LONG TERM DYNAMICS OF INVESTMENT AND GROWTH IN ELECTRIC POWER SYSTEMS: MODELING UNCERTAINTY

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ABSTRACT

This paper overviews recent research results on the use of system dynamics modeling for understanding long term investment in power system infrastructure. These computer models are intended for use by both policy makers and researchers. The main effort is focused on the simulation models that simulate both short-term behavior, such as, electricity prices and congestion in the near term, and long-term behavior, such as, investment in new generation and transmission. Our emphasis in this annual report is on modeling uncertainty and the role of feedback in minimizing such uncertainty.

KEY WORDS

Interdisciplinary modeling, bounded uncertainty, loss of load expectation, power plant construction, power system planning, system dynamics, transmission congestion.

1 INTRODUCTION

Arguments of the benefit for the deregulation of the electric power system have been largely based on conventional and general wisdom regarding separate topics such as competition, service reliability, economic efficiency and environmental protection. Few have looked carefully at the interplay between the economic, technical, social and environmental factors that influence the production, transmission and consumption of electric energy. Further, no one has carefully investigated the long term dynamics of the process that includes an understanding of the necessary engineering. Our research is developing models to study the long terms effects of deregulation, including interactions between regulatory policy, investor behavior, environmental impact and system engineering.

Figure 1 shows the spatial and temporal boundaries of our research on modeling the electric system. The system security modeling is represented by the 1st of three boxes located at the base of the diagram. The security model represents the power flow and system dynamics, which operate in seconds on a spatially complex grid system. Loads are described at the level of sub-stations, while the scope of the model extends to cover the entire WECC. The model calculates power flows, real and reactive reserves and system limits for a specified scenario. The grid structure of the WECC is represented in explicit fashion, so the system security model provides the foundation for proposed research on power networks. We highlight the system security "box" in Figure 1 with a double boundary to emphasize the extra challenges of representing the grid network in explicit fashion.

Our demand size research is depicted as the 2nd of three boxes. The research was launched to explain the response of California electricity consumers during 2000 and 2001. The study makes use of billing data from distribution companies to determine the extent and factors behind the surprising reduction in electricity consumption in the summer of 2001. Figure 1 depicts the spatial dimension ranging from individual service areas to cover an entire state. This work is not being expanded under EPNES but is shown here for completeness.

The 3rd box in Figure 1 depicts the WSU model of the western electricity market. The model operates with load and resource data from the four regions of the WECC. The model simulates hourly operations for a typical 24 hour day in each quarter of a year. We assume adequate interconnections between all loads and all resources in the west, so the wholesale market is treated as a single market. The simulations begin in 1998 and run for a decade or more to allow sufficient time to see the patterns of power plant construction. These models are being constructed using basic concepts from system dynamics, a simulation method pioneered by Forrester [1] and explained in texts by Ford [2] and Sterman [3]. System dynamics has its origins in control theory and has been defined by [4] as that *branch of control theory which deals with socio-economic systems and that branch of management science which deals with problems of controllability.* Such an approach is valuable in a rapidly changing electric industry with high uncertainty and high risk [5].

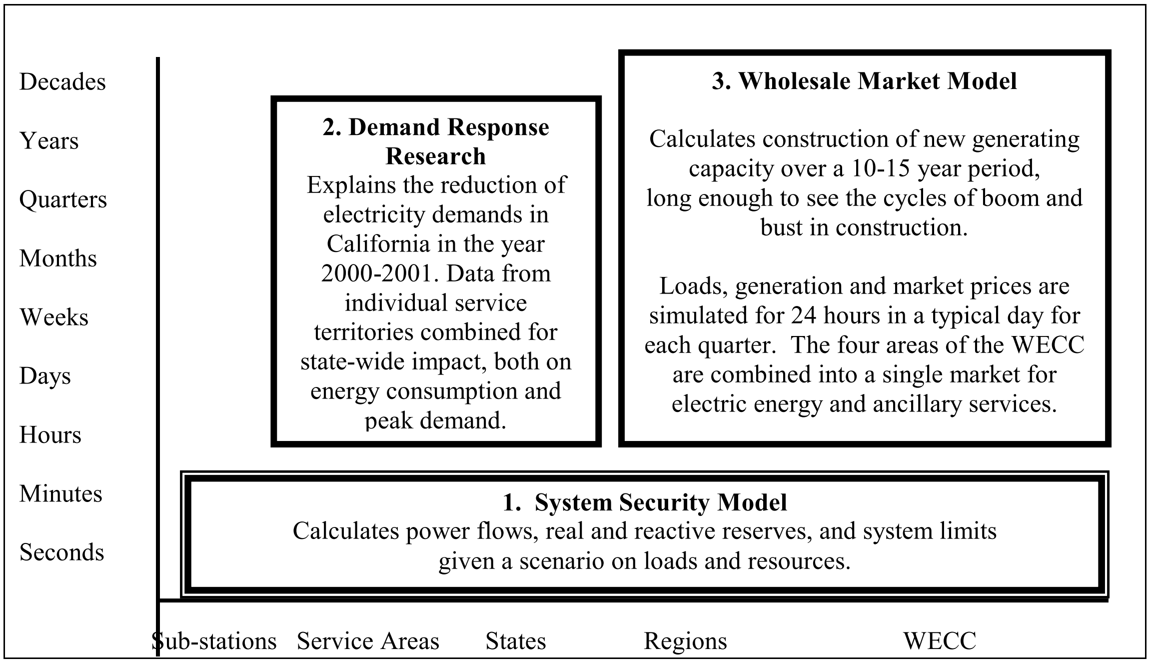

Figure 1. Spatial and temporal dimensions of previous research at WSU.

This report focuses on recent results related to uncertainties in such long term modeling for power plant construction, including wind units. This report contains excerpts from [6,7]. Further, details can be found in [8-10].

2 RECENT RESEARCH RESULTS

2.1 Market Feedback for Bounding Future Uncertainties in Power System Planning

From perhaps the beginning of power system planning, it has been recognized that long term planning entails a great amount of uncertainty about future conditions. The earliest attempts to address the uncertainties focused on analyzing typical scenarios. Such scenario analysis remains the foundation of power system planning at most utilities today. Probabilistic techniques, such as, probabilistic load flow [11], and sensitivity methods [12], were introduced many years ago. While these are an important step forward in terms of complexity, they have not been widely adopted in practice. Part of the difficulty arises from determining appropriate parameters for probabilistic models. In fact, the problem may be more fundamental since many of the uncertainties are not probabilistic in nature. Philosophically, probability assumes repeatable events and this is difficult to apply to future conditions 10 or 20 years in the future. Both sensitivity and probabilistic approaches suffer from separating the input uncertainty models from the decision-making process.

This vacuum has led researchers to introduce fuzzy sets, or interval methods, to approximate uncertainties [13] and incorporate expert decision-making. This has led to such interesting decision models as minimizing regret [14]. These types of approaches can be thought of as a generalization of sensitivity type calculations leading to a range of possible outputs based on a range of possible inputs coupled with criteria for choosing design options. The authors have developed a fundamental tool for fuzzy/interval analysis termed the boundary load flow (BLF) [15-17]. This tool allows for determining a range of possible power flows given uncertainties in the nodal demands. Still, there are two major drawbacks in these fuzzy set approaches. Notably:

- Interval uncertainties tend to accumulate, so that, for large systems, or longer-term studies with greater uncertainties, the output intervals become so large as to be meaningless (if solutions can be found at all). The typical approach is to either reduce the uncertainties to narrower intervals or to relegate the uncertainties to specific subsystems.
- Future conditions are assumed a priori and do not account for the more practical considerations of how those conditions will evolve over time. For example, if one assumes a relatively small number of generators will come on-line while at the same time load growth remains strong, it is clear the system reliability will decrease. Still in practice, when such conditions develop, it is likely that various remedial measures or new plans will be put in place to address the reliability. Thus, the more extreme conditions will not arise.

We take our inspiration for this work from natural systems. It is well known, in studies of ecosystems,

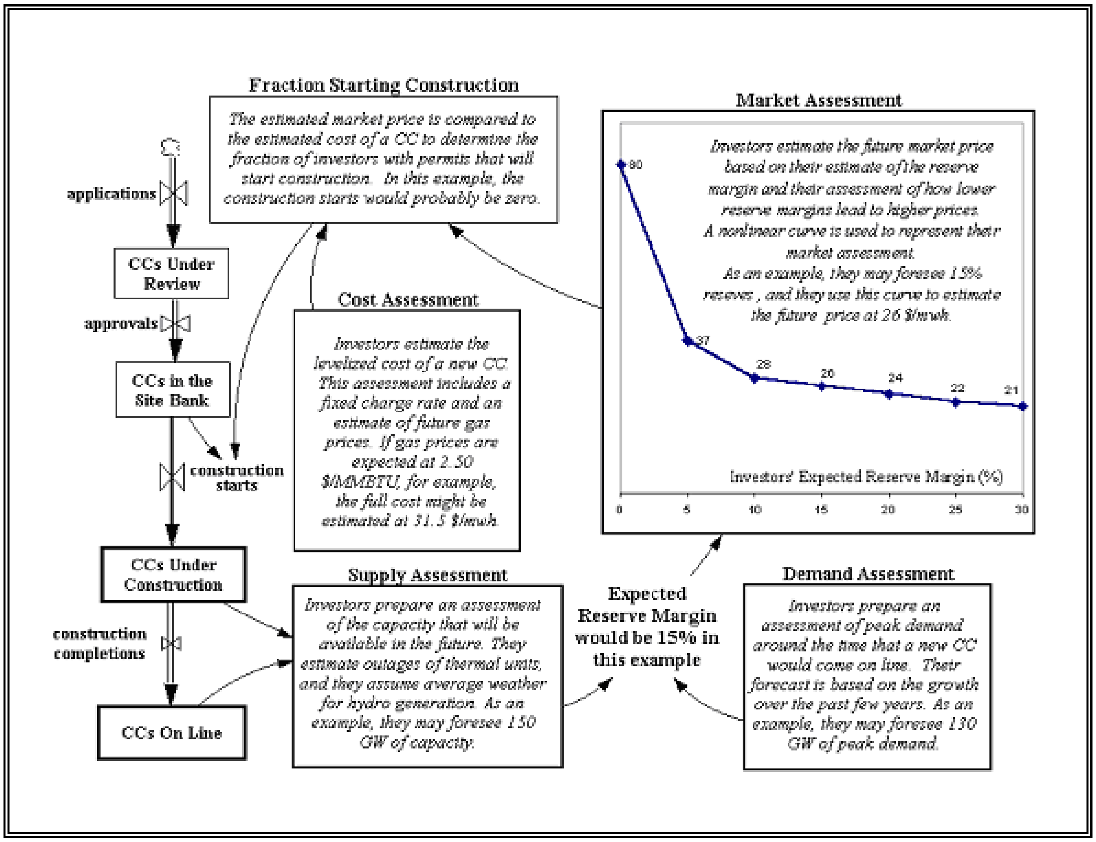

Figure 2. A simple model of construction of CC power plants [19].

financial markets and control theory, that feedback can act to limit future uncertainties [2]. So, for example, one can predict future species populations in a relatively narrow range given that in a limited habitat large populations will reduce survival rates. These modeling studies are often performed using techniques from the field of "system dynamics" [3]. This is a top-down modeling approach where the emphasis is on including the relevant inputs and understanding the overall system behavior rather than the detailed understanding of the subsystems.

With the introduction of electricity markets, it has become clear that the power system planning must be considered a dynamic process, particularly with regards to understanding investments in new transmission lines and power plants [18]. The authors have recently introduced a hybrid approach combining system dynamics modeling with the more traditional power system planning [10]. A framework for uncertainty is presented in the following.

2.1.1 Simulation Study of Investor Behavior Considering Uncertainties

This section briefly summarizes the modeling approach in our overall studies and presents some simple simulation studies. The initial wholesale market model was constructed to help one understand if power plant construction would appear in waves of boom and bust. Such boom/bust patterns arise commonly in industries from commercial real-estate to commodities. The salient feature tends to be wherever markets face long lead times to bring new capacity to market [18]. Historically, the construction of new power plants has also appeared in such waves and there is concerned that these will be exacerbated by deregulation. These cycles could be devastating due to dependence of the modern economy on a reliable electric supply.

Modeling the investment process for new generating capacity, includes the long delays for permitting and construction. Investors weigh the risks and rewards of investing in new plants, primarily gas-fired combined cycle (CC) capacity based on estimates of future market prices. The models have been tested on the Western Electric Coordinating Council (WECC) system and found to be successful in explaining the under-building that occurred in 1998-1999 and the over-building that appeared in 2000-2001 [18]. The boom and bust in this case arose from a combination of the delays in power plant construction and the limitations on investor's ability to anticipate the future trends in the wholesale market. The simple model of investor behavior as shown in Figure 2 is used. While the model is conceptually simple, simulations based on this model match historical data well.

To maintain simplicity, out of many possible uncertain parameters only one is assumed uncertain - demand growth rate. Demand uncertainty, in turn, makes future

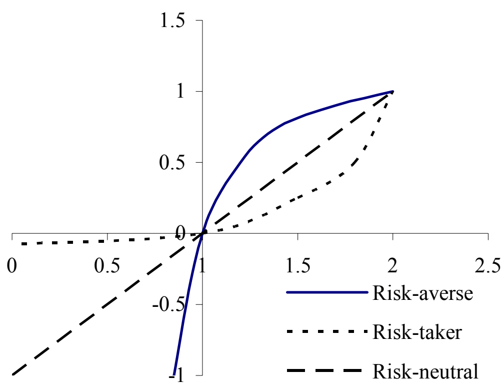

Figure 3. Risk profiles according to the Utility Theory

reserve margins and market prices uncertain. As a result, profits are uncertain and investors face risky decisions. Investors' behavior when facing risky decisions is modeled according to the Utility Theory (for example, [19]). This theory states that there are three main types of risk profiles: risk-averse, risk-neutral and risk-taker. Figure 3 shows one possible model for risk-averse and risk-taking persons. What is important is the shape of the functions: concave for risk-averse and convex for risk-taker. The risk-neutral player is modeled as a straight-line in the utility vs. profit plane.

The model of investors' behavior under uncertainty from Figure 3 was integrated in the model of plant construction shown in Figure 2 and various simulations were performed. In the simulations, uncertainty was simulated in two different ways. First, it was assumed that the demand growth is a random variable with some distribution whose value changes during the course of each simulated run. That is, the demand growth is a continuous stochastic process. The simulations performed correspond to 'sequential simulations' used in reliability evaluations. Second, it was assumed that the random variable follows the same distribution from one simulation to another, but within a simulation run it remains constant. Thus, the demand growth is fixed in time although its realization is uncertain and follows the given distribution. This is equivalent to sensitivity analysis.

Clearly, the sequential simulation is how a real power market will unfold. This is what careful investors should consider in their analyses. They may still speculate in different ways on future market conditions but they constantly readjust their position according to the past and current situation. Figures 4-7 show the results of investors' decisions to construct new CC capacity. The results are given for the two different perceptions of uncertainty and two different risk profiles. The results from sequential simulations when all of the investors are risk-averse and risk-takers are shown in Figures 4 and 6, respectively. Figures 5 and 7 show the same results from non-sequential simulations.

In each case simulated, it was assumed that the demand growth rate follows uniform distribution in the interval from 2.5% to 3.5% annually. The resultant variable, the CC power plants under construction, follows a different, time-dependent distribution, which can be obtained numerically from a set of various percentiles. The results presented here show the boundaries at 50%, 75%, 90%, and 100% percentiles.

It can be seen from these figures that there is much more variation in the results, i.e. much more uncertainty, when development is considered statically. The graph 'strips' that show different percentiles are much broader for non-sequential simulations than those from sequential simulations, which include uncertainty in the dynamics. This, in turn, shows that a real market would inherently bound the uncertainties one would have to consider in power system planning. Note that the investors' risk profile does not affect the uncertainty as much as one may have expected. The levels of CC under construction do change, in this case the amplitudes of the cycles, but the breadth of the variation is very similar for the two extreme cases, when all of the investors are risk-averse or all are risk-takers.

Note also the time shift in the resultant pattern of behavior in non-sequential simulations. In other words, the variation is stretched across the time axis as well. In sequential simulations, investors perceive uncertainty dynamically and there is no time delay in their actions. As a result, the variation is across the y-axis only. If some of the other parameters in the model are adjusted, then a fundamental change in the performance can be seen. For example, assume one, the levelized cost for a new CC plant is decreased from 32 $/MWh to 28 $/MWh, and two, the factor of accounted for plants concurrently in construction is increased from 50% to 100%. Under these conditions, the plant constructions no longer exhibit boom and bust cycles. Figures 8-11 repeat the earlier results for this situation. It can be seen that, although the pattern of behavior has changed, the same comments apply as from before.

2.1.2 Comments

Power systems are both dynamic and uncertain in nature. Such is the process of power system planning. Although market operations are a source of additional uncertainty in the system, this paper demonstrates that future uncertainties are bounded as a consequence of feedback. The investors take into account the past and current market conditions and make decisions accordingly. When facing risky decisions investors take actions in line with their risk profile. Contrary to what may be expected, this paper also shows that risk-averse investors do not necessarily reduce uncertainty by their decisions, nor do risk-taking investors necessarily increase uncertainty. While they determine the overall level of activity, this tends to influence the expected value more so than the variance, which is the measure of uncertainty or risk.

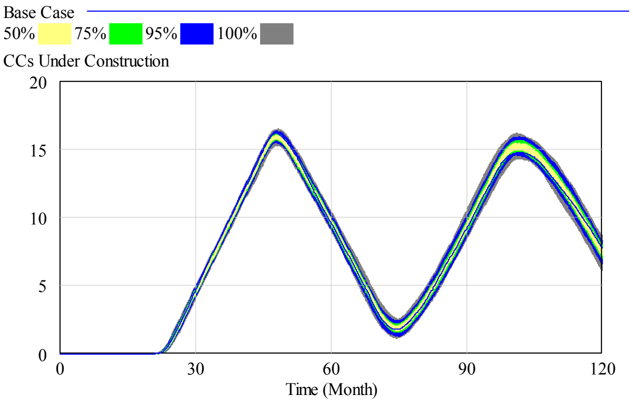

Figure 4. High cost, continuous growth, *risk-averse*

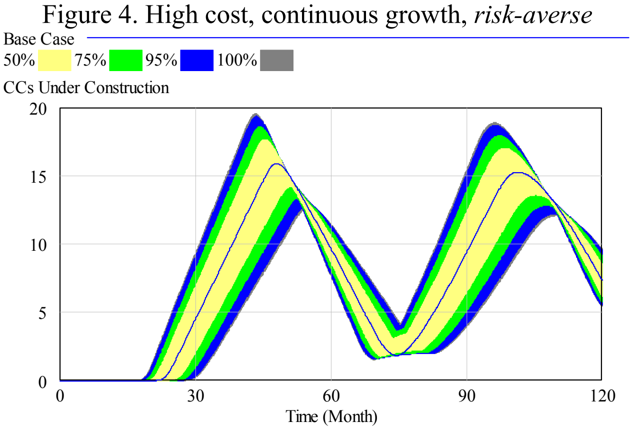

Figure 5. High cost, discrete growth, *risk-averse*

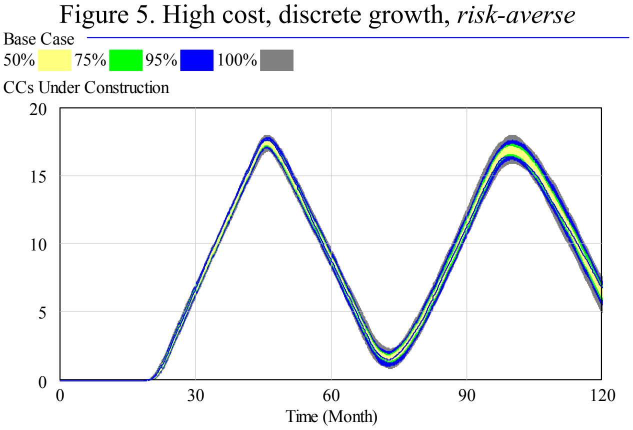

Figure 6. High cost, continuous growth, *risk-taking*

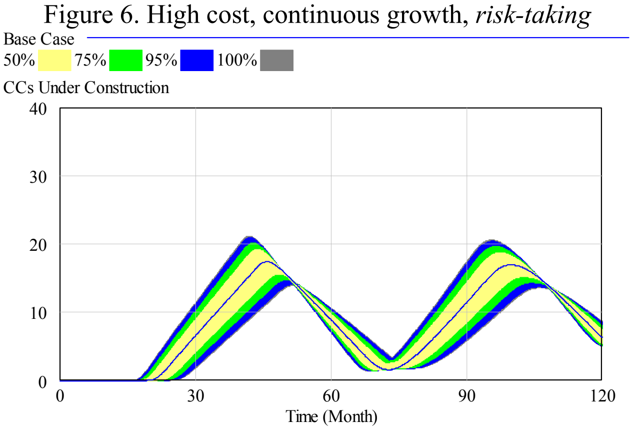

Figure 7. High cost, discrete growth, *risk-taking*

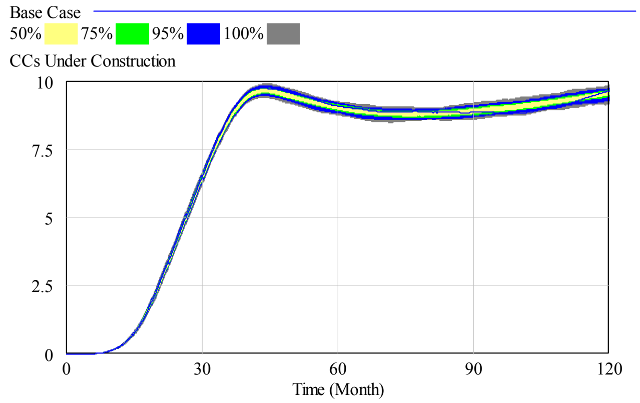

Figure 8. Low cost, continuous growth, *risk-averse*

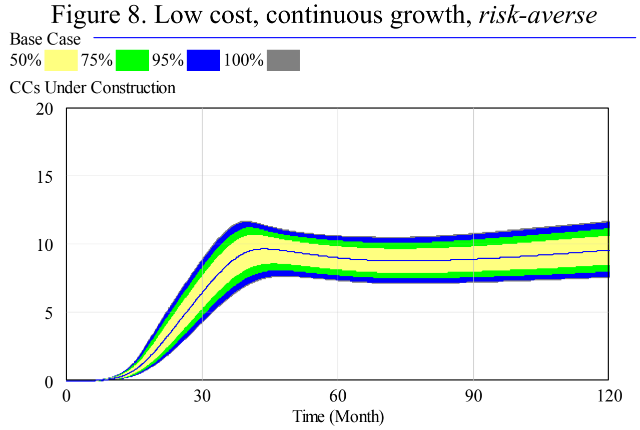

Figure 9. Low cost, discrete growth, *risk-averse*

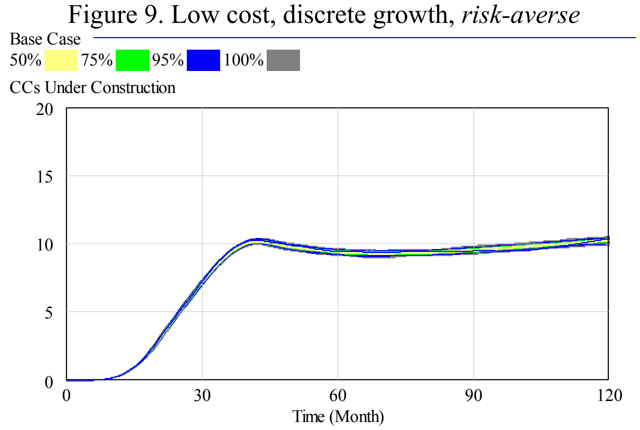

Figure 10. Low cost, continuous growth, *risk-taking*

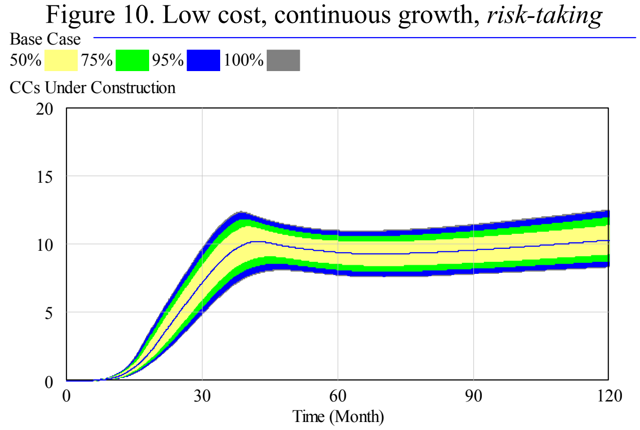

Figure 11. Low cost, discrete growth, *risk-taking*

2.2 Impact of Wind Generation Uncertainty on Generating Capacity Adequacy

Wind generation has become increasingly popular choice of technology for new capacity additions in power systems worldwide. Several factors have contributed to this trend. Environmental concerns and a constant increase in fossil fuel prices are central to these factors. Moreover, recent legislative moves for green-house gases limitation in the EU and similar laws currently under consideration in the US and other parts of the world make wind economically more competitive with other, traditional sources of energy. There are also other factors, such as, advances in the manufacturing and control technology, which also add to the attraction of wind as a 'green' source of energy.

Unfortunately, more than any other renewable source, wind is stochastic, and, unlike the other most important renewable source, water, it cannot be stored in its primary form for later use. The operational difficulties that this creates have been recognized for some time now and a number of papers and studies address this topic (for example, [21]). Still, wind uncertainty will impact power systems in a more fundamental manner when wind generation contributes a significant portion of the generation mix.

This paper addresses the issue of generating capacity adequacy in power systems with a considerable share of wind generation. It is one of the scenarios considered in our research project that deals with complex interacting issues in the long term investment dynamics of the WECC system (western US interconnection) [6, 10, 22]. For this purpose, the popular LOLP - loss of load probability is used as an objective, probability based, index. Other two popular, deterministic indices are reserve margin and largest unit reserve. It is well known that these indices are inconsistent in terms of risk. Risk in this context is the probability of not being able to serve the load. Two systems with the same reserve margin or largest unit reserve can have very different risks. We investigate how wind penetration in the generation mix affects these relations in a hypothetical example derived from the WECC system.

Wind uncertainty is modeled by adjusting the wind generation units FOR – forced outage rate. This parameter is uncertain itself and adjusting for wind uncertainty makes it even more so. The usual approach to modeling FOR uncertainty is to use a random variable with some probability distribution. Any distribution could be used but, unless it is normal, the result will be analytically intractable and Monte Carlo simulation has to be used. Thus, normal distribution is usually assumed and the LOLP index can also be assumed normally distributed with resultant mean value and variance. Mean value calculation is straightforward and not much different from the 'crisp' case. However, resultant variance calculation is complex and involves finding equivalent covariance matrix. Here, a different approach is used. Instead of assuming probability distribution, we assume an interval of possible values for the FORs. This corresponds to a rectangular possibility distribution of a fuzzy/interval number. The calculation of the resultant LOLP in this case is much simpler.

Another source of uncertainty in generating capacity adequacy assessment is the load profile. The load forecast is always uncertain and this uncertainty can considerably affect both LOLP's expected value and its variance, if probabilities are used. Still, this uncertainty is easier to include in calculations than the FOR uncertainty. Here, we use the same approach for modeling load uncertainty as FOR uncertainty. Load curve is assumed to consist of intervals of possible values. When such an uncertain load model is convolved with the uncertain generation model, the resultant risk index is the uncertain LOLP.

2.2.1 LOLE Index

Loss of load expectation (LOLE) is one of the oldest and probably the most frequently used index in generating capacity adequacy analysis and power system reliability [23]. It is usually referred to as LOLP (loss of load probability) although this is a misnomer, as it almost always represents the *expected* value of unserved load. It can be defined as [24]:

$$LOLE = T\sum_{j=1}^{N_G}\sum_{i=1}^{N_L} P_i P_j I_{ij}$$
$$I_{ij} = \begin{cases} 0 & L_i \le G_j \\ 1 & L_i > G_j \end{cases} \tag{1}$$

where:

- T - the total time length of the load curve;
- L_i - the i^{th} load level;
- P_i - the probability of L_i (fraction of total time when the load is equal or bigger than L_i);
- N_L - number of load levels in the discretized load curve;
- G_j - the j^{th} generation capacity level;
- P_j - the probability of G_j;
- N_G - number of generation capacity levels in the generation capacity probability table;

Since the load chronology is usually not of interest, it is advantageous to consider the load duration curve (LDC) instead. In this case, the relative LDC becomes the load probability distribution and the above formula describes a convolution of the two random variables of load occurrence and available generation capacity. Depending on the load curve used, the LOLE index holds various meanings. If the individual hourly load values are used, which is the usual meaning of LDC, the value of LOLE is in hours. If only individual daily peak load values are used, arranged in descending order to form a cumulative load model known as daily peak load variation curve (DPLVC), the value of LOLE is in days. Weekly and monthly peak load variation curves can also be defined, although that is not usual.

Calculating the equivalent generation capacity table (the discrete probability distribution of available capacity) is an extensive computational task, especially if there are a large number of units, each with multiple operating states. There are various approximating techniques that can be used in order to simplify and speed up this process [23].

A somewhat different approach is to convolve the load probability distribution with individual generation distributions one unit at a time, instead of building the equivalent generation distribution first and then convolving it with the load curve [25-26]. To illustrate this, let's assume that we are given an LDC, a set of n generation units with their corresponding capacities, Forced Outage Rates (FORs), and their loading order. For simplicity, we'll assume that each unit i has only two states and can be either fully available or fully unavailable with probabilities $p_i = 1\text{–FOR}_i$ and $q_i = \text{FOR}_i$, respectively. The production of the k+1 unit in the order, W_{k+1}, depends on whether the previous unit, k, is available or not:

$$W_{k+1} = \int_{\sum_{i=1}^{k} P_i}^{\sum_{i=1}^{k} P_i + P_{k+1}} D_k(P)dP \cdot p_k + \int_{\sum_{i=1}^{k-1} P_i}^{\sum_{i=1}^{k-1} P_i + P_{k+1}} D_k(P)dP \cdot q_k \qquad (2)$$

where $D_k(P)$ is the equivalent inverse LDC, obtained after convolving the k^{th} unit. The integrals in the above expression can be combined if they have the same lower and upper limits. For that purpose, the integrand of the second integral is shifted to the right along the x-axis for the capacity of k^{th} unit, P_k. The result is:

$$W_{k+1} = \int_{\sum_{i=1}^{k} P_i}^{\sum_{i=1}^{k} P_i + P_{k+1}} D_k(P)dP \cdot p_k + \int_{\sum_{i=1}^{k} P_i}^{\sum_{i=1}^{k} P_i + P_{k+1}} D_k(P - P_k)dP \cdot q_k \qquad (3)$$

From (3), we finally get:

$$W_{k+1} = \int_{\sum_{i=1}^{k} P_i}^{\sum_{i=1}^{k} P_i + P_{k+1}} D_{k+1}(P)dP \qquad (4)$$

where:

$$D_{k+1}(P) = D_k(P) \cdot p_k + D_k(P - P_k) \cdot q_k \qquad (5)$$

is the equivalent inverse LDC, obtained after convolving the unit k+1. It accounts for the actual load and the forced outages of all units up to k.

This process is illustrated on Figure 112. The curve after convolving unit k, D_{k+1}, is obtained as a sum of the curve before convolving unit k, D_k, multiplied by unit k availability, p_k, and the shifted $D_k(P\text{-}P_k)$, multiplied by unit k unavailability, q_k. In this particular case, P_k is 200 MW and q_k is 0.2.

Equation (5) gives the recursive formula for calculating the equivalent inverse LDC. At the beginning, D_0 is the original inverse LDC, obtained from the load profile. Proceeding in loading order, each unit's equivalent curve and production can then be calculated. After convolving all n units, the final curve D_{n+1} contains the information about the LOLE and the expected energy not served (EENS, also known as expected unserved energy, EUE):

$$LOLE = D_{n+1}\left(\sum_{i=1}^{n} P_i\right) \qquad (6)$$

$$EENS = \int_{\sum_{i=1}^{n} P_i}^{\infty} D_{n+1}(P)dP \qquad (7)$$

In the example shown in Figure 12, the final curve is obtained after convolving 9 units with total installed capacity of 1300 MW. Thus, the LOLE in this particular case is $D_{n+1}(1300) = 0.0123$. The EENS is the area under D_{n+1}, starting from 1300, and is equal to 1.2 MWh.

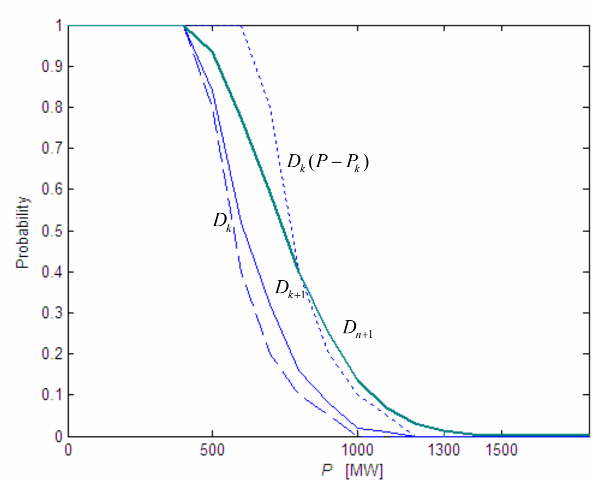

Figure 12. Convolving equivalent inverse LDCs in the process of LOLE and EENS calculation. Curve before convolving unit k, D_k – dashed line; shifted D_k – dotted line; Curve after convolving unit k, D_{k+1} – solid line; Final convolved curve D_{n+1} – thick solid line; LOLP = $D_{n+1}(1300) = 0.0123$.

2.2.2 Windpark Modeling

The power of wind is harnessed in windparks that can contain hundreds of individual units. The installed capacity of each unit is typically between 0.5 MW and 2 MW. The large number of units in one "wind plant" distinguishes this type of power plant from conventional thermal power plants. In addition, the FOR of wind units is typically several times less than that of thermal units. For the former, the FOR is somewhere around 1% or 2%, while for the latter the FOR is on average around 10%. This means that, unlike thermal plants, a windpark has nearly zero probability of being completely outaged and is always ready for service, at least to some extent.

For example, let's consider a windpark with 100 identical units each with 1 MW of installed capacity and 1% FOR. It's easy to show by using binomial distribution that the probability of having in service less than 76 MW (i.e. 76% of its installed capacity) is smaller than 10^{-4}. This is 1000 times less than the probability of a thermal unit with 10% FOR being completely shut down. If the FOR of wind units is 2% then the threshold with 10^{-4} probability drops down by not much to 63 MW.

Therefore, the unit FOR is much less of an issue with wind generation than it is with thermal technologies. It can be taken into account simply by appropriately adjusting the installed capacity of the entire windpark. Here, we should make two important comments. First, we neglect network issues in this paper, following tradition in generating adequacy analysis but, of course, an entire windpark can occasionally be in outage due to a network failure. Second, ready for service does not mean that the windpark will be in service. That depends on the availability of the wind.

The last comment points out the most important thing in defining the availability of a windpark. Due to wind stochasticity the production from a windpark is stochastic and intermittent. Different studies [21] show that the average capacity factor from a windpark is somewhere around 1/3. The capacity factor is defined as the ratio of the time ready for service and the actual time in service. An equivalent FOR for the entire windpark, equal to 1 – capacity factor, is used to model its stochastic production.

2.2.3 Parameter Uncertainty

The LOLE and EENS indices are probabilistic in their nature but, thus far, we have assumed that the load profile and units FOR are known with complete certainty (i.e., with 100% probability). In practice, this assumption, of course, is never true. Even for the present time these parameters are never precisely known and their uncertainty only grows as we project them further in the future. As said previously, the usual approach to take these uncertainties in account is to use random variables with some probability distributions, usually Gaussian [23]. The use of a normal distribution makes the results analytically tractable. In every other case, Monte Carlo simulation is the only feasible approach.

Here, we propose the use of interval numbers to model these uncertainties. There are two reasons to pursue this approach. First, we argue that using a probability distribution to model a future system's parameters violates the underlying assumption in probability theory of repetition of events. The future system will most likely be different and operate under different conditions in different environment. Second, interval arithmetic is almost always more straightforward and much simpler than dealing with random variables, even normal ones.

Extending the calculation of LOLE and EENS to interval numbers is simple. The recursive formula for calculating the equivalent inverse LDC in (5) is to be applied according to the rules of interval arithmetic. The LDC in this case is an interval value function, i.e., at any given time the load is described by not just one, but by an interval of values. Thus, D_k is a "thick" curve, has multiple values along the x-axis for the same probability. This, in turn, renders D_{k+1} and all subsequent curves "thick" as well. Finally, applying expressions (6) and (7) on a "thick" D_{n+1} results in interval values for LOLE and EENS.

Since interval numbers are just a special case of fuzzy numbers, which can be seen as lumped and nested intervals, we can easily extend further calculation of LOLE and EENS to the fuzzy case. Thus, we can calculate these indices with different possibilities representing different degrees of belief. This opens an interesting perspective in the planning process where one can calculate possibilities of different risks for various alternatives and weigh outcomes of different decisions accordingly.

2.2.4 Case Studies

Let's show a hypothetical example derived from the WECC system how different percentages of wind penetration affect generating capacity adequacy. The current thermal generation in this system consists of a large number of units utilizing different technologies. We will assume that they can be classified in 5 categories with maximum available capacities given in Table I. The maximum available capacity, P_{max}, is obtained from the total installed capacity reduced by the capacity on scheduled maintenance. Also, we will define an average unit capacity for each category, P_{avg}, and we will assume that all units within a category are the same and have that capacity. These data are also given in Table I.

TABLE I WECC THERMAL GENERATION CATEGORIES

Thermal Technology	Nuclear	Coal	Comb. Cycle	Gas Steam	Comb. Turbine
P_{max} [GW]	7.5	29.6	53.1	20.3	19.2
P_{avg} [MW]	750	400	250	125	125

On the demand side, Figure shows “thermal load” profile for a summer day. This load is obtained from data for the total demand in the system reduced by the production from hydro units. In this particular case, hydro units cover 29% of the peak demand and 25.4% of the daily energy.

We do not include the hydro portion of the system here for the sake of simplicity as this is a fairly complex problem by itself. Hydro units availability depend not only on equipment outages but also on the reservoir head and, therefore, on the level of reservoir depletion. The latter is a stochastic variable with seasonal variation and it can have a dominant effect on the unit availability, more than equipment outages which, on the other hand, are usually much less frequent in hydro units than in thermal. The usual approach is to deal with hydro production as a separate subproblem, obtain representative samples from its probability distribution with corresponding probabilities, and then solve the main problem with known hydro by using conditional probabilities.

With hydro portion of the system left aside, we’ll introduce another category for wind units with average unit size of 100 MW. As explained in the previous section on windpark modeling, the average unit here represents an entire windpark not an individual unit. We assume an equivalent FOR that accounts for windpark’s stochastic production of 2/3. Thus, its capacity factor is 1/3.

Let’s now increase the percentage of the wind generation in the total thermal generation mix of the system from 0% to 15%. In order to keep the same reserve margin, we proportionally increase the load at the same time. The results are displayed in Figure 14. The system LOLE index increases from $8{\cdot}10^{-18}$ to $8.7{\cdot}10^{-6}$ with increased wind penetration in the generation mix. Although the change is significant the final value still seems rather small. This can be attributed to the very large number of units in the system. Thus, the probability of significant outage simultaneously involving a large number of units is very small. However, this small number can be misleading as we show next.

Let’s compare the results with the established planning reference value for LOLE of 1 day in 10 years. In other words, the target planning LOLE is usually set at 1/3650 = $2.7{\cdot}10^{-4}$. This value is calculated on the basis of the daily peak load variation curve. In our case, since we have data for only one day, we will calculate the single probability of not meeting the peak load in this day. Note that in this case it is correct to refer to this value as LOLP.

The results of these calculations are shown on Figure . The LOLP index for the peak summer load increases from $1.8{\cdot}10^{-16}$ to $2{\cdot}10^{-4}$ with increased wind generation from 0% to 15%. If these results are extended to a 10 year period then the last value corresponds to 0.735, or 268 days a year the system will not be able to meet peak load!

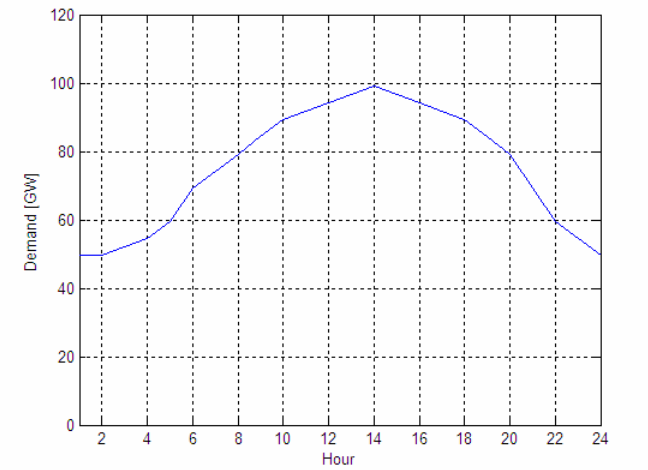

Figure 13. WECC thermal load profile – summer day.

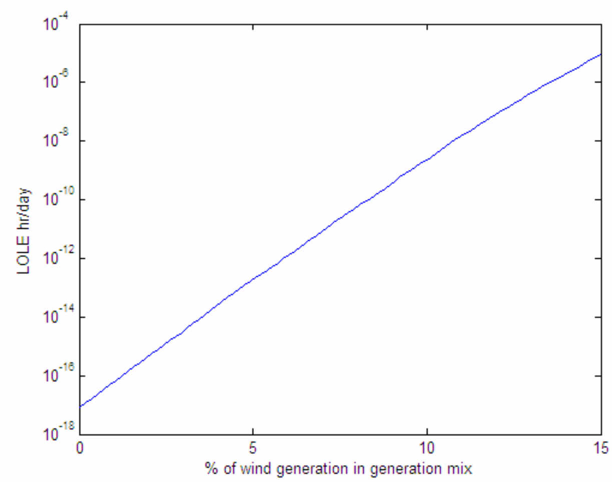

Figure 14. Dependence of the WECC LOLE index on the wind generation – constant reserve margin of 30.9%, 10% FOR for all thermal units.

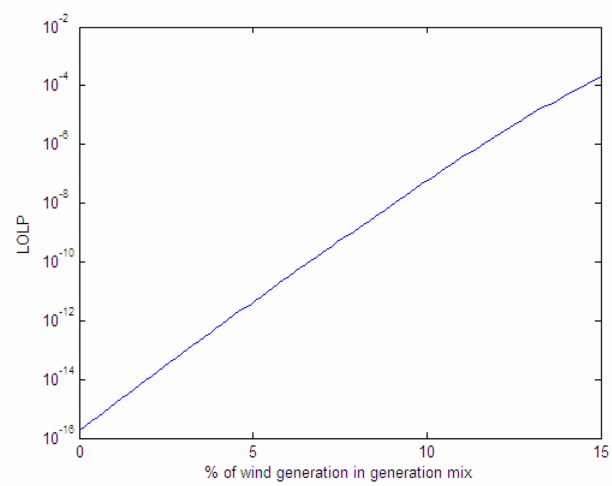

Figure 15. Dependence of the WECC LOLP index for a single peak summer load on the wind generation – constant reserve margin of 30.9%, 10% FOR for all thermal units.

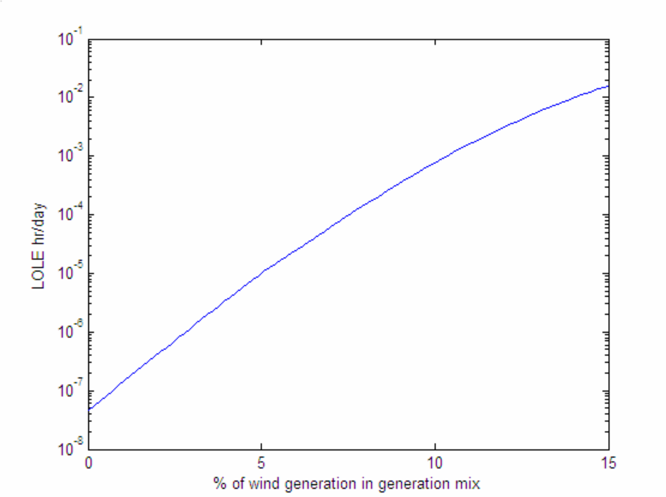

Figure 16. Dependence of the WECC LOLE index on the wind generation – constant reserve margin of 30.9%, 15% FOR for all thermal units.

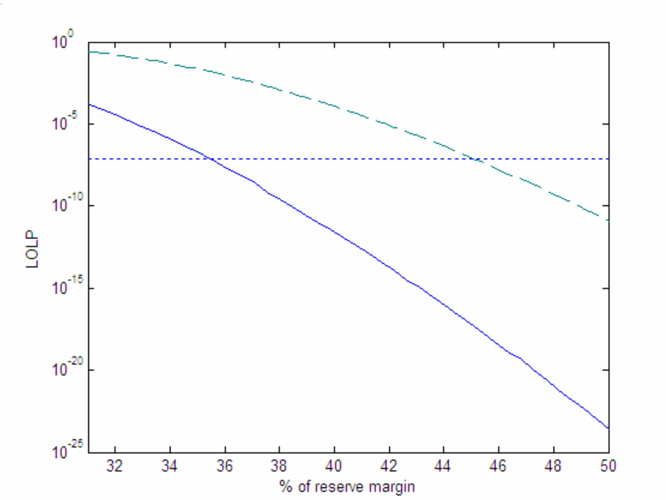

Figure 17. Required reserve margin in the WECC system to meet the target LOLE of 0.1 day/year (dotted line), with 15% wind generation, for two different values of thermal units FOR: 10% - solid line; 15% - dashed line.

This is by no means acceptable. True, this result is exaggerated as peak daily loads throughout the year will be smaller than the peak summer day load. However, the real LOLE will still have the same order of magnitude as the result just calculated.

In order to confirm the dramatic effect unit availabilities can have on system adequacy and further emphasize the impact of wind generation in such case, let's assume that all thermal units in the system have FOR of 15%. The results for this case are displayed on Figure 16. The system LOLE index increases from $4.6 \cdot 10^{-8}$ to an extraordinary 0.0159 hr/day with an increase of wind generation from 0% to 15%.

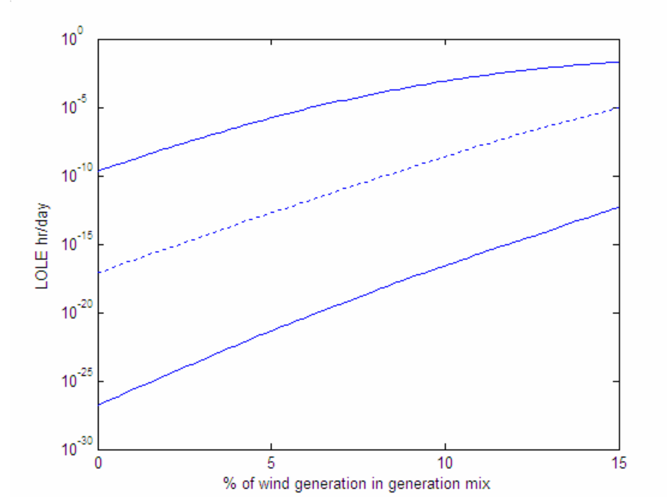

Figure 18. Upper and lower bound of the WECC LOLE index from Figure 14 with ±5% variation in load profile and unit FORs – reserve margin of 30.9%, 15% wind penetration.

All the results presented so far show that the system can not be left with the same reserve margin as the percentage of wind generation increases, or its reliability will suffer greatly. The more appropriate analysis is to determine the required reserve margin in order meet the reference LOLE of 1 day in 10 years, when the wind generation percentage is kept fixed at 15% of the total generation mix. Again, in the first approximation, we'll assume that all days are equal. This sets the target LOLP at $7.5 \cdot 10^{-8}$. The results of these calculations for two different values of FOR are shown on Figure 17. The required reserve margins are 45.1% and 35.4%, for the 15% and 10% values of FORs, respectively. If one takes into account the capacity from hydro units than the actual values are 32% and 25.1%, respectively.

If there is no wind generation in the system, the target LOLP will be satisfied for reserve margins at 32.9% and 23.2%, for the 15% and 10% values of FORs, respectively. Again, taking into account the hydro capacity, the real values are 23.3% and 16.5%, respectively. Thus with 15% wind generation, an additional 8.7% (8.6% for 10% FOR) of reserve margin is required to cover the uncertain 15% of wind. The amount of additional reserve is more than half the wind generation. If the system were purely thermal then an additional 80% reserve would be required. All these values, of course, depend on the specific case assumptions, units and system parameters, and cannot be strictly generalized.

Let's now see how parameter uncertainty affects adequacy of the system. Consider the same case as in Figure 14, but with ±5% variation in the load profile and unit FORs. In other words, one assumes the load to be defined as a set of intervals with upper and lower bounds at 95% and 105% of the values shown in Figure 13, respectively. Thermal units FORs are given with the interval number [9.5%, 10.5%] and wind units FORs with [63.3%, 70%]. Figure shows the upper and lower boundary for the resultant LOLE in this case. It also shows the crisp case result from Figure 14, which falls between the two boundaries. It can be seen that even a small uncertainty in parameters makes a significant difference. This is especially true for small values of LOLE at the extreme end of the D_{n+1} curve. The range of values gradually shrinks as the LOLE increases and moves away from the tip of D_{n+1}.

2.2.5 Comments

A significant increase in wind generation in modern power systems will have a profound impact on their operation and planning. This paper addresses the fundamental problem of generating capacity adequacy in expansion planning. An approach is used where the entire windpark is modeled as a single unit with an equivalent FOR that accounts for wind uncertainty.

It is shown on a hypothetical, but realistic example, that a considerable amount of additional, non-wind based, sources is needed to counteract wind stochasticity and maintain an acceptable level of risk. It is confirmed again that two systems with the same reserve margin or largest unit reserve can have very different risks levels. This discrepancy grows with the wind penetration.

The amount of additional reserves needed can range anywhere from more than half to more than 80% of the wind generation. These values, of course, depend on the particular case, units and system parameters. The tendency, however, is obvious and calls for careful planning of additional resources whenever wind units are to be a significant part of the system mix.

Finally, the use of interval numbers is proposed for modeling future system parameter uncertainty. It is a simpler and, the authors believe a more appropriate approach. It can also be easily extended to the use of fuzzy numbers, which allows for a more intuitive approach to decision making under uncertainty in the expansion planning process.

3 FURTHER WORK

The proposed modeling approach needs further developments in several areas that will be supported by case studies in order to highlight the value of the work. Specifically, the following is planned:

- studies of various transmission investment incentives and the impact on boom-and-bust cycles,
- incorporation of uncertainty modeling into the system dynamics modeling tools,
- detailed study of the benefits of the WAPP on electric power system development in West Africa, and
- major modification of senior power systems analysis course in Electrical Engineering and graduate course modeling course in Environmental Science.

ACKNOWLEDGEMENT

The work reported in this paper has been supported in part by the NSF and the Office of Naval Research under the NSF grant ECS-0224810.

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