September 2001 • NREL/CP-500-30363

Conference Paper

A Sliding Window Technique for Calculating System LOLP Contributions of Wind Power Plants

M.R. Milligan

Presented at AWEA's WINDPOWER 2001 Conference
Washington, D.C.
June 4–7, 2001

National Renewable Energy Laboratory

1617 Cole Boulevard
Golden, Colorado 80401-3393

NREL is a U.S. Department of Energy Laboratory
Operated by Midwest Research Institute • Battelle • Bechtel

Contract No. DE-AC36-99-GO10337

Available electronically at http://www.osti.gov/bridge

Available for a processing fee to U.S. Department of Energy
and its contractors, in paper, from:
U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831-0062
phone: 865.576.8401
fax: 865.576.5728
email: reports@adonis.osti.gov

Available for sale to the public, in paper, from:
U.S. Department of Commerce
National Technical Information Service
5285 Port Royal Road
Springfield, VA 22161
phone: 800.553.6847
fax: 703.605.6900
email: orders@ntis.fedworld.gov
online ordering: http://www.ntis.gov/ordering.htm

Printed on paper containing at least 50% wastepaper, including 20% postconsumer waste

A SLIDING WINDOW TECHNIQUE FOR CALCULATING SYSTEM LOLP CONTRIBUTIONS OF WIND POWER PLANTS

Michael R. Milligan
National Wind Technology Center
National Renewable Energy Laboratory
1617 Cole Boulevard
Golden, CO 80401
Phone: 303-384-6927
Fax: 303-384-6901
milligan@nrel.gov

ABSTRACT

As electricity markets undergo restructuring, it is becoming apparent that the responsibility for providing power and the ancillary services associated with power generation is being allocated to different entities. Former electric utilities enter spot markets and sign power-delivery contracts, and generating companies bid or otherwise offer electricity for sale. Operating units, such as Regional Transmission Organizations often take on a system-wide perspective that includes assessing reliability and securing related ancillary services. As the complexity of power contracting increases, reliability will almost certainly decline as the grid becomes stretched and the number of transactions increases. At the same time, the electricity produced by wind power plants is increasing in the United States and around the world. Given these developments, the ability to accurately measure intermittent power generators may become more important as we move towards the future.

Conventional generation reliability models do not typically recognize the probabilistic nature of the power variations from wind plants. Most models allow for an accurate hourly representation of wind power output, but do not incorporate any probabilistic assessment of whether the given level of wind power will vary from its expected value. The technique presented in this paper uses this variation to calculate an effective forced-outage rate for wind power plants (EFORW). Depending on the type of wind regime undergoing evaluation, the length and diurnal characteristics of a sliding time window can be adjusted so that the EFORW is based on an appropriate time scale. The algorithm allows us to calculate the loss-of-load probability (LOLP) on an hourly basis, fully incorporating the variability of the wind resource into the calculation. This makes it possible obtain a more accurate assessment of reliability of systems that include wind generation when system reliability is a concern.

INTRODUCTION

As the electricity industry moves towards restructuring, it seems clear that system reliability will continue to be an extremely important topic. Entities with a system-wide perspective, such as a power pool or other control area—or even generating companies with large generator portfolios—will most likely perform various types of reliability analyses to determine whether there is an adequate electricity supply. Many electricity-production simulation models have been adapted to the new market paradigm. However, wind-generating facilities are typically modeled in a way that does not allow the evaluation of a reliability index, such as LOLP, based on the variability of the wind resource.

To help compensate for this shortcoming, several advanced techniques have been proposed. These methods incorporate various time-series modeling to produce several wind-power sequences. The production simulation model is applied to each series one at a time. The benefit of this approach is that variance estimates of the wind plant's reliability contribution can be obtained. However, this approach can be expensive (for examples see [1] or [2]).

In this paper, I propose a method that can calculate generating system reliability more accurately in systems where wind-power plants provide significant levels of power. This technique is a straightforward extension to existing, well-known methods that are applied to conventional power plants.

CONVENTIONAL RELIABILITY ANALYSIS OF WIND PLANTS AS LOAD MODIFIERS

Electric-system-reliability calculations are based on the principle that there is always some probability that a generator will not be available at particular times. In a typical model, calculating the system reliability is performed on an hourly basis and is then converted into longer time scales, such as weeks, months, or years. The data required for these calculations includes the capacity and forced outages for each generator and the expected electrical load. Because of the potentially large number of generators, the computation folds data from each generator in a process called convolution. In this way, we can calculate the probability that the on-line generating capacity will not be sufficient to meet the load.

When wind-power plants are part of the generation mix, it is important to ensure that the variation of the wind power is taken into account. The usual way of accounting for this variation is to treat the wind plant output as an hourly "load-modifier." The model typically deducts the hourly wind generation from the expected electric demand for the corresponding hour. The remaining load is then subject to the usual unit commitment and economic dispatch for conventional generating units. The downside to this approach is that the wind-power-plant output is treated as an event with perfect certainty. An alternative approach is to specify the wind-power plant by specifying a given capacity level with an effective forced outage rate (FOR) that takes into account both mechanical and fuel (wind) availability. In fact, most, if not all, commercial reliability models do not provide a method that simultaneously addresses both the wind variability and the probability of its availability.

ADVANCED TECHNIQUES—SEQUENTIAL MONTE CARLO

One broad set of techniques has been developed to help address this issue, while also taking a broader perspective on wind variability. These collective methods are often called "Sequential Monte Carlo" (SMC) approaches. The SMC procedure has two components. The first component develops a probabilistic model of the underlying wind speed or wind power data. A number of techniques can be used for this, and examples include the auto-regressive integrated moving average approach applied by Billinton et. al [1] and the Markov modeling applied by Milligan [3] and Milligan and Graham [2]. These methods involve extensive computational time and effort, but produce probabilistic estimates of a number of parameters related to wind-power production. These probability distributions can help assess issues related to inter-annual variations in wind-power production and provide estimates of the expected wind-induced variation in reliability.

The technique proposed in this paper is designed to retain the hourly variability in wind power output, while retaining an assessment of the probability that the actual wind power production will be either above or below the expected level. This technique is an extension of the existing convolution procedure that is applied to conventional generators. However, a key part of these new methods involves assessing an effective FOR for the wind plant that changes through time.

A REVIEW OF CONVOLUTION

As a starting point for discussing the new methods, we begin with a simple example of the convolution procedure for a small system that consists of several identical plants. For the example, assume that we have six generating units, each with 50 MW of capacity and an FOR of 0.08 (this example is based on conceptual simplicity for the illustration). The convolution algorithm proceeds on a stepwise basis, adding one generator at a time to a numeric table called the capacity outage table. Given our example, we start with a single unit that has two possible states: either generating 50 MW with a probability of 0.92, or on forced outage with a probability of 0.08. Assuming an independence of outages at different plants, the second unit can now be convolved into the capacity table. For details, consult Billinton and Allan [4]. Table 1 shows the fully convolved capacity outage table for the six-unit test system.

The first column of the table shows various levels of capacity on outage. The second column shows the capacity available. For each row, the outage capacity plus the available capacity equals the total installed system capacity. Line 2 of the table indicates that there is approximately a 0.069 probability that 100 MW will be on outage. The cumulative probability shows that 100 MW or more will be on outage. This cumulative probability is also the LOLP. On line 5 of the table, we can see that there is a very low probability that 250 MW or more will be out at the same time, which implies the probability that insufficient generation will be available to meet a 50-MW load equals 0.00001835. In this test system, the LOLP corresponding to a load of 200 MW equals approximately 0.0773.

TABLE 1. CONVOLUTION OF 6 50-MW UNITS

	MW-Out	MW-In	Probability	Cumulative Probability
0	0.0000	300.0000	0.60635500	1.00000000
1	50.0000	250.0000	0.31635913	0.39364500
2	100.0000	200.0000	0.06877372	0.07728587
3	150.0000	150.0000	0.00797377	0.00851214
4	200.0000	100.0000	0.00052003	0.00053838
5	250.0000	50.0000	0.00001809	0.00001835
6	300.0000	0.0000	0.00000026	0.00000026

To adapt this approach to a wind power plant, we need a method that will calculate the EFORW. This is not a true measure of mechanical reliability, but rather represents the statistical expectation that the wind plant will not achieve a given output level over a specified time period. The approach we use here is a sliding window approach, which allows for the variability in wind power output through time. The window can be specified as a range of hours before and after the current hour and can be adjusted to take specific conditions into account. Figure 1 illustrates a 7-hour window for a hypothetical wind-power plant rated at 100 MW (for convenience, losses are ignored). The maximum wind power output in the window is 100 MW. The total wind energy during this period is 325 MWh, and if the maximum output had been sustained for the entire window period, 700 MWh would have been generated. The EFORW = 1 – (325/700) = 0.536. For the current hour, we can now convolve a 100-MW wind plant with an EFORW of 0.536 into the capacity outage table. For the next hour, the window slides forward one hour, as indicated in Figure 2. In this example, the maximum wind output within the window is still 100 MW (although output this hour has dropped to 50 MW), but the total wind output during the period is now 425 MW. This yields an EFORW = 0.393. This technique takes both the maximum capacity in the time window and the EFORW into account. As an example of how this calculation works during a period

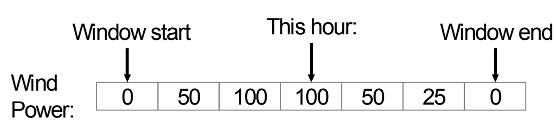

FIGURE 1. 7-HOUR SLIDING WINDOW

of low wind, Figure 3 shows that the maximum wind output is now 30 MW, and the EFORW = 1 – (100/210) = 0.524.

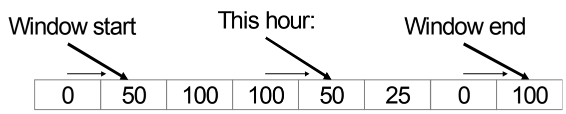

FIGURE 2. ADVANCING TO THE NEXT HOUR

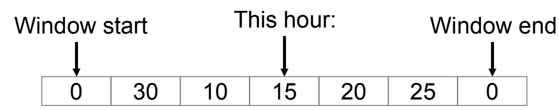

FIGURE 3. EXAMPLE OF LOW-WIND

The EFORW takes on different characteristics for different-sized windows. For relatively small windows, such as 6-24 hours, the EFORW tends to be somewhat less stable than for longer periods (as illustrated in Figures 4 and 5). In Figure 4, I have calculated the EFORW for a 6-hour moving window for a 4-week period in July and another 4-week period in December. The graphs show significant volatility over very

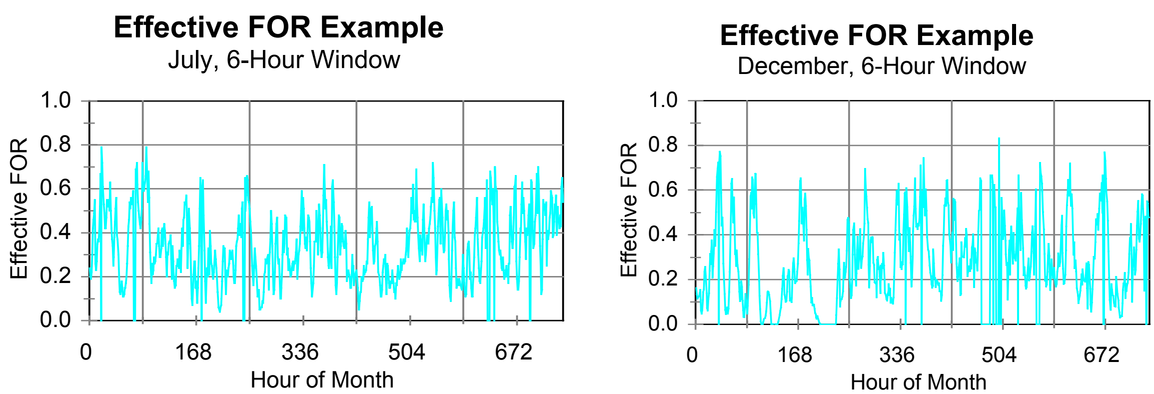

FIGURE 4. EFFECT OF SMALL WINDOW ON EFORW

short time periods. If a system peak should occur during a period in which the EFORW is changing rapidly, we would expect to find the capacity contribution of the wind plant to be less than if the EFORW remained high for the peak period. In Figure 5, we can see the effect of a very long moving window—168 hours (one week) in this case. The time period chosen for this graph is the same as for Figure 4. The graphs in Figure 5 show that the variation in the moving window is substantially reduced for such a broad window, reducing the accuracy of the reliability calculation. In fact, when the moving window is enlarged

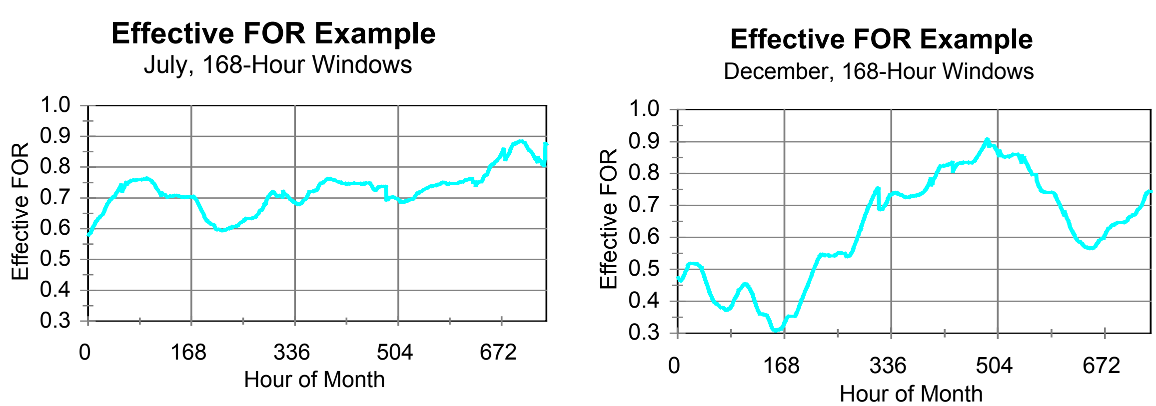

FIGURE 5. EFFECT OF LARGE WINDOW ON EFORW

to 8,760 hours (a full year), the result is the same as if we were to use 1 – CF (where CF = capacity factor) as the annual EFORW for this 100-MW wind plant. A window-width of one year does not allow the model to take into account any wind power variation when calculating system reliability. However, the analyst's ability to choose the appropriate window size does provide significant flexibility to this method.

BASIC METHOD

The Direct Convolution Approach proposed by this paper is built on the concept of the EFORW. To accurately assess the reliability of a system that includes wind power, the reliability calculation for the wind plant should match the approach that is applied to conventional units as closely as possible. The following discussion begins with a description of the basic method. Following that is an extension to the basic method that improves its accuracy by using the actual wind power distribution from the sliding window in calculating the capacity table.

The basic method simply involves convolving the maximum wind capacity and EFORW from the moving window into the effective capacity table. This is performed for each hour. On completing the hourly calculation, the moving window slides forward one hour, and the process is repeated. Table 2 shows the results of adding a wind plant (25-MW maximum output during the window, with an EFORW of 0.74) to the basic system of six 50-MW units above. Comparing the tables, we can observe that the overall system reliability has improved. For example, in Table 1 we see that there is a 0.0773 probability that the system will be unable to serve a 200-MW or lower load, whereas in Table 2, that probability declines to 0.0594. Of course, these numbers are simple examples that illustrate how the algorithm works and should not be interpreted as an assessment of a real system. Later discussion in this paper will illustrate some results applied to an actual system.

TABLE 2. CONVOLUTION OF 25-MW WIND PLANT, EFORW = 0.74

	MW-Out	MW-In	Probability	Cum Prob
0	0	325	0.15765230	1.00000000
1	25	300	0.44870270	0.84234770
2	50	275	0.08225337	0.39364500
3	75	250	0.23410576	0.31139162
4	100	225	0.01788117	0.07728587
5	125	200	0.05089256	0.05940470
6	150	175	0.00207318	0.00851214
7	175	150	0.00590059	0.00643896
8	200	125	0.00013521	0.00053838
9	225	100	0.00038482	0.00040317
10	250	75	0.00000470	0.00001835
11	275	50	0.00001339	0.00001365
12	300	25	0.00000007	0.00000026
13	325	0	0.00000019	0.00000019

The advantage of this approach is that the capacity outage table contains information that is related to both the wind output during the relevant time period and a probabilistic assessment of the output's variation. During a period in which wind output is consistently zero, the capacity outage table would reflect the lack of wind power by not recognizing any output from the wind plant. Conversely, if wind power output were sustained at a high level during the period, the capacity outage table would show the wind plant as a reliable resource during that period. In the case of high peak wind output that is not sustained during the time window, the capacity outage table would reflect a high-output resource with a relatively high probability of not meeting that high output during the period. Therefore, this method captures both the variation in wind output and a probabilistic assessment of whether that output is likely to be sustained over the period in question.

It is also useful to examine the implication of different sliding-window sizes with respect to other reliability modeling methods. First, consider the case of a very small window containing only one hour. Because we have only one data point in the window, the EFORW = 0. This is clearly true for each hour of the year. Therefore, the capacity table reflects a given level of wind output for the hour with certainty. This is theoretically and computationally equivalent to the load-modification approach, which is the basis for a significant quantity of wind-plant analysis.

At the other extreme, a sliding window that includes 8,760 hours (a full year except for leap year) would reflect the maximum wind-plant output for the year, and the EFORW would simply be 1 – CF, where CF = the annual capacity factor of the wind plant. If this modeling were done for a single year, the sliding window would have to wrap around from the end of the year to the beginning of the year, resulting in the same wind capacity and EFORW for every hour of the year. If multiple years of wind data were available, the sliding window could be set up to include six months prior and six months after the current hour, providing a minimal recognition of the wind power variation. Therefore, a sliding window of this size takes little or no account of the variation in wind output.

ENHANCEMENT TO A MULTIPLE-POINT METHOD

In conventional reliability analysis, it is sometimes desirable to provide a more accurate depiction of large units that can be run at different output levels. In cases like this, the model can be given data for the various capacity blocks of the generator. This data includes the capacity and availability rate associated with that capacity block. With conventional generators, the size of the capacity blocks is usually based on physical properties of the generator and is normally fixed for the duration of the analysis.

To improve the accuracy of the wind-plant calculations, we can borrow this technique. However, this application is somewhat more complicated than in the conventional generation case because of the statistical properties of the wind capacity data from the moving window as the window advances through time. Conceptually, however, this process is straightforward. For each hour of the analysis, we construct a frequency distribution of the hourly wind output. This distribution can be fed directly to the convolution routine, which is modified to handle a frequency distribution with a variable number of points, depending on the data within the current window.

This process is illustrated in Figure 6. A sliding window of 10 hours (4 ahead and 5 lagging) shows no wind output for 3 hours, followed by an increase to 10 MW, then to 25 MW, falling back to 10 MW, and finally back to no output. The wind-power data from this window is arranged into a frequency distribution, shown in Table 3. The EFORW for the example is 0.74, but this value is not directly used in the convolution. Instead, the relative frequency and wind power output from each row of the table are convolved into the capacity outage table. This provides a more accurate assessment of the wind power availability during the sliding window period than the basic method.

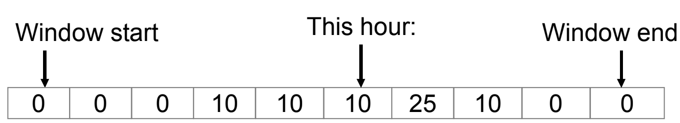

FIGURE 6. EXAMPLE OF MULTIPOINT WINDOW

Figure 7 compares the capacity outage table using both the basic and multiple-point methods. It is based on the simple test system used in the other examples in this paper. For the basic method, the capacity outage table reflects a wind plant achieving 25 MW maximum with EFORW = 0.74, which was calculated from the data in Figure 6. The multiple-point method uses the distribution that appears in Table 3. For outage capacity above 100

TABLE 3. EXTENSION TO MULTIPOINT CONVOLUTION

Frequency Count	MW	Total
5	0	0
4	10	40
1	25	25

MW, Figure 7 shows a close correspondence between the methods. However, in the range of 0–50 MW, we see a significant difference in the cumulative probability (or LOLP). It is at this point of the distribution that errors become more significant. In most systems, there is a relatively low outage capacity, although the specific values are dependent on the characteristics of the generators and loads under consideration. In any case, it is clear from the illustration that the multiple-point method provides a more accurate assessment of the reliability contribution of a wind-power plant.

CASE STUDY

To illustrate the method using data from a real system, I applied this model to Minnesota. The purpose of this case study is limited to a realistic illustration of the method and is not intended to analyze wind in Minnesota. The load and generating data were used in a previous study [5] and are aggregated from individual utility data. The wind data is from a composite of sites in Minnesota, and is described further by Milligan and Artig [6]. Generation sources in Minnesota include nuclear, coal, oil, gas, and small amounts of hydro and other resources. Although wind power is already a part of the generation mix in Minnesota, data was not available for this study.

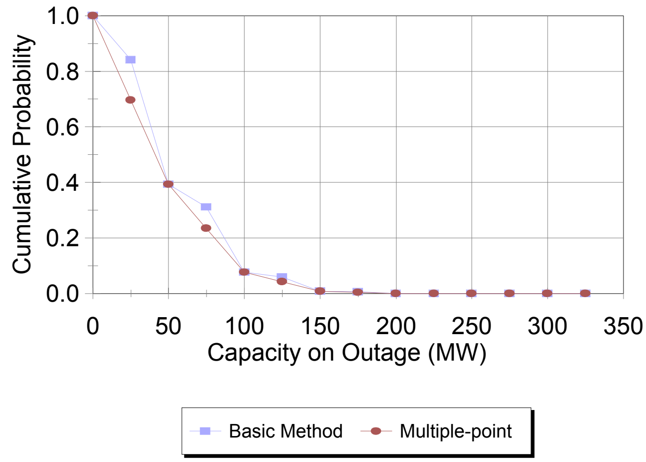

FIGURE 7. COMPARISON WITH BASIC METHOD

The question that we pose to this case study is whether there are significant differences in the system reliability if we compare the load modification method to the multiple-point, direct convolution method. Before proceeding with the description of the case study, a few terms must be defined. To facilitate comparisons, we define LMLOLP to be the LOLP as calculated by the load modification method, and DLOLP is calculated by the multiple-point direct-convolution method.

Figure 8 shows the results from two simulations that calculated LMLOLP and DLOLP for Minnesota. The graph shows the percentage difference between these reliability measures: LMLOLP – DLOLP, which can be either positive or negative. In the graph, we see the hourly calculations for the month of July. We can clearly see from the graph that differences between LMLOLP and DLOLP are only significant for peak and near-peak loads—those that exceed about 50% of the monthly peak. Furthermore, it is not possible to predict *a priori* which reliability measure will be larger. This is because the relative ranking of these reliability measures depends on the statistical properties of the wind data within the moving window, the load level, and the outage conditions at other power plants.

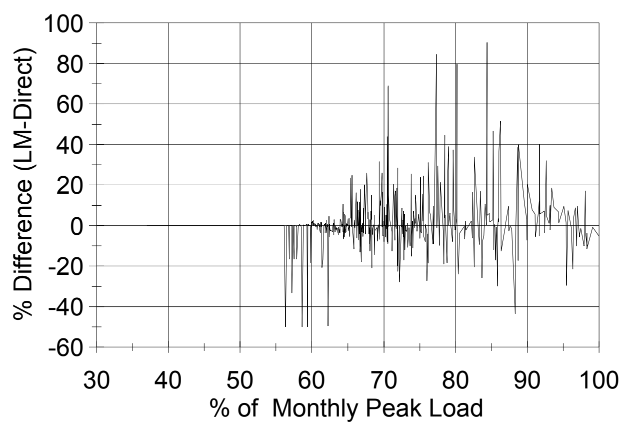

FIGURE 8. COMPARISON WITH LM METHOD: JULY

Figure 9 shows the results from the same set of simulations for December. Differences in the calculations only become apparent at loads exceeding about 65% of the monthly peak, which is similar to what we observed in July. In this case, it appears that LMLOLP usually exceeds DLOLP, which implies that the LM method overstates the LOLP. However, it is not possible to generalize these results without further study. What we can conclude is that there is a significant difference between the reliability measures.

CONCLUSIONS

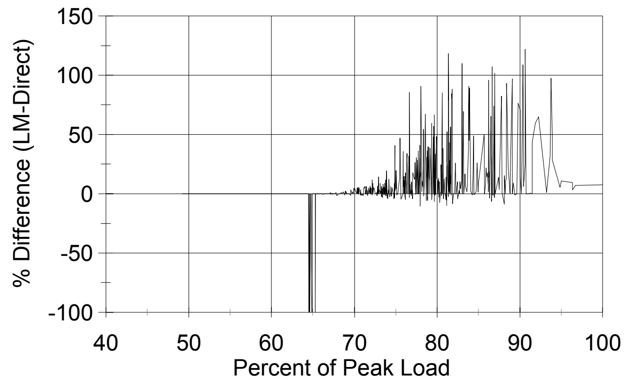

FIGURE 9. COMPARISON WITH LM METHOD: DECEMBER

This paper has proposed a method to incorporate wind power variability into the system reliability calculation. As restructuring moves forward, this type of analysis may be better suited to entities with a system-wide perspective, such as grid operators. It is clear that electric system reliability will continue to be valued in new markets, and, as the usage of wind-generated electricity increases, it will become more important to accurately assess the impact of wind generators on the overall system.

The multiple-point convolution method is a relatively simple extension to the well-known methods of calculating LOLP with conventional generators. Given that commercial reliability models typically handle conventional units with multiple operating levels and associated outage rates, adding a function to calculate the EFORW for wind generators would be a relatively straightforward task.

Incorporating information about wind power forecasts would be a significant improvement to this algorithm. As presented in this paper, the expected wind power output during the current time window is the maximum output during the period. Accurate wind forecasts would result in fewer unanticipated increases or decreases in wind power output, improving system reliability.

Additional enhancements could be made to the algorithm. For example, the moving window could be altered so that it spans multiple days for the specified time interval. Also, calculating the EFORW on a chronological basis could be used as the basis for a probabilistic allocation of reserves to operating power plants.

ACKNOWLEDGMENTS

Thanks to Kant Lee of the P Plus Corporation for helpful discussion and suggestions related to the multiple-point convolution method.

REFERENCES

1. Billinton, R., Chen, H. and Ghajar, R. *A Sequential Simulation Technique for Adequacy Evaluation of Generating Systems Including Wind Energy*. *IEEE/PES Winter Meeting*. 1996. Baltimore, Maryland

2. Milligan, M. and M. Graham. *An Enumerative Technique for Modeling Wind Power in Production Costing*. *5th International Conference on Probabilistic Methods Applied to Power Systems*. 1997. Vancouver, BC, Canada: International PMAPS Committee, BC Hydro. NREL/CP-440-22868.
3. Milligan, M. *Variance Estimates of Wind Plant Capacity Credit*. *WindPower '96*. 1996. Denver, CO: American Wind Energy Association. NREL/TP-440-21311.
4. Billinton, R.A., R., *Reliability Evaluation of Power Systems*. 1 ed. 1984, New York: Plenum.
5. Milligan, M. and R. Artig. *Choosing Wind Power Plant Locations and Sizes Based on Electric Reliability Measures Using Multiple Year Wind Speed Measurements*. *United States Association for Energy Economics Annual North American Conference*. 1999. Orlando, FL: IAEE. NREL/CP-500-26724.
6. Milligan, M. and R. Artig. *Optimal Site Selection and Sizing of Distributed Utility-Scale Wind Power Plants*. *International Conference of the International Association for Energy Economics*. 1998. Quebec: IAEE. NREL/CP-500-24312.

REPORT DOCUMENTATION PAGE

Form Approved
OMB NO. 0704-0188

1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September 2001	Conference paper

4. TITLE AND SUBTITLE
A Sliding Window Technique for Calculating System LOLP Contributions of Wind Power Plants

5. FUNDING NUMBERS
WER13230

6. AUTHOR(S)
Michael R. Milligan

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
National Renewable Energy Laboratory
1617 Cole Blvd.
Golden, CO 80401-3393

8. PERFORMING ORGANIZATION REPORT NUMBER
NREL/CP-500-30363

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT
National Technical Information Service
U.S. Department of Commerce
5285 Port Royal Road
Springfield, VA 22161

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*
Conventional electric power generation models do not typically recognize the probabilistic nature of the power variations from wind plants. Most models allow for an accurate hourly representation of wind power output, but do not incorporate any probabilistic assessment of whether the given level of wind power will vary from its expected value. The technique presented in this paper uses this variation to calculate an effective forced-outage rate for wind power plants (EFORW). Depending on the type of wind regime undergoing evaluation, the length and diurnal characteristics of a sliding time window can be adjusted so that the EFORW is based on an appropriate time scale. The algorithm allows us to calculate the loss-of-load probability (LOLP) on an hourly basis, fully incorporating the variability of the wind resource into the calculation. This makes it possible to obtain a more accurate assessment of reliability of systems that include wind generation when system reliability is a concern.

14. SUBJECT TERMS
wind energy; wind power plants; electric generation; reliability models

15. NUMBER OF PAGES

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL