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ABSTRACT

As the electric utility industry moves toward a new structure, the responsibility of providing a reliable portfolio of generating resources may be shifted among the various entities in the industry. To evaluate whether to undertake a construction project for new generating resources, utilities have traditionally used sophisticated models to assist in the comparison of alternative resources. It is not clear how this type of evaluation will be carried out after the restructuring dust has settled. What is clear, however, is that the market will require some way to measure capacity credit of new power plants, and future contracts will contain provisions under which buyer and seller must agree on capacity measures. This paper compares the traditional capacity credit calculations with algorithms that are not nearly so labor intensive.

1. INTRODUCTION

Markets for electricity are undergoing rapid change. As these markets change, the traditional vertical integration of electric utilities may evolve into separate industries for electricity generation, transmission, and distribution. Although the precise form of these new industries is not known with any degree of certainty, it is clear that the generating industry will continue to evaluate whether to build new generators. The companies that will perform this type of analysis will probably be very diverse, and include very large generating companies that result from the many recent mergers, as well as smaller companies that are currently considered as independent power producers.

Utilities have historically entered into agreements with each other, buying and selling electricity on the wholesale market as needs dictate. The structure of these contracts depends on the needs of the parties involved. In some cases, payment is based on only the quantity of electric energy purchased during the contract period. These are typically called “energy-only” contracts. In other cases, however, the payment is based, at least in part, on the capacity that is provided. This type of agreement is generally called a capacity contract. So that they can thoroughly evaluate the return on investment, investors must perform calculations that allow them to estimate long-term capacity sales, whether to retail customers or wholesale customers. In the deregulated market of the future, it is not clear market players will have the technical capability to perform the capacity and reliability analysis that has been done historically by the traditional utility. Various other methods have been proposed (see Milligan, 1996c and Milborrow, 1996 for discussions) that involve the use of the capacity factor to estimate the long-term capacity credit for a wind generating plant.

Generally, energy-only contracts are based on incremental costs such as fuel usage and operations and maintenance costs associated with the increased use of the power plant. However, renewable energy resources such as wind and solar use “free” fuel, and have low operation and maintenance costs. The owner of a wind plant who could sell only energy competes with the fuel cost of other plants. These payments must be sufficient over the life of the wind plant so that the capital is recovered. Currently, incremental energy and O&M costs are very low, so if a solar or wind resource is predicable or reliable enough, the potential for increased payment based on capacity is important (see Milligan, Miller, and Chapman, 1995 for further discussion of the benefits of forecasting).

Another difficulty arises because of the intermittent nature of renewable resources such as wind and solar. During windy periods, fuel is available to drive the wind plant. During lulls, fuel (i.e. the wind) is not available, and wind plant output will fall, possibly to zero. Should a wind plant operator enter into a capacity sale agreement during a period in which expected wind output did not occur, there would be a financial penalty to the seller. The purchaser may not have sufficient resources, and would perhaps be unable to meet customer loads. Additional purchases or generation would be required to make up the deficiency. Conversely, if the wind operator were to underestimate the capacity available during a particular time period, the excess capacity would go unused and unsold, reducing the payments to the wind plant. In this case, the purchaser would have greater capacity than needed. In cases of high excess capacity, conventional generators might need to back off, providing a bonus in fuel saving.

The need for accurate capacity assessment is clear. However, the traditional approach involves the use of complex planning models, which incur a significant cost in terms of data collection, analysis, expertise, and computer time. Various ad hoc approaches have been used to calculate rough estimates of capacity credit. For example, calculating the capacity factor of the resource over some relevant time period may provide a good general estimate of capacity credit. However, there are few studies that explicitly compare the result of this approach with the more rigorous, traditional approach that is based on sophisticated utility planning models, and none that provide a comparison using alternative numbers of load hours. The purpose of this paper is to evaluate simpler methods of calculating capacity credit for an intermittent renewable power plant. These methods should prove to be of value to a wide audience, including potential investors in, and owners of renewable power plants, and utilities who are evaluating renewable resources,.

2. METHODS FOR CALCULATING CAPACITY CREDIT

Currently, when a utility embarks on the evaluation of generator capacity additions, alternative energy sources are compared (see Kahn, 1991 for a discussion of generation project evaluation). Since generator capabilities vary according to fuel type and the method used to produce electricity, it is helpful to use a measure of capacity that can be applied to all types of plants. For example, the capacity value of a 100-MW coal plant might be equivalent to a 75-MW oil plant. A 300 MW (rated) wind plant might provide the same capacity measure as the 100 MW coal plant.

It is important to link this concept of planning capacity credit with operational capacity credit. Planning capacity credit is the value given to a generating plant over a long time horizon, and is typically in the context of utility generation planning, and is the topic addressed in this paper. Operational capacity credit is the capacity value that could be specified in a transaction between utilities. Over the long-run we would expect that the average operational capacity credit would approach the long-term value.

2.1 Utility Production and Reliability Modeling

The standard techniques that are used to evaluate the reliability of power systems and how these techniques are used to measure planning capacity credit are based on Billinton & Allan (1984). Conventional power plants experience unplanned outages, because of mechanical or other malfunction. Episodes such as this are called forced outages. It is unlikely that conventional generators will experience a forced outage because of fuel shortages. During extended periods of anticipated low-loads, generating units can be taken offline for routine maintenance. There is always a non-zero probability that any single generating unit will be on forced outage. Taking all such probabilities from each generator allows the calculation of the probability that enough generator units are on forced outage so that the utility will be unable to meet its load. This probability is called the “loss of load probability.” Most methods of assessing the capacity credit of a wind plant are based on a related reliability measure called loss of load expectation (LOLE). Of course the goal of the utility is to keep this probability as small as possible, given the trade-off between cost-minimization and reliability. A standard rule-of-thumb is to maintain a loss-of-load expectation of 1 day in 10 years.

2.2 Effective Load-Carrying Capability

Using the concepts and techniques from reliability theory (Billinton and Allan, 1984), we want to provide a measure of generating plant capacity credit that can be applied to a wide variety of generators. Although no generator has a perfect reliability index, we can use such a concept as a benchmark to measure real generators. For example, a 500-MW generator that is perfectly reliable has an effective load carrying capability (ELCC) of 500 MW. If we introduce a 500-MW generator with a reliability factor of .85, or equivalently, a forced outage rate of .15, the ELCC of this generator might be 390 MW. In general, the ELCC value cannot be calculated by multiplying the reliability factor by the rated plant output — the ELCC must be calculated by considering hourly loads and hourly generating capabilities. This procedure can be carried out with an appropriate production-cost or reliability model.

To find the ELCC of a new generator, one must evaluate the reliability curve at various load levels prior to adding the new generator to the system. Utilities will use a computer model that calculates LOLE or related measure. Although the level of detail of the input data varies between models, hourly electric loads and generator data is required, and common outputs include various costs and reliability measures. Some of these models are chronological, and others group related hours to calculate a probability distribution that describes the load level (Milligan, 1996b). Calculating the reliability curve is done by running the reliability model, altering the load, and plotting the resulting points in a graph such as that in Figure 1, below. The upward-sloping lines show the increasing risk of not meeting load, as measured with LOLE, that results from load increases. In the figure, the system load-carrying capability is just under 1,100 MW, assuming a risk level of 1 day in 10 years. The utility that finds itself above its preferred level of risk would add generation to its system. The new generator would shift the reliability curve to the right. The level of load increase that can be sustained at the same reliability level is the distance between the two risk curves, evaluated at the preferred risk level. Later discussion in this paper will use this method to determine the ELCC of a wind plant.

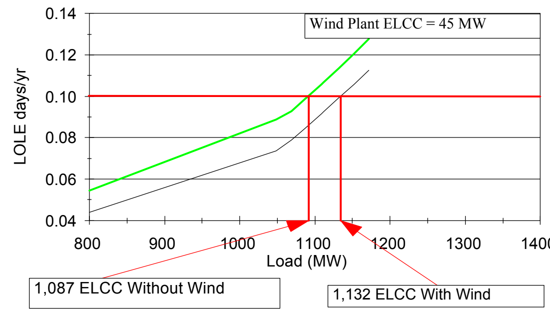

Fig. 1: Reliability curves for calculating the ELCC of a wind plant.

2.3 Application to Intermittent Resources

An important difference between an intermittent and conventional generators is the source of the forced outage, as described in the reliability model. From a mechanical standpoint, it is common for wind turbines to have very high availability, often exceeding 0.95. The forced outage rate would therefore be 0.05 in this case. However, wind turbines can only generate electricity when the fuel (wind) is available. When this is accounted for in the model, the forced outage rate of the wind plant might be in the range of 0.50-0.80. A conventional generator might have an overall forced outage rate of 0.10-0.25, but this rate is likely based on mechanical availability, not fuel availability.

Capacity credit results depend heavily on what happens during the utility's peak hour or several peak hours. Wind speed varies significantly from year to year and from hour to hour. Capacity credit estimates that are based on a single year of data and modeled without taking this variation into account should be suspect. Some analysts have corrected for this problem (Percival and Harper, 1982), whereas others did not (Bernow, Biewald, Hall, and Singh, 1994). Recent papers by Billinton, Chen, and Ghajar (1996), Milligan (1996a), and Milligan & Graham (1996) take related approaches that perform multiple simulations of wind speed, executing the production cost/reliability models over a large number of cases. Ignoring the potential for inter-annual wind speed variation can be perilous, and can result in significantly over- or under-estimating capacity credit.

2.4 Simpler Approaches

This discussion has focused so far on standard approaches of measuring power plant capacity credit. Although we believe that reliability models provide the best result, they require significant modeling effort. Various ad hoc methods for calculating wind plant capacity credit have been proposed, many of them using the capacity factor over some relevant time period. A related approach (Mid-Continent Area Power Pool, 1994) uses the median value of the wind plant over a recent history during the utility peak period. The purpose of this paper is to provide a benchmark of how well various capacity factor measures can approximate the ELCC, as calculated by a reliability model.

3. APPLICATION OF ALTERNATIVE METHODS

Although we use a wind power plant as an example, our techniques would be equally applicable to other intermittent technologies. We calculated hypothetical wind power output based on 13 years of hourly wind-speed data from a site in the great plains. Using a utility production cost and reliability model with one year of load and generator data from Tri-State Generation and Transmission, Inc., a wholesale power cooperative with service territory in Colorado, Wyoming, and Nebraska, we performed capacity credit calculations for each of the 13 years of data using the standard ELCC approach. We then used three alternative methods to calculate wind plant capacity credit. None of these alternative methods require the direct use of either a production cost or reliability model or generating data from conventional generating sources, although two of these methods do require a single reliability model run. The first method calculates the capacity factor (defined as the ratio of the average output to the total output) for the hours during the utility system peak. We performed this calculation for the top 30% of hourly peak loads.

Our second method also calculates the capacity factor, but uses hours in which risk of not meeting the load is highest. The determination of these hours is made by running the reliability model with no wind generation and calculating LOLP for each hour of the year. The hours selected by this method generally correspond to the hours of the highest loads, but differ to the extent that conventional resource availability is not constant throughout the year. The wind-power output for these hours is then used to calculate the wind plant capacity factor as an estimate of the capacity credit of the wind plant. These calculations are carried out for up to 30% of the hours of the year.

The third and final method used the same hours as method two. This final method uses normalized LOLP values as weights for the average capacity factor. This allows the method to recognize those hours in which LOLP is more severe, and weight them accordingly. The capacity factors are then calculated in the same way as those in the other approaches.

The wind data we used is from an air quality monitoring site in the high plains, scaled to match average wind-speeds from the Altamont Pass region in California. The series spans the years 1980 to 1992. The wind data collected from this site show a wide inter-annual variation. The highest simulated energy capture occurred in 1988. Values for other years range from about 72% to about 92% of the 1988 simulated energy. A caveat to our approach is that the utility and the wind site are separated by several hundred miles, and the utility data is for a single year. This implies that any correlation between loads and wind is not fully captured. This is a limitation that is likely in practice, because of the relative scarcity of long-term wind data.

4. RESULTS

We applied each calculation method to the full 13-year data set. For each year of wind data and each method, we calculated the wind plant capacity factor for the top 1%, 2%, ..., 30% of hours which were selected by the algorithms described above. Figures 2-5 illustrate some of the variation we found. Figure 2 shows the capacity factors for the year 1980 for the three methods. The "Load" series was created by taking the top system loads, the "LOLP" series by taking the hours for the maximum value of hourly LOLP, and the "Weighted" series uses normalized LOLP as the weights for the capacity factors. The ELCC value of 31.3 was calculated using the reliability model, and is the benchmark value we use. Figures 3, 4, and 5 are constructed in the same way for the years 1982, 1984, and 1990, respectively.

Points to the right of the 10% level of Figure 4 for all three methods appear to slightly underestimate the capacity credit, as calculated by ELCC. The weighted approach appears to be more accurate at low load percentages, but all three methods provide similar capacity credit estimates as they approach the 30% load level.

The results for 1982 are depicted in Figure 3, and are quite different. There is clear disagreement between method 1 and

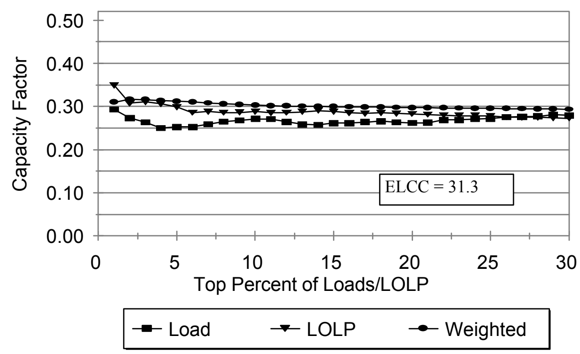

Fig. 2: Capacity factor for top hours, various methods, 1980.

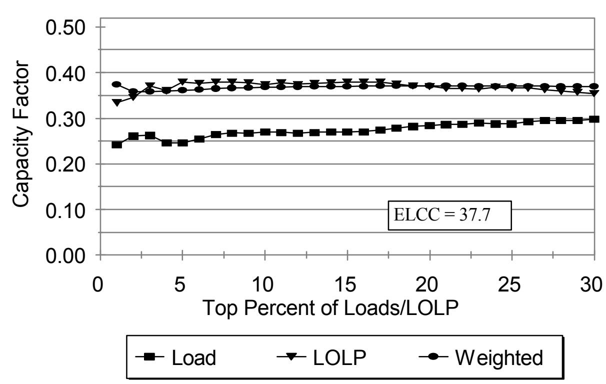

Fig. 3: Capacity factor for top hours, various methods, 1982.

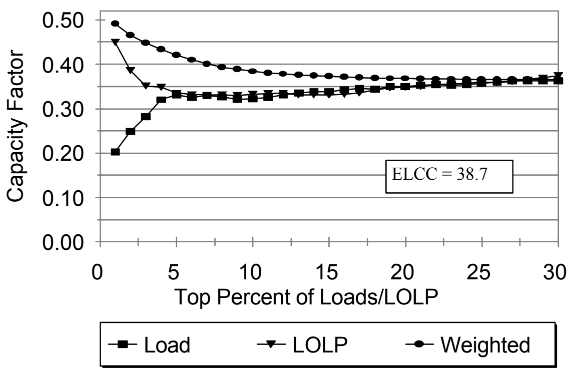

Fig. 4: Capacity factor for top hours, various methods, 1984.

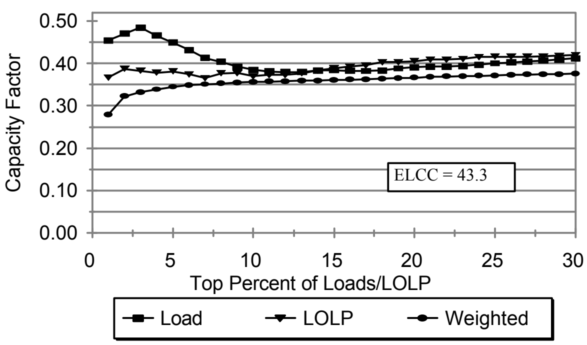

Fig. 5: Capacity factor for top hours, various methods, 1990.

methods 2 and 3. This result should come as no surprise, however. The ELCC measure is based on system reliability, which is a function of both load level and available capacity. Utility dispatchers will attempt to provide as much capacity as possible during system peak. Non-peak periods may have higher LOLP values, and thus lower reliability, if lesser capacity is available. In Figure 3, there is quite close agreement between the two methods that take LOLP into account, and these methods provide approximations that are very close to the ELCC value over a wide range of top load hours.

Figure 4 shows what can happen when wind generation during the utility extreme peak period is not typical of the wind generation over lesser peak periods. Choosing hours to evaluate based solely on load level severely underestimates the ELCC, although when a larger number of hours are included in the calculation this error quickly tails off. However, both of the LOLP-based methods substantially overestimate the capacity credit. Method 2 converges much more quickly than does method 3. When the top 30% of hours are used, all methods are quite close to the ELCC value.

Figure 5 is the final graph of this series. In this case, method 1 severely overestimates capacity credit when a small number of hours are used, whereas methods 2 and 3 are consistently below the ELCC value. These series do not converge very well, either to each other or to the ELCC value. Each of these methods underestimates capacity credit for 1980.

We can draw several conclusions from these results. First, although capacity factor might be useful as an approximation to capacity credit, it appears to consistently underestimate the ELCC value. Second, the accuracy of these capacity factor methods is very sensitive to both the number of hours used and the method used to select the hours. Third, wind power plants contribute to overall system reliability during non-peak hours.

5. COMPARISON OF METHODS

Although it is apparent that these capacity factor methods are not as accurate as ELCC methods for calculating capacity credit, we performed some simple calculations to rank these methods. For each of the 13 years of wind data and for each method, we calculated an error statistic:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(x_a - x_f)^2} \qquad (1)$$

where n = the number of hours used in the approximation, x_a is the actual capacity credit (as calculated using the ELCC approach), and x_f is the estimated capacity credit by method 1, 2, or 3. The RMSE was calculated only on the results based on the 30% of load hours. Figure 6 represents a simple scoring of the results—how many years did each method produce the lowest RMSE—alongside the average RMSE over the 13-year period. Although method 1 is tied with method 2 for the number of years with the lowest error, its average RMSE exceeds that of method 2. In spite of delivering impressive performance in 1982, method 3 has the highest composite error.

In our judgement the Load method provides a reasonable trade-off between accuracy and effort, either early in project assessment or if it is not possible to calculate the ELCC. In other situations, it might be possible to obtain LOLP output from a reliability model, but not possible to perform multiple runs to calculate ELCC. Here, the LOLP method performs better with a modest effort. Although the weighted method does not appear to perform well here, we suspect that this is likely because of the lack of correlation between load and wind, an artifact of the data sets available to us. We would be interested to apply this method to other data sets.

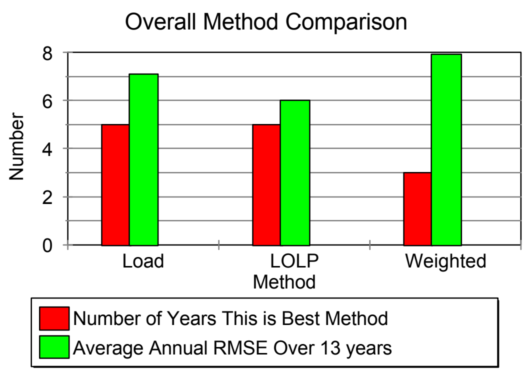

Fig. 6: Overall method comparison.

6. CONCLUSIONS

To fully measure long-term capacity credit of an intermittent power plant, we recommend using the standard ELCC measure and a full complement of reliability model runs. However, there may be cases in which this is impossible. If hourly LOLP values can be obtained from a reliability model run but multiple model runs can't be performed, we recommend using the LOLP method. If no reliability measures are available, the Load method appears to provide a reasonable approximation. There is clearly a trade-off between accuracy and effort.

As the restructuring of the utility industry moves forward, it will be important to continue to examine different calculation methods that can be easily applied by various players in the industry.

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