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The effects of geographical distribution on the reliability of wind energy

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Abstract

We examine the effects of geographic distribution of wind power plants (WPPs) on the reliability of electrical output within the Midwestern United States. North American Regional Reanalysis (NARR) data are extrapolated to 80 m using the power law and used to characterize the wind resource at 108 NARR grid points corresponding to existing WPPs. These sites are then organized, on the basis of nearest neighbors, into networks ranging from single WPPs to the full network of 108 WPPs. For each network, a suite of statistics is computed and used to characterize energy reliability as it relates to the number of WPPs within, and the area enclosed by, the network. The results demonstrate that WPP dispersion reduces variability and thereby improves the reliability of electrical output from WPPs. As scale increases, marginal improvements in reliability diminish, but there is no saturation of benefits on the scales considered here. The results are combined with wind resource information to identify sites that can further improve reliability for aggregated wind power in the study region.

Keywords: wind, power, energy, reliability, geographic, distribution

1. Introduction

Global wind energy resources far surpass current energy demand (Kempton et al. 2010). Wind power is the fastest growing energy source in the world with an annual growth rate of approximately 35% (Sathyajith and Philip 2011). However, the variability of wind, and the resulting intermittency of the wind power resource, is frequently cited as an obstacle to provision of baseload power by wind and its further penetration into the electricity market (DeCarolis and Keith 2005; Sovacool 2008). As an alternative to siting wind power plants (WPPs) only in regions with low wind variability, interconnection of WPPs through the transmission grid shows great promise for improving the reliability of electricity generated from wind (Khan 1979; Carlin and Haslett 1982; Simonsen and Stevens 2004; Archer and Jacobson 2007; Kempton et al. 2010). At a single site, or over the area occupied by a typical commercial WPP, wind speeds are highly variable. However, autocorrelation of wind speed decreases with distance (Robeson and Shein 1997), so that as area increases, average wind speed is less variable. Over a sufficiently large area, meteorological and topographic conditions vary enough to produce a balance between areas with high and low wind speeds, and more importantly, a reduction in the frequency of calm conditions throughout the network.

Kahn (1979) was the first to suggest that geographically dispersed WPPs could improve the reliability of wind power. He analyzed networks of two to 13 WPPs and found that instances of zero power decreased as sites were added to the network. Archer and Jacobson (2003) analyzed surface measurements at 1327 weather stations and sounding measurements from 87 stations from the National Climatic Data Center and found that the standard deviation of wind speed was consistently greater at individual locations than when averaged over multiple locations. They also found that, in an eight-site, 385,000 km^2 area stretching across parts of New Mexico, Oklahoma, and Texas, average wind speed at 80 m never fell below 3 m s^{-1}, which is significant because 3 m s^{-1} is a common cut-in speed for wind turbines (GE Energy 2010). Simonsen and Stevens (2004) analyzed one year of wind speed data at 28 sites across Iowa, North Dakota, Kansas, and Minnesota, and found that connecting the sites reduced the variability of power output by a factor of 1.75 to 3.4. Archer and Jacobson (2007) analyzed wind speed data at 19 sites spanning across parts of Kansas, New Mexico, Oklahoma, and Texas to determine if wind could be used as baseload power. They found that, on average, 33% of yearly averaged wind power could be used as baseload and that the standard deviation of wind power produced decreased by 35% from one site to 19 aggregated sites. Kempton et al. (2010) examined the power output of a hypothetical network of 11 offshore WPPs along the Eastern Seaboard. They found that compared to individual sites, hourly fluctuations of capacity factor of the entire network were dramatically reduced.

While the studies cited above have analyzed aggregated wind power over large geographic areas, the effects of aggregated wind power within an area corresponding to an Independent System Operator (ISO; the organization that manages the operation of the electrical power system within a region) have not been considered. Furthermore, existing studies have focused on either the number of aggregated WPPs or the area enclosed by a network of WPPs, but not both, resulting in confusion regarding the source of improvement in reliability. This study addresses these issues by examining the effects of aggregating the energy production of existing WPPs within the area corresponding roughly to the United States component of the Midwest ISO and evaluating the role of the number of WPPs relative to the geographic area covered by the WPPs. We also use our findings in conjunction with wind resource data to identify new areas for wind power development aimed at improving reliability.

2. Study area, data, and methods

The study area includes Illinois, Indiana, Iowa, Michigan, Minnesota, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin (Figure 1). The outline of the Midwest ISO is irregular and includes spatial discontinuities. Therefore, although sections of Illinois, Indiana, Iowa, Michigan, Nebraska and Ohio are not part of the Midwest ISO, they were included to simplify the organizational aspect of the study. Existing WPPs within in the study area with a nameplate capacity of at least 10 MW (n=116) were catalogued and are also shown in Figure 1.

Wind speed data from the North American Regional Reanalysis (NARR) (Mesinger et al. 2006) for the months of January and July 1979 - 2010 were used to assess the wind resource. January and July were chosen because they effectively represent the winter and summer wind regimes in the Midwest, and because they are at the extremes of electricity consumption due to heating (January) and cooling (July) (Energy Information Administration 2011). NARR consists of three-hourly meteorological data on a 32 × 32 km grid at the surface (10 m for winds) and 29 pressure levels from 1000 to 100 mb, covering the North American sector. It is the highest resolution reanalysis data set with complete coverage of the study region. Because the proximity of several WPP pairs was beyond the spatial resolution of the NARR, the 116 catalogued WPPs correspond to 108 unique NARR grid points. In the context of this research, the term 'WPP' will be used to refer to any NARR grid point that corresponds to an actual wind power plant.

NARR wind speeds were extrapolated to 80 m using the power law:

$$v_2 = v_1 \left(\frac{z_2}{z_1}\right)^{\alpha} \qquad (1)$$

where v_1 and v_2 are wind speeds (m s^{-1}) at heights z_1 and z_2 (m), and α is the roughness exponent (Arya 1988). Rather than extrapolate from 10 m, extrapolation distance was reduced by locating the pressure level nearest to, but below 80 m, and extrapolating from that height. Only rarely was the distance greater than 70 m. The roughness exponent (α) was calculated at each point for every time step:

$$\alpha = \frac{\ln(v_{b80}/v_{\mathrm{a}80})}{\ln(z_{b80}/z_{a80})} \tag{2}$$

where $v_{\mathrm{b}80}$ is the wind speed at the pressure level nearest to, but below 80 m, $v_{\mathrm{a}80}$ is the wind speed at the pressure level nearest to, but above 80 m, and z_{b80} and z_{a80} are the heights of those respective pressure levels (Oke 1987) (Figure 2).

The 80 m wind speeds derived from the NARR data were used to calculate the wind power at each three-hourly time step, assuming a single turbine at each WPP-associated NARR grid point. We also assume use of the GE 1.5 MW turbine, which was used in the study by Archer and Jacobson (2007). The GE 1.5 MW turbine has a cut-in speed of 3 m s^{-1} and a cutout speed of 25 m s^{-1}. It achieves its rated power output at 12 m s^{-1}. Between 3 m s^{-1} and 12 m s^{-1} the power output is described by two third-order polynomials:

$$P = \begin{cases} v^3 + 8v^2 - 53v + 60 & if\ \ v \geq 3\ and\ v < 8 \\ -11.25v^3 + 307.5v^2 - 2520v + 6900 & if\ \ v \geq 8\ and\ v < 12 \end{cases} \tag{3}$$

where *P* is power output in (kW) and *v* is wind speed in m s^{-1} (Figure 2).

To evaluate the effect of wind variability on power generated at various scales of aggregation, the WPPs were organized into networks by combining nearest neighbors. For example, if we consider the smallest networks formed by combining two WPPs, there are 85 unique networks. However, there are only 29 unique networks of 100 WPPs. Including the individual sites, there were 7704 unique networks. The area of each network was computed as the area of the convex hull defined by the points, accounting for the spherical shape of the underlying surface.

For each network, wind resource and the wind resource reliability statistics were computed. These included the mean and standard deviation of the wind speeds averaged over the network, the mean, standard deviation, and the capacity factor (the actual power output divided by the rated power output), the distribution of capacity factor fluctuations, and the firm capacity (the amount of power guaranteed to be available, also termed capacity credit) 70%, 80%, and 90% of the time. For example, if a 5000 MW WPP network has a firm capacity of 0.1 at 80% probability, then it can be relied upon for up to 500 MW 80% of the time. These three probabilities were chosen to compare varying degrees of WPP network dependability; they fall within the range of reliability of coal, gas, and nuclear power plants taking into consideration downtime for maintenance (North American Electric Reliability Corporation 2012).

3. Results

The variability of network-averaged wind speed is inversely related to both the number of WPPs in the network and the network area in both January and July (Figure 3). Greater variability during the winter is associated with generally higher winter wind speeds and enhanced synoptic activity as described by Klink (1999) and Coleman and Klink (2009). For the 108 locations considered here, the January mean 80 m wind speed is 6.4 m s^{-1} compared to 4.8 m

s^{-1} during July. We therefore use the coefficient of variation (CV = standard deviation / mean) to describe wind variability. To quantify the strength of the relationships between wind speed and network size and area, we used the nonparameteric Spearman rank correlation, which is defined as the Pearson correlation between the ranked variables (Wilks 2011). Using the ranks rather than the raw data provides an extension of correlation analysis to cases where the relationship is nonlinear. The Spearman rank correlation coefficients (all significant with $p < 0.001$ and shown in Figure 3) suggest that the relationship between network size and variability of network-averaged wind speed are stronger in January than July and stronger as a function of network area relative to the number of WPPs in the network. While most of the reduction of wind speed variance is due to connection of WPPs over relatively small distances (e.g., between individual WPPs and networks with areas of 200,000 km^2 as shown in Figure 3b and Figure 3d) there is no saturation of benefits present at the scales considered in this paper. In other words, increasing the area beyond the bounds presented here would likely result in some additional reduction in variability, albeit small. The variability of wind speeds is lower in the complete 108-WPP network than in any sub-network (Figure 3).

For assessment of wind power reliability via aggregation, it is necessary to consider industry-relevant statistics, such as those described in Section 2. Generation duration curves provide a graphical summary of the effects of aggregation on wind power (Figure 4). The frequency on the x-axis represents the percentage of time that the capacity factor is greater than or equal to the corresponding capacity factor on the y-axis. Note that in both January and July, larger networks have very high capacity factors less frequently, but also are able to provide power more reliably as evidenced by fewer instances with low or zero capacity factors. The generation duration curves have a gentler slope during January as a result of the higher average wind speeds during winter as previously described. Firm capacity improves as the network size increases (Figure 4). For small networks, the 70%, 80%, and 90% firm capacities are near zero; the networks cannot be relied upon for power at these time percentages. The average 70%, 80%, and 90% firm capacities increase with network size reaching maximum values for the 108-WPP network of 15%, 11%, and 7% for January and 6%, 4%, and 3% for July.

The capacity factor exhibits similar network behavior as the underlying wind speeds (Figure 5), with slightly stronger relationships between network size and variability, especially during January. In January, the CV for individual WPPs ranges from 0.94 to 1.39 while the value for the 108-WPP network is 0.70. In July, the numbers are slightly higher, ranging from 1.2 to 2.0 for individual WPPs and decreasing to 0.88 for the 108-WPP network (Figure 5). Like the wind speeds (Figure 3), the rate at which capacity factor variations decrease diminishes with scale.

The advantage of aggregation is also manifest as fewer instances of zero power output. At the site of a single WPP, there is an average of 11.9% and 24.4% of three-hour periods during January and July, respectively, when no power is produced. For networks with ten WPPs, these averages are reduced to 2.6% and 7.1%. For the larger networks, periods when no power is produced account for less than 1% of the observations. For the 108-WPP network, periods with no power disappear altogether.

Lastly, short-term reliability of wind power was improved by aggregation (Figure 6). As the scale of aggregation increases, the magnitude of short-term fluctuations in capacity factor decreases, and the frequency of periods of steady power output increases. For a single WPP (Figure 5a), three-hourly fluctuations in power output greater than 40% of capacity factor are rare, but do occur, while the network containing all 108 WPPs never experienced a fluctuation larger than 40%.

4. Siting new WPPs to maximize the benefits of aggregation

For the benefits of aggregation to be realized, wind power developers must consider the locations of existing WPPs in their development plans. Within a region (e.g. the Midwest ISO), an ideal location for a WPP might be identified as a site with a good wind resource that is distant enough from other WPPs to improve network reliability. The former can be assessed by simply computing the annual average wind speed. The National Renewable Energy Laboratory (NREL 2012) considers 6.9 m s^{-1} (Class 3) to be the minimum annual mean wind speed for a site to be economically feasible for wind energy development. However, recent studies (e.g., Pryor et al. 2012) have reported a potential underestimation of near-surface winds in the NARR data set. We therefore considered the resource to be "poor" if the annual mean wind speed was less than 4.9 m s^{-1}, "fair" if the annual mean wind speed was between 4.9 m s^{-1} and 5.9 m s^{-1} and "good" if the mean annual wind speed exceeded 5.9 m s^{-1}. To categorize the saturation of WPPs in the study area, it was necessary to determine a threshold network area beyond which marginal benefits of network expansion are less pronounced, and then determine a standard distance to measure WPP saturation. Figure 5 suggests that, beyond an area of approximately 200,000 km^2, reduction of the standard deviation of capacity factor is marginal. The mean distance separating WPPs within networks of this size is around 200 km, which was subsequently used as the standard distance for improving WPP reliability within the study area. To reduce saturation to a categorical variable, we classified areas as having high saturation if they were within the standard distance (200 km) of at least six WPPs, low saturation if they were within the standard distance of one to five WPPs, and no saturation if they were within the standard distance of zero WPPs.

The wind resource and saturation information were combined to produce a map of ideal locations for wind power development to improve reliability assuming aggregation within the study area (Figure 6). The map shows that there are vast areas of unexploited wind power potential in the study region, particularly in the Great Plains and over the Great Lakes. We must note, however, that areas with low saturation would likely require greater investments in transmission line expansion than areas with high saturation. These two factors thus present a trade-off in locating new WPPs, with saturation becoming more important as the proportion wind energy on the grid increases.

At present, the likelihood of the implementation of large-scale WPP aggregation within the study region, particularly for large WPP networks, is limited due to the cost of new infrastructure. However, projects designed to improve the power infrastructure and power transfer capabilities in other regions are already underway. For example, the Tres Amigas Electricity Superstation will connect the United States' three isolated power grids: the Eastern, Texas, and Western Interconnections. It will particularly aid in the distribution of renewable energy that is typically generated in rural areas remote from urban load centers (Tres Amigas LLC 2010). As part of the American Recovery and Reinvestment Act of 2009, the federal government allocated \$4.5 billion for electric grid modernization, which was matched with \$5.5 billion from the private sector (White House Press Secretary 2011). Much of that money is being used by ISOs to lay thousands of kms of new transmission lines, and to add sophisticated devices to existing lines that give grid operators more control over the system (Weeks 2010). As the existing power grid is updated and electricity can be more readily shared and transmitted over larger regions, the prospect of large aggregated WPP networks improves. As the U.S. grid is improved, it is foreseeable that in coming decades WPP networks will span beyond the boundaries of any single ISO. If balancing authorities were enlarged and/or merged, this would, in essence, interconnect WPPs so that within the system they will behave as if directly linked. Larger balancing authorities would also provide a greater mix of other energy sources to improve overall system reliability (Dragoon 2010). The results of this study imply that improvements to wind power reliability would continue to accrue if the analysis was extended beyond its current domain (e.g. the Eastern Interconnection) because there was no saturation in benefits identified (see Figures 3 and 5). Further research is required to determine how low the standard deviation of capacity factor must become to achieve various levels of wind penetration (20%, 35%, 50%, etc.). This also depends on the mix of other sources, with peaking power sources such as natural gas and hydropower having greater ability to counterbalance variations in wind power output than nuclear or coal, which are more often used as baseload.

5. Summary

The main objective of this study was to model the effect of aggregating WPPs on the reliability of generated power within a large region of the Midwestern United States corresponding roughly to the United States portion of the Midwest ISO. The data used for the study were wind speed data from the North American Regional Reanalysis (NARR) for 1979-2010 extrapolated to 80 m using the power law to match the hub height of the GE 1.5 MW turbine. Existing WPP locations within the region (n=116) were associated with their nearest NARR grid point (n=108) (see Figure 1) and then the NARR-derived 80 m wind speed data were aggregated into nearest neighbor networks ranging from pairs to a single network containing all 108 WPPs. January and July wind power statistics were calculated from NARR wind speeds and the power curve for the GE 1.5 MW turbine. It was found that, as scale increases, the variability in wind power output diminishes rapidly and continues to diminish at all scales up to and including the largest networks considered here. Wind variability, and therefore the variability of aggregated wind power, is more strongly related to the geographic area of the network than the number of WPPs in the network. The analysis provides support for the findings of previous studies (e.g., Robeson and Shein 1997; Simonsen and Stevens 2004; Archer and Jacobson 2007; Cassola et al. 2008; Milligan et al. 2009; Kempton et al. 2010) and contributes to a growing body of literature on the benefits of wind power aggregation. We additionally identified locations for new WPP development, with the goal of reducing the variability of extracted wind power. These locations, which have an adequate wind resource but are sufficiently distant from existing WPPs to reduce wind power variability across the network of aggregated WPPs, were located primarily across the Northern Great Lakes region and along the western edge of the study area (parts of Nebraska, South Dakota, and North Dakota).

It should be noted that a number of factors influence WPP siting, ranging from site access and the availability of transmission lines with spare capacity to local, state, and federal regulations and policies (Bohn and Lant 2008; Mann et al.). This study has demonstrated that large improvements to wind power reliability are possible through aggregation and has identified locations within the Midwestern USA that could provide further reliability improvements. The potential benefits of aggregation should be considered along with other factors that govern WPP siting decisions. Further research is needed to determine how much reliability improves at larger scales of electrical interconnectivity, such as the Eastern Interconnection or the entire North American system through Tres Amigas.

6. Acknowledgements

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1019620). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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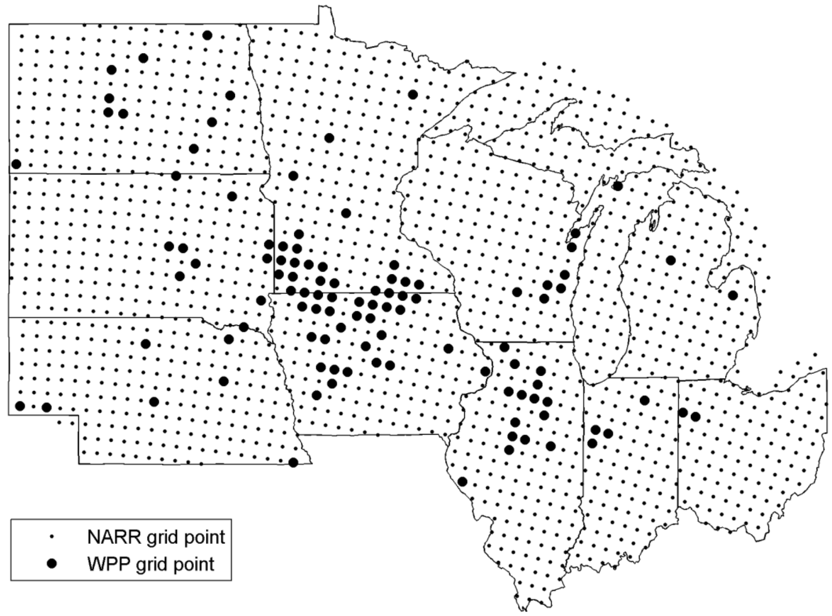

Figure 1. Map of the study area showing the locations of NARR grid points (small dots) and NARR grid points co-located with existing WPPs as larger black dots.

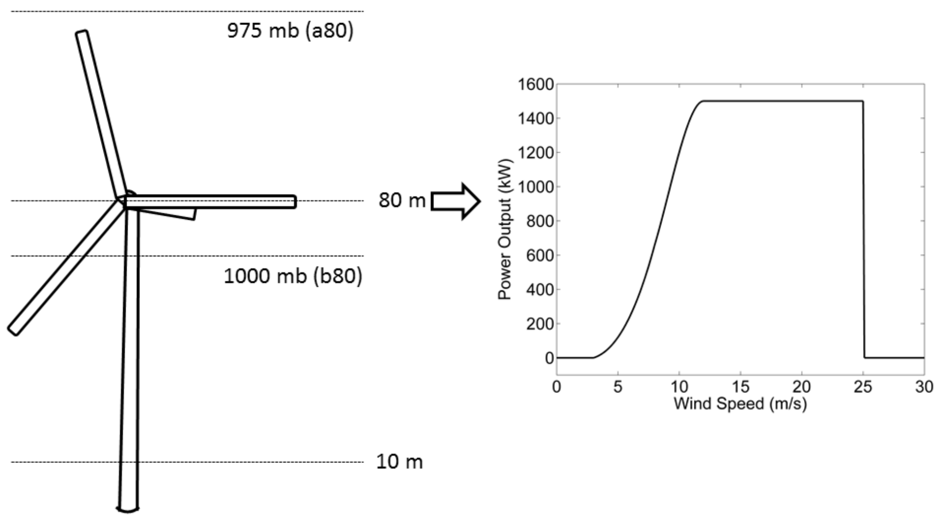

Figure 2. Schematic diagram showing the derivation of 80 m wind power from the nearest vertical layers in the NARR data. In this case, the NARR layer below and closest to 80 m (b80) is 1000 mb and the NARR layer above and closest to 80 m (a80) is 975 mb. At other times, 80 m lies between the 10 m level and the 1000 mb level. These levels are used in Equations 1 and 2 to derive the 80 m wind speed. Wind speed at 80 m is then used with the power curve (Equation 3) for the GE 1.5 MW turbine (right) to derive 80 meter wind power.

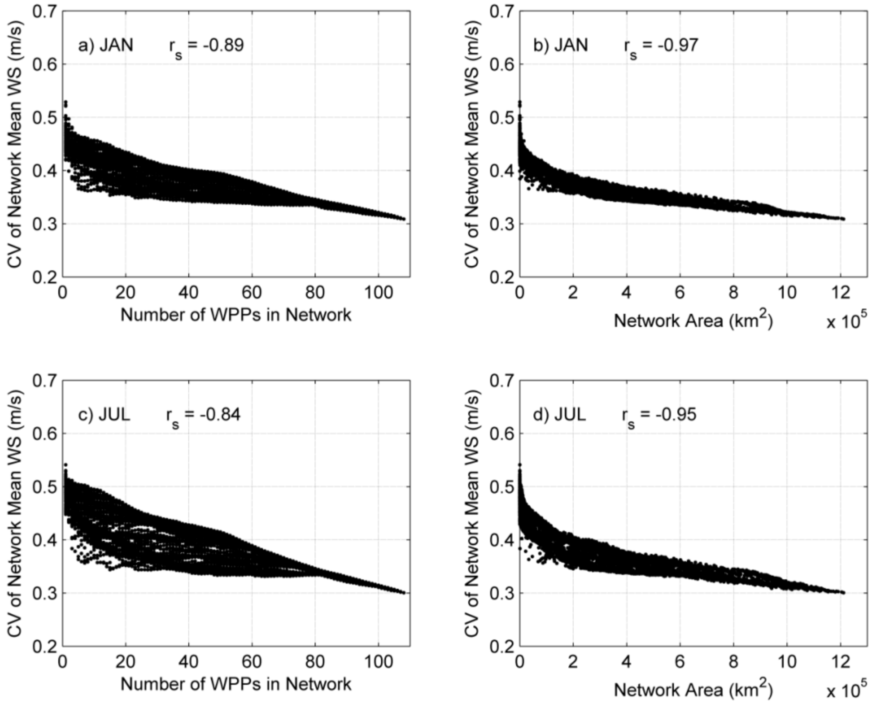

Figure 3. The coefficient of variation (CV) of network-averaged wind speed for January (a and b; top) and July (c and d; bottom). The CV is presented as a function of the number of WPPs in the network (a and c; left) and the network area (b and d; right). Also shown are the Spearman rank correlation coefficients (r_s), which are significant with α=0.01.

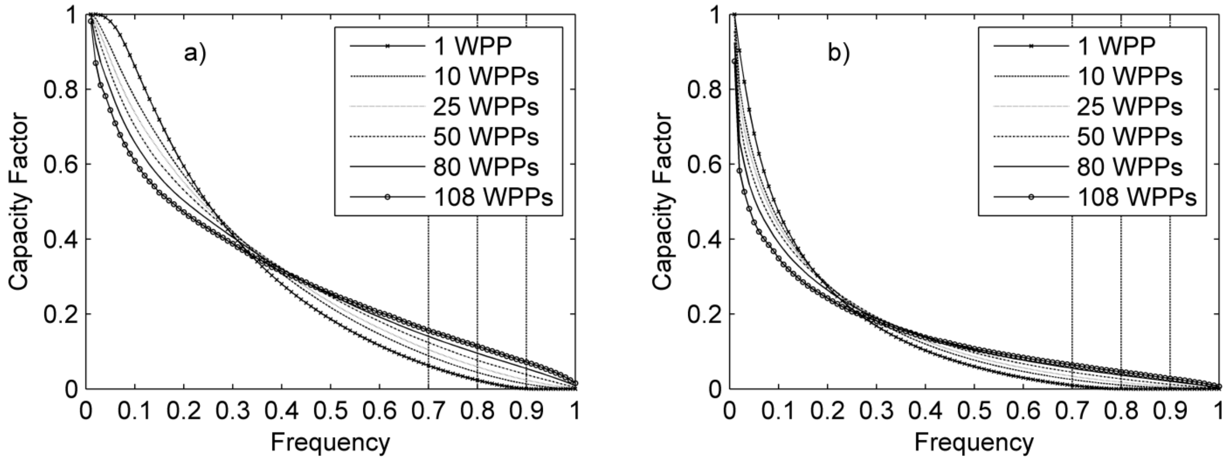

Figure 4. Generation duration curves for WPP networks during a) January and b) July. Points on the x-axis represent the percentage of hours in a year that capacity factor is greater than or equal to the value at the corresponding point on the y-axis. Areas between curves represent the difference in power production characteristics among different-sized networks. The firm capacities at 70%, 80%, and 90% can be determined by following the vertical lines at 0.7, 0.8, and 0.9, respectively, to the y-axis.

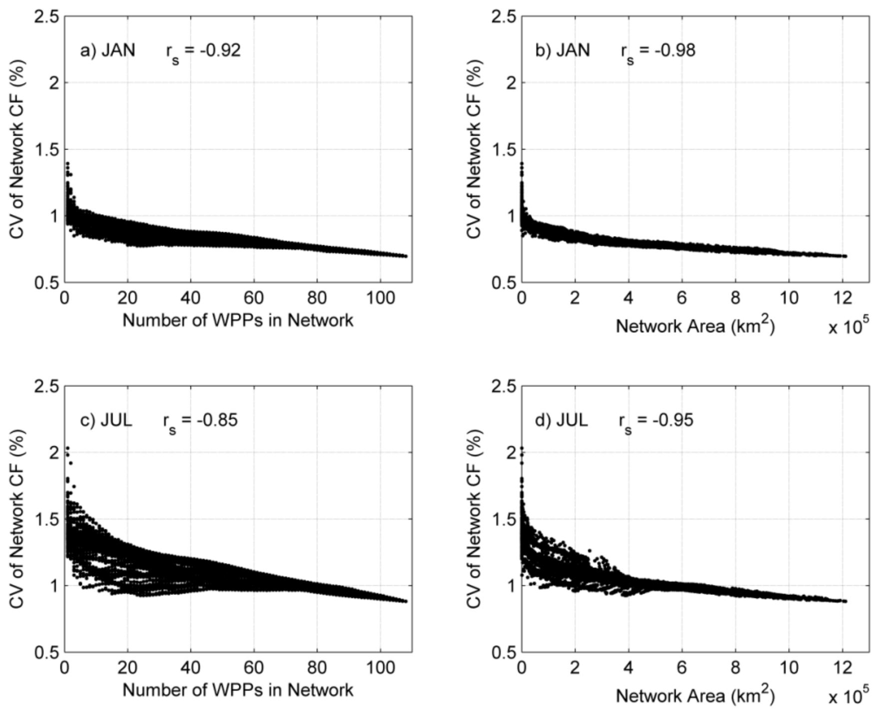

Figure 5. The coefficient of variation (CV) of network capacity factor (CF) for January (a and b; top) and July (c and d; bottom). The CV is presented as a function of the number of WPPs in the network (a and c; left) and the network area (b and d; right). Also shown are the Spearman rank correlation coefficients (r_s), which are significant with α=0.01.

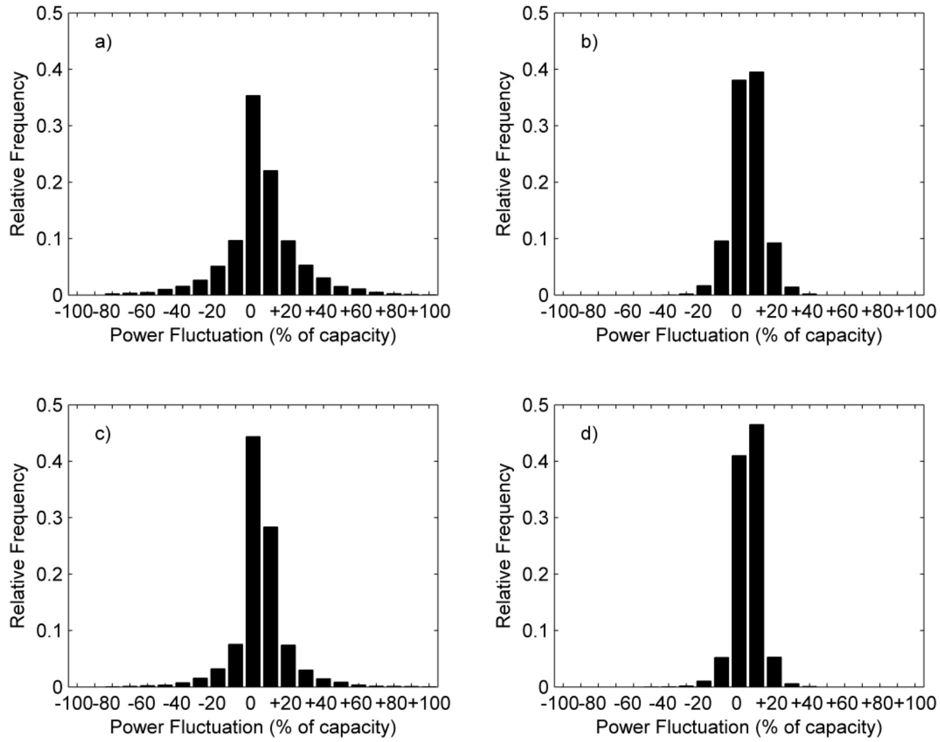

Figure 6. Short term (three-hourly) power fluctuations from individual WPPs in January (a) and July (c) compared to those from the 108-WPP network (b, d). Variability of power output for the 108-WPP is markedly reduced.

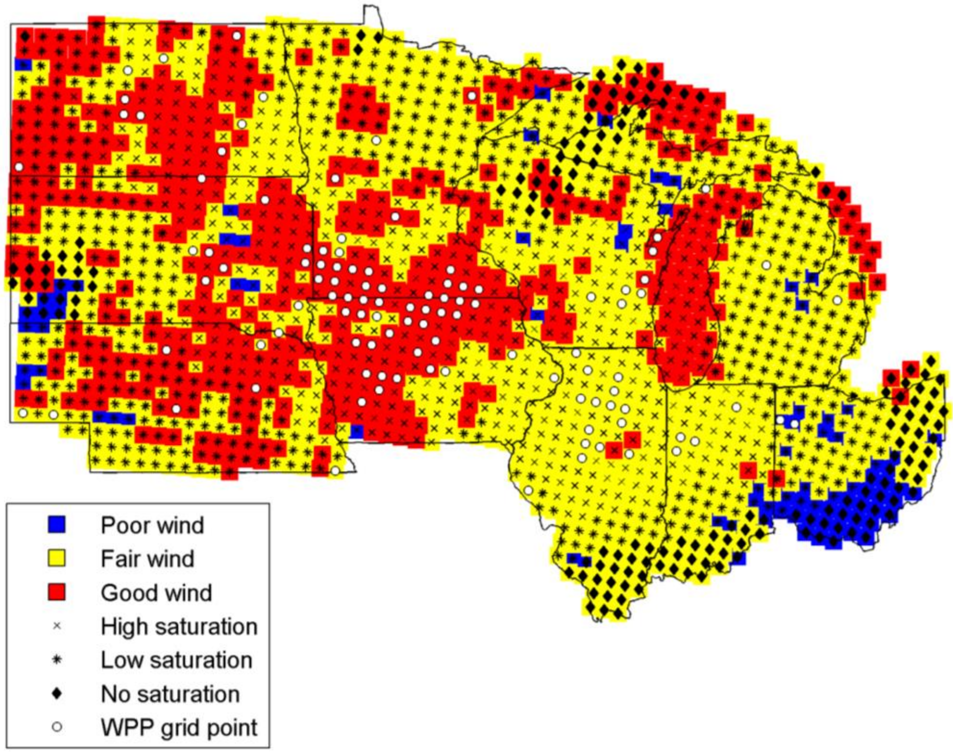

Figure 7. Map of the study area categorizing NARR grid points based on mean annual wind speed and proximity to existing WPPs. Mean annual wind speed must be less than 4.9 m s^{-1} to be classified as “poor,” between 4.9 and 5.9 m s^{-1} to be “fair,” and greater than 5.9 m s^{-1} to be “good.” Grid points must be within 200 km of six or more WPPs or contain a WPP to be classified as having “high saturation,” one to five WPPs to have “low saturation,” and zero WPPs to have “no saturation.” Grid points with good wind and no saturation are the optimal locations for future wind power development if reduction of wind power variability is the goal.