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Wind Energy Management System Integration Project

Incorporating Wind Generation and Load Forecast Uncertainties into Power Grid Operations

INTERMEDIATE REPORT

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September 2009

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Abstract

The power system balancing process, which includes the scheduling, real-time dispatch (load following) and regulation processes, is traditionally based on deterministic models. Because conventional generation needs time to be committed and dispatched to a desired megawatt level, the scheduling and load following processes use load and wind power production forecasts to achieve future balance between conventional generation and energy storage on one side and system load, intermittent resources (such as wind and solar generation), and scheduled interchange on the other. Although in real life the forecasting procedures imply some uncertainty around the load and wind forecasts (caused by forecast errors), only their mean values are actually used in the generation dispatch and commitment procedures. Since the actual load and intermittent generation can deviate from their forecasts, it becomes increasingly unclear (especially with the increasing penetration of renewable resources) whether the system would be able to meet conventional generation requirements within the look-ahead horizon, what additional balancing efforts would be needed as real time nears, and what additional costs those needs would incur.

To improve the system control performance characteristics, maintain system reliability, and minimize expenses related to system balancing functions, it becomes necessary to incorporate predicted uncertainty ranges into the scheduling, load following, and, in some extent, the regulation processes. It is also important to address the uncertainty problem comprehensively by including all sources of uncertainty (load, intermittent generation, forced outages of generators, etc.) for consideration. All aspects of uncertainty such as the imbalance size (which is the same as capacity needed to mitigate the imbalance) and generation ramping requirement must be taken into account. The unique features of the latter make this work a significant step forward toward the objective of incorporating wind, solar, load, and other uncertainties into power system operations.

This report presents a new methodology to predict the uncertainty ranges for the required balancing capacity, ramping capability, and ramp duration. Uncertainties created by system load forecast errors, wind and solar forecast errors, and generation forced outages are taken into account. The uncertainty ranges are evaluated for different confidence levels of having the actual generation requirements within the corresponding limits. The methodology helps to identify system balancing reserve requirement based on a desired system performance levels, identify system "breaking points" where the generation system becomes unable to follow the generation requirement curve with the user-specified probability level, and determine the time remaining to these potential events. The approach includes three stages: statistical and actual data acquisition, statistical analysis of retrospective information, and prediction of future grid balancing requirements for specified time horizons and confidence intervals. Assessment of the capacity and ramping requirements is performed using a specially developed probabilistic algorithm based on a histogram analysis incorporating all sources of uncertainty and parameters of a continuous (wind forecast and load forecast errors) and discrete (forced generator outages and failures to start up) nature. Preliminary simulations using California Independent System Operator (California ISO) real-life data have shown the effectiveness of the proposed approach. A tool developed based on the new methodology described in this report will be integrated with the California ISO systems. Contractual work is currently in place to integrate the tool with the AREVA Energy Management System (EMS).

Executive Summary

The work reported herein was performed by the Pacific Northwest National Laboratory (PNNL) and funded by the U.S. Department of Energy, Office of the Energy Efficiency and Renewable Energy (DOE EERE).

The work pursues the following objectives:

- Develop a probabilistic model to evaluate uncertainties of wind and load forecast errors and to provide rapid (every 5 minutes) look-ahead (up to 5-8 hours ahead) assessments of their uncertainty ranges.
- Elaborate similar models to evaluate uncertainties caused by generator random forced outages, failures to start up, and contingency reserve activation processes.
- Create an integrated tool that consolidates the above-mentioned continuous and discrete random factors contributing to the overall uncertainty to evaluate look-ahead, worst-case balancing generation requirements (performance envelopes) in terms of the required capacity, ramping capability, and ramp duration.
- Build a methodology and procedures for self-validation of the predicted performance envelope for each look-ahead step.
- Develop visualization displays to communicate information about expected ramps and their uncertainty ranges.
- Implement a prototype Unit Commitment program incorporating future uncertainties.
- Integrate the developed tools into the AREVA Energy Management System (EMS).
- Use actual California Independent System Operator (California ISO) data to perform the simulation.

The following results have been achieved in the current phase of the work:

- Innovative methodology and prototype tools have been developed that can evaluate future generation requirements including the required capacity, ramping capability, and ramp duration capability (performance envelope) in view of uncertainties caused by wind generation and load forecast errors as well as unexpected generation outages. The approach includes three stages: (1) statistical and actual data acquisition, (2) statistical analysis of retrospective information, and (3) prediction of future grid balancing requirements for specified time horizons and confidence intervals. Assessment of the capacity and ramping requirements is performed using a specially developed probabilistic algorithm based on a histogram analysis incorporating all sources of uncertainty and parameters of a continuous and discrete nature.
- A “flying brick” method has been developed to assess the look-ahead, worst-case performance envelope requirement to ensure system capability to balance against the uncertainties with a certain specified degree of confidence. The “flying brick” method simultaneously includes the ramp rate, ramp duration, and capacity requirements directly into the balancing process.

- A self-validation approach has been proposed. The purpose of the self-validation algorithm is to verify that the uncertainty ranges predicted based on retrospective information are valid for future dispatch intervals.
- A MATLAB prototype of the new probabilistic tool has been developed and tested.
- Simulations have been carried out using real-life data from California ISO. The data were provided by the California ISO engineering support team created for this project. Simulation results have shown that the proposed methodology is quite accurate and efficient.
- The concept of probabilistic tool integration into EMS has been developed. The concept includes three levels of integration: passive, active, and proactive. The passive integration level implies integration of wind forecast information and its visualization without introducing any changes to the EMS algorithms. On the active level, the Unit Commitment (UC) and Economic Dispatch (ED) procedures are repeated several times for every dispatch interval to determine whether the system can meet extreme generation requirements caused by uncertainties for a certain confidence level. The system "break points" are communicated to the user. The proactive level requires some modifications of the UC and ED algorithms in order to directly incorporate uncertainties into these procedures. In this case, the generation units will be committed and dispatched to prevent these uncertainties from creating "breaking points."
- A framework of probabilistic tool integration into the AREVA EMS has been developed.

The following are recommendations for the next phase:

- Develop a prototype and specification for an industrial software tool.
- Integrate PNNL's tool into the AREVA EMS. Continue similar integration work with the California ISO.
- Conduct real-time simulation using AREVA's test system.
- Continue development of the proactive integration approach.

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1.0 Introduction

Because conventional generators need time to be committed and dispatched to a desired megawatt (MW) level, the scheduling and load following processes use load and wind power production forecasts to achieve future balance between conventional generation and energy storage on one side and system load, intermittent resources (such as wind and solar generation), and scheduled interchange on the other. The power system balancing process, which includes scheduling, real-time dispatch (load following) and regulation processes, is traditionally based on deterministic models.

Uncertainties in forecasting the output of intermittent resources such as wind and solar generation, as well as system loads, are not reflected in an existing energy management system (EMS) and tools for generation commitment, dispatch, and market operation. With the growing penetration of intermittent resources, these uncertainties could result in significant unexpected load following and dispatch problems and pose serious risks to control and operation performance characteristics as well as the reliability of a power grid. Without knowing the risks posed by the uncertainties, system operators have limited means to assess the likelihood of occurrence and the magnitude of problems to mitigate adverse impacts they might cause. Some important questions need to be addressed in counteracting the impact of uncertainties. For instance, should one start more units to balance against possible fast ramps in the future over a given time horizon, and if so, when?

Furthermore, these uncertainties could require procuring additional costly balancing services. Major unexpected variations in wind power, unfavorably combined with load forecast errors and forced generator outages, could cause significant power mismatches that could be essentially unmanageable if these variations are not known in advance.

Because the actual load and intermittent generation can deviate from forecasts, it becomes increasingly unclear (especially with the increasing penetration of renewable resources) whether the system would be able to meet the conventional generation requirements within the look-ahead horizon, what additional balancing efforts would be needed as real time nears, and what additional costs would be incurred by those needs.

To improve the system control performance characteristics, maintain system reliability, and minimize expenses related to the system balancing functions, it becomes necessary to incorporate the projected uncertainty ranges into the scheduling, load following, and to some extent, regulation processes. This need has been realized already, and some wind forecast service providers already offer the uncertainty information for their forecasts. Efforts are already in place to develop methodologies and tools to incorporate these uncertainties into power system operations. Unfortunately, in many cases these efforts are limited to wind generation uncertainties only and ignore the fact that there are additional sources of uncertainty such as system loads and forced generation outages. Most of these efforts consider only the uncertainty ranges for MW imbalances and do not address additional essential characteristics such as ramps and ramp duration uncertainties.

It is very important to address the uncertainty problem comprehensively by including all sources of uncertainty (load, intermittent generation, forced outages of generators, etc.) for consideration. All aspect of uncertainty such as the imbalance size (which is the same as capacity needed to mitigate the imbalance) and generation ramping requirement must be taken into account. The unique features of the latter make this work a significant step forward toward the objective of incorporating wind, solar, load, and other uncertainties into power system operations.

In this preliminary report, the uncertainties associated with wind power generation forecasting, load demand forecasting, and generation supply interruptions caused by forced outages are taken into account in the evaluation of uncertainty ranges for the required generation performance envelope, including balancing capacity, ramping capability, and ramp duration. A probabilistic algorithm based on the proposed histogram analysis to assess the capacity and ramping requirements is presented. Preliminary simulation was performed using the California Independent System Operator (California ISO)'s system model and data. This report presents these simulation results confirming the validity and efficiency of the proposed solutions.

The report is organized as follows. Chapter 2 discusses the main proposed uncertainty tool concepts. Chapter 3 provides a methodology for evaluating the uncertainties associated with wind and load forecasts. Generation outages and generation requirements as sources of uncertainty are analyzed in Chapters 4 and 5, respectively. Chapter 6 describes how the newly developed tools can be integrated into the EMS environment (with the ARIVA EMS) of independent system operators (California ISO) and other potential customers. Preliminary results of simulation studies are given in Chapter 7. Conclusions are given in Chapter 8 followed by references provided in Chapter 9.

2.0 Main Uncertainty Analysis Tool Concepts

This section describes a staged approach to evaluate future uncertainty ranges around such important characteristics of the balancing process as the required generation capacity, ramping capability, and ramp duration capability. Without being able to provide for those characteristics, the generation fleet would not be able to follow the needs dictated by the load following and regulation processes. To address this challenge, Pacific Northwest National Laboratory (PNNL) is developing a set of new concepts and algorithms for the uncertainty prediction tool. Such a tool, integrated with a real EMS system, would help system operators to see potential balancing problems ahead of time, and ultimately, to modify the generation commitment patterns to successfully mitigate these problems.

The proposed methodology evaluates the uncertainty ranges for the required generation performance envelope, which includes the required balancing generation capacity, ramping capability, and ramp duration. It consists of three stages. The first stage deals with acquiring the actual retrospective data needed for the subsequent statistical analysis. The retrospective information is collected for a user-specified preceding period (e.g., for 1 to 2 months). It includes forecasted system load and its actual values, wind and solar generation forecasts and their actual values, as well as generation schedules. The second stage of the proposed approach includes a statistical analysis of the retrospective information acquired at stage 1. It consists of the following tasks:

- Determining statistical characteristics of the generation capacity requirements based on an empirical analysis of forecast errors;
- Evaluating statistical characteristics of the generation ramping requirements based on the "swinging door" algorithm;
- Calculating generation-forced outage statistical information based on the Markov models.

The third stage is an evaluation of future generation requirements for specified time horizons; e.g., 5 to 8 hours ahead and for the next day. These generation requirements include regulation and load following capacity requirements, ramping requirements, and ramp duration requirements for different confidence levels, such as, for example, 90 or 95 %.

The information provided by the three-stage approach described above could be used in three ways reflecting different levels of integration with the EMS system: passive, active, and proactive. In the passive level, the projected performance requirements can be compared against the actual capabilities of generators that are currently or will be online within the look-ahead horizon and are capable of performing relevant services. If the actual generation capability does not match the requirements, a warning will be issued to the system operators. The operators will be informed about the type and the size of the expected problem, its probability, and the time remaining for that situation. In the active level, the Unit Commitment (UC) and Economic Dispatch (ED) procedures are repeated several times for every dispatch interval to determine whether the system can meet the extreme generation requirements caused by uncertainties for a certain confidence level. The system "break points" are communicated to the user. The proactive level requires some modifications of the UC and ED algorithms to directly incorporate uncertainties into these procedures. In this case, the generation units will be committed and dispatched so that these uncertainties would not create "breaking points."

3.0 Load and Wind Generation Uncertainties Evaluation

This section describes an innovative methodology and prototype tools that are capable of evaluating future generation requirements including the required capacity, ramping capability, and ramp duration capability (the so-called performance envelope). The methodology incorporates uncertainties caused by wind generation and load forecast errors, as well as uninstructed generation deviations of conventional generation. These tools meet industry needs in a more robust (that is, more reliable for a range of possible future operating conditions) assessment of the balancing reserves required in a control area.

The efforts discussed in chapter 2 address only one source of uncertainty: that related to wind generation. Because the influence of other sources of uncertainty is not reflected in the resulting uncertainty assessment, the resulting confidence intervals could be misleading for system operators. Unlike existing approaches, the methodology discussed in this report addresses all sources of uncertainty including uncertainties surrounding load forecasts and those associated with forced generator outages.

The proposed approach includes three stages: (1) statistical and actual data acquisition, (2) statistical analysis of retrospective information, and (3) prediction of future grid balancing requirements for specified time horizons and confidence intervals. Assessment of the capacity and ramping requirements is performed using a specially developed probabilistic algorithm based on a histogram analysis[1] incorporating all sources of uncertainty and random parameters of a continuous and discrete nature.

A "flying brick" method has been developed to assess the look-ahead, worst-case performance envelope requirement to ensure system capability to balance against the uncertainties with a certain specified degree of confidence. The "flying brick" approach includes simultaneously the ramp rate, ramp duration, and capacity requirements directly into the balancing process and then looks for the worst combinations of these parameters located along the vertices' trajectories of the "brick".

3.1 Data Acquisition

A sliding window technique is used to acquire continuous statistical information on system load, wind, and solar power generation forecast errors. The time length and refreshment rate of the sliding window used in this study are from 1 to 2 months and once every 5 minutes, respectively. For future applications, these parameters need to be adjusted based on the characteristics of the actual power system.

Figure 3.1 represents a typical structure of the load and wind generation forecasts. The forecast resolution is the time interval between any two subsequent data records. The time horizon is the length of the look-ahead time interval, and the forecast update interval is the time interval for updating the forecast.

3.2 Assessment of Capacity Requirements

Wind generation has more features in common with electrical load than with traditional (dispatchable) generation. Therefore, it is assumed that wind generation can be considered as a negative load.

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[1] This approach is also called the time-varying probability density function (PDF) method, or the quantile method.

Electrical load and wind generation cannot be considered as independent statistical variables. Many studies show a correlation between the system load and wind generation (Makarov et al. 2009, General Electric 2008, CAISO 2007). To reflect this statistical dependence, the commonly used net load is applied in this work. Net load has the following definition: net load is total electrical load minus total wind generation output.

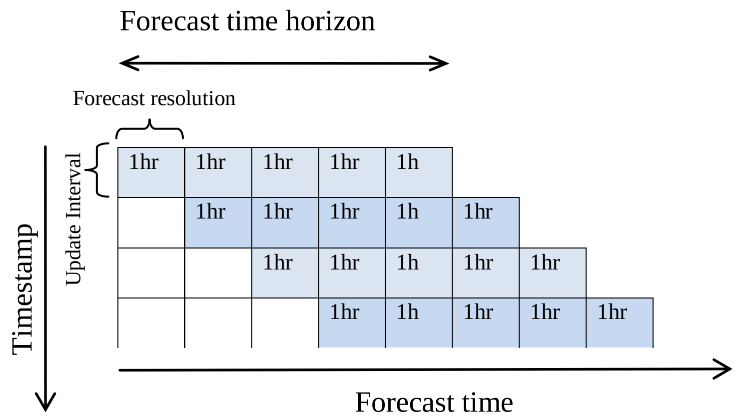


Figure 3.1. Example of Wind or Load Generation Forecast Structure

Statistical analysis based on the time-varying probability density function (PDF) approach is used in this study to determine the combined uncertainty ranges of wind and load forecast errors. When the data do not follow standard probability distribution, nonparametric models may be applied to reflect the statistical characteristics of the data. These models make no assumptions about the mechanism producing the data or the form of the underlying distribution, so no approximations are made (MathWorks Inc. 2009). Thus, instead of estimating parameters of a selected distribution, a nonparametric PDF can be assessed using the empirical cumulative distribution function (CDF).

The idea behind the empirical CDF is rather simple. It is a function that assigns probability 1 over *n* to each *n* observation in a sample. Its graph has a stair-step appearance, where the stair goes through the range of the analyzed random parameters changing from zero level to 1, and increases by 1/*n* at each point where a sample parameter is found. If a sample comes from a distribution in a parametric family (such as a normal distribution), its empirical CDF is likely to resemble this distribution. If not, its empirical distribution still gives an estimate of the CDF for the data (MathWorks Inc. 2009). Net load forecast error distribution and empirical CDF are presented in Figure 3.2.

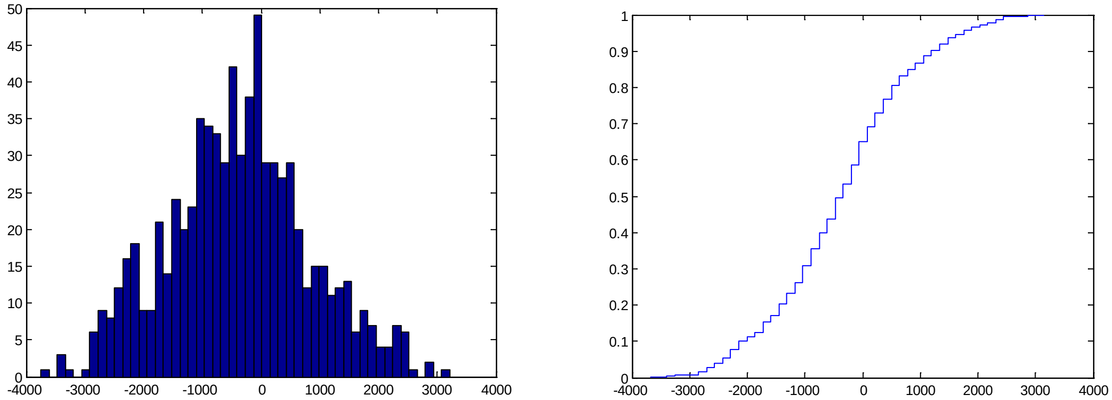


Figure 3.2. Net Load Forecast Error Distribution (CAISO data, June-August 2007); a) Histogram; b) Empirical CDF.

Figure 3.3 presents an example of wind generation forecast PDF for different look-ahead periods (1, 2, 3, 4, and 5 hours ahead). It can be observed that with shorter forecasting horizons, forecast errors become smaller, which results in higher PDF peaks and narrower shapes.

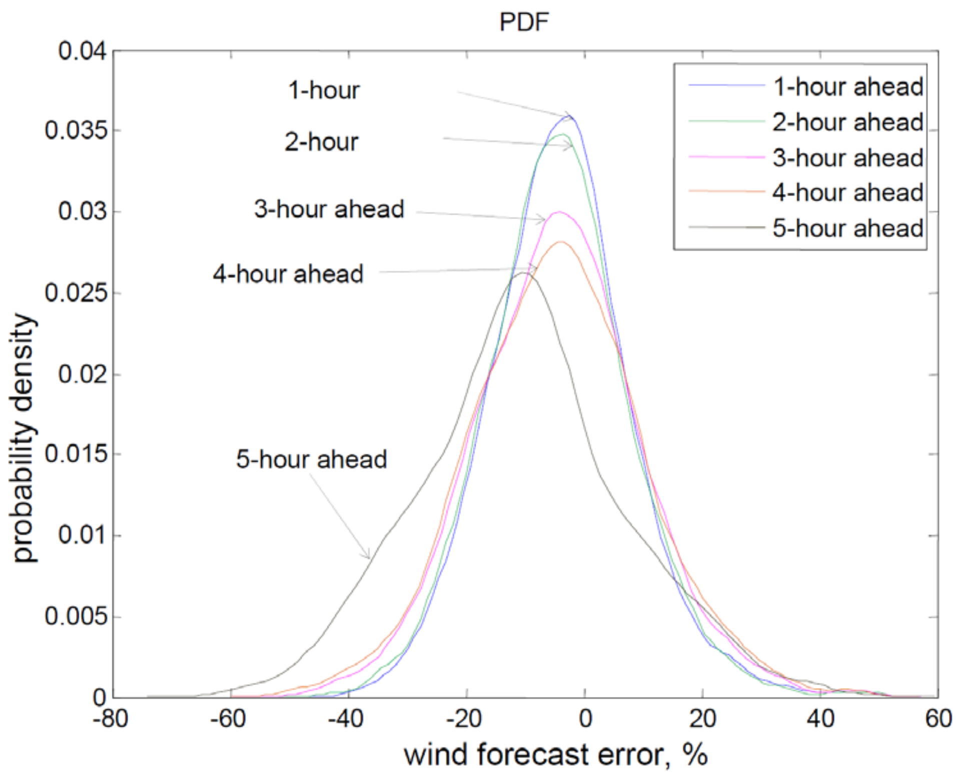


Figure 3.3. Wind Generation Forecast PDFs for Different Look-Ahead Periods

The uncertainty range defines an interval within which a random parameter is expected to lie with a specified level of confidence. To determine the uncertainty range, it is necessary to find solutions x_1 and x_2 of the inverse CDF function corresponding to certain levels of probability p_1 and p_2:

$$x_1 = CDF^{-1}(p_1),\ p_1 \in [0,1]$$
$$x_2 = CDF^{-1}(p_2),\ p_2 \in [0,1],$$

where

$$CDF(x_2) - CDF(x_1) = P(x_1 \le X \le x_2) = \int_{x_1}^{x_2} PDF(x)dx \qquad (3.1)$$

The inverse of the CDF is also called the quantile function. Inverse CDF functions for wind generation forecast errors for different look-ahead periods are presented in Figure 3.4. Uncertainty ranges evaluated at a 95% confidence level are also shown. The 95% uncertainty range corresponds to 2.5 to 97.5 percentile of the distribution. It is obvious from Figure 3.4 that the size of uncertainty ranges depends on look-ahead time. It can be seen that for the longer look-ahead period, the uncertainty range becomes larger.

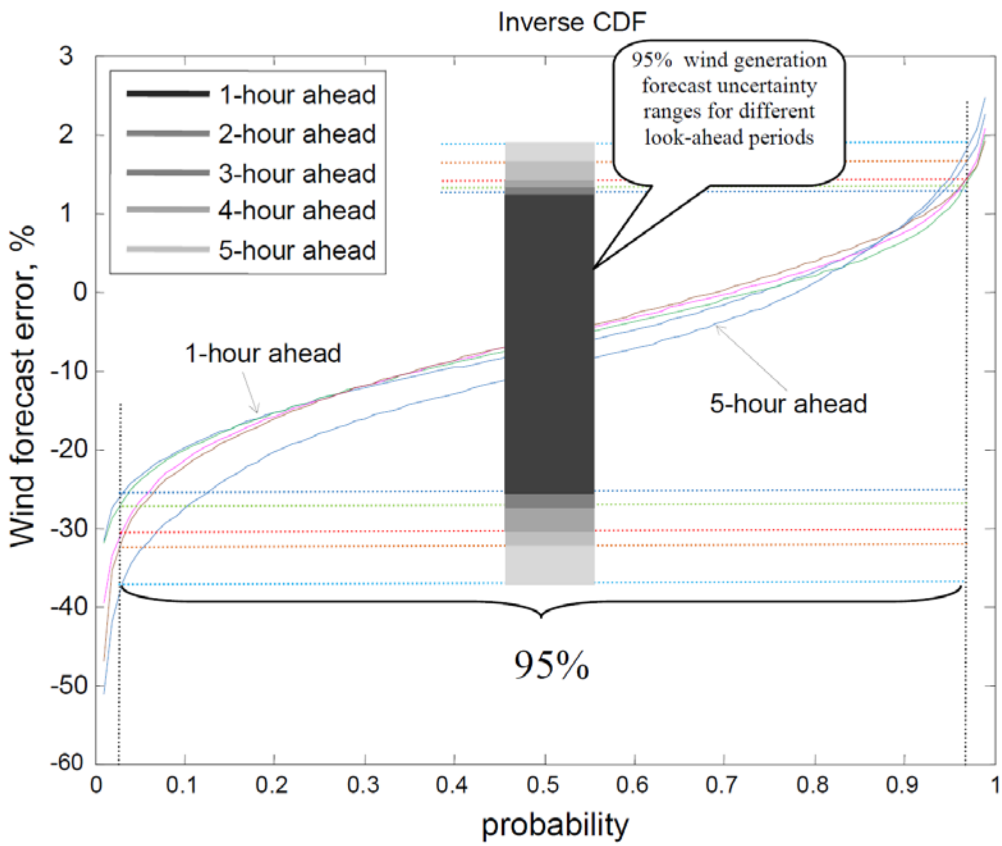


Figure 3.4. Inverse CDFs of Wind Generation Forecast for Different Look-Ahead Periods and 95% Uncertainty Ranges

3.3 Enhanced Capacity Uncertainty Assessment

Statistical characteristics of the wind generation forecast error depend on the level of predicted wind generation among some other variables. Therefore, the accuracy of the uncertainty range model can be further improved if the level of predicted wind generation is taken into account.

The wind generation forecast can be divided into several intervals depending on the level of predicted power production. The empirical statistical analysis presented in the previous section can be performed separately for each interval.

Figure 3.5 shows an example of inverse CDFs of wind generation forecast errors calculated for different wind generation levels. In the example, five intervals of wind generation forecast were considered: "low wind," "medium low wind," "average wind," "medium high wind," and "high wind,"

The error distribution of the "low wind" forecast is close to normal and varies within a ±20% range. The error distribution of "high wind" is biased. It can be explained by the fact that the forecasted wind generation cannot exceed the maximum installed wind generation capacity. Therefore, for the "high wind" forecast, the actual wind generation frequently is less than that forecasted.

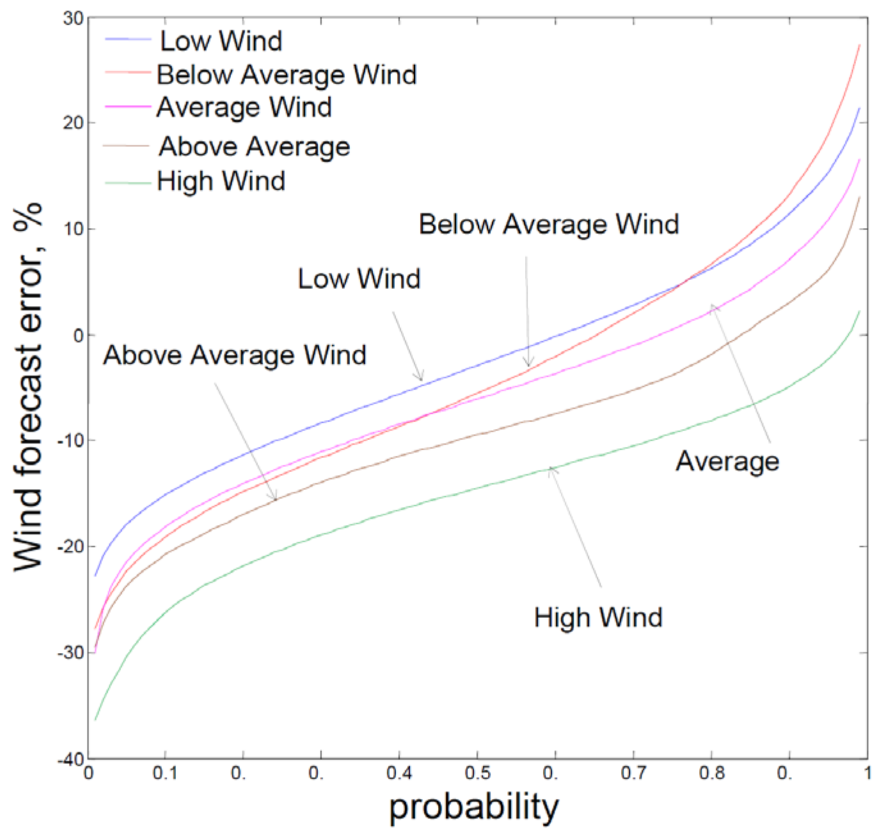


Figure 3.5. Inverse CDFs for Different Levels of Forecasted Wind Generation

3.4 Assessment of Ramping Requirements

The required ramping capability needed to follow the net load curve (which includes all system imbalances) can be derived from the shape of the regulation and load following curves – see details in Makarov et al. (2009.). The "swinging door" algorithm is proposed for this purpose (Makarov et al. 2009). This is a proven and widely used technical solution to compress and store time-dependent datasets.

Figure 3.6 demonstrates the concept of the “swinging door” approach. A point is classified as a “turning point” whenever, for the next point in the sequence, any intermediate point falls out of the admissible accuracy range $\pm\varepsilon_{\Delta G}$. For instance, for point 3, one can see that point 2 stays inside the window *abcd*. For point 4, both points 2 and 3 stay within the window *abef*. But for point 5, point 4 goes beyond the window, and therefore, point 4 is marked as a turning point.

Based on this analysis, we conclude that points 1, 2, and 3 correspond to the different magnitudes of the regulation signal, π_1, π_2 and π_3, whereas the ramping requirement at all these points is the same, $\rho_{1\text{-}3}$. The “swinging door” algorithm also helps to determine the ramp duration δ.

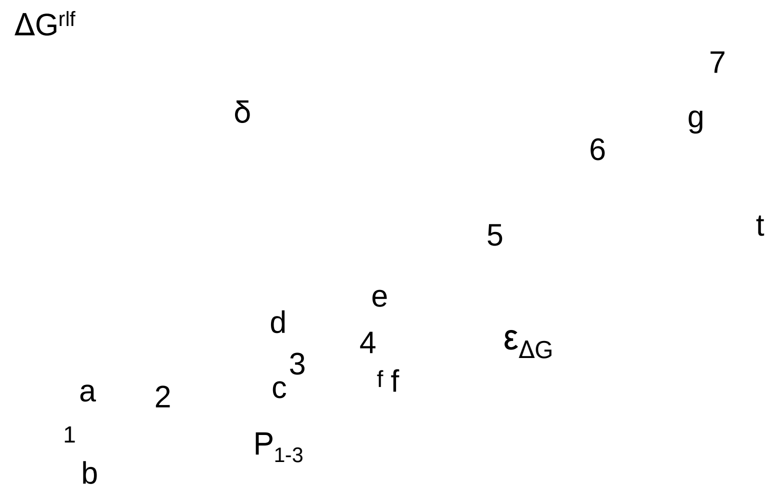


Figure 3.6. Illustration of the "Swinging Door" Concept

3.5 “Flying Brick” Method

A method called “flying brick” is proposed in this study to analyze the time-varying extreme (worst-case) requirements applied to the future generation capacity, ramping capability, and ramp duration. In the previous sections of this report, only the required generation capacity information was analyzed. The idea of the “flying brick” is to include the worst-case (for a given confidence level) combination of the ramp rate, ramp duration, and capacity requirements into the scheduling process. The three requirements are visualized as a three-dimensional probability box. Figure 3.7 demonstrates the idea of the “flying brick” method. In Figure 3.7, the blue curve in the center is the expected generation requirement curve, which meets the expected net load. The pink curve is the actual net load, which can deviate from its expected values. The generator requirement ranges with 95% and 93% confidence levels are also shown in Figure 3.7.

Suppose t_0 is the current time point. At this point, we apply the probability box algorithm to the 1-hour-ahead forecast errors. The three dimensions of the box are the ranges of the capacity, ramp rate, and ramp duration requirements. The worst combinations of these parameters shown by the vertices of the probability box set a criterion for the generation characteristics needed to meet the system needs with a certain level of confidence. For example, the edge could correspond to the maximum capacity, maximum ramp, and maximum ramp duration within the covered uncertainty range for these parameters.

For each time interval, the “flying brick” box is built based on the three-dimensional CDFs reflecting the ranges of the analyzed parameters induced by the forecasting errors.

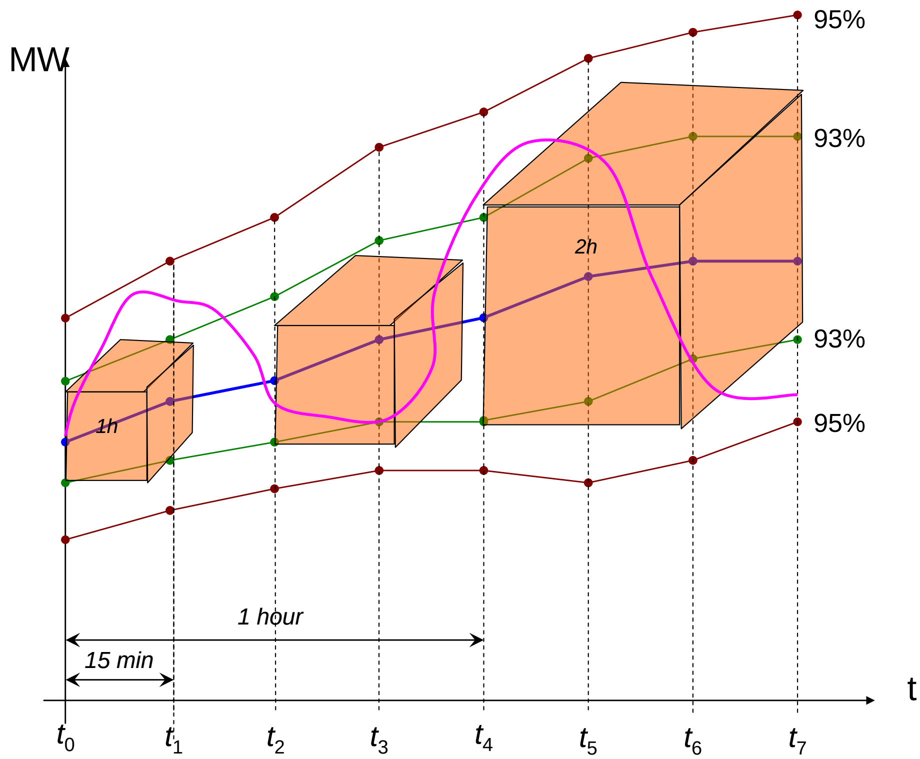


Figure 3.7. Idea of the “Flying Brick” Method

Inverse CDF functions of the ramping requirement distribution for different ramp durations obtained using the “flying brick” approach are presented in Figure 3.8. The uncertainty evaluation for the ramping requirements is similar to the capacity requirement evaluation (see Figure 3.4). Ramping requirement uncertainty ranges evaluated at the 95% confidence level are shown in Figure 3.8. It can be observed that the ramping ranges depend on ramp durations, and ramping requirements become lower for longer ramp durations.

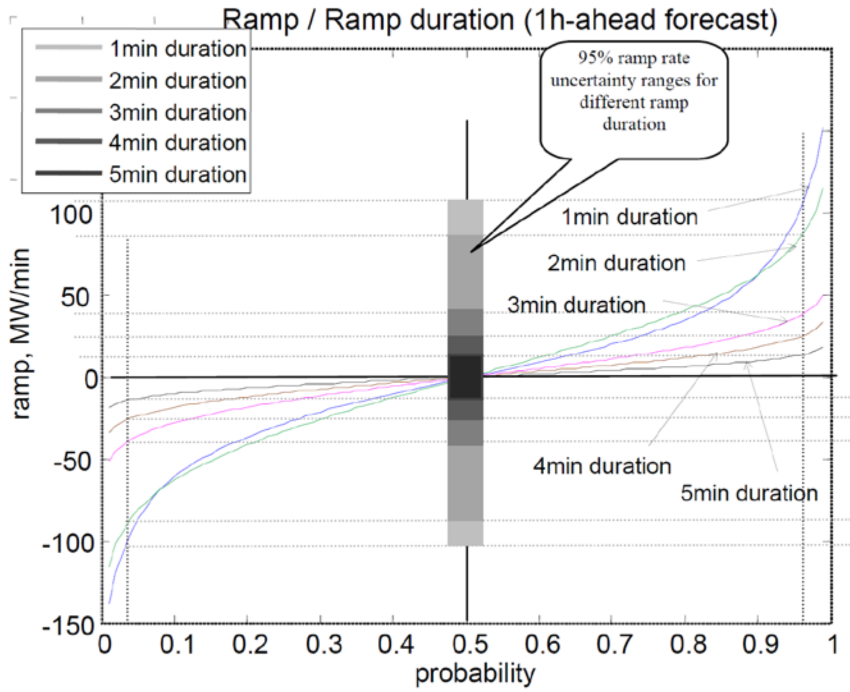


Figure 3.8. Ramping Requirement Inverse CDFs for Different Ramp Duration and 95% Confidence Intervals

4.0 Generator Forced Outage Analysis

This chapter presents the generator forced outage model. The term “generator forced outage” usually refers to the shutdown of a generating unit for emergency reasons or a condition in which the generator unit is unavailable for supplying the load because of an unanticipated breakdown. Generator outage is a discrete event and may or may not happen in any given dispatch interval. This characteristic contrasts with the continuous nature of wind and load variations. Also, the size of the power mismatch caused by a forced outage depends on the generator that is disconnected and the generators’ load at the moment of the event. Any of the generators that are online within a dispatch interval could be forced out. The main challenge to overcome in this development was to combine the uncertainty information on continuous parameters (such as the generation capacity requirement) with discrete information (such as forced generation outages). This challenge was successfully met in this project.

Forced outages of system generators cause temporary imbalances that must be eliminated within 10 minutes by activating the contingency reserve. Within this 10-minute interval, the system is exposed to an imbalance that can be as much as 1000 MW (the size of the largest generation unit in the system). The system inertia, governor response, and automatic generation control act to minimize the system power mismatch during the first seconds and minutes after the disturbance. Therefore, the generation controls and generation characteristics needed to balance the system must be sufficient to mitigate these possible mismatches. Again, there is an uncertainty associated with this process because the timing and the size of the forced outages are not known ahead of time, and the contingency reserve activation process is not a deterministic process (for example, it depends on the characteristics of activated generators and type of activated reserve – spinning or non-spinning).

The project developed a methodology that evaluates additional uncertainty caused by forced generator outages and incorporates this information into the overall framework. This advanced feature constitutes a significant step forward in handling the uncertainty information in modern EMS systems. As a result, the system reliability and control performance can be additionally improved.

Generator forced outages are stochastic events. Modeling statistical characteristics of generator forced outages is important for a correct evaluation of the future generation requirement. In this chapter, two types of generator forced outage models are described: the two-state Markov model and the four-state Markov model. The capacity outage probability table (COPT) and an example of COPT calculation are provided as are simulation results on the forced outage model. A contingency reserve activation model that incorporates the forced outage model is under development by a University of Washington team subcontracted by PNNL in this project (Dr. Richard D. Christie and Scott D. James Macpherson).

4.1 Forced Outage Rate Calculation

A generator outage is a discrete event, which may occur at any given moment. This contrasts with the continuous nature of the wind and load variations (Doherty and O'Malley 2005).

The simplest type of unit model is a two-state Markov model as shown in Figure 4.1. Here, the unit is assumed to always be in one of two states: up-fully available, running and subject to failure; or down-totally unavailable, not running, and undergoing repair (Billinton and Allan 1996, Billinton and Ge 2004).

Here, μ is the repair rate and $r=1/\mu$ is the mean downtime due to a forced outage (mean time to repair (MTTR)) and λ is the failure rate and $m=1/\lambda$ is the mean up time between failure events (mean time to failure (MTTF)). The unit's forced outage rate (FOR), the probability that the unit is down is:

$$FOR = \frac{\lambda}{\lambda + \mu} = \frac{r}{m + r} = \frac{FOH}{SH + FOH} \tag{4.1}$$

where FOH is the forced outage hours and SH is the service hours.

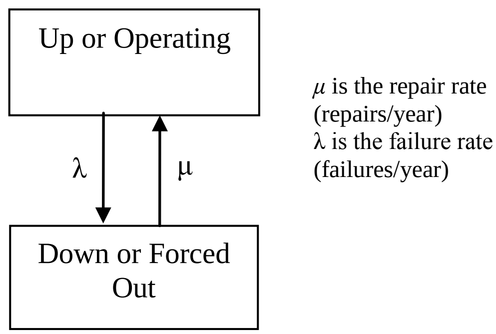


Figure 4.1. Two-State Markov Model

The two-state model is a valid representation for base load units but does not adequately represent intermittent operating units used to meet peak load conditions. The two-state model for a base load unit has been extended to the four-state peaking unit model shown in Figure 4.2, which is widely used in practice (Billinton and Ge 2004).

The model assumes that the generating unit is either fully available or totally unavailable but also considers that the unit may be either needed or not needed (Billinton and Ge 2004).

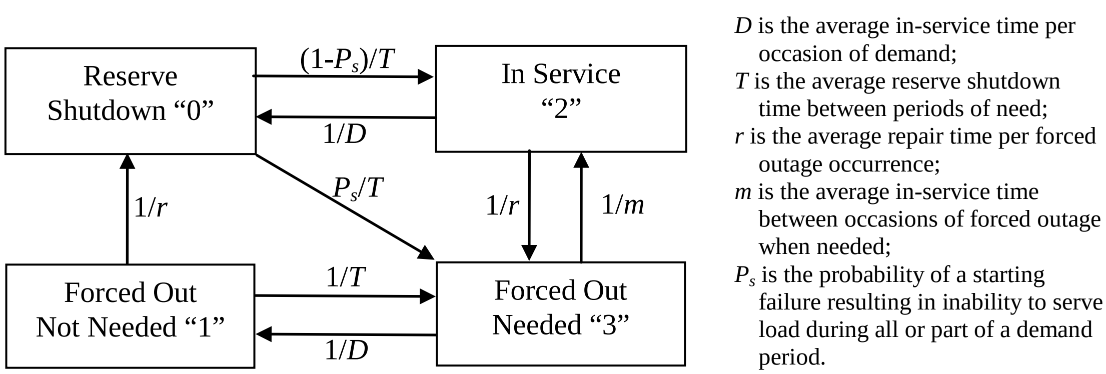


Figure 4.2. IEEE Four-State Markov Model

The frequency balance equations (Billinton and Allan 1996) for the four-state model shown in Figure 4.2 are as follows:

$$\begin{cases} P_2 \times \left(\dfrac{1}{D}+\dfrac{1}{m}\right) = P_0 \times \dfrac{1-P_s}{T} + P_3 \times \dfrac{1}{r} \\ P_3 \times \left(\dfrac{1}{r}+\dfrac{1}{D}\right) = P_2 \times \dfrac{1}{m} + P_1 \times \dfrac{1}{T} + P_0 \times \dfrac{P_S}{T} \\ P_1 \times \left(\dfrac{1}{T}+\dfrac{1}{r}\right) = P_3 \times \dfrac{1}{D} \\ P_0 + P_1 + P_2 + P_3 = 1 \end{cases} \tag{4.2}$$

where P_i is the probability of the state i and i=0…3.

According to Billinton and Allan (1996) P_1 and P_3 can be calculated using the following equations:

$$P_1 = \frac{r^2 T(D+mP_s)}{M} \tag{4.3}$$

$$P_3 = \frac{rD(D+r)(D+mP_s)}{M} \tag{4.4}$$

Demand factor f can be expressed as the function of the parameters given in Figure 4.2 as follows (Billinton and Allan 1996):

$$f = \frac{P_3}{P_3+P_1} = \frac{\dfrac{1}{r}+\dfrac{1}{T}}{\dfrac{1}{D}+\dfrac{1}{r}+\dfrac{1}{T}} \tag{4.4}$$

Forced Outage Rate demand (FORd):

$$FORd = \frac{f \times FOH}{f \times FOH + SH} \tag{4.5}$$

FORd is based on the four-state model and is the probability that a generating unit will not be available when required.

Equivalent Forced Outage Rate demand (EFORd) (Billinton and Ge 2004):

$$EFORd = \frac{f \times FOH + f_p \times EFDH}{f \times FOH + SH} \tag{4.6}$$

where f_p is the partial outage factor;

EFDH is the Equivalent Forced Derating Hours.

EFORd can be found in the North American Electric Reliability Corporation (NERC) Generating Availability Data System (GADS) (North American Electric Reliability Corporation 2009, Curley 2006). The difference between EFORd and FORd is that EFORd also includes derated states of the generator.

The full outage probability (FOP) of a unit is the probability that the unit will stop providing all of its current output in an hour period. Here, it is assumed that the trip causes the units output to be instantaneously unavailable. The hourly FOP of a unit can be related to the FOR and MTTR as (Billinton and Allan 1996):

$$FOP_i = \frac{FOR_i}{MTTR_i} \tag{4.7}$$

In the case of peaking units, EFORd can be used instead of FOR in (4.7)

4.2 Capacity Outage Probability Table

The capacity adequacy evaluation of generation systems requires the creation of a generation capacity model, known as COPT.

COPT gives the probability of occurrence for each possible outage capacity level (Billinton and Allan 1996).

Let us assume that the system has n independent generating units, and unit i has m_i discrete states with outage capacity C_{ij} and individual probability $p_{ij}=p(X_i=C_{ij})$, where $j=1\ldots m_i$ (Morrow and Gan 1993)..

Outage states of unit i are arranged in ascending order.

The COPT contains N+1 discrete states, where $N=C_{max}/\Delta$, C_{max} is the installed capacity of the system, and Δ is the resolution of the COPT.

The new individual state probabilities, after unit i is added to the system, can be calculated using the following recursive algorithm (Morrow and Gan 1993).

$$p(k) = \sum_{j=1}^{m_i} p_{ij}\, p'(k - \frac{c_{ij}}{\Delta}), \quad k = 0,1,2,\ldots,N \tag{4.8}$$

where $p(\cdot)$ is individual state probabilities after unit i is added;

$p'(\cdot)$ is individual state probabilities before unit i is added;

k is an index of discrete state.

The recursive convolution process starts with the initial values: $p(0)$ =1 and $p(k)$=0, k=1,2 ,... N. Note that $p(k)$=0 if k<0.

In summary, the recursive convolution procedure for building a COPT has the following basic steps (Morrow and Gan 1993):

1. Read unit data, determine Δ and $N=C_{max}/\Delta$
2. Set initial values: $p(0)=1$ and $p(k)=0$, $k=1,2,\ldots N$
3. Add unit i to the system, calculate $p(k)$, $k=0,1,2,\ldots,N$ using (Eqn. 4.8);
4. Repeat Step 3 for all the units.

Usually the table obtained by (Eqn. 4.8) is simplified by rounding the COPT to selected discrete capacity levels. The size of the round-off increment depends on the desired accuracy.

The cumulative probability of having $k\Delta$ MW to be forced out can be calculated using the following equation:

$$P(k)=\sum_{s=0}^{k} p(s) \tag{4.9}$$

4.3 Example of COPT Calculation

Let the system consist of two generators.

The first generator has a capacity of 100 MW and outage probability 10%, and the second generator has a capacity of 50 MW and outage probability 20%. Assume that generating units can have only two states: operating and forced out.

Then, the capacity matrix:

$$C=\begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}=\begin{bmatrix} 0 & 100 \\ 0 & 50 \end{bmatrix},$$

where $c_{11}=0$ and $c_{21}=0$ – correspond to operating states of generators one and two (no forced outage) and $c_{12}=100$ and $c_{22}=50$ – correspond to forced out states (nominal generator capacity).

Individual probability matrix is defined as:

$$P=\begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}=\begin{bmatrix} 0.9 & 0.1 \\ 0.8 & 0.2 \end{bmatrix},$$

where $p_{11}=0.9$ and $p_{21}=0.8$ are probabilities of operating state of generators one and two; $p_{12}=0.1$ and $p_{22}=0.2$ are probabilities of the forced out state.

The installed system capacity is $C_{max}=150$MW and the COPT resolution is $\Delta=50$MW. Therefore COPT contains four discrete states.

Let us set initial probability values *p(k)*in the COPT (Table 4.1).

Table 4-1. COPT (Initial Values)

State, *k*	Capacity, *c(k)* (MW)	Probability, *p(k)*
0	0	1
1	50	0
2	100	0
3	150	0

Now we will add unit one to the system and calculate new capacity outage probabilities using (Eqn. 4.8) (Table 4.2):

$$k=0: \quad p(0)=p_{11}\cdot p'(k-\frac{c_{11}}{\Delta})+p_{12}\cdot p'(k-\frac{c_{12}}{\Delta})=0.9\cdot p'(0-\frac{0}{50})+0.1\cdot p'(0-\frac{100}{50})=$$
$$=0.9\cdot p'(0)+0.1\cdot p'(-2)=0.9\cdot 1+0.1\cdot 0=0.9$$

$$k=1: \quad p(1)=p_{11}\cdot p'(k-\frac{c_{11}}{\Delta})+p_{12}\cdot p'(k-\frac{c_{12}}{\Delta})=0.9\cdot p'(1-\frac{0}{50})+0.1\cdot p'(1-\frac{100}{50})=$$
$$=0.9\cdot p'(1)+0.1\cdot p'(-1)=0.9\cdot 0+0.1\cdot 0=0$$

$$k=2: \quad p(2)=p_{11}\cdot p'(k-\frac{c_{11}}{\Delta})+p_{12}\cdot p'(k-\frac{c_{12}}{\Delta})=0.9\cdot p'(2-\frac{0}{50})+0.1\cdot p'(2-\frac{100}{50})=$$
$$=0.9\cdot p'(2)+0.1\cdot p'(0)=0.9\cdot 0+0.1\cdot 1=0.1$$

$$k=3: \quad p(3)=p_{11}\cdot p'(k-\frac{c_{11}}{\Delta})+p_{12}\cdot p'(k-\frac{c_{12}}{\Delta})=0.9\cdot p'(3-\frac{0}{50})+0.1\cdot p'(3-\frac{100}{50})=$$
$$=0.9\cdot p'(3)+0.1\cdot p'(1)=0.9\cdot 0+0.1\cdot 0=0$$

Table 4-2. COPT (Unit One Added)

State, *k*	Capacity, *c(k)* (MW)	Probability, *p(k)*
0	0	0.9
1	50	0
2	100	0.1
3	150	0

The next step is adding unit two and updating the values of COPT (Table 4.3):

$$k=0: \quad p(0)=p_{21}\cdot p'(k-\frac{c_{21}}{\Delta})+p_{22}\cdot p'(k-\frac{c_{22}}{\Delta})=0.8\cdot p'(0-\frac{0}{50})+0.2\cdot p'(0-\frac{50}{50})=$$
$$=0.8\cdot p'(0)+0.2\cdot p'(-1)=0.8\cdot 0.9+0.2\cdot 0=0.72$$

$$k=1: \quad p(1)=p_{21}\cdot p'(k-\frac{c_{21}}{\Delta})+p_{22}\cdot p'(k-\frac{c_{22}}{\Delta})=0.8\cdot p'(1-\frac{0}{50})+0.2\cdot p'(1-\frac{50}{50})=$$
$$=0.8\cdot p'(1)+0.2\cdot p'(0)=0.8\cdot 0+0.2\cdot 0.9=0.18$$

$$k=2: \quad p(2)=p_{21}\cdot p'(k-\frac{c_{21}}{\Delta})+p_{22}\cdot p'(k-\frac{c_{22}}{\Delta})=0.8\cdot p'(2-\frac{0}{50})+0.2\cdot p'(2-\frac{50}{50})=$$
$$=0.8\cdot p'(2)+0.2\cdot p'(1)=0.8\cdot 0.1+0.2\cdot 0=0.08$$

$$k=3: \quad p(3)=p_{21}\cdot p'(k-\frac{c_{21}}{\Delta})+p_{22}\cdot p'(k-\frac{c_{22}}{\Delta})=0.8\cdot p'(3-\frac{0}{50})+0.2\cdot p'(3-\frac{50}{50})=$$
$$=0.8\cdot p'(3)+0.2\cdot p'(2)=0.8\cdot 0+0.2\cdot 0.1=0.02$$

Table 4-3. COPT (Unit Two Added)

State, *k*	Capacity, *c(k)* (MW)	Probability, *p(k)*
0	0	0.72
1	50	0.18
2	100	0.08
3	150	0.02

Figure 4.3 and Figure 4.4 show the capacity discrete outage PDF and CDF based on calculated COPT.

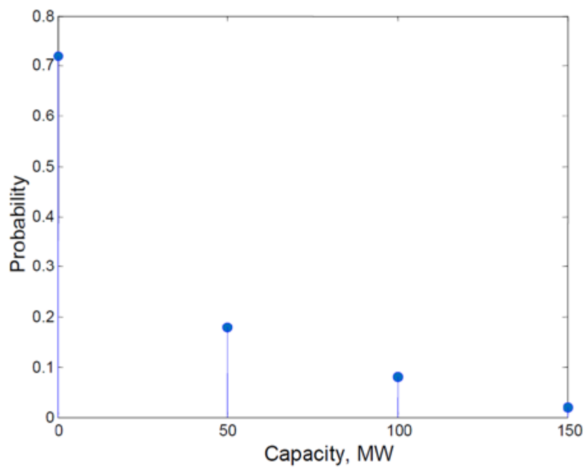


Figure 4.3. Discrete Probability Density Function

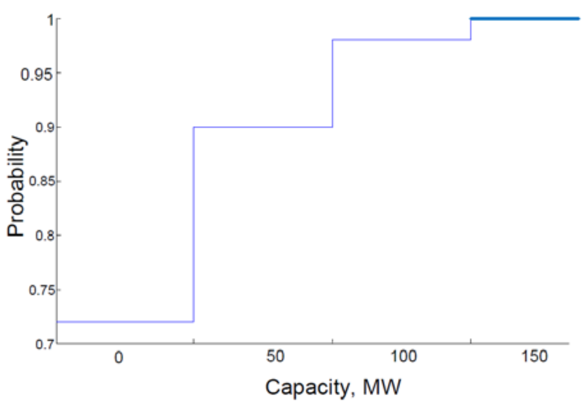


Figure 4.4. Cumulative Distribution Function

4.4 Preliminary Simulation Results (Forced outage model)

An example of a CAISO generation schedule is presented in Table 4.4 and Generation unit performance statistical characteristics taken from GADS (North American Electric Reliability Corporation 2009) are presented in Table 4.5.

COPTs are calculated to the each hour taking into account the generators' schedule. Figure 4.5 and Figure 4.6 show the capacity outage PDF and CDF functions for a 1 hour look-ahead period.

Table 4-4. Generation Schedule

Number	UNIT_ID	Unit Type	1h	2h	3h	4h	5h
1	Unit1	STUR	16	16	16	16	16
2	Unit2	STUR	20	20	20	20	20
3	Unit3	HYDR	16	16	16	16	16
4	Unit4	GTUR	0	0	0	0	0
…..	……………………	……	…	…	…	…	…
516	Unit516	STUR	3	3	3	3	3
517	Unit517	WIND	10	10	10	10	10
	Total Generation		**17792.9**	**16512.06**	**16113.22**	**15813.15**	**15811.15**
	Wind		1344	1310.28	1313.55	1299.14	1256.3

Table 4-5. Annual Unit Performance Statistic

GEN_TYPE	GEN_TECH	FUEL_TYPE	FOR	Service Hours	Number of occurrences
T	STUR	GEOT	0.5	8500	3.6
T	GTUR	GAS	46.33	270	3
T	STUR	GAS	8.29	2750	4
H	HYDR	WATR	4.92	4981	3
T	WIND	WIND	-	-	-
T	CCYC	GAS	7.33	3673	9
H	PTUR	WATR	3.71	2634	3.86

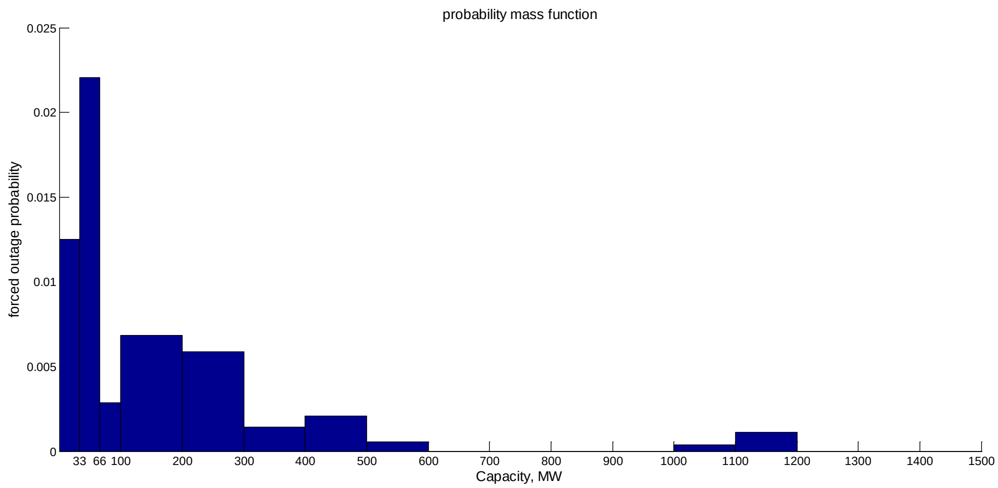


Figure 4.5. Capacity Outage Discrete PDF

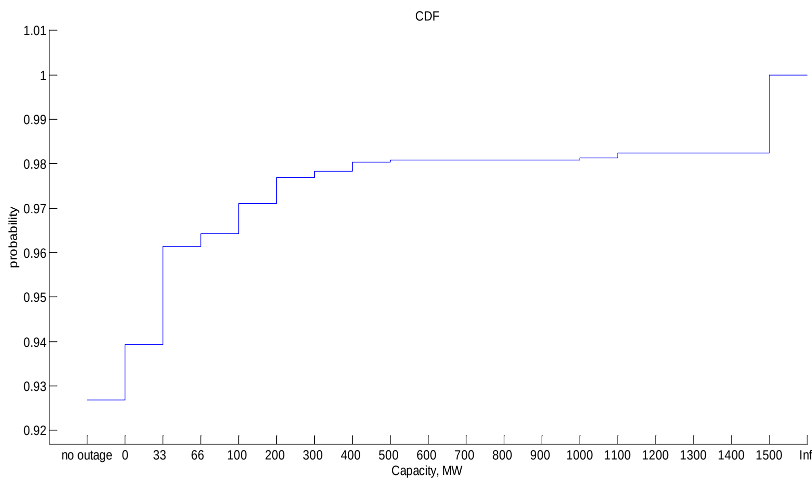


Figure 4.6. Capacity Outage CDF

5.0 Monitoring and Validation of Generation Requirements Uncertainty Range

This section describes two procedures used to monitor the future generation requirement uncertainty range applied to the capacity, ramping capability, and ramp duration capability characteristics and to validate the predicted uncertainty ranges against the actual ranges for the same periods observed post factum.

How future uncertainties around generation requirements for future dispatch intervals are presented to power system operators will influence acceptance of the methodology for developing industrial grade applications. PNNL scientists worked with California ISO engineers and managers as well as professional artists to work out a state-of-the-art procedure for the monitoring of future uncertainties.

The second procedure described in this section is for verifying the uncertainty ranges. Because these ranges are predicted for future dispatch intervals, one needs to be certain the prediction is accurate enough. This can be done by comparing the prediction against the actual uncertainty ranges observed later for the same periods. Such a process can be organized on a continuous basis and provides information to the system operators about whether any significant errors are found. In future development, this information could be fed back into the prediction algorithm to adjust the uncertainty ranges adaptively if significant errors are seen by the verification procedure.

5.1 Generation Requirement Monitoring Display

The generation requirement for the monitoring process includes assessment and visualization of generation capacity requirements, generation ramping, and ramp duration requirements.

The conceptual regulation capacity requirements screen developed in this project is shown in Figure 5.1. The blue line corresponds to the generation schedule or expected generation requirement determined based on load, wind, and solar generation forecasts and the interchange schedule. The 1-hour dispatch interval is considered in this example for simplicity. Uncertainty ranges are calculated for each dispatch interval by using the method presented in Chapter 3; i.e., by statistical analysis of historical information with consideration of the wind generation level. Note that the red line shown in Figure 5.1 is not actually displayed but drawn to describe the verification procedure in the next section.

This display is updated based on a repetitive process. The generation schedule, load and wind generation forecasts, and statistical characteristics of historical data are recursively updated each hour. A sliding window with a 1-hour refreshment rate is used to acquire statistical information.

Accordingly, the uncertainty ranges are also updated hourly taking into account changing generation schedules, load forecasts, wind generation forecasts, and other statistical characteristics.

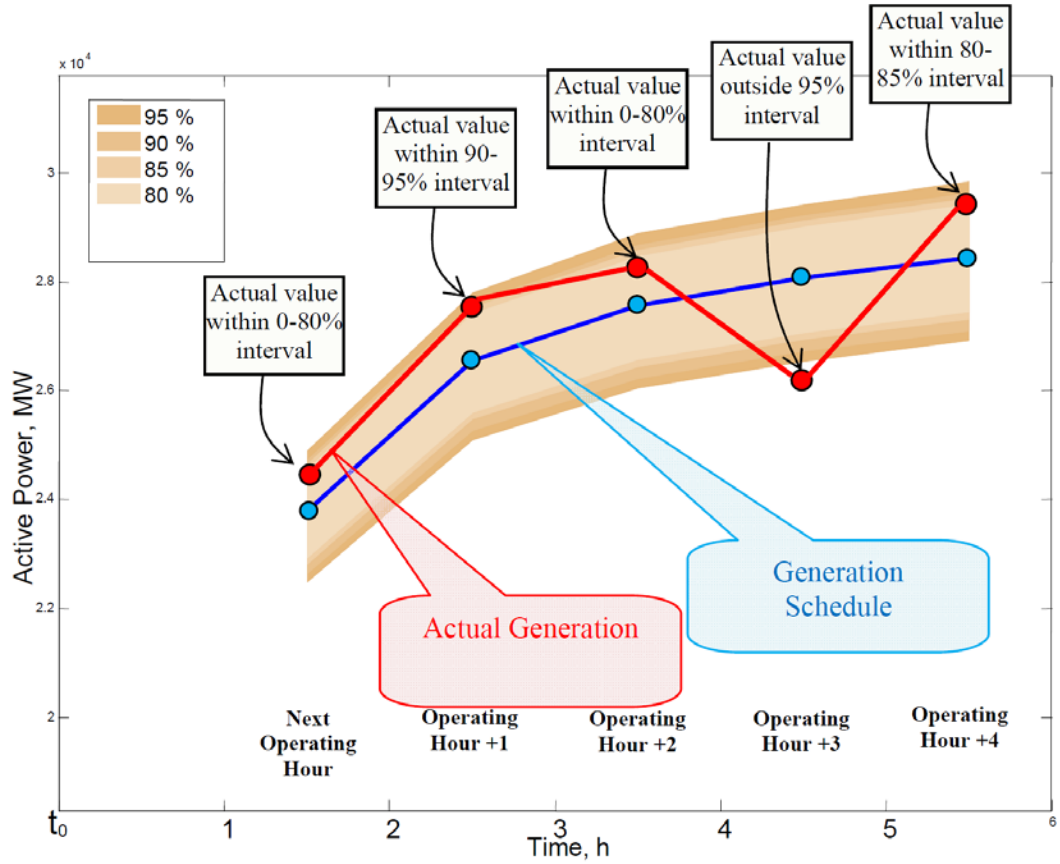


Figure 5.1. Validation Procedure

5.2 Validation Procedure

To validate the accuracy of the generation requirements uncertainty model, a validation approach is developed in this project. It is based on comparing the predicted uncertainty ranges against the actually observed ranges for the same dispatch intervals. The algorithm includes the following steps.

1. Acquire retrospective statistical information using the sliding window technique. The sliding window is updated hourly (or according to some other specified refreshment rate).
2. Perform a statistical analysis of the data acquired at step 1. The derived statistical characteristics are also updated hourly (or according to some other specified refreshment rate).
3. Evaluate uncertainty intervals for the future generation requirements using the statistical characteristics obtained at step 2. Uncertainty intervals are also updated according to a specified refreshment rate.
4. When the predicted dispatch interval is reached, overlay the actual generation values over the previously forecasted uncertainty intervals, as shown in Figure 5.1, and determine to which predicted uncertainty interval the actual generation value belongs.

At the end of simulation, the following calculations are made:

1. Count how many points belong to the predicted intervals with a specified confidence level, and calculate the percentage of points found within the intervals.
2. Compare the obtained percentages with targeted percentage values. The targeted percentages correspond to the confidence level of the interval. For example, for the 0 to 80% confidence interval, the targeted value is equal to 80%, and for the 80 to 85% uncertainty interval, the targeted value is equal to 5%, etc.

The uncertainty algorithm is validated if the calculated percentages and the targeted percentages are close.

6.0 Integration Into the EMS Environment

This section provides information regarding the California ISO generation dispatch timelines and considers practical aspects of integrating the developed methodologies into a real EMS system. Examples of the California ISO system and AREVA EMS systems are used in this section. The California ISO system is selected because the current PNNL project with the California Energy Commission (CEC) targets a practical allocation of the uncertainty prediction tool developed in this project at the California ISO. A practical integration framework with the AREVA system targeted by this DOE project is also described.

This section also describes the development of a concept of three different integration levels with a real EMS system. The concept includes three levels of integration: passive, active, and proactive. Developing such a concept helps to outline a path from initial integration ideas to future advanced integration levels, where the potential of the developed approach is fully exploited to increase system control performance and reliability at higher penetration levels of intermittent resources in the system.

6.1 California ISO Generation Dispatch Timelines

Integration of probabilistic tools into the real energy market or EMS systems should take into account operating practices of the specific balancing authority into which these tools are being integrated. To do this, an analysis of the California ISO system was undertaken.

Figure 6.1 shows the scheduling timeline implemented in the California ISO market system. The California ISO scheduling process includes day-ahead market (DAM), real-time unit commitment (RTUC), short-term unit commitment (STUC), and real-time economic dispatch (RTED). Although regulation (REG) capacity is procured in the day-ahead market for each operating hour of the next operating day, it is controlled by the EMS automatic generation control (AGC) system rather than the market software (CAISO 2006, Loutan et al. 2009). Additional ancillary services (AS) also can be procured in the real-time market (RTM) to meet additional AS requirements. AS include regulation-up reserve, regulation-down reserve, spinning reserve, and non-spinning reserve.

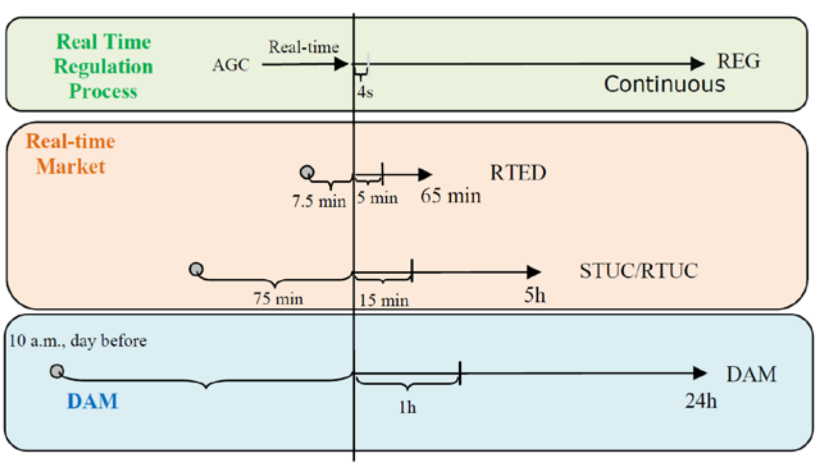


Figure 6.1. CAISO Timeline

The California ISO RTM consists of several applications, three of which, STUC, RTUC, and RTED work together. The STUC and RTUC applications ensure there is enough on-line capacity to meet a 5-minute demand. The STUC is performed in the RTM to commit units and balance the system resource and demand while enforcing transmission constraints. STUC is run once an hour and looks out 5 hours to commit resources that have start up times greater than 90 minutes. The RTUC application runs every 15 minutes and looks out between four and seven 15-minute intervals to determine if short-start and fast-start units need to be committed or de-committed.

The RTED process runs every 5 minutes to meet the imbalance energy requirements of the California ISO. This process looks ahead 65 minutes to ensure that enough capacity is on-line to meet real-time demand. It is expected that wind variability and the lack of accurate wind forecast would create challenges for the RTED applications. RTED is the lowest granularity of dispatch in the ISO market, except for regulating reserves, which is procured in the RTM but dispatched through the EMS AGC system every 4 seconds.

Figure 6.2 represents the California ISO new market design generation scheduling process. In the day-ahead (DA) timeframe, wind resources are not required to bid into the California ISO markets, which can significantly impact the unit commitment process in the DA timeframe. The California ISO must forecast the expected hourly production in the DA to ensure that enough resources are committed for next-day operation. Similarly, the California ISO load forecast is done in the DA and RT timeframes. In the DAM, the forecast of the California ISO's hourly demand is for three days in advance. The DA schedule is an hourly block energy schedule that includes 20-minute ramps between the hours. It is provided at 10.00 a.m. the day before the operating day. The real-time schedule is based on STUC/RTUC timelines. The RTM closes 75 minutes before the actual beginning of an operating hour as shown in Figure 6.1. RTED is provided 7.5 minutes before the dispatch operating target (DOT) and is based on real-time forecasts. Symmetrical ramping is used, which means that by dispatching for the average, the DOT ends in the center of the interval. In the RTM, the California ISO automatic load forecasting system provides a load forecast for each 15-minute and 5-minute interval. Load and wind forecasting errors can cause the RTM application to dispatch incorrect amounts of imbalance energy needs. RTED results are 5-minute dispatch instructions and advisory notice for the look-ahead timeframe.

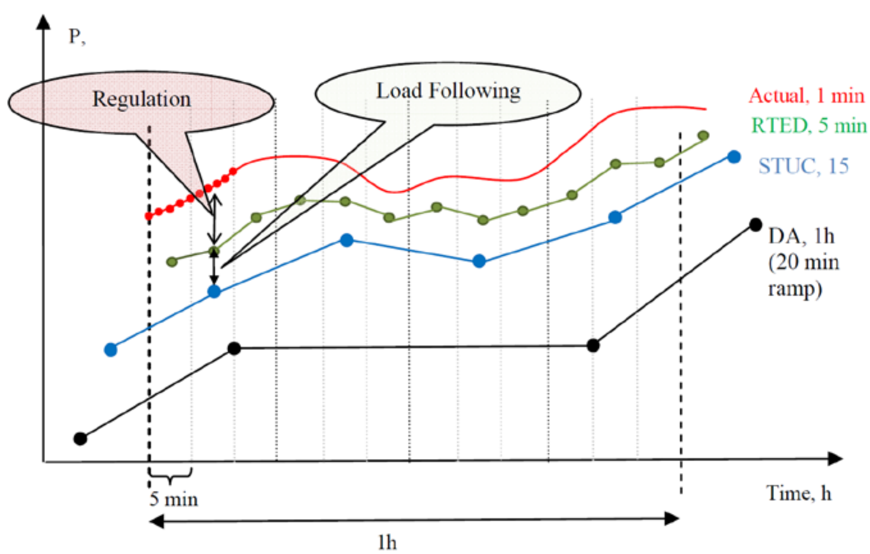


Figure 6.2. Generation Schedule

Thus, the load following or supplemental energy dispatch can be considered as the difference between RTED and STUC/RTUC curves. This is an instructed deviation caused by the real-time dispatch. Regulation is the difference between actual demand and the RTED curves (Figure 6.2).

The RTED, STUC, and DA schedules use forecasts provided for different look-ahead time horizons with different accuracies. Therefore, these forecasts have statistical characteristics.

6.2 Levels of EMS Integration

Three levels of integration of probabilistic tools into market applications and EMS are considered.

6.2.1 Level I (Passive)

The passive integration level implies integration of wind forecast information and its visualization without introducing any changes to the EMS algorithms. Passive integration is the initial and the simplest way of integration. In this case, the probabilistic tool provides for uncertainty visualization capability only. Displays with look-ahead generation capacity and ramping requirements are provided to system operators in real time. The displays will help operators assess balancing needs and make the right decision for short-term generation scheduling.

6.2.2 Level II (Active)

Active integration of the probabilistic tool is a higher level of integration. On the active level, the UC and ED procedures are repeated several times for every dispatch interval to determine whether the system can meet extreme generation requirements caused by uncertainties for a certain confidence level. The tool interacts with the processes of unit commitment (STUC and RTUC) and economic dispatch (RTED). The system "break points" are communicated to the user. In addition to an uncertainty visualization display, the probabilistic tool displays alerts of potential threats to the power system and advises operators on what kind of actions can be taken to avoid undesirable scenarios.

Active integration with UC does not necessarily imply any modifications in current operating practices. The probabilistic tool interacts with and uses existing UC engines to monitor the sufficiency of available balancing resources and to generate alternative generating schedules (advisories) in case of potential threats to power system reliability.

6.2.3 Level III (Proactive)

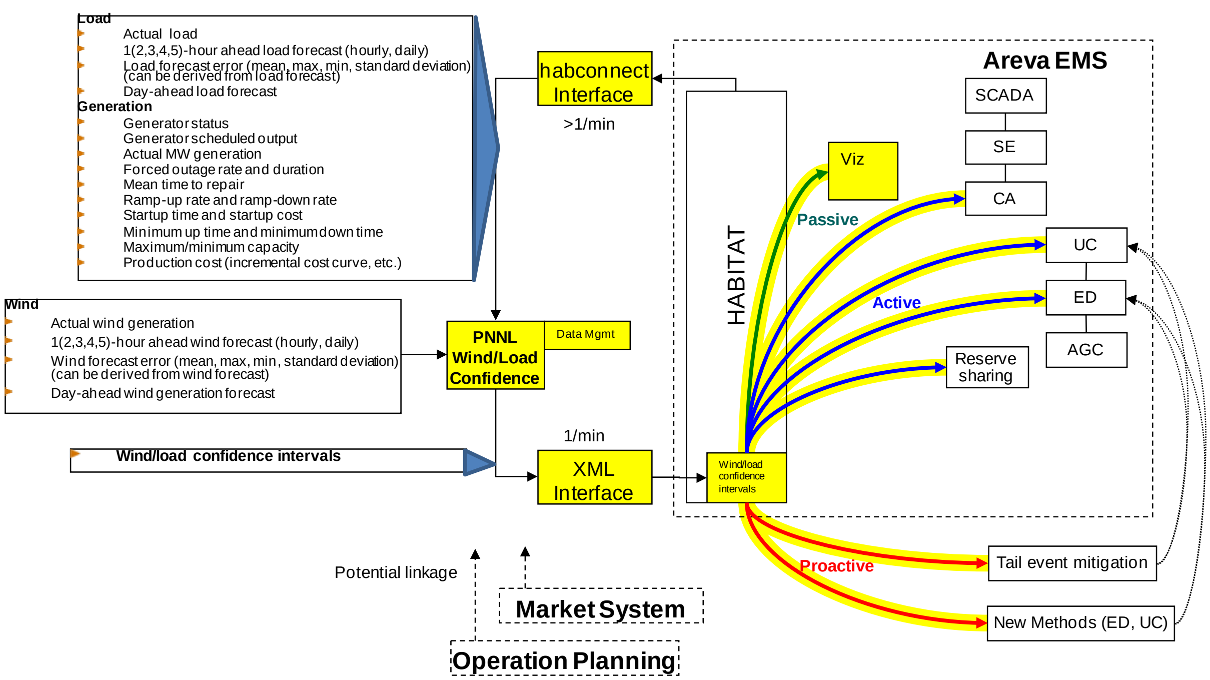
Proactive integration is the most advanced level of integration. It requires not only interaction with the UC, ED, and other systems in the market and EMS environment, but also implies modifications of current operating practices and algorithms. The proactive level requires modifications of the UC and ED algorithms in order to directly incorporate uncertainties into these procedures. In this case, generation units are committed and dispatched to prevent these uncertainties from creating "breaking points." For instance, new constraints such as capacity requirements and ramping requirements based on uncertainty evaluation can be incorporated into the unit commitment process. This will change the formulation of the UC problem and requires new algorithms to solve the new UC equations.

6.3 EMS Integration Design

To demonstrate the performance of the probabilistic uncertainty evaluation tool and its applicability to actual grid operation environments, market system integration design with the AREVA EMS system was developed for the first two levels of integration (passive and active). Figure 6.3 shows the overall design of the integration. The uncertainty evaluation tool (labeled as "PNNL Wind/Load Confidence") is a standalone module outside of the market and EMS environment. As shown in Figure 6.3, the evaluation tool needs data from the market and EMS in addition to wind forecast information. The output of the uncertainty tool needs to be imported back to the market systems and linked to applications such as RTUC and RTED.

The data export interface is based on an interface provided by the EMS vendor. The data to be exported from the market applications are shown in Figure 6.3.

The wind forecast data are shown to be provided by a third-party forecast service company external to market applications. This is based on the fact that current market applications do not have an interface for wind forecast information. However, considering that wind forecasts would be directly linked to market applications in the future, the design can be slightly altered to have the uncertainty tool receive wind forecast information using the same data export interface.



EMS – energy management system; UC – unit commitment; ED – economic dispatch; AGC – automatic generation control; CA – contingency analysis; SE – state estimation; VIZ – visualization;

Figure 6.3. Concept of Probabilistic Tool Integration Into EMS.

The uncertainty tool developed and described here can be integrated using any market system. Slight modification in integration procedure could be required depending on the system.

7.0 Preliminary Results of Capacity Requirements Analysis

Preliminary simulations were performed using a probabilistic prototype tool developed in MATLAB (MathWorks Inc. 2009). The 2007 California ISO data were used. The following parameters were used in the simulations:

- Simulated period: 70 days
- Sliding window length: 21 days
- Sliding window refreshment rate: 1 hour
- Generation schedule: Hour-ahead schedule (1 hour resolution)
- Wind and load forecasts: 1 hour resolution, updated hourly, over a 5-hour time horizon.

The results of model validation are presented in Figure 7.1. The percentage numbers labeled on the pie chart are the calculated percentages of points found within the confidence intervals. The targeted percentages are the intervals indicated in the legend; i.e., the blue portion of the pie has a targeted percentage of 80% and other colored portions have a targeted percentage of 5%. Figure 7.1 shows that the uncertainty method provides a quite accurate prediction of the uncertainties because the obtained percentage values are very close to the targeted percentage values.

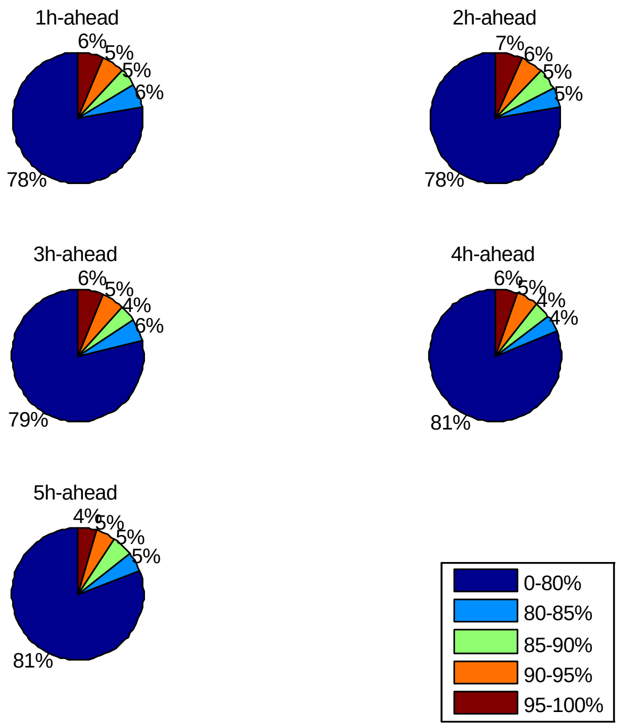


Figure 7.1. Results of Model Validation for 5-Hour Horizon (70-day time period)

8.0 Conclusions and Future Work

The conclusions are summarized as follows:

- A methodology capable of evaluating the impact of wind generation uncertainty, load variability, and unexpected generation outages on balancing resource requirements has been developed.
- A MATLAB prototype of a probabilistic tool based on the proposed methodology has been developed.
- Preliminary simulation studies using actual California ISO data have been performed. Study results have shown that the methodology of evaluating generation requirements for uncertainty management is quite accurate and efficient.
- The concept of probabilistic tool integration into an EMS environment has been developed.

Continuing and future work will be to implement the proposed design of the three-level integration and evaluate the implementation in terms of utility and usability for potential industry practices.

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