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3 AUTHORS, INCLUDING:

Claudia Rahmann

University of Chile

R.A. Torres

University of Chile

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Quantifying operating reserves with wind power: towards probabilistic–dynamic approaches

Claudia Rahmann[1] ✉, *Antonia Heinemann*[2], *Rigoberto Torres*[1]

[1]*Department of Electrical Engineering, University of Chile, Avenue Tupper 2007, Santiago, Chile*
[2]*Institute of Power Systems and Power Economics (IAEW), RWTH-Aachen University, Schinkelstraße 6, Aachen, Germany*
✉ *E-mail: crahmann@ing.uchile.cl*

Abstract: In this study, the economic benefits of using a probabilistic-dynamic approach (PDA) in the quantification of operating reserves are investigated and compared with more traditional quantification rules in power systems with high penetration levels of wind power. To do this, a comprehensive methodology to quantify different operating reserves categories within the real-time system operation is proposed. The quantification is based on an iterative process where the total costs of the system are minimised, that is the sum of the operating costs (including the additional costs of partially loading generating units due to operating reserves) and the costs of the expected energy not supplied. The PDA considers conventional generation outages; load and wind forecast uncertainty on an hourly basis as well as load and wind variability in a 10 min time frame. The authors use the Chilean power system to demonstrate the efficiency and advantages of the proposed reserve quantification approach.

1 Introduction

The international experience during the last years has shown that an increased use of wind energy leads to various challenges in power system operation. This is especially true when defining operation policies to be adopted by transmission system operators (TSOs) in which wind's variability and uncertainty are properly taken into account. In this context, different methodologies to quantify the additional operating reserves due to increased use of wind power have been presented during the last years [1–12].

Statistical methods based on the use of the standard deviation (σ) like the n-sigma criterion are one of the most widely used to quantify the effects of wind generation on operating reserves due to its simplicity. Nevertheless, power systems on which this criterion has been applied are usually assumed to have a wind power capacity installed throughout a relatively wide area with different wind flow regimes. Consequently, the variability of the total wind power injections is smoothed, even more with increasing number of wind turbines (WTs) installed at different locations [13–16]. Under these circumstances, the central limit theory is usually used to justify Gaussian distribution of both wind power variability [2–4] and wind forecast error (WFE) [2–4, 6, 11, 17, 18]. However, wind variability and forecast errors do not necessary follow a Gaussian distribution [1, 4, 6, 7, 11, 15]. On the other hand, the n-sigma criterion quantifies the additional operating reserves due to wind power by considering a reference confidence level (CL) defined a priori. However, no consensus is found about the optimal value of the CL to use in each case. For instance, regarding the load following reserves, it should be 2σ as in [19], 3σ as used in [17] or maybe 4σ as proposed in [2]. In principle, this factor should be different for each particular power system and type of operating reserve. Indeed, the optimal CL to use should be determined based on a cost–benefit analysis in which the operational costs of the system and some reliability criterion are properly taken into account.

In this paper, a probabilistic methodology to quantify different kinds of operating reserves in the presence of wind power is proposed. The methodology quantifies the operating reserves within the real-time system operation considering a day-ahead unit commitment (UC) defined a priori. The quantification is based on an iterative process where the total costs of the system including the costs of the expected energy not supplied (E[ENS]) are minimised. The probabilistic–dynamic approach (PDA) considers conventional generation (CG) outages; load and wind forecast uncertainty on an hourly basis; and load and wind variability in a 10 min time frame. The proposed methodology is especially suitable for power systems with cost-based economic dispatch like those in most Latin American countries and cannot be directly applied in power systems with bid-based dispatch.

The remaining of this paper is organised as follows: Section 2 summarised the impacts of wind energy on different operating reserves categories. In Section 3 some methods to quantify additional operating reserves due to increased wind power generation are presented. The methodology to quantify operating reserves in presence of wind power is exposed in Section 4. The case study is presented in Section 5. The obtained results and conclusions are summarised in Sections 6 and 7, respectively.

2 Impacts of wind power on system reserves

Wind generation is a variable energy resource with changing availability level over the time (variability), which cannot be predicted with perfect accuracy (uncertainty) [20]. As wind power increases, the additional variability and uncertainty introduced in the system will cause an increase of operating reserves in the system [12, 21, 22].

Depending on the time scale, different impacts of wind power on operating reserve requirements can be expected [3]. As general rule it is widely accepted that primary power reserves – from a contingency event viewpoint – remains unaffected as wind power increases [4, 12, 19, 23–25]. This is because wind power plants do not change the largest single severe contingency (largest generation unit) if fault ride through capability is assumed [4, 25, 26]. Moreover, due to the spatial variations of wind from turbine to turbine in a wind farm, the sudden and simultaneous trip-off of all WTs due to a decrease of wind speed is not a credible event [26].

During normal operation, the impacts of wind generation on operating reserves are usually separated into two main categories: those impacts that arise because of the natural variability of the wind (short term, inside an hour), and those that are caused by the uncertainty of wind injections (forecasting error) [3].

2.1 Variability of wind power

'Variability' of wind power refers to the natural output fluctuation derived from the natural resource availability, even if the forecast is accurate [27]. The variability of wind power can be reduced due to the well-known smoothing effect [3, 13, 15, 16, 21, 26]. The smoothing effect becomes stronger the more WTs and wind power plants are connected to the grid and the wider their geographical distribution [13, 14]. Nevertheless, at some stage, the smoothing effect will saturate and adding more turbines or sites will not result in a variability attenuation [2, 3, 13].

The variability of wind power also decreases as the time scale in question decreases [13, 26]. For instance, in the time frame of primary reserves (very short term), wind power variability is strongly smoothed [14, 25, 26]. As a consequence, the effect of wind power on primary reserves can be neglected [25]. Indeed, various studies and practical experience have shown that the impacts of wind variability on operating reserves are mainly observable in the time range of 10–15 min, thus strongly affecting secondary power reserves [25, 26]. Variability in longer time scales than the dispatch period is captured by the dispatch, so reserves need to cover only the variability within the dispatch period.

2.2 Uncertainty of wind power

'Uncertainty' of wind power refers to the difference between a perfect forecast and the actual forecast [27]. Accuracy of wind power production forecasts depends on several factors such as the forecast horizon, the size of the wind power plants and their geographical distribution, experience with wind power generation and the accuracy of the forecasts for individual wind power plants [5]. Large-scale shut down of WTs due to storm events can lead to large forecast errors [4]. Wind power forecast errors increase as the forecast horizon gets longer [5, 8, 10, 22]. Large geographical spreading of wind power will also increase predictability [2, 3, 13, 15].

WFEs have a large impact on power system reserves in the time range of 1 h [27], that is in the time frame of tertiary power reserves.

3 Methods to determine additional operating reserves due to wind power

During the last years, different methods have been proposed to quantify additional operating reserves required by power systems due to increased wind power generation.

3.1 Statistical approaches

In statistical methods, historical data from wind generation and load is analysed to study its statistical properties [8]. A well-known example of statistical approach is the *n*-sigma criterion. The *n*-sigma criterion is based on a comparison of the load and net load time series, where the latter is defined as load minus wind power production [2, 8]. The probability distribution function (pdf) of the net load is used to quantify additional operating reserves due to wind power at different time scales. If load and wind power are assumed to be uncorrelated, the standard deviation of the net load time series will be [2–5, 9, 10, 18, 22]

$$\sigma_{\mathrm{NL}} = \sqrt{\sigma_{\mathrm{L}}^2 + \sigma_{\mathrm{W}}^2} \tag{1}$$

where σ_{L} and σ_{W} are the standard deviations of the load and wind power time series, respectively. The time series of load and wind power can represent either variability or forecast error depending on the type of reserve [4]. The additional operating reserves $\Delta\mathrm{Res}$ due to wind power integration are then quantified according to [3, 4]

$$\Delta\mathrm{Res} = n(\sigma_{\mathrm{NL}} - \sigma_{\mathrm{L}}) \tag{2}$$

Table 1 Summary of works using *n*-sigma criteria for different kind of operating reserves

Operating reserve	$n\sigma$-criteria used					
	2σ	2–3σ	3σ	4σ	5σ	4–6σ
load following reserves – tertiary reserves	[19, 24]	[3][a]	[17]	[2]		
regulation reserves – secondary reserves			[23, 24]		[19]	[3][a]

[a]Referring other works.

Equation (2) shows that the additional reserves are a multiple of the difference between the standard deviation of the net load and load. The multiple n is defined a priori and represents the CL used. Typically, a value of three is used (the so-called 3σ method) [3, 8, 17, 23, 24] meaning a CL of 99.7% when Gaussian distribution is assumed. Nevertheless, other values between 2σ and 7σ have also been proposed [2, 8, 9, 19, 20, 24] depending on the type of reserve. However, as seen in Table 1, no consensus regarding this factor has been established until now.

The *n*-sigma method has been usually applied based on a static approach. In this case, load and wind data are used to estimate a single pdf for each type of reserve under consideration. Thus, a constant reserve level regardless power system operating point is obtained for every hour of the planning horizon. Nevertheless, this criterion can also be used considering a dynamic approach where the reserve requirements are modified each hour of the day based on hourly pdf.

3.2 Probabilistic approaches

Another way to quantify operating reserves by integrating different sources of uncertainties is using reliability theory of power systems [28]. The basis of probabilistic approaches is the so-called system generation margin defined as the difference between the total available generation and load. This function represents the amount that the available generating capacity exceeds the system load [1, 7]. Since this function is a function of two random variables, it is also a random variable [1, 7]. In order to compute the system generation margin distribution (f^{Margin}), the probability distributions of CG, wind power generation (W) and load (L) must be taken into account ($M = \mathrm{CG} + W - L$) [1, 7, 11]. For a specific level of reserve R, the distribution of $M + R$ describes the probability that R is sufficient to cover the shortage of generation.

Classical reliability indices such as the loss of load probability, the loss of load expectation or the E[ENS] can be calculated based on this distribution f^{Margin} [1, 7, 11, 28]. Usually, the operating reserves are computed in order to meet a specific reliability target. The authors of [5, 10] present a probabilistic-based methodology in which generator outage rates, system load forecast errors and wind power forecast errors are taken into consideration in an hourly basis. The reserve levels in the power system are related to the maximum number of load shedding incidents tolerated per year. Nevertheless, the reliability target is set a priori without any kind of economic consideration.

The authors in [6] propose a methodology to calculate the optimal amount of spinning reserves (SRs) considering generation outages and the forecast errors of load and wind power generation. The methodology determines the amount of SR by minimising the total cost of operating the system, that is, the sum of the operating cost and the socioeconomic cost associated with load shedding events. Only the time frame within the tertiary regulation is considered in the study. In [9], the same authors present a comparison between the traditional $n-1$ criterion and two probabilistic approaches to estimate the optimal amount of SR requirements. Similar as in [6], the optimal amount of reserves is such that the marginal cost of providing SR matches the marginal benefit derived from the availability of SR. Liu and Tomsovic [18] propose an approach to

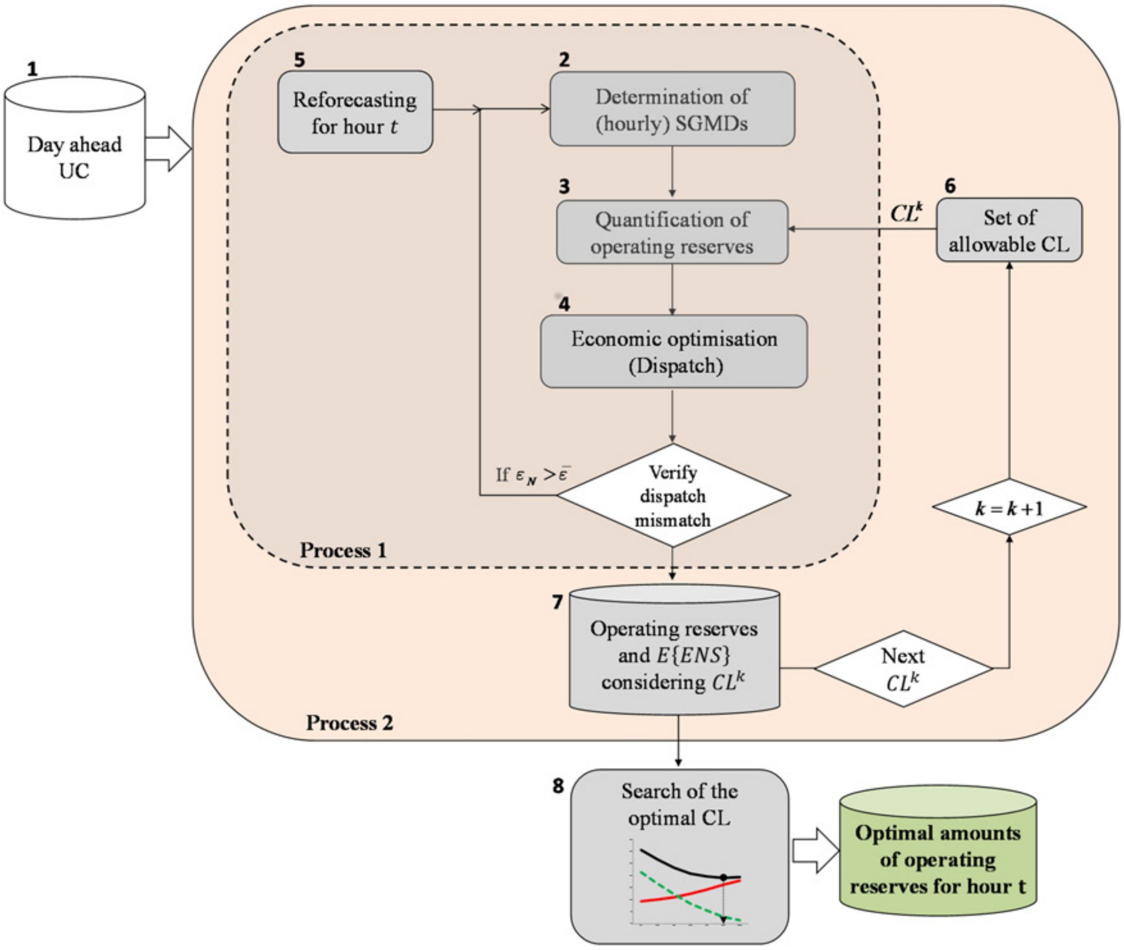

Fig. 1 *Methodology to quantify operating reserves in presence of wind power*

quantify additional SR required due to wind power generation. A security-constrained UC model, which minimises the cost of energy, SR and E[ENS] is proposed. The formulation takes into account the probability distributions of forecast errors for wind and load, as well as outage replacement rates of conventional generators. Two main disadvantages can be mentioned about the aforementioned works: (i) wind power forecast errors are assumed to follow a Gaussian distribution and (ii) SRs are considered in a general way without distinguishing among different reserve categories.

A work where Gaussian distribution is not assumed can be found in [7]. The authors address the problem of defining operating reserves in a market environment by presenting a reserve management tool (RMT). The system generation margin function is calculated through convolution of the probability distributions for generation outages and forecast errors for load and wind. Possible outages of wind power plants are also taken into account. In [11], the same authors present a comparison of probabilistic and deterministic approaches for setting operating reserves. The considered probabilistic approach is based on the already mentioned RMT of [7]. Nevertheless, in both works no details are given regarding the kind of operating reserves considered in the studies or the time scale involved.

None of the aforementioned studies carries out a comprehensive analysis including the different operating reserves categories involved. Indeed, the problem is usually addressed from an hourly basis without distinguishing intra hour time frames. However, distinguishing between different operating reserves in power systems is essential to determine the kind of resources needed to deploy in each case, especially in case of isolated power systems with poor frequency control capabilities and high penetration levels of wind power.

4 Proposed methodology PDA

The proposed methodology to quantify the amount of different kinds of operating reserves in presence of wind power is shown in Fig. 1. The algorithm calculates the operating reserves for the next hour within the real-time system operation based on an iterative process where the total costs of the system are minimised. The overall structure resembles the cost-based economic dispatch carried out in most Latin American countries including the traditional day-ahead UC and the real-time redispatch performed every hour of the day. Although the proposal has been conceived in an hourly basis, it can be easily adapted in accordance with the time resolution of the particular system.

The iterative process for hour t starts 1 h ahead of the real dispatch with the solution of the day-ahead UC for this hour (block '1' in Fig. 1). The UC is obtained assuming a fixed amount of operating reserves based on the operating experience of TSOs. Starting from this dispatch solution, the algorithm performs a 'fine tuning' of the amounts of (short-term) operating reserves by using fast starting generation units. We assume that the day-ahead UC process is solved in a proper manner regarding the schedule of slow-starting thermal units through a stochastic model. Although CG units and wind power can contribute to frequency regulation, we assume that only synchronous generators can provide operating reserves. Wind power injections and system demand are assumed to be re-forecasted every hour of the day (block '5' in Fig. 1).

On the basis of the initial dispatch solution obtained from the day-ahead UC, the system generation margin distributions (SGMDs) are determined for hour t (block '2' in Fig. 1). Using these SGMDs, each kind of operating reserves is quantified for a specific confidence level (CL^k). These reserve requirements are then used as input data to a modified economic dispatch program (block '4' in Fig. 1). If the dispatch of the generators obtained in this part differs from the dispatch initially considered in the calculation of the SGMDs, the process is carried out again but now considering the dispatch obtained from the modified economic dispatch. This iterative process runs until no major mismatches between both dispatches exist. The results of this stage ('Process 1' in Fig. 1) are the amount of operating reserves and the E[ENS] for hour t when considering a confidence level CL^k.

The process described above for hour t is performed for different values of CLs (block '6' in Fig. 1). The algorithm only considers a set of allowable CL defined a priori from a TSO perspective. This is done in order to ensure the practicability of the obtained solutions. By this way, CLs that could not be acceptable due to security/economic aspects are discarded at the beginning of the optimisation. The final amount of operating reserves for hour t will be the amount related to the CL that minimises the total costs of the system (block '8' in Fig. 1), that is the costs of the E[ENS] and the operating costs.

In the following subsections we present further details about the key steps of the proposed methodology.

4.1 Determination of (hourly) SGMDs

The SGMDs for hour t (block '2' in Fig. 1) are calculated based on the pdf of the uncertainties and variations in the system within this hour. In this work, the following phenomena affecting the SGMD are considered:

- WFEs in this work are defined as the difference between the hourly average of the real wind power injection and the forecasted value in the time frame of 1 h [27]. Wind power injections are assumed to be re-forecasted every hour of the day. If historical (real) wind power operation data is not available for several years, the pdf of the WFE can be constructed using hourly wind power generation series obtained through simulated ('synthetic') wind speed data [29]. WFE series are then calculated as the difference between these synthetic wind power generation series and the forecasted wind power generation series. Since the wind production 1 h ahead can be reasonably well forecasted by persistence [3, 5, 30], to generate the forecasted wind production series, persistence method can be used on the same synthetic wind power generation series. Nevertheless, more sophisticated forecasting methods can also be applied [31–35]. The pdf's of the (hourly) WFE are then determined by fitting probability distributions to the empirical distributions of the WFE.
- Load forecast error is defined as the difference between forecasted demand and average of real demand in an hourly time frame [3, 27]. The pdf of the load forecast error in hour t is modelled as a Gaussian distribution with a given standard deviation and zero mean [1, 5–7, 10, 11, 18, 22]. The load is also assumed to be re-forecasted every hour of the day.
- Wind variability in this work is defined as the difference between 10 min average wind power generation series and the pertinent hourly average [27]. To generate the pdf's of the wind variability, the same process based on synthetic wind power generation series explained for the WFE can be followed. Nevertheless, additional wind power generation series with 10 min resolution are also required in this case. The pdf's are then determined by fitting probability distributions to the empirical distributions of the wind variability. It is important to note that depending on wind/load patterns as well as the ramp capabilities of the CG units, other requirements related to wind variability may be necessary, for instance, within the time frames of 5 or 15 min. In these cases, additional pdf's related to wind variability should also be considered.
- *Load variability*: Defined as the difference between 10 min average load series and the average of the corresponding hour [27]. An empirical distribution is fitted for the load variability series for hour t.
- *Generation outages*: The discrete probability distribution for outages of CG units is calculated based on the capacity outage probability table (COPT) [28]. The COPT allows calculating the probability that a certain amount of load cannot be served because the capacity on outage exceeds the operating reserves. The COPT for hour t takes into account the dispatched generating units, the probability of forced outage of each generating unit, the amount of operating reserve that each unit can provide, and the load.

The proposed methodology quantifies both, secondary and tertiary reserves separately for each hour of the day. Following the $n-1$ criterion, primary reserves are assumed to be a constant amount given by the capacity of the largest scheduled generation unit in each period. In order to distinguish between primary, secondary and tertiary reserves, two hourly SGMDs are considered for hour t:

- System generation margin in the time frame of 1 h ($f_{1\,\text{h}}^{\text{Margin},t}$): Represents the probability of power imbalances in the time frame of 1 h within hour t, which have to be compensated by primary, secondary and tertiary reserves. The function $f_{1\,\text{h}}^{\text{Margin},t}$ results from the convolution of the pdf's of all sources of uncertainties in the system, that is wind variability $f^{\text{WVar},t}$, load variability $f^{\text{LVar},t}$, WFE $f^{\text{WFE},t}$, load forecast error $f^{\text{LFE},t}$ and CG outages $f^{\text{GOut},t}$ according to [Where * represent the mathematical operator for convolution]

$$f_{1\,\text{h}}^{\text{Margin},t} = f^{\text{WVar},t} * f^{\text{LVar},t} * f^{\text{WFE},t} * f^{\text{LFE},t} * f^{\text{GOut},t} \tag{3}$$

- System generation margin for the time frame of 10 min ($f_{10\,\text{min}}^{\text{Margin},t}$): Represents the probability of power imbalances in the time frame of 10 min within hour t, which have to be compensated by primary and secondary reserves. The function $f_{10\,\text{min}}^{\text{Margin},t}$ results from the convolution of the pdf's of wind variability $f^{\text{WVar},t}$, load variability $f^{\text{LVar},t}$ and CG outages $f^{\text{GOut},t}$ according to

$$f_{10\,\text{min}}^{\text{Margin},t} = f^{\text{WVar},t} * f^{\text{LVar},t} * f^{\text{GOut},t} \tag{4}$$

The aforementioned SGMDs are both calculated assuming independence between all the stochastic variables involved. The independence between the pertinent stochastic variables should be always checked for each particular case through a correlation analysis before the proposed methodology is applied.

4.2 Determination of operating reserves

The quantification of the operating reserves (block '3' in Fig. 1) is done through the SGMDs presented in Section 4.1. For a specific confidence level CL^k, the total amount of operating reserves during hour t, $(P+S+T)_t$, can be calculated based on $f_{1\,\text{h}}^{\text{Margin},t}$. This total amount includes primary-plus-secondary-plus-tertiary reserves. Similarly, primary-plus-secondary reserve requirements for hour t $(P+S)_t$ are calculated from $f_{10\,\text{min}}^{\text{Margin},t}$. The $(P+S)_t$ reserve

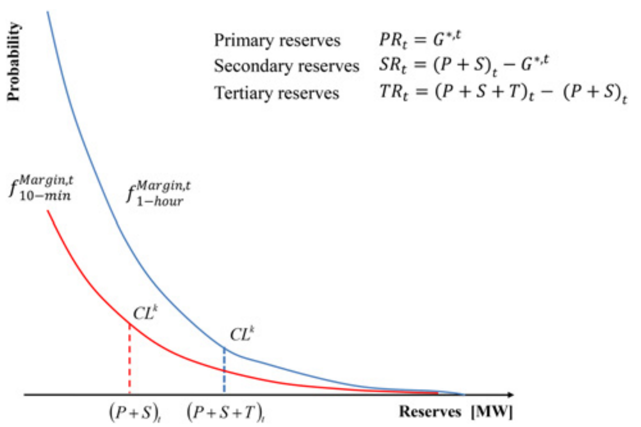

Fig. 2 *Breakdown of total operating reserves into primary, secondary and tertiary reserves*

requirements for hour t are then subtracted from the total operating reserves in the same hour. The obtained reserve amount is the required tertiary reserves for hour t, TR_t. Since primary reserve requirements are defined as the largest scheduled generation unit, secondary reserves SR_t are then obtained by subtracting the largest on line generation unit ($G^{*,t}$) from the $(P+S)_t$ reserves. Fig. 2 shows how the total amount of operating reserves $(P+S+T)_t$ obtained from $f_{1\,\mathrm{h}}^{\mathrm{Margin},t}$ is broken down into primary, secondary and tertiary reserves. The CL indicated in Fig. 2 is only there for illustrative reasons and is not related with the optimal solution. Indeed, as already mentioned in the introduction of this section, the whole process is carried out for different values of CLs. The final amount of operating reserves for hour t will be the amount that minimises the total costs of the system (related to a specific CL).

4.3 Economic optimisation (dispatch)

The next step of the methodology is a modified (deterministic) economic dispatch. The algorithm in this part determines the optimal scheduling for the conventional generating units by considering a set of technical constraints. The constraints are related to the operational limits of the generation units such as ramp rates, minimum and maximum power, and load/generation balance, among others. Particularly, the minimisation includes a minimum requirement for the operating reserves in order to ensure the amount of reserves determined in Section 4.2 for hour t. Although the results obtained through the methodology could be improved by using a stochastic dispatch model, the computational burdens of such models are still a challenge and therefore we simplify the problem by using a deterministic model. Nevertheless, the methodology can be directly applied by considering other dispatch methods such as those based on stochastic models [36–38]. This solution can be considered as a first approach still valid to get meaningful conclusions.

The objective function minimises the total operating costs of the system for hour t according to

$$\min \sum_{i=1}^{N} c_i\left(s_{i,t}, P_{i,t}\right) \quad (5)$$

where $c_i(s_{i,t}, P_{i,t})$ is the cost function of generator i at hour t; N is the amount of generation units; and $s_{i,t}$ is the state of generation unit i at period t (on/off).

The optimal scheduling obtained through this optimisation is compared with the dispatch initially used to calculate the SGMDs.

- If the mean squared error between both dispatches is major than a predefined threshold $\bar{\varepsilon}$, 'Process 1' of Fig. 1 is carried out again, but now considering the current dispatch for hour t and the operating reserves quantified in Section 4.2.
- If the mean squared error between both dispatches is less than or equal to $\bar{\varepsilon}$, the operating reserves quantified in Section 4.2 are saved as solution for hour t when considering the current confidence level CL^k. After that, 'Process 1' of Fig. 1 is performed again but now considering the next confidence level, CL^{k+1}.

4.4 Operating reserves and E[ENS] considering CL^k

Once the dispatch for hour t has been determined, the socioeconomic costs of the E[ENS] are calculated using the value of lost load (VOLL). The VOLL is the value that the customers place on each MWh of unserved energy. Its value depends on the economic activities carried out by customers of the power system [9]. The E[ENS] for a particular CL^k is calculated based on the SGMDs. Details about its calculation are given in [28].

4.5 Search of the optimal CL

The process described above for hour t ('Process 2' in Fig. 1) runs iteratively until all CL^k in the set of allowable CL have been considered. Once this iterative process is finished, the amount of operating reserves for hour t will be that related to the CL that minimises the total costs of the system, that is, the costs of the E[ENS] and the operating costs (including the cost of committing additional capacity). This part of the methodology is indicated as block '8' in Fig. 1.

5 Case study

The power system considered in the case study is the Northern Interconnected System (NIS) of Chile at year 2020. A wind power penetration level of 27% with respect to the total installed capacity of the system is assumed. The wind parks are installed at 11 locations throughout the system.

The NIS has a pure thermal generation matrix with a current total installed capacity of 4500 MW based on coal, oil and natural gas. The current peak load of the system is around 2000 MW. The lack of a utility interconnection and the presence of synchronous generators with low inertia, slow reaction times and limited ramp rates, are key factors affecting the system's ability to recover from power system imbalances and thus limiting the network integration of wind power from a frequency control viewpoint.

The model of the system at year 2020 has 42 CG units with a total installed capacity of 4900 MW (see Table 2 for details).

In this work, the VOLL in the time frame of 10 min is set to be 23.787 USD/MWh while in the time frame of 1 h its value is set to be 9.913 USD/MWh. Since the VOLL depends on the duration of the power outage, the E[ENS] is calculated separately for both time frames: 10 min and 1 h. Outages probabilities of generation units are taken from historical data available in [39].

Since historical (real) wind power operation data in Chile was still unavailable at the time of this study, hourly wind power generation series were constructed using wind speed synthetic data obtained from [40]. Multiple wind speed series reports were thus obtained for each wind farm considered in the case study to generate suitable statistics. Then, the methodology explained in Section 4.1 was used to generate the pdf's for WFE by fitting Gaussian probability distributions to the empirical distributions. However, it is important to note that the methodology does not depend on this particular distribution. In our practical exercise, we used Gaussian distribution to simplify the calculations and because there was no additional information for the Chilean system to fit an improved distribution. To increase the resolution of the 1 h series to 10 min, the methodology proposed in [41] was used. The pdf's for wind variability were calculated like the pdf's for the WFE.

6 Optimisation results

This section summarises the results obtained after applying the methodology proposed in Section 4 to a single bus model of the NIS. To do this, we simulate the operation of the NIS at year 2020. The methodology was systematically applied during each day of year assuming that the UC is carried out 1 day-ahead every

Table 2 Generation data

Generator	Total rated power, MW	Number of units	Outages probability
fuel oil	220	6	0.01%
coal	2900	12	0.10%
combine cycle	1650	11	0.04%
diesel	130	13	0.14%
wind	1800	—	—
total	6700	42	—

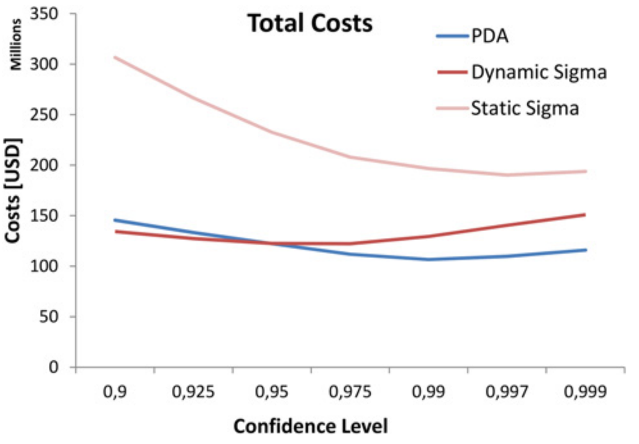

Fig. 3 *Evolution of total annual costs of the power system assuming a WFE of 10%*

day of the year and that load and wind are re-forecasted every hour of the optimisation horizon. To compare the proposed PDA with traditional operating reserves rules, we applied our methodology by considering the PDA as well as two versions of the *n*-sigma criterion: static and dynamic. In case of the *n*-sigma criteria, the reserves are quantified based on the probability distributions of the net load as summarised in Section 3. The (traditional) static *n*-sigma method is based on a single pdf for the whole year while the dynamic sigma approach uses hourly pdf's similar as the proposed PDA.

Fig. 3 presents the evolution of the total annual costs of the power system for different CLs. The total costs include costs of generation and costs of E[ENS] for a WFE of 10%. The breakdown of the total costs for each criterion is presented in Fig. 4. It is important to highlight that the numerical results presented below, are illustrative and valid for the Chilean case. To conclude about other power systems (with different characteristics) independent studies should be carried out.

Fig. 3 shows that independent of the CL, the total costs with the static sigma criterion are always significantly higher than those obtained when considering the dynamic sigma criterion or the PDA. These higher costs are either because the costs of E[ENS] are very high for low values of the CL, or because the reserve costs rise substantially as the CL increases. Taking into account that with the static sigma approach increasing the CL leads to higher reserve capacities for each hour of the year, it is not surprising that the reserve costs escalate when the CL tend to values close to unity. By this way, the economic advantages of dynamic approaches over static ones are fully confirmed. Comparing the dynamic sigma with the PDA, the differences during the optimisation process are less significant. For low values of the CL, the total costs with the dynamic sigma approach are marginally lower than the costs with the PDA while for CLs higher than 0.95, the economic gap between both approaches increases considerable and the PDA outperforms the dynamic sigma criterion. Nonetheless, minimum costs are finally reached with the PDA.

Table 3 shows the break-even points for each criterion. The CL at which the marginal benefit of providing an additional MW of reserve (i.e. marginal benefit of avoided E[ENS]) matches the marginal cost of providing an additional MW of reserve, represents the economical break-even point (CL*).

Results shown in Table 3 confirm the need of a dynamic determination of operating reserves since it provides considerable cost savings. Comparing all criteria, Table 3 shows that the proposed PDA is cheaper than both versions of the sigma criterion to setting operating reserve requirements. The total costs of the power system are minimised when considering the PDA in which case the optimal confidence level CL* is equal to 99%. Although the economic gap between the PDA and the dynamic sigma is not significant, when compared with the static sigma the total costs with the PDA are 55% lower thus making an important difference.

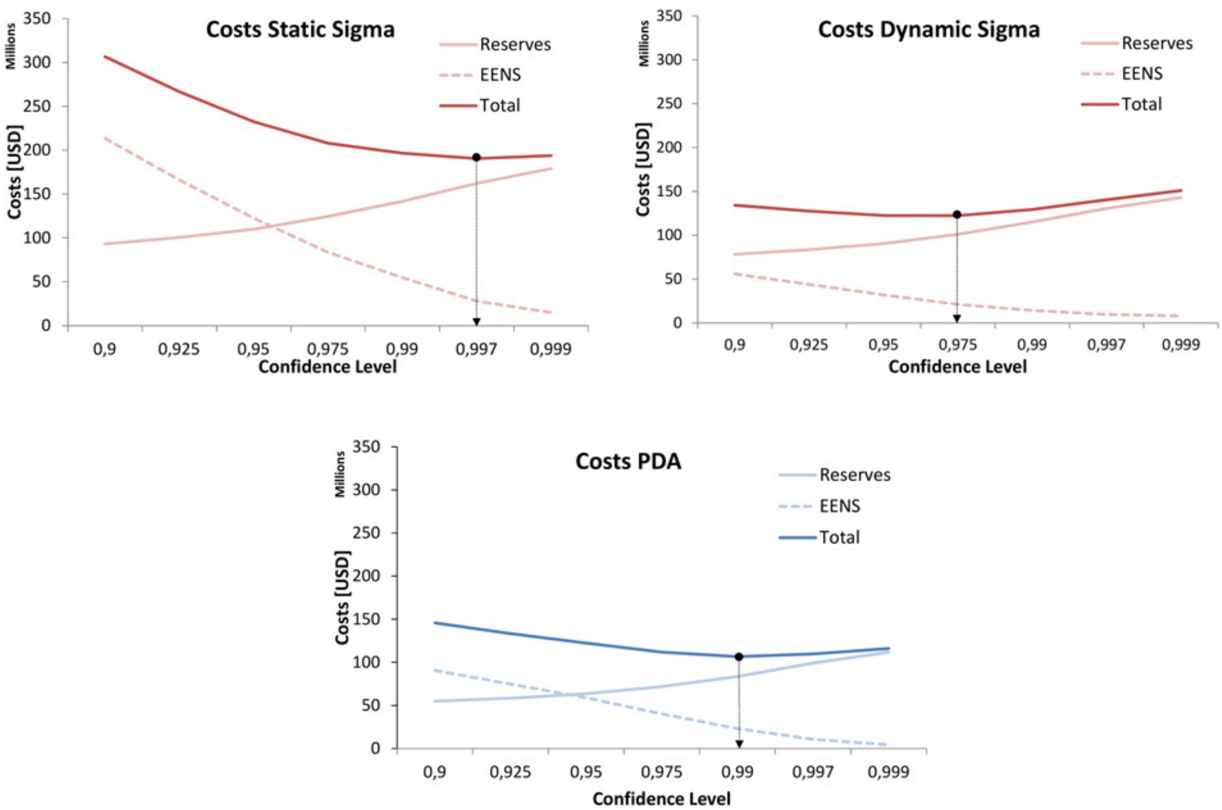

Fig. 4 *Breakdown of total annual costs of the system for each criterion*

Table 3 Break-even point

Criterion	Optimal CL*, %	Total costs (Mill. USD)/year
PDA	99.0	106.59
dynamic sigma	97.5 (2.24σ)	122.23
static sigma	99.7 (3σ)	190.35

Interestingly, Table 3 also shows that the optimal CL for the static sigma is 3σ of the Gaussian probability distribution. Although this criterion does not provide the best results from an economic point of view, its basic assumption regarding the CL is found to be consistent in this particular case. Nevertheless, this does not necessarily hold in other power systems since the optimal value of the CL depends on the power system itself.

Fig. 5 shows the amount of operating reserves obtained after the optimisation of both versions of the sigma criterion and the PDA over the course of 2 days. The days are chosen in order to have a representative pattern of the wind generation behaviour in Chile: more wind during the night than during the day. The reserve requirements are obtained by considering a WFE of 10%.

According to its traditional definition, the reserve requirements obtained with static sigma criterion have the same value during the whole day. Fig. 5 also shows that the shape of the operating reserves curves obtained with the dynamic sigma criterion and the PDA are very similar. Both curves follow the shape of wind power daily pattern in similar degrees. Thus, both approaches seem to be appropriate criteria to quantify operating reserve requirements if wind and load patterns are 'stable'. Nevertheless, if wind power generation or load deviate from normal behaviour, only the PDA will be able to adapt the reserve requirements to the present risks of imbalances correspondingly. This is because not only the statistics of system behaviour are used to determine reserve requirements, but also the present conditions of the power system (wind power, load and CG). The sigma criteria, however, perform poorly under such conditions because operating reserve requirements are independent from the present conditions of the power system (load, wind power and scheduled generation units). Instead it is implicitly assumed that present and future behaviour of the power system resembles observations of the past. If this assumption is not valid, the sigma criterion – or any statistical approaches – will fail.

Fig. 6 shows the annual duration curves for the operating reserves considering a WFE of 10%.

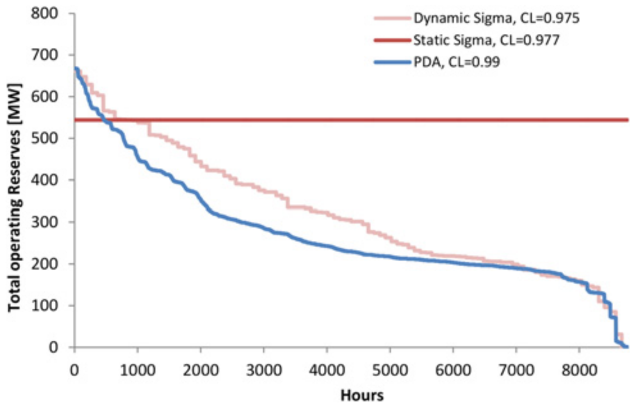

Fig. 6 *Annual duration curves for the operating reserves*

As expected, Fig. 6 shows that the static sigma criterion leads to an oversizing of operating reserves most of the year. According to the PDA, only around 6% of the time during the year (~500 h), the risk of a power deficit is high enough to justify larger amounts of operating reserves than those determined by the static sigma approach. The rest of the time the amount of operating reserves quantified by the static sigma should not be necessary. Fig. 6 also shows that the dynamic sigma criterion always lead to larger amounts of operating reserves than the PDA. When comparing the static and dynamic versions of the sigma criterion, it is evident that the dynamic version of the sigma criterion represents a significant improvement over its static version.

Since variability and uncertainty of wind power vary over the time, the amount of operating reserves that are induced by wind power is not constant during all hours of the year. As a consequence, using constant reserve requirements such as those obtained by the static sigma criterion will necessary lead to an oversizing of operating reserves most of the time. To avoid the need to hold back large amounts of reserves at every instant and thus the pertinent additional costs, a dynamic reserve allocation should be always considered. Several works have begun to recognise this fact and develop methodologies to quantify operating reserves in a dynamic way depending on current system operation conditions.

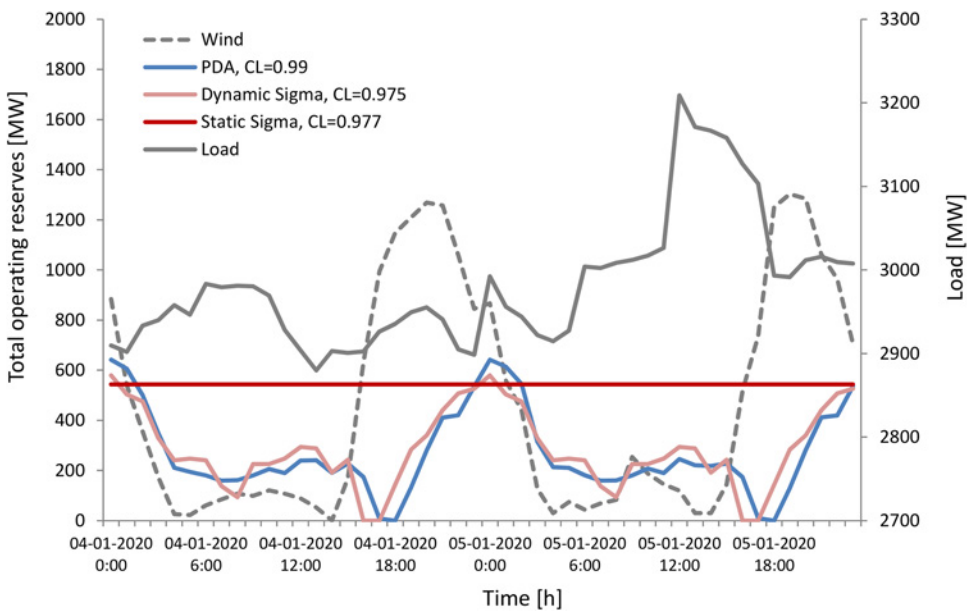

Fig. 5 *Amount of operating reserves over the course of two days*

7 Conclusions

This paper presents a new methodology to quantify different kind of operating reserves in the presence of wind power. The methodology takes into account CG outages; load and wind forecast uncertainty as well as load and wind variability. The methodology determines the amount of operating reserves for the next hour that minimises the total cost of the power system, that is, the sum of the operating costs and the socioeconomic costs related to the E[ENS]. The methodology is applied on the NIS of Chile by considering a PDA and two versions of the n-sigma criterion: static and dynamic.

Obtained results have shown that the PDA and the dynamic sigma criterion outperform the static sigma criterion under any given scenario. The main advantage of these both approaches compared with the static sigma results from the dynamic adjustment of power reserves, that is when reserve levels are not constant for all hours of the year but in fact a function of system operation conditions. This result gives an insight of how the quantification of operating reserves should be handled in power systems with high levels of wind power.

The optimisation process has shown that the proposed PDA is cheaper than both versions of the sigma criterion to setting operating reserve requirements in which case the optimal confidence level CL* is equal to 99%. Interestingly, in case of the traditional static sigma criterion, the optimal CL* obtained was 3σ of the Gaussian probability distribution. Although this criterion does not provide convincing results from an economic viewpoint, its basic assumption regarding the CL used is found to be consistent in this particular case. Nevertheless, this does not necessarily hold in other power systems since the optimal CL should depend on the power system itself.

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