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The Value of Windpower: An Investigation Using a Qualified Production Cost Model

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THE VALUE OF WINDPOWER:
AN INVESTIGATION USING A QUALIFIED PRODUCTION COST MODEL

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ABSTRACT

As a part of the U.S. Department of Energy's Wind Energy Program at the National Renewable Energy Laboratory, we are using the Environmental Defense Fund's Electric Utility Financial & Production Cost Model (Elfin) as a tool to determine the value of wind energy to specific utilities. The cases we have developed exercise a number of options in the way in which wind energy is treated: (1) as a load modifer (negative load), (2) as a quick-start supply-side resource with hourly varying output, and (3) probabilistically, using time-varying Weibull distributions. By using two wind speed distributions, two different wind turbines, and two different utilities, we show what the wind turbine cost/kW might be that results in a positive value of wind energy for these utilities.

INTRODUCTION

Wind energy has been effectively integrated into the California utility system for more than a decade. The developers of these resources were provided with both investment tax incentives and favorable purchase agreements for their power as Standard Offer contracts. The life of these contracts is ten years, and the last federal tax incentives were ended in 1985. Subsequently, wind energy developers are facing renegotiation of power purchase agreements with utilities in the future. Furthermore, in most states, utility regulating bodies are promoting the application of integrated resource planning (IRP) by utilities under their purview. This forces utilities to consider alternative energy sources as well as such measures as demand-side management (DSM). Throughout the United States, there are currently excesses of generation capacity reported; yet, forecasts into the early twenty-first century are for large deficits in generation capacity.

Wind energy in the United States is already a significant, cost-effective resource. New technology, advanced wind turbines, show promise of producing energy in the 4-5¢/kWh range in the very near future. Therefore it is incumbent upon us to be able to help utility planners in properly modeling wind in their production cost and generation expansion models. What wind data do you need for the models? What is the appropriate processing and manipulation of the data before its incorporation into the models? What sort of result should be expected? Can wind energy be added to a utility's current or planned generation mix in an economically beneficial way? Will the availability of wind energy have a detrimental effect on the utility's reliability? These and other questions demanded answers and provided the impetus for this study.

THE WIND DATA

The Elfin model works with various subsets of hourly wind data. To maintain the feasibility in our results, we have chosen to use wind data collected at or very near the hub height of the wind turbines. Any deviations between measured wind height and turbine hub height were corrected by extrapolating the measured wind speed to turbine hub height using the 1/7 power law. The hourly averages were calculated from two-minute, sampled data, thereby giving us a reasonable average value. The sites we chose to work with included a West Coast "pass" site and

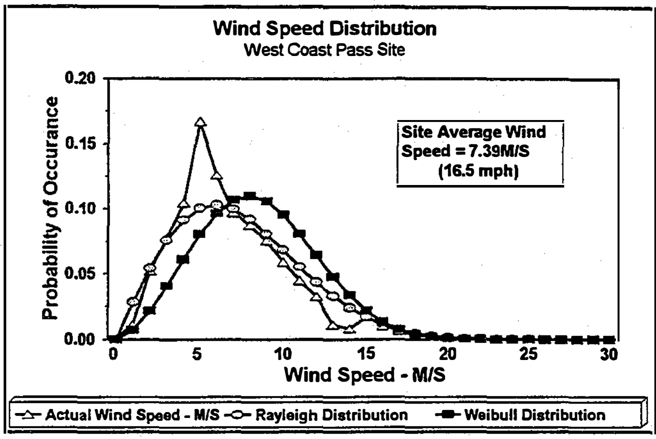

Figure 1 WIND SPEED DISTRIBUTION AT A WEST COAST PASS SITE. RAYLEIGH C AND K ARE 8.34 AND 2.0 RESPECTIVELY, AND THE WEIBULL C AND K ARE 9.53 AND 2.61 RESPECTIVELY.

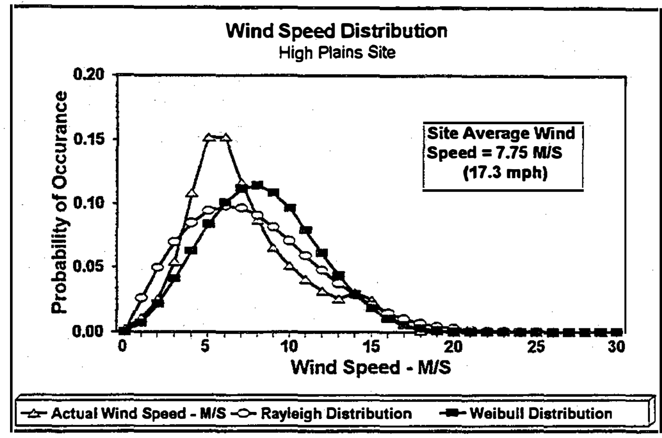

Figure 2 WIND SPEED DISTRIBUTION AT A HIGH PLAINS SITE. RAYLEIGH C AND K ARE 8.74 AND 2.0 RESPECTIVELY, AND THE WEIBULL C AND K ARE 9.31 AND 2.66 RESPECTIVELY.

a High Plains site. Plots of the wind speed distributions for the two sites, along with some of the pertinent numerical descriptors, can be seen in Figures 1 and 2. This investigation is not intended to promote wind energy at specific locations or for specific utilities, but rather to provide parametric results using real wind and utility input data.

To simulate the output of a 100-MW wind park, the hourly wind data were convoluted with the power curve of the turbine of interest and the result was multiplied by the appropriate number of wind turbines. Because the typical production cost models used by the industry use an hour as the smallest time step, we believe that the integrated spatial and temporal differences in output over a large array is fairly represented in this manner. To account for array wake losses, line losses and other losses incurred in the array, a 20% penalty was assessed as a conservative measure. Five percent of this penalty was assessed by Elfin as scheduled maintenance and 15% was subtracted during the preprocessing performed by the WInd Power Simulator (WIPS, described below).

We selected two utilities for this investigation and refer to them as U1 and U2. Utility U1 has a generation mix made up of approximately 26% hydro power, 48% oil- and gas-fired steam, 15% nuclear, 2.5% combustion turbine, and 8.5% other (non-coal). Besides this owned capacity, U1 purchases approximately 40% of it's energy from other utilities. Utility U2 has approximately 7.5% hydro power, 57% oil- and gas-fired steam, 16.5% nuclear, 4% combustion turbine, and 15% coal-fired steam. Utility U2 also purchases approximately 45% of it's energy needs. This information is included here so that the reader can develop some feel for what wind energy is working with and displacing, where possible.

Two similar yet different turbines were used in this study. In both cases, they were in the 300 - 400 kW category that industry refers to as "utility size" turbines. Both were three bladed, upwind turbines and both had some history of operation. In both cases, the power curves were obtained from field tests. Because the turbine power curves are field generated and represent average hub-height winds and bus-bar power, accounting for mechanical losses was unnecessary and points out that the 20% loss factor makes all of the results conservative. However, even with this high penalty factor, many of our wind scenarios resulted in benefits to the utility in question.

WIND POWER SIMULATOR DESCRIPTION

An important part of production-cost modeling with wind energy is the proper treatment and characterization of wind data and wind turbine characteristics. WIPS is a pre-processor model we developed to calculate hourly power output of an array of wind turbines, given any appropriate hourly wind data and power-curve data. Once the appropriate calculations have been completed, WIPS inserts the data into an Elfin data set.

WIPS provides several alternative ways to model the wind power data it calculates. The first method derives one week per month from at least one year of wind data. Using a wind turbine power curve and hourly wind data, average wind power is calculated for each hour of the week. This approach allows wind to be modeled as either a load modification or as a traditional quick-start generating unit with hourly varying capacity. However, calculating average wind power will rarely, if ever, allow a wind park to reach its rated capacity during the typical week. Likewise, the number of zero-output hours will probably be artificially small. One of the questions we posed earlier asked whether the addition of wind energy would have an effect on the reliability of the utility system. If wind power output varies significantly from hour to hour, the utility must provide additional generating reserves so that the system load can be met when wind output falls. If wind power output is modeled using a smoothing technique, its variation is masked, making it impossible to determine whether additional reserves are required. As a result, using wind power values that are based on applying a smoothing technique to the wind data may result in an upward bias to the economic benefit of wind energy.

A second method allows the user to select 12 "typical" weeks of hourly wind data. This process can be viewed as drawing a contiguous sample of 168 points from a population. It therefore allows the wind park to reach both rated capacity and zero capacity, allowing the full range of turbine output. Based on a wind turbine power curve, WIPS creates windpower data that can be processed by Elfin. This approach is also useful for performing an analysis that models wind energy as either negative load (load modification [LM]) or as a quick-start unit with time-varying capacity (CP). Selecting a typical data set allows the wind farm output to range from zero to rated capacity, depending on the wind regime, and does not therefore suffer from the smoothing effect described above.

The final option available from WIPS is the probabilistic option. Here, one typical day per month is developed. The typical day is divided into 24 hours, each of which is characterized by a probability distribution. Thus, we have a probability distribution for January at 8:00 AM, another distribution for 9:00 AM, etc. The probability distribution used can be selected from Weibull, Rayleigh, or the actual distribution. For example, if the Weibull is the distribution chosen, we have 24 values for the Weibull K and C for each of the 12 months. Each probability distribution is used as the basis for expected wind-farm output. Elfin uses these values as if they were multiple-block output levels from a thermal plant, applying each output level and its associated probability to the convolution of the load duration curve.

DESCRIPTION OF ELFIN

Elfin[1] is the electric utility production cost and expansion simulation model used in this study. Elfin is a probabilistic model that uses a version of the Baleriaux-Booth economic dispatch algorithm and is similar to EGEAS (EPRI, 1982) and other models that share in this approach. Elfin uses hourly electric load data for one typical week per month. Generation resources can be modeled in a variety of ways: quick-start units, units with a minimum of constraints, hydro, pumped storage hydro, and others. For each generating unit, data are provided for plant capacity and energy, fuel type and cost per unit input, maintenance and forced outage rates, and capacity blocks. Emission rates and costs can also be specified in the model. The model then simulates the economic dispatch of the generating system, subject to the constraint of meeting projected load. Each year is divided into 12 typical weeks, each of which represents one month. Each typical week is further divided into no more than 8 subperiods. Each subperiod represents a number of contiguous hours during the day/week. Model output includes production cost by plant for each subperiod, week, and year, along with fuel usage and reliability estimates.

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[1]Elfin was created by the Environmental Defense Fund, which holds full and exclusive proprietary rights to the Elfin model.

Elfin uses the Iterative Cost Effectiveness Methodology (ICEM), as adopted by the California Energy Commision, as the generation expansion algorithm. In general, this procedure runs the model with and without the expansion unit to determine the cost-effectiveness of adding to the generation mix.

Modeling wind energy in probabilistic production costing models such as Elfin has traditionally been done by calculating hourly wind capacity, subtracting from system load, and performing an economic dispatch of the conventional hydro-thermal system on the remaining load. The argument in support of this technique is that, because wind is a non-dispatchable technology with near-zero variable cost, the utility will take all wind generation whenever it is available. However, this approach does not explicitly address the probabilistic nature of the wind resource (see Percival & Harper (1982) for one solution to this problem).

Although Elfin allows this so-called negative-load approach to wind, it also is possible to describe a wind resource probabilistically, using forced-outage rates to simulate the underlying wind probability distribution[2]. The calculations in support of this approach are carried out by WIPS and are made available to Elfin.

ANALYSIS AND RESULTS

We have analyzed all possible combinations of two utilities, two wind sites, and two modern wind turbines. For each combination of utility, site, and turbine, we have used four different types of simulations to point out some areas that need further research. The various run types are (1) probabilistic, using all available wind data from each site; (2) hourly average wind capacity values, calculated from all available wind data from each site; (3) hourly wind capacity values, chosen from a representative week; and (4) hourly load modification using the same representative data as (3). In each run, we specified wind turbine installed costs per kW ranging from $800 to $1,200/kW to find plausible break-even turbine costs. We allowed Elfin to choose the number of wind farms to add to the generation mix, where each wind farm consists of 125 MW gross output capacity (100 MW after losses). The benefit/cost ratio is calculated by taking the present values of the benefits and costs of adding one wind-farm to the existing generating capacity.

The economic benefits of wind include the avoided operational cost of running installed thermal units. This consists largely of fuel costs, but may also include avoided variable operations and maintenance (O&M) costs. Elfin also calculates the cost of capacity shortages, based on the Energy Reliability Index (ERI) and Shortage Cost method. Capacity shortages are valued at the cost per kW of a combustion turbine. Wind can reduce the shortage cost, resulting in a benefit to the system. The shortage cost reduction can be viewed as a proxy for financial capacity credit. However, the dependable-capacity from which shortage cost is calculated relies very heavily on the system annual peak. It is possible that a wind farm could have an extremely high capacity factor except during the hour of system peak, and therefore have a very low dependable capacity value. Although the wind resources may contribute to capacity, say 11 of the 12 months, it would be penalized for its lack of contribution during the peak month.

The cost of wind energy consists of fixed costs spread over a 30-year lifetime, and O&M costs, which we estimated at 7.5 mills/kWh. The lifetime benefit/cost (B/C) ratios in our study are always higher than the first-year B/C ratios because of the assumed escalation of fuel prices, in real terms. We used an annual B/C (benefit/cost) ratio for the first year to compare the simulation cases. The discount rate used for the present value calculation is based on the rates used by the utilities. All other parameters, such as fuel costs, are those used by the utilities.

Our first set of simulations examined the benefits and costs of adding 125 MW to the existing utility system. The original utility data showed a very low loss-of-load probability (LOLP) for both U1 and U2, indicating a lack of need for additional generation resources. This set of simulations did not give any capacity credit to wind turbines. Therefore, these so-called "fuel-saver" cases yielded extremely low B/C ratios. This result indicates that, for the utilities in this case study and at prevailing fuel prices, the addition of wind turbines to reduce fuel consumption

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[2]Thanks to Dan Kirschner and Francis Chapman of the Environmental Defense Fund for the suggestion of using multiple-block forced-outage rates and for many helpful discussions and suggestions about modeling wind energy.

may not be cost effective at turbine costs exceeding approximately $350/kW.

We then experimented by adding emission penalties to see what effect that would have on the B/C ratio. The values we chose are based on those used in the heavily populated areas of California. The values assigned are in dollars/ton as follows: NO_x - $10,795, SO_x - $8,719, particulates - $5,605, reactive gases - $10,588, CO - $ 2,284, CO_2 - $29. At these relatively high penalties, we found it cost-effective in our scenarios to use wind as a fuel saver at turbine prices below approximately $500/kW.

The next set of experiments postulated a 10% increase in customer load for utility U1, with an increase in load for utility U2, such that resulting LOLP was the same for both U1 and U2. In this way, we were able to model two utilities that were in need of additional generation. The remaining cases in this discussion are based on this 10% load growth. A similar increase in LOLP could be caused by the retirement of older generating units at the original load level.

For the remaining cases, we have included the valuation for emissions. This gives wind energy a decided benefit, because the reduction in emissions due to wind energy is valued financially and enters into the B/C ratio calculation. It is important to note that, if a value is not placed on emissions, many more of the B/C ratios in this study fall below the break-even line. As an example, the B/C ratios in one of our scenarios would have been approximately 24% lower at each capital cost level, had emissions not been valued.

We have used several simulation methods to represent wind energy. The first method treats wind energy as a load modifer: wind energy is subtracted from system loads prior to economic dispatch. Variations of this method are the most common way of treating wind in a Baleriaux-Booth framework (see EPRI, 1982, and Percival & Harper, 1982). We have labeled this the "LM" case. The hourly wind power values were calculated by WIPS using the appropriate turbine power-curve and 12 user-selected representative weeks of hourly wind data. The primary advantage to the LM approach is that the hourly wind power is subtracted from load prior to beginning economic dispatch. This implies that the economic dispatch algorithm is applied to the load without wind generation. Furthermore, hourly variations in wind power output are incorporated into the net load curve.

The next method is the "CP" case, which utilizes the user-selected representative wind data. Here, we have modeled wind as a quick-start unit with hourly varying capacity. Wind is "dispatched" along with the other resources, in relative merit order. Because there is no fuel cost associated with wind energy, wind turbines are typically "dispatched" after any must-run units but before other fuel-using units. Of course, wind turbines are not dispatched in the usual sense; we refer here to the simulated running of the turbines when wind conditions are appropriate. The hourly varying capacity values were calculated by WIPS and are the same as those used in the LM case.

We also set up a variation of the CP case to calculate one typical week per month using all available wind data from the site. Each typical week is represented by 168 hourly averages, calculated by convolving the power curve and wind data prior to averaging. This method is the "YR" case.

The final method is the probabilistic (PR) method described above. We calculate 24 Weibull distributions per month, allowing Elfin to use the underlying wind distribution to calculate expected wind energy.

Our results are presented in Table 1. The table illustrates the results for each utility, U1 and U2, wind sites WC (West Coast pass site) and HP (High Plains site), and wind turbines A and B. For each combination of utility, site, and turbine, four cases are presented. Cases PR (probabilistic) and YR (hourly capacity) both use all available data, whereas cases CP (hourly capacity) and LM (load modifier) use selected, typical data. The difference between the CP and YR cases is an indication of the data sensitivity between a typical week and an average week.

Perhaps the most striking aspect of the results is the wide variation in the table's values. In particular, wind resource HP is much more beneficial to utility U1 than is wind resource WC. Two factors are responsible: the higher average wind speed at HP and the higher correlation between the wind and loads. The latter is accentuated even more because of the high level of wind output (60 MW) during the system peak. This causes a higher shortage benefit than is the case with wind site WC, which contributes 37 MW on peak.

Table 1 SIMULATION RESULTS - BENEFIT/COST RATIOS

				Turbine Cost ($/kW)				
Utility	Site	Turbine	Case	800	900	1000	1100	1200
U1	WC	B	PR	1.03	0.91	0.82	0751	0.69
			YR	0.86	0.76	0.68	0.62	0.57
			CP	1.27	1.13	1.16	0.92	0.85
			LM	1.43	1.27	1.14	1.04	0.95
U1	WC	A	PR	0.93	0.83	0.74	0.68	0.62
			YR	0.79	0.70	0.63	0.58	0.53
			CP	1.17	1.04	0.94	0.85	0.78
			LM	1.32	1.17	1.06	0.96	0.88
U1	HP	B	PR	1.85	1.65	1.48	1.35	1.24
			YR	1.51	1.34	1.21	1.10	1.01
			CP	1.69	1.50	1.35	1.23	1.13
			LM	2.07	1.84	1.66	1.51	1.38
U1	HP	A	PR	1.74	1.55	1.39	1.27	1.16
			YR	1.46	1.30	1.17	1.06	0.97
			CP	1.78	1.58	1.43	1.30	1.19
			LM	2.02	1.79	1.61	1.47	1.34
U2	WC	B	PR	0.92	0.82	0.74	0.67	0.62
			YR	0.86	0.77	0.69	0.63	0.55
			CP	1.19	1.05	0.95	0.86	0.79
			LM	1.30	1.15	1.05	0.94	0.86
U2	WC	A	PR	0.96	0.85	0.77	0.70	0.64
			YR	0.83	0.73	0.66	0.60	0.55
			CP	1.12	0.99	0.89	0.81	0.74
			LM	1.18	1.05	0.94	0.86	0.79
U2	HP	B	PR	1.33	1.18	1.06	0.96	0.88
			YR	1.29	1.14	1.03	0.93	0.86
			CP	1.30	1.16	1.04	0.95	0.87
			LM	1.52	1.35	1.22	1.11	1.02
U2	HP	A	PR	1.23	1.09	0.98	0.89	0.82
			YR	1.25	1.11	1.00	0.91	0.83
			CP	1.24	1.10	0.99	0.90	0.83
			LM	1.44	1.28	1.15	1.05	0.96

The table results also make it clear that, for a given wind farm, different utilities will benefit to different degrees. For example, utility U1 benefits from site WC turbine B at turbine prices less than about $900/kW, whereas utility U2 requires a turbine price about $100 lower.

The benefits include reduced variable cost (consisting of fuel and variable O&M cost), reduced emission penalties, and reductions in shortage cost. As an example of the break-down in benefits, we present the case for utility U1, site HP, turbine A, method PR, at a turbine cost of $1,000/kW. For that scenario, the variable cost benefit is 54% of the total benefit. The percentages for the emissions and shortage benefits are 28% and 19%, respectively.

Some general comments and conclusions about the results can be made. First, it is clear that identical wind farms are *not* identical in the impact on two different utilities. Adding a new wind farm to a utility trades off an avoided cost, which is represented by the marginal-cost function of the utility. This, in tum, is a function of the specific generation mix and is thus highly dependent on the utility in question.

Second, wind sites do indeed matter. Variations in mean wind speed between two sites are magnified because of the cubic nature of the power-curve function. This translates directly into improved B/C ratios for larger average wind-speeds. Also, the wind energy value is dependent on its relationship to the utility's load pattern. High wind output during system peak is more valuable than during off-peak times.

Third, results are quite sensitive to assumptions made about the wind data. This is illustrated by the difference between our YR and CP cases. When representing site wind data, what is the appropriate method? Using a representative week (or month or year) can be viewed as drawing a statistical sample from a population. However, the relative lack of wind data makes it difficult to perform repeated samplings from a large population.

Fourth, the results are sensitive to the modeling technique chosen. This is apparent if we compare two sets of cases: PR with YR, and CP with LM. Cases PR and YR utilize the same wind data, but case PR uses the probabilistic approach whereas YR uses hourly varying capacity. The difference is due at least in part to the fitting of the Weibull distribution to the wind data. The closer the fit, the more correspondence between cases PR and YR. Although we generally hold to the principle that more data are better, it is not immediately clear which of these four cases most closely models reality. From a conceptual standpoint, the probabilistic case is attractive. It explicitly captures the underlying wind distribution, and it appeals to the framework provided in utility planning models by using availability rates at varying levels of generator output. It is also the only method that provides a probabilistic framework in which to analyze wind energy. Although it is our method of choice, we reserve judgement about its accuracy until further research can establish the accuracy of these methods against a chronological model.

In comparing cases CP and LM, we find that the LM case favors wind more than does CP. The LM case is an extreme example of the smoothing problem discussed above in the context of calculating average wind data. In the LM method, wind energy is subtracted from system load prior to calculating the load-duration curve (LDC), and economic dispatch is performed on this modified LDC. The LDC has been reordered from the CP case, smoothing out the wind variation across time periods and increasing the B/C ratio.

We show the results of the simulations for utility U1, wind turbine B, at sites WC and HP in Figures 3 and 4. Each graph shows the B/C ratio as a function of installed turbine cost in $/kW. We have shown only the PR and LM simulation methods for clarity.

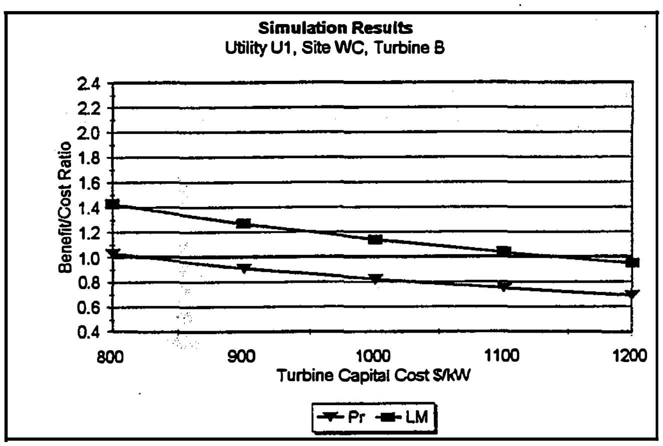

Figure 3 EXAMPLE SIMULATION OUTPUTS, WEST COAST SITE

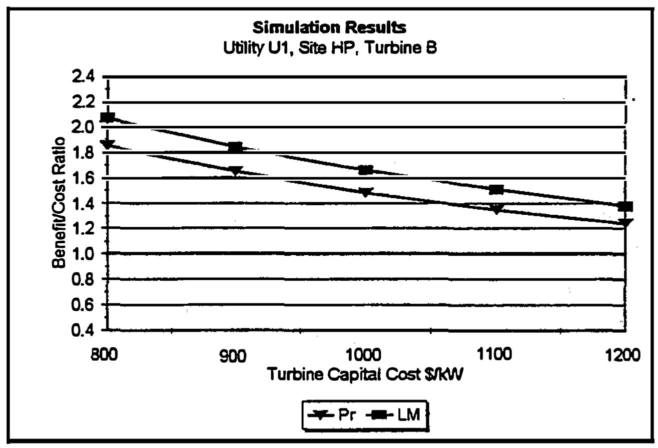

Figure 4 EXAMPLE SIMULATION OUTPUTS, HIGH PLAINS SITE

The two lines in each figure illustrate a range of break-even values for wind for utility U1. Method PR utilizes all available wind data, about 24 months of hourly averages. Method LM utilizes only 12 representative weeks of user-selected, typical wind data. Part of the difference between the break-even lines results from the higher wind energy output in the user-selected wind data than in the PR case. Other differences arise from the smoothing problem in the LM case, as discussed above.

The PR case shows a break-even value of just under $900/kW for utility U1 using turbine B at wind site WC. This implies that, for turbine costs less than $900/kW, wind will be cost-effective. The LM case, by contrast, calculates a break-even cost of about $1,200/kW and implies that any turbine costing less than about $1,200/kW will be economically beneficial.

If utility U1 were faced with a decision between site HP and site WC, the choice would be clear. The graph for site HP, Figure 4, shows that wind is beneficial for any turbine cost on the graph. The simulation results indicate that the reductions in production cost, emission cost, and shortage cost all result from a large increase in power production relative to the WC site.

SUMMARY AND CONCLUSIONS

The factors that influence the value of wind energy to an electric utility are numerous. They include the wind characterstics, turbine specifications, generation mix of the utility, and the match between the utility and the wind resource. Aside from these technical issues are important economic considerations, including whether and to what degree emissions are valued, the correct degree and valuation of capacity credit for wind, and the cost function of the utility. Added to all of these important factors are the sensitivities to modeling technique and data selection with a given wind site. Given all these caveats, however, our results indicate that the right combination of utility, wind site, and turbine, with a competitive cost can yield significant benefits to the utility.

Because even chronological production cost models use one hour as the minimum time step, it seems that hourly wind data are the minimum required. There is still some question about the usefulness of the higher moments (i.e., standard deviation, skewness, and kurtosis) but, intuitively, they do provide some qualitative information about the wind characteristics that might become useful in the future. There is no substitute for good-quality, long-term wind data. It is obvious from our results that there are significant differences in the output of the model, depending on the particular method by which the wind/power data are modeled. Only more research will help answer the question of which method is the most appropriate. It seems that, although the load modifier (negative load) method produces the highest cost benefit ratios, this may be a function of the site wind/utility load correlation as well as the smoothing discussed earlier and may not always provide the most benefit to the utility. Finally, although we do not specifically mention it, the addition of wind in our cases evidenced no adverse impact to the system reliability (LOLP) and in fact showed an increase in reliability.

We believe that a great deal of research remains to be done. Although we whole-heartedly endorse the use of models in the Baleriaux-Booth genre for utility planning, we remain unconvinced of these models' ability to answer certain important questions about intermittent energy sources. Future research should certainly include simulations using a chronological production-cost/generation expansion model, perhaps benchmarking the performance differences between different modeling paradigms.

We believe that the development and use of the WIPS pre-processor was a necessary step in the evaluation of wind energy in production cost and generation expansion models. WIPS is available to any interested parties.

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