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Determining the Capacity Value of Wind: A Survey of Methods and Implementation

Preprint

M. Milligan, Consultant
National Renewable Energy Laboratory

K. Porter
Exeter Associates, Inc.

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DETERMINING THE CAPACITY VALUE OF WIND:

A SURVEY OF METHODS AND IMPLEMENTATION

Michael Milligan
Consultant
National Renewable Energy Laboratory
1617 Cole Blvd.
Golden, CO 80401
303-384-6927
303-384-6901 (fax)
michael_milligan@nrel.gov
www.nrel.gov/wind

Kevin Porter
Senior Analyst
Exeter Associates, Inc.
5565 Sterrett Place
Suite 310
Columbia, MD 21044
410-992-7500
410-992-3445 fax
porter@exeterassociates.com
www.exeterassociates.com

Abstract

Regional transmission organizations, state utility regulatory commissions, the North American Electric Reliability Council, regional reliability councils, and increasingly, the Federal Energy Regulatory Commission all advocate, call for, or in some instances, require that electric utilities and competitive power suppliers not only have enough generating capacity to meet customer demand but also have generating capacity in reserve in case customer demand is higher than expected or if a generator or transmission line goes out of service. Although the basic concept is the same across the country—ensuring enough generating capacity to meet customer demand for electricity—how it is implemented is strikingly different from region to region.

Related to this question is whether wind energy qualifies as a capacity resource. Wind's variability makes this a matter of great debate in some regions. However, many regions accept that wind energy has some capacity value, albeit at a lower value than other energy technologies. Recently, studies have been published in California, Minnesota,

and New York that document that wind energy has some capacity value. These studies join other initiatives in PJM, Colorado, and in other states and regions.

This paper focuses on methodologies for determining the capacity value of generating resources, including wind energy. It summarizes several important state and regional studies that examine the capacity value of wind energy, how different regions define and implement capacity reserve requirements across the country, and how wind energy is defined as a capacity resource in those regions.

Introduction and Overview

An interesting feature of electric power markets is the near unitary elasticity of demand. There is little customer response to increasing electric prices as customers either have little incentive to respond to higher electric prices (because of rate freezes or flat pricing structures) or do not have the technical ability to respond (because of older meter technology). [1]

In recognition of this problem, load-serving entities (LSEs) such as electric utilities generally maintain some percentage reserve margin of capacity over and above their load requirements to maintain reliable electric service. State regulators, and even state statutes, may also require LSEs to maintain a certain reserve margin. The North American Electric Reliability Council (NERC) also requires regional reliability councils to meet certain reliability standards, and as part of that, regional reliability councils will require LSEs to have reserve capacity (generators that can respond quickly) and planning reserve capacity (generators that do not have to respond quickly). The regional capacity standards are voluntary, differ by region, and depend in part on how each region determines the capacity value of a generator. Regional transmission organizations also may require LSEs to have a capacity reserve margin.

Although the source of the capacity reserve requirements may differ, common elements are present in all of them. For instance, the nameplate capacity of a generating plant is discounted to reflect the probability of the plant going off-line for scheduled or unscheduled maintenance. A time differentiation for capacity may also be applied, as it is generally (but not always) recognized that available capacity is more valuable at times of peak electric demand than at other times.

An important trade-off is involved with capacity reserve requirements. Almost by definition, capacity reserve requirements involve making financial investments in generating capacity that will not be used or not used often. One could "overpay" for reliability by having too much reserve capacity. Therefore, the trade-off is enough reserve capacity to ensure reliable electric service while minimizing the costs of having reserve capacity.

[1] In some regions, regulators, utilities, and market participants are working on better enabling customer response to higher electric prices, otherwise known as demand response. Because this article is focused on wind energy as a capacity resource, demand response will not be discussed further.

A central element of preserving electric reliability is to ensure that more generating capacity is available than is necessary to serve demand for electricity, or load. During the height of electric power restructuring initiatives, however, capacity requirements were sometimes viewed as a vestige of monopoly regulation, to be replaced by competitive markets where a multitude of market participants compete to provide energy to customers. Reserve capacity requirements were therefore not seen as necessary. The California electricity crisis of 2000 and 2001, when California did not have a reserve capacity requirement, prompted a reconsideration of reserve capacity requirements.

With nearly 7 GW of installed wind capacity in the United States at the end of 2004 and another 2.5 GW expected to come on-line in 2005, the question of whether wind energy is a capacity resource is gaining more attention. Wind's low cost and environmental benefits, and the higher cost of competing fuels such as natural gas, mean that system planners will need to grapple with how to determine the capacity value of wind energy.

Wind generators occupy a unique place in the determination of capacity and effective load carrying capability (ELCC). Wind generators have typically very high mechanical availability, exceeding 95% in many instances (i.e., the forced outage rate is often below 5%). However, because wind generators only generate electricity when the wind blows, a wind generator arguably has a forced outage when the wind does not blow. Therefore, the effective forced outage rate for wind generators may be much higher, from 50% to 80%, when recognizing the intermittent availability of wind. In addition, wind's value to the electric system may also vary. The output from some wind generators may have a high correlation with load and thereby can be seen as supplying capacity when it is most needed. In this situation, a wind generating plant should have a relatively high capacity credit. The output from other wind generating plants may not be as highly correlated with system load, and therefore would have a lower value to the electric system and should receive a lower capacity credit (Milligan and Parsons 1999). The correlation of wind generation with system load, along with the wind generator's outage rate, will determine how much capacity credit a wind generator will receive.

This article discusses how capacity is valued for reliability purposes, compares how different regions around the country determine capacity reserve margins, and illustrates how the capacity value of wind is calculated. The notion of wind energy as a capacity resource is not a universally accepted one, and this article will discuss that as well. After all, wind energy is a variable resource, with production only occurring when the wind blows.

Methods for Calculating Capacity Credit

This section examines some methods that can be used to calculate the capacity value of an intermittent generator such as wind. The intermittency of wind transforms this problem into one of additional complexity. Capacity value methods for wind plants that are in use today differ in some respects. In part, this is because of different definitions of capacity value, but it is also because capacity value is used in several different contexts, as discussed.

To begin, it is useful to discuss the properties that a desirable capacity credit metric should possess. A capacity metric should be capable of assessing all types of generators, whether baseload, conventional, or intermittent. Because all generators have some probability of failure during critical times, the metric should recognize this potential, and plants that experience more outages should have a capacity value less than a plant that experiences fewer outages. An intermittent (or conventional) generator that never delivers during high-risk (peak) periods should have a low or zero capacity value, whereas an intermittent (or conventional) generator that consistently delivers on peak should have a relatively high capacity value. A generator that sometimes delivers during peak periods should have a capacity value somewhere in between these extreme values. In this case, a "sometimes-available" generator cannot be counted on with a high degree of certainty, but it *does* reduce the risk of insufficient generation when it is available. The capacity value must therefore be a probabilistic-based metric that can take these generator characteristics into account and rank the relative contribution of the generator fleet to the reduction of system risk.

To properly value generators with different capacity contributions, it is useful to adopt the principle of vertical consistency. This concept, borrowed and adapted from public economics, says that power plants with a high capacity contribution should be ranked above power plants that have a lower capacity contribution. Plants that are equivalent in their reliability (and delivery) should receive the same ranking. This latter approach is horizontal consistency. These fundamental principles, while very simple, can help guide us toward a suitable metric.

Effective Load Carrying Capability

Fortunately, such a metric does exist that possesses these properties, and it has been used for several decades. It is based on well-established reliability theory and practice and can be applied to all generators. This metric is based on one of several reliability metrics, such as loss of load probability (LOLP), loss of load expectation (LOLE), or expected unserved energy (EUE). The metric itself is ELCC and can be carried out with a power system reliability model, with appropriate tweaking to properly account for the stochastic and variable nature of wind generation. ELCC can discriminate among generators with differing levels of reliability, size, and on-peak vs. off-peak delivery. It effectively rewards plants that are consistently able to deliver during periods of high demand, and it ranks less reliable plants by calculating a lower capacity credit. For intermittent generators such as wind, the method can discriminate between wind regimes that consistently deliver during high-risk periods, sometimes deliver during high-risk periods, or never deliver during high-risk periods. In fact, ELCC can provide for a continuum of capacity values over these potential outcomes.

To calculate ELCC, a database is required that contains hourly load requirements and generator characteristics. For conventional generators, rated capacity, forced outage rates, and specific maintenance schedules are the primary requirements. For an intermittent resource such as wind, at least 1 year of hourly power output is required, but more data is always better. Over the decades that ELCC has been widely applied, it has been used with a number of different reference units. Some early work (for example, Garver 1966) measured the capacity value of a generator against a perfectly reliable unit. Because such a unit does not exist, we prefer the alternative of measuring capacity value relative to a benchmark unit. Although we would prefer a widely adopted benchmark value (for example, a gas unit with a forced outage rate of 5%) to allow for easier comparison among studies, it is important that the benchmark unit is clearly identified, and *all* units in a given region, such as a balancing authority, should be measured against the same benchmark.

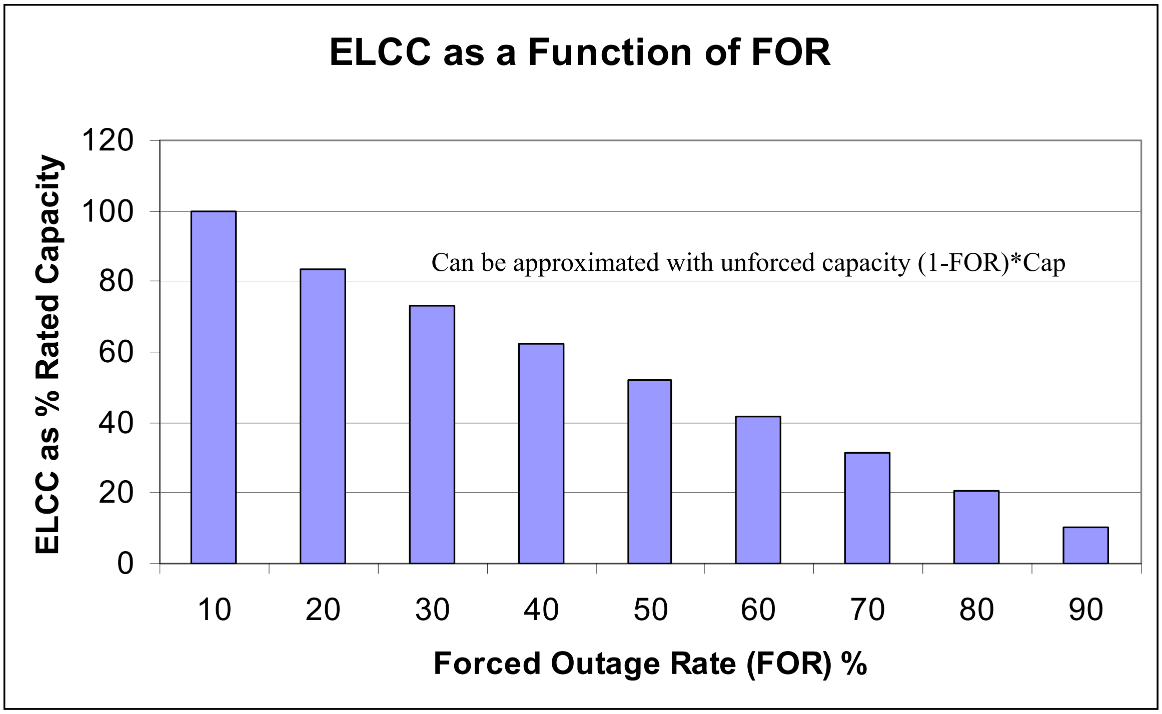
Although there are some variations in the approach, ELCC is calculated in several steps. Most commonly, the system is modeled without the generator of interest. For this discussion, we assume that the generator of interest is a renewable generator, but this does not need to be the case. The loads are adjusted to achieve a given level of reliability. This reliability level is often equated to a loss of load expectation (LOLE) of 1 day per 10 years. This LOLE can be calculated by taking the LOLP (a probability is between zero and one and cannot by definition exceed 1) multiplied by the number of days in a year. Thus LOLE indicates an expected value and can be expressed in hours/year, days/year, or other unit of time.

Once the desired LOLE target is achieved, the renewable generator is added to the system and the model is re-run. The new, lower LOLE (higher reliability) is noted, and the generator is removed from the system. Then the benchmark unit is added to the system in small incremental capacities until the LOLE with the benchmark unit matches the LOLE that was achieved with the renewable generator. The capacity of the benchmark unit is then noted, and that becomes the ELCC of the renewable generator. It is important to note that the ELCC documents the capacity that achieves the same risk level as would be achieved without the renewable generator.

One concern is what happens if the generator does not generate at the level that was estimated by a prior ELCC calculation. For example, a conventional base load unit may go out of service during the peak period. Although this can put stress on the grid (and the system operator), proper planning usually alleviates the problem because the system is planned, built, and operated to account for such risks. This is why planning reserves are often calculated to be 15% to 20% of projected peak load, allowing for the possibility that some units may not be available when needed. Planning processes in the United States often do not perform risk-based analyses of the system but instead rely on deterministic approaches for capacity planning, such as adding the installed capacity of all the individual generators and applying a planning reserve margin on top. Many of these analyses use rules of thumb that were originally derived from probabilistic methods, and in some regions there is a slow return to probabilistic methods. The potential difficulty of deterministic approaches is that two hypothetical systems that are identical in almost every way could face significantly different risks. This can happen because units with high forced outrage rates (FORs) impose a higher risk of not meeting load than otherwise identical units with low FORs. If one system is characterized by generating units with high FORs and the other by low FORs, the system LOLP/LOLE will be different. Clearly, the objective is to carefully plan for contingencies and to quantify risks whenever possible. Using probabilistic approaches such as ELCC allows these risks to be quantified and calculated in a systematic, data-driven way.

It is useful to examine how a conventional unit would fare under an ELCC evaluation. A generator's ELCC is driven by several factors, the most important one being the plant's capacity and forced outage rate. As part of the work assessing the costs of renewable energy integration for the California renewable portfolio standard, a hypothetical conventional unit was modeled at several alternative FORs. An ELCC value was calculated at each FOR so that the impact of the FOR could be seen on ELCC. The benchmark unit is a gas-combined cycle with a FOR of 4% and maintenance outage rate of 7.6%. Figure 1 illustrates the results and shows that the ELCC of this unit declines as a function of the FOR. For example, a unit with a FOR of 60% would have approximately 40% ELCC relative to its rated capacity and the benchmark unit. For conventional generation, the ELCC value often tracks the unforced outage rate (1 – FOR). This is not always true, however, and depends in part on the level of system risk that is used for the base case.

Figure 1. Comparing a Generic 100-MW Conventional Plant to a Gas Benchmark Unit



To derive the ELCC of wind, one ideally would have access to several years of wind generation data, load data, and other generation data. The wind ELCC could then be calculated using multiple years of data, which would provide confidence that inter-annual variability has been captured. But because a long wind generation record often does not exist, it is reasonable to expect that wind's capacity value could vary from year to year. As wind projects come on-line, wind generation data will become available and a database can be created and updated to calculate some type of moving average of the wind capacity value. Examples of how some power pools and regional transmission organizations (RTOs) handle multiple years of data is discussed later in this paper.

One way to help solve the problem of the year-to-year variability of the capacity value for wind is to create wind generation scenarios using meso-scale meteorological models. Conceptually there are many variations on this approach. For the Minnesota Department of Commerce (MN/DOC), for instance, Enernex and WindLogics developed a 3-year wind data record by re-creating the actual weather and normalizing to the long-term trend. A variation of this approach may involve the re-creation of several additional years of weather data, then running the reliability model for each of these several years to capture a longer time period. Other approaches have been used that involve Sequential Monte Carlo simulation, discussed further below.

Factors that Influence the ELCC of Wind

Regardless of the method used to calculate wind ELCC, a number of factors can influence the results. The key influence is the interaction of the system LOLP curve, such as the one displayed in Figure 1, and the timing of the wind delivery. Wind that delivers significant capacity during the times of relatively high system risk achieves a high capacity value. Conversely, wind that generates little or no output during these high-risk periods will have a low or zero capacity value. Good siting practices, technology characteristics, and geographic dispersion of the wind plant can all affect the potential delivery and timing of wind generation to the grid, and therefore the ELCC of the wind project.

The LOLP curve is subject to several influences. The mix of other generation units, their capacity, and forced outage rates can play a key role. The way that these parameters interact with the load shape has an important influence on the shape of the LOLP curve.

In a system with significant hydro generation, there can be two distinct influences on the LOLP curve. The first is from the non-controllable hydro (run of river) that has arbitrary influences on the LOLP curve. This will vary from year to year as a function of the hydro flow and changing load shape. Controllable hydro is generally operated so that it benefits the system in some optimal way. Generally, controllable hydro is used to mitigate high risk and therefore will lower LOLP during peak periods. This has the effect of altering the shape of the LOLP curve and can perhaps shift the highest risk hours to near-peak hours from peak hours.

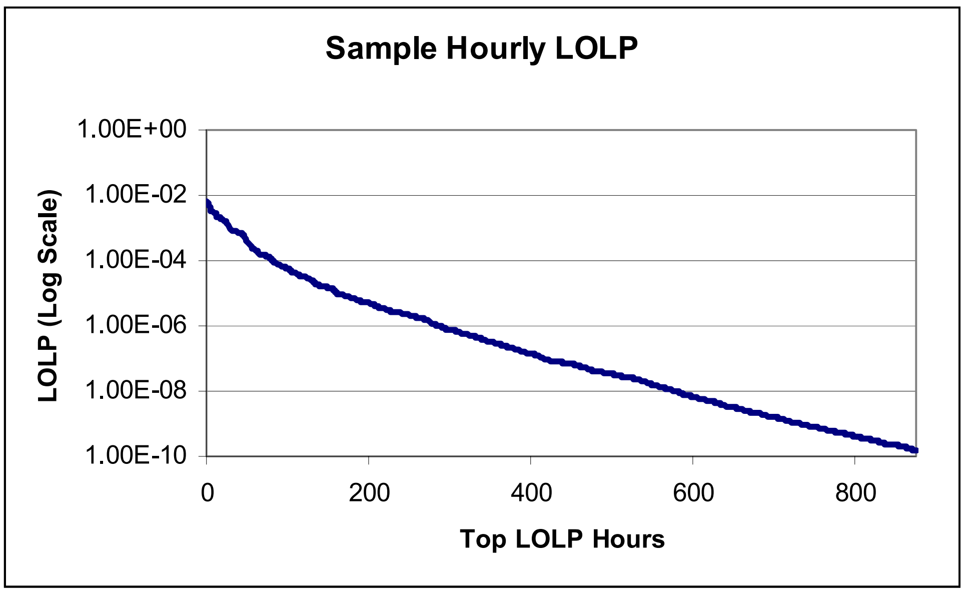
Off-system purchases can also influence the risk profile. Because system operators want to ensure sufficient resources during peak periods, it is not uncommon to schedule purchases during peak periods. Of course, that will influence the risk profile and the ELCC of wind.

Maintenance on generators is normally deferred to off-peak months in the spring or fall. This is done for obvious reasons: the system operator wants to ensure that all generation is available during the peak periods when the system is most constrained and at highest risk. However, it is not uncommon for the spring or fall maintenance periods to drive up the system risk to levels at or near those found during peak periods. This significantly alters the risk profile and therefore can play a large role in determining the ELCC of a wind plant.

Wind and the System LOLP Curve

For a system with a reliability target of 2.4 hours/year LOLE (1 day per 10 years), the system risk identified by significant LOLP is generally confined to a relatively small number of hours. The number of hours will vary based on several system characteristics, the most important of which is the load profile. Figure 2 is a LOLP duration graph that is based on work performed as part of the California RPS Integration Cost study. The graph shows LOLP on the vertical axis and the top risk hours on the horizontal axis. The hours in the graph are not necessarily contiguous and generally consist of hours of high demand. For the California work, a policy decision was made to eliminate scheduled maintenance from the modeling so that renewable capacity values would be independent of these schedules. In reality, maintenance scheduling of conventional units can have a profound influence on hourly LOLP, and therefore on capacity value for renewable energy. In Figure 2 the area under the curve can be integrated and is 2.4 hours/year. Any generation that is unable to deliver during these hours will not receive any capacity value. Conversely, a unit (or units) that are able to fill the LOLP curve will receive a perfect capacity value. In general, the ELCC calculation finds the area under this LOLP curve that is covered by the benchmark unit. Then the capacity value of the renewable generator is the fraction of the risk reduction achieved by the benchmark unit.

Figure 2. Loss of Load Probability by Top Risk Hours



This helps us see the impact of two otherwise identical wind plants with alternative chronological delivery profiles. Assume for our discussion that wind plant A averages 30% of rated output during high-risk periods (generally high load) and wind plant B averages 5% of rated during the same periods. The annual energy for the two plants is the same. It should be clear that plant B does little to alleviate the risk of insufficient generation, whereas A does reduce this risk. However, it is important to realize that the capacity value of A and B may not be the same as their output during system-critical periods, although in some cases we have found that the capacity factor during peak periods can do a passable job of estimating the capacity value of the wind plant. We discuss this further below.

Visualizing the curve helps us understand why generators' ELCC declines as the unit size increases. In the simplest case for illustration, suppose that the addition of a 500-MW unit were to reduce all the risk under the curve. At that point, LOLP would essentially be zero for all hours of the year. If the 500-MW unit were replaced by a 1000-MW unit, the capacity value of the 1000-MW unit would be approximately 500 MW because there would be no risk-reduction benefit of the second 500 MW.

Representing Wind in Reliability Models

Wind can be represented in reliability models using several approaches. Studies that investigate the capacity value of wind can be either prospective or retrospective. A retrospective analysis might focus on historical performance of a wind generator or generators to analyze the impact on reliability. A retrospective analysis can best be accomplished by using hourly wind generation data along with actual load data in the reliability model. This provides the most accurate fidelity for a backward-looking evaluation, and is relatively simple to accomplish in most modeling frameworks. For this approach, the hourly wind generation is subtracted from the hourly load, and the reliability calculation then proceeds to determine the LOLP by applying this net equivalent load to the hourly outage probability table. As additional wind production data becomes available over time, a multi-year analysis that pairs actual wind and load data is possible, and it can provide significant insights into inter-annual variability and ELCC over time.

A prospective analysis of how wind may affect future system reliability may involve modeling wind in a probabilistic way. The details of this approach will depend on the capabilities of the reliability model. However, the approach generally involves modeling wind as a multi-block conventional generator. Several levels of wind output are calculated and matched with the probability of obtaining that output. These values are then converted into the form that is acceptable by the reliability model so that these capacities and probabilities look like forced outage rates at different output levels. It is critical that these probabilities represent the diurnal and seasonal characteristics of the wind resource. This approach is discussed further in Milligan (Wind Energy Journal Part 2).

A prospective analysis might estimate the reliability impacts of alternative future wind scenarios. Because of the stochastic nature of the wind resource, it is sometimes desirable to apply Monte Carlo techniques in the modeling process so that a range of potential outcomes can be considered. Work at NREL in the 1990s applied a Sequential Monte Carlo approach. The basis of the method was a Markov process that used a separate state transition matrix (STM) for each month. This method generated a large number of hypothetical wind time series based on wind speed, which was then converted to hourly power output estimates. Each of these replications was then run through a reliability model, and the results from each case were then captured and summarized.

Conventional utility reliability models often have a built-in procedure for Monte Carlo analysis. This is often implemented with an STM, which quantifies the probability of moving from one state (wind power output level) to another. This general approach is well suited to wind because it can capture the significant persistence pattern that is commonly found in wind speed and wind power time series data. This method was used in the MN/DOC study and in the recently completed PacifiCorp Integrated Resource Plan. Because of an aggressive schedule in the MN/DOC study, the scope of the investigation into some of the modeling options could not be investigated. However, the approach has value, and there is interest in examining this further. At the same time, there may be ways to enhance the capability of reliability models to better capture the unique characteristics of wind generation. For example, in the MN/DOC and PacifiCorp studies, the seasonal and diurnal nature of the wind resource may not have been fully captured. Conceptually, it is obvious that these patterns should be retained in the simulated time series to the extent that they exist in the actual data. However, the details for such an algorithm are not clear, and the relatively limited number of data points available to populate segregated STMs may further complicate the problem. Some of the NREL work used a modified Markov approach that was based on both the previous state and the time of day. But when a single year of data is used to populate the monthly STM, approximately 30 data points must be used to populate several bins of power output that span the output of the wind plant (or the range of relevant wind speeds, depending on how the Monte Carlo algorithm is applied). Although this approach appears to have merit, the relative lack of data to populate the matrices suggests that an alternative method might be more appropriate.

An additional issue is whether any underlying systematic relationship exists between wind and load. The existence and extent of such a relationship will depend on the situation. For example, if large wind plants in Montana are used to export power to the Northwest markets, any systematic relationship may be weak at best. Conversely, there may be a relationship between wind and load, at least during high-risk load hours, in cases such as those analyzed in New York by General Electric and the New York State Energy Research Development Authority (GE/NYSERDA), as discussed later in this paper. Consequently, a one-size-fits-all approach is probably not appropriate.

There are other modeling approaches that are not Monte Carlo-based techniques. One example is the sliding window approach (Milligan 2001). This approach retains the diurnal and seasonal characteristics of the wind generation and explicitly convolves alternative wind power output levels and their probabilities into the LOLP calculation.

Based on these points, there is still work that can be done to improve the way that wind generation is captured in reliability models.

Approximation Methods

Because of the potential difficulty of assembling the appropriate database to use for the ELCC calculation, interest in simpler methods has emerged over the past several years. To evaluate the capacity value of a wind plant, it would be desirable to have the ability to carry out the calculation using only the relevant wind data and whatever minimal auxiliary data set. Although several methods can be used to approximate ELCC, an unfortunate aspect of all of these methods is that they are indeed approximations.

However, in cases in which ELCC can't be calculated because of data or other limitations, these methods can be useful. In this section we examine several techniques that we are familiar with. Other methods may exist or may be developed in the future.

Broadly speaking, the approximation techniques fall into two categories: risk-based or time-period-based. Risk-based categories develop an approximation to the utility's LOLP curve throughout the year. Time-period-based methods attempt to capture risk indirectly, by assuming a high correlation between hourly demand and LOLP. Although this relationship generally holds, it can be compromised by scheduled maintenance of other units and hydro conditions. A further limitation of time-period-based methods is that all hours considered by the method are generally weighted evenly, whereas ELCC and other risk-based methods place higher weight on high-risk hours and less weight on low-risk hours. However, time-period-based methods are much simpler and are easy to explain in regulatory and other public proceedings.

Risk-Based Simple Methods

Risk-based methods utilize hourly LOLP information either from an actual reliability model run or as an approximation. The first technique summarized here can be carried out in a spreadsheet, and although it is not terribly difficult, the details are beyond the scope of this paper.

1. California RPS Method

California's Renewables Portfolio Standard (RPS, Senate Bill 1078) requires the investor-owned utilities to acquire 20% of their energy mix from renewable sources by 2017. In addition to price, prospective renewable energy generators compete in utility renewable energy solicitations on the basis of a "least-cost, best-fit" metric. A part of this metric includes capacity value. The California Energy Commission (CEC) adopted ELCC as the method to calculate capacity value for all renewable generators and renewable technologies under the RPS requirements. A team was assembled to investigate the capacity contribution of renewable generators and to assess the integration cost of the various renewable energy technologies. Although one goal of the work (CWEC 2004) was to develop a simplified approximation to ELCC, methods investigated did not provide the required accuracy.

The RPS method contains several steps and is predicated on the output of a reliability model execution that does not consider the renewable generator of interest. The approach proceeds as follows. First, data for hourly LOLP, system load, and wind generation are collected for the top 10% of load hours for the year. A logarithmic risk metric that is a variation of LOLE over this discontinuous period is calculated and normalized. This provides us with a measure of risk over the top 10% of load hours that is normalized to one. This new metric is called the risk share, and for each hour, represents the fraction of risk that occurs in that hour. For each of these hours, the wind generator output is multiplied by the risk share, and the total of all of these hourly values represents the relative risk contribution of the wind plant. This is converted to a percentage of the rated capacity of the wind plant.

The second step proceeds independently and is subsequently combined with the results of the first step. This approach develops a set of load-ratio shares over the top 10% of load hours. These hourly share values are also normalized and multiplied by the hourly wind generation in the appropriate hour. This can be converted to a percentage of the rated capacity of the wind plant.

The third step calculates the ratio of the standard deviation to the mean for the wind plant, also known as the coefficient of variation (COV), over the top 10% of load hours. For this method, the COV was expressed as a percentage.

For the California RPS study, this procedure was carried out for each renewable generator aggregate, and the results were used to estimate a regression equation. This equation used the results from each of the steps above to fit a set of coefficients that provided a best fit to ELCC. Although the specific regression equation would not be expected to provide accurate results for all generators in all areas, a similar approach could be used to develop a set of weights for a wind generator in another region. When applied to wind generation at the three resource areas in California (Altamont, San Gorgonio, Tehachapi), selected solar and selected geothermal resources, the method had a mean absolute percentage error of 1.2% of the actual ELCC value. Because these results could not be obtained when the hydro system was included, the method may only be applicable to systems in which hydro generation is not significant.

2. Risk-Based Method 2: Garver's Approximation

Garver's 1966 paper is indeed a classic in the power system reliability literature. The Garver technique to estimating ELCC was applied to conventional generators and was developed to overcome the limited computational capabilities that were available at the time. The technique is based on the development of a risk-approximation function, and in some respects it is similar to the CA RPS method.

The approach approximates the declining exponential risk function (LOLP in each hour, LOLE over a high-risk period). It requires a single reliability model run to collect data to estimate Garver's constant, known as *m*. Once this is done, the relative risk for an hour is calculated by

$$R' = \mathrm{Exp}\{-[(P-L)/m]\}$$

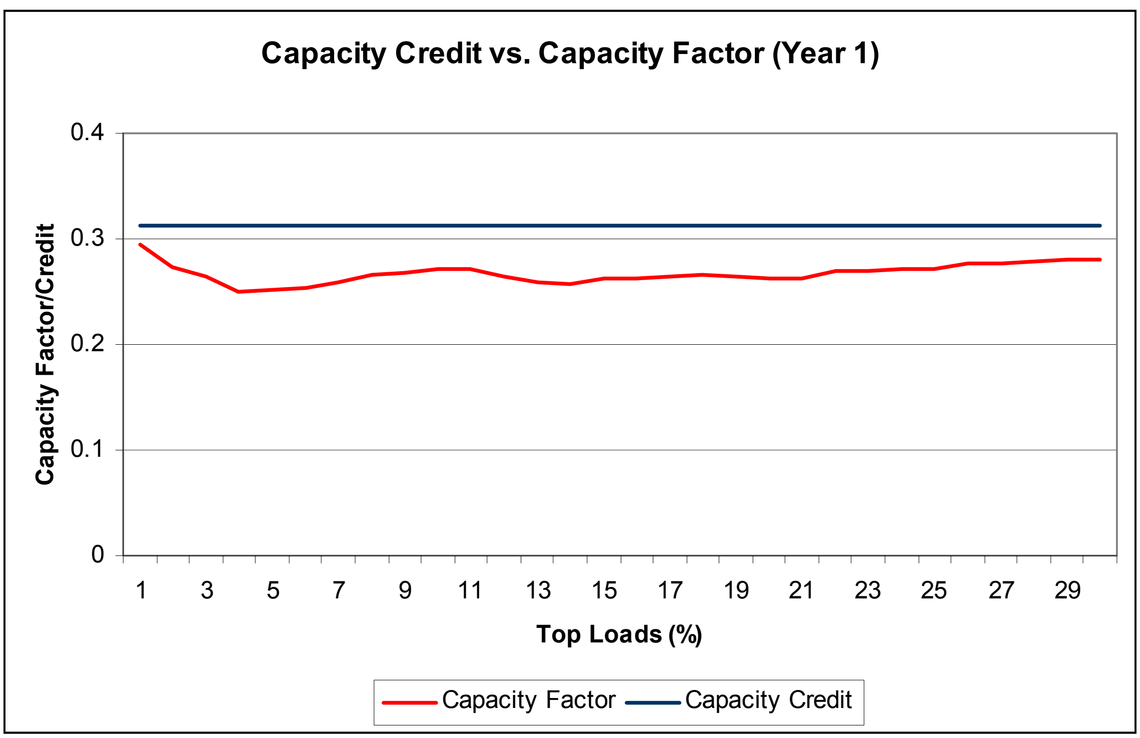
where P = annual peak load, L = load for the hour in question, R' is the risk approximation (LOLP), measured in relative terms (peak hour risk = 1). A spreadsheet can be constructed that calculates R' for the top loads. Then modify the values of L by subtracting the wind generation in that hour.

Calculate LOLE approximation for (a) no-wind case and (b) wind case by summing the hours. Use all hours for which no-wind risk exceeds some tolerance – probably around 500 hours. Compare to gas plant or other benchmark, de-rated by its forced outage rate.

Time-Period Methods

To avoid using a reliability model altogether, it is possible to collect only hourly load and wind data for at least 1 year and use these data to calculate an approximation to ELCC. This approach is appealing in its simplicity, but it does not capture the potential system risks that are part of the other methods discussed above. Milligan and Parsons (1999) compared the ELCC with a series of calculations for hypothetical wind generation to determine whether these simpler approaches are useful. Although several alternative methods were compared, the most straightforward approach was to calculate the wind capacity factor (ratio of the mean to the maximum) over several times of high system demand. The calculations were carried out for the top 1% to 30% of loads, using an increment of 1%. Figure 3 is taken from that study. Although an ideal match was not achieved, the results show that at approximately 10% or more of the top load hours, the capacity factor is within a few percentage points of the ELCC.

Figure 3. Comparing Capacity Credit Versus Capacity Factor



Methods to Assess Wind Capacity Credit in the United States

In this section we survey some of the approaches that are in use today to evaluate wind capacity credit. These methods come from a variety of entities, ranging from RTOs, Public Utility Commissions, utilities, or studies carried out on behalf of these organizations.

Pennsylvania-New Jersey-Maryland Regional Transmission Organization

PJM is an RTO that encompasses all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and the District of Columbia. PJM includes more than 56,000 miles of transmission lines and more than 1,000 generating units. PJM has more than 163,000 MW of capacity, and it serves about 131,000 MW of peak demand (PJM 2005).

In general terms and on an annual basis, PJM requires LSEs to have a reserve margin of capacity above what is required to serve load. To meet that requirement, LSEs can self-supply capacity, enter into bilateral arrangements with generators for capacity, or purchase capacity through a PJM-administered capacity market. In both PJM East and PJM West, the capacity market consists of daily, monthly, interval, and multi-month markets. PJM's current required reserve margin is 15%.

The capacity credit for wind in PJM is based on the wind generator's capacity factor during the hours from 3 p.m. to 7 p.m., from June 1 through August 31. The capacity credit is a rolling 3-year average, with the most recent year's data replacing the oldest year's data. Because of insufficient wind generation data, PJM has applied a capacity credit of 20% for new wind projects, to be replaced by the wind generator's capacity credit as noted earlier once the wind project is in operation for at least a year. As an example, a new wind generator will receive a capacity credit of 20% the first year; the average of 20% and the wind generator's capacity factor during the hours from 3 p.m. to 7 p.m. from June 1 through August 31 in the second year; and the average of 20% and the wind generator's capacity factor during the hours from 3 p.m. to 7 p.m. for June 1 through August 31 for years two and three, and so on. In addition, wind generators are also required to bid into PJM's day-ahead energy market, along with other generators receiving capacity credit in PM.

If PJM receives enough wind generation data, PJM will replace the 20% capacity credit for new wind projects with the average capacity factor during the 3 p.m. to 7 p.m. hours from June through August for all wind generators that have been in operation for 3 years or more in PJM.

New York ISO

The New York ISO (NYISO) consists of the transmission assets of eight transmission owners located in New York and a small part of New Jersey. The NYISO includes about 36,500 MW of generating capacity and serves about 31,000 MW of load (Lampi 2004). The NYISO also requires LSEs to have capacity reserves over their load requirements.

Like PJM, the NYISO has a financial market for capacity, but the NYISO has three auctions for capacity: a 6-month strip auction held twice a year, prior to the summer and winter capability periods; a series of monthly auctions; and a monthly spot auction for LSEs that have not met their reserve obligations.

Unlike PJM, the NYISO values capacity for other months besides summer, since the NYISO winter peak is close to the summer peak. The NYISO allows wind projects over 1 MW in capacity to qualify for capacity credit. Wind generators can submit the results of a 4-hour sustained maximum output test, for both summer (June 1 through September 15) and winter (November 1 through April 15).[2] The results of the tests are the wind generator's initial capacity credit in the NYISO. The NYISO adjusts the capacity credit monthly based on data submitted by the generator on actual generation and maintenance hours the previous month. Intermittent generators such as wind are exempt from having to bid into the day-ahead energy market in the NYISO, a requirement for other non-intermittent generators.

As noted later in this paper, the GE/NYSERDA wind integration study found that onshore wind projects had a lower capacity value (9%) than is currently provided to wind by the NYISO. The NYISO will likely investigate changing the methodology for determining the capacity credit of wind.

ISO New England

ISO New England operates in six states and includes more than 32,000 MW of capacity (ISO New England 2005) and serves about 25,000 MW of load (LaPlante 2004). ISO New England changed its energy market to incorporate a day-ahead energy market along with a real-time energy market in 2003, similar to PJM.

Three wind generators are registered with ISO New England, at a total capacity of about 1.5 MW. These wind generators participate in the ISO New England energy market as "settlement only" resources, a category for generating resources under 5 MW. Settlement-only resources sell electricity into the grid at real time and receive the real time market clearing price. These resources are not assessed any operating charges for schedule deviations or imbalances and receive a capacity credit equal to the unit's capacity, multiplied by 1 minus its forced outage rate.

[2] PJM does similar tests to determine the eligible capacity credit for non-wind generators, although PJM only considers the results from the summer test, even though tests are done in both summer and winter.

Wind generators over 5 MW would be classified as intermittent power resources and can schedule into the ISO New England's day-ahead market. If intermittent power resources do not submit bids into the day-ahead market, then before the next operating day, these resources must self-scheduled the capacity amount for each hour. If in real time the capacity amount is different than the self-schedule amount, the intermittent power resource must contact the ISO and re-declare its schedule. As with settlement-only resources, intermittent power resources are not assessed operating charges for scheduled deviation or imbalances and receive a capacity credit equal to the unit's capacity, multiplied by 1 minus its forced outage rate.

Southwest Power Pool

The Southwest Power Pool (SPP) recently adopted a method to calculate wind capacity contribution (SPP GWG 2004). The process of developing the method was managed by the Generation Working Group of the SPP, and it involved numerous discussions. The method that emerged is a monthly method and therefore results in 12 capacity measures for the wind plant. The process first examines the highest 10% of load hours in the month. Wind generation from those hours is then ranked from high to low. The wind capacity value is selected from this ranking, and it is the value that is exceeded 85% of the time (the 85^{th} percentile). Up to 10 years of data are used if available. For the wind plants studied in the SPP region, the capacity values ranged from 3% to 8% of rated capacity. According to SPP's Generation Working Group (SPP GWG) presentation, this method is used for long-term planning. Although it appears counter-intuitive to us, the SPP GWG believes that ELCC/LOLP methods are better used to determine the level of desired spinning or operating reserves and not to determine the reliability impacts of wind.

Rocky Mountain Area Transmission Study

The Rocky Mountain Area Transmission Study (RMATS) is a multi-stakeholder, regional transmission study in the west. RMATs encompassed Colorado, Idaho, Montana, Utah, and Wyoming and was established by the governors of Wyoming and Utah to assess the feasibility of investing in new transmission to either access remote coal and wind resources or to export generation to other areas in the West (RMATS 2004). RMATS used 20% of rated capacity for all wind plants in the region. Although this is clearly a simplification and does not take account the significant differences between wind delivery profiles and the match to load, the wind capacity contribution is an important factor in determining the required capacity of other generation resources to meet loads during the study period. Because the RMATS modeling was based on local/regional load modeling and respected transmission constraints, it is likely that the wind capacity contribution across the RMATS region would vary, perhaps considerably.

GE/New York State Energy Research and Development Authority

A recently completed study by General Electric for the New York State Energy Research and Development Authority examined the impact of 3,300 MW of wind on the New York bulk power system (GE Energy Consulting 2005). Although the study focused on reliability impacts and operational issues, the team assessed the capacity contribution of wind using ELCC. The study used simulated wind data from more than 100 sites throughout the state, matched to the year of load data. This important step accounts for any underlying systematic correlation that may exist between wind and load. (This correlation would be expected to vary by region, and it would likely be nonlinear with a potentially complex lag structure). The study found that on-shore wind plants would be expected to have approximately 9% capacity value relative to rated capacity, and off-shore wind would be approximately 40%. For the on-shore wind scenarios, the modelers found that a time-period based approach did a good job of approximating the capacity value. For the summer season, calculating the wind capacity factor during the hours from 1:00 p.m. to 4:00 pm.

Minnesota Department of Commerce/Xcel

The Minnesota Department of Commerce (MN/DOC) study examined the impact of 1,500 MW of wind capacity distributed at various locations in southwest Minnesota. This represents approximately 15% wind penetration, based on the ratio of rated wind capacity to peak load. One of the tasks of this study was to calculate the capacity contribution of wind. The study used a Sequential Monte Carlo method, which performed repeated sampling of an annual state transition matrix that was calculated based on the wind data used in the study. The intent of this approach is to capture some of the impact of the interannual variation of wind so that estimates of ELCC may be more robust. The SMC cases found a 26.7% capacity contribution for the prospective wind plants. For comparison, the study also used a simple “load-modifier” method that calculates reliability based on a simple netting of the wind generation against hourly load. When this approach was used, the prospective wind capacity value was 32.9% of rated capacity.

PacifiCorp

PacifiCorp recently completed a new Integrated Resource Plan (Pacificorp 2005). Wind generation was modeled using the same Sequential Monte Carlo approach used by Enernex in the MN DOC study. For the several prospective wind locations analyzed by PacifiCorp, the capacity contribution of wind averaged approximately 20% of rated capacity. The capacity value from the IRP is used as part of an evaluation to determine how much additional capacity is needed to meet future load forecasts.

Electric Reliability Council of Texas (ERCOT)

ERCOT evaluated the operating wind plants to determine the capacity contribution of wind. The analysis was based on wind generation from 4:00 p.m. to 6:00 p.m. during July and August, the peak period for ERCOT. During this time period, the average output of the wind was 16.8% of rated capacity. Because of the variability of wind generation, the ERCOT Generation Adequacy Task Group is developing a confidence factor. Although the method of evaluation of this confidence factor is unclear from the document, the recommendation under consideration is to use 2% of rated wind capacity as the capacity value.

Mid-Continent Area Power Pool (MAPP)

The Mid-Continent Area Power Pool (MAPP) approach is a monthly method that calculates wind capacity value based on the timing of its delivery relative to peak. Up to 10 years of data (wind and load) can be used if available. For each month, a 4-hour time window surrounding the monthly peak is selected. Any contiguous 4-hour period can be selected, as long as the peak hour falls within the window. The wind generation from that 4-hour period in all days of the month is then sorted, and the median value is calculated. The median value is wind's capacity value for the month. If multiple years of data are available, the process is carried out on the multi-year data set. The results of these calculations are used in operational planning in the power pool.

Portland General Electric (PGE)

Portland General Electric (PGE) assumed a 33% capacity factor in its 2002 Integrated Resource Plan as a placeholder and plans to review additional studies and data as they become available (Bolinger 2005). PGE's IRP calls for 195 MW of wind.[3]

Idaho Power

Idaho Power gives wind a 5% capacity credit, based on a 100-MW wind plant's projected output that would occur 70% or more of the time between 4:00 p.m. and 8:00 p.m. during July, Idaho Power's peak month (Bolinger 2005). Therefore, Idaho Power's method is similar to SPP's by multiplying a subjective statistical number by actual capacity factor values.

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[3] Portland General Electric. *Final Action Plan: 2002 Integrated Resource Plan*, March 2004. Available at http://www.portlandgeneral.com/about_pge/regulatory_affairs/pdfs/2002_irp/actionPlan_final.pdf.

Puget Sound Energy (PSE)

Puget Sound Energy just released its 2005 Integrated Resource Plan that includes a wind integration study as an appendix. Although not specified in the plan, a personal communication with a PSE representative determined that PSE's determination of a capacity credit for wind is the lesser of 20% of nameplate capacity, or 2/3 of the capacity factor of a wind project in January, which is PSE's peak month.

The 95% Fallacy: Using X Percentile to Calculate Capacity Credit

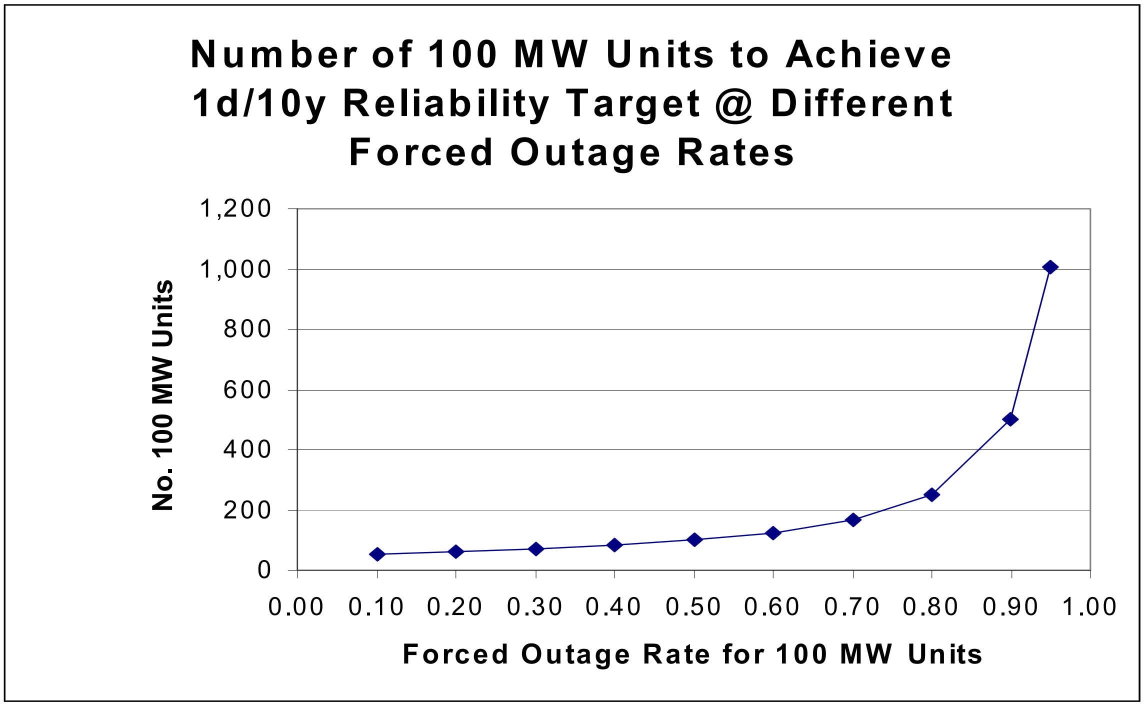
New gas plants are capable of achieving low forced outage rates—high levels of reliability. Because gas plants have often been the generator technology of choice in recent years, it can be tempting to use this gas plant characteristic in an attempt to estimate the capacity value of an intermittent generator such as wind. To carry out this approach, one collects wind generation over the relevant high-load period (for example, the top 10% of load hours). The next step is to calculate the 95th percentile of wind generation—the level of wind generation that is achieved 95% of the time during these load hours. A variation of this approach, one that we have encountered, is to then feed this 95th percentile generation into a reliability model to calculate the ELCC of the wind plant. In both of these variations, the method *only* values capacity levels that are exceeded 95% of the time. All other capacity levels are assigned a value of zero. The use of a percentile arbitrarily discounts reliability contributions that are achieved at levels below the percentile value. These approaches are based on fallacious use of probability theory, and they ignore the statistical independence of outages and the fact that system reliability can be achieved at a very high level (such as 1 day in 10 years LOLE) even though every unit in the system is somewhat unreliable.

To illustrate, we set up a series of reliability cases. Rather than specifically calculate ELCC, these cases illustrate how increasingly unreliable generators can still achieve a 1-day-in-10-year level of system reliability. We emphasize that we do *not* recommend the pursuit of unreliable generators, as this would be costly. However, the point is to illustrate that even highly unreliable plants contribute *something* to overall system reliability, albeit at a very low rate. Plants that have higher forced outage rates have correspondingly lower ELCC values.

The case study uses hourly load data from the California ISO. Instead of using the existing generator fleet, a hypothetical generator mix was developed that consists of 95 500-MW units, each with a forced outage rate of 9%. The base case also included 54 100-MW units, each with a forced outage rate of 10%. This mix of generation achieved a 1-day-in-10-year reliability level.

To illustrate the impact of less reliable plants, the forced outage rates on the 100-MW units was increased in steps of 10% up to 90%. And just for fun, we also included a case with all the 100-MW units and a 95% forced outage rate. The purpose of these scenarios is to show that the 1d/10y reliability target can be achieved even with the 95% forced outage fleet. Figure 4 captures the results of the simulation scenarios. The graph shows that even with unreliable units, a reliability target of 1 day per 10 year LOLE can be achieved. The point of this exercise is not to argue for unreliable generators. The point is to show that even unreliable units can contribute to a reliable system, although it would take many of these generators to do so!

Figure 4. 1 Day/10 Years Can be Achieved With Unreliable Generators



Summary of Study Results

We have chosen the results from several recent studies to illustrate the range of capacity values found to apply to wind. Figure 5 is taken from the California RPS Integration Cost Study (phase 3) and shows the capacity value for the three wind resource areas (this study was completed prior to completion of High Winds near Sacramento) and other renewable generation in California. All of these capacity values were based on ELCC, and the graph shows the range of wind capacity values in the mid-20s along with the much higher geothermal and solar gas-assist capacity values.

Figure 5. Selected California RPS Phase III Results
Relative to a Gas Reference Unit

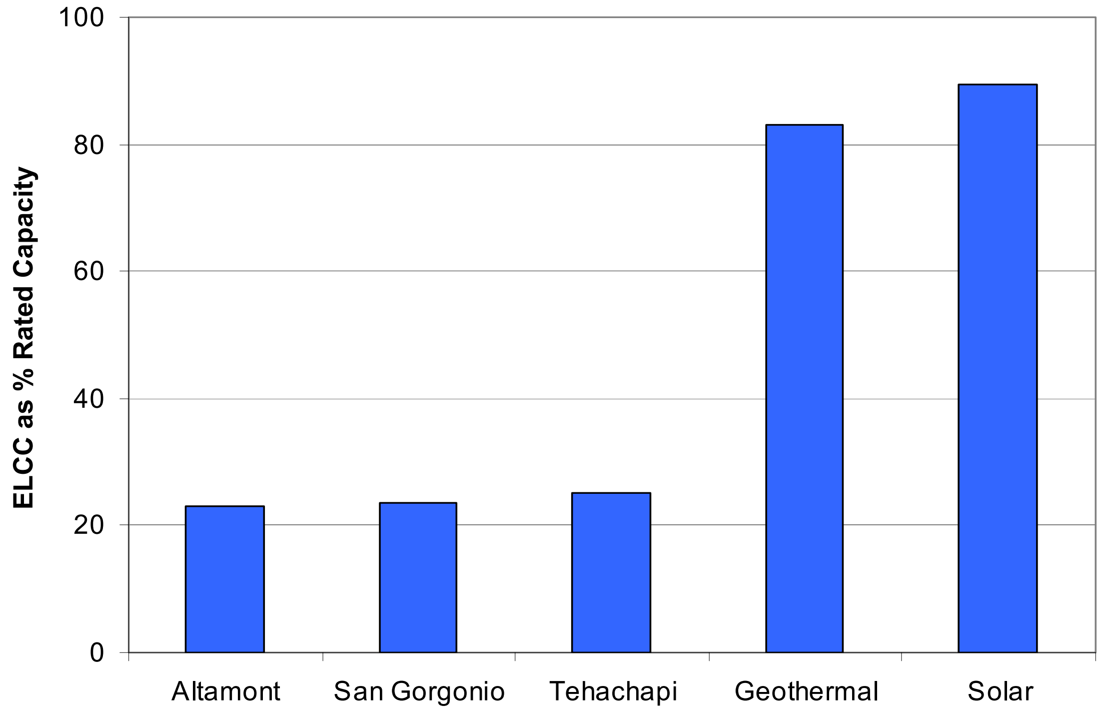
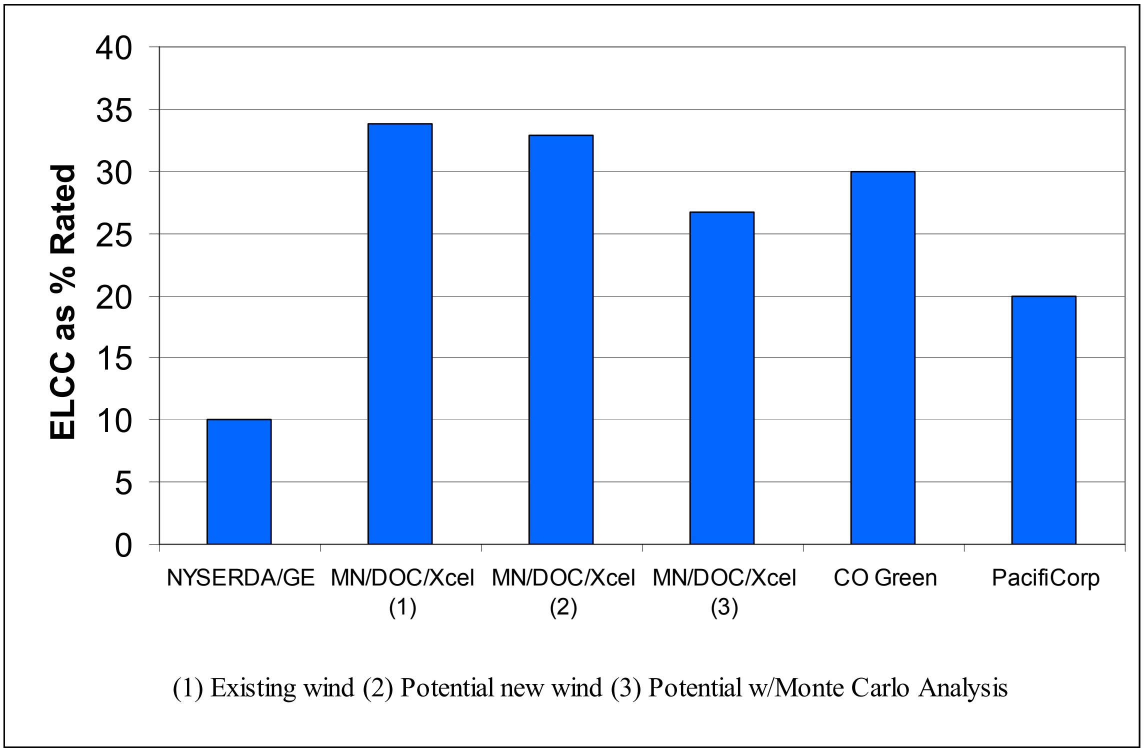


Figure 6 shows other capacity credit values for wind measured by ELCC. Many of the results came from the MN/DOC study recently completed by Enernex. The ELCC values from that study ranged from the upper 20s to low-mid 30s, depending on the modeling technique used for the scenario and whether wind is the currently installed wind or prospective wind expected to be developed within the study horizon.

Figure 6. Other Selected Wind Capacity Values



A more complete summary of wind capacity value appears in Table 1. Most approaches use either ELCC or a time-period basis to calculate wind capacity factor.

Table 1. Wind Capacity Value in the United States

Region/Utility	Method	Note
CA/CEC	ELCC	Rank bid evaluations for RPS (low 20's)
PJM	Peak Period	Jun-Aug HE 3pm-7pm, capacity factor using 3-year rolling average (20%, fold in actual data when available)
ERCOT	10%	May change to capacity factor, 4:00-6:00pm, Jul (2.8%)
MN/DOC/Xcel	ELCC	Sequential Monte Carlo (26-34%)
GE/NYSERDA	ELCC	Offshore/onshore (40%/10%)
CO PUC/Xcel	ELCC	PUC decision (30%) and possible followup to current Enernex study; Xcel using MAPP approach (10%) in internal work
RMATS	Rule of thumb	20% all sites in RMATS
PacifiCorp	ELCC	Sequential Monte Carlo (20%)
MAPP	Peak Period	Monthly 4-hour window, median
PGE		33%
Idaho Power	Peak Period	4pm-8pm during July (5%)
PSE and Avista	Peak Period	PSE will revisit the issue (lesser of 20% or 2/3 Jan C.F.)
SPP	Peak Period	Top 10% loads/month; 85th percentile

Potential Changes to Financial Capacity Markets in the Northeast

The three northeastern RTOs are unique in that they all have separate financial markets for capacity to ensure that utilities and other load-serving entities have enough capacity to meet electricity demand, plus a pre-determined reserve margin. Although each northeastern RTO has separate capacity markets by time (daily, monthly, multi-monthly), there typically is not a locational element to the capacity market. In other words, a generating plant located in a remote and perhaps unconstrained area may receive the same capacity value as a generating plant that is located in a transmission-congested region.

All three northeastern RTOs are considering significant changes or have significantly changed their financial capacity markets. Motivations for the changes include concern that new entry is not encouraged; that the location of the generator is not valued; that the volatile results of capacity prices perpetuate a "boom-bust" generation cycle; and that other desirable characteristics of generation (quick response, fast ramping) are not valued.

PJM also plans to revamp its capacity reserve requirements by providing locational premiums to generating capacity in transmission-constrained areas and abandoning an annual capacity reserve determination in favor of adjusting capacity payments, with lower payments when there is higher reserve capacity and the converse when there is a lower amount of capacity.

PJM's proposal, called the Reliability Pricing Model (RPM), would attempt to differentiate among generators for their true reliability or capacity value and provide some longer-term price signals. Generators would still receive a base capacity price, but some generators could receive additional payments for capacity resources that have locational value (i.e., in transmission constrained areas, as determined by PJM's transmission planning process) or provide operational flexibility (such as quick start capability, dispatchability, supplemental reserve, and flexible cycling). PJM also would abandon its annual setting of the reserve margin in favor of a range of resource requirements based on the probability of not having enough capacity to serve load for 1 day in 10 years. PJM would apply a pricing factor that would increase as reserve levels approach the 1-day-in-10-years factor and decrease when reserve levels are higher.

The NYISO incorporated a "demand curve" into the monthly auction part of their capacity market by paying a declining price for capacity over their capacity requirement, instead of not paying anything. The NYISO also includes a locational element to their capacity market design by requiring that LSEs in New York City and Long Island obtain part of their capacity from within those areas. ISO New England also plans to develop a demand curve but will subdivide their region-wide capacity market into five zones beginning in January 2006: Maine; Northeastern Massachusetts and Boston; Southwest Connecticut; the rest of Connecticut; and a combination of Vermont, New Hampshire, Rhode Island, and the rest of Massachusetts. Each zone can have its own unique capacity price, and regions can be added or subtracted annually.

The PJM and ISO New England proposals are controversial, and it is not clear they will move forward—Connecticut has sued FERC over its approval of ISO New England's proposal. Should these initiatives be implemented, the implication for wind projects is the amount that they get paid for their capacity may depend on where the wind project is located. Although it will vary with the particular circumstances, potential offshore wind energy projects may see more benefit, as they may have higher capacity factors at times of peak demand (as exhibited in the GE/NYSERDA study in New York). In addition, offshore wind projects may be located near transmission-constrained areas, perhaps further increasing their potential capacity value. In contrast, onshore wind projects in remote areas may see lower capacity payments.

Assessment and Recommendations

A capacity-based metric is useful in several alternative contexts, from adequacy determination to financial settlement markets. Capacity from a generator at some time in the future is not guaranteed. Because all generators are subject to outage, even during system-critical times, a probabilistic approach to calculating capacity value is appropriate. This is especially true for intermittent resources such as wind power plants. Because of the stochastic nature of the wind, and therefore wind energy, a method that can explicitly quantify the risks associated with this resource is critical. Standard power system reliability theory exists that can be used for this purpose.

When a reliability-based approach is used to calculate the capacity credit of wind power plants, risk is explicitly embodied in the calculation. The ELCC method is rigorous, data-driven, and can finely distinguish among generators that have different impacts on system reliability. However, the method requires datasets that are not always available and is influenced by many system characteristics. For these reasons and others, simplified methods have been developed. These methods are sometimes based on wind generation during a time period that corresponds to high system risk hours. In other cases, methods can approximate the system LOLP curve so that high-risk hours receive more weight than other hours. We favor experimentation with such methods but suggest that it would be helpful to benchmark simple methods against ELCC. This will help eliminate the sometimes-arbitrary assumptions that can be introduced by some simple calculations we have encountered.

Interannual variability of wind generation is an important issue, and it can have an effect on any capacity metric. We recommend that multiple years of data be used in capacity value calculations. If that is not possible, we think that several approaches covered in this paper can be useful. Going forward, we expect that the capacity value of wind generating plants will continue to be a topic that receives significant attention. We encourage open analysis and reporting of the findings that increasing experience with wind will bring.

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14. ABSTRACT *(Maximum 200 Words)*

Regional transmission organizations, state utility regulatory commissions, the North American Electric Reliability Council, regional reliability councils, and increasingly, the Federal Energy Regulatory Commission all advocate, call for, or in some instances, require that electric utilities and competitive power suppliers not only have enough generating capacity to meet customer demand but also have generating capacity in reserve in case customer demand is higher than expected, or if a generator or transmission line goes out of service. Although the basic concept is the same across the country, how it is implemented is strikingly different from region to region.

Related to this question is whether wind energy qualifies as a capacity resource. Wind's variability makes this a matter of great debate in some regions. However, many regions accept that wind energy has some capacity value, albeit at a lower value than other energy technologies. Recently, studies have been published in California, Minnesota and New York that document that wind energy has some capacity value. These studies join other initiatives in PJM, Colorado, and in other states and regions.

This paper focuses on methodologies for determining the capacity value of generating resources, including wind energy and summarizes several important state and regional studies.

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wind energy; wind plant; wind farm; capacity; grid; California; Minnesota; New York

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