Scaling of Wind Energy Variability Over Space and Time

Mehdi Shahriari^a and Seth Blumsack^{b,*}

^a John and Willie Leone Family Department of Energy and Mineral Engineering, The Pennsylvania State University, University Park, PA 16802, USA, email: mehdi@psu.edu

^b John and Willie Leone Family Department of Energy and Mineral Engineering, The Pennsylvania State University, University Park, PA 16802, USA, email: sab51@psu.edu

* Corresponding Author

Abstract:

We use a large data set of simulated wind energy production in the United States to quantify the geographic and temporal scaling of energy output variability reduction when multiple sites are aggregated. We add to the existing literature on “geographic smoothing” by (i) quantifying the scaling of geographic smoothing over multiple spatial and temporal scales; (ii) bounding such smoothing through the use of an algorithm that produces minimum-variance sets of wind energy production sites; and (iii) quantifying inherent tradeoffs in optimizing wind energy site selection to minimize output variability along a specific frequency. The number of wind farms required to minimize output variability increases linearly with spatial scale of aggregation, but the scaling factor is small, on the order of 10^{-6} relative to geographic distances. These scaling factors increase by a factor of two as the frequency considered increases by three orders of magnitude (minutes to months). Our analysis indicates that optimizing wind deployment over one particular frequency increases output variability over other frequencies by nearly 30% in some cases.

Keywords: wind energy variability, US Eastern Interconnect, geographic smoothing, variance minimization, spatial analysis

1. Introduction

Wind energy is experiencing considerable growth in its penetration in the US power grid. While this growth can bring about several economic and environmental advantages, it comes with a number of system integration challenges. Since wind energy output cannot be predicted perfectly (although predictive abilities are improving and changes in wind energy output over short times scales are generally not extreme [1]), the power system operator needs to hold a portfolio of complementary resources such as capacity markets and ancillary services [2, 3], which has the potential to increase the costs of large-scale wind integration. Specifically, in [4], Hoogwijk et al. concluded that as share of wind output in electricity generation mix rises other factors such as increased requirement for back-up power and building wind farms at less suitable locations will cause an increase in overall system costs, and these costs tend to

increase as wind penetration increases [5]. Another subject of interest is the incentives for other sources of electricity generation such as thermal power plants when wind power penetration is increasing. For the case of German grid, it has been argued that if the market prices are lowered by more than 5 percent then it would considerably decrease the incentives for investing in new natural gas plants [5].

A number of studies have focused on the smoothing effect from interconnecting wind plants over wide geographic regions to reduce volatility of output, which would directly affect wind integration costs. This aggregation has been encouraged by some power grid operators in the United States through attempts to limit market participation by renewable energy operators that have not aggregated with complementary resources. The research literature is in broad agreement that wind energy production output can be smoothed with sufficiently clever geographic diversity, amounting to interconnecting wind sites with low correlation. Short term variability of wind power can be smoothed even by having a single wind farm that uses only two wind turbines within small distances from each other (about 170 meters). However, in order to increase wind power supply reliability over longer time periods a larger catchment area is needed. These results can be shown by employing correlation coefficient of power change [6]. Holttinen et al.[7] studied the variability of wind power and reserve requirement using standard deviation as the measuring unit.

Another study found out that by adding more sites to an interconnected queue, correlation among sites become smaller and the reserve requirement for an array of 19 sites will be 47% less than the reserve requirement for a single site [8]. The effect of long distance interconnection on average hourly change in power output have been studied in [9]. They found out that connection of a few wind farms will reduce the average hourly change in output but enlarging the region will not result in considerable reduction of this measure. Further, they concluded that interconnection will increase firm power output.

Gunturu et al. [10] studied the variability of wind power across Independent System Operator (ISO) regions in the US. They incorporated generation duration curves to show that even with aggregation, a large number of hours without wind (or less than 5% capacity) can be observed. Further, by using coefficient of variation they showed that benefits of aggregation vanish quickly after aggregating several wind sites. Rose and Apt used reanalysis datasets to study the variability of wind power [11]. Their results indicated that wind aggregation could significantly reduce the annual coefficient of variation (5-12% for individual wind sites versus 3% for the portfolio). Aggregating windfarms across large regions will reduce the variability of wind power output because correlation between windfarms decreases as distances between sites become larger [12]. Using datasets from three regions (USA, Canada and Australia), the authors calculated the extent of geographic diversity required to make the aggregation effective. Louie [13] performed a statistical analysis of wind aggregation in several RTOs in the US. He found out that the correlation between RTOs are very similar to the correlation between single wind sites.

However, the former exhibits larger magnitudes relative to the later. Handschy et al. [14] used 9 windfarms from different regions across the US which results in low correlation between each pair of windfarms. They found out that the number of low power hours will decrease as the number of windfarms increase. This decline has an exponential trend. Huang et al. [15] concentrated on meteorology aspects of wind power. They concluded that by aggregating 5-10 wind farms the high frequency variability can be significantly eliminated. Authors in [16] used Monte Carlo simulations to determine the number of effective generators that provide firm capacity. Apt [17] uses the power spectral density of wind sites to study different types of fill-in power that can efficiently compensate for variations in wind power.

Other studies have focused on investigating the benefits of hybrid renewable systems. Suomalainen et al. [18] studied the correlation of hydro and wind resources with electricity demand and prices. Their analyses showed that using wind sites that have negative correlations with hydro resources, could reduce high price fluctuations in hydro-dominant electricity systems. Further, they found out that both the spatial and temporal distribution of wind resources should be analyzed in order to create a combined wind-hydro system that maximizes the correlation between supply and demand. Hirth [19] incorporated a numerical model to show that in hydro-dominant electricity systems, the drop in wind value is much smaller compared to systems without hydro power. He concluded that flexibility of hydro power benefits wind aggregation. By studying high penetration of wind and solar in the electricity system of Croatia [20], authors found an optimal mix of renewable generation technologies that would reduce electricity import and lower CO₂ emissions. Further, a number of papers have identified other measures of facilitating wind integration into the grid by coordinating generation and expansion planning [21] and improving forecast capabilities [22].

While this large body of research has articulated the potential benefits in variability reduction from geographic aggregation of wind energy, there has been no settlement on a best-case magnitude of that variability reduction, and very little discussion of best-case aggregation scenarios over different spatial and temporal scales. We add these missing pieces to the existing body of literature by using a large public data set of simulated wind energy production to examine the smoothing of wind power output through aggregation across spatial scales from thousands to millions of square kilometers. We perform a best-case bounding assessment of the potential for geographic smoothing and to understand quantitatively how geographic smoothing scales over multiple spatial and temporal scales. Our best-case approach introduces a variance minimizing algorithm that sequentially connects wind farms based on the variance of their joint power output, yielding an evolution of wind energy penetration that is consistent with best-case output variance minimization.

Consistent with previous research [9, 10], we find that geographic aggregation of wind energy does reduce output variability, but only to a point. While other studies [7, 9, 10, 12, 13, 15, 17] have focused

on finding the efficient number of wind sites or the geographic scope to minimize the wind output volatility or increase firm power output by considering available wind site locations, we have proposed a systematic method to find wind site locations that achieve the same goals. Unlike previous work, we do not consider the location of wind sites as already given; our analysis, rather, is intended to describe the location of wind build-out over space in order to achieve best-case variability reduction over several temporal scales. Although this study provides a valuable statistical characterization of wind aggregation over various spatial and temporal scales, the actual deployment path of wind farms in the developed world is likely to be different, since minimizing output variance is not the same objective as maximizing profits or wind energy output. As such, our critical contributions to the existing body of work on geographic smoothing of wind energy are : 1) minimizing wind output variability over low frequency time scales will yield higher capacity factors and higher wind output than optimizing wind site selection to minimize output variability over higher frequency time scales; 2) optimizing wind farm deployment to achieve output variance minimization over one-time scale does not imply minimizing output variance over other time scales; 3) quantification of the inter-temporal tradeoffs associated with building wind energy capacity to maximize aggregation benefits at a specific time scale (for example, we find that building out wind energy capacity to minimize hourly output variance actually increases output variance at slower frequencies); 4) the number of wind farms required to achieve minimum output volatility grows with spatial scale of aggregation, but the scaling factor is small relative to geographic scale; and 5) minimizing wind output volatility over different time scales requires different siting criteria.

The main study area we use covers the US Eastern Interconnect (basically the area of the North America power grid east of the Rocky Mountains) and includes more than 1,300 simulated windfarms, with data taken from the NREL Eastern Wind Interconnection and Transmission Study [23]. The existing literature [24] points out that this data set tends to under-estimate power output variability at shorter time scales, i.e., sub-hourly. This does not qualitatively affect our conclusions since we observe less variability over longer time scales. In this dataset, wind power generation is available for 1,326 simulated wind farms. These wind farms are shown in figure 1. The data is available in 10-minute interval format for a period of three years from January 2004 to December 2006; therefore, each wind farm is described by a vector with 157,824 elements. These wind sites have different capacities; therefore, we have normalized the wind generation data by dividing each wind site's data by its capacity. By normalizing the data, wind power output for all wind sites would be in the range of 0 to 1. We have considered different portfolios of wind farms at state, regional and continental spatial scale. The results suggest that in larger geographical scales a larger number of wind farms are needed to minimize the output variability, and this exhibits linear scaling. At a specific geographic scale, the number of wind farms that minimizes output variability will increase as we optimize deployment along higher-frequency time scales. The difference between

planning and operational time scales becomes more evident as we move to larger geographic areas, although these differences are not large in magnitude. Furthermore, when wind energy deployment optimization occurs over faster time scales a larger geographic footprint is required to achieve minimization of output variance. At operational time scales (minutes to days), optimal deployment of wind farms is geographically less concentrated around a geometric mean center than would be the case if deployment was optimized over a planning time scale (weeks to months).

2. Methods

Our analysis proceeds by assuming that the set of wind farms in the NREL data set is sequentially built out in a way that minimizes the incremental variance between existing wind sites and a new wind site. This approach implicitly assumes that integration cost (aside from hardware costs such as transmission) is an increasing function of output variability. While production variance is admittedly a blunt proxy for integration cost, higher variability in output would imply a higher cost to provide balancing and ramping capabilities [25, 26]. While actual wind site development decisions depend on a variety of factors such as local energy prices, land acquisition costs and transmission interconnection costs, our variance-minimizing algorithm yields a wind build-out sequence that is advantageous from the perspective of the power system operator.

Figure 1- Locations of 1,326 simulated wind farms on the US Eastern Interconnection grid.

Our approach differs from some previous research [27], which added wind farms to minimize correlation rather than variance. Since the sum of the variance of two wind farms will generally not be equal to the sum of the variances, minimizing correlation is not equivalent to minimizing variance. We also note that our algorithm not only minimizes the incremental variance with each additional wind farm added to the portfolio, but also minimizes the overall variance if blocks of wind farms are added concurrently. A proof of this result is given in the Appendix. We choose this approach since our interest is in understanding the *evolution* of wind energy variability as additional wind farms are integrated into a single power grid. Nevertheless, we adopt some shorthand in this paper and refer to this algorithm as “variance minimizing.”

Our algorithm aggregates wind farms in a step-wise fashion such that output variance is minimized at each step for a given frequency in the time domain (e.g. ten-minute frequency, hourly frequency and so forth). The first step of the algorithm is to assume that a specific wind site is developed first. The second step would be to then choose the wind site that, when aggregated with the first site, would yield the lowest variance of output along the chosen frequency. The variance of joint power output is calculated by using the following equation:

$$Var(A + B) = Var(A) + Var(B) + 2 * Cov(A, B) \quad (1)$$

Where $Var(A)$ and $Var(B)$ are respectively the output variance of sites A and B . $Cov(A, B)$ is the covariance between sites A and B .

The third step would be to choose the wind site that, when aggregated with the first two sites, would yield the lowest variance of output. The algorithm proceeds in this iterative fashion to produce a sequence of wind site deployment and all sites under consideration have been deployed. The new power output (i.e. power output of the aggregated sites) is calculated by using the weighted average equation:

$$Aggregate\ output = \frac{P_1 * j + P_2}{j + 1} \quad (2)$$

Where P_1 is the power output of the already aggregated sites, P_2 is the power output of the site that would be added to the aggregated sites (i.e. the site that would yield the lowest variance of output when aggregated with the first site), and j , is the number of aggregated sites (i.e. sites that created P_1).

A pseudo code for the variance minimizing algorithm, specific to our data set from NREL, is as follows:

Variance minimizing algorithm

-
1. Construct a matrix of wind generation data for all wind farms.
 2. Set N equal to number of wind farms.
 3. Create a sequence array with length of N .
 4. Start at specific wind farm i ($i = 1, 2, \dots, 1326$).
 5. *for* ($i=1:N$)
 6. Put the number of this wind farm in the first cell of the sequence array. Call this wind farm P_1 .
 7. *for* ($j=1:N-1$)
 8. Calculate wind farm i 's variance with all other wind farms using equation 1.
 9. Select the wind farm that has the lowest variance of power output with wind farm i .
 10. Put the number of this wind farm in the $(j+1)$ th cell of the sequence array. Call this second wind farm P_2 .
 11. Calculate the average power output of these two wind farms using equation 2.
 12. Replace the output of wind farm i in the generation matrix with this new power output and remove wind farm j .
 13. end for
 14. end for
-

Note that this procedure will produce one sequence for each initial wind farm, or N sequences in total.

We emphasize that the sequences developed for wind farm deployment are best-case scenarios for minimizing variance of output at each deployment step. It does not address the potential profitability of the wind sites being developed and does not consider any costs of development including transmission interconnection. Considering revenues and costs would likely affect the sequences generated [18, 19] but we leave that as a valuable extension for future research.

3. Results

3.1. Wind output variance minimization

Figure 2 shows the output of the variance-minimizing algorithm using all 1,326 sites in the NREL data set at various frequencies corresponding to relevant time horizons for power system operations [28]. Each point in the figure represents an average over 1,326 sequences. With the incremental addition of 35 wind farms out of more than 1,300 the standard deviation declines by more than 61% by using the variance minimizing approach at ten-minute frequency. Following this threshold point, the standard deviation of power output increases as additional wind sites are added.

Figure 2 also shows results from the variance-minimizing analysis at hourly, daily, weekly and monthly time steps (calculated by averaging modeled ten-minute output over the appropriate time frame). We chose time steps based on importance for planning and operations decisions by electric grid operators. High frequency variation (sub-hourly), for example, is relevant for frequency regulation and management

of operating reserves. Low frequency variation (hourly and longer), on the other hand, impacts economic dispatch, unit commitment and longer-range planning. Figure 2 shows that wind power variation is larger over low frequency time scales. Moreover, the increase in standard deviation beyond the threshold point is more evident at low frequency time scales. We conclude that effects of wind aggregation on wind variation at different time scales follow similar trends but vary in terms of magnitudes. The output smoothing effect of spatial wind aggregation vanishes after a relatively small number of wind sites are developed. This phenomenon is invariant to the time scale considered for calculating output variance and is consistent with some previous research [9].

Figures 3 and 4 show this analysis at different geographic scales. Figure 3 shows the evolution of wind power output variability for three different Regional Transmission Organizations (RTOs) that operate within the Eastern Interconnect. These RTOs are similar in geographic scope, ranging from 500,000 to 1,500,000 square kilometers, but vary by the number of modeled wind sites in the NREL data set. We have hence used percentage terms (rather than the absolute number of wind sites as in figure 2) in describing the number of wind sites deployed. Panel (a) shows how standard deviation of output changes as more wind sites are aggregated at 10-minute time scale. Panels (b) and (c) correspond to daily and monthly time scales. This figure shows that magnitudes of output variability are different for an RTO over different time scales. For example, a portfolio of wind sites in PJM is less volatile than a portfolio of wind sites in ISO-NE over 10-minute and daily time scales. However, over monthly time scale, wind sites in ISO-NE are less volatile than wind sites in PJM.

Figure 4 shows similar analysis for four specific states (one within each of the four RTOs). Two of the states (Iowa and Nebraska) are in the Midwestern U.S. with relatively high wind potential, while the other two states (Pennsylvania and Maine) are Northeastern U.S. states with varied topology and more limited wind potential. We observe different magnitudes of variability over different time scales. For example, over operational time scales (10-minute and daily), wind sites in Iowa exhibit higher output variance than wind sites in the other three states. Over planning time scales (monthly), however, wind sites in Iowa exhibit lower levels of output variability.

At a ten-minute output frequency, the variance-minimizing threshold number of aggregated wind sites occurs at 3% of the total number of wind sites in the Eastern Interconnect, 5-12% of the total number of wind sites within larger multi-state RTOs, and 11% to 40% of the total number of sites within a state. We observe a similar magnitude of output variation reduction in the MISO, SPP and PJM RTO regions (51%, 47% and 47% for 10-minute frequency) as in the Eastern Interconnect as a whole. The reduction of standard deviation through geographic aggregation is higher for Midwestern states (Iowa and Nebraska in figure 4) versus an eastern state (Pennsylvania).

Figure 2- Standard deviation of power output for wind farms in the eastern interconnect at different time scales (averaged over 1,326 iterations)

Figure 3- Standard deviation of power output for wind farms in MISO, SPP, PJM and ISO-NE at different time scales a) 10-minute, b) daily, c) monthly (respectively averaged over 563, 356, 212 and 112 sequences)

Figure 4- Standard deviation of power output for wind farms in Iowa, Nebraska, Pennsylvania and Maine at different time scales a) 10-minute, b) daily, c) monthly (respectively averaged over 94, 90, 55 and 40 sequences)

3.2. Scaling over space and time

We have repeated the variance minimizing approach for different regions and states, over a number of different time scales corresponding to operational and planning decision time frames for the power grid. A summary is shown in figure 5. Each point on this figure identifies the number of wind farms that minimizes the variance of wind energy output within a state, a multi-state RTO region or the Eastern Interconnect. As the geographic area for wind energy interconnection grows, a larger number of wind farms are needed to achieve variance minimization. Expanding the integration region from by three orders of magnitude, from 10^4 square kilometers (the size of a small state) to 10^6 square kilometers (the Eastern Interconnect) requires an increase in the number of wind farms of less than one order of magnitude in order to achieve minimization of standard deviation in output ($\sim 10^1$ wind farms for a small state to less than 10^2 wind farms for the Eastern Interconnect), and this scaling is linear in geography; the linear coefficient ranges from 9×10^{-6} (for 10 minute time step) to 2×10^{-6} (for monthly time step). We also observe that the number of wind farms required to minimize standard deviation decreases as the time scale for averaging increases. Minimizing standard deviation over a ten-minute time step requires roughly half the number of wind farms as minimizing standard deviation over a monthly time step when the geographic area of integration is large (10^5 to 10^6 square kilometers). At smaller areas of geographic integration, we observe less variation across the frequency domain in the variance-minimizing number of wind sites.

Figure 5- Wind aggregation over different spatial and temporal scales. Each point represents the area of a state or region and the number of wind farms required to minimize standard deviation of output at that state or region. Note that the figure is in log-log space.

Figure 6 shows the relationship between geographic scope and percentage decrease in standard deviation of wind output. Each point in this figure represents an area (state, region or interconnect) and the magnitude of decrease in standard deviation of wind output at the point where output variance is minimized. Geographic scaling in this case is logarithmic; the logarithmic coefficient ranges from 0.064 to 0.074. Based on figures 5 and 6 we conclude that the number of wind sites required to achieve variance minimization is increasing in the scope of geographic space, although the percentage required is decreasing in the scope of geographic space. In smaller geographic regions, wind production from different sites is more highly correlated. Therefore, the potential to decrease wind power variation is smaller and the minimum standard deviation can be achieved by incorporating a smaller number of wind farms (although it does require aggregating a larger percentage of total wind sites).

Figure 6- Percentage decrease in standard deviation of wind output at different geographical areas for different time scales.

3.3. Spatial Analysis

A more explicit spatial analysis proceeds by identifying how the geographic dispersion varies as wind energy output variance is minimized over different time scales. We index time scales by j , so $j = \{10 \text{ minutes; hourly; daily; weekly; monthly}\}$ and we index individual wind farms by k , so $k = \{1, \dots, 1326\}$. We start by generating sequences $\{N_{k,j}\}$ as described in the variance minimizing algorithm in Section 2 (k here denotes the first wind farm added to each sequence). For each sequence $\{N_{k,j}\}$ we find the number of wind farms $N_{k,j}^*$ necessary to minimize variance of power output at time scale j , when the sequence of adding wind farms starts with wind farm k . Since the first wind farm added in each sequence is effectively arbitrary, we eliminate the first wind farm from each sequence and are thus left with the $N_{k,j}^* - 1$ wind farms that achieve the variance minimizing point for each sequence $\{N_{k,j}\}$ and denote the sub-sequence of wind farms up to the $N_{k,j}^* - 1^{\text{th}}$ wind farm as $\{\widehat{N}_{k,j}\}$. Finally, we choose all unique wind farms from the sub-sequences $\{\widehat{N}_{k,j}\}$ to include in our spatial analysis.

Figure 7 shows the spatial distribution of variance-minimizing wind farm deployment at different time steps. As we move from high frequency time scales to low frequency time scales fewer wind farms are

selected from the east coast. Specifically, a smaller of number wind farms are chosen from the Southeast (North Carolina and Tennessee) and PJM (Pennsylvania and New Jersey). In contrast, more wind farms are chosen from the Midwest and Great Plains. We quantify this geographic shift using different measures of spatial clustering and dispersion. First, we identify the geographic center of the collection of variance-minimizing wind farms for each time scale. The geographic center can be determined as a point $(\bar{X}, \bar{Y})$ defined as follows:

$$\bar{X} = \frac{\sum x_i}{n} \quad (3)$$

and

$$\bar{Y} = \frac{\sum y_i}{n} \quad (4)$$

where x_i and y_i are respectively x and y coordinates of wind farms and n is number of wind farms [29]. We also calculate the magnitude of spatial dispersion at different time scales using the standard distance measure, defined as the square root of the sum of variances of x -coordinates and variances of y -coordinates [29]:

$$\text{Standard Distance} = \sqrt{\sum (x_i - \bar{X})^2 + \sum (y_i - \bar{Y})^2} \quad (5)$$

where x_i and y_i are respectively x and y coordinates of wind farms and $\bar{X}$ and $\bar{Y}$ are the averages of x -coordinate and y -coordinate of wind farms.

The geographic centers and standard distances for ten-minute, daily, weekly and monthly time scales are shown in figure 7. In each panel the standard distance circle is shown, whose center is the geographic center of the variance-minimizing collection of wind farms and whose radius is equal to the standard distance.

Figure 7- Spatial distribution of standard deviation minimizing wind farms. For each time scale, location of wind farms that minimize standard deviation of wind output is shown. Each star shows the geographic center of the wind farms in the relative time scale. The circles correspond to standard distance circles centered at geographic center with their radiuses equal to the standard distance. a) 10-minute time-step, b) daily averaged, c) weekly averaged, d) monthly averaged.

The standard distances for variance-minimizing wind farm deployment are shown comparatively in figure 8. The location of the centroid of the standard distance circle varies by more than 750 kilometers as the frequency unit of analysis increases. At 10-minute time step, the centroid is located in northern Indiana. As the frequency unit of analysis decreases, the centroid is moved to Illinois (Daily and Weekly) and Minnesota (Monthly). The radius of the standard circle scales from 920 to 1240 kilometers, with the highest value observed at daily time scale. Results from Figure 8 suggest that at operational time scales wind farms should spread over a larger area in order to minimize wind power variation. We have performed the same spatial analysis for multi-state RTOs like PJM, MISO, SPP and ISO-NE. The results are shown in figure 9. In MISO, SPP, and ISO-NE, the standard distances are bigger over planning time scales. This shows that a larger geographic footprint is required to minimize output variance over high frequency time scales. In PJM, however, we observe the exact opposite results; standard distance is larger over operational time scales and decreases as the frequency increases.

Figure 8- Standard distance and geographic footprint at different time scales. The standard distance is the radius of standard distance circles shown in figure 7. The geographic footprint is the area covered by the standard distance circle.

Spatial clustering can also be quantified using the K and L functions. K function [30] counts the number of points within a specific distance from each point in the study area:

$$K_i(d) = \frac{1}{\lambda} E(\text{number of points within distance "d" of an arbitrary point "i"}) \quad (6)$$

Where, λ is the point density. For each wind farm W_i in the study area we count the number of wind farms W located within distance d . This amounts to drawing a circle of radius d centered around wind farm W_i . We then count the number of wind farms located within this circle and divide by the density of points to arrive at $K_i(d)$. For each d , the aggregate $K(d)$ function is calculated as the average of all $K_i(d)$ within a given value of d . $K(d)$ is defined mathematically as [31, 32]:

$$K(d) = \frac{\sum_{i=1}^n \#[W \in C(W_i, d)]}{n\lambda} \quad (7)$$

Figure 9- Standard distance for different RTOs over various time scales.

If the distribution of points follows a random process, the expected value of $K(d)$ is equal to πd^2 [32]. Since K increases proportionally with squared distance, it would be difficult to observe small changes as d becomes large. To get around this problem we use a related measure known as the L function [32]:

$$L(d) = \sqrt{\frac{K(d)}{\pi}} - d \quad (8)$$

The expected value of $L(d)$ when points are randomly placed in a space of radius d is equal to zero. Larger values of L are thus associated with higher clustering. Negative values of $L(d)$, on the other hand, illustrate higher geographic dispersion where points are more evenly spaced. Figure 10 shows the $L(d)$ function for variance minimizing wind sites in the Eastern Interconnect. We have calculated the $L(d)$ function for these sites across various time scales. We have also computed the $L(d)$ function for all wind farms in the Eastern Interconnect (shown by All Windfarms line in Figure 10).

Further, we have used Monte Carlo simulation to compute $L(d)$ for randomly selected wind sites. We have randomly selected N wind sites (approximately equal to number of unique variance minimizing sites) and calculated the $L(d)$ function for these sites. This process has been repeated 1,000 times. The average line corresponds to the average of these simulations. The ranges illustrate the minimum and

maximum values of $L(d)$ for a given distance across all 1,000 simulations. The low frequency range is associated with daily, weekly and monthly time scales. The high frequency range corresponds to 10-minute and hourly time scales. It was required to consider two ranges because the number of unique wind sites are significantly different for low and high frequency time scales.

Figure 10 shows that variance minimizing wind sites are more clustered over low frequency time scales. At distances smaller than 600 kilometers (200 kilometers), variance minimizing wind sites over monthly (daily) time scales are more clustered than any random selection of wind sites. Over larger distances (larger than 500 kilometers), variance minimizing wind sites are less clustered (more evenly spaced) than all wind farms and random site selection. Further, at small distances (smaller than 50 kilometers), spatial clustering of wind sites is very similar across different time scales. Figure 11 shows similar results for spatial clustering in RTOs. Overall, we can summarize the results as follows: 1) wind sites are more clustered over low frequency time scales, 2) wind sites are more evenly spaced over large distances (>500 kilometers), 3) spatial clustering of wind sites at small distances (<50 kilometers) is very similar over different time scales. This analyses shows that siting wind farms with the goal of minimizing output volatility follows different criteria for high frequency and low frequency time scales.

Figure 10- L function for variance minimizing sites in the Eastern Interconnect

Figure 11- L function for different RTOs

We also investigate the relationship between minimizing output variance and topographical variation. We first identified the wind sites that minimize the standard deviation of wind output for different regions over various time scales. We then calculated the average elevation of the base of each wind site which is available from NREL dataset. The results are shown in figure 12. The dotted horizontal lines correspond to average elevation of wind sites in each region. In MISO and SPP, the elevation of variance minimizing sites is larger than the average elevation of sites in their respective regions. In PJM and ISO-NE, however,

the average elevation is much larger than the average elevation of variance minimizing sites, suggesting that the placement of wind farms on mountaintops and ridgetops, while possibly capturing the highest wind speed events, may add volatility to the overall portfolio of wind farms, imposing greater system costs. In order to further investigate these results, we calculated the correlation between the standard deviation and elevation of wind sites in different regions. The results are shown in table 1. In regions with higher correlation between standard deviation and elevation (PJM and ISO-NE), the variance minimizing sites are selected from lower elevations. On the other hand, in regions where correlation between standard deviation and elevation is smaller (MISO and SPP), wind sites from higher elevations are selected by the variance minimizing algorithm.

Figure 12- Average elevation of variance minimizing sites. The dotted horizontal lines show the average elevation of wind sites in each region.

Table 1- Correlation between the standard deviation and elevation of wind sites in each region

Region	EI	MISO	SPP	PJM	ISO-NE
Correlation	0.17	0.14	0.13	0.31	0.37

We also investigate the potential for tradeoffs between wind energy output and output volatility by examining the capacity factors of our variance-minimizing wind portfolios over different spatial and temporal scales. Similar to the previous section, we identified the wind sites that minimize the standard deviation of output for different region over various time scales. We then calculated the aggregate capacity factors of these wind sites. Figure 13 shows the results. We can observe that in all regions, the average capacity factor is higher over planning time scales. This shows that wind sites with higher capacity factors should be selected in order to minimize output variance over low frequency time scales. This means that variance minimization over low frequency time scales would yield higher power output.

Figure 13- Capacity factors of variance minimizing wind sites

Further, we capture the temporal tradeoffs involved in optimizing wind site selection based on a single time interval by calculating the change in wind output variance across multiple temporal scales based on site selection to minimize incremental variance at a particular time scale. The nature of the tradeoffs is shown in Figure 14. As an example, if wind energy sites were chosen explicitly to minimize incremental variance at a ten-minute time scale, the resulting portfolio of wind sites would exhibit a 10% higher standard deviation in weekly wind output than in a scenario where wind sites were chosen explicitly to minimize incremental variance at a weekly time scale. Similarly, variance minimization at the ten-minute

time step would yield a 25% higher standard deviation of output at a monthly time scale. Figure 14 suggests that planning wind energy installations to minimize output variance at higher frequencies (10-minute and hourly time steps) is associated with an increase in output variance at much slower frequencies. Planning wind energy installations to minimize output variance at the slowest frequencies, however, yields an increase in the standard deviation of output at most other frequencies.

Figure 14- Temporal tradeoffs in wind energy output from minimizing variance along a single time scale in the US Eastern Interconnect.

We have repeated the same analysis for all other regions (RTOs and states). A summary of the results is shown in figure 15. Each panel of figure 15 shows the increase in standard deviation of output over space and time when wind deployment is planned to minimize output variance at a given temporal scale. Note that each point on these graphs identifies the percentage increase in the variance of wind energy output within a state, a multi-state RTO region or the Eastern Interconnect when the planning and variance minimizing time scales are different.

For example, panel (a) of Figure 15 shows how the standard deviation of output at hourly, daily, weekly and monthly time scales increase if wind deployment is planned to minimize incremental variance at the 10-minute time scale. Optimizing wind energy deployment to minimize incremental output variance at the highest frequency in our data set (10-minute frequency) increases the standard deviation of output

at an hourly frequency by less than 0.025% if wind planning happens over a geographic scope similar to that of an individual state ($\sim 10^4 \text{ km}^2$), and increases the standard deviation of hourly output by around 0.075% if wind planning happens over an interconnect-wide geographic scale ($\sim 10^6 \text{ km}^2$). Increases in standard deviation of output at slower frequencies (daily, weekly and monthly) tend to be larger in magnitude.

We also note some asymmetry in this standard deviation penalty from planning wind deployment to minimize incremental output variance across the fastest and slowest time scales. Planning wind to minimize incremental variance at the 10-minute frequency (panel (a) of Figure 15) yields a standard deviation penalty that is typically 10% or less except at the monthly frequency where the standard deviation penalty approaches 30%. Planning wind deployment to minimize incremental variance along monthly frequency, however, yields a standard deviation penalty approaching 25% - 30% for every other temporal scale considered except the weekly scale.

Overall, the penalty (increase in standard deviation of output) becomes larger as we move into larger geographic areas. This means that output volatility is less sensitive to the variance minimizing frequency in smaller regions. Further, geographic scaling is best explained by a quadratic function which can be seen by the dotted lines fitted to the data points.

Finally, we study the magnitude of increase in the standard deviation of output over various timescales to investigate the preferred frequency for variance minimization. As our results suggest, wind power variation over low frequency time scales is smaller compared to high frequency time scales. Thus, an RTO might prefer to forego benefits of minimizing variance over low frequencies (higher capacity factor and a smaller geographic area) to achieve smaller output variance over high frequencies which reduces operational balancing costs and facilitates day-to-day management of the grid. Thus, we calculate the magnitude of increase in standard deviation of output across multiple temporal scales based on site selection to minimize incremental variance at a particular time scale. Figure 16 shows this magnitude increase for different regions. For example, in the Eastern Interconnect, if we minimize the variance over 10-minute timescale, the standard deviation of output over monthly timescale increases by 0.01. However, minimizing variance over monthly time scales increases the 10-minute standard deviation by 0.03. This is 3 times larger than the penalty for monthly timescale when variance is minimized over 10-minute timescale. The results are similar for other regions such as MISO, SPP and PJM. Therefore, from an RTO perspective, minimizing output variance over high frequency timescales (i.e. 10-minute or hourly) would be preferred in order to minimize the magnitude increase in standard deviation.

Figure 15- Temporal tradeoffs in wind energy output from minimizing variance along a single time scale (shown in the title of each panel) over different geographic regions. Note that the x-axis is in log scale.

Figure 16- Increase in the standard deviation of wind output from minimizing variance along a single time scale

4. Conclusion

We have quantified the scaling of the geographic smoothing effect for large-scale wind energy deployment over various spatial and temporal scales, using a bounding deployment scenario that seeks to incrementally minimize the variance of power output from a portfolio of wind sites. While a larger number of wind farms is required to minimize output variation over a larger geographic area, the number of wind farms required scales linearly with geographic scope. Temporal analysis over geographic scope of 10^5 to 10^6 square kilometers (a region or subcontinental scale) illustrates that a larger number of wind

farms is required to reduce variation over sub-hourly time scales as compared to lower-frequency time horizons such as days to months. In smaller regions, however (10^4 kilometers or less – roughly the size of an individual state), the differences between high and low frequencies are negligible. Spatial analysis of different time scales determined that at high frequency time scales wind farms should be spread over larger areas in order to minimize variation. Wind farms should be built farther from each other only if the goal is to minimize wind power variation at high frequencies. Moreover, we find that an incremental variance minimization over lower frequencies correlates with higher overall power output. The tradeoff from such a wind build-out strategy is higher output variability at higher frequencies.

The primary policy implications of this analysis are that a single aggregation of wind sites is unlikely to minimize operational integration costs over multiple time scales and decision horizons, and that the system benefits of geographic smoothing of wind energy decline quickly regardless of spatial or temporal scale. High frequency time scales are important for operational purposes such as dispatch and balancing, and over these time scales we observe that a larger number of wind farms is required to minimize output variance. Low frequency time scales, on the other hand, impact short term and long term planning (unit commitment and new investment, for example) and we observe that a smaller number of wind farms is required to minimize output variance. This means that the scale of geographic diversity necessary to reduce the risk of extended unavailability (low wind episodes that lasts a month or longer) is smaller than the scale of diversity necessary to reduce the risk of unavailability in the unit commitment or dispatch time frame.

From a power systems integration perspective, our results suggest a fundamental tradeoff between planning and operational decision criteria for siting large-scale wind. A wind energy development goal of minimizing low-frequency output variance carries with it the benefits of higher capacity factors and deployment over a smaller geographic region, but would also yield higher balancing costs over operational time scales (operating reserves and frequency regulation). The opposite wind energy development goal – minimizing high-frequency output variance and thus operational balancing costs – yields a greater need for installed capacity reserves and greater regional coordination of wind energy operations since deployment would span a larger geographic area covering multiple system operators.

Our approach is limited to a best-case deployment scenario with a goal of minimizing wind variation in order to reduce the costs of balancing fluctuations. This benefits system operators, but may not be the deployment strategy that maximizes profits or wind energy output. We leave the examination of such tradeoffs for future research. Our results do suggest that siting criteria for wind installations based on system impact measures would be appropriate and could influence how wind energy continues to be built out.

Acknowledgement

Authors acknowledge financial support from the US National Science Foundation [award number CNS-13376].

References:

- [1] Wan Y-h, Bucaneg D. Short-term power fluctuations of large wind power plants. ASME 2002 Wind Energy Symposium: American Society of Mechanical Engineers; 2002. p. 353-60.
- [2] Hirth L. The market value of variable renewables: The effect of solar wind power variability on their relative price. *Energy Econ.* 2013;38:218-36.
- [3] Woo C-K, Horowitz I, Moore J, Pacheco A. The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. *Energy Policy.* 2011;39:3939-44.
- [4] Hoogwijk M, Van Vuuren D, de Vries B, Turkenburg W. Exploring the impact on cost and electricity production of high penetration levels of intermittent electricity in OECD Europe and the USA, results for wind energy. *Energy.* 2007;32:1381-402.
- [5] Traber T, Kemfert C. Gone with the wind?—Electricity market prices and incentives to invest in thermal power plants under increasing wind energy supply. *Energy Econ.* 2011;33:249-56.
- [6] Czigisch G, Ernst B. High wind power penetration by the systematic use of smoothing effects within huge catchment areas shown in a European example. *Windpower.* 2001.
- [7] Holttinen H, Milligan M, Kirby B, Acker T, Neimane V, Molinski T. Using standard deviation as a measure of increased operational reserve requirement for wind power. *Wind Eng.* 2008;32:355-77.
- [8] Archer CL, Jacobson MZ. Supplying baseload power and reducing transmission requirements by interconnecting wind farms. *J Appl Meteorol Climatol.* 2007;46:1701-17.
- [9] Fertig E, Apt J, Jaramillo P, Katzenstein W. The effect of long-distance interconnection on wind power variability. *Environ Res Lett.* 2012;7:034017.
- [10] Gunturu UB, Schlosser CA. Behavior of the aggregate wind resource in the ISO regions in the United States. *Appl Energy.* 2015;144:175-81.
- [11] Rose S, Apt J. What can reanalysis data tell us about wind power? *Renew Energy.* 2015;83:963-9.
- [12] Martin CMS, Lundquist JK, Handschy MA. Variability of interconnected wind plants: correlation length and its dependence on variability time scale. *Environ Res Lett.* 2015;10:044004.
- [13] Louie H. Correlation and statistical characteristics of aggregate wind power in large transcontinental systems. *Wind Energy.* 2014;17:793-810.
- [14] Handschy MA, Rose S, Apt J. Is it always windy somewhere? Occurrence of low-wind-power events over large areas. *arXiv preprint arXiv:160706702.* 2016.
- [15] Huang J, Lu X, McElroy MB. Meteorologically defined limits to reduction in the variability of outputs from a coupled wind farm system in the Central US. *Renew Energy.* 2014;62:331-40.
- [16] Handschy M, Rose S, Apt J. Reduction of wind power variability through geographic diversity. *arXiv preprint arXiv:160806257.* 2016.
- [17] Apt J. The spectrum of power from wind turbines. *J Power Sources.* 2007;169:369-74.
- [18] Suomalainen K, Pritchard G, Sharp B, Yuan Z, Zakeri G. Correlation analysis on wind and hydro resources with electricity demand and prices in New Zealand. *Appl Energy.* 2015;137:445-62.
- [19] Hirth L. The benefits of flexibility: The value of wind energy with hydropower. *Appl Energy.* 2016;181:210-23.
- [20] Komušanac I, Ćosić B, Duić N. Impact of high penetration of wind and solar PV generation on the country power system load: The case study of Croatia. *Appl Energy.* 2016.
- [21] Zhang N, Hu Z, Shen B, Dang S, Zhang J, Zhou Y. A source-grid-load coordinated power planning model considering the integration of wind power generation. *Appl Energy.* 2016;168:13-24.
- [22] González-Aparicio I, Zucker A. Impact of wind power uncertainty forecasting on the market integration of wind energy in Spain. *Appl Energy.* 2015;159:334-49.

- [23] NREL. Eastern Wind Dataset. <http://www.nrel.gov/grid/eastern-wind-data.html>, [accessed 13.08.06]
- [24] Dowds J, Hines P, Ryan T, Buchanan W, Kirby E, Apt J, et al. A review of large-scale wind integration studies. *Renew Sustain Energy Rev.* 2015;49:768-94.
- [25] Milligan MR, Kirby B. Calculating wind integration costs: separating wind energy value from integration cost impacts: National Renewable Energy Laboratory; 2009.
- [26] Milligan M, Holttinen H, Kirby B, Kiviluoma J, Estanqueiro A, Martín-Martínez S, et al. Wind integration cost and cost-causation. *Proceedings of the 12th Wind Integration Workshop* 2013.
- [27] Choudhary P, Blumsack S, Young G. Comparing decision rules for siting interconnected wind farms. *System Sciences (HICSS), 2011 44th Hawaii International Conference on: IEEE*; 2011. p. 1-10.
- [28] Von Meier A. *Electric power systems: a conceptual introduction*: John Wiley & Sons; 2006.
- [29] Mitchel A. *The ESRI Guide to GIS analysis, Volume 2: Spatial measurements and statistics*. ESRI Guide to GIS analysis. 2005.
- [30] Ripley BD. The second-order analysis of stationary point processes. *J Appl Probab.* 1976;255-66.
- [31] Dixon PM. Ripley's K function. *Encyclopedia of Environmetrics*. 2002.
- [32] O'Sullivan D, Unwin D. *Geographic information analysis*: John Wiley & Sons; 2014.

Appendix

Here, we show that if we incrementally add 2 wind farms to an initial wind farm, the results would be similar to the case if we select the two wind farms in a single step. The proof is as follows:

We can write the total variance of three aggregated wind farms as follows:

$$Var(A + B + C) = Var(A) + Var(B) + Var(C) + 2 * Cov(A, B) + 2 * Cov(A, C) + 2 * Cov(B, C)$$

Using the conventional formula for the variance of a sum, we can write the variance of an aggregate wind farm [A+B] and a third individual wind farm C as follows:

$$Var(A + B) = Var(A) + Var(B) + 2 * Cov(A, B)$$

$$Var([A + B] + C) = Var(A) + Var(B) + 2 * Cov(A, B) + Var(C) + 2 * Cov([A + B], C)$$

The sequential addition of wind farms ([A+B] then C) will yield the same covariance as the concurrent addition of three wind farms (A+B+C) if the following condition holds:

$$Cov(A, C) + Cov(B, C) = Cov([A + B], C)$$

Expanding each side of the equation yields the desired equality:

$$\begin{aligned} Cov(A, C) + Cov(B, C) &= \sum \frac{(A_i - \bar{A})(C_i - \bar{C})}{n} + \sum \frac{(B_i - \bar{B})(C_i - \bar{C})}{n} \\ &= \sum \frac{(A_i - \bar{A})(C_i - \bar{C}) + (B_i - \bar{B})(C_i - \bar{C})}{n} \\ &= \sum \frac{(A_i - \bar{A} + B_i - \bar{B})(C_i - \bar{C})}{n} = \sum \frac{(A_i + B_i - \bar{A} - \bar{B})(C_i - \bar{C})}{n} \\ Cov([A + B], C) &= \sum \frac{[(A_i + B_i) - (\bar{A} + \bar{B})](C_i - \bar{C})}{n} = \sum \frac{(A_i + B_i - \bar{A} - \bar{B})(C_i - \bar{C})}{n} \end{aligned}$$