IMPROVING THE RELIABILITY OF WIND POWER THROUGH SPATIALLY DISTRIBUTED WIND GENERATION

by

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B.S., Eastern Illinois University, 2010

A Thesis
Submitted in Partial Fulfillment of the Requirements for the
Master of Science.

Department of Geography & Environmental Resources
in the Graduate School
Southern Illinois University Carbondale
August 2012

THESIS APPROVAL

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in the field of

Geography & Environmental Resources

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July 3, 2012

AN ABSTRACT OF THE THESIS OF

SAMUEL MARTIN FISHER, for the Master's of Science degree in GEOGRAPHY & ENVIRONMENTAL RESOURCES, presented on May 10, 2012, at Southern Illinois University Carbondale.

TITLE: IMPROVING THE RELIABILITY OF WIND POWER THROUGH SPATIALLY DISTRIBUTED WIND GENERATION

MAJOR PROFESSOR: Dr. Justin Schoof

Wind power is a fast-growing, sustainable energy source. However, the problem of wind variability as it relates to wind power reliability is an obstacle to its large-scale deployment. It is possible to improve the reliability of wind power by interconnecting wind generation. In this study, wind power plants within the Midwest ISO were aggregated to examine the effect on reliability. Wind speed data from the North American Regional Reanalysis were used to calculate wind power data. It was found that the reliability of interconnected wind power was improved relative to individual wind power plants in both the short-term and the long-term, and that the most significant improvements were at the highest scales of interconnection. It was also found that the reliability of interconnected wind power is more directly related to the area of the network rather than the number of wind power plants in the network.

DEDICATION

I would like to dedicate this thesis to my parents, Dennis and Marie. I thank them for encouraging and nourishing my interest in science from a young age, and for their constant support during periods of self-doubt. I would also like to dedicate this thesis to my brother, Andrew, who has been my best friend since I was three years old. Thank you for all your love and support.

ACKNOWLEDGMENTS

First and foremost, I would like to thank Dr. Justin Schoof for all of his guidance, indispensable expertise, and time spent helping to shape and realize this thesis. This research would not exist without him.

I would also like to thank Dr. Matthew Therrell for his valuable insight, Dr. Leslie Duram for making sure the project got off the ground, and Dr. Christopher Lant for providing the inspiration for this thesis.

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CHAPTER 1

INTRODUCTION

1.1 Background

The objective of this study is to determine the extent to which the geographic dispersal of wind power plants (WPPs) can mitigate the effects of wind variability on power generation. Wind is an ideal source of energy because it is clean and renewable, but its spatial and temporal variability, and the resulting variability of wind-derived power generation is a major impediment to the large-scale deployment of WPPs (DeCarolis and Keith 2005; Kempton et al. 2010). Overcoming the problem will lead to faster large-scale deployment of WPPs and earlier mitigation of environmental impacts associated with non-renewable energy sources.

The question of how to satisfy our growing energy demand is central to many of the most pressing issues facing humanity. Coal, oil, and natural gas supplies, the dominant power sources, are finite and have been drastically depleted in the last century (Heinberg and Fridley 2010). Beyond the fact that fossil fuels are nonrenewable, burning them to generate energy releases carbon compounds and a host of toxic chemicals into the atmosphere. Coal is the second most widely consumed fossil fuel after crude oil and the largest single source for electricity generation. It provides 41% of worldwide electricity generation and half of electricity generation within the U.S. (Shindell and Faluvegi 2010). Carbon dioxide, the principal gas released during fossil fuel combustion, is a greenhouse gas. Increasing energy demands have led to the burning of fossil fuels at such a rate that humans have increased the concentration of carbon dioxide in the atmosphere by over 30% since the start of the Industrial Revolution, reaching levels higher than any in the last 650,000 years (IPCC 2007). Climate scientists believe with greater than 90% certainty that most of the observed global warming over the last 50 years is the result of anthropogenic emissions of greenhouse gases, mainly carbon dioxide. Further, there is greater than 90% certainty that the 21st century will be even warmer than the 20th century if greenhouse gas emissions continue at current rates or accelerate (IPCC 2007).

Wind power is a renewable energy source derived from the natural movement of air in the atmosphere. Global wind energy potential is an estimated 72 TW, far greater than the energy needs of humanity (Kempton et al. 2010). The U.S. is in the midst of a rapid growth in installed wind capacity (Constantinescu et al. 2011; Mann et al. 2011). A number of factors are behind this rapid growth, including the Federal Production Tax Credit, state renewable portfolio standards, as well as the inherent economic and environmental advantages of wind power (Smith et al. 2007). Manufacturing, fabrication, transportation and eventual disassembly and disposal of the turbines account for some carbon emissions, but the actual generation of electricity from wind is 100% clean. A significant economic advantage of wind power is that, unlike fossil fuels or nuclear power, the "fuel" that contains the energy does not require transport, and can be withdrawn as needed. Wind is not a physical commodity susceptible to price fluctuations. It does not require the large volumes of water necessary to run thermoelectric generators. Further, wind power does not require large swaths of land to be sacrificed to energy production. Only 1 - 5% of the land in an array of turbines is physically occupied by actual turbines and infrastructure (Wiltshire and Prose 1987). Many WPPs are actually on farmland, generating power amongst agricultural fields. Beyond its environmental benefits, wind energy promotes energy independence, domestic economic growth, national security, and diversifies the U.S. energy portfolio.

While the advantages of wind power are numerous, it does have some drawbacks. Because of the bold visual impact an array of turbines has on the landscape, many people are opposed to wind power development near where they live, or areas of aesthetic value (Pasqualetti 2000). There is also concern about blade noise and shadow flicker (Wolsink 2007). Ecologists note the increased level of bat and avian mortalities around WPPs (Cryan and Barclay 2009). The above-mentioned problems can be addressed through close cooperation among wind energy developers and local communities, government and private landowners (Pasqualetti 2000), and ecologists (Cryan and Barclay 2009). The high cost of electricity transmission is another challenge for wind power. Within the United States, areas with the greatest potential for wind power generation are often great distances from urban load centers, meaning that costly infrastructure would need to be built to distribute the electricity to areas with the greatest demand. The final drawback, and the focus of this study, is that wind is variable; that is, winds speeds fluctuate, reducing the reliability of electricity generated using wind power.

1.2 Problem Statement

This study focuses on assessing the geographic distribution of WPPs as a means to mitigate the effects of wind variability on power generation. The variability of wind power poses a significant challenge to renewable energy developers. At the site of a single turbine, temporal variability of wind is high, but when distributed over an entire array of turbines, it is lower. The larger the area, the less variable the average wind speed will be (Archer and Jacobson 2007). Therefore, as WPPs are geographically distributed and connected, fluctuations in the power output are smoothed, and the reliability of power output is improved (Holttinen and

Hirvonen 2005).

The U. S. electric grid is organized as a patchwork of independent service operators (ISOs) and regional transmission organizations (RTOs) that oversee the distribution of power within their boundaries. ISOs and RTOs are composed of a patchwork of balancing authorities, that actually match generation to demand. The balancing authorities within an ISO do not aggregate their generation capacity, meaning that WPPs located in one balancing authority are effectively isolated from neighboring balancing authorities. Often the area covered by an ISO is referred to by the name of the ISO, so that the governing body and the area itself are interchangeable. Previous studies have addressed geographic dispersion as a means of reducing the effect of wind variability on power generation using multi-state study areas (Simonsen and Stevens 2004, Archer and Jacobson 2007, Kempton et al. 2010), but there has not been a study that analyzes the effects of geographic dispersion and interconnection of WPPs within an entire ISO/RTO. This study will examine the effects of connecting WPPs on power generation within the U.S. component of the Midwest ISO (see Figure 1.1).

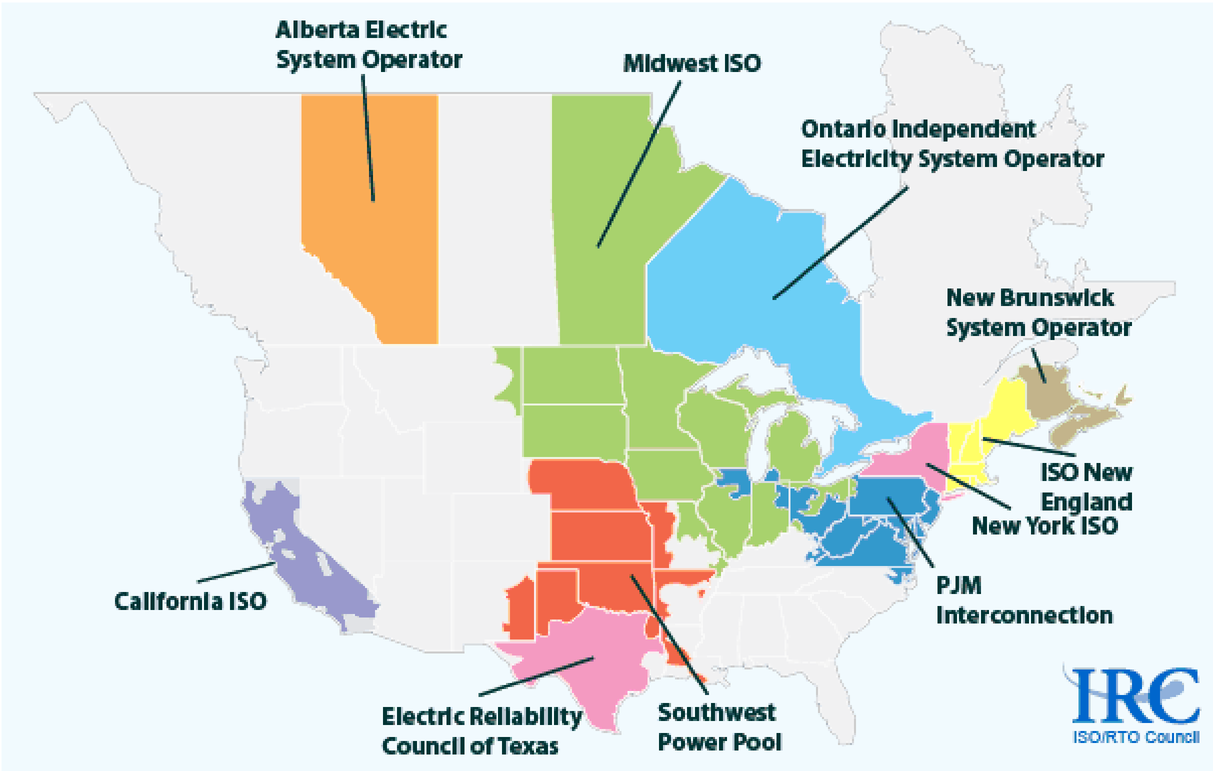

Figure 1.1. Map showing the regional transmission organizations (RTOs) and independent system operators (ISOs) of North America (ISO/RTO Council 2011). Areas within each RTO or ISO belong to a common electric grid, and allow for easy transfer of power within their boundaries. This study focuses on Illinois, Indiana, Iowa, Michigan, Minnesota, North Dakota, Ohio, South Dakota, and Wisconsin, the states covered by the Midwest ISO.

The analyses presented herein are focused on wind power during the months of January and July. January and July were chosen because they are at the extremes of electricity consumption due to heating (January) and cooling (July)(EIA 2011). Moreover, the difference in weather patterns in January and July represent the winter and summer circulation patterns in the Midwest (Coleman and Klink 2009). Further work applying the same methods to every month is planned for the future. Specific attention is given to comparing different metrics of aggregation, specifically the relationships between the reliability of wind and power and both the number of connected WPPs in the network and the area of the network, an approach that has not yet been utilized. Archer and Jacobson (2007) based their analysis on the number of WPPs in a connected network, and Kempton et al. (2010) focused on distance between WPPs along the Eastern Seaboard, but neither examined the relationship between network area and variability of power generation.

1.3 Research Questions

This study aims to characterize the effect of the interconnection of WPPs on the variability and reliability of generated power. Specifically, the following research questions are addressed:

1) *What is the effect of interconnecting WPPs on the variability of generated power within the Midwest ISO?* It is already known that the reliability of wind power is improved when WPPs are interconnected (Khan 1979; Robeson and Shein 1997; Simonsen and Stevens 2004; Archer and Jacobson 2007; Cassola et al. 2008; Milligan et al. 2009; Kempton et al. 2010), but the effect of interconnection on wind power reliability within the entire Midwest ISO (or any ISO or RTO) has never been studied. It is vital to understand the effect of interconnection on wind generated electricity within the Midwest ISO because it covers a region of large population centers and significant wind resources, particularly in the west (NREL 2012), and contains over 100 WPPs of 10 MW capacity or higher (The Wind Power 2011). Three reliability metrics will be employed to answer this question: standard deviation of power produced, % of time with zero power produced, and firm capacity (see section 3.4).

2) *Is the number of sites in a network or the area of the network more directly related to the variability of interconnected wind power?* The answer to this research question will inform the

planners of any future WPP network so that the maximum reliability of the network can be realized. The same reliability metrics employed to address the first research question were used here. Statistics were generated based on both network characteristics and then compared to determine whether the number of connected sites in the network or network area was more important to reliability.

1.4 Significance of the Study

The need for clean, renewable sources of energy like wind power will increase as energy consumption increases in the U.S. and the rest of the world (Keay 2007). Ramping up coal, oil, natural gas and nuclear power production would exacerbate ongoing environmental effects related to power production, such as climate change and mining-related landscape degradation, as well as cause increased reliance on fuels whose prices are subject to fluctuation. The expansion of wind power would help alleviate those problems. Wind turbines have a minimal impact on the environment, and generate energy while releasing zero greenhouse gases during their operating lifespan (Pasqualetti 2000). Variability of generated power from the wind resource has been frequently cited as a limitation to further expansion of wind power (Milligan et al. 2009).

There has yet to be a study that examines the effects of interconnection on the reliability of wind power over an entire ISO. The results of this study will serve as the basis for further, more exhaustive analyses of wind interconnection. This study is valuable because as the need for renewable power sources like wind increases, the challenge of improving the reliability of wind power must to be addressed. Because this study utilizes a data set with high spatial and temporal resolution, the North American Regional Reanalysis (NARR) (Mesinger et al. 2006), that has not been widely applied to study wind power, it offers an unprecedented opportunity to conduct an analysis of the potential improvements of wind power in the United States, and allows for an updated method for implementing the power law for the vertical extrapolation of wind speed that reduces the potential for extrapolation error. The NARR data are utilized to produce an 80 m wind speed map of the Midwest ISO. The results of the analysis are used to produce a map showing optimal locations for new WPPs to maximize wind power reliability through interconnection. This study is useful to utilities and grid operators for planning new wind transmission and interconnection infrastructure, and offers new insights into the geography of wind energy.

1.5 Description of Chapters

The remainder of this study is organized into four chapters. Chapter 2 provides a survey of literature on the conventional energy sources, wind power meteorology, methods for vertical extrapolation of wind speeds, spatial aspects of wind power, and wind power integration. Chapter 3 provides a description of the study design, the study area, the data used for the analyses, and a description of methods. The results of the analyses are presented in Chapter 4, with further discussion and summarization in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Energy Challenges

The main driver of wind power development in the U.S. is the Federal Production Tax Credit (Smith et al. 2007), which was conceived as a response to environmental concerns of carbon dioxide emissions and global warming. Armaroli and Balzani (2006) published a study that surveyed the major energy sources of coal, oil, natural gas, and nuclear power, as well as renewables, and provided an analysis of the environmental and economic costs of each energy source. They point out that the most easily accessible fossil fuel reserves are being depleted, necessitating the exploitation of more environmentally damaging reserves, like shale gas and coal recovered through mountain-top-removal.

Nuclear energy is the second largest generator of power worldwide after coal, accounting for 15% of global generation, and contributes dramatically less carbon emissions per unit of power generated, almost zero (Sovacool and Cooper 2008). However, nuclear power has major drawbacks. The exorbitant cost required to insure a nuclear power plant means that nuclear energy has been heavily subsidized in the United States. The Price-Anderson Act sets a cap of $200 million on the cost of private insurance. In the case of nuclear power, the extra liability required is provided by American taxpayers. Some observers question whether any nuclear power plants would ever have been built in the U.S. without taxpayer support (Armaroli and Balzani 2006). Beyond the cost, serious safety factors must be considered if nuclear power is to be expanded. There is a small, though omnipresent risk of a reactor meltdown like the catastrophe at Chernobyl in the Ukraine in 1986, or the Fukushima disaster in 2011.

The continuing use of coal as a major energy source is largely due to the perceived low cost of coal power. Coal power is the largest single source of electricity worldwide, accounting for 41% of all electricity generated, and half of the electricity generated in the U.S (Shindell and Faluvegi 2010). There is a movement to try to mitigate the negative effects of coal burning by capturing the carbon emissions underground, a technology called carbon sequestration. This technique and other "clean coal" technologies face a host of environmental, technical, economical, and political obstacles. The scope of the challenges facing clean coal technologies strongly suggests that it will not become a viable large-scale energy source (Ehlig-Economides and Economides 2010).

Jacobson and Masters (2001) demonstrated that coal power is not the cheapest source of energy, and is in fact more expensive than wind power when all externalities are taken into account. For a coal power plant, energy costs are low, only 3.5 - 4 cents per kilowatt hour (kWh). When health and environmental costs are added to that figure, including the federal black-lung disease benefits program that has cost $35 billion since 1973, the actual cost of coal energy is 5.5 - 8.3 cents/kWh. Even without the health and environmental costs factored in, wind power is competitive with existing coal power. When turbine manufacture and scrapping costs are considered, the average energy costs of a large wind turbine equates to 3 - 4 cents/kWh (Jacobson and Masters 2001). Because the capacity factor of wind power (proportion of nameplate capacity that the WPP is producing at any given moment) can be estimated at about 30 - 35% of nameplate capacity, a third of wind generation can be used as baseload power, while the remaining energy can be used for powering batteries in electric cars or other uses (Archer and Jacobson 2007). Wind power can therefore be considered a future energy source of tremendous importance. A role of this study is to gain knowledge that will make large-scale wind energy more economically feasible.

2.2 Wind Power Meteorology

Because this study deals with the spatial relationships of wind speed as it relates to power production, it is important to understand the factors that affect wind power, and the science of maximizing wind power potential. Wind power meteorology is a relatively new subfield of atmospheric science that brings together aspects of meteorology, climatology, and physical geography. Most research is conducted within the atmospheric boundary layer, the layer of air adjacent to the earth's surface. The thickness of the layer fluctuates diurnally and based on wind conditions. It ranges from about 100 m above the surface on a clear night with low wind speeds, to 2 km above ground in the middle of a summer day. The surface layer, referring to the bottom 10% of the atmospheric boundary layer, is of primary concern for harnessing wind energy because the logarithmic law for the wind profile (the linear relationship between wind speed and logarithm of height) only applies there (Petersen et al. 1998).

The variability of wind speed as it relates to wind power output is of central importance to this study. Figures 2.1a and 2.1b illustrate the high variability of wind generation at a single site. In the two-week period shown, fluctuations of capacity factor greater than 0.5 are not uncommon, nor are extended episodes of zero power output. In one instance capacity factor drops from 1 to under 0.2 in a three-hour span. The average capacity factor of the site over the entire two-week period is 0.31, which is nearly equal to January mean wind speed for all WPP sites in the MISO (see Table 4.1). The rapid transition between times of peak output and zero output is likely related to the passage of synoptic-scale weather systems, which generally pass every few days in the mid-latitudes during winter.

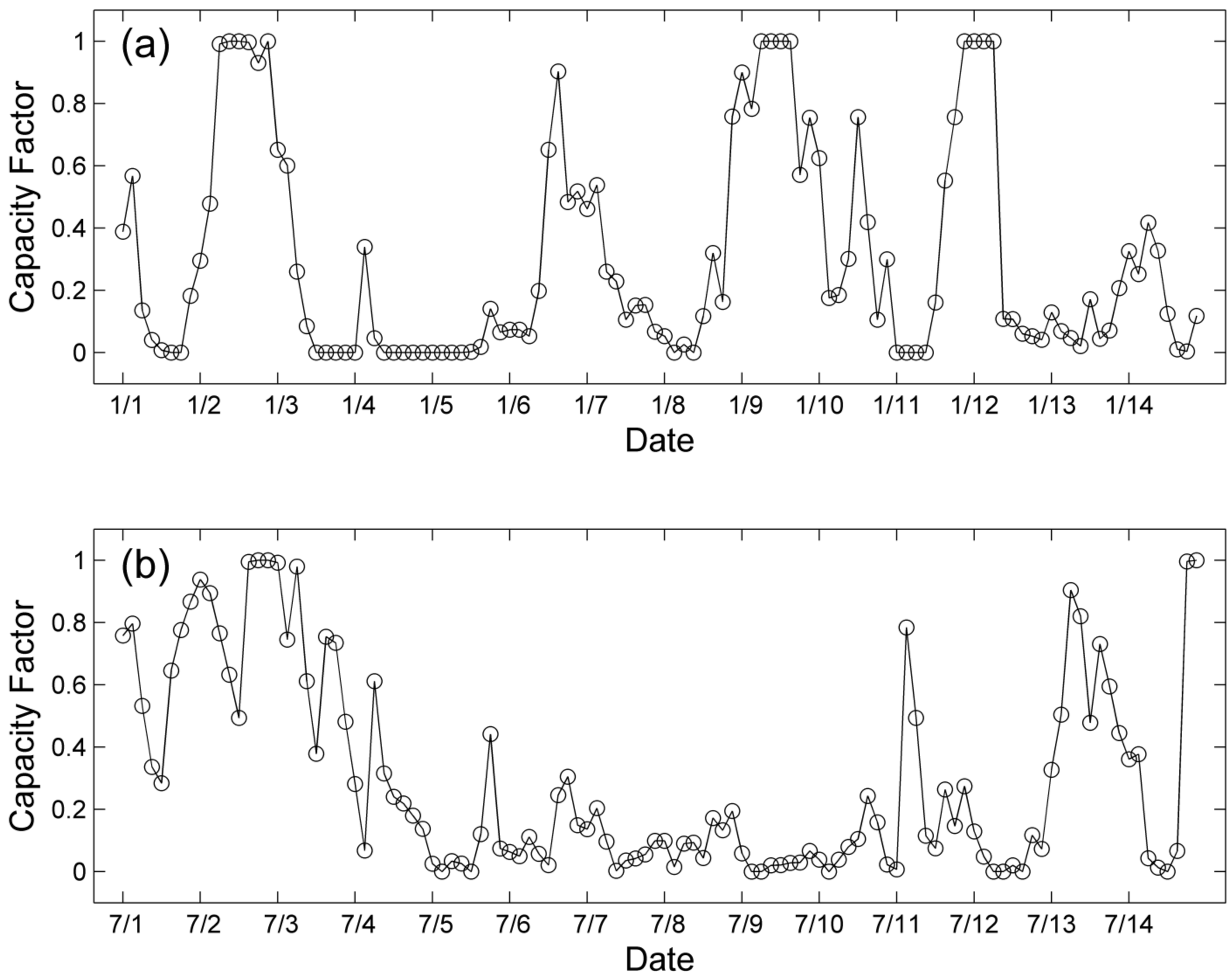

Figure 2.1. (a) Capacity factor of a single GE 1.5 turbine at 47.4861 N, 101.1729 W in central North Dakota, based on wind speed data from the NARR data set. The site was chosen because its January mean wind speed was closest to the January mean of all sites in the study area. The two-week period shown is from January 1, 2010 to January 14, 2010, and the data are divided into three-hour intervals. (b) Same as Figure 2.1a, but the two-week period shown is from July 1, 2010 to July 14, 2010.

For instance, on January 2, 2010 a mid-latitude cyclone was passing over central North Dakota, causing strong winds and high wind power output. By the next day the cyclone had passed the site, and for the next couple of days power output was minimal. Mid-latitude cyclones do not explain all of the wind patterns during the winter months, but play an important role in determining periods of significant wind power output. Figure 2.1b differs from Figure 2.1a in that there is a lack of an obvious synoptic-scale cycle, and an average capacity factor that is visibly lower in July. The more northerly position of the jet stream over North America during summer, and relative weakness compared to that of the winter jet stream leads to diminished cyclonic activity in the U.S. (Coleman and Klink 2009), which helps explain the lower mean wind speed and lack of synoptically-induced variability in the July period, as discussed in section 4.2 (see Figure 2.1b and 4.5, and Tables 4.3 and 4.4).

The natural variability of wind affects the variability of wind generation on all time scales. On a second-to-second time scale, variations are largely smoothed out because of the inertia of the turbine blade. A single turbine's output can vary from second-to-second up to 7% of capacity in extreme cases. However, most of the time these variations are not significant, and are negligible when an entire WPP is considered (Petersen et al. 1998). Hourly variations can reach 30% of capacity in extreme cases in Denmark, but these decrease as the area considered increases. On average hourly variations are 5% of the capacity (Holttinen and Hirvonen 2005). This study looks at how three-hourly variations (finest temporal resolution afforded by the data set) in capacity are affected by WPP interconnection.

Perhaps the most important function of wind power meteorology is the short-term prediction of wind power potential, from seconds to days ahead. Prediction systems usually consist of a numerical weather prediction (NWP) model output, input of observations, a model, and the output (Landberg et al. 2003). The output of a prediction system consists of estimated energy production of the WPP, normally in hourly or three-hourly steps from 0 to 48 hours into the future, along with an estimate of the error of each prediction, represented as standard deviation or confidence intervals. Power system operators rely most heavily on predictions for a few minutes to hours in the future (Dragoon 2010). Also relevant to power system operators is the probability distribution of power output, the range of the distribution, and seasonal and diurnal patterns of the generation. (Holttinen and Hirvonen 2005).

The Western Wind and Solar Integration Study found that weather forecast error causes the most serious challenges for grid operators (GE Energy 2010a), and the Eastern Wind and Transmission Study found that the average cost attributable to forecast error is $2.57 (in 2024 dollars) per MW/hour of wind power generated. In a scenario with 20% wind penetration nationwide, improved forecasts could save up to $2.1 billion in wind integration costs annually (EnerNex 2010). The need for wind power prediction as a result of wind variability. Predicting wind at the meso-scale (local to regional) is a difficult and computationally intensive endeavor that is limited by the chaotic processes that are fundamental to weather. However, the theoretical limit of forecast technology has yet to be reached.

Continuing advancements in computer technology and data compiling allow for increasing accuracy of wind forecasting (Dragoon 2010), as seen in the recent partnership between the National Center for Atmospheric Research (NCAR) and Xcel Energy, which serves customers in Colorado, New Mexico, Texas, and the Upper Midwest. In 2009, NCAR began developing improvements to Xcel's wind prediction system, saving the company $6 million in 2010 (UCAR 2011). Accurately predicting power potential for a WPP allows grid managers to plan the dispatch of baseload power, and to take full advantage of generated wind power (Landberg et al. 2003; Giebel 2003). Cutting-edge forecasting has been shown to provide 80% of the benefits that, in retrospect, perfect forecasting would have provided (GE Energy 2005).

One way to reduce forecasting error is to increase the size of the area served by the forecast (Milligan et al. 2009; Marquis et al. 2011), a benefit similar to the improvement in reliability caused by interconnection of WPPs, the focus of this study.

2.3 Extrapolation of Wind Speeds

Wind speed measurements are not routinely collected at the standard hub height of modern wind turbines (80 m). Therefore, wind speeds must be extrapolated up to turbine hub height in order to be useful to studies concerning wind energy. Two commonly used methods for extrapolating wind speed data are the logarithmic law method and the power law method (Petersen et al. 1997; Robeson and Shein 1997; Archer and Jacobson 2003; Ray et al. 2006). The logarithmic law is given:

$$u_2 = u_1 \frac{\ln(z_2/z_0)}{\ln(z_1/z_0)}$$

where u_1 and u_2 are wind speeds (m/s) at heights z_1 and z_2 (m), and z_0 (m) is roughness length, a measure of surface roughness (Oke 1987). It assumes neutral atmospheric stability where buoyancy is unimportant. In unstable conditions, heating of the surface and robust vertical mixing reduce the vertical wind speed gradient, while cooling at the surface and stifled vertical mixing amplify the vertical wind speed gradient in stable conditions (Petersen et al. 1997). Because the equation for logarithmic wind speed increase requires a specific value for roughness length, the method is flawed for extrapolating wind speeds over large areas with varying roughness lengths. The differing roughness lengths between a forest and agricultural land, or hilly land and flat land makes a significant difference in the value of u_2.

The power law is another method for extrapolating wind speed (Petersen et al. 1997; Robeson and Shein 1997; Archer and Jacobson 2003), and is given:

$$u_2 = u_1 \left(\frac{z_2}{z_1}\right)^{\alpha}$$

where u_1 and u_2 are wind speeds (m/s) at heights z_1 and z_2 (m), and α is the roughness exponent, typically (1/7)(Arya 1988). Like the logarithmic law, the power law is dependent on a roughness variable that varies widely over large areas. Although it lacks the theoretical basis of the logarithmic law, the power law does describe observed wind profiles with an acceptable level of accuracy (Archer and Jacobson 2003). Musgrove (2010) provides estimates of the power law's roughness exponent for various landscapes: $\alpha \approx 0.1$ over the sea; $\alpha \approx 0.14$ for open countryside; $\alpha \approx 0.24$ for open countryside with scattered hedges and trees; and $\alpha \geq 0.3$ for urban areas. Because both of the above methods require just a single constant parameter, they are simple to apply, and provide an approximation of the vertical wind speed profile.

The wind speed data used in this study had to be vertically extrapolated to 80 m. It was determined that the power law was most applicable, due to the necessary assumption of neutral atmospheric stability for the logarithmic law. While the power law is only a method of approximating wind speed at different altitudes, the pressure level data employed in this study (Mesinger et al. 2006) allow for a decreased extrapolation distance, potentially mitigating a source of error.

2.4 Spatial Aspects of Wind Power

Literature addressing the relationship between space and wind power is of vital importance to this study. Studies indicate that spatially distributed WPP networks are more reliable than isolated individual WPPs, which provides the context for the first research question. Archer and Jacobson (2003) analyzed surface measurements for the year 2000 at 1327 weather stations and sounding measurements from 87 stations from the National Climatic Data Center and found that 24% of the U.S. has economically viable wind energy potential, meaning that these areas have mean annual wind speeds of 6.9 m/s or greater at a height of 80 m (NREL 2012). The objective was to determine if a large network of WPPs could provide a reliable and steady source of power. It was found that standard deviation of wind speeds was always less when averaged over multiple locations than when taken at any individual location. In an eight-station area, stretching across parts of New Mexico, Texas, and Oklahoma, 550 × 700 km, the average 80 m wind speed never fell below 3 m/s, which is significant because 3 m/s is the cut-in speed of the GE 1.5MW turbine used in this study.

Robeson and Shein (1997) analyzed wind speed data from the Solar and Meteorological Surface Observation Network, consisting of hourly measurements at 37 stations from 1961 - 1990 in Illinois, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin, in an effort to evaluate the spatial variability of wind resources in the study area, and also to assess the effectiveness of methods for the spatial analysis of wind. It was found that the distance-decay relationship of wind speeds lack coherence on an annual scale. Monthly wind speeds are more spatially coherent, but it was at the daily and hourly scales that wind speed correlations decreased predictably with distance (Figure 2.2).

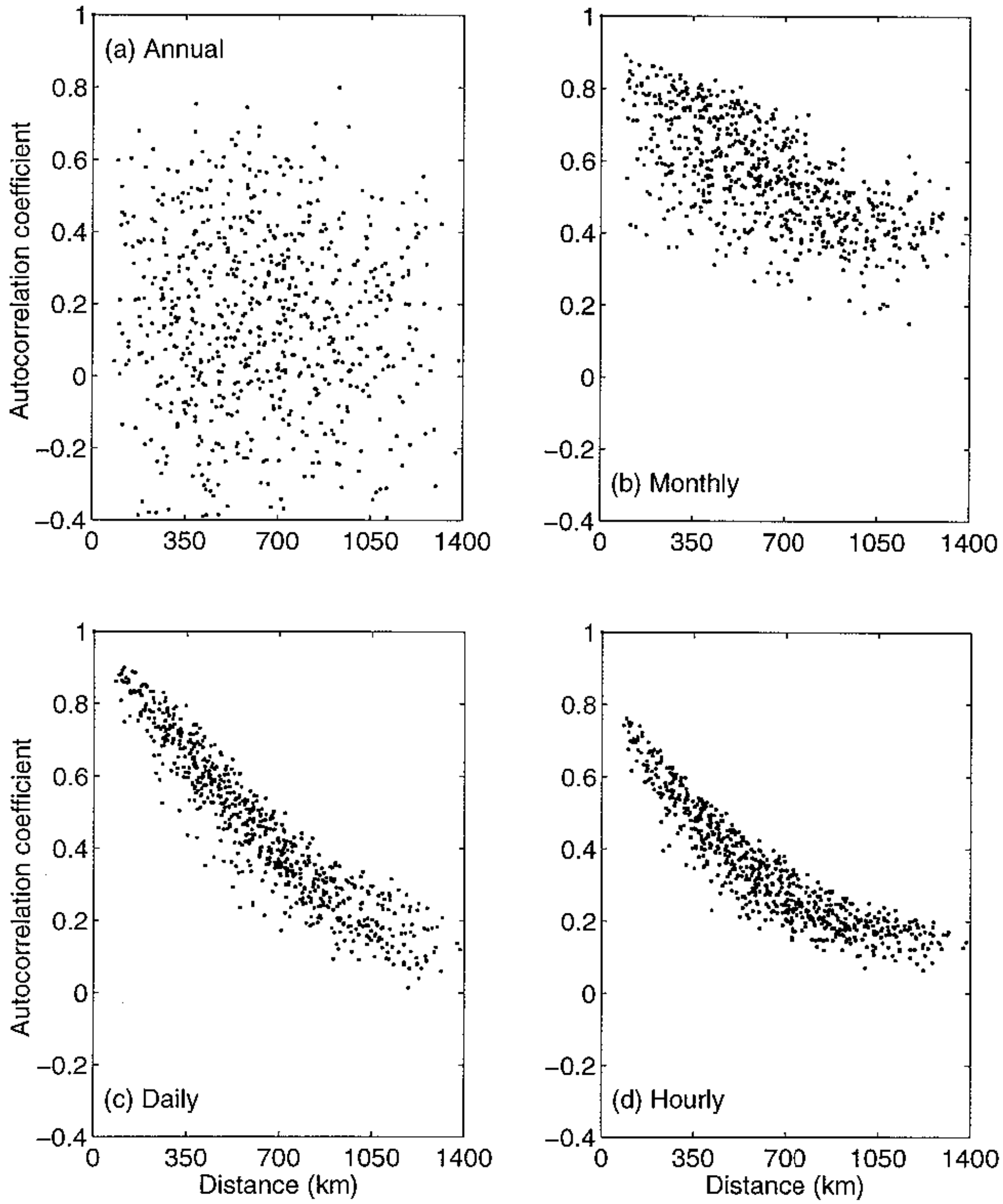

Figure 2.2. Spatial autocorrelation functions for (a) annual, (b) monthly, (c) daily, and (d) hourly wind speeds for the 37 stations over the period 1961 to 1990. The daily and hourly data show the greatest spatial coherence; however, much of this coherence is caused by nonstationarities in the data (e.g., diurnal and annual cycles)(Robeson and Shein 1997). Reprinted with permission from *Physical Geography*, 1997, 18, 6, pp. 487. ©Bellwether Publishing, Ltd. All rights reserved.

This is important because minute-to-minute and hour-to-hour are the time scales in which WPPs are able to balance one another's power generation, and because it reinforces the concept of interconnection of WPPs as a method of improving reliability.

In regards to reliability, it has been universally found that interconnecting WPPs reduces the variability of power output (Khan 1979, Simonsen and Stevens 2004, Archer and Jacobson 2007, Kempton et al. 2010). Reliability for interconnected WPPs increases as separation distance increases (Kempton et al. 2010) and as the number of WPPs in the interconnection increases (Archer and Jacobson 2007). In the first study to address dispersed wind power generation, Kahn (1979) found that the average correlation between site pairs decreased when the number of WPPs interconnected went from two to 13. Kempton et al. (2010) analyzed data from 11 weather stations along the eastern seaboard from the Florida Keys to Maine, as well as data from the North American Regional Reanalysis data set. They found that correlation of wind speeds between sites fell to 0.1 at distances greater than 1000 km, and that fluctuations in output were greatly diminished. In regards to WPP interconnection, Archer and Jacobson (2007), using 19 sites across Kansas, New Mexico, Oklahoma, and Texas, found that as plants are added to the network, power generation becomes more reliable (Figure 2.3). Interconnecting more WPPs decreased the standard deviations of array-average wind speeds and power output, and reserve requirements. These marginal benefits decreased as more plants were added to the network, but there was no saturation of benefits, so marginal benefits were always found. Connecting WPPs to a common point was found to reduce the long-distance portion of transmission capacity up to 20%, while losing only 1.6% of energy (Archer and Jacobson 2007).

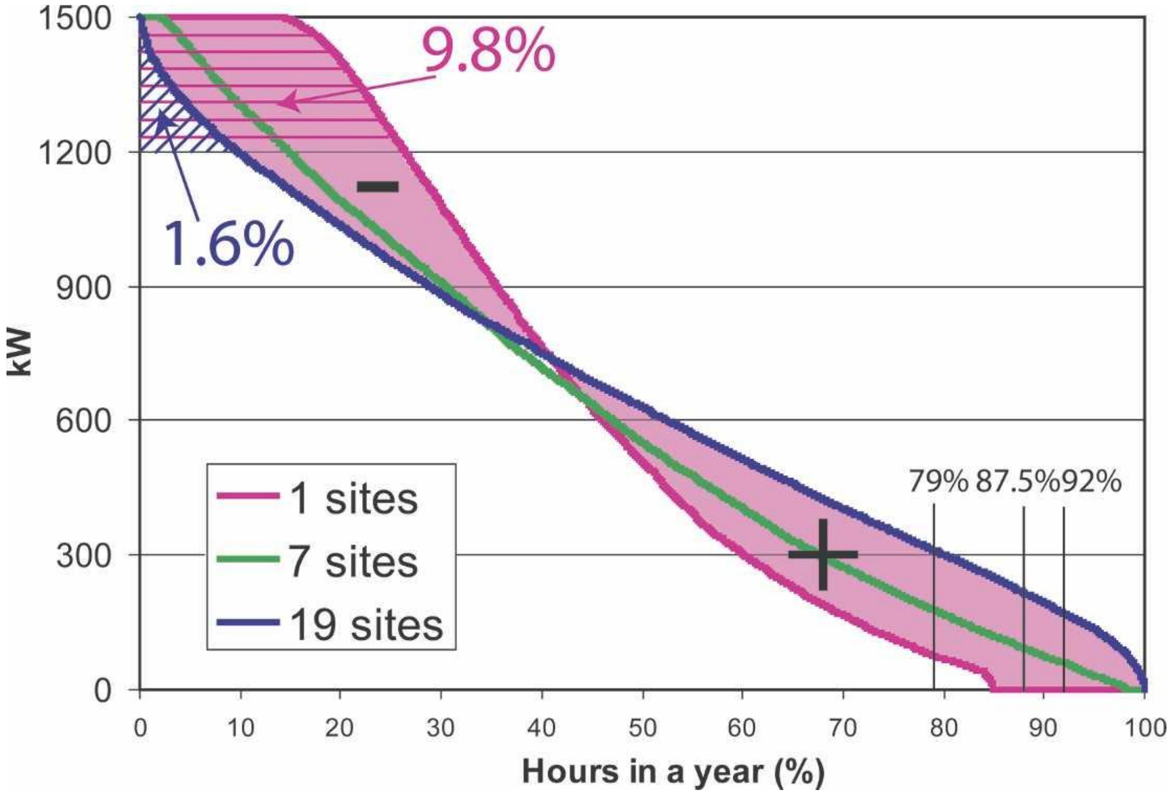

Figure 2.3. Generation duration curves for base-case array configurations: single-, 7-, and 19-site arrays. Each point on the x axis represents the percent of hours in a year that wind power production is greater than or equal to the corresponding power (y axis) on the curve. The area below the generation curve represents the total energy (kWh) produced in a year by the array. Shaded areas represent the difference in total energy produced between single-sites and 19-site arrays. The thatched areas are the energy lost (9.8% and 1.6%) if the size of the transmission lines is reduced from 1500 to 1200 kW for the 1- and 19-site arrays, respectively (Archer and Jacobson 2007). ©American Meteorological Society. Reprinted with permission.

Simonsen and Stevens (2004) analyzed one year of wind speed data at 28 sites across Iowa, Kansas, Minnesota, and North Dakota. They found that compared to any one of the sites individually, those 28 geographically dispersed WPPs reduced the overall variability in power output by a factor of 1.75 to 3.4. They also found that their array had a less pronounced diurnal pattern than a single turbine, and that power output peaked in the afternoon, the same time as peak demand.

It has been demonstrated that the reliability of wind power is improved when generation is aggregated (Robeson and Shein 1997; Simonsen and Stevens 2004; Archer and Jacobson 2007; Cassola et al. 2008; Milligan 2009; Kempton et al. 2010). The literature lacks a study that examines the effect on reliability of interconnecting existing WPPs within an entire ISO or RTO, a situation that provides the impetus for the first research question. Further, no study has explicitly compared the relationship between reliability and the number of WPPs in a network with the relationship between reliability and the area of the network, which allows for the second research question.

2.5 Wind Power Integration

Understanding the effects of integrating wind generated power into the electric grid is important, because the relevance of this study rests on the likely premise that the share of load served by wind power will increase in years to come, a view supported by DeCarolis and Keith (2005) and Dragoon (2010). As wind power's load share increases, certain wind integration costs arise. For instance, the variability of wind power generation necessitates increased reserves to balance supply and demand. The need for increased reserves is an example of a wind integration cost, as is new transmission. Importantly, however, the economic benefits of wind energy could actually lower the cost of electricity for the entire system, thereby minimizing the significance of wind integration costs (Milligan et al. 2009; Marquis et al. 2011).

A significant aspect of the value of wind power comes from the decreased operating costs and emissions that occur when generation from conventional power plants is reduced. The ability to maximize these savings is strongly tied to the accuracy of wind generation forecasts

(Dragoon 2010), as discussed in section 2.1. A study in Texas (Cullen 2008) found that on average 1 MW/hr of wind power displaced 0.19 MW/hrs of coal power, a disparity caused by coal being a low-variable cost, baseload generation that is generally not displaced at high volume by wind. However, if a carbon dioxide penalty were placed on coal plants the circumstances could change significantly, and wind generation could start to displace coal generation at more substantial levels.

In order to be cost-effective, power plants are rated by their marginal operation costs, a rating known as merit order. Power plants with the lowest marginal operating costs are at the top of the merit order, and are in operation all the time. Units with higher marginal operating costs are generally scheduled for times with higher demand. Wind power plants are at the top of the merit order because they have very low operating costs, so their power is deployed as it is produced, offsetting the production of conventional energy sources like coal plants (Holttinen and Hirvonen 2005).

There are some in the energy community who assert that because of the variability of wind, and the looming probability that little or no wind power will be available during times of peak load means that wind power cannot be a factor in contributing to meeting peak loads (Pavlak 2008). This argument does not consider the fact that conventional generators occasionally experience unplanned outages during peak load periods. As noted by Archer and Jacobson (2007), between 2000 and 2004 coal plants in the U.S. were shut down due to scheduled maintenance 6.5% of the time, and unscheduled maintenance or forced outage 6% of the time, so in that period electricity from coal plants was assured only 87.5% of the time, with a range of 79 - 92% (Giebel 2000; NERC 2005). In fact, there is evidence that the addition of wind generation, when coupled with new equipment designs and appropriate plant engineering, can improve system stability in the face of a significant plant or line outage (GE Energy 2005).

There is also some conjecture that wind power will never be able to provide for any more than a small fraction of total demand, because of the costs that variability imposes on grid operation. DeCarolis and Keith (2005) argue that there is no threshold (the fraction of power demand that wind power serves) above which wind imposes prohibitive costs due to variability. They assert that undispatchable wind energy imposes costs on grid operations that increase linearly and smoothly as the fraction of wind power serving demand increases, an assertion verified by Demeo et al. (2005). They point out that arguments for the hypothetical threshold assume that the grid will remain static as the fraction of wind power serving demand increases. DeCarolis and Keith (2005) believe that because large scale wind power penetration (one-third of demand or more) will take at least a few decades to achieve, it is likely that the grid will co-evolve with wind power and will be better equipped to handle wind variability, as discussed in Chapter 5 of this study.

The Tres Amigas project is an example of future grid technology. The project is a planned “SuperStation” to be located in Clovis, New Mexico, that will connect the Western Interconnection, the Texas Interconnection, and the Eastern Interconnection (Tres Amigas LLC 2010). The station will connect the grids with a combination of underground direct current superconducting cables, voltage source converters, and energy storage systems. The initial power transfer capacity will be 5 GW, equivalent to the power used by about 5 million U.S. households, with room to eventually grow to 30GW. To grid operators in each interconnection, the station will behave like a large generator. The project has the potential to mitigate stability and voltage problems caused by variations in power generation like wind power variability.

While the expansion of wind power does entail some integration costs, they are not prohibitively expensive. The U.S. Department of Energy devised the Joint Coordinated System Plan (DOE 2008a), a theoretical transmission and generation plan for large portions of the Eastern U.S. In a 20% wind penetration by 2024 scenario, it was found that benefits outweighed all costs (including transmission) by 1.7 to 1. Taken alone, the costs of expanding transmission to accommodate 20% wind penetration are a mere 2% of the projected total wholesale energy costs for 2024. Further, according to the 2008 Annual Report on U.S. Wind Energy Markets (Wiser and Bolinger 2008), for the period 1998 - 2007, average wind power prices have been near or less than the low end of the wholesale power price range.

Demeo et al. (2005) summarized the findings and insights of individual wind integration studies, and derived some broad conclusions concerning wind power integration. Wind variability imposes modest costs on system operation, usually less than 10% of the wholesale value of the energy, and sometimes substantially less. In fact, in power systems with a large fraction of demand served by natural gas, wind power provides a buffer against fluctuations in gas costs (Demeo et al. 2005). Systems with a significant natural gas component are also suited to wind power in that variations related to wind variability can be corrected by quick ramping up of natural gas generated electricity (DeCarolis and Keith 2005). Wind power forecasting has considerable value, especially in the day-ahead time frame because of its influence on decisions regarding unit-commitment (Demeo et al. 2005). WPPs have some non-zero capacity credit, meaning that the addition of wind power to the system increases the total capacity of the system, rather than only subtracting from the load devoted to conventional power sources. The specific value of the credit is influenced primarily by wind energy availability during peak hours. The transmission characteristics of the system have a strong bearing on the system operating costs arising from wind power variability, and can hinder the system's ability to accommodate wind power variability if not sufficiently extensive. The system operating costs imposed by wind's variability are strongly related to the size (in MW) of the associated balancing authority, as discussed in Chapter 5. Larger balancing authorities that include multiple WPPs would effectively interconnect wind generation, smoothing power output and reducing wind integration costs.

2.6 Summary

Existing research shows that the problems associated with fossil fuel-based energy sources (e.g., increasing atmospheric greenhouse gas concentrations (IPCC 2007), ecological destruction (Armaroli and Balzani 2006), damage to human health (Epstein 2000), rising fuel prices (Keay 2007) necessitate an expansion of clean, renewable energy sources. Wind power is a clean, renewable, and abundant alternative energy source. The science of wind power meteorology has developed over the last few decades, and aims to understand the dynamics of the atmospheric boundary layer as it relates to wind power in order to optimize the siting of WPPs, improve wind power prediction capabilities, and understand the variability of wind power, which is a major hurdle in the large-scale implementation of wind power.

Studies have shown that aggregating spatially distributed WPPs mitigates the effects of wind variability on power generation. However, further research is needed to determine the effect of interconnecting existing WPPs over an entire ISO. The integration of wind power into the system does impose costs associated with variability, but these costs are outweighed by the benefits of wind power integration. Further, the costs of wind power integration will decrease as grid technology and infrastructure becomes more sophisticated.

This study reinforces the link between interconnection of WPPs and improved wind power reliability. The study fills a gap in the literature by using high-resolution wind speed data applied to the locations of WPPs within the Midwest ISO to examine the effect of interconnection on the reliability of wind power across the entire ISO. It also provides a new method for vertical extrapolation of wind speed to 80 m based on the North American Regional Reanalysis (NARR), which has been under-utilized in wind power studies (see section 3.3). Finally, the results of the study are utilized to suggest optimal locations for future wind power development.

CHAPTER 3

METHODOLOGY

3.1 Study Design

This study is designed to gain a better understanding of the relationship between the geographic distribution of wind power generation and the reliability of wind power within the Midwest ISO by examining the effect on reliability of interconnecting WPPs. Reliability of wind power refers to the variability of power generation. Networks with low variability of power generation are more reliable than those with higher variability. The standard deviation of the capacity factor is one measure of the variability of wind power generation. A low standard deviation of capacity factor signifies a reliable power source. This study also seeks to determine whether it is the number of WPPs in an interconnected network or the area of the network that most directly affects the reliability of interconnected wind power, and how the mean capacity factor is affected by interconnection.

3.2 Study Area

The study area corresponds with the U.S. section of the Midwest ISO. It consists of the states of Illinois, Indiana, Iowa, Michigan, Minnesota, North Dakota, Ohio, South Dakota, and Wisconsin (see Figure 3.1). Small sections of Illinois, Indiana, and Michigan, and large areas of Ohio, as well as Nebraska, are not covered by the Midwest ISO, but were included in the analysis to simplify the organizational aspect of the study. The area corresponding to the

Midwest ISO was chosen as the study area because of its large size, and for the fact that the distribution of electricity within in its borders is overseen by one body, aiding integration of geographically dispersed wind power into the system. It also an area of widely varying population densities and significant wind power potential. Significantly, a study on the effects of interconnection on wind generation has never been conducted on such a large scale.

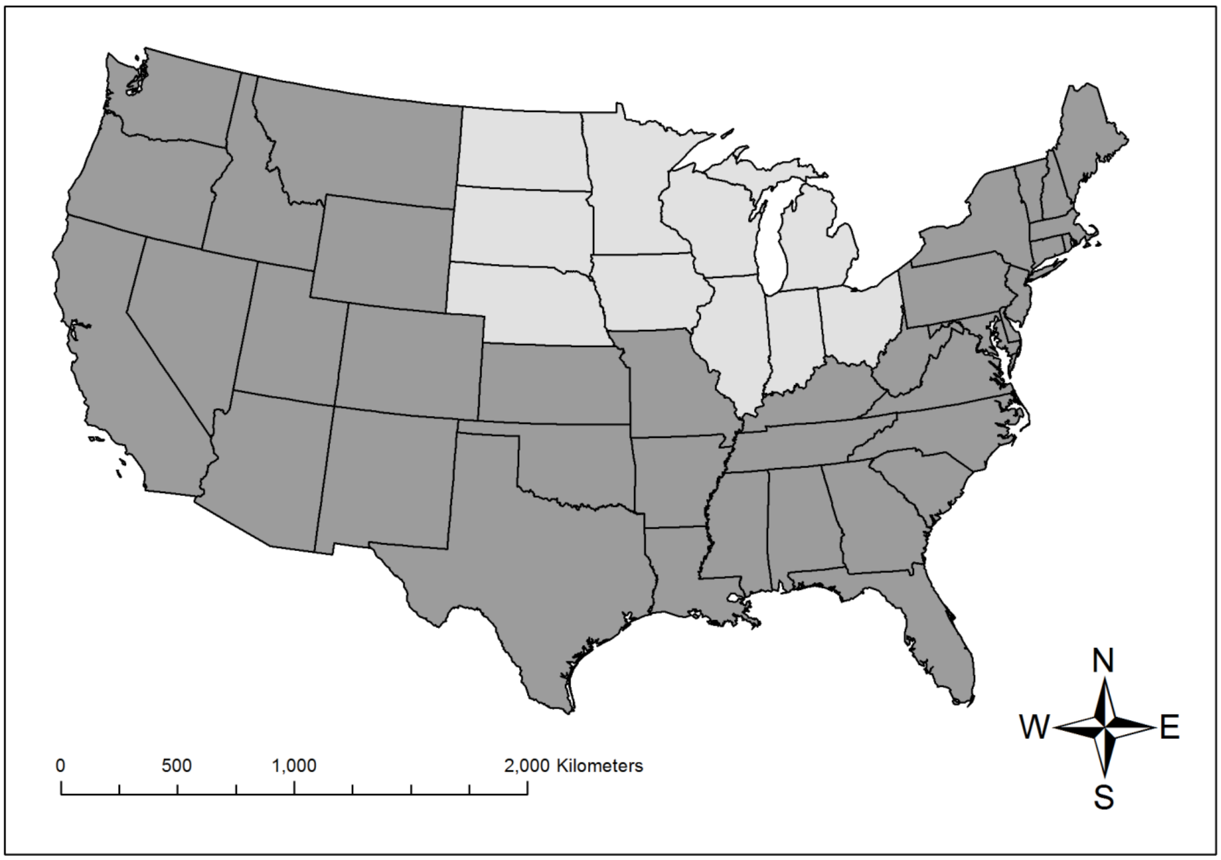

Figure 3.1. Map of the U.S. with study area in light grey.

3.3 Data

This study utilizes the North American Regional Reanalysis (NARR) (Mesinger et al. 2006). Reanalysis projects are created by assimilating data from synoptic weather stations, radiosondes (high altitude weather balloons), aircraft, ships, buoys, and satellites (Figure 3.2) (Petersen et al. 1998). Reanalysis data sets are complete, containing no missing values in the data. This is a significant advantage over observational data, which are often incomplete for large scales of analysis, and do not even exist for some areas. Further, observational data can give the false impression of climatic trends and shifts when new forecast models or analysis schemes are introduced. Reanalysis data are especially valuable when undertaking analysis of climatic conditions or trends for an area with large holes in observational data. However, there are flaws associated with reanalysis data sets. Errors or inconsistencies derived from observational data can be promulgated through the process of creating the data set, or the model used to compute the data set may have unrealistic atmospheric parameters. Programming bugs or human error can introduce flaws into the data set as well (ESRL 2011). While reanalysis data sets are not perfect, they are a valuable resource for atmospheric scientists, and are under-utilized in studies of wind power.

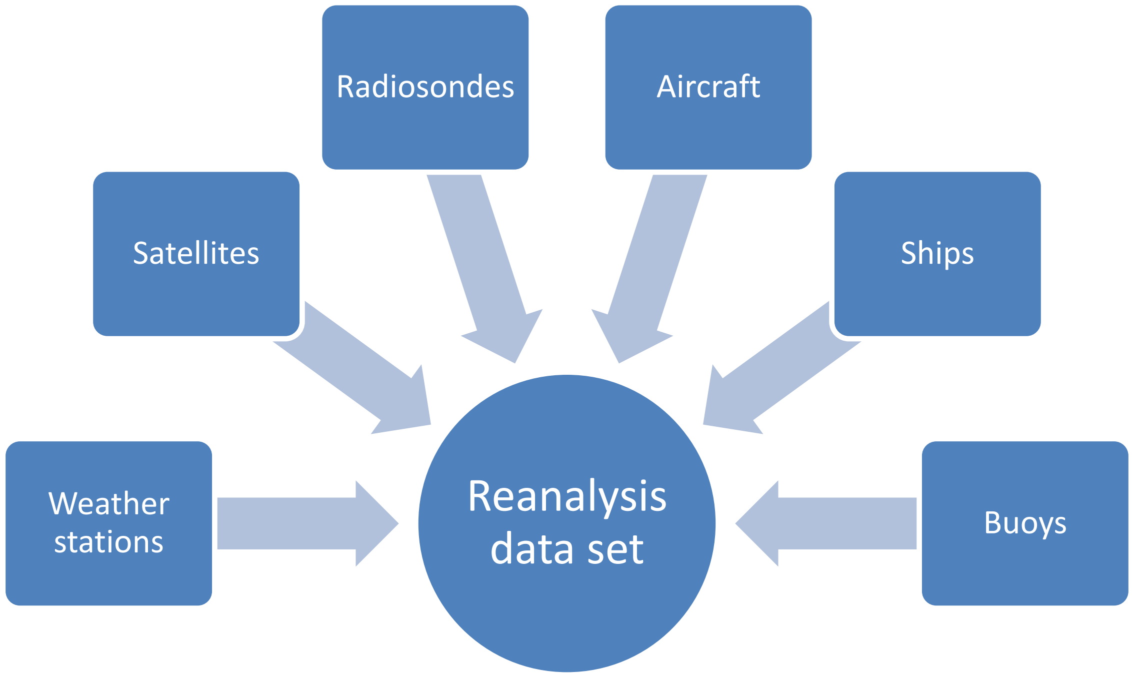

Figure 3.2. Chart illustrating the types of data that are assimilated to create reanalysis data sets.

The NARR is a comprehensive set of climatic model output constrained by various types of observational data for the North American sector. The NARR was conceived as a regionally-focused outgrowth of the NCEP-NCAR Global Reanalysis project. It assimilates improved versions of data sets used in the Global Reanalysis, as well as additional data sets. The goal of the NARR was to improve the depiction of the hydrologic cycle, the diurnal cycle, and other meteorological and climatic variables. The NARR covers January 1, 1979 to the present, and is updated daily (Mesinger et al. 2006).

The NARR spatial coverage consists of assimilated data of multiple climatic variables on a 32 × 32 km grid, formatted as a Lambert Conformal Conic Projection, for the North American sector; the highest spatial resolution of any reanalysis data sets covering North America (Mesinger et al. 2006). The NARR vertical resolution extends to 29 pressure levels from 1000 mb to 100 mb at 25 or 50 mb intervals, and includes the heights of each pressure level. The

NARR temporal coverage consists of climatic variable data in three-hour intervals, at every grid point and pressure level. The data used in this study cover the month of January from 1979 to 2010, and July from 1979 to 2010. Because of its exceptional spatial, vertical, and temporal resolution, the NARR is well-suited for studies of North American climatic variability. Further, the high vertical resolution offers an opportunity to mitigate potential sources of error in estimates of 80 m wind speeds that are normally based on surface station measurements that are subject to numerous discontinuities, including, but not limited to, changing roughness around the station through time, unreported station relocation, and deterioration of anemometer performance (DeGaetano 1998).

3.4 Objectives

In order to address the research questions, several objectives were formulated:

1. Determine locations of existing WPPs within the study area and match each to its nearest NARR grid point. There is no freely available data set with the locations of each U.S. WPPs, so such a set was compiled.
2. Extrapolate NARR wind speeds to 80 m. The NARR does not contain explicit 80 m wind speeds, so the power law was used to calculate 80 m winds.
3. Convert 80 m wind speeds into wind power capacity factors. To accomplish this Archer and Jacobson's (2007) power curve for the GE 1.5MW turbine was utilized.
4. Aggregate WPPs into networks. Because this study looks at the reliability of interconnected wind power, WPPs were aggregated into networks ranging in size from pairs to all WPPs within the study area.

5. Calculate reliability statistics. The results of the study come from the analysis conducted for this objective.

These objectives are addressed in further detail below.

3.4.1 Locate WPPs within the MISO

Data processing and analysis was done using MATLAB. The study area was extracted from the NARR by delineating the boundaries using latitudinal and longitudinal coordinates, and the locations of existing wind power plants within the study area were determined. Because there are no free, ready-made data sets with the locations of all the wind power plants in the U.S., such a data set was compiled. Noting only those wind power plants with a nameplate capacity of 10 MW or greater, a data set was compiled using the list of U.S. wind power plants on The Wind Power website as a guide (The Wind Power 2011). In total, 116 wind power plants were catalogued within the study area, but the locations of only 108 were used in the analysis because some wind power plants are so near to one another that they are beyond the spatial resolution of the NARR (Figure 3.3). WPPs were individually identified with their nearest NARR grid point so that wind speed and wind power could be calculated at each three-hour time step for every WPP in the study area.

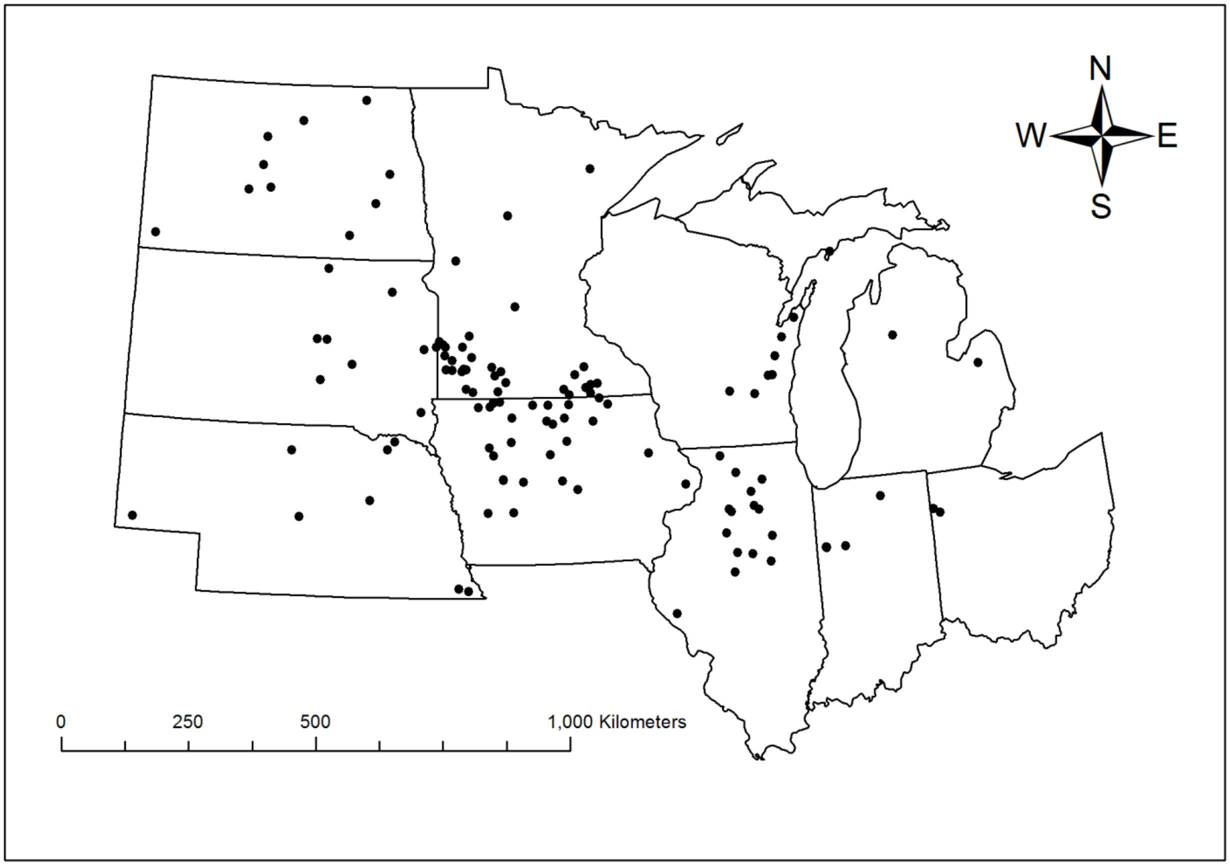

Figure 3.3. Map of the study area showing the locations of existing WPPs as black dots.

3.4.2 Extrapolate Wind Speeds to 80 m

The NARR separates wind speed into its zonal and meridional components, so wind speed had to be calculated by combining both components into a single value (Mesinger et al. 2006). For assessment of the wind power resource at each site, it was assumed that a single GE 1.5 turbine was used, which has a hub height of 80 m (GE Energy 2010b), so wind speeds at 80 m are required. One of the significant challenges inherent in the research was the process of extrapolating wind speeds to 80 m. Wind speeds at 80 m are not routinely observed, nor included explicitly in the NARR data. The NARR includes wind speeds at various pressure levels ranging from 1000 millibars (mb) to 100 mb, at 25 or 50 mb intervals. Usually the 1000 mb pressure level is below 80 m. The power law method was utilized, a common approach for extrapolating wind speeds to higher heights (section 2.3). Normally the power law is used to extrapolate based on single near-surface (i.e. 10 m) station measurements, but the high vertical resolution of the NARR potentially allows for a higher degree of precision in estimating 80 m wind speeds. The power law is defined:

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

where v_1 and v_2 are wind speeds (m/s) at heights z_1 and z_2 (m), and α is the roughness exponent (Arya 1988). For surface station measurements the roughness exponent is typically assumed to be 1/7 (Musgrove 2010), but the vertical resolution of the NARR allows for varying values of the roughness exponent based on the atmospheric conditions at each grid point and each time step. The roughness exponent, α, was determined using the following equation:

$$\alpha = \frac{\ln(\mathrm{v_{b80}}/\mathrm{v_{a80}})}{\ln(z/z_{a80})}$$

where $\mathrm{v_{b80}}$ is the wind speed at the pressure level nearest to, but below 80 m, $\mathrm{v_{a80}}$ 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). 80 m wind speed estimates derived from 10 m surface station measurements require extrapolation spanning 70 m, which can introduce a large error. In this study wind speeds were extrapolated to 80 m from the pressure level nearest to, but below 80 m, which is generally a much shorter distance, potentially minimizing error.

To gain an idea of the how the NARR data characterized the wind resource in the study area, a map was produced (Figure 3.4).

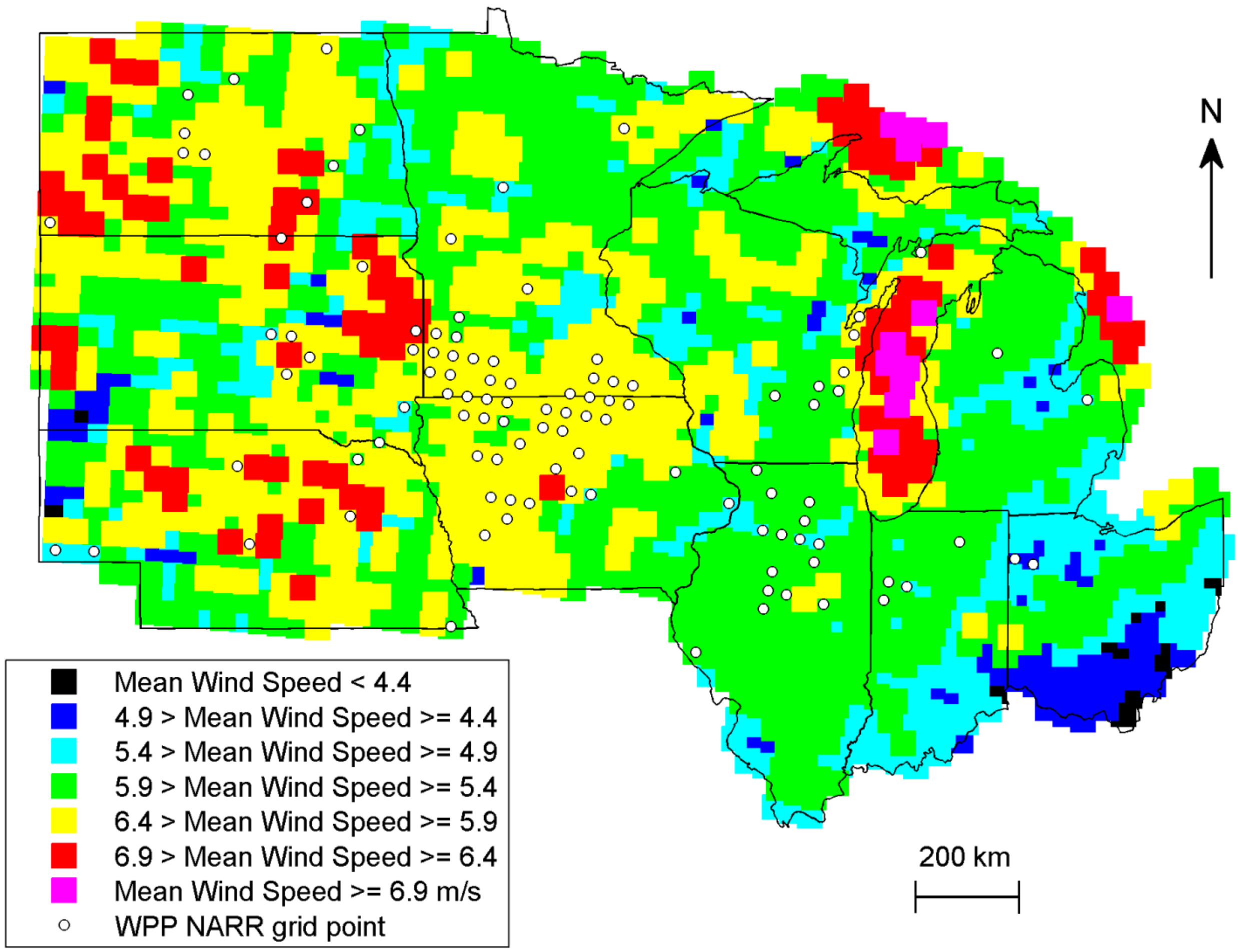

Figure 3.4. Map of mean annual wind speeds at 80 m for the study area, derived from the NARR data using the power law method of extrapolation. White circles represent the NARR grid points nearest to existing WPPs.

It is intuitive that the majority of WPPs are in the upper distribution of wind speeds, because it does not make economic sense to build a WPP in an area with a poor wind resource. However, according to the NARR data, none of the WPPs are in areas with annual mean wind speeds above 6.9 m/s, the minimum for a site to be considered fit for wind power development. This is not due to poor WPP siting, but rather to the NARR's underestimation of wind speeds in the Midwest (Pryor et al. 2012). It is also likely related to the use of the power law for extrapolation, which according to Archer and Jacobson (2003) causes underestimation of 80 m wind speeds.

3.4.3 Calculate Capacity Factor

The wind speeds were converted into wind power at each WPP grid point for every three-hour time step. Each WPP grid point was assumed to have one GE 1.5 MW turbine. The GE 1.5 is a widely deployed turbine in the United States with over 10,000 active units. It has a nameplate capacity of 1.5 MW, a cut-in wind speed of 3 m/s, a cut-out speed of 25 m/s, and power generation maxes out at 12 m/s (GE Energy 2010b). Archer and Jacobson's (2007) power curve for the GE 1.5 was used to compute wind power (Figure 3.5).

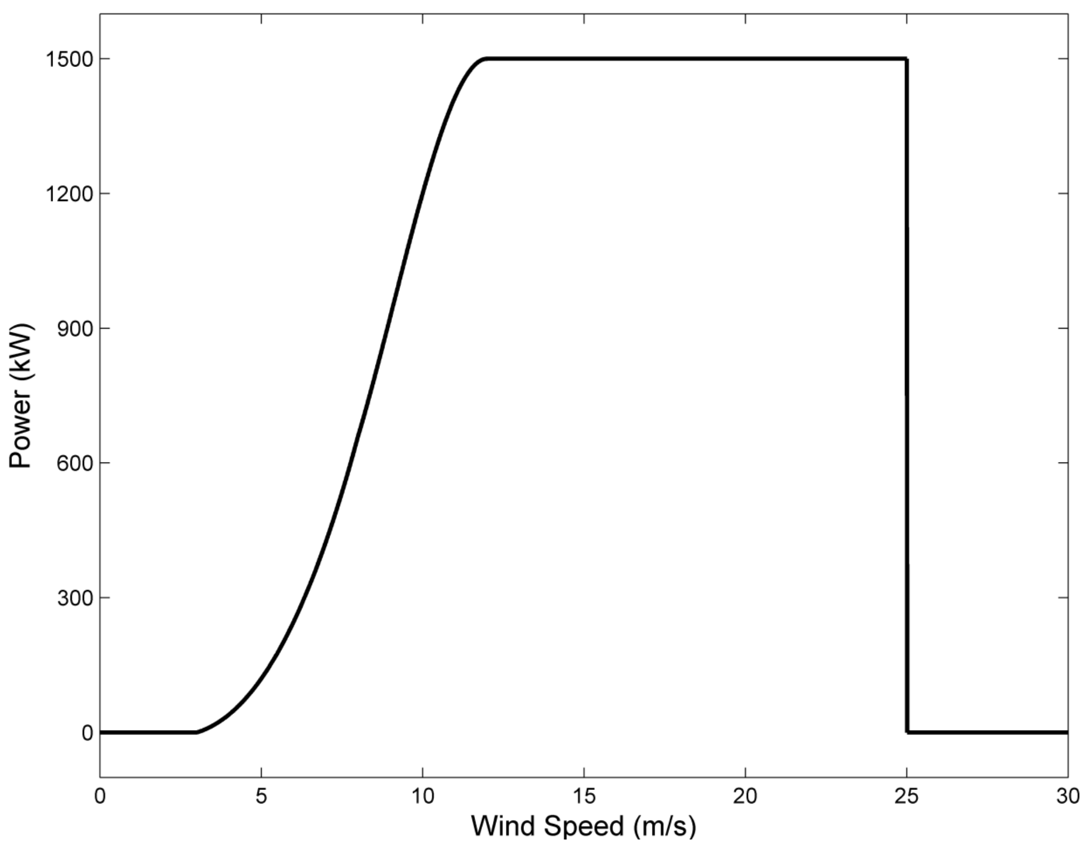

Figure 3.5. Power curve for the GE 1.5 MW turbine.

Two third-order polynomials are needed to calculate wind power, one for the portion of wind speeds below the sign change of the concavity of the power curve (wind speed of 8 m/s), and one for the portion of wind speeds above the sign change:

$$P_{lower} = v^3 + 8v^2 - 53v + 60$$

$$P_{upper} = -11.25v^3 + 307.5v^2 - 2520v + 6900$$

where P_{lower} is the power (kW) produced below the sign change of the concavity of the power curve, P_{upper} is the power (kW) produced above the sign change of the concavity of the power curve, and v is the wind speed (m/s).

Capacity factor was calculated by dividing the wind power at each time step and grid point by 1500, the maximum kilowatt output of the GE 1.5. The capacity factor therefore represents the proportion of the total possible power output of the WPP that is being produced at any given moment.

3.4.4 Aggregate WPPs

The WPP grid points were organized into groups, or networks, based on proximity to neighboring WPP grid points. Point pairs were organized first, by simply taking each point and pairing it with the nearest neighbor, only considering unique point pairs. Networks containing 3 - 108 WPPs were then organized on the same basis, only including unique network combinations. Including individual sites, there were 7704 unique networks analyzed.

3.4.5 Calculate Reliability Statistics

Information regarding the networks' geographic and power production characteristics was computed. For each unique network the following information was computed:

Table 3.1. Reliability statistics and definitions.

Variable	Definition
Minimum distance	Minimum distance between any two sites in the network (zero for individual sites)
Mean distance	Mean distance among the sites in the network (zero for individual sites)
Maximum distance	Maximum distance between any two sites in the network (zero for individual sites)
Area	Area of the convex hull polygon defined by the sites in the network (zero for individual sites and pairs)
Mean wind speed	Mean wind speed of the site(s) in the network for the entire study period (m/s)
Standard deviation of wind speed	Standard deviation of wind speed of the site(s) in the network for the entire study period (m/s)
Mean capacity factor	Mean capacity factor of the site(s) in the network for the entire study period (m/s)
Standard deviation of capacity factor	Standard deviation of capacity factor of the site(s) in the network for the entire study period (m/s)
Percentiles of capacity factor	1st, 2nd, 3rd, … , 99th percentiles of capacity factor for the site or network
Distribution of capacity factor fluctuations	Percentage of time step pairs with a -90%, -80%, … 0%, … +100% change in capacity factor for the site or network
Firm capacity at 70%	Proportion of site or network capacity that can be depended on at any given time at a 70% probability
Firm capacity at 80%	Proportion of site or network capacity that can be depended on at any given time at a 80% probability
Firm capacity at 90%	Proportion of site or network capacity that can be depended on at any given time at a 90% probability

Firm capacity, a measure of the dependability of power (Archer and Jacobson 2007), is included in the above table. 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. The three above probabilities were chosen arbitrarily in order to compare varying degrees of WPP network dependability.

CHAPTER 4

RESULTS

4.1 Introduction of Results

In Chapter 1, two research questions were introduced: (1) What is the effect of interconnecting wind power plants on the variability of generated power within the Midwest ISO? (2) Is the number of sites in a network or the area of the network more directly related to the variability of interconnected wind power? In regards to the first research question, the results show that interconnecting WPPs reduces the variability of wind power within the study area. Short-term fluctuations in power output are smoothed, and the frequency of large fluctuations in power output is greatly diminished. The frequency of low capacity factors is reduced with interconnection, and the overall reliability of wind power within the study area is improved. In regards to the second research question, the results show that network area more efficiently mitigates the variability of wind power than the number of WPPs (n) in the network. In the case of networks with equal n, those networks with larger areas were more reliable.

4.2 Interconnection and Reliability

In accord with previous studies (Robeson and Shein 1997; Simonsen and Stevens 2004; Archer and Jacobson 2007; Cassola et al. 2008; Milligan et al. 2009; Kempton et al. 2010), it can be concluded that as (n) and/or network area increase, reliability improves (Tables 4.1 – 4.4).

Table 4.1. Performance statistics for networks of connected wind power plants as a function of n for the month of January (1979 - 2010). For details see section 3.4.

No. of WPPs per network (n)	1	3	10	25	50	80	108
No. of networks analyzed	108	88	90	91	78	60	1
Min. network area (thousands of km^2)	0	0.02	5.20	29.65	117.45	490.79	1211.01
Mean network area (thousands of km^2)	0	1.88	32.71	113.89	285.25	640.68	1211.01
Max. network area (thousands of km^2)	0	23.39	123.16	391.46	568.56	880.11	1211.01
Network mean wind speed (m/s)	6.35	6.40	6.39	6.41	6.43	6.40	6.35
St. dev. of network wind speed (m/s)	2.91	2.81	2.68	2.54	2.38	2.18	1.97
Network mean capacity factor	0.29	0.30	0.30	0.30	0.30	0.30	0.29
St. dev. of network capacity factor	0.31	0.30	0.28	0.26	0.25	0.23	0.20
Percentage of time with zero power produced	12.44	7.07	2.61	0.38	0	0	0
Network firm capacity at 70% probability	0.06	0.07	0.08	0.10	0.12	0.14	0.15
Network firm capacity at 80% probability	0.02	0.03	0.04	0.06	0.07	0.09	0.11
Network firm capacity at 90% probability	0	0	0.01	0.02	0.03	0.05	0.07

Table 4.2. Performance statistics for networks of connected wind power plants as a function of network area for the month of January (1979 - 2010). For details see section 3.4.

Range of network areas (thousands of km^2)	0	0 – 6.5	6.5 - 18	18 - 50	50 - 200	200 – 400	> 400
Mean network area (thousands of km^2)	0	2.29	11.55	33.30	116.90	294.97	653.56
Number of networks within range (n)	108	447	368	719	1900	1676	2486
Size of smallest network within range	1	2	3	3	5	12	27
Mean n within range	1	4.73	11.11	18.49	32.06	47.94	76.92
Size of largest network within range	1	11	20	33	57	74	108
Network mean wind speed (m/s)	6.35	6.46	6.45	6.44	6.42	6.39	6.40
St. dev. of network wind speed (m/s)	2.91	2.85	2.78	2.68	2.53	2.33	2.18
Network mean capacity factor	0.29	0.31	0.30	0.30	0.30	0.30	0.30
St. dev. of network capacity factor	0.31	0.30	0.29	0.28	0.26	0.24	0.22
Percentage of time with zero power produced	12.44	6.65	3.49	1.43	0.06	0	0
Network firm capacity at 70% probability	0.06	0.07	0.08	0.09	0.10	0.12	0.14
Network firm capacity at 80% probability	0.02	0.03	0.03	0.04	0.06	0.07	0.09
Network firm capacity at 90% probability	0	0	0	0.01	0.02	0.04	0.05

Table 4.3. Same as Table 4.1, but for July. For details see section 3.4.

No. of WPPs per network (n)	1	3	10	25	50	80	108
No. of networks analyzed	108	88	90	91	78	60	1
Min. network area (thousands of km^2)	0	0.02	5.20	29.65	117.45	490.79	1211.01
Mean network area (thousands of km^2)	0	1.88	32.71	113.89	285.25	640.68	1211.01
Max. network area (thousands of km^2)	0	23.39	123.16	391.46	568.56	880.11	1211.01
Network mean wind speed (m/s)	4.81	4.86	4.87	4.88	4.92	4.88	4.81
St. dev. of network wind speed (m/s)	2.35	2.28	2.00	2.01	1.86	1.67	1.44
Network mean capacity factor	0.15	0.15	0.15	0.15	0.16	0.15	0.15
St. dev. of network capacity factor	0.21	0.20	0.19	0.18	0.17	0.15	0.13
Percentage of time with zero power produced	24.91	15.89	7.11	1.82	0	0	0
Network firm capacity at 70% probability	0.01	0.01	0.02	0.03	0.04	0.05	0.06
Network firm capacity at 80% probability	0	0	0.01	0.02	0.03	0.04	0.04
Network firm capacity at 90% probability	0	0	0	0.01	0.01	0.02	0.03

Table 4.4. Same as in Table 4.2, but for July. For details see section 3.4.

Range of network areas (thousands of km^2)	0	0 – 6.5	6.5 - 18	18 - 50	50 - 200	200 – 400	> 400
Mean network area (thousands of km^2)	0	2.29	11.55	33.30	116.90	294.97	653.56
Number of networks within range (n)	108	447	368	719	1900	1676	2486
Size of smallest network within range	1	2	3	3	5	12	27
Mean n within range	1	4.73	11.11	18.49	32.06	47.94	76.92
Size of largest network within range	1	11	20	33	57	74	108
Network mean wind speed (m/s)	4.81	4.88	4.88	4.87	4.90	4.83	4.88
St. dev. of network wind speed (m/s)	2.35	2.31	2.24	2.13	2.00	1.78	1.66
Network mean capacity factor	0.15	0.15	0.15	0.15	0.15	0.15	0.15
St. dev. of network capacity factor	0.21	0.21	0.20	0.19	0.18	0.16	0.15
Percentage of time with zero power produced	24.91	15.22	8.86	4.72	0.93	0	0
Network firm capacity at 70% probability	0.01	0.01	0.02	0.02	0.03	0.04	0.05
Network firm capacity at 80% probability	0	0	0.01	0.01	0.02	0.03	0.04
Network firm capacity at 90% probability	0	0	0	0	0.01	0.01	0.02

Standard deviation of mean capacity factor decreases significantly. Percentage of time with zero power produced decreases as n and area increase. Firm capacity at each probability level also improves uniformly as n and network area increase (Tables 4.1 – 4.4).

The effects of interconnection on wind power reliability, even at small scales, are consistent. The standard deviation of capacity factor decreases, percentage of time with zero power decreases, and firm capacity increases. However, the most dramatic effects are to be observed for large-scale interconnection. In January the mean standard deviation of capacity factor among individual WPPs is 0.31, compared to a mean capacity factor of 0.29, while in July the mean standard deviation of capacity factor among individual WPPs is 0.21, and mean capacity factor is 0.15. Among WPP networks greater than 400,000 km^2, the standard deviation of capacity factor is two-thirds of mean capacity factor in January (0.22), and equal to mean capacity factor in July (0.15).

Short-term reliability of wind power was improved by interconnection (Figures 4.1 – 4.2). For a single WPP (Figure 4.1a), three-hour fluctuations in power output greater than 50% of capacity factor are rare, but do occur. At the largest scales of interconnection, power fluctuations greater than 40% within a three-hour period do not occur. Wind speed, like most meteorological phenomena, and indeed most geographic phenomena, is more similar to wind speed at closer locations than to farther locations, and so as the area of a network of WPPs increases, sites are further apart and wind speeds are less correlated (Robeson and Shein 1997). It is less likely that low wind speeds will be experienced by multiple networks at the same time, thereby balancing the power output of the network.

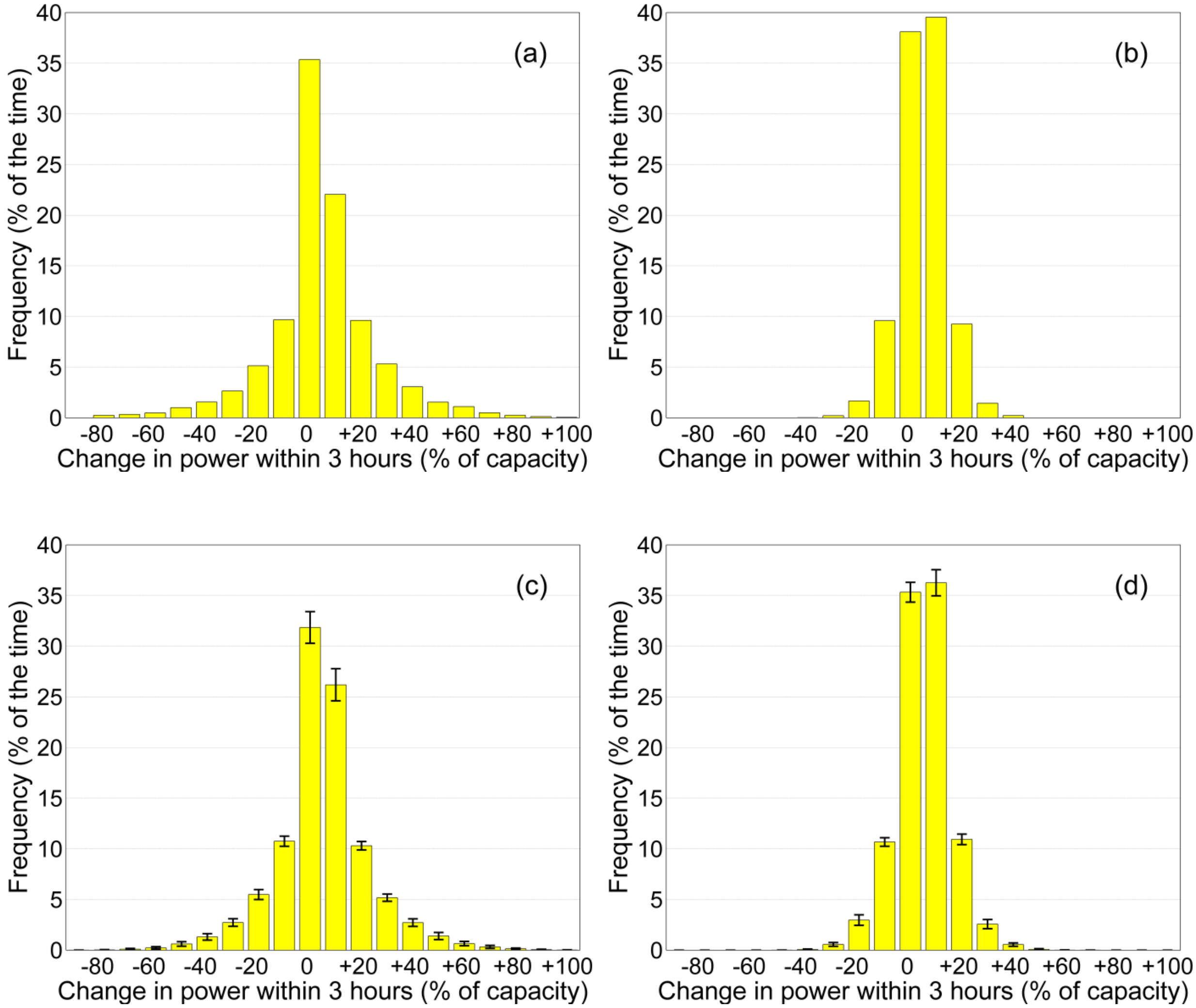

Figure 4.1. Histograms of the frequency of various magnitudes of changes in the capacity factor on the three-hour scale for the month of January (1979 - 2010). (a) single WPP at 47.4861 N, 101.1729 W in central North Dakota, (b) all 108 WPPs in the study area, (c) mean of networks between 0 and 6500 km^2 in area, and (d) mean of networks greater than 400,000 km^2 in area. The error bars signify one standard deviation above and below the mean.

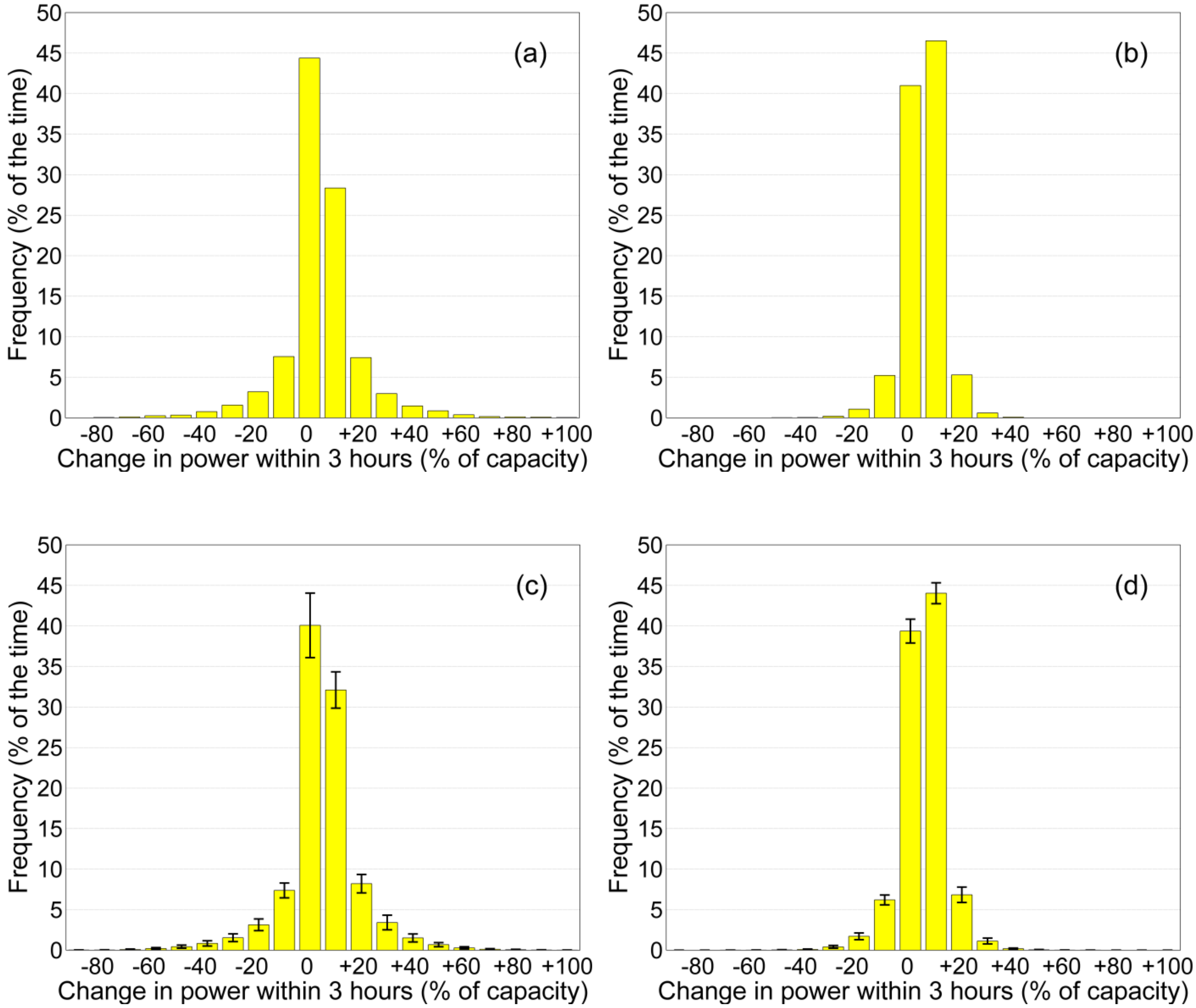

Figure 4.2. Same as in Figure 4.1, but for July (1979 - 2010).

Figures 4.1a-b and 4.2a-b show short-term power fluctuations as a function of n, and the same trends as in Figures 4.1c-d and 4.2c-d are visible. As the scale of interconnection increases, the magnitude of short-term fluctuations in capacity factor show demonstrable decreases, and the frequency of periods of steady power output show demonstrable increases. Also, the variability in power fluctuations among networks of equal n or area decreases as the scale of interconnection increases, as demonstrated by error bars in Figures 4.1c-d and 4.2c-d. Therefore, the power output of WPP networks becomes more predictable at larger scales of interconnection.

The standard deviation of capacity factor decreases as n and area increase, and so reliability improves. Figures 4.3 and 4.4 demonstrate the effects of interconnection on the standard deviation of capacity factor. The immediate benefits of interconnection are more pronounced at small scales of interconnection, and begin to diminish as n goes beyond 15 WPPs, or about 50,000 km^2 for the month of January. Improvements to reliability do not reach a saturation point, and would likely continue if the study area was enlarged and more WPPs were added to the analysis. The results for July are more complex, and are likely related to the sporadic nature of wind events during the summer in the Midwest. When looking at July standard deviation of capacity as a function of n, the decreases in variability are smooth. Similar to January, the benefits to reliability are most pronounced at small scales of interconnection. As a function of network area, variability is less predictable, although it still follows the same decreasing trend. Up to network areas of about 25,000 km^2 variability decreases rapidly, almost 11%. In some cases variability increases slightly as network area increases. It should also be noted that there is an observable point in both Figure 4.3b and 4.4b, between about 20,000 and 25,000 km^2, where the mean line flattens out, suggesting that improvements in reliability reach a minor plateau at that area, although benefits continue to accumulate at higher levels of interconnection. In Figures 4.3b and 4.4b a second plateau occurs at approximately 200,000 km^2, which is discussed further in Chapter 5.

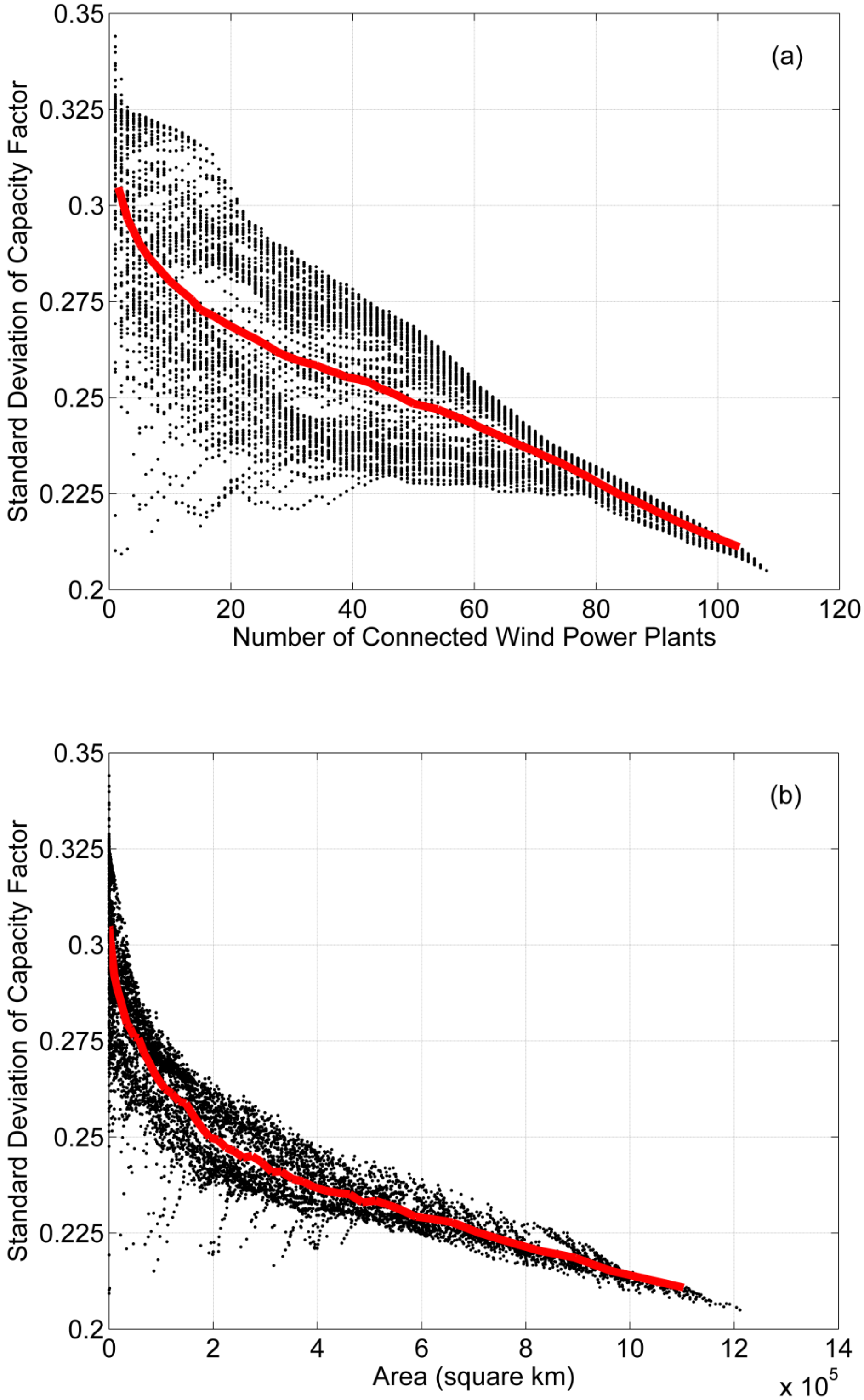

Figure 4.3. Standard deviation of capacity factor in January (1979 – 2010) as a function of n (a), and, (b) as a function of network area, for individual WPPs and WPP networks in the study area. Each point represents one individual WPP or network. The red line denotes the mean standard deviation of capacity factor for each n or area quantile.

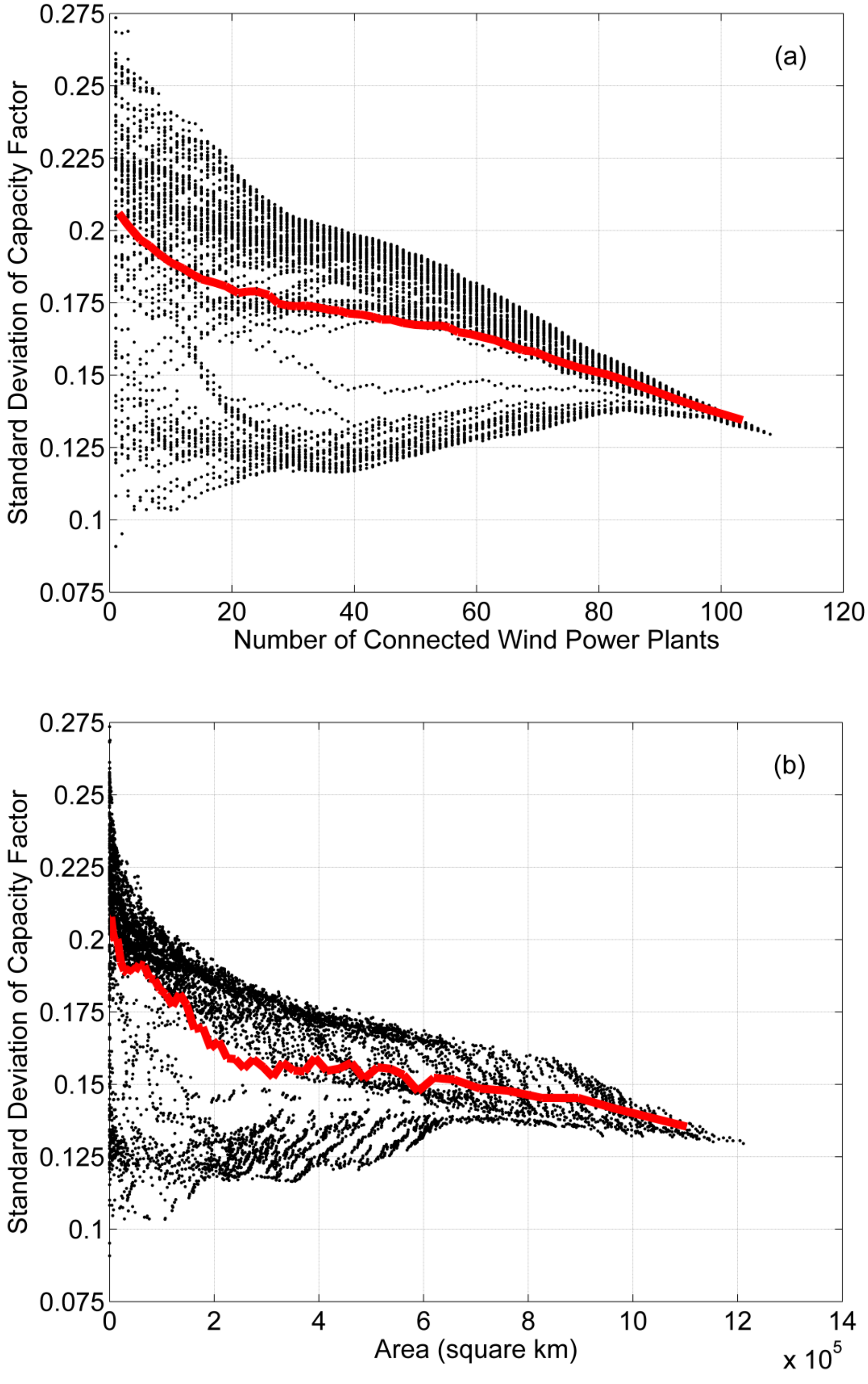

Figure 4.4. Same as Figure 4.3, but for July (1979 – 2010).

For a small subset of networks in January and a sizeable minority of networks in July, standard deviation of capacity factor increases as area increases (see Figures 4.3 and 4.4). This is most likely not random statistical noise. Most of these networks have very low mean capacity factors, meaning that the standard deviation of capacity factor is low as well. As n and/or network area increase, including larger proportions of WPPs with higher mean capacity factors, mean capacity factor increases, and standard deviation of capacity factor increases in tandem (Figure 4.5).

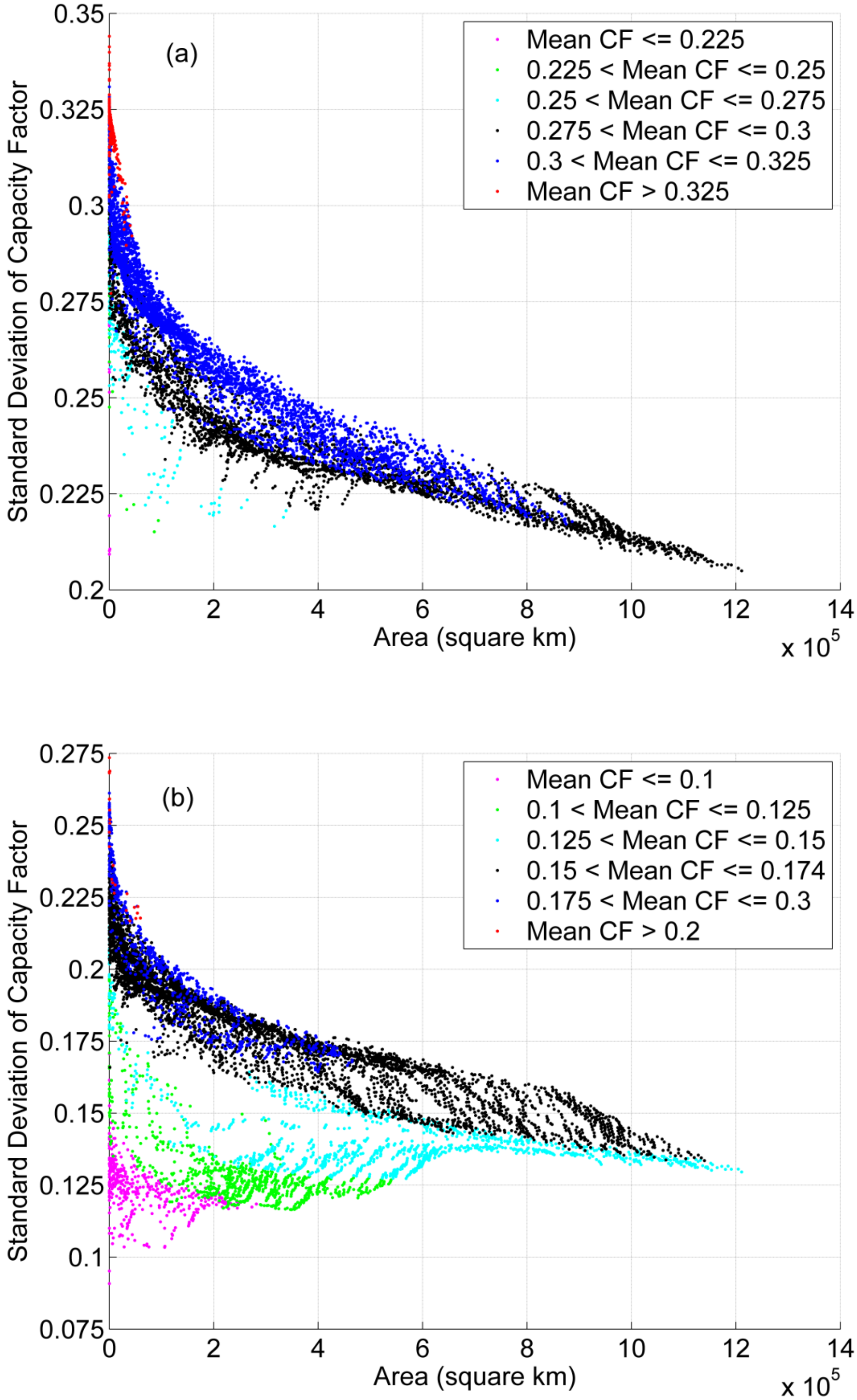

Figure 4.5. Standard deviation of capacity factor in (a) January, and (b) July (1979 – 2010) as a function of network area for individual WPPs and WPP networks. Each point represents one individual WPP or network. Points are color-coded to denote the January mean capacity factor of each network.

The effect of interconnection on wind generation was also analyzed by looking at the frequency of 50 quantiles of capacity factor as a function of n and network area (Figures 4.6 and 4.7).

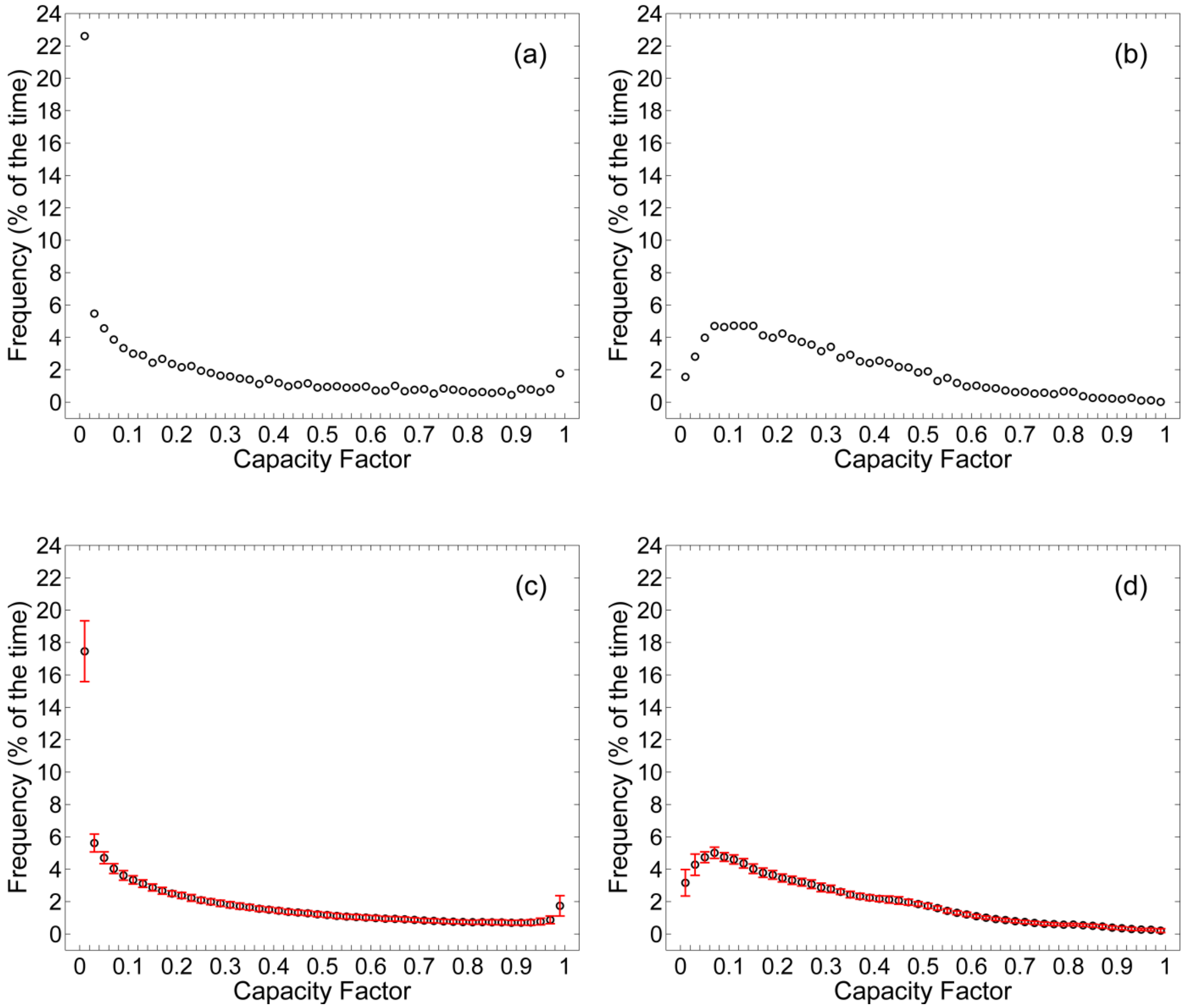

Figure 4.6. Frequency of 50 quantiles of mean capacity factor for the month of January (1979 – 2010). (a) single WPP at 47.4861 N, 101.1729 W in central North Dakota, (b) mean of all 108 WPPs, (c) mean of networks between 0 and 6500 km^2 in area, and (d) mean of networks greater than 400,000 km^2 in area. The error bars signify one standard deviation above and below the mean.

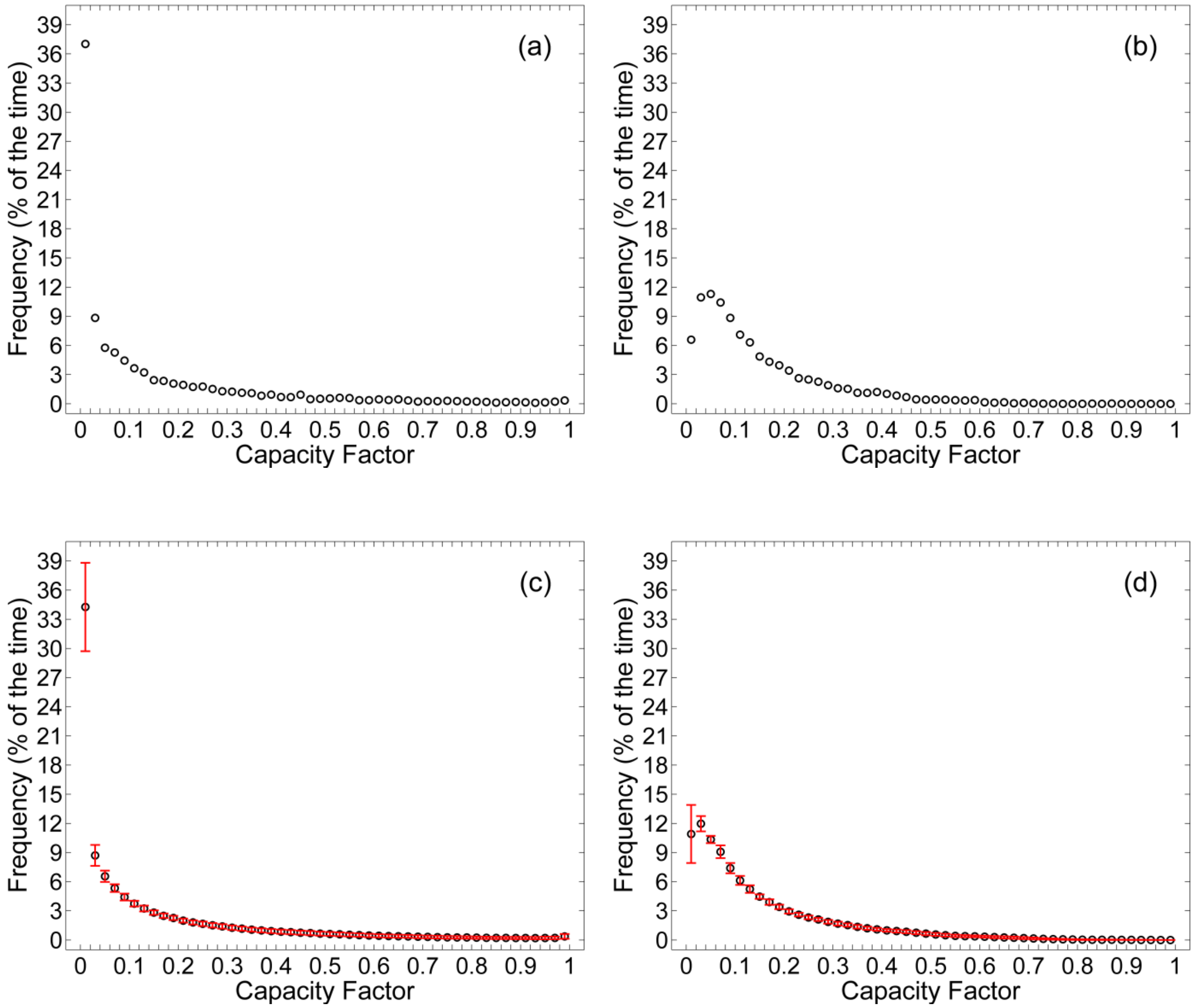

Figure 4.7. Same as Figure 4.6, but for July (1979 - 2010).

A single WPP in north-central North Dakota experiences a capacity factor between 0 and 0.02 roughly 23% of the time for the month of January (Figure 4.6a), and experiences a capacity factor between 0 and 0.02 about 37% of the time in July (Figure 4.7a). The lowest quantile is the most prevalent by a significant margin for single WPPs. In January and July, the 0 – 0.02 range of capacity factors is not the most prevalent quantile when all networks are aggregated (Figure 4.6b and 4.7b), nor for networks larger than 400,000 km^2 (Figures 4.6d and 4.7d). The January and July distribution of capacity factors are similarly affected by interconnection, but with some differences. In both months lower-range capacity factors (roughly 0.02 – 0.1) increase in frequency as the lowest quantile decreases in frequency, due to interconnection. At high levels of interconnection those lower-range capacity factors decrease as slightly higher-range capacity factors increase (Figures 4.6d and 4.7d). In July the lower-range capacity factors remain more frequent as interconnection increases than do their January counterparts due to the lower mean wind speed in the Midwest in July (4.81 m/s versus 6.35 m/s in January).

Generation duration curves provide a sophisticated look at the reliability of a power source (Figures 4.8 – 4.9). As the scale of interconnection increases, networks can be counted upon to produce power more frequently. In January, for approximately 20 - 35% of the time, the mean of individual WPPs produced more power than the networks (Figure 4.8a – b). However, approximately 65 - 80% of the time networks out-generated the mean of individual WPPs, on the basis of n in January. In terms of network area in January, networks produced more power about 78 - 85% of the time (Figure 4.8b). In July for n, networks out-generated the mean of individual WPPs approximately 75 – 90% of the time, although the difference is miniscule in the 0.4 – 0.6 capacity factor range (Figure 4.9a –b). Networks outperformed the mean of individual WPPs for about 80% of capacity factors based on network area in July.

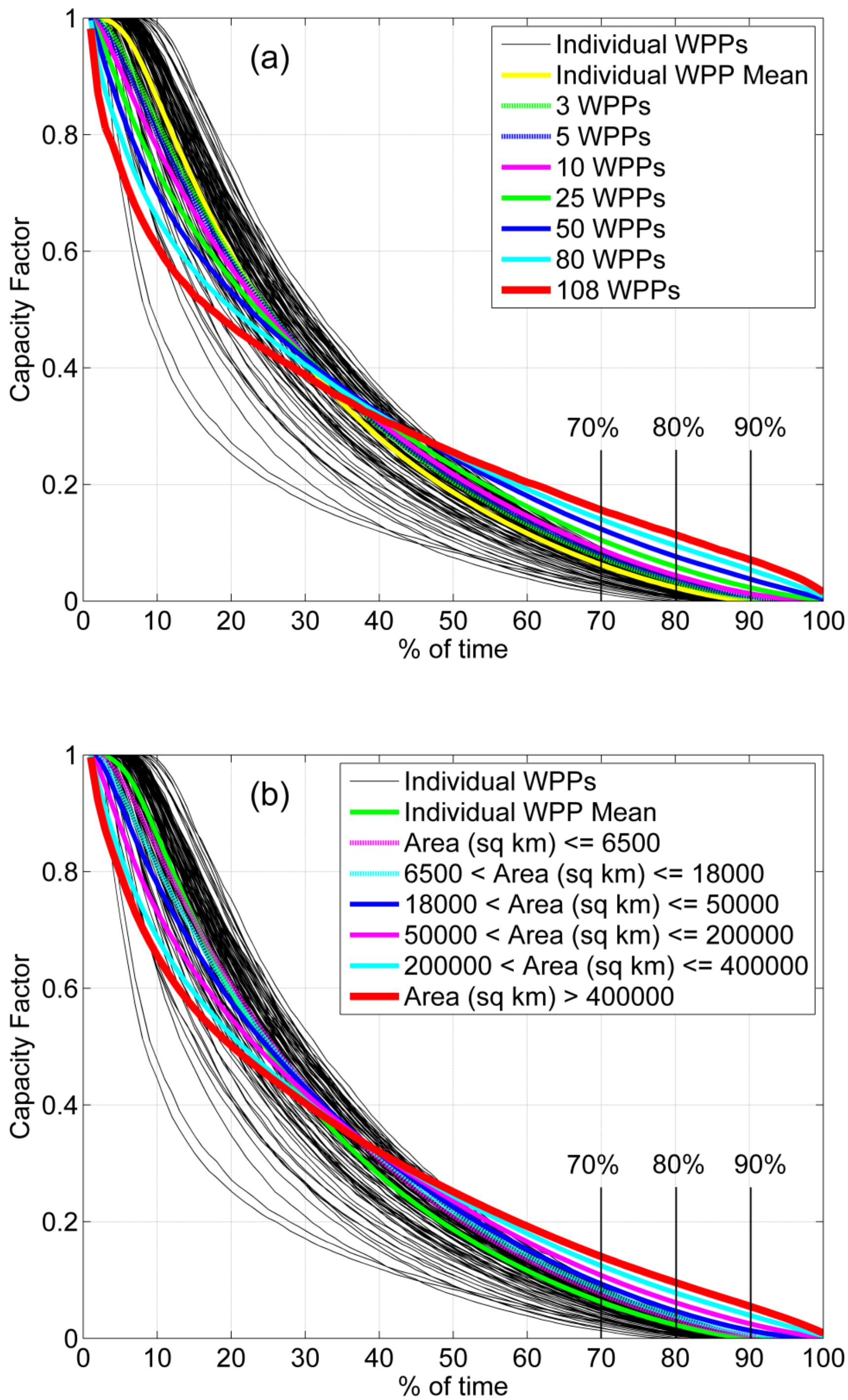

Figure 4.8. Generation duration curves of the mean capacity factors (a) as a function of n, and (b) as a function of network area for January (1979 - 2010). Each point on the x-axis signifies the percentage of time that wind generation is greater than or equal to the corresponding capacity factor on the curve. Firm capacity for each network at 70%, 80%, and 90% is the capacity factor at the intersection of the percentage line with the generation duration curve.

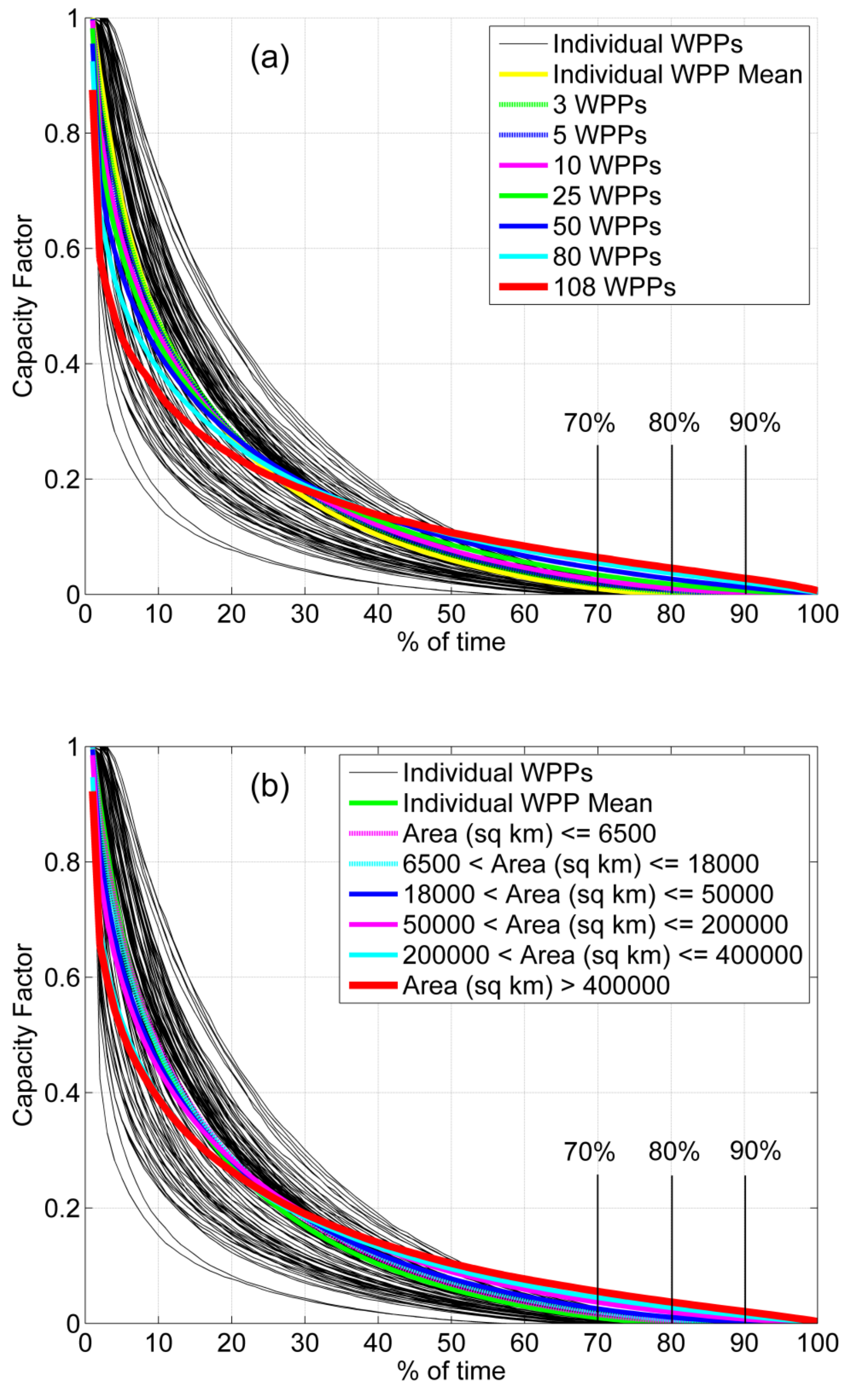

Figure 4.9. Same as Figure 4.8, but for July (1979 - 2010).

4.3 Number of WPPs vs. Network Area

To address the second research question, comparisons can be made between the relationship of n and network area to the reliability of wind power output (Tables 4.5 and 4.6, also see Tables 4.1 – 4.4). It can be concluded that the network area is more directly related to variability than n. This is apparent when comparing Figures 4.3 and 4.4. Also, the distribution of points in the area-based graphics (Figures 4.3b and 4.4b) are more constrained than in the n-based graphics (Figures 4.3a and 4.4a).

Table 4.5. Comparison of reliability statistics based on network area within groups of size n for the month of January (1979 - 2010). The numbers on the left of each column are the mean statistics of networks whose areas are lower than the median area for the column, while the numbers on the right represent the mean of those networks whose areas area greater than the median column area.

No. of WPPs per network (n)	**3**		**10**		**25**		**50**		**80**	
Median network area (thousands of km^2)	0.52		14.21		81.45		285.57		624.22	
St. dev. of network mean wind speed (m/s)	2.87	2.77	2.81	2.55	2.70	2.39	2.49	2.26	2.20	2.17
St. dev. network mean capacity factor	0.31	0.29	0.30	0.26	0.28	0.25	0.26	0.24	0.23	0.23
Percentage of time with zero power produced	7.66	6.47	4.11	1.11	0.78	0	0	0	0	0
Network firm capacity at 70% probability	0.07	0.07	0.08	0.09	0.09	0.11	0.11	0.13	0.13	0.14
Network firm capacity at 80% probability	0.03	0.03	0.03	0.05	0.05	0.07	0.07	0.08	0.09	0.09
Network firm capacity at 90% probability	0	0	0.01	0.02	0.01	0.03	0.03	0.04	0.05	0.05

Table 4.6. Same as Table 4.5, but for July (1979 - 2010).

No. of WPPs per network (n)	3		10		25		50		80	
Median network area (thousands of km^2)	0.52		14.21		81.45		285.57		624.22	
St. dev. of network mean wind speed (m/s)	2.30	2.26	2.29	1.98	2.21	1.81	1.99	1.72	1.65	1.68
St. dev. network mean capacity factor	0.20	0.20	0.21	0.17	0.20	0.16	0.18	0.15	0.15	0.15
Percentage of time with zero power produced	17.91	13.86	9.96	4.27	3.16	0.49	0	0	0	0
Network firm capacity at 70% probability	0.01	0.02	0.02	0.03	0.04	0.02	0.04	0.05	0.05	0.06
Network firm capacity at 80% probability	0	0.01	0	0.02	0.02	0.01	0.02	0.03	0.03	0.04
Network firm capacity at 90% probability	0	0	0	0	0.01	0.01	0.01	0.01	0.02	0.02

Among networks with equal n, there is a large range of areas (see Tables 4.1 – 4.4). The least expansive network containing three WPPs covers 200 km^2, while the largest three-WPP network covers 23,390 km^2. Networks containing five WPPs range from 5200 km^2 to 123,160 km^2. Because some WPPs are clustered near one another, particularly in Iowa and southern Minnesota, the benefits of interconnecting nearest neighbors in some areas are not as great as when connecting more distant WPPs. This is an important reason why network area has a greater effect on reliability than n, and can be demonstrated by comparing percentage of time with zero power produced as a function of mean network area. For networks containing 10 WPPs, mean network area is 32,710 km^2 and percentage of time with zero power produced is 2.61% in January, and 7.11% in July. Networks covering between 18,000 and 50,000 km^2 had a mean network area of 33,300 km^2 and percentage of time with zero power produced is 1.43% in January and 4.72% in July (Tables 4.1 – 4.4). This is a reinforcement of the idea that a large network area is more effective at mitigating wind variability than large n.

The relationship to between wind power variability and n versus network area was directly compared by dividing networks of a particular n into those whose areas are less than the median area for networks of size n, and those with larger areas, and then comparing the two groups (see Tables 4.5 and 4.6). Almost without exception networks with larger areas performed better than those with smaller areas in the same n group. The difference is most significant for the middle range of aggregation (n = 10, 25, 50), and less pronounced at the small scale (n = 3) and the large scale (n = 80). In several cases there is no difference in a reliability statistic for a group, and in one case (standard deviation of network mean wind speed for n = 80, July) the networks below median area perform slightly better, but for the vast majority of measures a larger area corresponds to a more reliable network more closely than does a large n.

4.4 Summary of Results

A central goal of this study is to determine the effect of interconnecting WPPs within the Midwest ISO on the reliability of wind power. It can be concluded that the interconnection of WPPs within the Midwest ISO improves the reliability of wind power. As n and network area increase, standard deviation of capacity factor decreases. Firm capacity at 70%, 80%, and 90% probability levels increases as the scale of interconnection increases. Instances of zero power output become rarer, and eventually stop occurring entirely as interconnection increases (see Tables 4.1 – 4.4). In regards to the effects of interconnection on short-term reliability, fluctuations in generation on the three-hour scale are diminished as n and network area increase (Figures 4.1 and 4.2). Another central goal of this study, addressed by the second research question, is to determine if the reliability of interconnected wind power is more closely related to n or network area. It can be concluded that network area has a more direct relationship with wind power reliability than n (see Tables 4.5 and 4.6; Figures 4.3 and 4.4). The magnitude of fluctuations of capacity factor decreases as the scale of interconnection increases, due to its lower standard deviation.

CHAPTER 5

DISCUSSION AND CONCLUSION

The main objective of this study was to determine the effect of interconnecting WPPs on the reliability of generated power within Midwest ISO (see Figure 3.1). The variability of wind power is a major impediment to its implementation. This study was undertaken to promote greater development of wind energy by providing a better understanding of the relationship between space and wind power reliability.

The raw data for the study were wind speed data at 10 m and various pressure levels from the North American Regional Reanalysis (NARR). Using the power law, wind speeds were extrapolated to 80 m, the hub height of the GE 1.5 MW turbine assumed in the study. 108 WPPs within the Midwest ISO were associated with their nearest NARR grid point (see Figure 3.2). The WPPs were aggregated into nearest neighbor networks ranging from pairs to a single network containing all 108 WPPs. January and July wind power from 1979 to 2010 was calculated from NARR wind speed data and the power curve for the GE 1.5 MW turbine (see Figure 3.3), which was assumed at each site. Analysis was then conducted based on the two research questions. The key findings of this study are:

1. Interconnecting WPPs within the Midwest ISO mitigates the effects of wind variability on wind power and improves reliability, with greater improvements at larger scales of interconnection.
2. The variability of interconnected wind power is more directly related to the area of the network than the number of WPPs in the network.

The analysis confirms what previous studies have found; aggregating dispersed WPPs improves wind power reliability and reduces variability of power generation (Robeson and Shein 1997; Simonsen and Stevens 2004; Archer and Jacobson 2007; Cassola et al. 2008; Milligan et al. 2009; Kempton et al. 2010). Significantly, no previous studies have compared the relationship between reliability and the number of WPPs in a network (n) vs. network area. This study found that network area is more important than n in determining the reliability of the network, and therefore makes an original contribution to the science of wind power geography. The results of this study can be used to plan WPP networks that maximize reliability.

In order to suggest the optimal locations for new WPPs on the basis of network area, it was necessary to determine a threshold-area beyond which reductions in standard deviation of capacity factor are diminished. Using the mean line from Figures 4.3b and 4.4b as a guide, 200,000 km^2 was isolated as the approximate network area where a plateau in marginal improvements to standard deviation of capacity factor occurs. A minimum distance for new WPP sites, based on an optimal network area of 200,000 km^2, from existing WPPs was calculated (Figure 5.1).

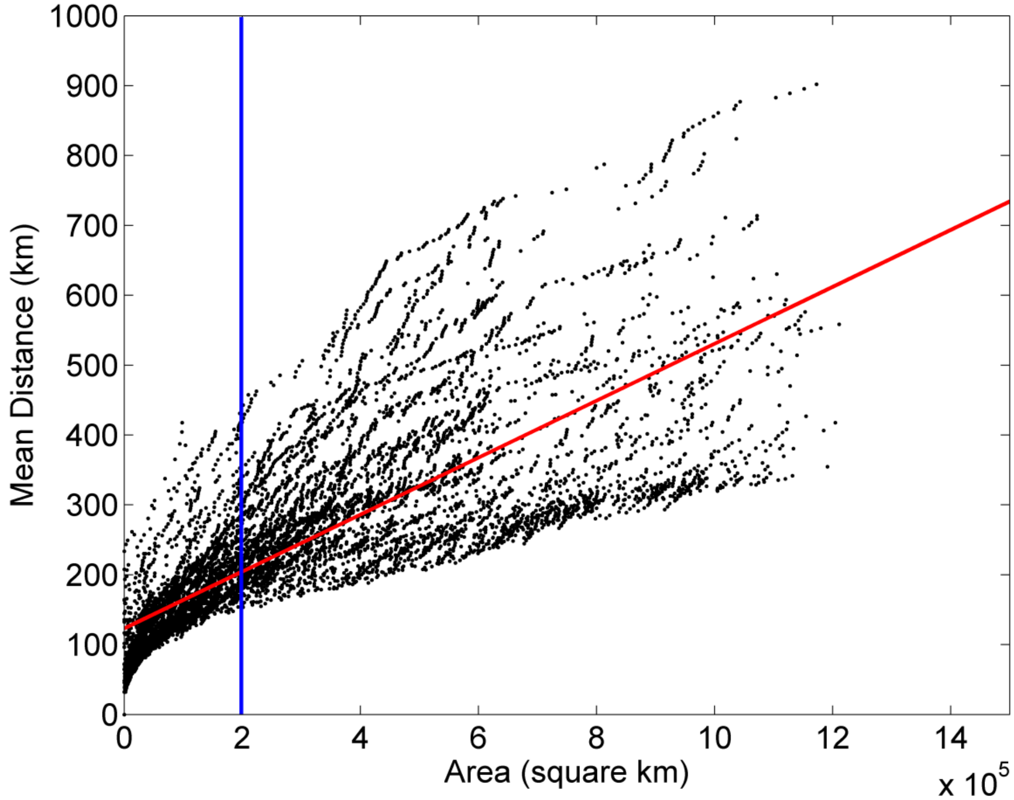

Figure 5.1. Mean distance among WPPs in networks as a function of network area. Each point represents one individual WPP or network. The red line is a linear fit to the points in the scatter plot. The blue line is based on the diminishing improvements to reliability once networks are larger than 200,000 km^2 (see Figure 4.3b and 4.4b).

The intersection of the blue line and red line in Figure 5.1 marks the minimum distance among WPPs in a network that appreciably reduces the standard deviation of capacity factor for the network: 200 km. A map showing the different degrees of saturation of WPPs in the study area was made, using the 200 km distance as a benchmark (Figure 5.3).

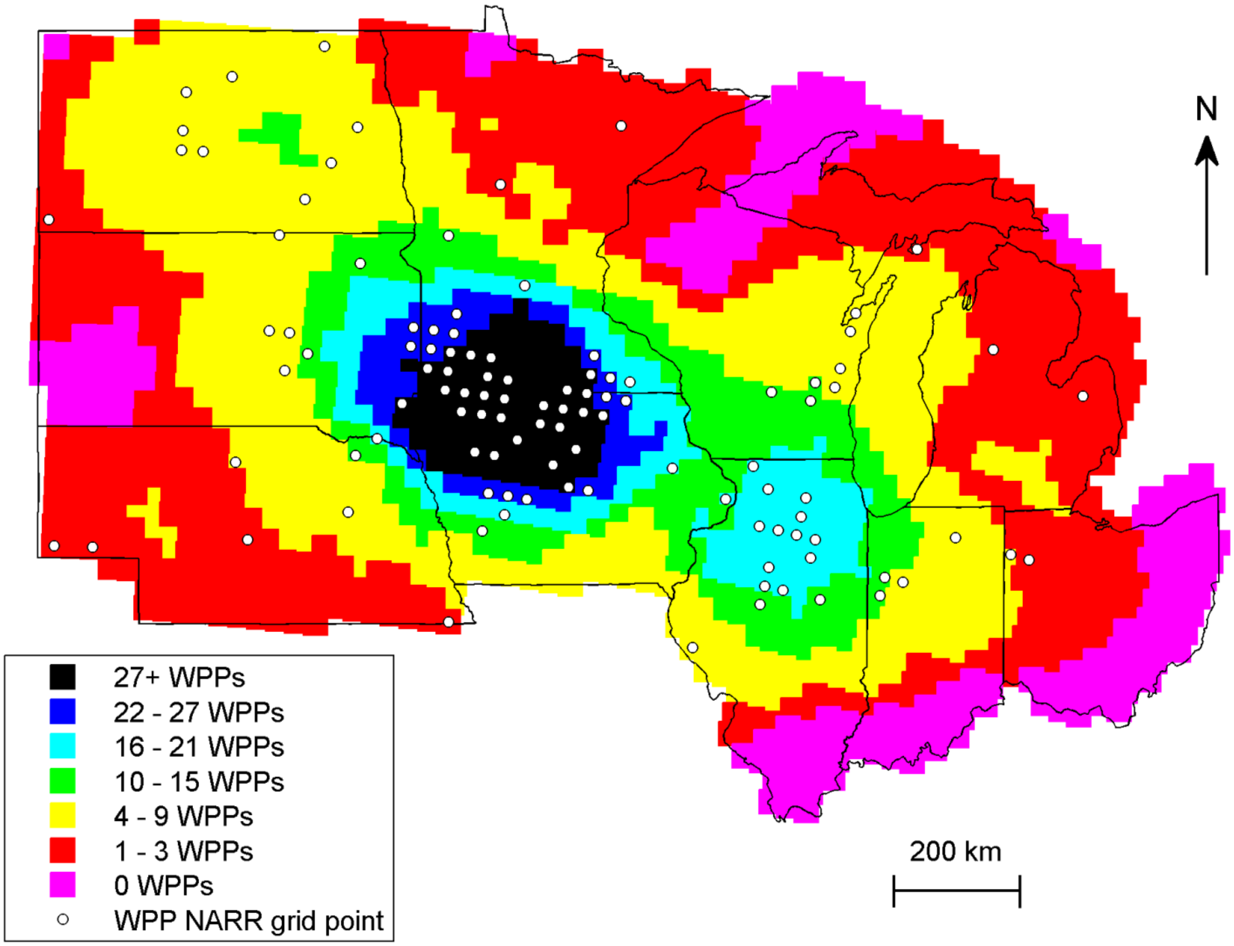

Figure 5.2. Map of the study area showing saturation of WPPs. The map is color-coded to show the number of WPPs that are at least 200 km from each NARR grid point (colored square). For example, points in red areas are within 200 km of 1 to 3 WPPs. Points that are at least 200 km from a high number of WPPs are better locations for wind power development. White circles represent the NARR grid points nearest to existing WPPs.

A cluster of wind development in Iowa and southern Minnesota is apparent. Based on the analysis, greater improvements in wind power reliability can be made by increasing wind power development in remote areas, rather than near clusters of existing WPPs, because of the greater smoothing effect on power fluctuations provided by large catchment areas versus smaller areas.

In preparation for a map that suggests locations for future wind power development based on both the wind resource and WPP saturation, a categorical map was produced showing the 80 m wind resource of the study area, based on Figure 3.4 (Figure 5.3).

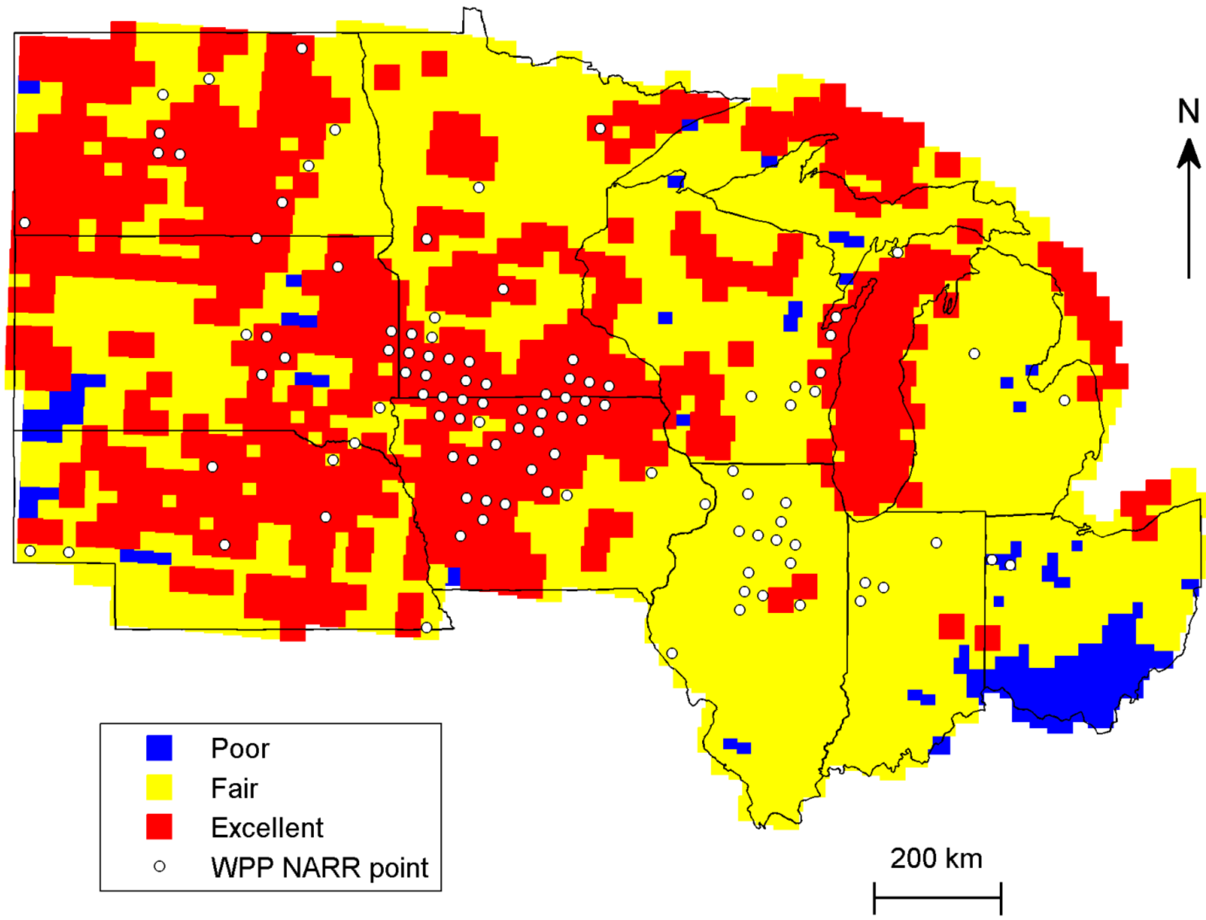

Figure 5.3. Map of the study area showing mean annual wind speeds at 80 m. Areas with a "Poor" wind resource have mean annual wind speeds less than 4.9 m/s, "Fair" areas have mean annual wind speeds between 4.9 and 5.9 m/s, and "Excellent" areas have mean annual wind speeds greater than 6.9 m/s. Map is a categorical description of wind speeds using the same data from Figure 3.4.

In order to more realistically estimate the optimal locations for future wind power development, the information presented in Figures 5.2 and 5.3 were combined into one map (Figure 5.4).

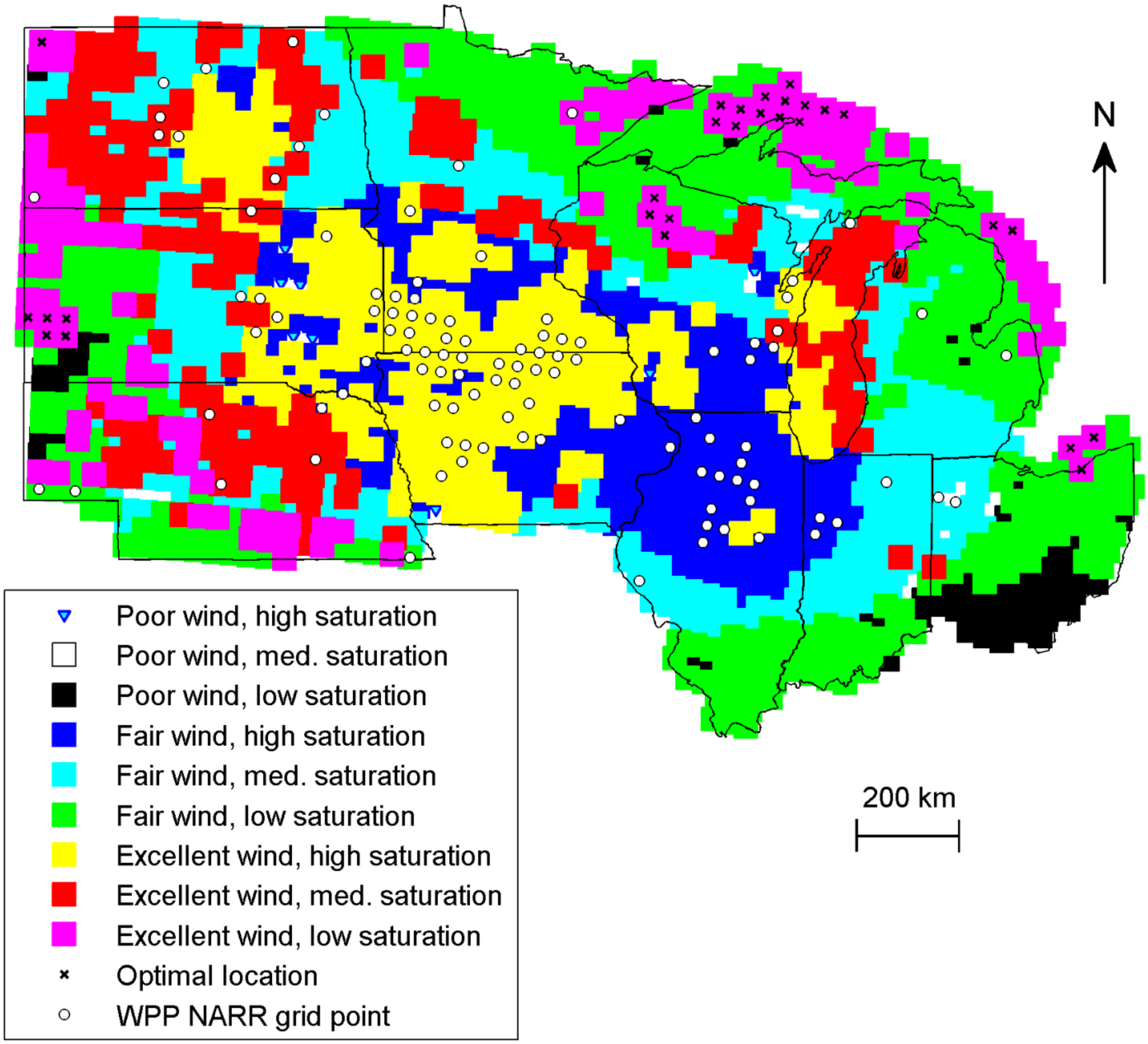

Figure 5.4. Map of the study area that suggests optimal locations for new wind power development based on mean annual wind speeds, and proximity to existing WPPs. Areas with high mean annual wind speeds and low saturation of WPPs are the best locations for future development. Areas with high saturation are within 200 km of at least eight WPPs, areas of medium saturation are within 200 km of three to seven WPPs, and areas of low saturation are within 200 km of two or less WPPs. Locations with an "x" are within 200 km of zero WPPs. Wind categories are the same as those in Figure 5.3.

Areas in magenta and red can be considered the best areas for new WPPs in order to maximize the reliability of interconnected wind power, while those locations marked with an "x" are the best of the best because they have an adequate wind resource and are at least 200 km distant from any existing WPPs. The choice of 200 km as a distance threshold was made based on Figure 5.1. The wind speed categories were chosen with the recognition that the NARR likely underestimates wind speeds in the Midwest. Therefore, areas with 80 m mean annual wind speeds above 5.9 m/s were deemed "excellent", even though according to NREL (2012), 80 m mean annual wind speeds must be above 6.9 m/s in order for wind power to be economically viable on a large scale. The categories represent the same wind speed divisions used in Figure 3.4, aggregated into three categories. The map shows that there are vast areas of unexploited wind power potential in the Midwest ISO, particularly in the Great Plains and over the Great Lakes. In some cases the map shows optimal locations for wind development directly adjacent to areas with a "poor" wind resource, as in southwestern South Dakota. This specific case is likely due to topographically-induced variations in wind speed caused by the Black Hills that are not resolved at the 32 × 32 km scale of the NARR data. Further, there are several areas with a "poor" wind resource and a high saturation of WPPs. It is possible that those areas are also subject to microclimatic variations in wind speed that the NARR data are unable to resolve. In the case that areas with WPPs that are represented as having a poor wind resource actually aren't economical choices for wind development, it is possible that the Production Tax Credit for WPPs (Smith et al. 2007) made construction of the plant lucrative for developers. It should be noted that Figure 5.4 does not consider other factors important to WPP siting, such as proximity to high-voltage transmission lines, urban load centers, airports, roads, migration pathways, and conservation areas (Mann et al. 2011).

At present the likelihood of the implementation of the results of this study, specifically for larger WPP networks, is limited due to the cost of new infrastructure. However, as the existing power grid is updated and electricity can be more readily shared and transmitted over larger regions and between ISOs and RTOs, the prospects of large WPP networks improve. In regards to such a scenario, the statistics of large-scale connected networks are useful because the gains made with regard to wind power reliability with networks covering tens and hundreds of thousands of km^2 are much more dramatic than for networks covering several thousand km^2. As the U.S. grid is improved, it is foreseeable that in upcoming decades WPP networks will span beyond the boundaries of any single ISO. The results of this study infer that improvements to wind power reliability would continue to accrue if the analysis was extended beyond the Midwest ISO, because there was no saturation in benefits found (see Tables 4.1 – 4.4 and Figures 4.3 – 4.4). This is important, because as network area increases and the standard deviation of wind power is reduced, wind's potential penetration of system load is increased. Further research is required to determine to what threshold(s) standard deviation of capacity factor must be reduced in order to for the system to accommodate various levels of wind penetration (20%, 35%, 50%, etc.).

Projects designed to improve the power transfer capabilities of the grid are already under way, like the Tres Amigas project discussed in Section 2.5. The Tres Amigas Electricity Superstation will connect the U.S.'s three isolated power grids: the Western, Texas, and Eastern 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 and RTOs to lay thousands of miles of new transmission lines, and to add sophisticated devices to existing lines that give grid operators more control over the system (Weeks 2010).

Because of the rapid growth in wind energy (39% per year from 2004 to 2009; Marquis et al. 2011), wind may serve up to 20 or even 30% of U.S. energy needs within the next few decades (DeMeo et al. 2005; DeCarolis and Keith 2006; Smith et al. 2007; Milligan et al. 2009). The U.S. Department of Energy (2008b) undertook a study to examine the costs, impacts, and benefits of 20% wind penetration by 2030. It was found that larger balancing authorities would decrease energy costs in systems with wind, as well as improve reliability, a finding supported by Smith et al. (2007). Having larger balancing authorities would, in essence, interconnect WPPs so that within the system they behaved as though they were directly interconnected. Larger balancing authorities would also provide a larger mix of other energy sources to improve overall system reliability. It is also conceivable that balancing authorities buy and sell electricity in real-time, liquid power markets, which would expand the effective utilization of wind power (Dragoon 2010). Wind power forecasting errors are also reduced when larger geographic areas are considered (Milligan et al. 2009; Marquis et al. 2011). Smith et al. (2007) posits that a "deep, liquid, real-time" energy market with WPP participation would lower the cost of wind power and help to provide the balancing energy for WPPs.

There are caveats to this study. Because of the reliance on the NARR, any errors or inaccuracies in that data would be manifest in the results. In order to provide spatially and temporally complete wind speed data over such a large and geographically diverse area, over-generalizing may have taken place. For instance, there are microclimatic variations in wind speed that are not resolved by the NARR. 80 m wind speeds are likely conservative (and as a result, capacity factor as well) because of the NARR underestimation of wind speeds in the Midwest (Pryor et al. 2012), reliance on the power law method of vertical extrapolation, and possibly because of the roughness exponent equation detailed in section 3.4.2. Archer and

Jacobson (2003) found that their least-squares method of extrapolation was more accurate than the power law and the logarithmic law when compared to the wind profiles from twice-daily soundings, and that on average wind speeds at 80 m were 1.3 – 1.7 m/s faster than those calculated using the other two methods. The least-squares method requires data that are unavailable using the NARR data, and so could not be used in this study. If Archer and Jacobson are correct, then by using the power law, this study may have underestimated the magnitude and reliability of wind power within the Midwest ISO (see Figure 3.4) and therefore represents a conservative estimate of the benefits of interconnection; however, because the NARR vertical resolution allowed for reduced extrapolation distance, it is hoped that wind speeds were not underestimated due to the method of the study. It is possible that one or more WPPs were not catalogued, and therefore not included in the analysis. Lastly, the analysis does not account for variations in wind speed that take place over time periods shorter than three hours.

This study is the starting point for future wind power analysis using the NARR. While January and July effectively represent winter and summer wind regimes, analysis needs to be extended to the entire calendar year. Analysis also needs to be extended geographically, to areas outside of the Midwest ISO. There are other possibilities for continuing the research begun with this study. For instance, the times of day with the highest demand for electricity could be isolated for each month and subjected to the same analysis conducted in this study to gain a better understanding of how wind power can be made more valuable for high-demand scenarios. A directional component could be introduced to the way that networks are aggregated to compare the reliability of networks with different geographic orientations.

In closing, this study is an important addition to the literature on wind power. It confirms that the interconnection of WPPs improves the reliability of wind power in the Midwest ISO. It demonstrates that network area plays a more important role in wind power reliability than n, and suggests new locations for wind power development based on that finding. Finally, it provides a starting point for further research concerning the geography of wind power.

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APPENDICES

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Correspondence related to Figure 2.2

from: Samuel Fisher smfisher3@siu.edu
to: abond@bellpub.com
cc: bhayman@bellpub.com, cfeinman@bellpub.com
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Thank you

--

Samuel Fisher
Graduate Assistant
Dept. of Geography & Env. Resources
Office: 4532 Faner Hall
Southern Illinois University,
Carbondale, IL 62901-4514

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subject: Permission to use a figure

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Graduate Assistant
Dept. of Geography & Env. Resources
Office: 4532 Faner Hall
Southern Illinois University,
Carbondale, IL 62901-4514

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to: Samuel Fisher <smfisher3@siu.edu>
date: Thu, Mar 22, 2012 at 11:04 AM
subject: RE: Permission to use a figure

Dear Mr. Fisher--

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Jinny

Jinny Nathans

AMS Permissions

jnathans@ametsoc.org

617 226-3905

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to: Jinny Nathans <jnathans@ametsoc.org>
date: Thu, Mar 22, 2012 at 11:23 AM
subject: Re: Permission to use a figure
mailed-by: siu.edu

Jinny,
The figure is Figure 3. Here is the citation:

Archer, C. L. and M. Z. Jacobson. 2007. Supplying Baseload Power and Reducing Transmission Requirements by Interconnecting Wind Farms. *Journal of Applied Meteorology and Climatology* 46, 1701-1717.

I will not be publishing the figure, but I will be including it in the literature review of my master's thesis. Thank you

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Regards,

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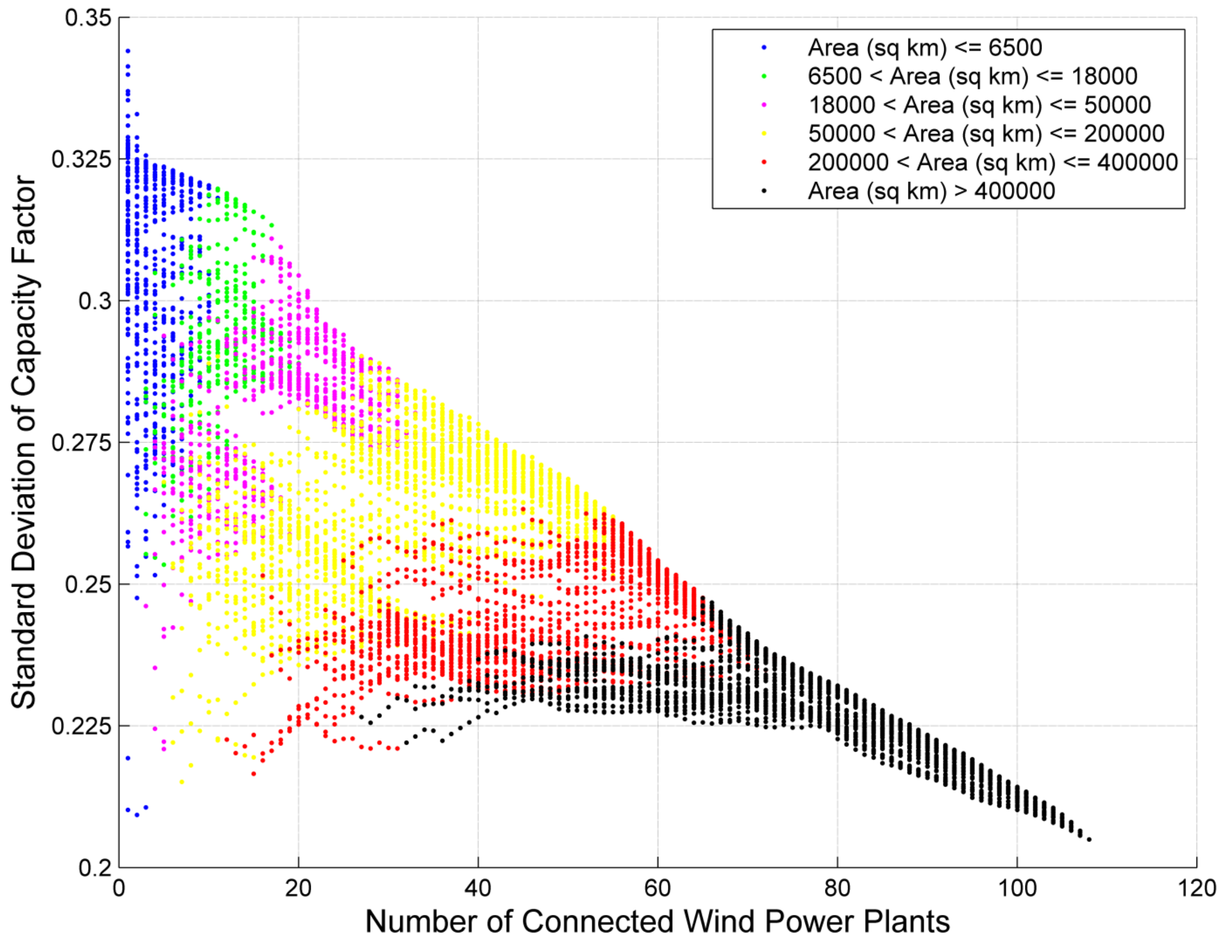
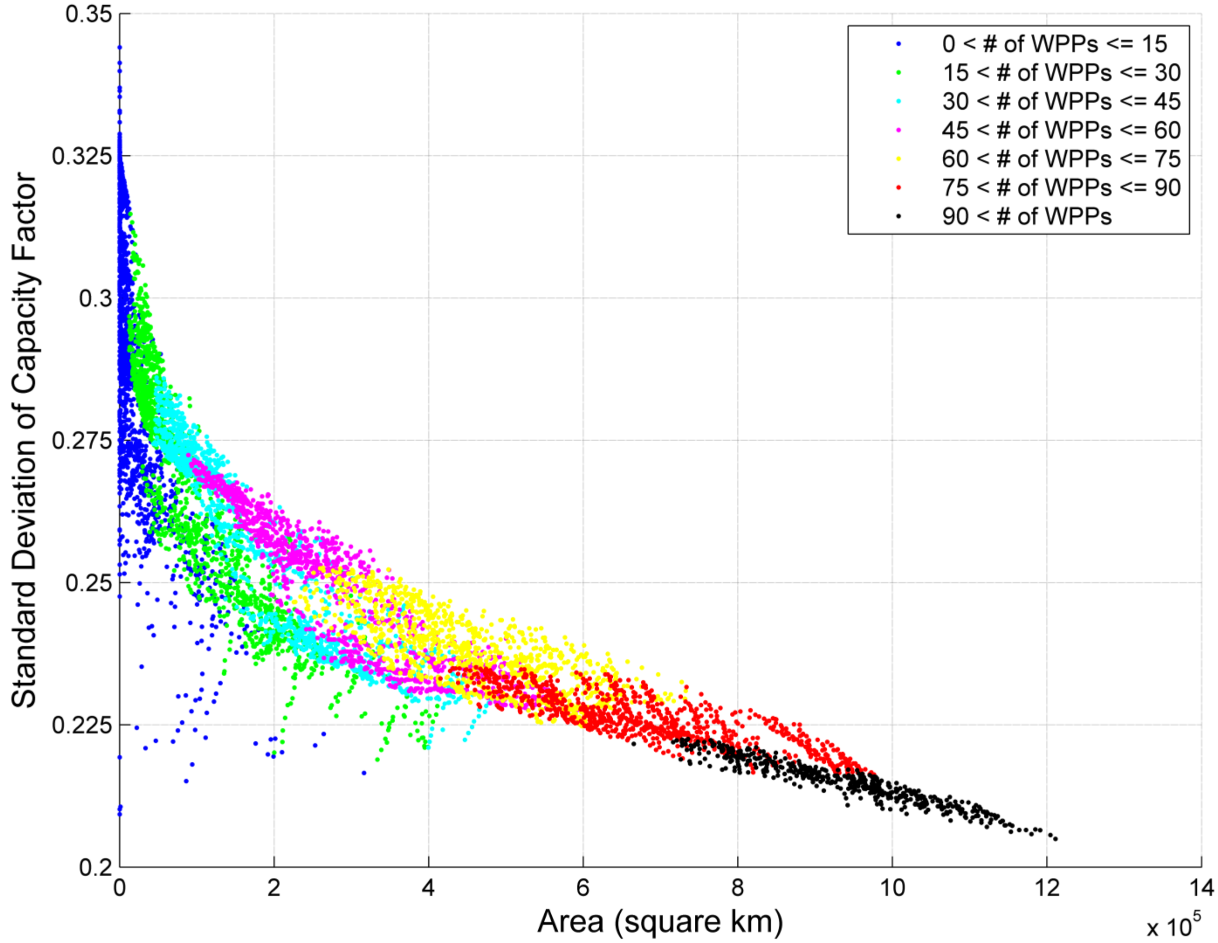
APPENDIX B

Standard deviation of capacity factor in January (1979 – 2010) as a function of n for individual WPPs and WPP networks. Each point represents one individual WPP or network. Points are color-coded according to the area range to which each network belongs.



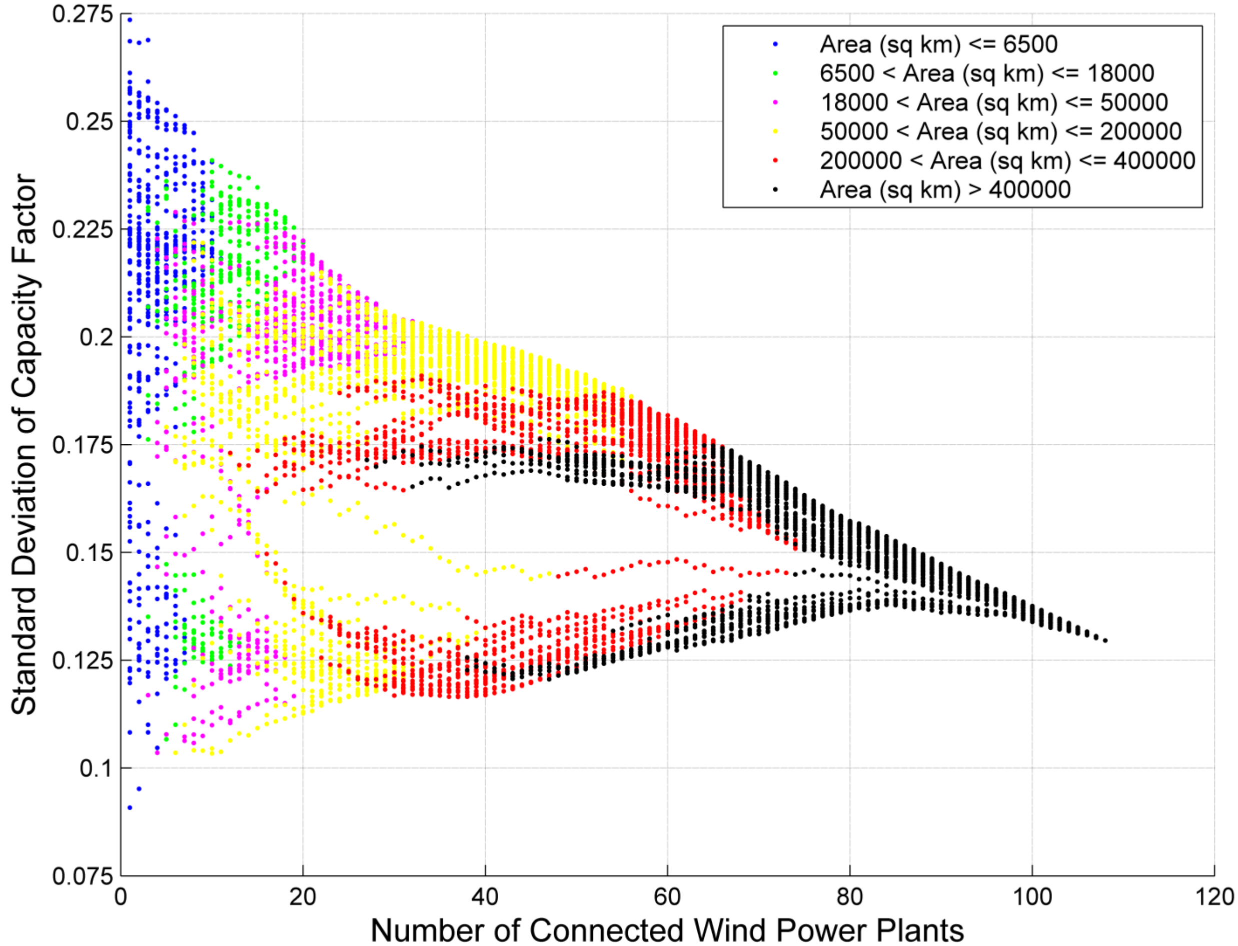
APPENDIX B

Standard deviation of capacity factor in January (1979 – 2010) as a function of network area for individual WPPs and WPP networks. Each point represents one individual WPP or network. Points are color-coded according to the n of that network.



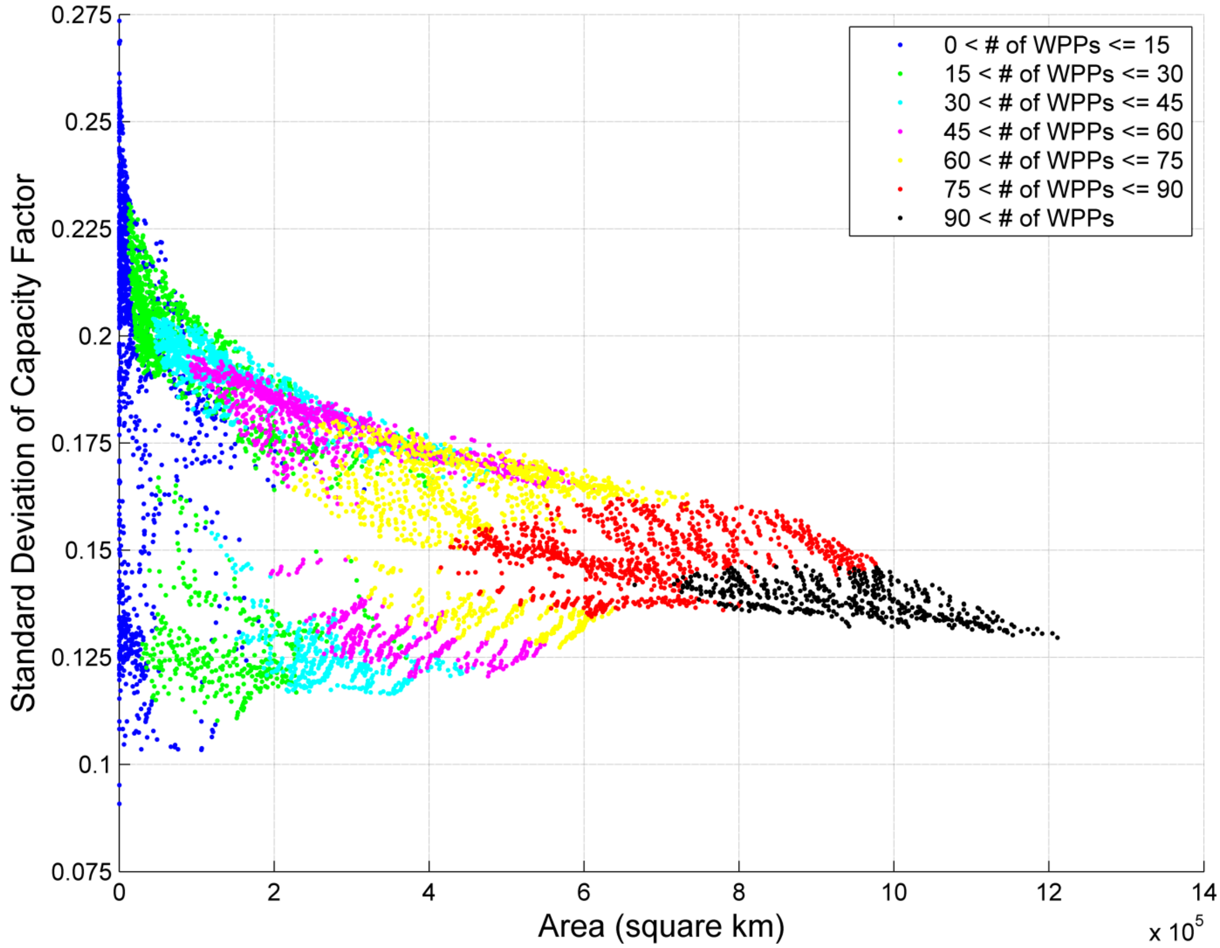
APPENDIX B

Standard deviation of capacity factor in July (1979 – 2010) as a function of n for individual WPPs and WPP networks. Each point represents one individual WPP or network. Points are color-coded according to the area range to which each network belongs.



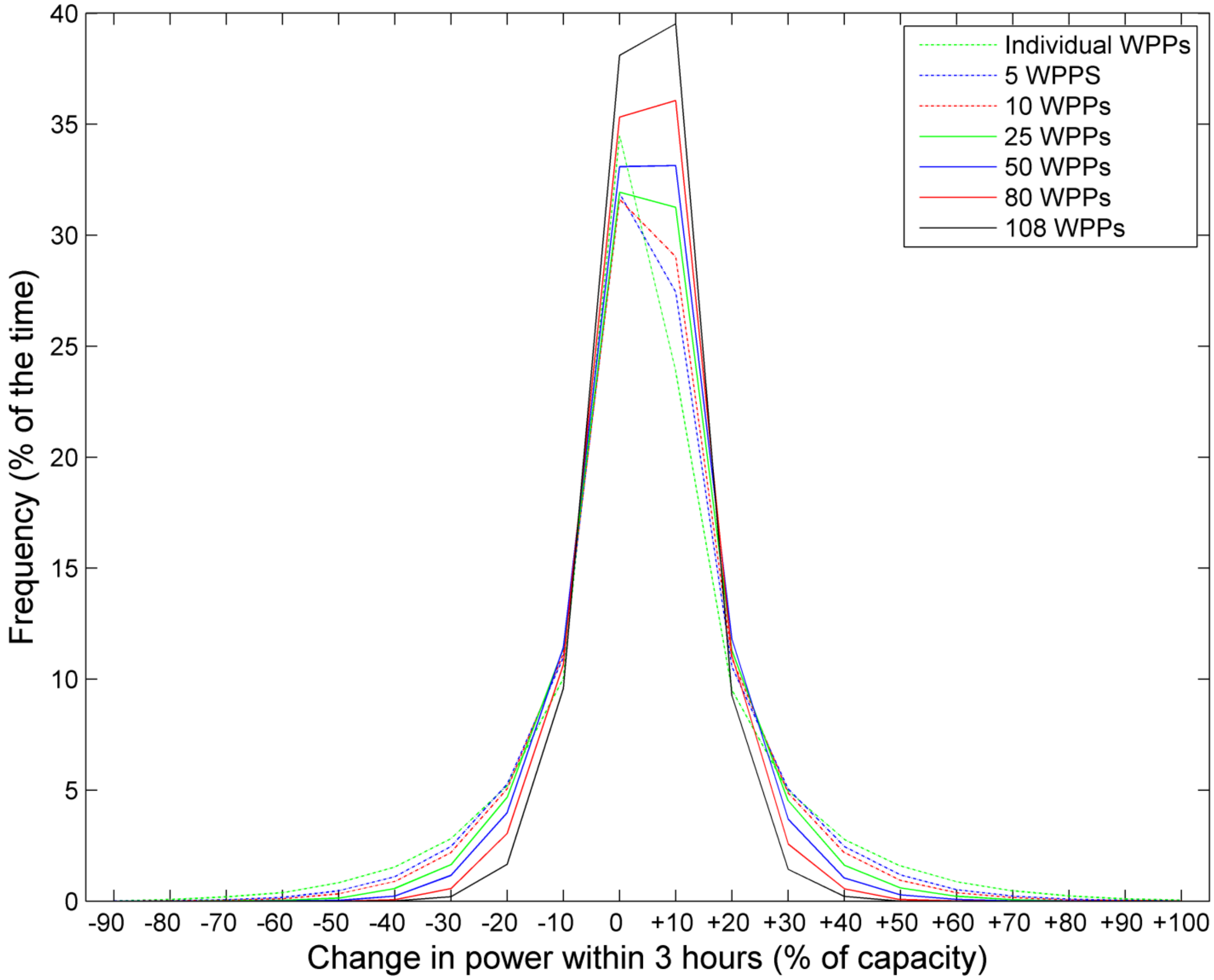
APPENDIX B

Standard deviation of capacity factor in July (1979 – 2010) as a function of network area for individual WPPs and WPP networks. Each point represents one individual WPP or network. Points are color-coded according to the n of that network.



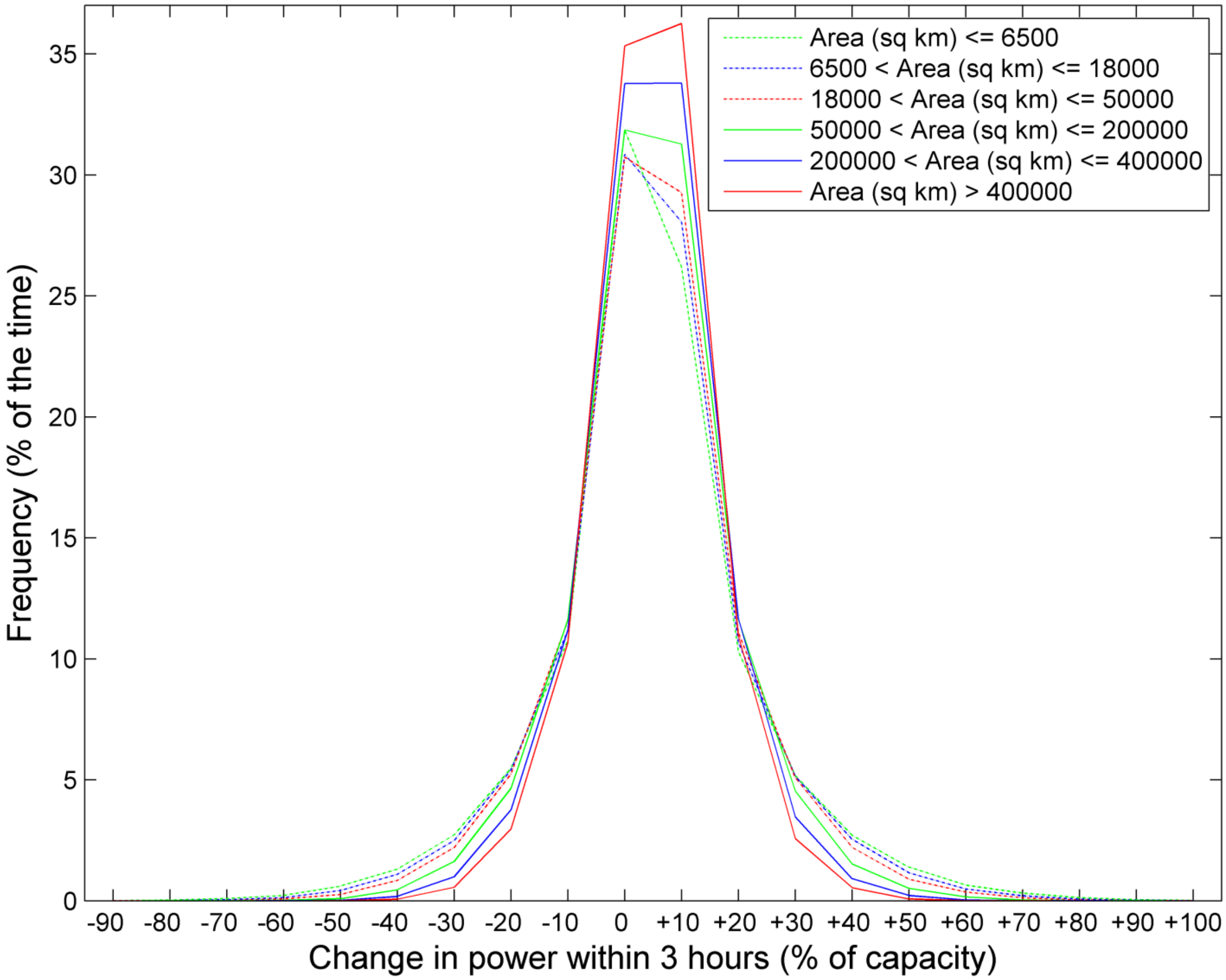
APPENDIX C

Histograms of the frequency of various magnitudes of changes in the capacity factor on the three-hour scale for the month of January (1979 - 2010), as a function of n.



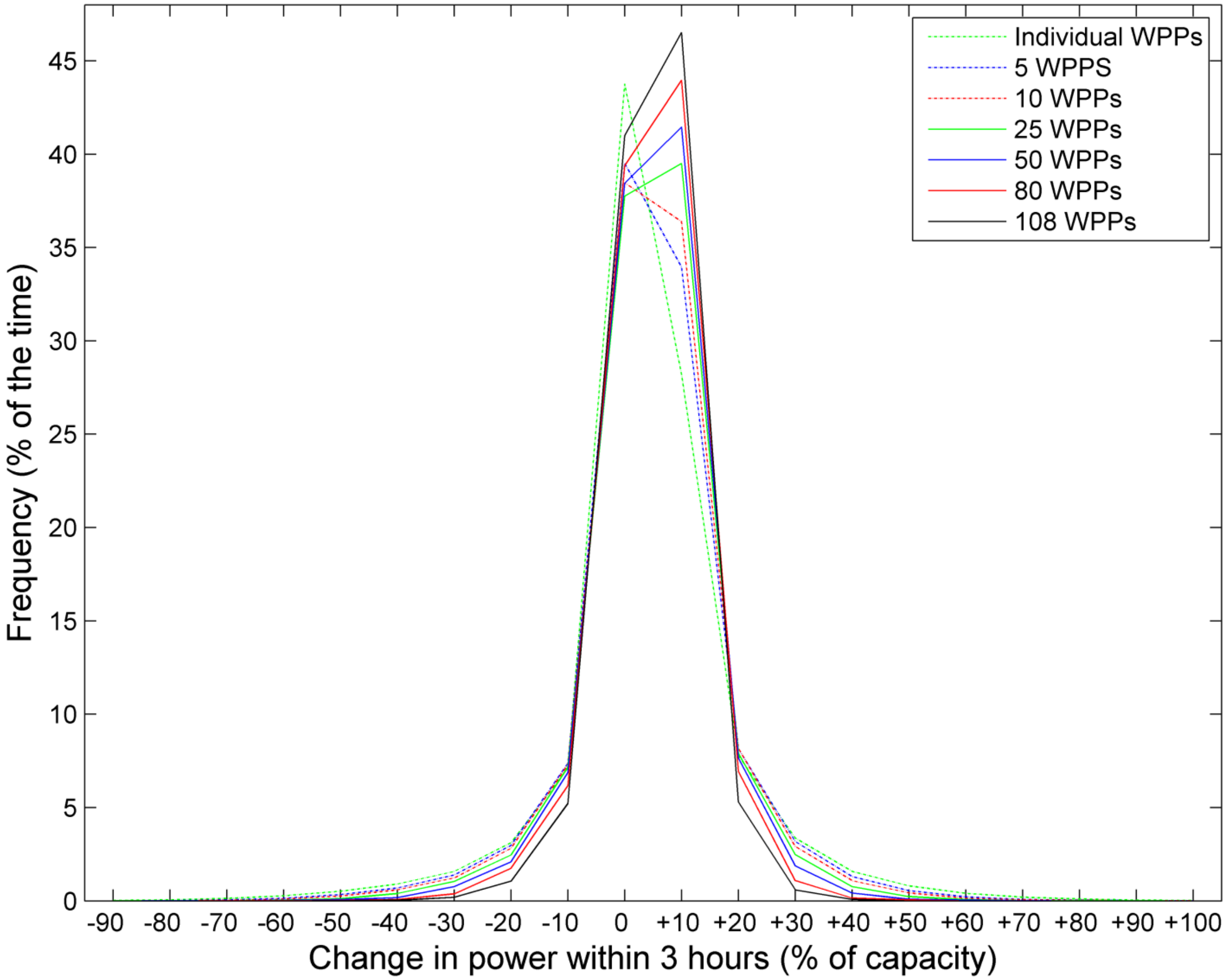
APPENDIX C

Histograms of the frequency of various magnitudes of changes in the capacity factor on the three-hour scale for the month of January (1979 - 2010), as a function of network area.



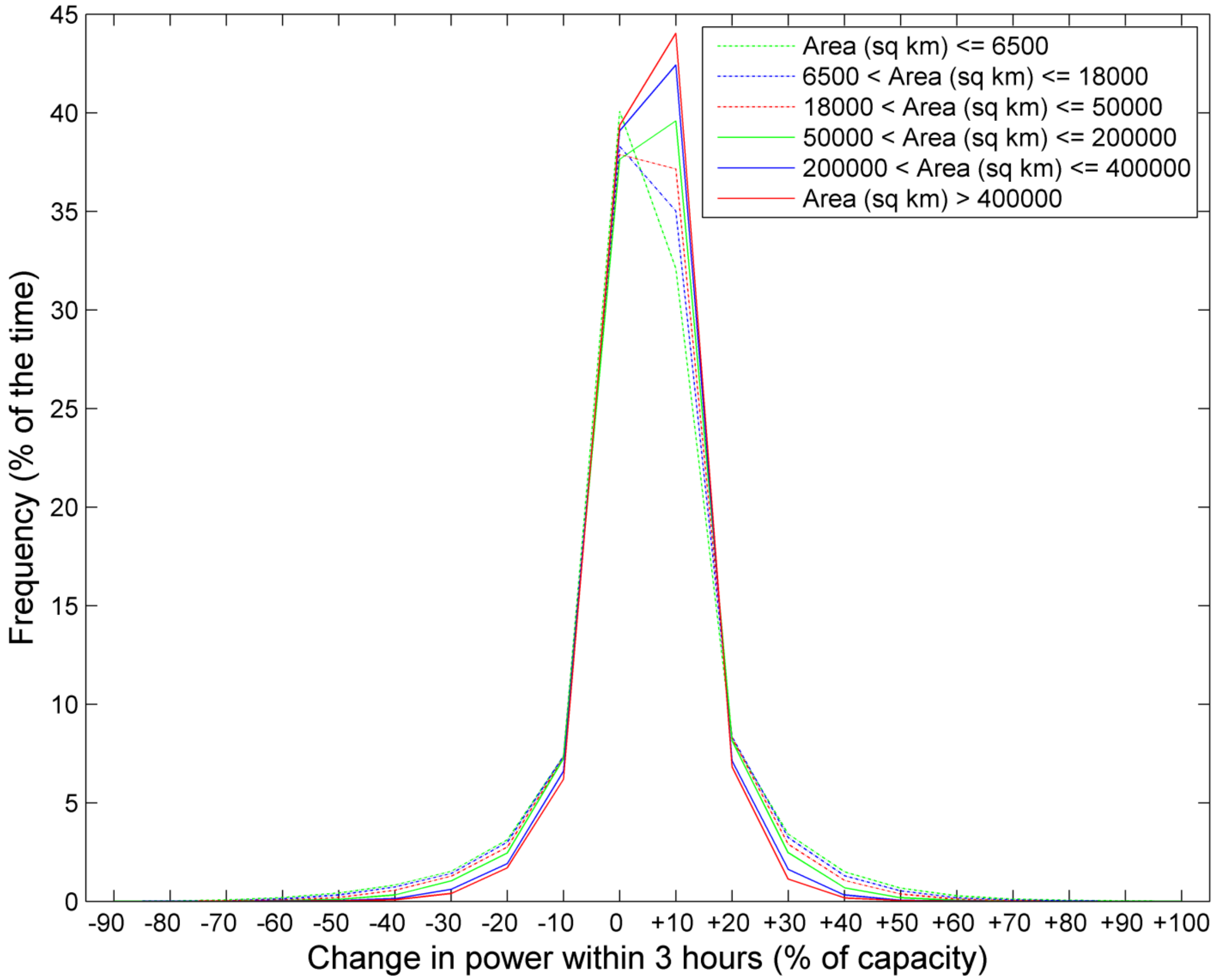
APPENDIX C

Histograms of the frequency of various magnitudes of changes in the capacity factor on the three-hour scale for the month of July (1979 - 2010), as a function of n.



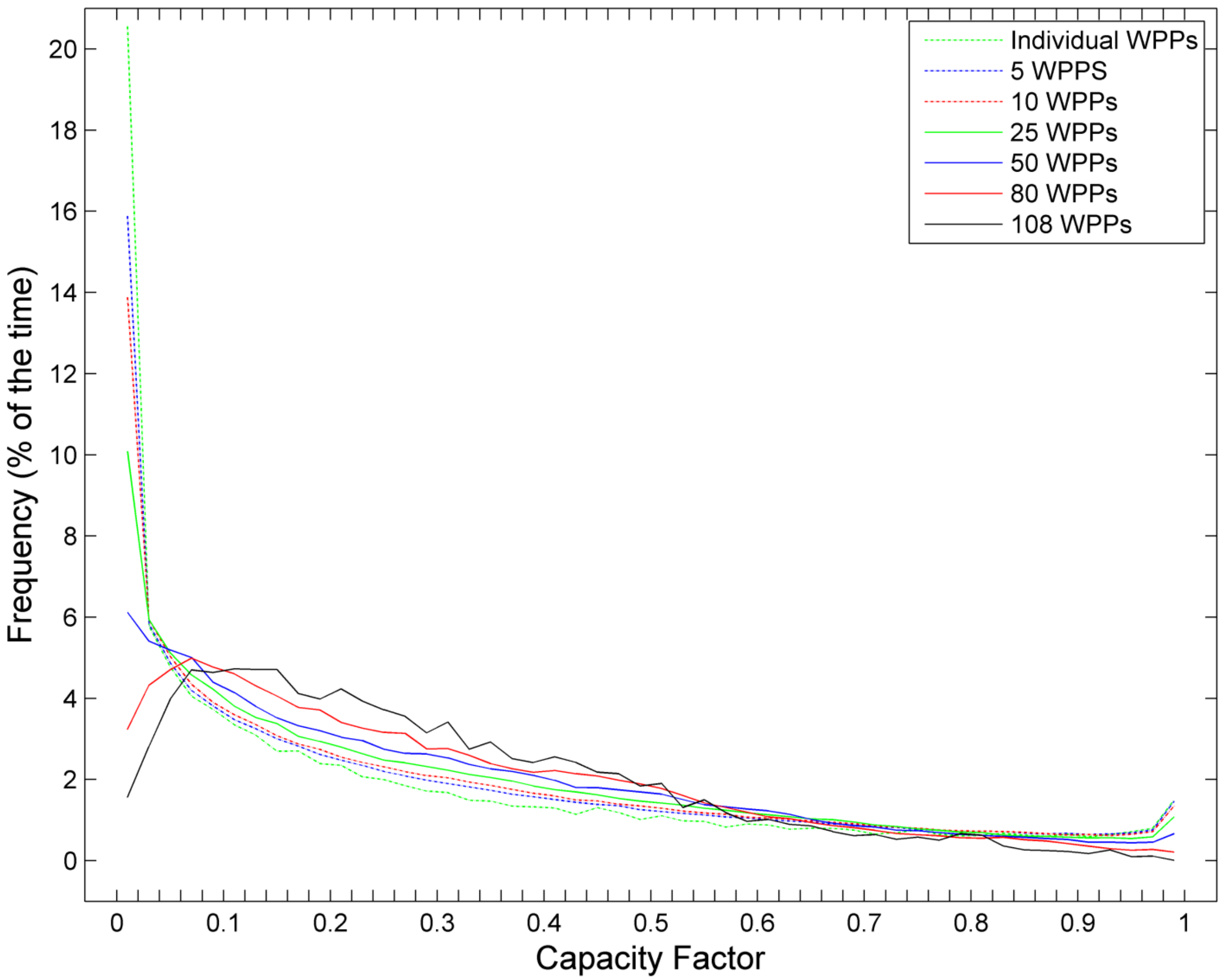
APPENDIX C

Histograms of the frequency of various magnitudes of changes in the capacity factor on the three-hour scale for the month of July (1979 - 2010), as a function of network area.



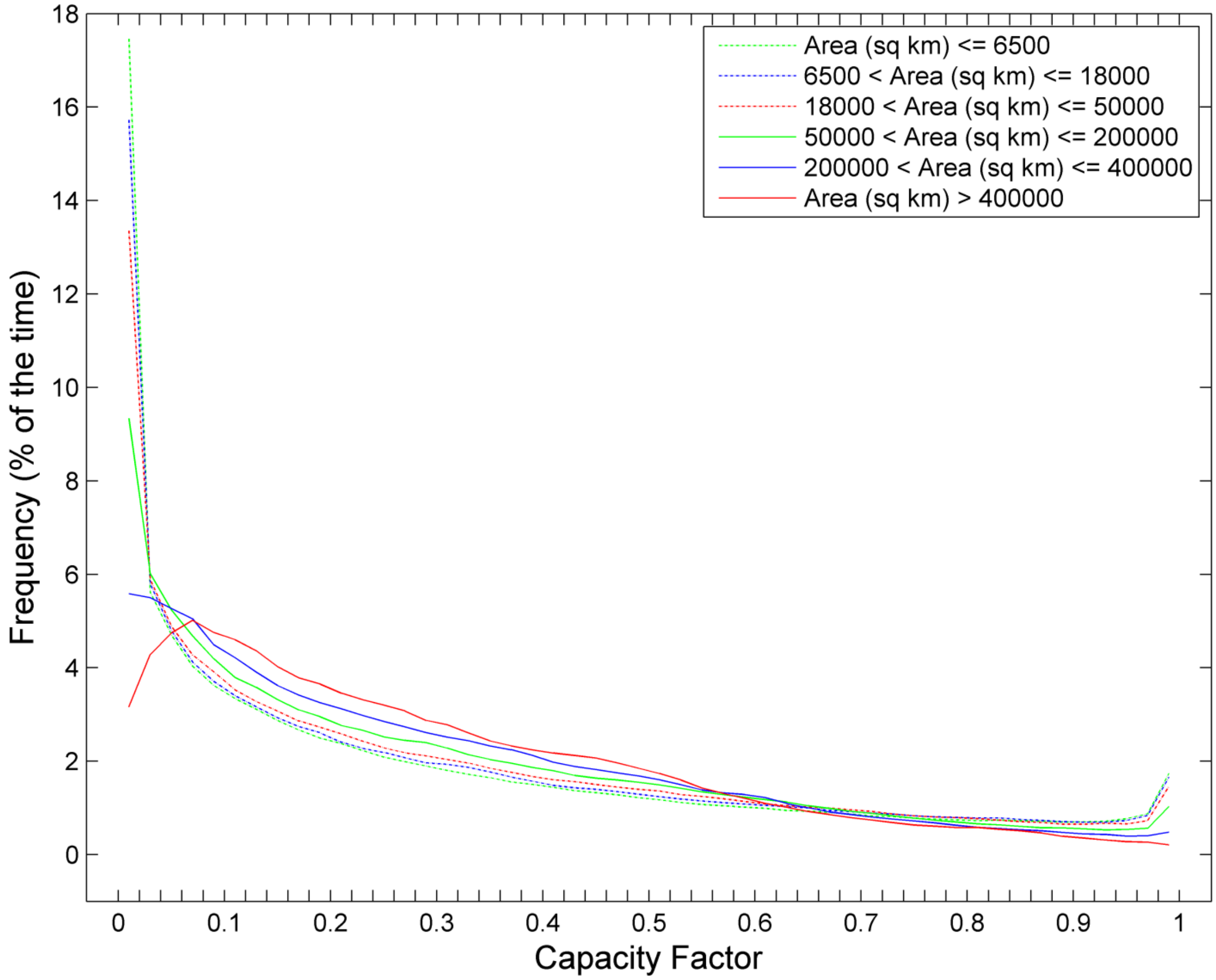
APPENDIX D

Frequency of 50 quantiles of mean capacity factor for the month of January (1979 – 2010), as a function of n.



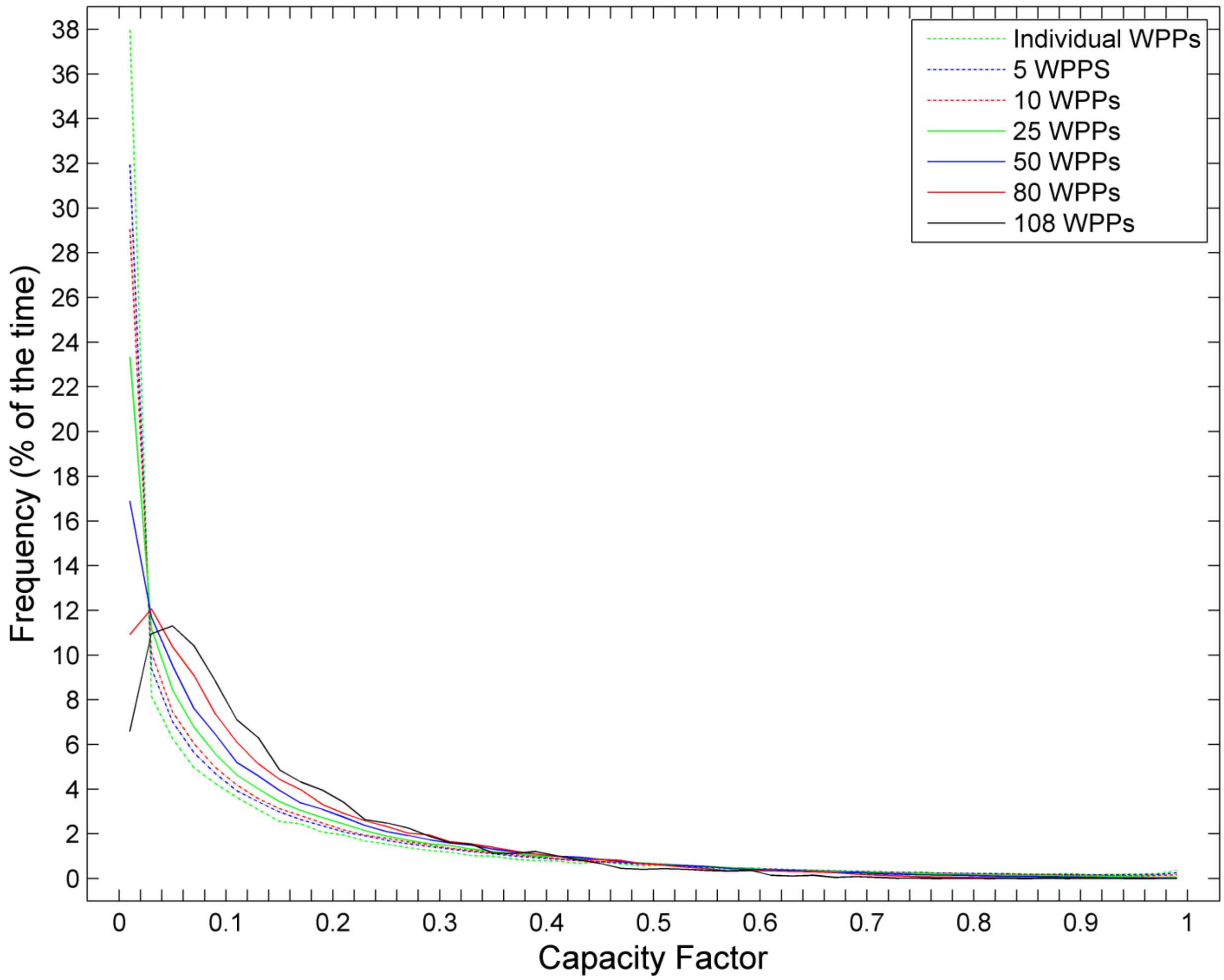
APPENDIX D

Frequency of 50 quantiles of mean capacity factor for the month of January (1979 – 2010), as a function of network area.



APPENDIX D

Frequency of 50 quantiles of mean capacity factor for the month of July (1979 – 2010), as a function of n.



APPENDIX D

Frequency of 50 quantiles of mean capacity factor for the month of July (1979 – 2010), as a function of network area.