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Application of a Dynamic Fuzzy Search Algorithm to Determine Optimal Wind Plant Sizes and Locations in Iowa

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Application of a Dynamic Fuzzy Search Algorithm to Determine Optimal Wind Plant Sizes and Locations in Iowa

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Abstract: This paper illustrates a method for choosing the optimal mix of wind capacity at several geographically dispersed locations. The method is based on a dynamic fuzzy search algorithm that can be applied to different optimization targets. We illustrate the method using two objective functions for the optimization: maximum economic benefit and maximum reliability. We also illustrate the sensitivity of the fuzzy economic benefit solutions to small perturbations of the capacity selections at each wind site. We find that small changes in site capacity and/or location have small effects on the economic benefit provided by wind power plants. We use electric load and generator data from Iowa, along with high-quality wind-speed data collected by the Iowa Wind Energy Institute.

I. INTRODUCTION

In the United States there has been a significant level of wind power development. In the 12 months ending in June 1999, 1,073 megawatts (MW) in new wind-generating equipment was installed in the United States. This increase occurred because of several factors. The Federal Production-Tax Credit, first enacted in 1992, provided an inflation-adjusted \$0.015/kilowatt-hour (kWh) credit for wind-generated electricity, and several public opinion polls supported the increased use of renewable energy sources. Wind turbines in Iowa currently generate about 1.8% of the state's annual energy. The Iowa Department of Natural Resources is evaluating whether to submit legislation requiring Iowa utilities to provide 10% of the state's energy requirement using renewable resources by 2015. In this paper, we model Iowa's electricity supply system, and apply a dynamic fuzzy search procedure to help evaluate the best way to choose wind capacity levels at 12 possible locations.

II. IOWA WIND RESOURCE ASSESSMENT

Beginning in 1993, the Iowa Wind Energy Institute began a wind resource assessment of Iowa. This included the installation of twelve 50-meter wind-monitoring stations around the state. The sites were chosen because of their high potential for wind farm development. They are well exposed, with a large developable area, near to transmission lines, and geographically dispersed. Iowa has significant wind energy resources, with substantial areas of class 3 winds and above. The northwest corner of the state is adjacent to the Buffalo Ridge area in Minnesota, a location where significant wind power plant development continues to take place. Some of the sites monitored by the Iowa Wind Energy Institute are in the proximity of Buffalo Ridge.

The wind-speed data were compiled into a database and checked to assure high quality. Sensor and logger failures, tower wind shadowing effects, and lightning and icing events were identified, and missing or otherwise invalid data were replaced using either a shear correction to other working anemometers on the tower, correlation to nearby stations, or National Climatic Data Center archived data. Cleaning of the data was performed jointly by Tom Factor and consulting meteorologist Ron Nierenberg.

For this study we used wind data for the calendar year 1997. This year was chosen because it was very close to the long-term norm, so that the wind data would be consistent with the latest Iowa utility load data available at the time of this study. The hourly wind data were scaled by comparing the 1997 average to the four-year average that was measured at the 12 sites. This was done to make the wind data more representative of long-term norms. We also considered the relationship of 1997 to the 20-year norms provided by the National Weather Service. The wind-monitoring sites appear in Fig. 1.

We ran a large number of power production-cost simulations for this study, using the Elfin model. (Elfin is a product of the Environmental Defense Fund.) This modeling process is described in greater detail below. After an initial set of runs was completed, we examined the sites that were selected by the model for significant wind energy development. A wind speed, wind power density, and turbine output map of each 20 x 20 kilometer area surrounding each wind-monitoring site selected by the Elfin model was made. We used the WindMap software developed by Michael Brower. The maps used United States Geological Service (USGS) digital elevation models to a 100-m grid cell, surface roughness data, and wind rose data for each ground measurement station. The area was then modeled for relative exposure, elevation, and terrain roughness to create a graphical map of wind speeds and turbine power outputs. This map was used to determine the average wind speed and output for an array size suggested by initial runs of the Elfin model. The maps were used to determine the average wind speed for the size of terrain required to meet the recommendation of the Elfin model at a density of 10 MW per square mile. This allowed us to account for declining average wind speed as sites are more fully developed. The wind speed used originally by the model was then adjusted up or down, and the Elfin model was re-run to yield more accurate results. In the case of the Estherville site, which was initially selected by Elfin as the largest generation facility, two monitoring stations a half-mile apart at 50-foot different elevations were used to further refine the modeling of this area.

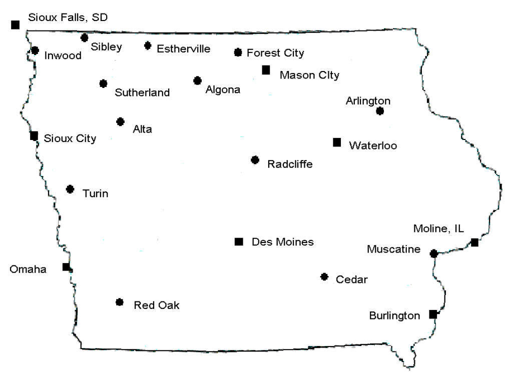

Fig. 1. Iowa wind monitoring sites. Circles represent Iowa Wind Energy Institute sites, squares are National Weather Service sites.

The adjustments to wind speed we made were as follows: Sibley + 2.3%, Estherville - 2.4%, and Algona -.04%. Alta was not adjusted because nearly 200 MW is already installed at that site. Radcliffe, Sutherland, and Forest City were unchanged because sufficient similar terrain was found in the area to support increased development (pending landowner acceptance and transmission access).

III. LOAD AND GENERATOR DATA

Additional data were required to run the production-cost model. We combined the electric load and generator data from the Iowa utilities so that our study would come closer to a statewide or regional dispatch, as might occur under restructuring. The load and generator data are publicly available for all of the investor-owned utilities, cooperatives, and municipals in the state of Iowa. This data includes hourly electric load data and data for each generator in the state. In some cases we combined small generating units with similar characteristics, such as fuel type and heat rate. We also modeled energy inflows and outflows in Iowa. These data were adjusted to reflect recent and projected interchanges as accurately as possible. These exchanges include base economy energy, intermediate economy energy, peaking capacity and energy, and emergency capacity purchases from other utilities in the control region. These purchases are projected to decline at about 1,000 gigawatt-hours (GWh) per year from a current level of about 9,000 GWh. We also incorporated projected gas-fired simple-cycle and combined-cycle capacity into the future resource mix.

Wind energy is becoming cost competitive with fossil fuel alternatives for new energy production in Iowa. Although wind energy is considered non-dispatchable because it is intermittent, areas outside the United States that have reached the 10% level report no disruption in their ability to meet load requirements. There is also a very favorable public climate towards wind energy. Taking these facts together, we decided to analyze the ten- percent target for renewable energy applications in the next 15 years. We used the utility projections for load growth through 2015 and calculated the wind capacity that would be required to meet 90% of the 10% mandate for renewable energy. This yields a 1,600-MW target. Although wind energy is the most cost-effective renewable energy technology in Iowa, there may also be significant contributions by biomass, small hydro, and other renewable resources.

IV. POTENTIAL BENEFITS OF GEOGRAPHICALLY DISPERSED WIND GENERATORS

Several studies have examined the issue of geographically disperse wind sites. Kahn's [1] analysis is based on data collected in California. Grubb [2] analyzes the effects of smoothing from wind generating units in Britain. Milligan and Artig [3] examined a reliability optimization for the state of Minnesota, but did not address economic benefits. Ernst [4] provides an analysis of short-term data in Germany. All of these studies find that the geographic spread of wind generators provides a smoothing benefit. The principle behind this benefit is that lulls in the wind tend to be more pronounced locally than over a wide geographic area. Building wind capacity at different locations may help reduce the problems caused by the intermittency of the wind resource. The hourly wind-speed data from the 12 Iowa sites allow us to examine this question in some detail. If 1,600 MW of wind capacity were to be built in Iowa, how much capacity should be put at each of the sites? Should all, or some sites be used? One approach might be based on an optimization target of smoothing the hour-to-hour variations in wind output. Fig. 2 provides an example of how this might work. In the figure, we calculated the hourly wind output for a hypothetical 25 MW wind power plant at each of the 12 sites in Iowa. The graph shows the first differences of this data, calculated by finding the difference in the wind output for successive hours. We then calculated the maximum and minimum changes in wind power output, which are represented by the I-beams for each of the 12 sites. We then combined each of the 12 sites into a composite site, choosing approximately 2.08 MW per site, for a total of 25 MW. The I-beam for this composite site appears on the right side of the figure, and shows that the maximum and minimum hourly power swings are significantly reduced by spreading the wind capacity to several geographically dispersed sites.

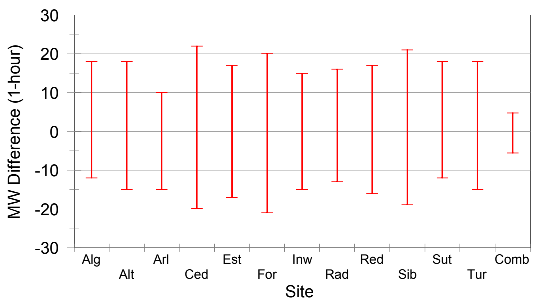

Fig. 2. Hour-to-hour differences in wind power output, July 1997.

There are several possible optimization targets that could be chosen. Using Fig. 2, for example, we could select the combinations of wind sites that provide the smoothest aggregate output over some suitably defined peak period. But the generation mix of most utilities or generating companies includes some regulating capacity that can be adjusted to adequately cover fluctuations in demand. The optimal generation mix can be found by solving the traditional least-cost dispatch problem, which can account for hourly load-swings and how to best meet those changes in demand. We chose to perform optimizations based on two targets. The first target is based on maximizing the economic benefit from the selected wind sites. The wind sites and capacities are chosen so that power production cost savings from conventional generators is maximized. The second target is to choose the combination of locations and capacities that maximizes a reliability index. Our preference for the reliability index is expected energy not served (ENS).

V. MODELING METHODS

We ran our model for two different optimization targets. The first target is economic benefit, and is defined as the cost reduction in conventional generation that results from installing wind capacity in the generation mix. The second target is a reliability target. We use ENS for our reliability measure, and calculate the increase in reliability that the combined wind sites contribute to the system reliability based on the no-wind case. Both optimization processes utilize the same basic algorithm. We describe the economic benefit optimization first.

Since we do not have specific price information on wind development and production at these sites, we assume that the installed cost in \$/kW is the same at all sites. Our procedure could be adapted to cases in which costs are known, and differ between sites. There is a difference in efficiency and reliability between sites because of the different winds at each of the 12 different locations, and our optimization does take this into account.

Our economic optimization algorithm searches for the combination of installed wind capacity, totaling 1,600 MW, at the 12 sites that maximizes reduction in costs of running conventional generators. The most significant component of this benefit is the reduction in conventional fuel costs. However, we have also specified a reliability penalty for unserved energy of \$4.00/kWh. Equation (1) is the benefit function,

$$b = \Gamma(W) \tag{1}$$

where $\boldsymbol{W}$ is a vector populated with the rated wind plant capacity at each of the 12 locations consisting of rows w_i at each wind site, i is the index of the wind site, $1 \le i \le 12$, and Γ maps the installed capacity vector $\boldsymbol{W}$, to the benefits b, calculated as a reduction in production cost. Finding the optimal mix of resources assuming the same price/kW at each site implies that we choose the quantity of wind resources up to the point at which the marginal products of each site are equivalent [5]. Written in terms of partial derivatives, we have

$$\partial\Gamma_i(w_i)/\partial w_i = \partial\Gamma(w_j)/\partial w_j \tag{2}$$

Equation (2) says that, for the optimal mix of wind sites and locations, the marginal contribution to economic benefits at each chosen site must be equal to the marginal benefit of all other chosen sites. Classical optimization methods that can be used to solve Equation (1) subject to Equation (2) include the method of Lagrangians, linear programming, or Kuhn-Tucker methods if the problem is nonlinear. However, these techniques assume that the solution set is convex. As indicated in Fig. 3, our problem is not so simple. The figure shows the marginal economic benefit of each of the wind sites. This graph shows the restricted case in which output at each of the other 11 sites is 0. Compounding this problem is the chronological nature of unit commitment and economic dispatch. Given various constraints of the individual generators, these additional binding constraints add another level of complexity to the problem. Because of these factors, the interaction between wind sites, and our desire to select a combination of wind sites, we are quickly left with the curse of dimensionality that is so often associated with complicated optimizations over non-convex surfaces. Our solution must satisfy Equation (2); however, the process of finding this solution involves a search process over a non-convex surface.

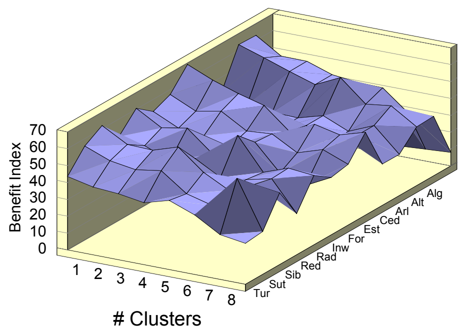

Fig. 3. Marginal benefits of increasing wind penetration.

We employ a dynamic search algorithm that proceeds in a stepwise fashion. Procedurally, our problem is similar to the standard microeconomics problem of a consumer who maximizes utility subject to a budget constraint. The process is described in [6]. We selected a step size, or cluster, of 50 MW of wind capacity. The choice of a 50-MW cluster was a compromise between greater accuracy and increased computer run time with small cluster sizes. Our optimization process simulates building one cluster at each of the 12 sites. The model then selects the cluster that contributes most to the economic benefit target. That site is then chosen for the first cluster. At the next step, an additional cluster is checked at each site, given the previously built cluster. The best site is chosen, and the process is repeated until the desired capacity is reached. This modeling method does not rule out the possibility that the highest benefit may be met from a single wind site. If that were the case, this algorithm would find a single-site solution.

The process that has been described to this point is based on a deterministic, or crisp, selection logic. At each step of the way, a deterministic selection procedure ranks each site and chooses the best. However, in many cases a very good site may be consistently passed over in favor of a site that was only slightly better. The use of a fuzzy selection procedure allows us to consider several very good or good solutions, for which ranking differences may not be significant. The justification for such a fuzzy selection procedure is based on a number of issues. First, there is the possibility of errors in the data. In spite of the adjustment procedure we carried out on the wind-speed data, it is possible that the single anemometer reading for each site is slightly above or below actual average for the site. Any measurement errors are further magnified by the wind turbine power curve, which is a cubic function of wind speed. Other data errors may occur. Over time, load forecasts may not correctly predict annual or daily changes in load shape. Both marginal cost and system reliability measures are functions of the hourly load, so modeling that is based on load data is subject to some small errors. Second, although we would not expect large variations in relative wind site performance from year to year, there could be enough small variation, perhaps caused by changes in the annual average latitude of the jet stream, that could cause a different ranking of sites that are closely competitive. Third, smoothing effects from multiple locations may provide benefits that are not easily captured by the model. There is local smoothing that occurs within a cluster of wind turbines that we are unable to capture in our modeling [4]. Fourth, because of the important role that wind forecasting plays in optimizing unit commitment from conventional units, forecast errors will tend to be smaller across larger geographic areas. Therefore, choosing a combination of sites that provide a slightly lower measured benefit may make it easier for accurate wind forecasting [7]. Fifth, modeling a complex process such as power generation must, by necessity, simplify reality. Even chronological or shorter-tem unit-commitment models cannot fully capture this complexity. This introduces the possibility of modeling errors that are distinct from data measurement errors. And finally, given the large number of combinations of 50-MW clusters among 12 sites, it may not be possible to find a global optimum. Many other complex factors can influence the siting of a large cluster of wind turbines, such as land-use constraints, transmission constraints, and local voltage and volt ampere reactive (VAR) support. Rather than finding a single solution from our optimization process, we are more interested in finding a set of solutions that offer significant economic or reliability benefits to the system. Given this discussion, we alter our selection logic as

$$b_p(1-\delta) \le b_i \le b_p(1+\delta) \qquad (3)$$

where b_p is the economic benefit of the best site, δ is the fuzzy parameter expressed as a decimal, and b_i represents the benefit of plant i, $1 \le i \le 12$, $1 \le p \le 12$and $p \ne i$. This modified selection procedure means that we will select all sites for which the optimization target falls in the range specified by the fuzzy parameter, δ.

We also investigated the optimal combination of sites based on a reliability target. The formulation of this companion optimization problem is similar to the benefit-maximization problem described above. We can describe the reliability level as a function of installed MW at each site:

$$e = \Phi(X) \tag{4}$$

where e = a reliability benefit index, as measured by the increase of ENS over the no-wind case, and $\boldsymbol{X}$ is a vector populated with the rated wind plant capacity at each of the 12 locations. The function Φ maps the installed capacity of wind at the various sites to reliability benefit. Written in terms of partial derivatives, we have the optimization condition that must be satisfied

$$\partial\Phi_i(x_i)/\partial x_i = \partial\Phi(x_j)/\partial x_j \tag{5}$$

where x_i is one of the rows of X, i and j index the wind site locations, and $\forall\ i, j$ such that $1 \le i \le 12$ and $1 \le j \le 12$ and $i \ne j$. The fuzzy selection criterion is

$$e_p(1-\xi) \le e_i \le e_p(1+\xi) \tag{6}$$

where e_p is the reliability of the most recently added cluster at the best site, ξ is the fuzzy parameter expressed as a decimal, and e_i represents the reliability of the most recently added cluster of plant i, $1 \le i \le 12$, $1 \le p \le 12$ and $p \ne i$. This modified selection procedure means that we will select all sites for which the optimization target falls in the range specified by the fuzzy parameter, ξ. The dynamic search process based on Equations (4)-(6) follows the same stepwise algorithm as the economic-benefit maximization problem, adjusted for the reliability target.

VI. RESULTS

The results from the fuzzy economic benefit-maximization appear in Fig. 4 and Fig. 5. The first of these figures shows the range of installed capacity at each of the six selected sites. The remaining six sites were not chosen by the optimization process. Fig. 4 shows that there is

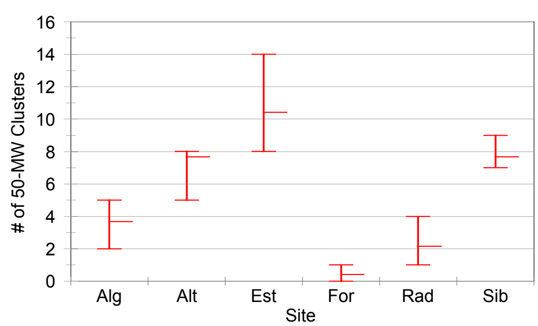

Fig. 4. Range of cluster sizes selected by economic benefit optimization.

substantial variation in the ranges of cluster sizes that can be chosen at each site. The middle tick-mark in the graph is the mean value of the number of clusters chosen by the optimization process for the respective site. The wide range of capacity chosen for Estherville illustrates that even though Estherville is often chosen as the best site, it faces close competition from other sites. This can be confirmed by the graph in Fig. 5. This graph shows the 12 solutions from the dynamic fuzzy process. (The numbers at

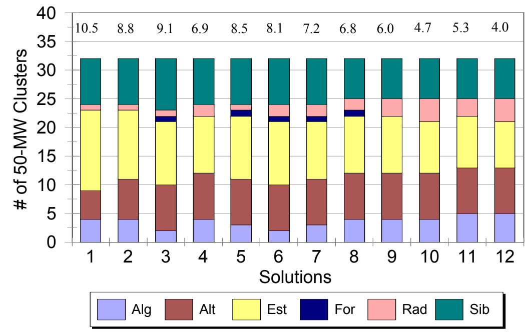

Fig. 5. Fuzzy solutions, highest economic benefit.

the top of the graph are described below.) Each of the bars shows the capacity mix chosen. The bar on the far left represents the narrowest fuzzy band δ = 0.01, with progressively wider bands as we move to the right (up to δ = 0.026 in increments of 0.01). In some cases we found that duplicate solutions were found by different values of δ. These duplicate solutions were dropped, resulting in the 12 solutions in Fig. 5. The capacity level selected for Estherville is initially high (16 clusters), dropping to 9 clusters in the rightmost bar. We can trace the closest competitors of Estherville in each widening of the fuzzy band. As we can see from the transition from bar 1 to bar 2, Alta is the closest competitor to Estherville. Capacity at Alta is further expanded in solution 3, which also shows competition from Forest City and Sibley. The complexity of the non-convex solution set and the interdependence of wind site contributions to economic benefit can be seen by the somewhat irregular appearances by Forest City. This site is chosen in solution 3 and solutions 5-8. The sites that were selected for significant development all have an average annual wind speed of at least 7.2 m/s, resulting in estimated capacity factors of at least 35%. Forest City has an estimated annual capacity factor of approximately 32%; the sites that were not selected all have capacity factors significantly less than 35%.

We ran a similar set of optimizations based on reliability. Fig. 6 and Fig. 7 contain the results of those simulations. Fig. 6 shows the variation in cluster sizes and locations for fuzzy parameters $0.02 \le \xi \le 0.45$. The range of cluster choices for the reliability optimization is significantly wider than the range we found for the economic-benefit optimizations. Forest City, the marginal site from the economic-benefit simulations, was not chosen by the reliability search. Conversely, Inwood, Red Oak, and Sutherland were selected in the reliability optimization, although the latter 2 sites were selected only at a very low capacity. In several cases, the fuzzy search algorithm found the same solution for different values of ξ. After eliminating these duplicate solutions, we are left with 10 simulations from this process. Each of the bars in the graph of Fig. 7 shows the number of clusters that were selected for each site. Consistent with Fig. 6, Fig. 7 shows substantial variation in sites chosen for the reliability target.

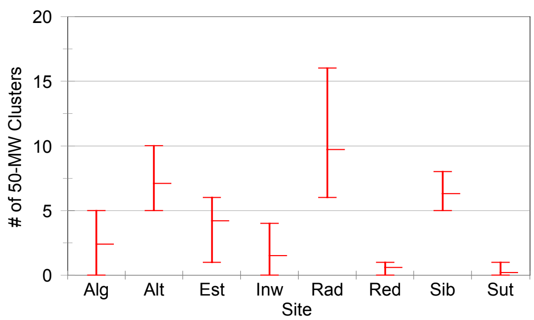

Fig. 6. Range of fuzzy solutions for reliability target.

A decision maker faced with the choices presented in this paper has considerable flexibility from the combinations of sites and capacity levels we have presented so far. We have a set of over 20 very good ways in which to distribute wind capacity, chosen from over 5 x 10^9 combinations of 50-MW clusters that satisfy the build-out of 1,600 MW. Solutions based on highest economic benefit would likely be the best choices, but reliability may also be a consideration. Compromises between the most economic and most reliable sites can be calculated by weighting solutions in a way that captures preferences and trade-offs between these two optimization targets.

As an example of how these choices can be analyzed, we used a pattern-matching technique to find similarities between economic-benefit solutions and reliability solutions [8]. The pattern-matching algorithm we used is the nearest-neighbor technique, which calculates the geometric distance in n-space between two points. The distance function can be defined as

$$d_{i,j} = \sqrt{\sum_{k=1}^{12} (c_{i,k} - c_{j,k})^2} \qquad (7)$$

where i indexes the economic-benefit solution and j indexes the reliability solutions, and each $c_{i,k}$ is the capacity at the site indexed by k. We calculated this distance metric for all possible pairs of solutions. Although the distance measure allows us to rank the "closeness" of solution pairs, it is an ordinal value only, so absolute differences between distance measures cannot be clearly interpreted. After performing this pattern-matching exercise, we can find the economic-benefit capacity mix that most closely matches a reliability capacity mix.

Applying this algorithm to the solution sets, we found that one of the reliability cases was the solution that matched all of the economic-benefit cases. This reliability case is identified as solution 7 in Fig. 7 below. So that we can compare the economic solutions with the reliability solution, we return to Fig. 5. The numbers at the top of the bars in Fig. 5 represent the nearest-neighbor distance of each of the economic benefit cases to reliability case 7. The closest economic solution is shown in bar 12, which represents the case with the widest fuzzy band.

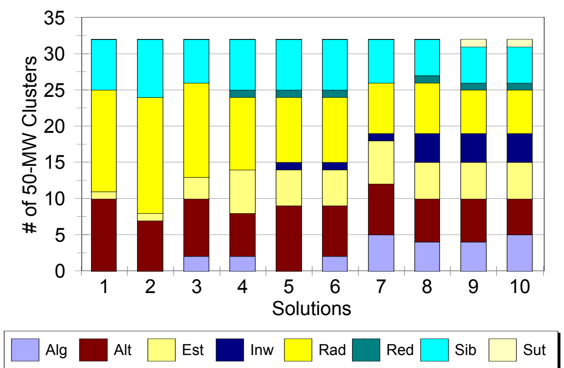

Fig. 7. Fuzzy solutions, most reliable combination of wind sites.

VII. SENSITIVITY TO SMALL CHANGES IN WIND CAPACITY AND LOCATIONS

Our solution set is not exclusive—there may be other solutions that are close to those selected by our search process. To investigate how economic benefits vary with small changes in cluster sizes and locations, we applied a linear stepwise probe. This probe begins with a selection of clusters from the dynamic search process. It then adds a single cluster, one at a time, to each of the 12 sites. So that our maximum 1,600 MW of wind capacity is not violated, the probe decrements the number of clusters at each of the remaining 11 sites, one at a time. Clearly, sites that were not selected by the dynamic search cannot be decremented; however the probe investigates the impact of adding a cluster at each of these sites, trading off a cluster at each of the other locations, as appropriate.

This initial probe gives us another set of solutions. Given the non-convex solution set, we applied the probe again, this time using the solution set from the first probe as the input to the second probe. Applying this two-stage probe to the economic-benefit solutions from our dynamic search process gives us approximately 3,000 alternative solutions, all of which are within ±2 clusters/site of the original solution. The question we are interested in answering with this process is how sensitive are the initial solutions to small variations in cluster selections at the 12 sites? Our results indicate that there are 2,080 possible combinations of clusters that provide economic benefits within 1% of the best cluster combination.

The existence of these alternative solutions with similar economic benefits confirms that our use of fuzzy selection criteria is appropriate. Furthermore, these multiple solutions provide significant latitude to take other constraints into account that our modeling process does not recognize. Some of these constraints include transmission constraints, land-use constraints, or other operational issues such as local voltage or VAR support. Several wind sites were not selected by our dynamic search process. By running a 2-stage probe or other sensitivity analysis, we can investigate the merit of building a small amount of capacity at one of the less-than-optimal sites, given that we make small changes in the capacity recommendations at the remaining 11 sites. We think this provides decision makers with extraordinary latitude in selecting the locations and sizing of geographically dispersed wind power plants.

VIII. CONCLUSIONS

Because there are so many ways of distributing 1,600 MW of wind capacity at 12 sites, planning a large system of geographically dispersed wind energy systems is a complicated exercise. At each site, additional development may come at the expense of lower energy yields from the site because the best locations tend to be built up first. There is also the question of interannual variability, and how that might affect the potential mix among sites. The potential for data and modeling inaccuracies implies that a nondeterministic procedure, such as our fuzzy search algorithm, should be used.

According to our analysis, it is advantageous to distribute wind capacity in Iowa at several sites. We have shown that there are abundant sites on exposed cropland with wind speeds in excess of 7.2 m/s, access to transmission lines, low population density, and with low environmental impact that are viable for wind energy development. We further conclude that the geographic distribution provides the greatest economic benefit when it is kept within the 7.2 m/s and above wind regions, rather than simply the widest geographic distribution occupied by lower-wind areas. We ran well over 10,000 different simulations in an attempt to find plausible ways in which to distribute wind capacity at multiple sites. Based on initial simulation results, we modified the site average wind speed based on site-specific data to account for the expected changes in energy yield that are caused by extensive development. We can't guarantee that our modeling process has identified the global optimum solution for this highly non-convex problem. However, we have identified a large number of possible solutions that offer similar economic benefits. Our approach provides several options that can be further explored and refined in the context of other goals or constraints that are related either to the electrical system or to other social or institutional issues. We have also provided a way to help match solutions from multiple optimization targets.

The wind sites and capacity levels chosen by our analysis should be consistent with actual development in Iowa. Because wind energy sites are most likely to be chosen based on economics and transmission access, limited transmission capacity in any one area naturally leads developers to locate new areas for wind development. But the first choice will always be the highest-benefit wind site that does not infringe upon higher population densities, or environmentally sensitive areas such as wetlands. These two natural constraints will likely lead wind energy developers to choose a similar mix of wind resource sites, such as those indicated in this study. And, as our study concludes, this will lead to a combination of wind sites that maximizes some mix of the economic and reliability contributions of the wind power plants.

IX. ACKNOWLEDGMENTS

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XI. BIOGRAPHIES

Michael Milligan is a consultant to the National Wind Technology Center at the National Renewable Energy Laboratory. His research focuses on utility modeling and analysis of large-scale wind power plants. He received a B.A. in mathematics and philosophy from Albion College, and an M.A. and Ph.D. in economics from the University of Colorado. He was formerly associated with Tri-State Generation and Transmission Association, Inc., where he performed resource analysis, rate studies, and load forecasting. He is a member of IEEE, the International Association for Energy Economics, and the American Economics Association.

Tom Factor has been the director of the Iowa Wind Energy Institute since 1993. Under grant to the Iowa Energy Center, he has created Iowa's state wind resource assessment and wind power estimations for 2,400 cities in Iowa. He is a consultant to numerous utilities and wind energy developers, and is an academic member of the American Wind Energy Association. Born in 1949, Tom is a graduate of the California Institute of the Arts. He was previously the president of Global Video Productions, and is currently the director of the Division of Energy and Environment of the Institute of Science, Technology and Public Policy. Tom Factor lives in Fairfield, Iowa, with his wife, Roxanne.

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13. ABSTRACT *(Maximum 200 words)*
This paper illustrates a method for choosing the optimal mix of wind capacity at several geographically dispersed locations. The method is based on a dynamic fuzzy search algorithm that can be applied to different optimization targets. We illustrate the method using two objective functions for the optimization: maximum economic benefit and maximum reliability. We also illustrate the sensitivity of the fuzzy economic benefit solutions to small perturbations of the capacity selections at each wind site. We find that small changes in site capacity and/or location have small effects on the economic benefit provided by wind power plants. We use electric load and generator data from Iowa, along with high-quality wind-speed data collected by the Iowa Wind Energy Institute.

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