Changing the Operations Planning Paradigm When Integrating Renewable Energy Sources into a Power System

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Abstract

Renewable energy plants are replacing conventional plants in power systems with a view to reducing emissions. Energy from wind and solar sources, intermittent and variable in nature, displays uncertainties linked to imminent meteorological conditions. These uncertainties are different from those considered previously on conventional power system variables. To mitigate such uncertainties, power system operations maintain various types of reserves. In the past, uncertainties on conventional variables resulted in quasi-constant reserve requirements. Now in response to the new uncertainties, novel practices must be established. We present a methodology to compute reserves to mitigate all forecast uncertainties over the operations planning horizon.

Key words: power systems operation, renewable energy, reserves.

1. Introduction

New renewable energy sources (RES) have taken a large share of generation portfolios in electrical power systems over the last twenty years or so. This is a consequence of two important factors. First, there is a general awareness of the need and a political will in many countries to counter the climate-changing effects of greenhouse gases. Burning fossil fuels to generate electricity constitutes a major motor of the climate change we are witnessing. It is therefore imperative to develop clean energy sources with a view to replacing fossil-fuel plants. Second, with the emergence of enabling technologies, bountiful new renewable energy sources can be harnessed worldwide, often in regions which up to now have imported much of their energy.

Recent advances in renewable energy technologies have focused on the development of electrical generation from wind and solar sources. Large-scale wind power generation was first to emerge and is now based on a mature technology. Solar power generation has made great strides, and over the last decade has been implemented both in small-scale and large-scale projects. Along with clean energy generation technologies, proposals have emerged for technologies for cleaner energy end-use. Two examples are the move towards electric vehicles and clean self-generation installed in many industrial / commercial buildings to cover a portion of their electrical needs.

To date most conventional power system technologies, however complex they may be, can be scheduled using deterministic tools. It is not that uncertainties surrounding these technologies are inexistent. Those seen in a longer time scale are dealt with in a planning stage while those seen on a shorter time scale are recurrent, and system practices are easily adjusted to consider them.

The new energy generation and load technologies are fundamentally different in two respects. First, they exhibit an intermittent and uncertain behavior the nature of which had not been seen before, with characteristics much different in form and size. Second, coming with their proper controllers, modifications must be made to integrate these sources into the network. Conventional technologies have always relied on their controllers, but now controllers are found in a much higher proportion of system components and play a more important role in the system operation. The integration of these new technologies opens up entirely new domains for analysis and operations planning, requiring adapted new tools. We briefly mention four areas considered in Hydro-Quebec (HQ) studies in which problems were encountered when integrating wind power generation, namely technology, integration, planning and operation.

– Technological problems were faced in integrating approximately 4000 MW of wind generation capacity into the HQ network, related to the complexity of the electrical behavior of the equipment, of their interactions among themselves and with the existing system. The time-horizon considered here is from milliseconds to seconds. Efforts have concentrated on coordinating the multiple equipment controls to assure robust operation. Real-time power-system simulation tools have been useful in resolving the problems encountered [1].

– Integration problems were tackled at an engineering level with modifications to the electrical codes of the transmission and distribution providers. These codes specify requirements for the connection of the new energy technologies to the system and the parameters of their operation. They require that complete power engineering studies be performed before connection is allowed. In future, further considerations should be given if these technologies are to be included in large numbers.

– In system multi-year planning, one question that arises is how much conventional capacity can a RES reliably replace? Equivalently, how much additional load can a given capacity of RES accommodate as reliably as with conventional generation? This is the notion of capacity credit. Since RES are weather dependent, data must be collected over a sufficiently long period of time to reach a significant result. Unsurprisingly, many considerations go into its computation. For example at HQ, the capacity credit for the annual peak load period in winter must consider that extreme cold temperatures can close down some wind farms [2].

– In operations planning, a set of functions assesses the upcoming energy needs of the end-users and prepares the resources required to satisfy them at an overall system level. The time horizon considered here is typically a few days, which is the look-ahead time of system forecasts. We contend that now to evaluate operating requirements in the presence of several fundamentally different sources of uncertainty, it is necessary to adapt deterministic operations practices by embedding in them probabilistic tools. This constitutes an important change in paradigm for these functions [3].

One operations function impacted by this change is the evaluation of reserves, i.e. of capacity made available beforehand to mitigate uncertainties, which present themselves as time evolves as deviations from a deterministic operations schedule. Reserves are evaluated over different consecutive time horizons, each with its own characteristics.

This paper considers the fundamental changes in reserve evaluation on two time horizons, intra-hourly and over several hours, each addressing different aspects of uncertainty. In this paper we motivate the change in paradigm, describe a new methodology to evaluate reserves using probabilistic tools, and then present and discuss results using this methodology applied to the latter time horizon. This methodology was tested at length incorporating wind generation characteristics from the Hydro-Québec system, but could be expanded to include other renewable energy sources.

2. Uncertainties in power system operations planning

Here we describe the uncertainties associated with the major components of a power system.

- The generation of energy is performed using a mix of energy sources and generation technologies. Conventional plants – fossil-fuel, hydro, nuclear – share one common characteristic in that their output is fully controllable. Uncertainty on conventional plants is not on the output level but rather on the unexpected loss of availability.

- Renewable wind and solar plants can be controlled to some extent, but commercially in many energy markets their entire production is taken as generated. Without regulation, these renewable energy plants exhibit important uncertainty on their output.

- The transmission network comprises equipment to route power from generation to load while assuring a quality of service. Modern networks have been designed to be always very reliable. Thus in the operations planning time horizon, the uncertainties on network unavailability are not considered.

- Although the individual loads are granular and diverse in nature, an aggregate system load is considered in operations planning. It follows a fairly predictable diurnal pattern but is conditioned by daily weather. This load exhibits relatively little uncertainty on its forecasted values, but since this is the largest component in operations planning studies, its absolute value is important in relation to other uncertainties.

Uncertainty considered here can be analyzed on two time-horizons. Uncertainty on an intra-hourly time horizon reflects the inherent variability on load together with the renewable power generation, defined as the net-load. On a time horizon of several hours, the uncertainties represent forecast errors on net-load and the generation unavailability of conventional plants [3,4].

3. Power system reserves

In light of these system uncertainties, to be able to satisfy the load at a given time with high reliability, capacity including sufficient reserves must be secured beforehand. Typically four categories of reserves, summarized in Table 1, are maintained [2].

Table 1. Reserve types			
Type	**Purpose**	**Time-frame**	**Present Sizing**
Contingency	Ensures the stability of power systems following disturbances	Partly online / partly off-line but available on short notice	Fixed targets based on generation and network capacities
Intra-hourly			
Automatic generation control (AGC)	Maintains system frequency	Control of online generation adjusted every few minutes	Static predefined values
Regulating / load following reserves	Follows system load by monitoring system frequency	Control of online generation adjusted regularly within hour	Static predefined values
Several hours			
Balancing reserves	Ensures adequacy of supply in spite of forecast uncertainties	Calls on all generation / load resources over the next day or two	Predefined set of values over the time window

- Contingency reserves ensure the stable behaviour of the power system frequency immediately following a system disturbance. This frequency must be strictly maintained for the system to operate properly. A portion of these reserves must be present on-line while offline components should be available on short notice. At HQ, these reserves are sized as fixed targets based on generation and network capacities.

  The next two types of reserves act in real time to counter slower variations in system frequency, linked to changes in system load and uncontrolled renewable generation. These types mitigate variability on system variables and no forecast comes into play. Presently at HQ their sizing takes on fixed predefined values meant to counter worst-case conditions.

- In a time frame of minutes, the automatic generation control counters frequency variations.

- In a time frame of over several minutes but within the hour, part of the changes in system variables is anticipated. Discrepancies between the anticipated and actual behaviors are mitigated by the regulating/load-following reserves.

- In a time frame of 1 to 48 hours ahead, the balancing reserves hedge against forecast uncertainties in load and renewable generation forecasts. They act as a form of insurance, and like insurance are deployed sparingly as needed. Consequently these reserves can consist in large measure of reservations of offline resources. Deviations that would exceed these reserves as the time of deployment is approached can still be corrected in time by human operators. Such last minute adjustments can be costly, are not desirable and are best avoided by better preparing the reserve requirements.

4. Motivating the sizing of reserves in the new environment based on imminent conditions

Since load and new energy sources are dependant on imminent meteorological conditions, so too are their uncertainties. Reserve requirements that mitigate these uncertainties should also respond to imminent conditions. Of the reserves types from Table 1, the regulating and balancing reserves could benefit from a methodology incorporating imminent conditions in which reserves are crafted for the situation at hand by attributing just enough reserves but no more.

5. Solution to Operations Planning Problems Incorporating Variable Reserves

Two approaches for assessing and procuring variable reserve targets in the operations planning horizon are brought forward. The first involves the Unit Commitment (UC) which determines the on-off status of the generators in the system, typically hourly for a look-ahead time horizon of 24 hours. In recent formulations of UC, the forward uncertainties in the inputs are incorporated using plausible load/generation scenarios each with a given probability of occurrence. Risk-related constraints appear, as the solution is restricted to satisfy a high percentile of input scenarios. The existence of a solution guarantees the sufficiency of capacity and dictates the most economic procurement. The entire process is computed within a closed loop formulation. This is illustrated in Figure 1 (a).

Alternatively, variable reserve targets can be computed on their own decoupled from system constraints. Here the forward uncertainties are described using time-evolving probability distributions of generation and load. Under certain conditions, these reserve targets can be incorporated directly into the operations planning tool, as for example in a massively hydraulic generation system such as that of Hydro-Québec. This is because assuming that sufficient reserve capacity exists, it can be brought on line quickly without being hampered by dynamic time-coupling generation constraints prevalent in thermal systems as illustrated in Figure 1 (b).

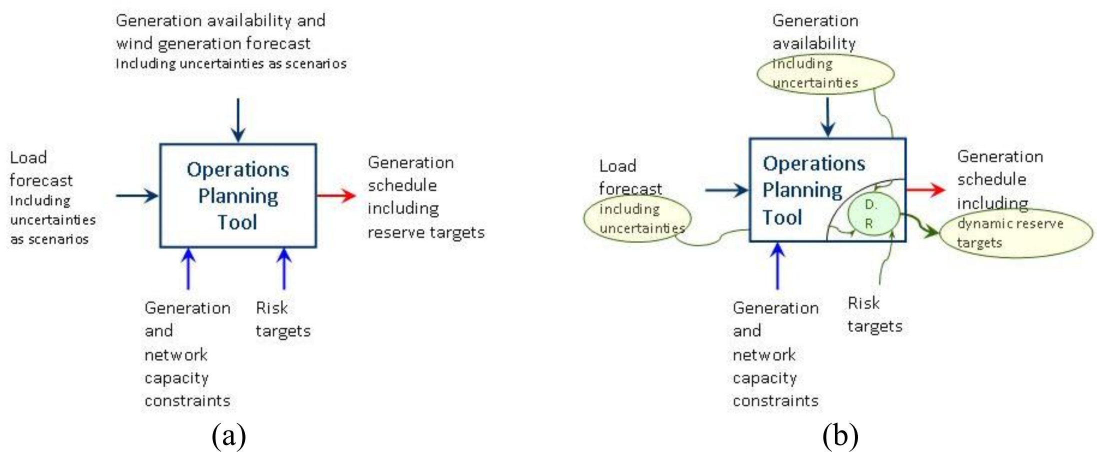


Figure 1. Two structures of operations planning tools incorporating variable characteristics of input uncertainties and providing reserve targets.

In a general mathematical formulation, the conditions on reserves are represented by (1) for the UC approach and by (2) for the decoupled approach.

$$\Pr_{Scenarios}\left[\sum_{i\in Gen}\left(P_i^{\max}-P_i^{gen}\right)\geq \mathrm{Res}\right]\geq \mathrm{F} \tag{1}$$

$$\Pr\left[\sum_{i\in Gen}\tilde{P}_i^{gen}+Res\geq \tilde{P}_d\right]\geq F \tag{2}$$

where the notation $i \in G$ represents the set of committed generators. In (1) reserves in the solution meet or surpass a pre-defined reserve minimum bound, Res, for a proportion F of the plausible scenarios. This differs from (2) where reserves, Res, together with the generation will satisfy with a high probability F the load including forward uncertainties from all sources. Clearly, in (2), with varying uncertainties accompanying the imminent conditions, the reserves Res vary necessarily over time.

6. Methodology for sizing risk-based reserve targets

6.1. Theoretical development

The methodology to evaluate reserves in the decoupled approach is based on satisfying equation (2) with a pre-defined reliability F [3, 4, 5]. Equivalently, we define the probability of not satisfying (2) as a risk. Applying this methodology, the system will be exposed to a given predefined risk. As a result, the reserve targets vary over time to counter the varying uncertainties, as opposed to the current practice in which the predefined reserve targets protect the system against a variable (and often unsuspected) risk.

The sizing of risk-based reserves emerges from the analysis of short-term supply adequacy. Supply adequacy is defined by the ability of the system to meet the aggregate power and energy requirements of all consumers at virtually all times. It is connected with the ability of a system to match supply and demand.

The deterministic power balance equation stipulates that the generation is equal to the load (including the losses) at all times.

$$p_d(t) = p_c(t) + p_w(t) \tag{3}$$

The three components considered here in the power balance are instantaneous demand, conventional generation and wind generation respectively, and *t* represents real time. When forecasts are considered, uncertainty is present and these quantities must be represented as random variables. In what follows, we represent each component as a sum of deterministic (over-lined) and random elements, and t represents a future time.

$$\begin{aligned}
\tilde{p}_d(t) &= \overline{p}_d(t) + \varepsilon_d(t) \\
\tilde{p}_c(t) &= \overline{p}_c(t) - \varepsilon_u(t), \quad \varepsilon_u(t) \geq 0 \\
\tilde{p}_w(t) &= \overline{p}_w(t) + \varepsilon_w(t)
\end{aligned} \tag{4}$$

In this context for a future time, the power balance cannot be satisfied exactly, but rather is satisfied with a certain probability. We call risk the probability that the total generation is insufficient to meet demand. This probability is expressed as follows.

$$\begin{aligned}
Risk(t) &= \Pr\left[\tilde{p}_d(t) > \tilde{p}_c(t) + \tilde{p}_w(t)\right] \\
&= \Pr\left[\varepsilon_d(t) + \varepsilon_u(t) > \varepsilon_w(t)\right] \\
&= \Pr\left[\varepsilon_d + \varepsilon_u - \varepsilon_w > 0\right]
\end{aligned} \tag{5}$$

where without loss of generality the notion of time was removed in the final expression. As expected, the final expression retains only the random terms. It corresponds to the situation where the committed generation is equal to the anticipated demand in the forecast horizon. Without further consideration, the risk is always high. To avoid this situation and to ensure an acceptable risk, balancing reserves (BR) are made available. This has the effect of adding an additional term to the expression of risk.

$$\begin{aligned} Risk &= \Pr\left[\varepsilon_d + \varepsilon_u - \varepsilon_w \geq BR\right] \\ &= 1 - \Pr\left[\varepsilon_d + \varepsilon_u - \varepsilon_w \leq BR\right] \triangleq 1 - F_X\left(BR\right) \end{aligned} \tag{6}$$

The first expression in (6) introduces an amount of BR. The second expresses the risk as a function of the aggregate error distribution F_X evaluated at the value BR. This shows that risk evolves inversely to BR and that it is possible to reduce the risk to any desired level by increasing BR.

Expression (6) is general. It does not exploit any special property of the uncertainties and leaves room for any form of distribution. In our implementation we assumed that the error components in (4) are statistically independent. Hence F_X may be calculated by convolving the distributions of the individual components. To reach the final result F_X, the most arduous task is to form the densities f_x of the various terms, ε_i, in (6).

Now restoring the notion of time, knowing that the statistical characteristics of the error terms evolve over time, the ensuing risk also evolves over time.

6.2. Risk-Balancing reserve relation and the impact of a new source of uncertainty on *BR* requirements

Figure 2 illustrates graphically the $Risk - BR$ relations at a given instant described by (6), all obtained from typical operating data. The risk with conventional uncertainties, i.e. on load and unavailable generation, as a function of balancing reserves is represented by the curve R_{d+u}. With wind as an additional source of uncertainty the risk curve moves to the right. Examples for two levels of wind generation forecast uncertainties are given by curves R_{d+u-w} and R_{d+u-W}. We observe that the original risk, R_0, depends on both the statistical characteristics of the global forecast uncertainties and on the balancing reserves level, BR_0.

- For constant balancing reserves, BR_0, the risk increases with increasing total input forecast uncertainties as illustrated along the ΔR vertical line.
- For maintaining a constant risk, R_0, the required BRs increase with increasing total input forecast uncertainties, as illustrated along the ΔBR horizontal line.

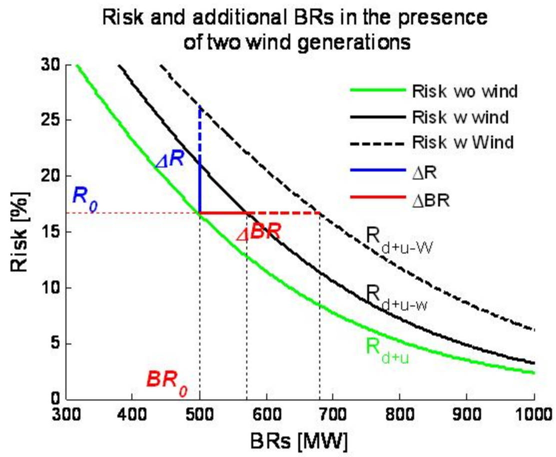


Figure 2. Qualitative illustration of the risk and additional balancing reserves for two different wind generation penetration levels whose forecast errors are represented by zero mean Gaussian distributions.

The $Risk - BR$ relationship is nonlinear. It is thus difficult to extract rules of thumb associating variations of balancing reserves corresponding to variations in uncertainties.

6.3. Implementation in the several hours-ahead time frame

The risk-based methodology for evaluating BRs provides reserve targets for given risk levels (or vice versa) as a function of lead time. The highlights of the methodology are illustrated in Figure 3 (a). The input variables – the time evolution of statistical densities of uncertainties on conventional generation unavailability, imminent load and imminent wind power generation – are shown in the left box of the figure. The desired risk levels constitute input parameters. From these, the methodology forms the statistical properties of an aggregate uncertainty on the three input variables. The center box displays several aspects of this in the form of average, standard deviation, density and distribution function surfaces of reserve/risk versus lead time. From these results can be extracted the curves of required balancing reserves versus lead time to meet specific risk targets, shown in the right box.

Figure 3 (b) highlights the desired result, the BR schedules for three risk levels and their combination over 48 hours starting at the beginning of the next hour. In the combined schedule, shown with a thick line, a risk of not satisfying the system load of 15% is accepted for the first 6 hours, followed by 10% for the next 18 hours, and 5% thereafter. These risk levels were initially thought to best represent the risks incurred when applying the nominal BRs presently in use at HQ. In the figure, the variable BRs are compared to the nominal BR levels which form a staircase.

In operations planning a single BR schedule is in use at a given time, covering the next few days, as in Figure 3 (b). In a dynamic mode, to keep abreast of imminent conditions, new schedules are recomputed regularly. At HQ, BR computations are evaluated every hour, each over a horizon of a few days with a resolution of one hour.

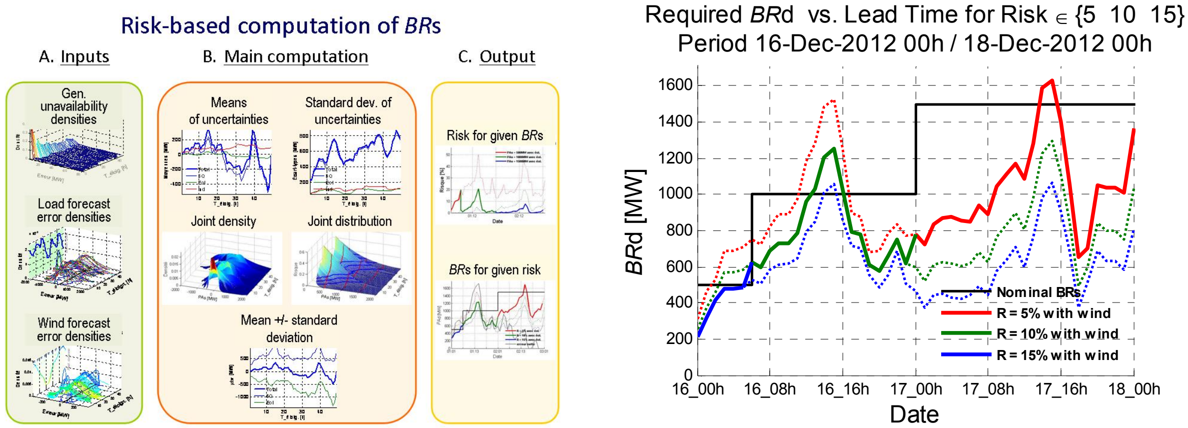
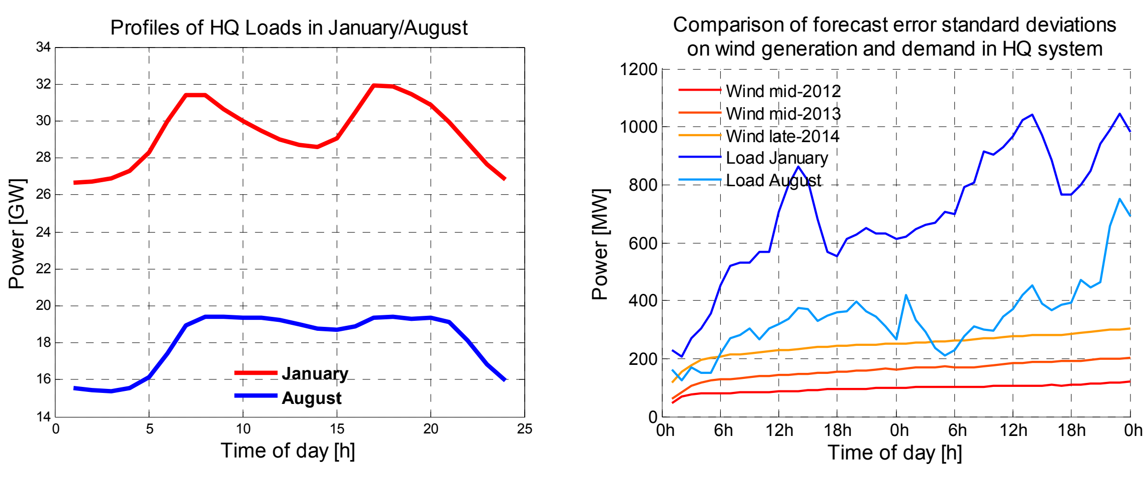


Figure 3. (a) Illustration of the methodology to compute a single balancing reserve schedule.
(b) Nominal *BR* targets & variable *BR* schedule for required risk levels.

7. Some Results

7.1. Statistical characteristics of the input data

As discussed in the previous section, it is expected that the risks and BRs should be tightly linked to the statistical characteristics of the input uncertainties. We mention however, that interestingly enough, the timing of the maximum risk and BR levels do not coincide with that of the peak loading times as will be shown later. Figure 4 (a) shows typical load profiles for a winter and a summer month. Figure 4 (b) shows the standard deviations of the forecast errors on the HQ load for these months, and those of the total HQ wind generation from 2012 to 2014 with the addition of generation capacity.



(a) (b)

Figure 4. Load profiles (a) and standard deviations (b) of forecast errors of HQ system load and wind generation.

We note that despite a low wind generation penetration of the order of 7%, here defined as the ratio of installed wind generation capacity to maximum system load, the contribution of wind generation forecast errors approaches that of the load forecast errors for the summer months. This is seen in figure (b) by comparing the standard deviations associated with each quantity.

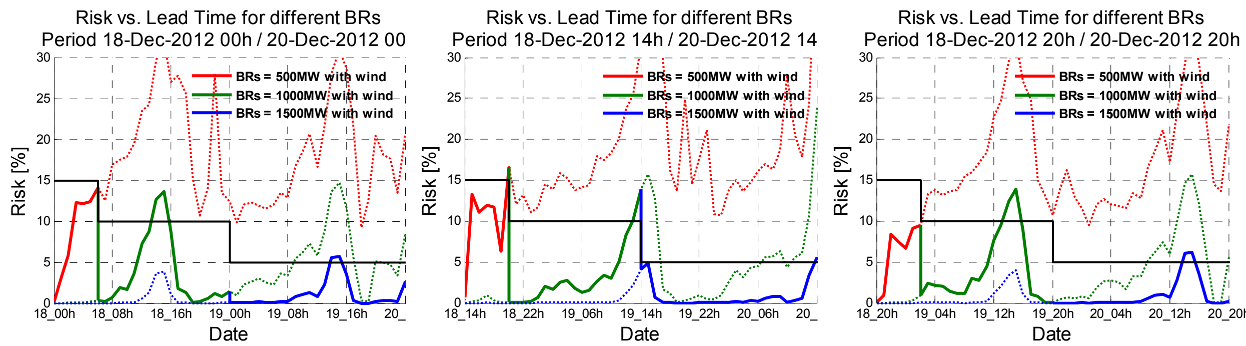
7.2. Risks and *BR*s

It will be seen that presently the main contributions to the BR curves come from uncertainties on the system load. This is certainly the case in the examples of Figures 5 to 7.

Figures 5 (a) – (c) show the risks incurred with nominal BRs of 500/100/1500 MW for December 18th 2012. Dotted lines show the risks associated with each nominal BR level for the entire time horizon. A solid curve retains the contributions for each time segment on the horizon corresponding to the time of application for each BR level, i.e. 0-6, 7-24 and 25-48 hours ahead. Each contribution is displayed by its own color. The three-tiered staircase represents three target risk levels 15/10/5% for each time segment. Figures 5 (a) – (c) are snapshots calculated with imminent conditions known at midnight, 14:00h and 20:00h. In figure (a), the risk approached 15% twice, after 6 hours at the 500 MW level and before the next peak loading time at the 1000 MW level. In figures (b) and (c), the maximum risk attained other levels, but they appear in the same circumstances. In general, maximum risk levels are obtained around 14:00 hours, a bit before the afternoon peak loading time.

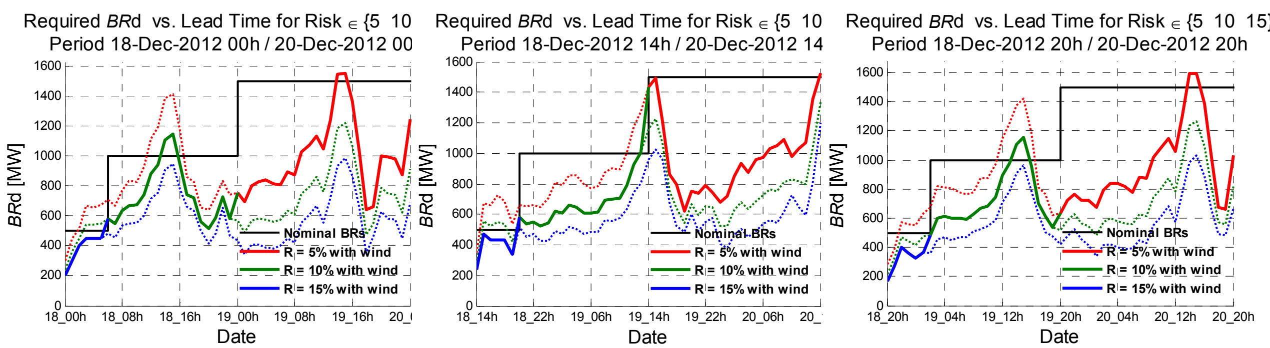
Figures 6 (a) – (c) show the variable BRs required to maintain the three risk levels for the same dates / times as in Figure 5. Here too, the dotted curves show BRs associated with each risk level over the entire time horizon. A solid curve retains the contributions for each time segment / BR level on the horizon with its own color. The three-tiered staircase represents the nominal BRs . Peaks in the BR schedules fall just before peak loading times and there they exceed the nominal BRs . The rest of the time however, the variable BRs are considerably lower than the nominal ones. In figure (a), the peaks occur at the centers of the latter two time segments. In figure (b), they occur at the ends of those time segments, preceding peak loading on the following two days. In this case, the requirements for the upcoming peak loading period, with a two hours lapse, are small because the associated input forecasts made available at 14:00h are relatively accurate. In figure (c), we observe that risks in the 0-6h time segment are relatively small because they correspond to late night loading conditions which are less error prone. As above, the maximum BR levels are obtained around 14:00 hours, a bit before the afternoon peak loading time.

Figure 7 displays consecutive variable BR schedules concatenated a posteriori. These cover two days leading up to the dates in the two previous figures. The figure reveals a regular pattern of peaks and valleys at certain hours of the day. Again the BR peaks correspond to times just preceding the afternoon peak loading period, and valleys fall between those peak load periods. The nominal BRs are shown as a three-level blue/green/red staircase.



(a) (b) (c)

Figure 5. Risks encountered with nominal BRs 500/1000/1500 MW, for imminent conditions on December 18th at different times of the day 00/14/20 h.



(a) (b) (c)

Figure 6. BRs required to satisfy risk targets of 15/10/5% on December 18th at different times of the day 00/14/20 h

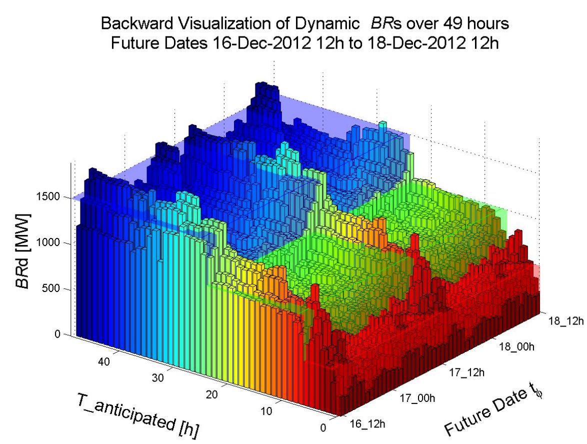


Figure 7. Concatenation of consecutive BR schedules exhibiting periods of high/low requirements.

8. Discussion

The methodology was used to evaluate variable BR requirements over the entire year 2012 at hourly intervals with real HQ system data and with a set of pre-defined risk levels [6]. The study revealed that in many situations the BR requirements are advantageous with respect to the nominal BRs. On one hand, by maintaining pre-defined risk levels it assures that the system operator, preoccupied with system security, will prepare sufficient reserves to endow the system with high short-term reliability. On the other hand, when variable reserve requirements fall far short of the nominal ones, it will allow the energy producer to release unnecessary reserve capacity for other uses.

The notion of dynamic reserves goes one step further than that of the variable reserves. Variable reserves become dynamic in nature when inputs reflecting imminent conditions are constantly refreshed. The resulting risk-based dynamic reserves are valuable at all times and especially in situations of tight system loading with volatile meteorological conditions.

Similarly to balancing reserves, intra-hourly reserves can be computed using the same risk-based methodology with uncertainty associated to the variability of the system variables [7].

9. Conclusions

With the integration of renewable energy sources, power system operation practices have to be modified to account for new forms of uncertainties accompanying these sources. After a general description of problems associated with this integration, we focused on the evaluation of balancing reserves, to mitigate uncertainties over the next several hours. This approach uses a concrete objective, risk, to provide the system operator with a quantifiable measure. The methodology is simple, and can be applied to all forms of uncertainty to counter both the variability and forecast errors in both the time horizons considered.

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