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Spatial Diversification of Wind Farms: System Reliability and Private Incentives

Christopher M. Worley and Daniel T. Kaffine
Colorado School of Mines
USA

1. Introduction

A growing literature suggests that intermittency issues associated with wind power can be reduced by spatially diversifying the location of wind farms. Locating wind farms at sites with less correlation in wind speeds smooths aggregate electricity generation produced by the multiple sites. However, technical studies focusing on optimal siting of wind farms to reduce volatility of total wind power produced have failed to address the underlying private incentives regarding spatial diversification by individual wind developers. This chapter makes a simple point: Individual wind developers will in general seek out the windiest sites for development, and as these locations are likely to be highly correlated in a given region, this pattern of development will tend to amplify (rather than smooth) problems associated with the variable nature of wind power. As such, private wind developers cannot be depended upon to provide reliability benefits from spatial diversification in the absence of additional incentives.

Wind power is growing rapidly in the United States and throughout the rest of the world. As concerns about global climate change intensify, policymakers and power utilities look to less carbon-intensive energy sources.[1] As a near-zero emission source of generation, wind provides a mature alternative technology with some of the most competitive renewable energy costs.[2] However, the potential for wind power to provide a substantial percentage of world electricity is hindered by the stochastic nature of the wind resource. Due to this intermittency, electricity from wind power cannot be dispatched like electricity from a coal boiler or a natural gas turbine. The day-to-day and hour-to-hour variability of wind power requires power utilities to maintain excess capacity of dispatchable electricity or face a potential shortfall when wind speeds diminish.

The capacity credit of wind power—the amount of dirty capacity that can be removed from the grid—is around 20% when wind power is initially added to the generation portfolio. In other

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[1] The precise level of emissions avoided by wind power is a topic of much debate, and likely varies considerably with the existing generation mix, load levels, and other factors (Kaffine et al., 2011; Novan, 2010). The intermittency issues addressed in this chapter are in fact related to emission savings from wind power, as substantial variability in wind generation levels may require aggressive (emissions-intensive) ramping of thermal generation for load balancing.

[2] The Energy Information Administration Annual Energy Outlook 2011 (DOE/EIA-0383) gives U.S. national averages for the levelized costs of energy for different energy sources, including wind ($97.0/MWh), conventional coal ($94.8/MWh), solar PV ($210.7/MWh), and solar thermal ($311.8/MWh) under an assumed $15 per metric ton of CO_2 emissions fee.

words, a wind farm with a nameplate capacity of 100 MW may only remove around 20 MW of dirty capacity. Furthermore, each additional marginal megawatt of wind capacity installed has a diminished ability to remove dirty generating capacity.[3] If the aggregate supply of wind power were more reliable, then less backup generation capacity would be needed per MW of wind capacity. Thus, improving the reliability of wind power reaching the grid may provide economic benefits by allowing system operators and utilities to better schedule generation and reduce backup generation, not to mention the environmental benefits of reducing reliance on dirty generation.

Empirical work has shown that sites with high mean wind speed also have high variance in wind speeds.[4] Given this, there are two ways that the variability of wind power produced by multiple wind farms may be reduced. First, wind farms could be built on sites with low variance. Unfortunately, wind developers have little incentive to build on sites with low wind speed variance because those sites also tend to have low mean wind speeds. The second method for reducing the variability of wind generation would be to diversify the supply of wind power over sites with low spatial correlation (an algorithm for determining the variance-minimizing locations for wind farms is presented in Choudhary et al. (2011)). Just as a diversified investment portfolio has less risk than investing in a single asset, a spatially-diversified portfolio of wind capacity could improve the reliability of wind power, reduce the risks of outage, and increase the capacity credit of wind power.

Kempton et al. (2010) examined offshore wind resources along the length of the Eastern Seaboard of the United States and found that wind speed correlations between sites dropped to 0.25 at around 500 km, implying that wind farms spread far apart could reduce the volatility of wind power reaching the electrical grid. Based on their simulation results, it may be socially beneficial if wind developers would hedge the unreliability of wind power by developing wind power at spatially disparate sites with less correlated wind speeds. Kempton et al. (2010) note that such a system may prove to be difficult to develop because electricity generation is largely a state-level concern, and it may be difficult to align the incentives of the many states required for a system of interconnected wind farms along the Eastern Seaboard. In the particular case of the Eastern Seaboard, achieving such a spatial diversification of wind farms would require the input and cooperation of four electricity reliability councils, the public utilities commissions of fifteen states, dozens of power companies, and many, many individual wind developers.

In fact, the role of locational investment incentives may be even more important at the individual firm level. Roughly 80% of wind farms are independent power producers (IPP), which are not owned or operated by power utilities.[5] These wind developers search for windy sites on which to build, and then negotiate a Power Purchase Agreement (PPA) with the utility to lock in a fixed rate for electricity sales. These independent wind developers are motivated purely by the private cost-benefit analysis of site development, so they hunt for "jackpot" sites with the greatest return (typically the very windiest sites with correspondingly high variance). Furthermore, wind farms in a region are likely to be closely co-located in space because meteorological wind speeds are spatially correlated. As a result, individual wind

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[3] A technical report from the National Renewable Energy Laboratory summarizes capacity credit estimates from around the U.S., which tend to fall in the 5-35% range (Milligan & Porter, 2008).

[4] As such, one potential model for wind speeds is a Weibull or Rayleigh distribution. Beenstock (1995) argues that a Rayleigh distribution is a useful assumption that is a good baseline approximation of the true wind distribution.

[5] This estimate comes from interviews with wind researchers and wind industry professionals.

developers are unlikely to ultimately build on sites that enhance the reliability of the total supply of wind generation.

To illustrate the central point of this chapter, we first develop a simple theoretical model to compare the optimal siting decisions of individual wind developers versus the optimal siting decisions of system operators.[6] Given a 1-dimensional region with a concave distribution of wind speeds, all individual wind developers will choose to build as close to the wind speed maximum as possible. As such, wind speeds at these wind farms will be highly correlated and thus aggregate wind generation will be highly volatile. In contrast, the system operator will trade off the benefits of generating electricity at the windiest site for a more reliable supply of wind power, spreading out wind farms farther from the location of the wind speed maximum. To provide further economic intuition, we present a closed-form analytical solution for siting decisions that can be generalized for up to n wind farms.

To highlight the divergence of incentives between decentralized wind developers and the system operator, we develop a spatial optimization model, loosely calibrated to the plains of eastern Colorado, whereby agents maximize profit by choosing a number of locations for wind farms. In the case of individual, decentralized wind developers, each firm maximizes their expected private returns by selecting the most profitable site for development, given wind speed of known mean and variance. On the other hand, for the case of the system operator, a single agent selects locations that maximize expected total returns from development and includes costs associated with the reliability of aggregate wind power reaching the grid. The model generates Rayleigh-distributed, correlated wind speeds for each site over a lengthy time horizon. Importantly, wind speed correlation between sites declines over distance and we allow for differing mean wind speeds for each site. Both the individual wind developers and system operator select the location that maximizes their objective functions based on the generated wind speeds.

There is a significant divergence between the optimal locational decisions of the individual wind developers and the system operator. Individual wind developers choose to build on the windiest sites, and as wind power produced at those sites is highly correlated, high reliability costs are incurred. By contrast, the system operator internalizes the tradeoffs between system reliability generated by diversified siting decisions and the profits associated with the windiest sites, resulting in more spatially diverse locations being selected and an improvement in reliability and total economic value. We note that providing the correct siting incentives to individual wind developers will require those incentives to be conditioned on the siting decisions by all other wind developers, and we finish this chapter with some concluding remarks and suggestions for further work.

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[6] There are many parties that may receive benefits from wind reliability, including Independent System Operators (ISO) responsible for load balancing, or rate payers who ultimately pay the cost of maintaining backup generation, or public utilities who must ramp their thermal generation units for load balancing. We use the 'system operator' as a catch-all for all such parties that receive reliability benefits (in addition to economic returns from generation) and would therefore internalize these benefits into their optimal decisions regarding wind farm location. We also recognize that the economic incentives of real-world system operators may not precisely match those of the economic agent that we have dubbed the 'system operator' in the analysis below. Ultimately we are interested in comparing the siting decisions of individual wind developers interested in purely private profits versus an economic agent with a more systemic outlook, concerned with system profits including benefits and costs associated with system reliability. Determining the distribution of the costs and benefits of reliability to the various parties is outside the scope of this study.

2. Background

The electricity and wind engineering literatures have analyzed the role of wind farm locations in electrical grid reliability as far back as Kahn (1979), who first notes that the variance of wind power output decreases as the geographic distance between wind farms increases. Since then, much work has been done to analyze this issue at many scales. Cassola et al. (2008) proposes a procedure for minimizing wind power variance through optimal siting of wind farms over the island of Corsica, which is slightly smaller than the State of Delaware. Milligan & Artig (1999) analyzes potential wind sites in Minnesota, while Milligan & Factor (2000) analyzes sites in Iowa and find that state-level diversification allows power utilities to reduce wind power supply risk. Archer & Jacobson (2007) select nineteen sites in four mid- and southwestern states (i.e., Kansas, Oklahoma, Texas, and New Mexico) and find results similar to those of previous studies, mainly that reliability benefits increase with distance between wind farms and reduced variability translates into fewer high and low wind events. Choudhary et al. (2011) develop a variance-minimizing algorithm for wind farm additions in Oklahoma, and find that the algorithm will select the site that is geographically most distant from existing stations. Kempton et al. (2010) used five years of wind data from eleven offshore sites along the Eastern Seaboard of the United States to test the reliability benefits of spatially diversifying wind farms on a synoptic-scale, meaning that they test reliability with respect to differing pressure patterns at distances of 1,000 km or greater. They find that such a system experienced few periods of complete power outage or full capacity, and power levels changed slowly over time.

While all of these studies show that there are reliability benefits of spatially diversified wind farms (in terms of reducing power variance), they fail to address how the incentives of wind power developers may affect reliability. In fact, this issue has been overlooked by the economics literature as well. To remedy this, we present a spatial optimization model that simulates the differing locational incentives of wind power players. Spatial optimization models have been broadly used for many types of land-use issues like optimal managing of timber harvests with wildlife habitats (Hof & Joyce, 1992), the trade-offs of biodiversity and land-use for economic returns (Kagan et al., 2008), and efficient utilization of urban areas (Ligmann-Zielinska et al., 2008) among other types of problems. Before simulating the decisions of wind power developers, we develop an analytical model to better understand the intuition behind locational investment decisions.

3. Analytical model

How might we illustrate the differing incentives of private wind developers and a system operator? We develop a simple analytical exercise that captures the spatial variation in wind speeds and corresponding impacts on reliability.[7] Let wind speed v be distributed over a 1-dimensional space $(-\infty, \infty)$ given by the concave function $v(x)$ where the maximum windspeed v_{max} is located at the origin $x = 0$. At a given site x, wind can be converted into electricity (kWh) as represented by the function $W(v(x))$ (where $W_v > 0$). Each of two individual wind developers will chose their privately optimal wind farm location (x_1 and x_2) that maximizes this objective:

$$\max_{x_i} \pi = pW(v(x_i)) - F \qquad \forall i = 1, 2 \qquad (1)$$

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[7] In the spirit of using the simplest possible model to make an analytical point, much of the real-world complexity of siting decisions have been stripped out.

where p is the per-unit price of electricity (\$/kWh) and F is the fixed cost (\$) of operating the wind farm over the time horizon. The first-order conditions for building wind farms x_1 and x_2 are given as:

$$\pi_{x_i} = p\frac{dW}{dv}\frac{dv}{dx_i} = 0 \qquad\qquad \forall i = 1, 2 \qquad (2)$$

Because $v(0) = v_{max}$, the location that maximizes profit for both wind developers exists at the maximum of the wind speed distribution, such that $x_i^* = 0, \forall i = 1, 2$. Thus, when the wind developers choose wind farm locations based on their private incentives, both wind farms will be built as close as possible to the point with the highest mean wind speed. Due to their proximity, wind speeds at these sites will be highly correlated, resulting in a supply of wind power that is less reliable than had the two sites been located farther apart. Thus, any benefits from spatial diversification are not realized under this setting where individual wind developers select locations for wind development.

By contrast, the system operator internalizes the reliability benefits of spatial diversification when locating wind farms. These reliability benefits will be simply expressed by the function $r(d)$ (where $r_d > 0$), such that the distance between wind farms is given as $d = x_2 - x_1$. The system operator's optimization problem is given as the joint maximization of profits from locating two wind farms plus reliability benefits from spatial diversification:

$$\max_{x_1, x_2} \pi = [pW(v(x_1)) - F] + [pW(v(x_2)) - F] + r(d) \qquad (3)$$

Given this objective, the first-order conditions are as follows:

$$\pi_{x_1} = p\frac{dW}{dv}\frac{dv}{dx_1} - r'(d) = 0$$
$$\pi_{x_2} = p\frac{dW}{dv}\frac{dv}{dx_2} + r'(d) = 0 \qquad\qquad (4)$$

Given positive benefits of spatial diversification ($r_d > 0$) and comparing against the decentralized first-order conditions in equation 2, the system operator will choose to build on either side of $x = 0$ (where $v(x) < v_{max}$). Relative to the case of individual wind developers, the system operator will spread the wind farms farther apart ($x_2 - x_1 > 0$) as long as there are positive marginal benefits from spatial diversification, $r_d > 0$. While wind speeds are slower and less power is produced at locations away from the location corresponding to v_{max}, the system operator offsets those power losses with the gains from a more reliable supply of wind power.

These results can be generalized to the case of multiple wind farms. Individual wind developers will choose to build all wind farms as close to v_{max} as possible ($x_i^* = 0, \forall i = 1, \ldots, n$). On the other hand, the system operator realizes reliability benefits depending on the pairwise distances between wind farms, $r(d_{ij})$.[8] The system operator's objective function when choosing to develop three sites is given as the following:

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[8] More formal and realistic treatments of how reliability benefits might enter the system operator's objective function are certainly possible, though the basic intuition outlined below will still hold. For simplicity, we will assume $r'(d_{ij}) = r'(d)$.

$$\max_{x_1,x_2,x_3} \pi = [pW(v(x_1)) - F] + [pW(v(x_2)) - F] + [pW(v(x_3)) - F]$$
$$+r(x_3 - x_2) + r(x_3 - x_1) + r(x_2 - x_1)$$
(5)

Given this objective, the first-order conditions are given as:

$$\pi_{x_1} = p\frac{dW}{dv}\frac{dv}{dx_1} - 2r'(d) = 0, \quad \pi_{x_2} = p\frac{dW}{dv}\frac{dv}{dx_2} = 0, \quad \pi_{x_3} = p\frac{dW}{dv}\frac{dv}{dx_3} + 2r'(d) = 0 \quad (6)$$

where the system operator locates one wind farm at the origin, and the remaining two wind farms on either side of the origin.

A closed-form solution of the optimal development locations cannot be obtained without some assumptions on the parametric forms of the spatial distribution of wind, wind power production function, and reliability benefits of spatial separation between sites. Supposing $v(x) = v_{max} - bx^2$, $W(v) = \gamma v$, and $r'(d) = \bar{r}$ we arrive at the system operator solution for the two wind farm case:[9]

$$x_1^* = -\frac{\bar{r}}{2p\gamma b}, \qquad x_2^* = \frac{\bar{r}}{2p\gamma b} \qquad (7)$$

and the three wind farm case:

$$x_1^* = -\frac{\bar{r}}{p\gamma b}, \qquad x_2^* = 0, \qquad x_3^* = \frac{\bar{r}}{p\gamma b} \qquad (8)$$

These closed-form solutions yield some intuitive comparative statics that illustrate the tradeoffs that the system operator faces. As the benefits from spatial diversification, $\bar{r}$, increase, the wind farms will be located further away from v_{max}. By contrast, as the price of electricity p increases, the system operator will value the profitable generation associated with high wind speeds near v_{max} relative to the reliability benefits. As a result, they will build closer to v_{max}. In fact, an increase in any parameter in the denominator will shift the optimal wind farm sites for the system operator closer to $x = 0$. The parameter b captures the curvature of the spatial distribution of wind speed. As this parameter increases, the curvature of the wind speed distribution becomes steeper, further reducing the wind speed at sites away from the origin and pushing development towards $x = 0$ and v_{max}. Finally, the parameter γ describes the efficiency of the wind turbines for producing electricity. When γ increases, turbines become more efficient at producing power, and the reliability benefits of spatial diversification become less valuable than building closer to the higher wind speeds located at $x = 0$.

These results can be extended to the case of n wind farms as given in table 1. In short, for an even number of wind farms, the system operator will build matching wind farms equidistant on either side of $x = 0$. For an odd number of wind farms, the system operator will build one wind farm on $x = 0$, and build matching pairs of wind farms further and further away from v_{max}. By contrast, the individual wind developers will build as close to $x = 0$ as physically possible.

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[9] As noted in Beenstock (1995), electricity is generated as a cubic function of the wind speed. While the linear function $W(v) = \gamma v$ fails to capture real-world characteristics of wind, this assumption allows us to find a closed-form solution.

Number of wind farms	1	2	3	4	5	...	n
Individual developer locations							
Wind farm $1\ldots n$	0	0	0	0	0	...	0
System operator locations							
Wind farm 1	0	$-\frac{\bar{r}}{2p\gamma b}$	$-\frac{\bar{r}}{p\gamma b}$	$-\frac{3\bar{r}}{2p\gamma b}$	$-\frac{2\bar{r}}{p\gamma b}$	...	$-\frac{(n-1)\bar{r}}{2p\gamma b}$
Wind farm 2	-	$+\frac{\bar{r}}{2p\gamma b}$	0	$-\frac{\bar{r}}{2p\gamma b}$	$-\frac{\bar{r}}{p\gamma b}$	...	$\frac{(n-3)\bar{r}}{2p\gamma b}$
Wind farm 3	-	-	$+\frac{\bar{r}}{p\gamma b}$	$+\frac{\bar{r}}{2p\gamma b}$	0	...	$\frac{(n-5)\bar{r}}{2p\gamma b}$
Wind farm 4	-	-	-	$+\frac{3\bar{r}}{2p\gamma b}$	$+\frac{\bar{r}}{p\gamma b}$	...	...
Wind farm 5	-	-	-	-	$+\frac{2\bar{r}}{p\gamma b}$	...	...
...	...	...	...	...	...	...	...
Wind farm $n-1$	-	-	-	-	-	...	$+\frac{(n-3)\bar{r}}{2p\gamma b}$
Wind farm n	-	-	-	-	-	...	$+\frac{(n-1)\bar{r}}{2p\gamma b}$

Table 1. Optimal wind farm location decisions for individual wind developer and the system operator

This analytical model is a very simplified version of the real-world spatial incentives of wind development. In the next section, we design a numerical simulation model that is multidimensional, has stochastic and spatially-correlated wind speeds, and features a more realistic power curve. Calibrating the simulation model to real-world parameters allows us to capture the relative scale of the trade-offs involved.

4. Simulation model

To highlight the differing incentives of individual wind developers and the system operator, we next develop a spatial optimization model. As in the previous section, we will be comparing the optimal siting decisions of individual wind developers with those of the system operator. The physical space is a 3-x-3 grid of $n = 9$ potential sites for development with wind speeds of known mean and variance. We generate Rayleigh-distributed, spatially-correlated random wind speeds for each site over 1,000 days (with one random draw per day), allowing differing mean wind speeds for each site.[10] The windiest sites are located near each other (see figure 1(a)), and the wind speed correlation between sites declines with the pairwise distance between sites (see figure 1(b)).
We very loosely calibrate the model to the northeastern plains region of the State of Colorado, a windy part of the state with some wind development. Each of the sites in figure 1(a) would be 100 km on each side, meaning that the nine sites would roughly cover an area from the northeastern corner of the state to Colorado Springs (roughly located in the center of the state). The U.S. Department of Energy provides state level wind maps, showing that Colorado has windy locations along the eastern border with Nebraska, Kansas, and Oklahoma.[11] The general pattern of wind speeds from these state level wind maps provide the basis for the mean wind speed distribution across the nine sites in the model. Site 9 is the windiest

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[10] The procedure for generating Rayleigh-distributed, spatially correlated wind speeds is adapted from Natarajan et al. (2000) and Tran et al. (2005)

[11] The DOE Office of Energy Efficiency & Renewable Energy maintains a website that provides maps of wind resource potential at 80 meter heights (`http://www.windpoweringamerica.gov/wind_maps.asp` Accessed 2/18/2011).

Site 7	Site 8	Site 9
6.50	6.75	7.00
Site 4	Site 5	Site 6
6.25	6.50	6.75
Site 1	Site 2	Site 3
6.00	6.25	6.50

(a) Mean wind speed (m/s)

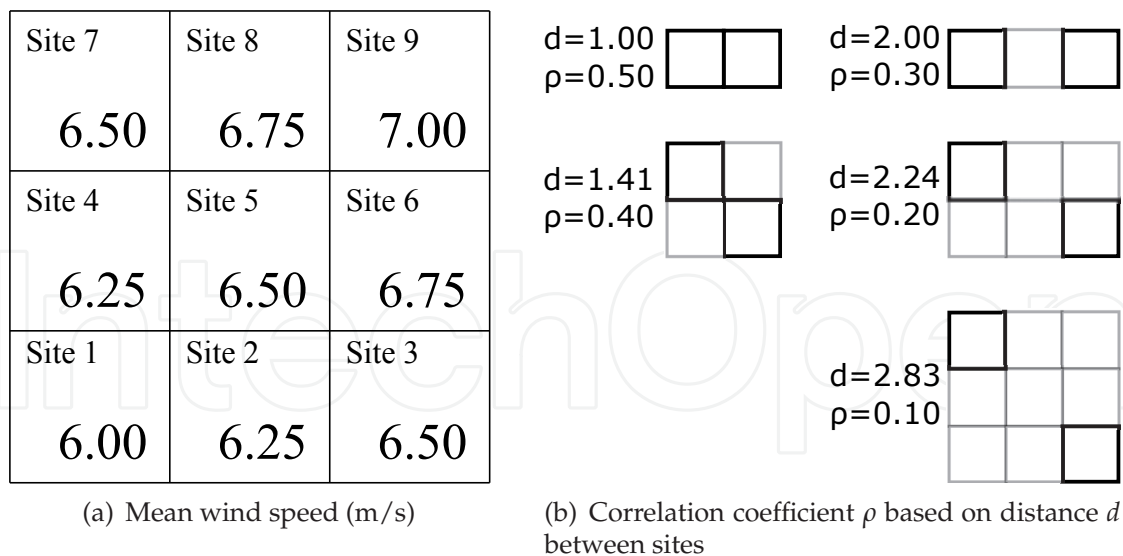(b) Correlation coefficient ρ based on distance d between sites

Fig. 1. Mean wind speed and pairwise correlations for 3x3 scenarios

site with wind speeds decreasing with distance from Site 9, meaning that Site 1 is the least windy location. We generate wind speed correlations between sites that decay over distance in the spirit of Kempton et al. (2010, Fig. 2). We stress that the quantitative results below are primarily illustrative, with the primary insights of the simulation model arising from the qualitative comparison of the siting decisions made by individual wind developers versus the system operator.

4.1 Individual wind developer model

We begin by simulating two wind farm developers each choosing the site $(1, \ldots, n)$ that maximizes their expected profit over the time horizon, $T = 1000$. As in the analytical model developed above, individual wind developers are only interested in the private economic return from developing a given site for wind power. Each wind developer i has an identical objective function:

$$\max_{X_i} \pi = \sum_{i=1}^{n} \sum_{t=1}^{T} pk_{it}X_i - \sum_{i=1}^{n} c_iX_i \tag{9}$$

The binary choice variable, X_i, equals 1 when the developer builds a wind farm on site i and 0 otherwise, and a developer cannot build on a site that has already been built upon by the other developer.[12] The parameter p is the price of electricity, which we assume to be \$0.10.[13] We assume that the fixed costs of operating a wind farm, c_i, are equal at all sites, which we estimate to be \$557,160 over the 1,000 day time horizon.[14] The variable k_{it} is the

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[12] The size of the wind farm (i.e., the number of turbines) arbitrarily affects the model, only scaling the magnitude of each scenario's profit and power produced. While one could simulate 10, 20, or 100 turbines, we simplify the model by assuming that each wind farm consists of one turbine.

[13] A value close in scale to estimates in the Energy Information Administration Annual Electric Power Industry Report (Form EIA-861).

[14] This is based on estimates from Elkinton et al. (2006) that annualized fixed costs plus yearly variable costs of 3.7 cents/kWh - 5.5 cents/kWh. We choose levelized production costs of 6.0 cents/kWh. Given that the mean power produced at Site 9 at any given time is 9,286 kW, we arrive at a fixed cost of \$557,160 over the 1,000 day time horizon. This is held constant over all sites even though the levelized production costs may differ for sites with slower mean wind speeds.

generation (in kWh) at site i in time period t. This is calculated from the spatially-correlated Rayleigh-distributed randomly drawn wind speeds v_{it} via the following power function:

$$k_{it} = \begin{cases} 0 & \text{if } 0 \leq v_{it} < 4 \\ \lambda \cdot v_{it}^3 & \text{if } 4 \leq v_{it} < 11 \\ \lambda \cdot (11)^3 & \text{if } 11 \leq v_{it} \leq 25 \\ 0 & \text{if } v_{it} > 25 \end{cases} \tag{10}$$

The parameter λ is the power proportionality constant that converts wind speeds in m/s to electricity generation in kWh.[15] Wind turbines are able to generate electricity only over certain wind speeds. No electricity can be generated for wind speeds below 4 m/s as the wind is too slow. For wind speeds above 4 m/s, electricity is proportional to the cube of wind speed, topping out at 11 m/s. Constant generation is produced for windspeeds between 11 - 25 m/s, and for speeds above 25 m/s, turbines are shut down for fear of damage.
Each developer is constrained to build on only one site:

$$\sum_{i=1}^{n} X_i \leq 1 \tag{11}$$

Thus, given a draw of 1,000 Rayleigh-distributed, spatially correlated wind speeds v_{it} at each site i for each period t, each wind developer selects the site for development that maximizes private profits.

4.2 System operator model

The system operator chooses the location of two wind farms by balancing the high revenues associated with concentrating development at windier sites with the reliability cost of spatial diversification. The objective function looks similar to that of individual wind developers except for the addition of the reliability cost variable, R_t, in each time period t. The system operator incurs a nonnegative reliability cost (in dollars) for each time period when the system supply of wind power is less than the expected level.[16] The system operator's objective function is as follows:

$$\max_{X_1, X_2} \pi = \sum_{i=1}^{n} \sum_{t=1}^{T} p k_{it} X_i - \sum_{i=1}^{n} c_i X_i - \sum_{t=1}^{T} R_t \tag{12}$$

The system operator is constrained to build on two sites:

$$\sum_{i=1}^{n} X_i \leq 2 \tag{13}$$

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[15] For an assumed 1.5 MW wind turbine rated at 11 m/s, the power proportionality constant is equal to 1128 (found by simply dividing 1,500,000 by 11^3)

[16] Thus, reliability costs are incurred when the sum of wind power from the two wind farms falls below expected levels. It should be noted that we are only considering the reliability costs associated with a shortfall in wind generation. However, it may also be the case that a temporary overabundance of wind generation can also be problematic from the perspective of the system operator. For example, large amounts of wind power reaching the grid may require sudden and costly curtailment of other generation sources, which then have to be ramped back online when wind power diminishes. Including such considerations would further sharpen the contrast between the incentives of individual wind developers and the reliability-internalizing system operator.

The system operator model has two additional constraints that define and ensure nonnegativity of the reliability cost. This first constraint calculates the value of the reliability cost, which we conceptualize as the cost of maintaining backup generating capacity or purchasing electricity on the wholesale market when a wind farm's generation k_{it} does not meet the mean generation level $\overline{k_i}$.[17] The parameter z is the per-unit reliability cost, which we set at \$0.10.[18] The difference $\sum_{i=1}^n (\overline{k_i} - k_{it}) X_i$ is the system power shortage in period t. The parameter M is an arbitrarily large number and the binary variable β_t is equal to 1 when there is a system shortage of wind power and equal to 0 otherwise.[19]

$$R_t \geq z \cdot \sum_{i=1}^n (\overline{k_i} - k_{it}) X_i - M(1 - \beta_t) \qquad \forall t \qquad (14)$$

This second constraint forces the reliability cost to be zero when $k_{it} > \overline{k_i}$.

$$\sum_{i=1}^n k_{it} \cdot X_i \geq \sum_{i=1}^n \overline{k_i} \cdot X_i - \beta_t \cdot M \qquad \forall t \qquad (15)$$

The system operator problem is solved by jointly selecting the two best sites, accounting for the benefits from spatial diversification.

4.3 Results

Before discussing the optimization results, we begin with a cursory examination of wind power produced from randomly generated, Rayleigh-distributed, spatially correlated wind speeds at sites with varying levels of spatial diversification. Figure 2 compares the capacity factor of two wind farms over a horizon of 100 time periods for three different groupings of the two wind farms.[20] We wish to compare the variability in power supplied when there are two wind farms located on Site 3, one on Site 3 and one on Site 5, and one on Site 3 and one on Site 7. Visual comparison in figure 2 of the joint capacity factor across groupings is somewhat difficult, but there are fewer dramatic peaks when wind farms are spatially diversified in figure 2(c) compared to when wind farms are co-located in figure 2(a). This suggests that the volatility of wind supply from wind farms on Sites 3 and 7 is less than that of two wind farms co-located on Site 3.

As noted in figure 1(b), these three sites have the same mean wind speed and variance, but when wind farms are located at less spatially correlated sites, there is a reduction in the total variance of total power produced. For two wind farms co-located on Site 3, the sample variance in capacity factor is 0.093. The sample variance decreases as the wind farms are located farther apart. For wind farms on Sites 3 and 5, the sample variance is 0.076, and for Sites 3 and 7, the sample variance is 0.061.

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[17] As noted previously, this is a simplification of the cost imposed on the utility when they have an unreliable source of power, but it allows for a tractable solution with easily interpretable results.

[18] We believe this to be a reasonable cost, as this might be the price that a utility pays for electricity on the spot market or for natural gas backup generation.

[19] The variable β and the parameter M are used in these constraints to ensure nonnegativity of the reliability cost as is consistent with "Big-M" formulations.

[20] Capacity factor is the percentage of nameplate capacity that a turbine produces at a given point in time. For example, a 2 MW turbine operating with a capacity factor of 0.6 would produce 1.2 MW of electricity.

(a) Two wind farms on Site 3   (b) Wind farms on Sites 3 and 5
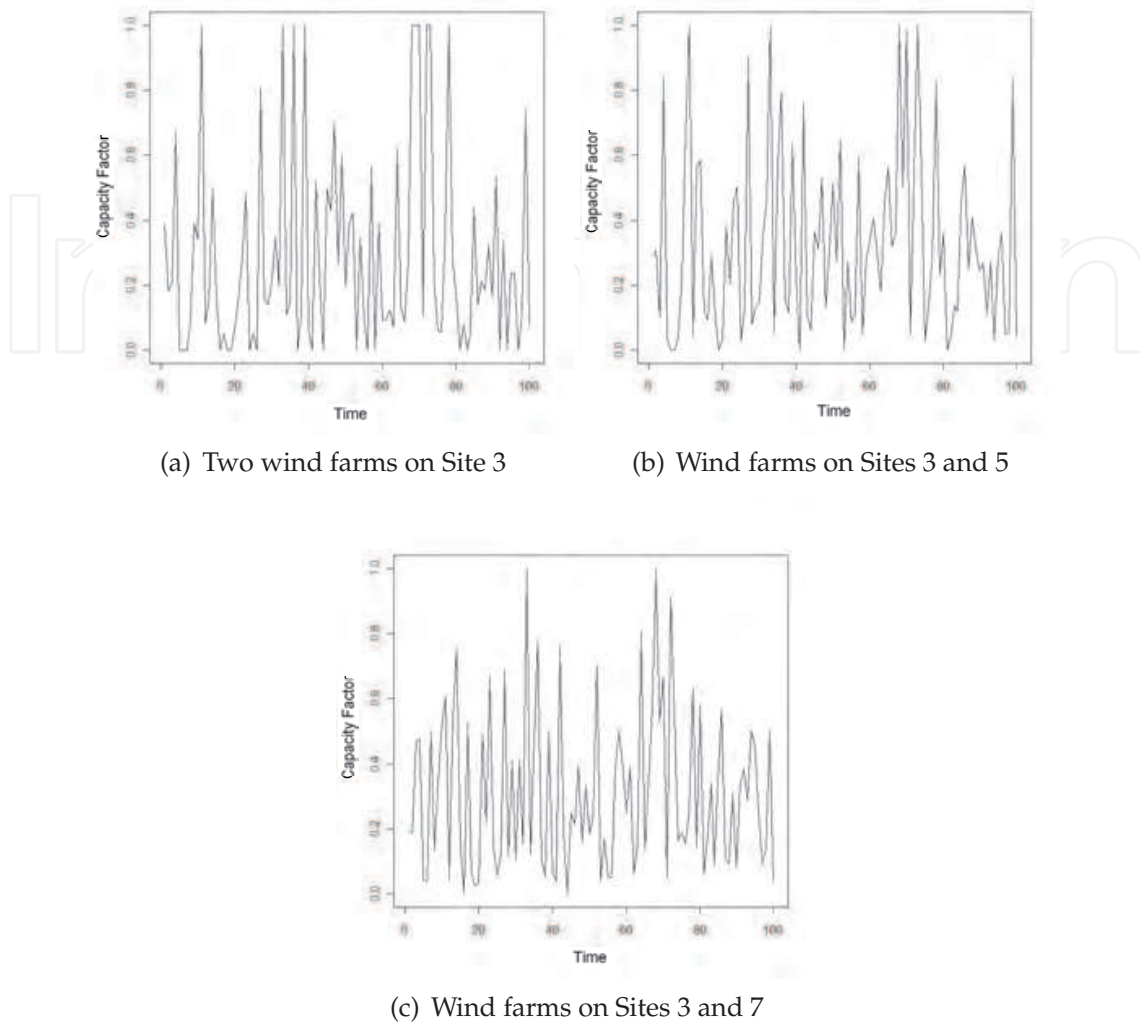

(c) Wind farms on Sites 3 and 7

Fig. 2. Capacity factor of two wind farms

As theory suggests, spatial diversification reduces the volatility of the supply of wind power. But how do agents respond to these diversification incentives? We run the optimization model over the 1,000 day time horizon with daily random wind speed draws for each site and determine the optimal siting decisions of individual wind developers and a system operator. However, the locations chosen represents the optimum for a specific set of 1,000 day random draws. To get a better sense of the incentives as play, the model itself is simulated over 1,000 runs, with the optimal decisions for each run recorded and reported in distribution form below.

As discussed in the analytical model, because individual wind developers do not receive any benefits from spatial diversification, they will look to develop on the sites with the highest expected electricity production (and therefore profits). The simulated optimal siting decisions for the individual wind developers are shown in figure 3.

As the model is run 1,000 times, the results in (figure 3(a)) give the number of times out of 1,000 that site was selected for a wind farm by the individual wind developers. As suggested in the analytical model, most wind development is clustered around the site with the highest mean wind speed, Site 9. Sites 6 and 8 are the next windiest sites and are selected the next greatest

(a) Wind farm locations

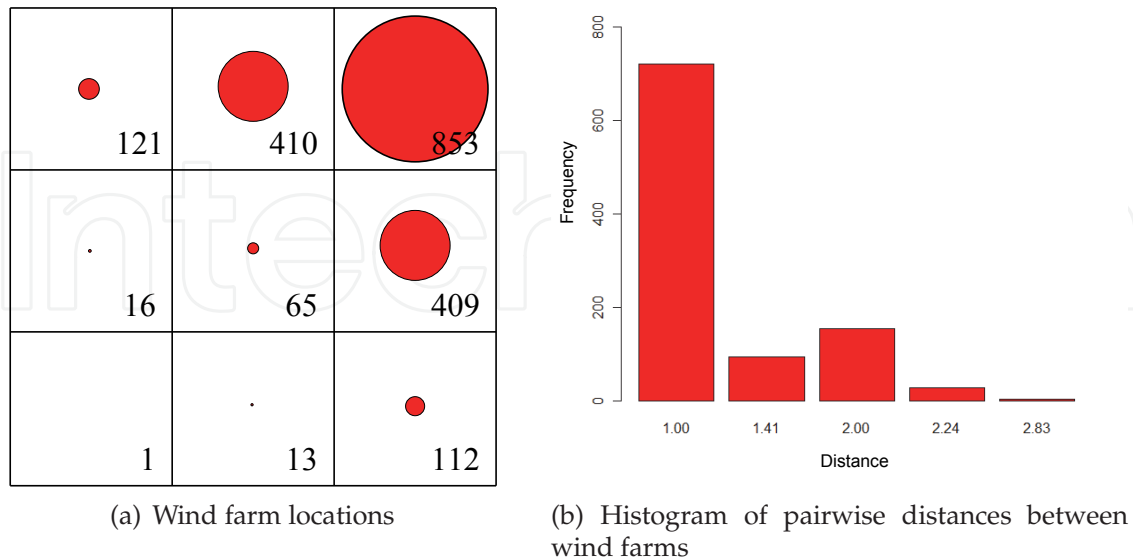(b) Histogram of pairwise distances between wind farms

Fig. 3. Individual wind developers location results

number of times. The pairwise distance between wind farms is calculated for each run, and, as expected, most wind farms built by individual developers are built a single unit apart (figure 3(b)). Thus, individual wind developers are typically selecting the jackpot outcome in the northeast corner of the grid and are not spatially diversifying wind farms.

In contrast to individual wind developers, the system operator benefits from higher wind speeds but also incurs the costs of any demand shortfall should the wind not blow. The system operator maximizes profit by jointly considering windy sites and the benefits from a more reliable wind portfolio. We again present the results of the simulation model as a distribution of optimal siting decisions and a histogram of the pairwise distance between wind farms for each run (figure 4).

In contrast to the locations chosen by individual wind developers, the system operator chooses to develop sites all around the map (figure 4(a)). In particular, locations near the center of the grid (Site 5) are eschewed in favor of more spatially disparate sites due to the reliability benefits from less correlated wind speeds. The histogram makes this point even more clear (figure 4(b)), as the most common pairwise distance between sites is 2.24 units (Sites 6 and 7 for example - the equivalent of a 'knight-move' in chess), followed by the maximum distance of 2.83 units (Sites 3 and 7 or Sites 1 and 9, corresponding to the corners). The system operator is willing to choose sites with lower mean wind speed due to the benefits of a reliable supply of wind power.

In addition to the differences between the optimal siting decisions of individual wind developers and the system operator, system profits and total power produced differ as well.[21] Table 2 lists total power and system profit results for the individual wind developer and system operator scenarios averaged over the 1,000 simulated runs. Noting again that the quantitative values are subject to the various parameter assumptions, we focus on the

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[21] We define system profit as total revenue - fixed costs - reliability cost, ignoring which party actually receives the revenues and costs in each scenario. The total power shortage is defined as the sum of power shortages at both wind farm over all time periods.

(a) Wind farm locations

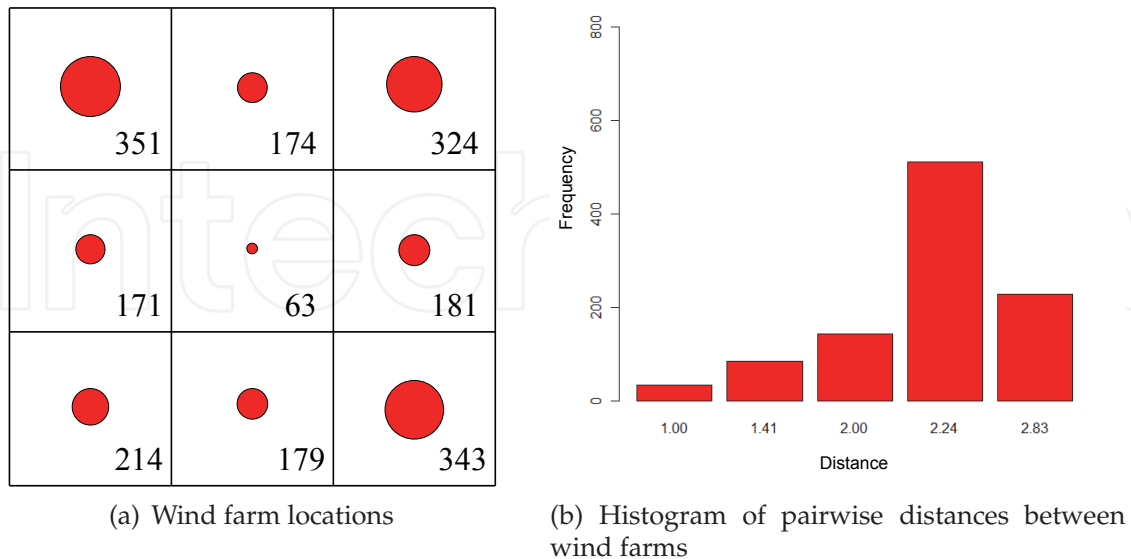(b) Histogram of pairwise distances between wind farms

Fig. 4. System operator location results

relative differences between the two scenarios. Most notably, the reliability cost is reduced by 27% under the system operator scenario as compared to the individual wind developer scenario, reflecting the less volatile wind supply at sites chosen by the system operator. Correspondingly, the locations selected by the system operator reduce total power shortage by 15% relative to the sites selected by individual wind developers. As the system operator internalizes reliability costs when selecting sites, total system profit increases by 8% under the system operator scenario relative to the individual wind developer scenario. However, by trading off windier sites for a more reliable supply of power, the total power produced decreases under the system operator, but only by about 2%.

Scenario	System Profit ($)	Reliability Cost ($)	Total Power Produced (kWh)	Total Power Shortage (kWh)
Individual wind developers	942,542	481,740	25,385,700	6,278,120
System operator	1,015,220	350,656	24,801,600	5,344,600

Table 2. System profits, reliability costs and power results

These results show that while individual wind developers are privately better off when they choose the windiest sites for development, they pass along large reliability costs as an externality that is directly borne by the system operator (or other economic agents). By contrast, the system operator trades off the benefits of high wind speed sites for a reliable portfolio of sites, resulting in an increase in system profit and only a minor decrease in total power produced.[22]

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[22] To the extent that wind power offsets emissions-intensive forms of generation, changes in total power produced may also have economic efficiency implications. However, in this particular case, the extra power production under the individual wind developer scenario comes at the substantial cost of 12 cents of system profit per additional kWh of generation.

5. Discussion

We conclude with a discussion of how incentives may be structured to encourage individual wind developers to appropriately internalize reliability costs. We also discuss how additional factors omitted from the above analysis might affect spatial diversification and end with some concluding remarks and directions for future work.

5.1 Incentives for individual wind developers to spatially diversify

While spatially-diversified wind farms may generate reliability benefits, if individual wind developers do not receive those benefits, their locational decisions for development will not internalize these benefits and the total supply of wind power will be less reliable. Creating incentives for individual wind developers to internalize their reliability effects and spatially diversify would likely take two forms: price premiums or penalties. First, site-specific deterministic prices could be built into PPA's, whereby a relative price premium would be attached to sites that improve reliability. Second, some form of deterministic or stochastic penalty could be levied conditional on the generation level produced by individual wind developers.

Whatever form these incentives take, they must be set conditionally with respect to the locations and spatial correlations of all other wind farms. So for a deterministic site-specific pricing system, the price paid for development at a given site would have to appropriately internalize the marginal impact of an additional wind farm on system reliability. For a penalty system, the penalty applied to an individual farm would need to be tied to systemic shortfalls in generation from *all* wind farms to generate the correct incentives to spatially diversify.[23] By contrast, a flat wind integration charge, such as the 0.6 cents per kWh charge imposed by the Bonneville Power Authority (BPA) (Choudhary et al., 2011), will not provide any incentive for an individual wind farm to spatially diversify and choose a location that improves system reliability.[24]

5.2 Additional factors affecting locational decisions

The preceding analysis explored the optimal siting incentives of individual wind developers versus the system operator. Locational incentives were driven by differences in mean wind speeds and spatial correlations between sites. However, factors such as access to transmission lines and interactions between wind farms also play a role in siting decisions. In particular, transmissions costs and constraints are likely to generate additional incentives for spatial clustering of wind farms as individual wind farms minimize any private costs incurred with transmission. By contrast, wake effects between wind farms (Kaffine & Worley, 2010) may lead to some spatial diversification by individual wind farms, however the scale of wake

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[23] See Worley (2011) for a further exploration of different penalty structures and the corresponding impacts on locational decisions and system profit, reliability and power. In particular, Worley (2011) finds that a penalty leveled on individual wind developers when aggregate wind generation levels fall below a threshold power level will provide individual wind developers the correct incentives to spatially diversify like the system operator. Despite the theoretical appeal of a penalty system that generates individual penalties based on system performance, such a penalty scheme may be difficult to implement. A penalty scheme of this nature is similar to ambient pollution taxes (Segerson, 1988) which have appealing theoretical properties but have not been frequently employed.

[24] Note that we are not commenting on the wisdom of such a charge as there are obviously other reasons for imposing such charges (such as cost-recovery). We simply mention it as an example of a penalty scheme that would not provide incentives for spatial diversification.

effects (5-20 km) is likely too small relative to the large scale required for reducing system volatility.

5.3 Concluding remarks

Our results show that individual wind developers choose sites with the highest mean wind speed, while the system operator will trade off the increased revenue of windy sites for a more reliable wind supply. Because wind speeds are correlated over space, individual wind developers in a given region will choose to build on windy sites that are likely to be closely located to one another. By contrast, the distance between wind farms built by the system operator is likely to be larger in order to capture the benefits of a reliable supply of wind power from less correlated wind farms.

These results raise further questions about the reliability benefits of spatial diversification. Further work could be done to estimate the magnitude of reliability benefits (or equivalently, the costs of intermittency), or to estimate the effect of serially-correlated, hourly wind speeds on reliability benefits. Additionally, work could be done to more accurately calibrate the simulation model to the real world using historical wind speed data and installed wind capacity for a given region. Using this information, it would be possible to choose locations that provide the most reliability benefits to the electrical grid (Choudhary et al., 2011) while balancing generation and revenue considerations. Finally, another avenue of research might examine the effect of reliability incentives on intensive and extensive margins of investment in wind development. Internalizing the costs of reliability will decrease the private profitability of wind power and reduce overall wind development, which may be in conflict with other policy objectives.

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Wind Farm - Technical Regulations, Potential Estimation and Siting Assessment

Edited by Dr. GastÃ³n Orlando Suvire

The evolution of wind power generation is being produced with a very high growth rate at world level (around 30%). This growth, together with the foreseeable installation of many wind farms in a near future, forces the utilities to evaluate diverse aspects of the integration of wind power generation in the power systems. This book addresses a wide variety of issues regarding the integration of wind farms in power systems. It contains 10 chapters divided into three parts. The first part outlines aspects related to technical regulations and costs of wind farms. In the second part, the potential estimation and the impact on the environment of wind energy project are presented. Finally, the third part covers issues of the siting assessment of wind farms.

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