NREL/CP-440-22868

An Enumerative Technique for Modeling Wind Power Variations in Production Costing

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Presented at
International Conference on Probabilistic Methods Applied to Power Systems
Vancouver, British Columbia, Canada
September 21–25, 1997

National Renewable Energy Laboratory
1617 Cole Boulevard
Golden, Colorado 80401-3393
A national laboratory of the U.S. Department of Energy
Managed by Midwest Research Institute
for the U.S. Department of Energy
under contract No. DE-AC36-83CH10093

Work performed under task number WE712010

April 1997

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Abstract—**Production cost, generation expansion, and reliability models are used extensively by utilities in the planning process. Most models do not provide adequate means for representing the full range of potential variation in wind power plants. In order to properly account for expected variation in wind-generated electricity with these models, we describe an enumerated probabilistic approach that is performed outside the production cost model, compare it with a reduced enumerated approach, and present some selected utility results. Our technique can be applied to any model, and can considerably reduce the number of model runs as compared to the full enumerated approach. We use both a load duration curve model and a chronological model to measure wind plant capacity credit, and also present some other selected results.**

I. INTRODUCTION

Representing wind power plants in utility production cost and reliability models poses a challenge to modelers because of the wide range of potential variability of the resource. As utilities evaluate wind power plants for possible future resource additions, it is important to accurately quantify both the capacity value and energy value of the wind plant. Renewable power plants, such as wind, may also contribute other benefits. Among these are fuel diversity and reduced emissions from conventional plants. In this paper we illustrate two related techniques that can be used to help capture some of this variability. We apply the techniques to measuring capacity credit, but our approach can be used for any of the outputs of a production cost or reliability model. The first method was introduced by [7], and is an enumerated probabilistic approach (EPA). The second method is based on a selective reduction in the multiple models runs, and is called the reduced enumerated probabilistic approach (REPA).

Capacity credit measures of wind power plants help utility planners and decision-makers evaluate this intermittent resource in the context of other types of power plants. The term "capacity credit" refers to the level of conventional generation that can be replaced with wind generation. To avoid complications of how to compare the many types of conventional generation, analysts will either compare wind to an ideal generation source or to a specific type of generator.

There are many techniques that can be used to calculate wind plant capacity credit. The choice of method is influenced by several factors, such as data availability and scope of the study. When capacity credit calculations are performed using a production-cost or reliability model, the wind power plant capacity credit can be measured by a reliability index. The most common approach calculates the effective load carrying capability (ELCC) and is described in [1].

The usefulness of the concept of "wind plant capacity credit", as measured by traditional reliability methods, may be undergoing change as a result of the deregulation in the utility industry. However, the final outcome of the deregulation process is not clear, and we believe that some entity in the brave new world will continue to be interested in effective-load-carrying capability (ELCC) and other reliability measures of the generating system to ensure adequacy of the system [12].

Two of the most critical shortcomings of the standard techniques used to evaluate wind plant capacity value are 1) variability of the resource and 2) the lack of adequate wind data. Intermittency and the high variability of wind make it difficult for models to adequately measure capacity credit. One site for which we have data exhibits wide interannual variation in average wind speed, which would result in significant variation in wind energy [9]. Capacity credit results depend heavily on what happens during the utility's peak hours. Because wind speed can vary significantly from year to year and from hour to hour, capacity credit estimates that are based on a single year (or less) of data and modeled without taking this variation into account are not credible.

Because of the temporal interactions between load, wind power, and conventional generating capacity, wind plant capacity credit measures are often little more than random draws from a probability distribution whose characteristics are largely unknown. To properly account for the large number of potential interactions, some form of multiple-scenario or Monte Carlo simulation is necessary. An excellent discussion of this technique in the context of chronological production cost models can be found in [6]. [7] illustrates a Monte Carlo method that is external to the load-duration curve production cost model. This approach creates a set of many wind power series, each of which can be run in the production cost or reliability model. This process is called the enumerated probabilistic approach (EPA) to differentiate it from the Monte Carlo approaches that can sometimes be found in production cost and reliability models. This paper uses the EPA that is implemented outside the production cost/reliability model, which can then be executed for any number of data realizations. We then illustrate a variation of the EPA method that uses a reduced number of enumerated cases. This is called the Reduced EPA, or REPA. The advantage of the REPA method is that it is not as computationally demanding as the full EPA method, although it is possible that the REPA results would exhibit some loss of accuracy.

This paper illustrates a technique that can be applied to any production-cost/reliability model, and extends earlier work by [7]. We use two production-cost models: Elfin, a load-duration curve (LDC) model produced by the Environmental Defense Fund, and POWERSYM+ (P+), a chronological model that is a product of the P Plus Corporation. We used the Elfin model to establish a base case of 1000 EPA simulations, then used both Elfin and P+ to perform a set of REPA simulations using a subset of the 1000 simulations. The paper concludes with some selected results and comparison of the EPA and REPA results.

II. MODELING APPROACH

The utility data we used is from Tri-State Generation and Transmission Association, Inc. Tri-State is a non-profit generation and transmission cooperative utility, supplying wholesale electric power to 33 distribution cooperatives in Colorado, Wyoming, and western Nebraska. Resources include both Tri-State-owned and jointly-owned coal and oil-fired generation. Tri-State also purchases power from the Western Area Power Administration (Western) and Basin Electric Power Cooperative (Basin).

To provide a plausible analysis of wind plant reliability and ELCC, we apply a Markov [3] wind-speed analysis and simulation tool to a single year of wind data. Other similar Markov applications can be found in [5] and [2]. The wind data is from the Nebraska Energy Office. We chose the Imperial, Nebraska site because of its proximity to Tri-State's service territory. For each month, a state transition matrix is calculated. Then multiple realizations of the data are calculated by repeatedly sampling from the state transition matrix. This technique preserves important time-scale properties of the wind speed data and captures some of the variation that could reasonably be expected at a wind site, without multiple years of data. This method has the obvious limitation that only a single year of wind data is used to calculate the state transition matrices. Including additional wind data, if available, would increase the ability to represent long-term data, or, in the limit, negate the need for a wind-speed simulation tool altogether.

This analysis focuses on October, 1995, a month in which there appears to be significant variability in the wind resource. To satisfy both models' requirement for 168-hour weeks, we ran each model for 6 full weeks and obtained calendar summaries for October. Some weekly results are reported below. For this month Tri-State's peak load was 1,440 MW. To minimize differences between production models we reduced this load by 90 MW to account for a time-varying purchase from Basin. Net peak load was 1,350 MW. The maximum hydro purchase from Western was 400 MW, with 1,152 MW of base and intermediate generation and 120 MW of peaking capacity. We modeled a hypothetical 100 MW (nameplate) wind plant.

The wind-speed state transition matrix for October appears in Figure 1. This graph shows the probability of occurrence of each wind speed at time *t* as a function of velocity at time *t-1*. Some utility control areas, pools, or reliability regions estimate generating plant capability on a monthly basis, so the choice of time frame is consistent with those approaches. Our method could be appropriately applied to other time scales. Once the multiple wind-speed realizations have been simulated, we can calculate the hourly wind power output from a hypothetical wind plant for each realization. We can then perform the analysis of all wind speed realizations (EPA) or of the cases selected for the REPA analysis. We describe both below.

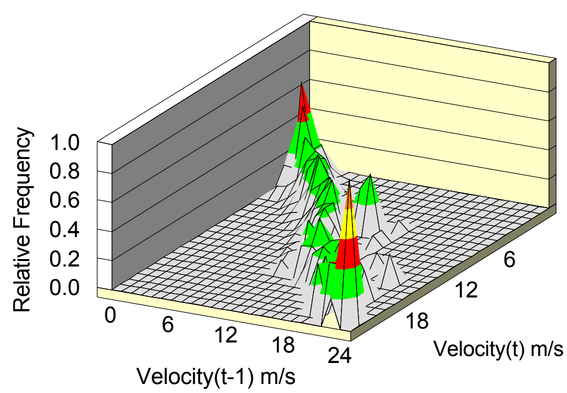

Fig. 1 Wind-speed state transition matrix for October.

For the EPA runs, each hypothetical wind power realization is input to the Elfin model, which is executed for each one. From this process we obtain the ELCC of each realization, which can then be summarized for further analysis.

The REPA method is an attempt to reduce the number of reliability model executions with a minimal reduction of accuracy. Our approach is to group the 1000 wind-power series based on energy output during the utility system peak. The data are then grouped and assigned weights corresponding to the wind energy frequency distribution. Representative wind-power realizations are then selected from each of the groups. The model is then run once for each selected case. Weighted averages are then computed for the outputs of interest. We performed this analysis with both the Elfin and P+ models.

Similar techniques are used for calculating net equivalent load with chronological models and load-duration curve models, and are covered in detail in [8]. We modeled wind power as a load modifier in Elfin and as a fixed hourly transaction in P+. This approach causes each model to treat the wind power plant in the same way. The hourly load is reduced by the level of wind generation in that hour, and conventional resources are committed and dispatched accordingly.

The process of selecting the various wind realizations for the REPA involves some judgement. Our intent is to select the data bins in such a way that the variation of the binned data closely represents the variation in the ungrouped data. In our judgement, grouping the data with 5 bin sizes corresponding to the mean and ±1 and ±2 standard deviations resulted in a relatively poor representation of the variation we found in the ungrouped cases. Faced with a tradeoff between execution time and accuracy, we did not want to use a large number of bins, since the saving in model runtime compared to the EPA method would not be significant. However, we chose to use 11 bins, each of which has a width of one-half of the standard deviation of wind-energy produced during the utility's peak. Basing our bin selection on all cases within 2.5 standard deviations of the mean energy allowed us to retain the variation in the full EPA data sets, but with a significant reduction in the number of windspeed realizations. Figure 2 illustrates the distribution of the wind energy during the utility's peak period in October. We believe that our choice of bin width and number did a good job of capturing the variation in the full EPA results.

Figure 3 shows the bins and resulting weights that we selected for the analysis. This grouping retains the shape of the original distribution, while adequately representing the variation in the data.

III. CAPACITY CREDIT RESULTS

After making the adjustments to the load data as described

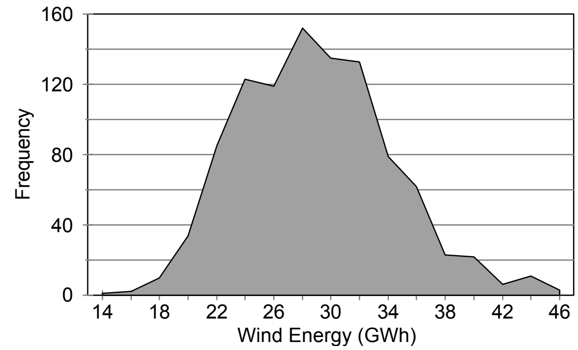

Fig. 2. Wind energy distribution for multiple data sets for October.

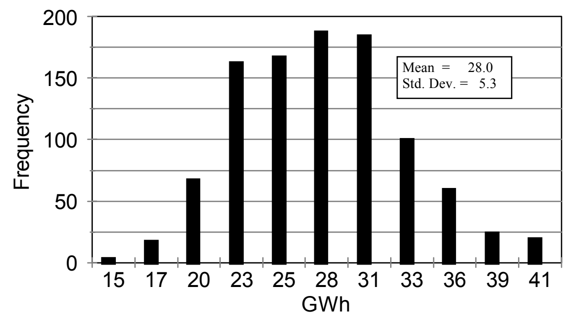

Fig. 3. Wind energy distribution, binned by standard deviation.

above, both Elfin and P+ were executed to obtain base-case results with no wind generation. Table 1 shows the reliability outputs from each model using Expected Unserved Energy (EUE) and Loss-of-Load Hours (LOLH). It is clear from the table that the EUE reliability measures are in closer agreement than the LOLH measures. On a percentage basis, the EUE difference is about 4%, whereas the LOLH difference is about 5% [4]. In our judgement, the EUE is likely to be more accurately estimated than LOLH, as measured by the two models, and this is what we use as the basis for our ELCC calculations.

TABLE 1.
INITIAL RELIABILITY INDICES FOR ELFIN AND P+, OCTOBER

Model	**Expected Unserved Energy (GWh)**	**Loss-of-load Hours**
Elfin	6.6	46.1
P+	6.9	43.9

We chose to maintain as realistic a depiction of the utility as possible, and therefore decided not to adjust loads to an artificial reliability level such as 1 day in 10 years loss-of-load expectation, or equivalent. The ELCC values we calculate are based on those calculated in the base cases illustrated in the table.

To take full advantage of Monte Carlo simulations such as our EPA, one should be able to specify convergence criteria and run the model until the specified target is reached. Because Elfin is a scenario based model with no intrinsic Monte Carlo capability, we were unable to specify convergence criteria; only the number of runs to perform. See [6] for further discussion.

For the 1000 simulations of the EPA, Figure 4 illustrates the range of ELCC values as a percentage of installed wind capacity. Although these results appear to be consistent with the annual results reported in [7], here we have a larger variance of capacity credit because of the larger variation in wind plant output over the month than would occur over a year. Each bin for the figure represents a width of *s/2*, where *s* is the sample standard deviation. Our data indicates that all but about 2% of the values are within two standard deviations of the mean.

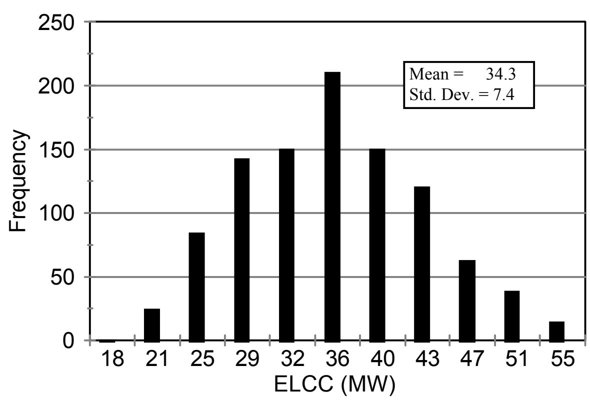

Fig. 4. Capacity credit distribution of EPA runs.

From the 1000 cases run for the EPA method, we identified those that most closely matched the mean ELCC, and the mean plus or minus *s/2*, *s*, *3s/2*, *2s*, *5s/2* of ELCC. This resulted in 11 of the wind-power realizations from the full data set, which were used to perform the REPA analysis.

The results of the ELCC calculations are presented in Figure 5. As the figure indicates, there appears to be a closer correlation between the unweighted ELCC from the REPA and EPA than between the weighted REPA and EPA. The chronological model's weighted REPA appears to do a better job than the LDC model's weighted REPA. The monthly capacity factor is also shown for comparison, and is virtually the same as the full EPA ELCC value. The standard deviation of the EPA and REPA differ somewhat, as shown in Table 2.

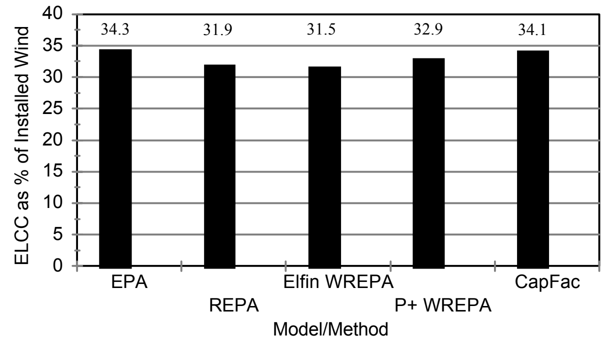

Fig 5. Capacity credit results from various methods.

The table indicate that the representative cases we selected overestimate the variation of the larger sample, as indicated by the standard deviations. Conversely, the reduced-sample mean value appears to underestimate that of the larger sample. Although our REPA process exhibits a higher standard deviation than the full EPA runs, this still likely underestimates the monthly variation that could be expected from year to year [9].

TABLE 2.
COMPARISON OF EPA AND REPA MEANS AND STANDARD DEVIATIONS

Statistic	P+ REPA	Elfin REPA	All 1,000 Cases: Elfin EPA
Mean	33.4	31.9	34.7
Std. Dev.	11.8	9.9	7.4

Figure 6 shows the ELCC results for all of the REPA cases for both models. The case numbers in the diagram indicate increasing wind energy levels that correspond to intervals we chose for the REPA analysis. Although one would generally expect that higher levels of wind energy would result in higher ELCC estimates, the graph shows that this is not entirely true. ELCC is a function of the reliability level of the generating system, which is in turn a function of load and available capacity. As described in [10] higher levels of wind energy during a specific period will not always increase the ELCC of the wind plant. This can also be observed in Figure 7, which plots energy vs. ELCC of the wind plant. The upward trend shows the positive correlation between higher energy and ELCC values, but there are cases in which higher energy will not correspond to higher capacity credit. The diagram also shows a difference in the capacity credit from the two models. This is likely because of the difference in commitment

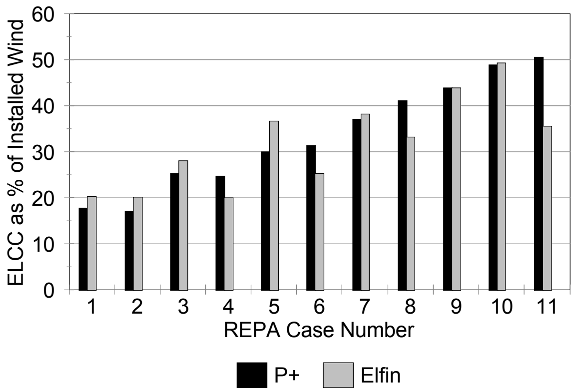

Fig. 6. Comparison of the REPA cases by model.

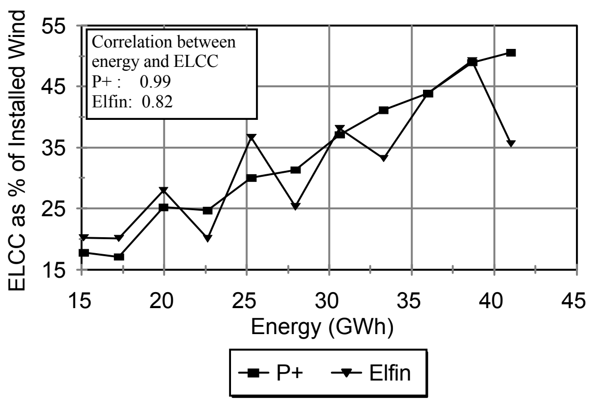

Fig. 7. Correlation between energy and ELCC.

algorithms used by chronological and LDC models [8].

It is also important not to lose sight of our objective: we want to develop a computationally efficient way to provide plausible estimates of wind plant output and *variation* in output. To that end, we believe that the REPA method has accomplished our goal. Further work should be done to explore the impact of the utility's peak period and overall reliability level on these results.

IV. OTHER SELECTED RESULTS

It is useful to view other results from our model runs. As a chronological model, P+ can produce hourly results for each day and week. Figure 8 illustrates the weighted hourly change in generation for a 1-week. This week was chosen to illustrate some substantial variation in hourly wind power output. Other weekly model outputs are similar. Using our REPA approach and bin selection process results in 11 similar graphs, one for each bin, each representing various plausible scenarios. Utility planners and analysts then have a range of such outputs on which to base their decisions. Figure 9 shows the reduction in conventional generation for a typical day. The solid line shows the weighted average of the reduced data set, and the other lines show selected results from two of the bins.

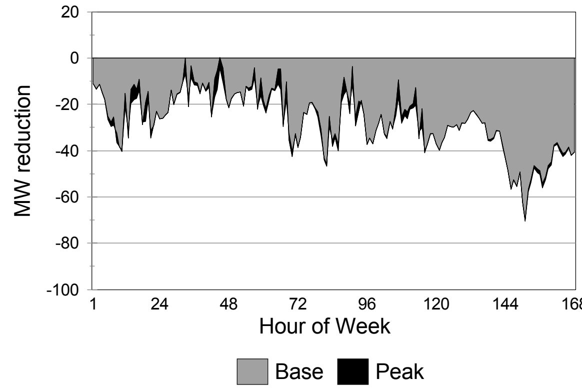

Fig. 8. Generation reduction, week of October 9.

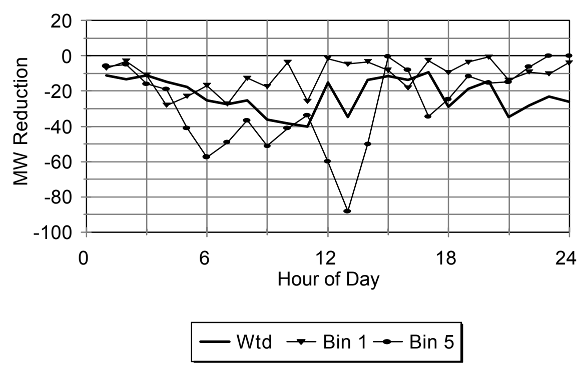

Fig. 9. Generation reduction, October 9.

V. CONCLUSIONS

This paper has outlined a computationally efficient way to examine the impact of possible variations in wind plant output. Instead of implementing or modifying a Monte Carlo routine in a production-cost or reliability model, we illustrate a method that can be performed to provide the model with a small number of wind power data sets. The model can then be run for each of the enumerated series, and the results analyzed appropriately for the study at hand. Further refinements can be made in a couple of areas. First, the method of simulating wind data does not have to be Markov, but can consist of any appropriate method. Second, additional experimentation with bin selection could result in a reproducable method that could be converted into a computer algorithm. In our judgement, the bin sizes and ranges we selected are reasonable. Although the REPA is not as accurate as the EPA, it does capture the variation in the wind resource.

VI. ACKNOWLEDGMENT

The authors gratefully acknowledge the assistance of Chok Pang of the P Plus Corporation in the preparation and submittal of this paper.

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