSO) in defining on-line the operating reserve needs for the daily and intraday markets. Decision strategies like setting an acceptable risk level or finding a compromise between economic issues and the risk of loss of load are explored. A case-study based on the Portuguese power system demonstrates the usefulness and efficiency of the tool.**

Index Terms--**multicriteria decision, operating reserve, operating risk, uncertainty, wind power forecast.**

I. INTRODUCTION

THE benefit of accurate wind power forecasting to power systems management is being increasingly recognized. It becomes an important issue in defining the operation planning policies to be adopted by a TSO (Transmission System Operator), namely in accepting high wind penetration [1]. Currently, increasing the value of wind generation through the improvement of prediction systems' performance with new algorithms is one of the priorities in wind power forecasting.

However, even the best tools are unable to eliminate the uncertainty associated to each particular forecast. The combination of generation and consumption variability and high uncertainty of forecast can make it more difficult to fit wind generation into conventional procedures for power system operations, such as setting reserve levels or scheduling. Therefore, a correct management of the power system must take into account the uncertainties when making decisions.

The integration of large shares of wind generation requires an increase in the amount of reserves that are needed to balance generation and load according to the different time frames defined by UCTE [2]. Studies in [3] showed that large scale integration of wind generation does not create problems in terms of primary reserve levels. So, the analysis should only be considered in terms of the operating reserve management.

Generally, the methods employed by the TSO to define operating reserve requirements are deterministic, as can be seen in the survey presented in [4] about reserve categorization that reviews the criteria used across eight electrical systems. Sometimes, the UCTE rule [2] for defining reserves is used as a reference for deterministic criteria. The rule depends only on the size of the typical load variations and is insensitive to the level of wind power of the system.

The variability of wind generation tends to increase, becoming a source of stress for the operations personnel. This leads to a highly conservative attitude and an adoption of high safety margins to minimize the risk, and consequently increases the operational costs. The main limitation of deterministic approaches is that they are incapable of assessing the risk and so they treat all operation scenarios as having the same risk. In a market environment, where the reserve cost will be part of the tariff paid by all customers, a trade-off between cost and risk should be considered instead of avoiding risk at almost any cost. On the other hand, since deterministic approaches do not in fact measure the risk, it may happens that, in some circumstances, complex risky situations are not covered. Therefore an approach based on deterministic criteria may lead, either to higher operational cost, or to excessive risk.

Recent research in the field for operating reserve requirements includes in the models the uncertainty of wind power forecast. *Strbac et al* [5] calculate the square root of the sum of the square of the standard deviations of hourly wind power forecast errors with the square of the standard deviations of load forecast errors. The reserve is defined to cover all variations contained within 3σ of the total system forecasting error, which means that 99.74% of variations are covered. The same approach is used by *Holttinen* [6], where the main goal was to estimate the increase in hourly load-following reserve requirements based on wind power generation and hourly load data in the four Nordic countries. *Doherty et al* [7] present a methodology that relates the reserve level on the system in each hour to a specified reliability level of the system over the year. The reliability criterion is defined as being the number of load shedding incidents tolerated per year. Load and wind forecast errors are incorporated in the model as Gaussian errors.

These approaches represent the wind uncertainty through a

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Gaussian distribution. However, wind forecast error is well known to have a non-Gaussian distribution [8]. An alternative approach is not assuming any distribution for the uncertainty. *Pahlow et al* [9] studied the impact in load curtailment and reserve cost of several criteria based on the use of ensembles that provide a set of forecasts which cover the range of possible uncertainty.

Nevertheless, most methods compute reserve requirements based on a prior setting of a reference risk level. As stated above, a trade-off between cost and risk should be considered. *Leite da Silva et al* [10] describe a methodology for evaluate the operating reserve requirements in a deregulated electrical market. They use system interruption costs, represented by LOLC (loss of load cost), and the reserve bid prices to balance risk and cost. *Wang et al* [11] compute the optimal reserve capacity in the operating reserve market by minimizing the social cost, defined as the sum of the reserve cost with the expected cost of interruptions, represented by the Interrupted Energy Assessment Rates (IEAR). *Ortega-Vazquez et al* [12] balance the spinning reserve cost and benefit in an electrical market with unit commitment. The benefit is a function of the reduction in the expected energy not supplied (EENS), and converted into socioeconomic cost by using the VOLL (Value of lost load).

This paper presents a new reserve management tool (RMT) intended to support the TSO in defining on-line the reserve needs for the daily and intraday markets. Based on wind and load forecast uncertainty, reliability risk indices are calculated that give information to the TSO about the consequences of setting each possible reserve level. After interaction with the TSO, the RMT outputs the reserve levels to set for the next day (or current day) that either: 1) lead to an acceptable risk level at minimum cost; 2) respect a trade-off between risk and reserve cost.

The structure of this paper is as follows: Section II presents the problem and the general methodology. In Section III, the details of the probabilistic model that computes the system margin distribution are described. Decision-making issues are discussed in section IV. The management tool is demonstrated by a case-study in Section V. Section VI presents the conclusions.

II. General Methodology

The RMT addresses the problem of defining the operating reserve needs in a deregulated electrical market environment where the TSO may acquire all of the reserve needed for the control area, in order to maintain a minimum reliability level. However, the methodology can be applied to other balancing mechanisms without difficulty.

A. Operation

In the daily market the TSO at day D is in charge of defining the reserve needs for the next day (day D+1) after the technical constraints management that leads to a viable program. The TSO at time instant t_m determines and publishes the reserve needs for each look-ahead time of day D+1, the time gap k_m between the beginning of day D+1 and the decision instant being equal to 24-t_m. These reserve amounts should then be split into secondary and tertiary reserves according to TSO operating rules (problem not addressed in this paper).

The relevant inputs are the following variables: total load and wind forecast uncertainty made at time instant t_0 for each look-ahead time of day D+1, (k_0 is the time gap between the beginning of day D+1 and the forecast instant, 24-t_0); scheduled generation by technology decided by the market mechanisms (viable program) at time instant t_m for each look-ahead time of day D+1; failures rates of the conventional generation; interconnection power levels resulting from the market.

Also in each intra-daily market (IDM) session the TSO has to define the reserve needs for the next day or for the remaining hours of the current day. The same framework is used, the input data being “refreshed” with the new forecasts and with the scheduled generation decided by the intra-daily market.

B. Methodology

The approach computes first the probability distribution of the system total generation (G), for each look-ahead time, by integrating the conventional generation unavailability distribution and wind generation forecast uncertainty. Then, the system margin probability distribution (M), defined as the difference between total generation and load (L), is computed, taking into account the load forecast uncertainty. For a specific level of operating reserve R, the distribution of M+R describes the probability of the reserve being (un)sufficient to cover the deficit of generation.

In the second step of the methodology, the decision problem is formulated in a way suitable to incorporate the preferences of the Decision Maker (in this case the TSO), and the final level of reserve is decided. Fig.1 shows the complete structure of the tool.

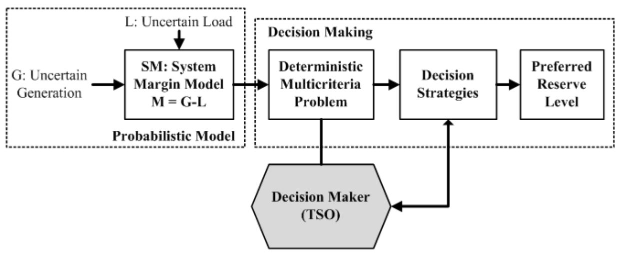

Fig. 1. Reserve Management Tool Structure

Risk indices related with the amount of loss of load are derived from the system margin probability distribution, for a specific level of reserve (with its inherent cost). The aim here would be to minimize simultaneously risk and cost, which is impossible due to the conflict between the two minimizations. So, the decision strategies model helps the decision maker (DM) to find a preferred solution based on his preferences.

The output of the decision strategies model is the reserve level to be set for each hour of the time horizon.

III. Probabilistic Model

A. Representation of Uncertainties

a) Conventional Generation

The probability mass function (*pmf)* of the conventional generation is analogous to the discrete probability distribution of the possible capacity states, better known as the capacity outage probability table (COPT) [13][14]. Note that, because the subject is operating reserve, the outage replacement rate (ORR) is used instead of the forced outage rate (FOR) [13].

The method used in this paper to build the COPT is similar to the one described in [15], that it is based on the FFT (Fast Fourier Transform) algorithm [16]. This method is computationally and mathematically attractive, since the computational time grows linearly with the number of machines in the system and can also accurately compute the COPT for systems with small ORR (which is the case, as probabilities of failure during the lead time are very low).

The approach followed for the conventional generation consists in build a COPT based on the conventional dispatch that results from the market (viable program).

b) Wind Generation

Two sources of uncertainty in wind power are taken into account by the model, one coming from the forecast error and the other from possible wind turbines outages.

The first source of uncertainty is related with the impossibility of producing perfect wind power forecast. Research work has been developed to estimate uncertainties in wind power forecast. As a result from the ANEMOS project (http://anemos.cma.fr/), different methods to estimate the uncertainty of deterministic (or point) forecasts were developed in ANEMOS [17].

The uncertainty of the deterministic forecast can be approached by different representations. The most common representation is a non-parametric probabilistic forecast [8] represented by quantiles, intervals or probability density functions. The other two representations take the form of risk indices [8] linked with the forecasts, and scenarios [18] incorporating temporal or spatial interdependence structure of prediction errors. In this paper we used a non-parametric probabilistic forecast, with the form of a set of quantiles.

The second source of uncertainty is related with the possible outages of the wind turbines and could be addressed the same way we did for conventional generation. However, since we are dealing with a large number of similar wind turbines (identical failure rate λ and size) a simpler model can be used. For instance, for a system with 2000 similar wind turbines, a failure rate of 10 failures/year, and a lead time of 24 hours, the mean power (β) is 97.26% of the rated power, the coefficient of variation (σ/β) is 0.38%, so the probability of having at least 96% of the rated power is 99.995% (β-4σ). Therefore, an adjustment in the forecasted values using the mean value of the COPT (0.9726 in this case) is sufficient to capture this kind of uncertainty.

c) Load

Generally, load uncertainty is modeled through a Gaussian distribution with a given standard deviation and zero mean [13]. The load forecast uncertainty represented by a Gaussian distribution is approximated by a set of quantiles (intervals with equal probability).

So in order to set the parameter σ, it is possible to establish a relation between the value of the MAPE (mean absolute percentage error) and σ, assuming Gaussian distribution of the forecast errors. The following holds under Gaussian errors:

$$P(|e| < MAPE) = 0.5 \quad \Leftrightarrow P(e > MAPE) = 0.25 \qquad (1)$$

then the relation between the two is MAPE=0.67449σ.

Note that no changes are necessary in the methodology if the forecast uncertainty is a non-parametric representation (e.g. set of quantiles).

B. System Margin Model

The generation margin is the amount that the available generating capacity exceeds the system load, *Margin = Available Generation-Load*. Since the margin is a function of system load and generation, it is also a random variable In order to compute the system margin distribution (M), we take as input the probability distributions of wind power generation (W), of load (L) and of conventional generation (C).

The first step is to compute the *pmf* of the sum of wind and conventional generation (G=W+C) for each look-ahead time step. Assuming independence, the sum can be computed by applying the convolution definition [19]:

$$P_G(W + C = z) = \sum_{k=-\infty}^{\infty} P_W(W = z - k) \cdot P_C(C = k) \qquad (2)$$

However, a more efficient way to compute the convolution is in the frequency domain with the FFT method adapted from the one described in [20].

Finally, the system margin is the difference between the generation (G) and the load (L), which requires also a convolution, assuming independence:

$$P_M(G - L = z) = \sum_{k=-\infty}^{\infty} P_G(G = z + k) \cdot P_L(L = k) \qquad (3)$$

It is important to stress that the dependence between the load and wind generation uncertainties in one hour is negligible. Note that we are talking about independence between the uncertainties (or prediction of them) of generation and load in a specific hour, not between wind generation and load as a function of time. Therefore the hypothesis of independence is acceptable.

The system margin distribution is a discrete probability distribution for each look-ahead time, represented by its *pmf*, as depicted in Fig. 2. Note that the mean value of this initial margin tends to be close to zero, since it resulted from a balancing exercise (C=L-W).

Now, after setting a value for the operating reserve, the translation of the margin distribution (M+R) can be used to calculate the probability of losing load and other risk indices. Fig. 3 shows the effect of setting a reserve level of 700 MW in the same situation of Fig. 2.

At this point, different risk related attributes meaningful for the DM can be computed. Following the approach described in

[21], the idea is to replace the system margin distribution by a set of risk attributes, resulting from different concerns, in order to give information to the DM about the impact of a potential reserve level.

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 energy not supplied (EENS) [13]. For instance, LOLP=0.49 and EENS=157.1 MWh in the situation depicted in Fig. 2, but the effect of the reserve considered in Fig. 3 (700 MW) is reducing EENS to only 5.38 MWh

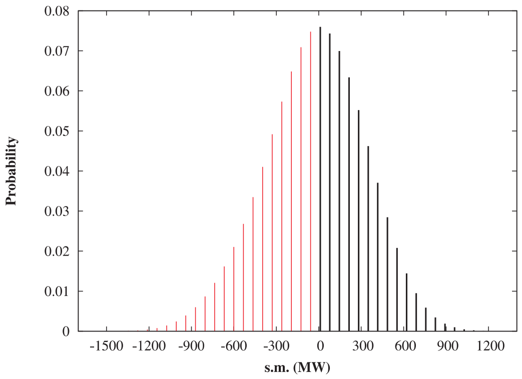

Fig. 2. pmf of the system margin for a specific look-ahead time

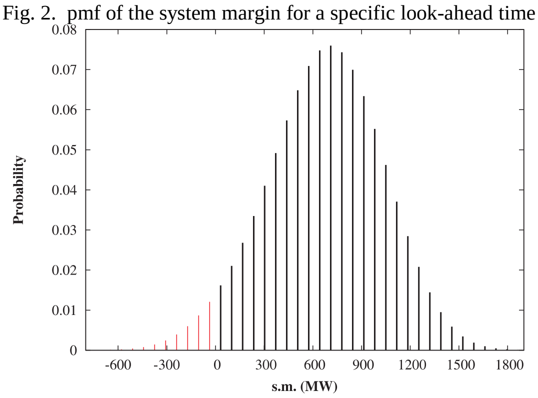

Fig. 3. pmf of the system margin for a operating reserve of 700 MW

If we take the cumulative distribution of the negative margin, a direct reading of some risk attributes (LOLP, LOLE) is possible. More elaborated indices (EENS) just require some statistical manipulation. An example of this kind of risk/reserve curve is depicted in the top of Fig. 4

Finally, note that other measures of risk, such as the conditional expected value of loss of load (XLOL), reserve-at-risk or conditional reserve-at-risk [22] could be computed.

C. *Reserve Cost*

The cost of buying reserve in the market can be assessed by a curve representing the reserve bids offered by the market agents for selling up and down regulation reserve. The bids for selling regulation are paid at the bid price or by the marginal price [23]. A typical curve of the reserve cost can be seen in the bottom of Fig. 4.

IV. Decision-making Issues

The preceding analyses and results are not sufficient to set the level of operating reserve, so a decision-making phase is needed where the DM introduces his preferences and makes the final decision. The preferred solution can be different for different DM, because each one has different preferences and values differently risk and cost, based on his global perception and judgments. The participation of DM during this process is absolute imperative.

A. *Setting a Threshold*

The simplest approach consists in comparing the risk measure of a potential reserve level with a prespecified reference threshold. If the proposed reserve level leads to an unacceptable risk then the reserved level is increased until the risk value is lower than the threshold. This reference risk should be maintained through each hour of the scheduling horizon, therefore the reserve is adjusted in each hour to maintain a uniform risk level.

For instance, in Fig. 4, a $EENS_{ref}$ equal to 5 MWh would require a reserve level of at least 625 MW. The reserve cost would be 1812.5€.

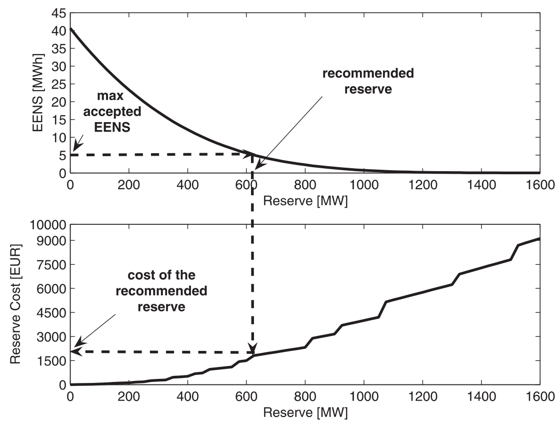

Fig. 4. Reserve that corresponds to the reference 5 MWh of EENS for a specific look-ahead time

Note that this approach does not take into account the reserve cost, and this may request expensive additional generation to maintain the risk below the threshold.

B. *Multicriteria Approach*

If, instead of just setting a threshold, the DM wants to balance risk and reserve cost, a multicriteria problem results. The risk indices to use must be meaningful for the DM, and more than one risk attribute can be used at the same time. The alternatives of the multicriteria problem are defined by the reserve level.

a) Equivalent Cost Approach

The equivalent cost function uses a constant trade-off between reserve cost and an associated risk measure (e.g. EENS). The trade-off μ is the rate at which the DM is ready to give up ΔC units of one criterion in exchange for gaining ΔE units in the other criterion, while remaining indifferent between the two solutions. For example, if the two criteria are EENS and cost, the trade-off can be interpreted as how much the DM is willing to pay to decrease the EENS, and would be expressed in €/MWh.

In this approach, we just need to find the reserve level r that minimizes the equivalent cost $Eq.Cost(r) = Cost(r) + \mu \times Risk(r)$.

b) Value Function Approach

In order to capture more complex preference structures than the ones behind a constant trade-off, nonlinear value functions can be used. We will restrict the approach to additive value functions [24], but more complex functions could be used.

The approach consists in building an individual normalized value function for each criterion, and then assessing weights to build the multi-attribute value function whose maximization leads to the preferred reserve level r. Note that, if the individual value functions are all linear, the problem reduces to the one discussed in the previous section.

So, a possible multi-attribute value function for this problem would be:

$$v_{Cost,EENS}(r) = k_{Cost} \cdot v_{Cost}(Cost(r)) + k_{EENS} \cdot v_{EENS}(EENS(r)) \quad (4)$$

where and v_{Cost} and v_{EENS} are the individual values functions for the two criteria and k_{Risk} and k_{Cost} are parameters, usually know as weights (k_{Cost}+k_{EENS} =1).

The shape of the individual value functions reflects the way the DM values the variation of the corresponding attribute. The individual value function of the cost is usually linear, because the increase in DM satisfaction is independent of the attribute level. On the other hand, we may see different attitudes regarding EENS: (i) Some DM are very favorable to the decrease of the EENS when its level is high, but not so favorable when the EENS level is already acceptable or low; (ii) Other DM, on the contrary, would intensify their willingness to pay for reducing risk when approaching the best (lower) levels of EENS. Neither of these attitudes can be classified as correct or incorrect – they simply correspond to different managing styles and external constraints.

So, in order to capture the DM attitude regarding risk (in this case through EENS), an exponential value function is proposed, due to its flexibility:

$$v_{EENS}(EENS(r)) = \frac{e^{b \cdot \frac{EENS^{\max} - EENS(r)}{EENS^{\max} - EENS^{\min}}} - 1}{e^{b} - 1} \quad (5)$$

In fact, by changing parameter b it is possible to change the underlying preference structure. For negative values of b the value function models the attitude (i) described earlier, while positive values of b correspond to attitude (ii).

The last step consists of determining the weights k_{Cost} and k_{EENS}. It must be stressed that these parameters shouldn't be asked explicitly to the DM as the relative importance of the criteria, since they also include scaling factors. When using predefined value functions, an iterative process is used where artificial solutions successively are presented to the DM until an indifferent is found. For instance, the indifference between solutions A and B leads to $v_{Cost,EENS}(A) = v_{Cost,EENS}(B)$ that, in conjunction with $k_{Cost}+k_{EENS}=1$ turns it possible to compute the weights.

V. Case-Study

A. Description

The case-study used to demonstrate the methodology is a single bus model based on the Portuguese power system. The total installed capacity of conventional generation is 10395.8 MW. Presently the system has 2742 MW of wind power capacity.

The forecasted load curve for the 24 hours period of a weekday is shown in Fig. 5, where the peak load is 7600 MW at 20:00. The load forecast uncertainty is modeled through a Gaussian distribution with standard deviation computed from a MAPE of 2%.

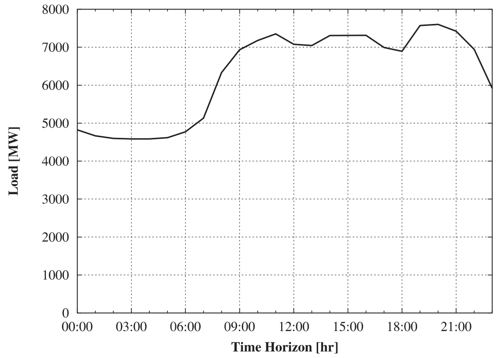

Fig. 5. Forecasted load for a 24 hours period

Global system wind power forecasts and uncertainty are similar to the ones produced by the ANEMOS platform. For this case-study the uncertainty was estimated with a local quantile regression [25] using as input the point forecast of a single wind farm rescaled for the total system capacity (2742 MW).

For testing purposes, a day with a representative pattern of the wind generation behavior in Portugal (more wind during the night than in the day), was chosen. In Fig. 6 and 7 a forecasted distribution for each hour, represented by 21 percentiles, is depicted for scenarios with high wind generation (scenario H) and low wind generation (scenario L).

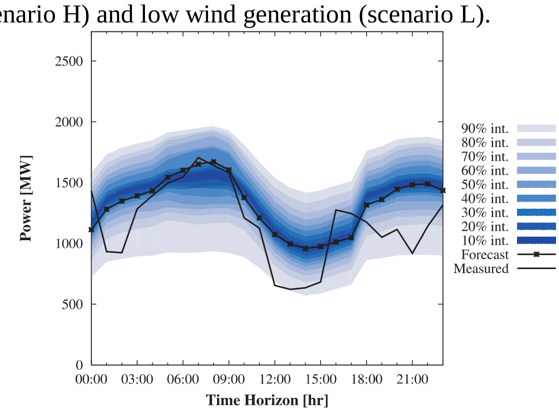

Fig. 6. Point forecast and a set of interval forecasts for scenario H

Since in Portugal wind energy doesn't go to the market (Iberian Market MIBEL), the market load (conventional generation) is the difference between the point forecast of the wind generation and the load forecast. The system has 119 units of conventional generation.

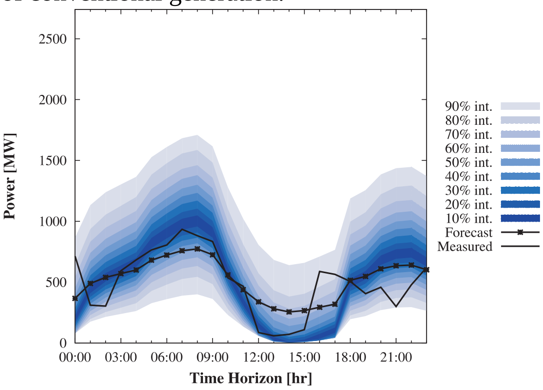

Fig. 7. Point forecast and a set of interval forecasts for scenario L

In this test, the reserve needs are estimated by the TSO for the next day in the daily market session of the MIBEL market.

We will now apply the methodology to this case study. However, for comparison, the following rules will be also used:

Rule A) Secondary reserve given by the UCTE rule plus the loss of the largest on-line generating unit [2].

Rule B) The rule presently used in Spain to compute the reserve needs for the next day [4].

Rule C) The rule described in [5] including the standard deviation of the COPT. The standard deviation of the wind generation was computed directly from the forecasted uncertainty.

B. Using a risk threshold

We first simulate a situation where a threshold for the LOLE was previously set by the DM. In this case, the reserve level can be obtained directly from the risk/reserve curve. In Fig. 8 a comparison is depicted between the reserve needs obtained using the RMT and rule C for scenario H. The contribution of combined conventional generation and load uncertainty for the reserve needs is identified (with wind generation deterministic forecasts). The threshold for the LOLE was 1 min/hour (which corresponds to 2.13σ, in rule C), defined by the DM. For the same threshold level, in Fig. 9, a comparison is depicted between the RMT and rules A, B and C.

The shape of the reserve needs curve obtained with the load and conventional generation uncertainty is similar to the load shape. As expected, the integration of the wind generation uncertainty in the model leads to an increase in the reserve requirements. With this additional uncertainty the shape of the reserve needs curve becomes similar to the wind generation daily pattern. For situations where more wind generation exists in the system additional reserve is needed, for the opposite, less reserve is required.

The reserve needs obtained with rule A have almost the same value all day, the only variation being due to the capacity of the largest on-line unit. On the other hand, Rule B seems to ask for additional reserve in order to deal with the wind generation variability. Applying rules A and B does not provide the TSO information about the risk he is taking.

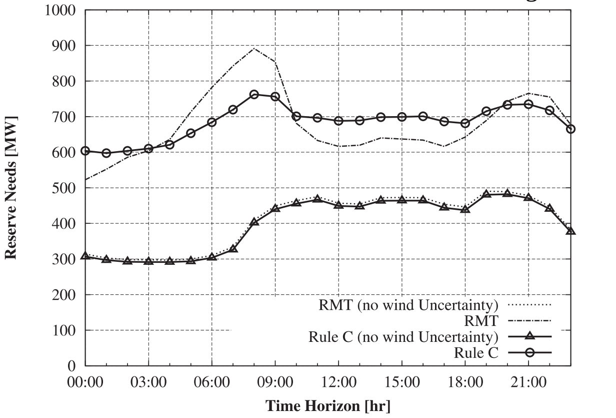

Fig. 8. Reserve needs with and without wind generation uncertainty using the RMT and rule C

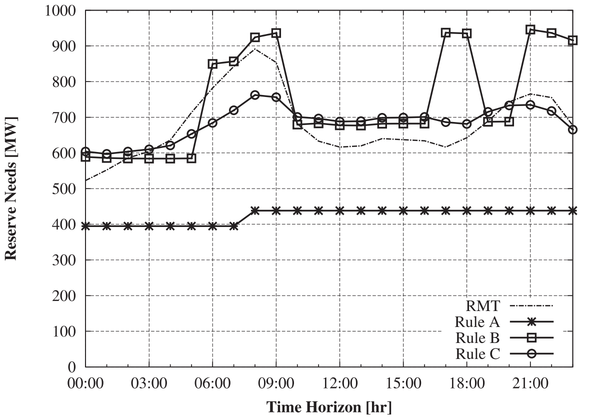

Fig. 9. Reserve needs obtained using RMT and rules A, B, C

Rule C allows the definition of the acceptable level of risk. The reserve needs without wind uncertainty are almost equal to the ones obtained with the RMT. The difference becomes significant when the wind uncertainty is added; in this case, the results differ significantly. This is due to the Gaussian assumption for wind uncertainty incorporated in rule C, which is not confirmed.

In order to analyze the quality of each suggested reserve level a Monte Carlo simulation was performed for hour 8:00. The quality criterion is the number of loss of load occurrences in a simulation with 20000 random samples taken from the distributions of each variable. The results are presented in Table I.

TABLE I
RESULTS OF THE MONTE CARLO SIMULATION FOR HOUR 8:00

	Loss of load occurrences (%)	min/hour
RMT	1.37	0.82
Rule A	19.21	11.52
Rule B	1.07	0.64
Rule C	6.60	3.96

The result obtained with the RMT is consistent with the risk threshold defined. Rule C presents a LOLE value higher than the max accepted level. The assumption of a Gaussian distribution for wind uncertainty is not adequate, since it leads to a higher risk value. This happens because the skewness of error distribution is generally positive [8] and therefore the density of the distribution is concentrated on the over-prediction part. If the DM is comfortable with a risk of 1 min/hour, then rule B leads to an excessive reserve and rule A leads to an excessive risk since it is only related with the load.

The impact of the wind generation uncertainty is also assessed by comparing the reserve needs for scenarios H and L; depicted in Fig. 10 for a threshold of 1 min/hour.

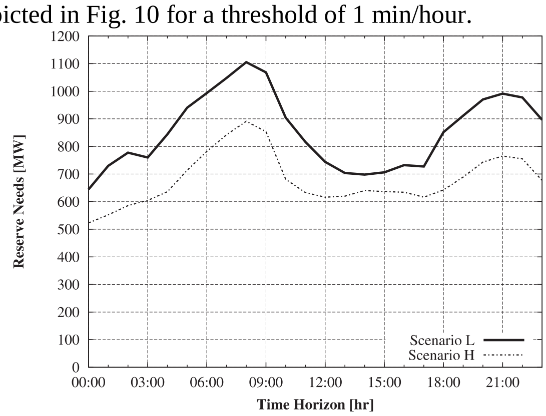

Fig. 10. Reserve needs of scenario H and L

As shown in Fig. 10, although wind generation in scenario L is lower than scenario H, the reserve needs for scenario L are higher when compared with the ones obtained for H. This is due to the higher forecasted uncertainty of the scenario L, since the inter-quantile range of scenario L is higher. Thus, the wind power level has impact on the reserve needs, but the main contribution comes from the amount of wind generation uncertainty in each hour.

C. Risk/Cost Based Decisions

For simplicity, and without loss of generalization, only look-ahead time 8:00 of scenario H is analyzed in this section.

Each equivalent cost function value defines a family of linear indifference curves, set of alternatives that are valued in the same way by the decision maker, which describes the preference structure of the DM and their slope is the reference trade-off value.

Fig. 11 shows these indifference curves and the candidate solutions curve for a reference trade-off of 50 €/MWh. Each curve connects all points that are indifferent for the DM, since they have the same equivalent cost. The equivalent cost of the indifference curves decreases as they are close to the zone with minimum cost and risk.

The preferred solution is the one in the indifference curve that has an equivalent cost of 5084.8€ and corresponds to a reserve of 512 MW, EENS=27.2 MWh and cost=3724€. Now, a different DM, more concerned with the level of EENS, sets a greater trade-off of 150 €/MWh, leading to the indifference curves depicted in Fig.12. Therefore, the preferred solution will be different: more reserve (730 MW); less risk (EENS=6.7 MWh) and higher cost (5352€).

When comparing Fig. 11 and 12, we see that the slope of the indifference curve changes according to the preferences of the DM, moving the preferred solution along the risk/cost curve.

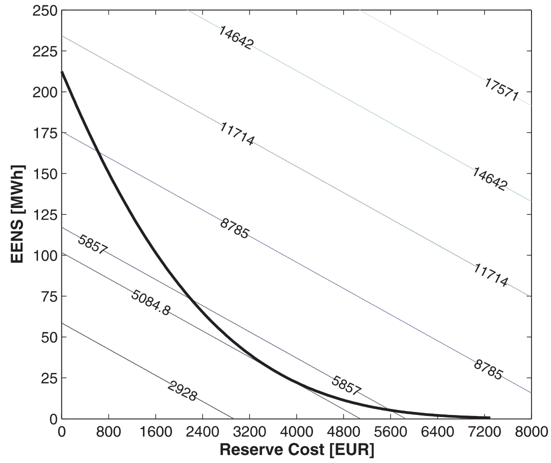

Fig. 11. Indifference curves of the constant tradeoffs (μ=50 €/MWh)

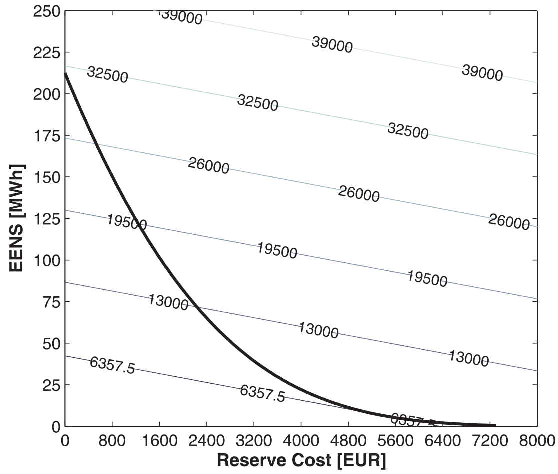

Fig. 12. Indifference curves of the constant tradeoffs (μ=150 €/MWh)

For more complex preference attitudes, a nonlinear value function can be used. For a DM indifferent between (5000,60)~(5500,50) and accepting an exponential function with b=-4 (see eq.5) for the EENS valuation, the (nonlinear) indifference curves depicted in Fig. 13.

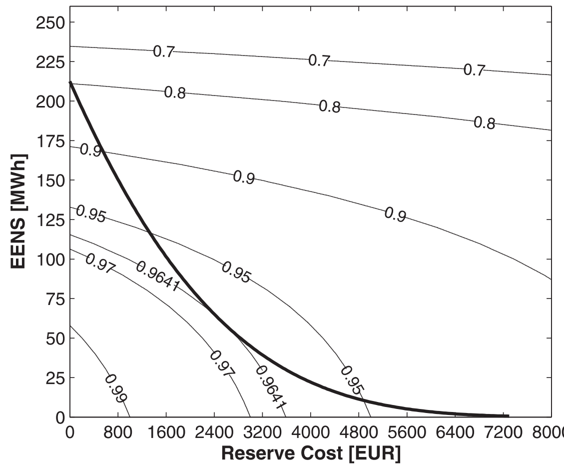

Fig. 13. Indifference curves of the exponential function with b=-4

Since the trade-off is not constant, in the area of high EENS, a small decrease in EENS offsets a large increase in reserve cost (the indifference curves are little sloped), because the decision maker is prepared to pay the necessary to avoid high values of EENS. By contrast, in the low EENS, a big decrease in EENS offsets a small increase in reserve cost, since the values of EENS are tolerable by the decision maker, he will just pay something if a large decrease of EENS happens. In summary, the trade-off in the first area of the curve is very high, and in the second is very low. Of course, intermediate values of EENS conduct to intermediate values of the trade-off.

The preferred solution in the indifference curve with value 0.9641 and corresponds to a reserve of 340 MW, EENS of 62.3 MWh and cost of 2474€.

VI. Conclusions

This paper describes a methodology developed to support TSO in defining on-line the operating reserve needs, taking into account conventional generation outages, load forecast uncertainty and wind forecast uncertainty.

The tool is oriented for a deregulated energy market. However, the methodology can easily be adapted to other reserve definition mechanisms or can be combined with a unit commitment procedure.

The methodology avoids making assumptions on the wind forecast distribution. The illustrative example shows the correctness of this approach and the difficulties in applying rigid decision rules or Gaussian assumptions, when compared with calculating on-line the risk associated to a specific reserve level.

Besides the risk/reserve curve computation, the reserves management tool addresses the decision making issues, namely when cost and risk must be included simultaneously in the decision process. The methodology is able to model different attitudes and values of the DM, as illustrated in the case study, in order to support a rational decision process.

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VIII. Biographies

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