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Choosing Wind Power Plant Locations and Sizes Based on Electric Reliability Measures Using Multiple-Year Wind Speed Measurements

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1. INTRODUCTION

The utility industry is undergoing change on several fronts. On one hand, the clear move towards restructured electricity markets is propelling companies towards more analysis of competition and the working of private markets. Countering this is growing concern over the potential of environmental harm caused by many traditional sources of electricity. Competitive pressures are driving least-cost planning principles with a new intensity and in some new directions. The cost of wind-generated electricity continues to fall, increasing its viability, as demonstrated by a recent Minnesota Public Utilities Commission ruling that requires one of the state's large utilities to expand its wind capacity by 400 MW in the next 13 years. Other states, most notably Iowa, are planning on significant wind electric capacity in the near future. Such developments call for the need to address site selection and sizing. Clearly, if 400 MW of additional wind capacity is to be constructed, it is important to know *where* that capacity should be placed, and *how much* to put at each location.

The question of optimal sizing and location is also of interest to potential wind power plant developers. Under some restructuring scenarios, capacity is bid into a day-ahead pool. As a stochastic resource, there is some uncertainty associated with the timing of wind capacity, that results in bids that are either too high or too low. Either error has associated costs. However, power output from geographically disperse sites tends to smooth out chronological fluctuations in power output and reduce the risk of incorrect bids.

Milligan and Artig (1998) demonstrated methods for calculating an optimal mix of wind generating capacity at various sites. The data we used were collected by the Minnesota Department of Public Service. Since that time, additional data have become available, and we have been able to extend our analysis. Interannual variation in wind energy capture and capacity credit are well known (Milligan, 1997). This paper extends our earlier analysis to account for multiple years of wind data, which changes the optimal mix and location of wind capacity. The paper begins with a review of some literature on interannual variations in energy capture and capacity credit of wind power plants, followed by illustrations that show the benefit of geographically disperse wind plant development. Next is a discussion of the methods used in the paper, followed by some results from Minnesota. The objective function of the optimization is a reliability measure, carried out with a standard electricity production-cost and reliability model. This model includes data for hourly electric loads and generator characteristics for all generators in the state. We also provide estimates of hypothetical hourly wind power output from several wind sites. The constraints are enforced by an optimization shell and we can alter how it calculates and approaches the optimal solution.

The wind resource data used in this study were collected through the Minnesota Department of Public Service's (DPS) wind resource assessment programs and the DPS/U.S. Department of Energy (DOE) Tall Tower Wind Shear Study. The approximate site locations appear in Figure 1. DPS has conducted wind resource assessment since the early 1980s, providing utilities, developers, and other interested persons with wind data collected at sites around the state. Since the programs began, DPS has expanded and improved the data collection process by adding new monitoring sites and more sophisticated equipment. The data used in Milligan and Artig (1998) were for the year 1996. The data monitoring project described in that paper has continued, and so we were able to extend our study by incorporating data from 1997 and 1998.

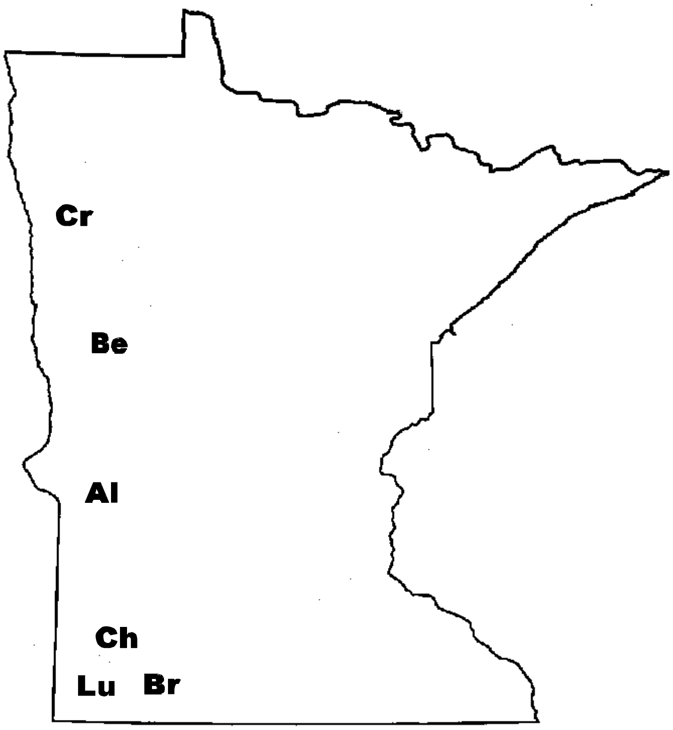


Figure 1. Wind sites chosen for this study

The monitoring program was described in our previous work in some detail. We summarize briefly here. The monitoring sites use existing communication towers and have monitoring levels at 30, 50, and 70 meters above ground level. Data is sent from cellular loggers to the data collection computer. Each tower is equipped with wind vanes at the 30 and 70 meter levels. In addition to the internal logger temperature, some of the sites are equipped with external temperature probes mounted at approximately 4 meters above ground level. For this study, we used data from 6 sites that represent a reasonable degree of geographic spread, increasing the likelihood that we would maximize the potential benefit of disperse wind power generation.

2. SOME BENEFITS OF GEOGRAPHICALLY DISPERSE DEVELOPMENT

The benefits of geographic dispersion have been postulated for some time. The idea is that the distance between turbines or clusters of turbine would create a smoothing effect on the aggregate power output with respect to time. These benefits can occur either with very short time scales of seconds to minutes, or longer time scales on the order of hours. Research at the National Renewable Energy Laboratory has begun to quantify the benefits of dispersion for very short time frames, along with the implication for ancillary services that must be provided either by the wind plant or for the wind plant. Ernst et al. (1999) provide a discussion and analysis.

Geographic dispersion over time frames of 1—6 hours can help with the load-following function of the utility dispatch center. Extremely high hourly variability in any resource can make the dispatch of conventional generating units more difficult, particularly when operating constraints play such an important role for base and intermediate generating units. To the extent that aggregate wind power output can be smoothed over the hourly time scale, risk of committing dispatch errors can be mitigated.

Figure 2 illustrates how this might work. For each of the sites in our study, we calculated the hypothetical hourly power output of a 25 MW cluster of modern wind turbines, accounting for electrical, mechanical, and wake losses. For the month of July 1996, we chose five of the six sites with significant wind power output throughout the month. Using a sliding 6-hour window over the hourly power data, we calculated the coefficient of variation (COV) for each of the sliding 6-hour windows. We then calculated the mean value of all of the COVs, first by wind site, then for an aggregation that represents 5 MW per site. The graph shows the single-site mean COVs varying from just over 60% to just under 80%. For the combined site, the COV is about 40%. This represents an improvement ranging from nearly 20% to nearly 40%, depending on the site to which the comparison is made.

We can see this improvement from another perspective. Wind power plants are sometimes criticized on the basis of wide power swings from hour to hour. However, as pointed out by Ernst et al. (1999) local geographic dispersion within the wind farm has significant smoothing effects. Our data comes from anemometers that are mounted on a single tower, one tower per wind site. Therefore, the hourly generation output swings we calculate are likely to be much more severe than would actually be experienced by a real wind farm. Keeping this caveat in mind, we see the beneficial effects of geographic dispersion for five sites in Figure 3. The graph shows the maximum and minimum consecutive changes in hourly power output from each of the four sites, and from a site representing the combination of individual sites. The most dramatic improvement is with respect to Currie, which has a maximum increase in power of about 21 MW and a maximum decrease of about 18 MW. The combined site, however, shows a maximum/minimum swing of about 7 MW. This is a rather dramatic improvement. In a real wind farm, we would expect to see the individual site maximum and minimum swings to be somewhat less than depicted in the graph. It is also probable that the combined site would exhibit less variation than is shown by our data.

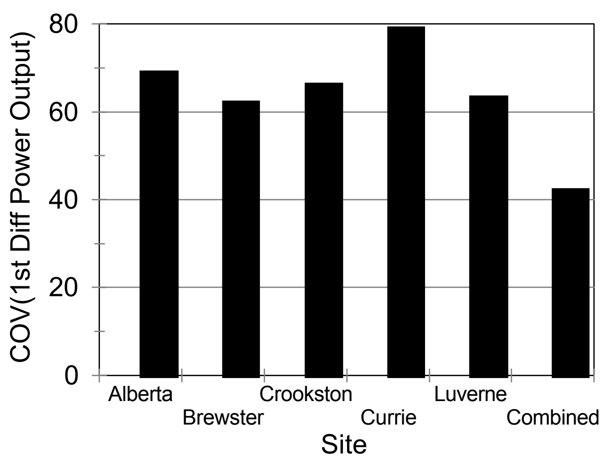


Figure 2. Mean 6-hour coefficient of variation, July 1996

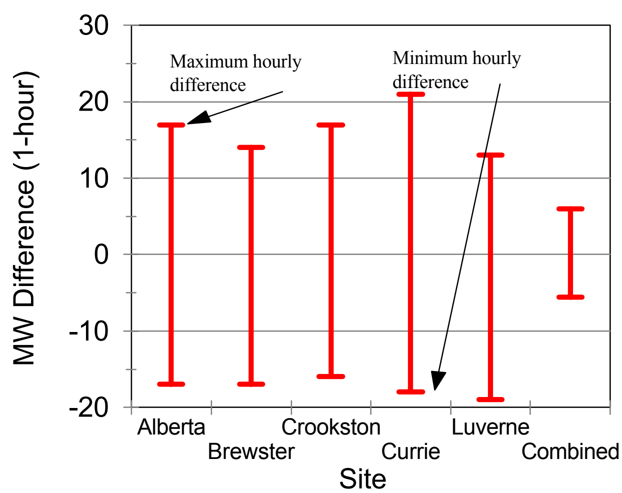


Figure 3. Hour-to-hour power differences in hypthetical 25-MW wind plant output, July 1996

3. INTERANNUAL VARIATIONS

It is well known that weather patterns and wind characteristics vary from year to year. The extent and importance of this variation to wind power production depends heavily on the site location, the size of the wind power plant relative to the utility load, and other factors. Ideally, evaluation of potential wind power plants would depend on a long time-series of reliable wind-speed data, taken over a number of years. When that is not possible, correlations can sometimes be made to nearby long-term weather data to extrapolate the effects of interannual variability.

When we consider the effect of changing weather patterns on generating system reliability, the problem becomes complex. Reliability is a function of loads, generator capacities, and generator availability rates. Two years with similar wind energy capture may have different impacts on reliability because of the timing of the wind power delivery. Milligan (1997) studied these effects using a 13-year wind-speed data set, utility generator and load data, and an electric production-cost/reliability model. He calculated a common reliability measure known as the Effective Load Carrying Capability (ELCC) and compared that with energy capture from fictitious wind power plants based on the actual wind data. He found that, although there is a high degree of correlation between energy capture and ELCC, lower annual energy capture is sometimes associated with higher ELCC. The opposite effect is sometimes found as well. The implication is that in order to maximize system reliability benefits, the wind site with the highest energy capture may not always be the best choice. Extending that to an analysis with multiple potential wind sites implies that there are complications in choosing the best wind sites.

Figure 4 shows the range of capacity factors (the ratio of average output to maximum output) at the six Minnesota sites over the 3-year period. The I-beams in the chart show the maximum, minimum, and mean values. If this 3-year period can be taken as typical (although there is evidence that El Niño and La Niña disrupted weather patterns during this period) we see that the means are often not in the middle. So it would appear that Brewster had a singularly high year, Crookston had an unusual low year, and Luverne had an unusual high year. However, given the likelihood of significant weather disruptions during this period, it seems likely that 1997 and 1998 are not representative years.

The relationship between energy production and capacity credit, as measured by ELCC, was further explored by Milligan and Parsons (1997). They determined that wind plant capacity factor could be calculated for the top 1—30% of annual loads in increments of 1%. This process is carried out by finding the top 1% of hourly loads for the year, and then calculating the wind plant capacity factor for those hours. The process is repeated at 1% increments (2%, 3%, etc.), stopping at the top 30% of load hours. These values were compared to the ELCC values in an attempt to determine whether a capacity factor at some percentage of the top peak hours could be used to approximate the ELCC. They found that, in most cases, there was agreement at percentages at or above 10%. For the Minnesota data, we calculated capacity factors in the same way for all three years. The results are depicted in Figures 5, 6, and 7. For each year, the hypothetical hourly wind power output was matched with the actual electric load in Minnesota for the same time period. There are few, if any, resemblances of the patterns in the three diagrams. In 1996, most sites have relatively high capacity factors for the top 1—3% of loads, but they all decline significantly for broader measures of the annual peak. In 1997 the situation is reversed for Becker City, Crookston, and Alberta, each of which start with very low capacity factors for the top load hours, then increase. The other three sites are relatively good, with a short drop at about 3%, then with slowing increasing capacity factors for larger percentages of the peak. The 1998 graph shows Currie, Alberta, and Brewster with fairly high capacity factors at low percentages of peak, with significant drops. Beginning at about 5% of peak, all the sites have generally upward trends. The implications of these graphs to optimal site selection are unclear, except that the high degree of interannual variation in the relationship between the wind sites and the electric load will likely lead to differences in selections if each year is used separately.

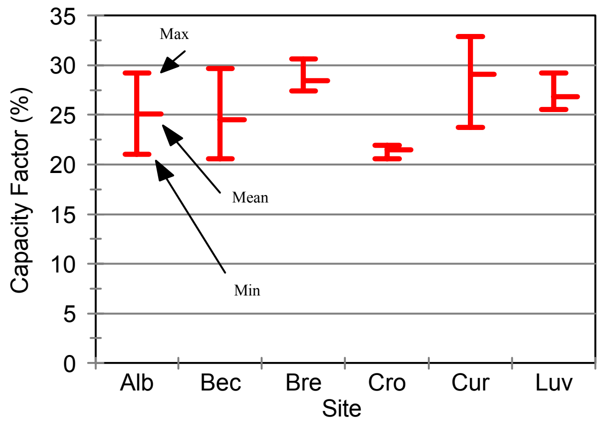


Figure 4. Range of capacity factors, 1996-1998

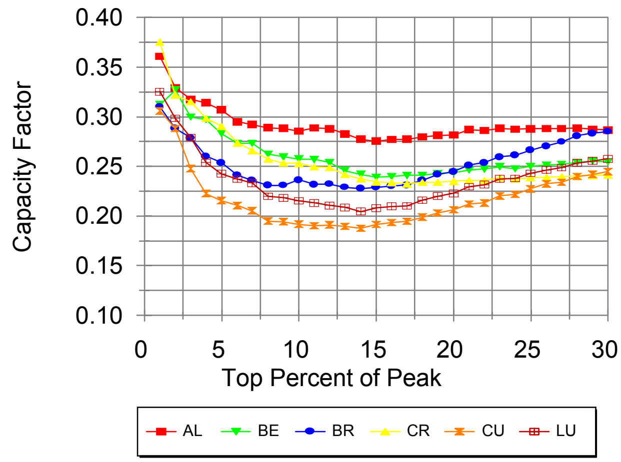


Figure 5. Top load capacity factors, 1996

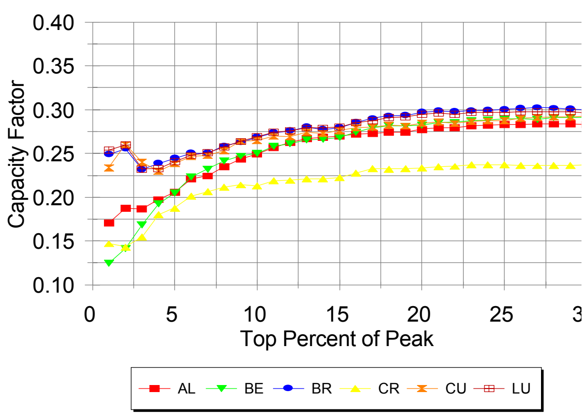


Figure 6. Top load capacity factors, 1997

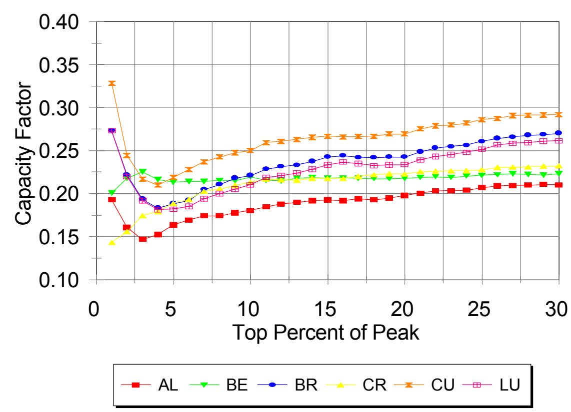
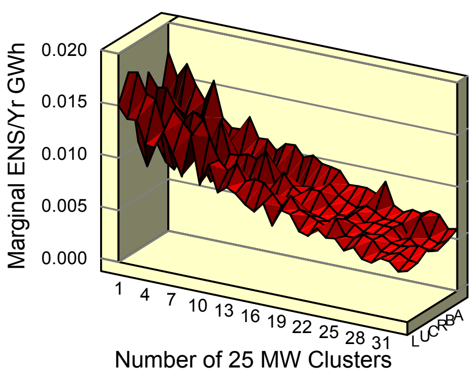


Figure 7. Top load capacity factors, 1998

4. MODELING

We applied one of the modeling techniques from our 1998 paper to each year of wind and electric load data. The method utilized is based on fuzzy logic (Milligan and Artig, 1998). We applied the model to each of the two reliability measures: expected energy not served (ENS) and loss of load expectation (LOLE). Our approach is incremental. The procedure calculates the marginal reliability for 25 MW clusters at each location. The best location is selected, and the installation of 25 MW of wind capacity is simulated by the model. Wind power changes the required generation from conventional units. After a block of 25 MW is "installed," the model is rerun after accounting for the new 25-MW block of wind capacity. The process is repeated until the desired level of wind capacity (nameplate) has been developed.

A well-known result from neoclassical microeconomic theory is that inputs to a productive process can be optimally employed up to the point at which the ratio of marginal benefit to marginal cost is the same for all inputs. In our case, we use reliability, not profit, as the objective function. So to maximize reliability we must choose clusters at each wind site so that the marginal reliability level per installed capacity is the same. Adding a cluster of wind turbines into the generation mix changes the reliability profile of any future wind cluster that is evaluated by the optimal selection process. We can get an idea of the complexity of the geometric surface that is created by this process by examining Figures 8 and 9. In both of these graphs, we have presented a static view of the reliability surface, ignoring the changes that result from the addition of each new cluster. Figure 8 shows a reliability index based on ENS for up to 33 clusters of wind turbines. Each cluster is 25 MW, rated capacity. Each of the six wind sites is shown on the graph (L=Luverne, etc). The figure clearly shows the downward trend in marginal reliability as new clusters are added, as we would expect. In fact, each of the sites exhibits this behavior. What is unusual, however, is that each of the marginal reliability curves is not uniformly decreasing. This occurs because of the lumpiness inherent with the timing of each wind resource, and the complex interaction with both the load and other generators in the reliability model. Figure 9 shows the same phenomena, but uses a reliability index based on LOLE.



A = Alberta, B = Becker City, R = Brewster, C = Crookston, U = Currie, L = Luverne

Figure 8. Marginal ENS provided by wind power

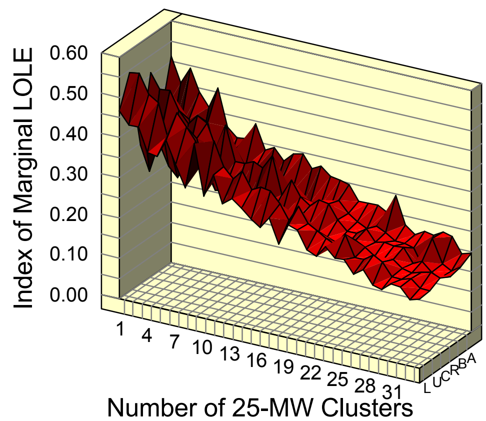


Figure 9. Marginal LOLE provided by wind power, 1998

Our modeling process can be described in terms of these graphs. If we are optimizing based on ENS, the algorithm calculates ENS for each of the sites, using a 25 MW cluster. The best cluster is chosen, subject to the possibility that the fuzzy logic selection will choose a cluster from one or more additional sites simultaneously. The best site will be that site with the highest peak, starting from the left side of the diagram. After the best cluster has been identified, a new version of the graph is recalculated, accounting for the 25 MW of newly installed wind capacity. The process is repeated until the desired capacity of wind generation has been added. The only substantial modification of this process posed by the fuzzy logic is that more than a single site may be chosen during any iteration. If that is the case, then the new version of the graph that is recalculated must take the multiple selections into account.

5. RESULTS

Results of the modeling are presented in Figures 10—12. Each graph shows the capacity chosen by each optimization target: ENS and LOLE. We recall from our earlier work that ENS is a measure of the area remaining under the load duration curve after all generators have been dispatched. LOLE is the height of this distribution tail. As we expressed in our earlier paper, our preference is for the ENS measure, but we have also presented the results for LOLE. The wide range of results is slightly distressing. For 1996, neither Becker City nor Crookston were selected by the optimization process, whereas Becker City was the favorite in 1997, and significant capacity at Crookston was chosen in 1998. Currie, Luverne, and Brewster appear to be the most consistent of all the sites, but there is significant variation in those sites as well.

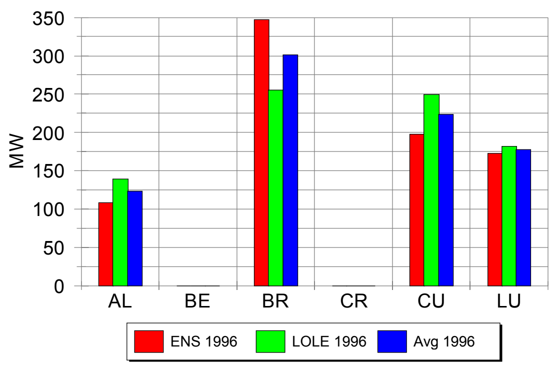


Figure 10. Optimal distribution of wind capacity using 1996 data

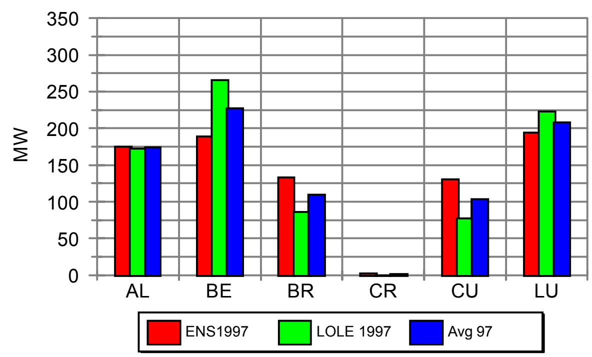


Figure 11. Optimal distribution of wind capacity using 1997 data

The wide variation in wind sites that were selected by the optimization process is caused by several factors. First, the ranking of sites tends to exaggerate differences in reliability between sites. Second, there was substantial variation in wind energy during this 3-year period. For example, at the Chandler monitoring site (Minnesota Department of Public Service, 1999) the energy in the wind during January 1997 at 60 meters was 9.1 watts per square meter (w/m^2); in January 1998 this declined to 6.0 w/m^2. We see this effect in many of the other monitoring sites in Minnesota. Further exacerbating this effect is the malfunction of monitoring equipment at Alberta in 1998 and Crookston in 1997.

If we turn back to Figure 4, we can get some additional guidance to properly interpret the results. Luverne and Brewster have the most consistent capacity factors for this 3-year period. Currie has a broader range, but also has the highest annual capacity factor of all sites for any year. Becker City has a very wide ranging capacity factor, and ties for the lowest of the period with Crookston. Alberta appears somewhat mediocre, with a fairly high variation, but not as high as Becker City's. Some of this variation at Alberta is because of sensor failure. If we were to make a decision based solely on Figure 4, it might be as follows: Build a significant proportion of the capacity at Luverne, Brewster, and Currie. The remaining capacity could be divided among Alberta, Becker City, and Crookston. Subjectively, we might choose to put a very small amount at Crookston because of its very low capacity factor over the period. Choosing between Alberta and Becker City would be more complex without the knowledge of sensor malfunction at Alberta. When taking that into account, we might tend to favor Alberta over Becker City, perhaps putting a smaller amount of capacity at Becker City.

Figure 13 shows the 3-year results in an unweighted average. A more detailed study might involve the correlation of our data with weather-station data over a longer period. One could then establish weights for each year that would correspond with the historical record. The unusually high wind in 1997 and unusually low wind in 1998 might suggest using lower weights for those years. The figure shows unweighted averages for the LOLE, ENS, and combined cases. Our preferred measure, ENS, indicates about 214 MW at Brewster, 198 MW at Currie, and 153 MW at Luverne. This represents about 68% of the 825 MW target. The remaining capacity is divided as follows: 113 MW at Alberta, 84 MW at Becker City, and 63 MW at Crookston.

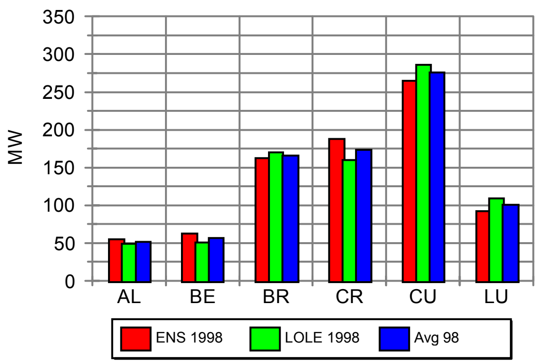


Figure 12. Optimal distribution of wind capacity using 1998 data

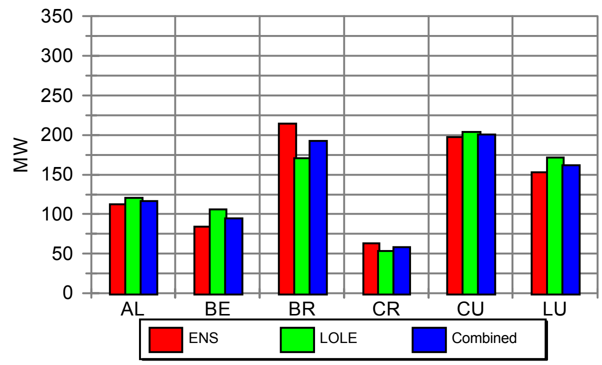


Figure 13. Average optimal mix, 1996-1998

So what did we learn from the 2 years of additional data? Becker City and Crookston might have something to offer, even though they were both dropped from the single-year optimization for 1996. Based on the 3-year data set, we can see that Luverne and Brewster offer some interannual stability. Currie has an upside potential that must be traded off against its downside potential. This is apparent from inspection of Figure 4 and from a comparison of Figures 11 and 12. Had we based our decision solely on 1998 data, the lion's share of capacity would have been build at Currie. There appears to be significant information content in the data we have used in this project, even though the results are not as consistent as we might like them to be.

6. CONCLUSIONS

Choosing among multiple wind sites is a way to reduce risk. We have shown some of the hour-to-hour smoothing benefits that can be achieved by geographically disperse wind power plant development. Our stepwise marginal reliability optimization method produced significantly different results over the 3-year period, but we were able to trace that back to the original wind data. Each year of data has information content, and can help utilities, investors, wind plant developers, and other decision makers make some of the complex decisions surrounding multiple-site wind power plant development. There are many other factors that are relevant to the siting of large-scale wind power plants. Some of these include land-use constraints, variation in development costs that result from more complex terrain, transmission system constraints, and local voltage and VAR support. The results of a study such as this one should be used as a starting point to address these important issues.

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