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A COMPREHENSIVE MEASURE OF THE ENERGY RESOURCE POTENTIAL OF A WIND FARM SITE

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ABSTRACT

Currently, the quality of wind measure of a site is assessed using Wind Power Density (WPD). This paper proposes to use a more credible metric namely, one we call the Wind Power Potential (WPP). While the former only uses wind speed information, the latter exploits both wind speed and wind direction distributions, and yields more credible estimates. The new measure of quality of a wind resource, the Wind Power Potential Evaluation (WPPE) model, investigates the effect of wind velocity distribution on the optimal net power generation of a farm. Bivariate normal distribution is used to characterize the stochastic variation of wind conditions (speed and direction). The net power generation for a particular farm size and installed capacity are maximized for different distributions of wind speed and wind direction, using the Unrestricted Wind Farm Layout Optimization (UWFLO) methodology. A response surface is constructed, using the recently developed Reliability Based Hybrid Functions (RBHF), to represent the computed maximum power generation as a function of the parameters of the wind velocity (speed and direction) distribution. To this end, for any farm site, we can (i) estimate the parameters of wind velocity distribution using recorded wind data, and (ii) predict the maximum power generation for a specified farm size and capacity, using the developed response surface. The WPPE model is validated through recorded wind data at four differing stations obtained from the North Dakota Agricultural Weather Network *(NDAWN). The results illustrate the variation of wind conditions and, subsequently, its influence on the quality of a wind resource.*

Keywords: Energy, farm siting, reliability based hybrid functions, response surface, wind resource potential

INTRODUCTION

In recent years, people are more concerned and sensitive to the need for environmental friendly energy sources, such as wind and solar energy. In the case of wind energy, planning an appropriate location for a wind farm (farm siting) is crucial to the performance and the economy of the farm. Available wind resource, distance to power grid connections, local topography,

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access to transportation, and likely environmental impact are the major factors that need to be considered in wind farm siting. Owing to this highly stochastic nature of wind, distribution of the potential of a wind resource, and prediction of the optimal power generation capability of a farm at that site remain challenging tasks.

WPD is a useful way to evaluate the wind resource available at a potential site. The WPD, measured in *watts per square meter*, indicates how much energy is available at the site. WPD (W/m^2) is a nonlinear function of the *probability density function* (*pdf*) of wind speed, which is expressed as [1]

$$WPD = \frac{1}{2}\rho \int_0^{U_{max}} U^3 f(U) dU \tag{1}$$

where U represents the wind speed; U_{max} is the maximum possible wind speed at that location; ρ represent the air density; and $f(U)$ is the *pdf* of the wind speed.

Karsli and Geçit presented a preliminary examination of wind potential of Nurdagı-Gaziantep district in Turkey [2] by estimating the *Wind Power Density* (WPD), based on Weibull wind speed distribution. Celik studied the wind energy potential based on the Weibull and the Rayleigh models [3]. The wind resource varies significantly from one location to another. The effective force of the wind at a particular location can be rated by the WPD, which is evaluated based on the distribution of wind speed and air density [4–6].

Motivation and Objectives

WPD is a leading factor in determining the net power generated by a wind farm. In energy potential estimating, other factors such as (i) the distribution of wind direction, (ii) the layout of the wind farm, and (iii) the appropriate turbine type selection, might further restrict the maximum power generation of a farm. These factors thereby are critical for (i) the determination of the quality of a wind energy site, and (ii) the design of an optimum wind farm configuration on that site. One of the objectives in this paper is to investigate the effect of wind distribution and optimal farm layout on farm siting.

An optimal layout of turbines that ensures maximum farm efficiency is of utmost importance in conceiving a wind farm project [7]. For a given farm layout, the direction of wind has a strong influence on the wakes created (i.e. the shading effect of a wind turbine on other turbines downstream from it) & subsequently on the overall flow pattern in the wind farm. Therefore, the direction of wind plays an important role in evaluating the quality of wind resource (wind energy potential) at a farm site.

Motivated by the previous research, this paper is to exploit a more comprehensive method to characterize and predict the quality of a wind resource. We develop a Wind Power Potential Evaluation (WPPE) model, considering the distribution of both wind speed and wind direction. The remainder of the paper is organized as follows. The WPPE model is developed in the following section. Then, two numerical examples are presented to illustrate the use of the WPPE model. Concluding remarks and future work are given in the last Section.

THE WIND POWER POTENTIAL EVALUATION (WPPE) MODEL

The Wind Power Potential Evaluation (WPPE) model makes significant assumptions and approximations in modeling the optimal wind farm power generation, including: (i) fixed farm orientation (biased towards certain wind directions) is used; (ii) particular turbine type (biased towards certain wind speeds) is used; and (iii) the distribution of wind speed and wind direction (bivariate normal distribution) is an unimodal distribution. The WPPE model is developed to evaluate the wind power potential (maximum power generation for a specified farm size and installed capacity) for differing locations, by observing the following sequence of four steps.

STEP 1: Using recorded wind data at a location, bivariate normal distribution [8] is used to simultaneously characterize the variation of wind speed and wind direction. The parameters of bivariate normal distribution include five variables: (i) the mean of the wind speed distribution, μ_U; (ii) the mean of the wind direction distribution, μ_θ; (iii) the variance of the wind speed distribution, σ_U; (iv) the variance of the wind direction distribution, σ_θ; and (v) the correlation coefficient between wind speed and wind direction, ρ. Every unique combination of these five parameters represents a unique sample distribution of wind speed and wind direction.

STEP 2: The five parameters of the bivariate normal distribution are sampled using Sobol's quasirandom sequence generator [9].

STEP 3: For each sample distribution of wind speed and wind direction, we maximize the net power generation through farm layout optimization. To this end, we employ the Unrestricted Wind Farm Layout Optimization (UWFLO) methodology [10].

STEP 4: A response surface is constructed to represent the computed maximum power generation as a function of the parameters of the bivariate normal distribution. We use the recently developed Reliability Based Hybrid Functions [11] method for this purpose.

For any farm site, according to the recorded wind data, we can (i) estimate the parameters of wind velocity distribution, and (ii) predict the maximum power generation for the specified farm size and capacity, using the WPPE model. In the subsequent subsections, we discuss the details of each step.

Distribution of Wind Speed and Wind Direction

The power generated by turbine-j (P), for an incoming wind speed U_j, is given by

$$P_j = k_g k_b C_p \left(\frac{1}{2}\rho\pi\frac{{D_j}^2}{4}{U_j}^3\right) \tag{2}$$

where C_p, k_b, and k_g are the power coefficient, the mechanical and the electrical efficiencies of the turbine; and ρ represents the density of air. The power generated by each turbine is determined using approximated power curves that are developed based on the *Cut-in*, *Rated* and *Cut-out* power and wind speeds of the corresponding turbine-types.

The net power generated, P_{farm}, is given by

$$P_{farm} = \sum_{j=1}^{N} P_j \tag{3}$$

where P_j represents the power generated by Turbine-j; N is the number the turbines in the farm;

The power generated by an individual turbine is a cubic function of the approaching wind speed (as seen from Eqn. (2)). On the other hand, the wind direction, together with the farm layout, are two major factors that regulate the overall flow pattern (wake patterns) inside the wind farm. The determination (or prediction) of the annual power generation from a wind farm should thereby account for the variations in both wind speed and wind direction. This prediction is accomplished using the following two-step procedure:

1. Estimate the annual distribution of the wind speed and wind direction (as a probability distribution function).
2. Integrate the power generation model (for a given wind speed/direction) over the entire annual wind distribution.

By far the most widely used distribution for characterization of wind speed is the 2-parameter Weibull distribution [12–17]. Other distributions used to characterize wind speed include 1-parameter Rayleigh distribution, 3-parameter generalized Gamma distribution, 2-parameter Lognormal distribution, 3-parameter Beta distribution, 2-parameter inverse Gaussian distribution, singly truncated normal Weibull mixture distribution, and maximum entropy probability density function [14, 17]. Vega and Letchford [18] used Weibull distribution to estimate the wind speed probability, and have taken the shape parameter and the scale parameter as functions of wind direction. Carta et al. [19] presented a joint probability density function of wind speed and wind direction for wind energy analysis. Erdem and Shi [20] compared three differing bivariate joint distributions (angular-linear, Farlie-Gumbel-Morgenstern, and anisotropic lognormal approaches) for wind speed and wind direction data.

In this paper, bivariate normal distribution is adopted to simultaneously characterize the variation of wind speed and wind direction.

$$P(U,\theta) = \frac{1}{2\pi\sigma_U\sigma_\theta\sqrt{1-\rho^2}}\exp\left[-\frac{z}{2(1-\rho^2)}\right] \quad ,where \tag{4}$$

$$z \equiv \frac{(U-\mu_U)^2}{\sigma_U^2} - \frac{2\rho(U-\mu_U)(\theta-\mu_\theta)}{\sigma_U\sigma_\theta} + \frac{(\theta-\mu_\theta)^2}{\sigma_\theta^2} \tag{5}$$

where U and θ represent the wind speed and wind direction, respectively; μ_U and μ_θ are the means of the wind speed distribution and the wind direction distribution, respectively; σ_U and σ_θ represent the variances of the wind speed distribution and the wind direction distribution, respectively; ρ is the correlation coefficient between wind speed and wind direction. The covariance matrix (Σ) is expressed as

$$\Sigma = \begin{pmatrix} \sigma_U^2 & \rho\sigma_U\sigma_\theta \\ \rho\sigma_U\sigma_\theta & \sigma_\theta^2 \end{pmatrix}$$

The parameters of the distribution can be estimated using the *maximum likelihood estimators* (MLE). The expressions of the estimated means ($\hat{\mu}$) and unbiased covariance matrix ($\hat{\Sigma}$) are

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad and \quad \hat{\Sigma} = \frac{1}{n}\sum_{i=1}^{n}(X_i-\hat{\mu})(X_i-\hat{\mu})^T \tag{6}$$

where $X_i = [U_i \quad \theta_i]$; n is the number of data points.

It is important to note that the bivariate normal distribution may not accurately characterize the distribution of wind speed and wind direction in some siting locations. However, the objective of evaluating wind farm siting in this paper is not to develop an accurate distribution of wind speed and wind direction. The main concern in this paper is to capture the difference of wind distribution among siting locations, thereby to develop a response surface representing the computed maximum power generation as a function of the parameters of the wind velocity distribution. To this end, the bivariate normal distribution can successfully capture the difference of wind distribution among different farm sites.

Estimating the Annual Energy Production

The total annual energy produced by a wind farm (in kWh), E_{farm}, at a particular location can be expressed as

$$E_{farm} = 8760 \int_{0^\circ}^{360^\circ} \int_{0}^{U^{max}} P_{farm}(U,\theta) P(U,\theta) \, dU d\theta \qquad (7)$$

where, U^{max} is the maximum possible wind speed at that location, and $P_{farm}(U,\theta)$ represents the power generated by the farm for a wind speed U and a wind direction θ. In Eqn. (7), $P(U,\theta)$ represents probability of occurrence of wind conditions defined by speed U and direction θ. The power generated by the entire wind farm is a complex function of the incoming wind properties, the arrangement of turbines, and the turbine features. Hence, a numerical integration approach [21] is suitable for estimating the annual energy production as given by Eqn. (7).

In this paper, we integrate using the Monte Carlo method that is implemented through the Sobol's quasirandom sequence generator. This class of integration methods is easy to apply (for multidimensional integrals), and is likely to provide greater accuracy for the same number of function evaluations (at sample points), when compared to the repeated integrations using one-dimensional methods (deterministic Quadrature Rule methods). The approximated total annual energy produced by the wind farm is then expressed as

$$\begin{aligned} &E_{farm} = \sum_{i=1}^{N_p} P_{farm}\left(U^i,\theta^i\right) p\left(U^i,\theta^i\right) \Delta U \Delta\theta, \quad \text{where} \\ &\Delta U \Delta\theta = U_{max} \times 360^\circ / N_p \end{aligned} \qquad (8)$$

and where N_p is the number of sample points used; the parameters U^i and θ^i, respectively, represent the speed and direction of the incoming wind for the i^{th} sample point. Hence, the annual energy is readily determined by the summation of the estimated power generation (P_{farm}) over a set of randomly distributed N_p wind velocities.

Parameter Sampling

In the case of problems with simulated data, the choice of an appropriate sampling technique is generally considered crucial for the performance of any surrogate modeling approach. The parameters of the wind velocity distribution are sampled using the Sobol's quasirandom sequence generator [9]. Sobol sequences use a base of two to form successively finer uniform partitions of the unit interval, and then reorder the coordinates in each dimension. The algorithm for generating Sobol sequences is explained in Bratley and Fox, Algorithm 659 [22].

In order to develop the response surface to represent the computed maximum power generation as a function of the parameters of the wind velocity distribution, 100 sample points (of wind velocity distribution) are generated as training and test points. For each sample set of distribution parameter, we maximize the net power generation. The farm size and the installed capacity is fixed. The sampling ranges are defined as follows: (i) $1m/s < \mu_U < 15m/s$ at 3 meters height; (ii) $0^\circ < \mu_\theta < 360^\circ$; (iii) $0.5 < \sigma_U < 4$; (iv) $11.25 < \sigma_\theta < 90$; and (v) $0 < \rho < 1$.

Unrestricted Wind Farm Layout Optimization (UWFLO) Methodology

The UWFLO methodology introduced by Chowdhury et al. [23] avoids the limiting assumptions presented by other methods, regarding the layout pattern and the selection of turbines. In the UWFLO method, the turbine location coordinates are treated as continuous variables, which allows all feasible arrangements of the turbines. The UWFLO method is applicable to both experimental scale wind farms and full scale commercial wind farms, by

1. using the wake growth model proposed by Frandsen et al. [24],
2. implementing the wake superposition model developed by Katic et al. [25],
3. including the estimated distribution of the wind speed and wind direction,
4. modifying the power generation model to allow turbines with different hub heights and performance characteristics, and
5. implementing a newly developed mixed-discrete Particle Swarm Optimization (PSO) algorithm [10].

The overall optimization problem is defined as

$$\begin{aligned} &\text{Max} \;\; f(V) = \tfrac{P_{farm}}{NP_{r0}} \\ &\text{subject to} \\ &\qquad g_1(V) \leq 0 \\ &\qquad g_2(V) \leq 0 \\ &\qquad V = \{X_1, X_2, \ldots\ldots, X_N, Y_1, Y_2, \ldots\ldots, Y_N\} \\ &\qquad 0 \leq X_i \leq X_{farm} \\ &\qquad 0 \leq Y_i \leq Y_{farm} \end{aligned} \qquad (9)$$

where P_{r0} is the rated-power of the reference turbine (used for normalizing) and P_{farm} is the power generated by the farm; $f(V)$ represents the farm efficiency. X_i and Y_i are the coordinates of the wind turbines in the farm. The parameters X_{farm} and Y_{farm} represent the extent of the rectangular wind farm in the X and Y directions, respectively. The inequality constraint g_1 represents the minimum clearance required between any two turbines. To ensure the placement of the wind turbines within the fixed size wind farm, the X_i and Y_i bounds are reformulated into an inequality constraint, $g_2(V) \leq 0$.

Response Surface Development

In the literature, we can find a wide variety of surrogate modeling techniques that include: (i) Polynomial Response Surface method (PRSM) [26], (ii) Kriging [27, 28], (iii) Radial Basis Functions (RBF) [29], (iv) Extended Radial Basis Functions (E-RBF) [30, 31], (v) Artificial Neural Networks (ANN) [32], and (vi) Support Vector Regression (SVR) [33, 34]. The recently developed Reliability Based Hybrid Functions (RBHF), which has been shown to be a robust surrogate modeling technique by Zhang et al. [11], is adopted in this paper.

Reliability Based Hybrid Functions (RBHF) The RBHF formulates a reliable trust region, and adaptively combines characteristically differing surrogate models. The weight of each contributing surrogate model is represented as a function of the input domain, based on a local reliability measure for that surrogate model. Such an approach could fully utilize the advantages of each component surrogate, thereby capturing both the global and the local trend of complex functional relationships. In this paper, the RBHF integrates four component surrogate models: (i) QRSM, (ii) RBF, (iii) E-RBF, and (iv) Kriging, by characterizing and evaluating the local reliability of each model.

The hybrid surrogate modeling methodology adopted in this paper introduces a three tier approach:

1. Determination of a trust region - numerical bounds of the estimated parameter (output) as a function of the independent parameters (input vector), over the feasible input space.
2. Characterization of the local reliability (using probability distribution functions) of the estimated function value, and representation of the corresponding distribution parameters as functions of the input vector.
3. Generation of characteristically different surrogate models (component surrogates); and, weighted summation of the estimated function value based on the local reliability (modeled in the previous step).

Considering a set of training points D, three steps are followed to formulate the RBHF surrogate model as illustrated in Fig. 1. We formulate the RBHF surrogate model by reliability based adaptive selection of weights for the three surrogate models (RBF, E-RBF and Kriging). At each point, the RBHF approximate function value is a weighted summation of estimated values through the three surrogates, as given by

$$\tilde{f}_{rbhf} = \sum_{i=1}^{n_s} w_i(x)\tilde{f}_i(x) \tag{10}$$

where n_s is the number of surrogates integrated into the RBHF, and $\tilde{f}_i(x)$ represents the estimated value by each surrogate. The weights w_i's are functions expressed in terms of the estimated

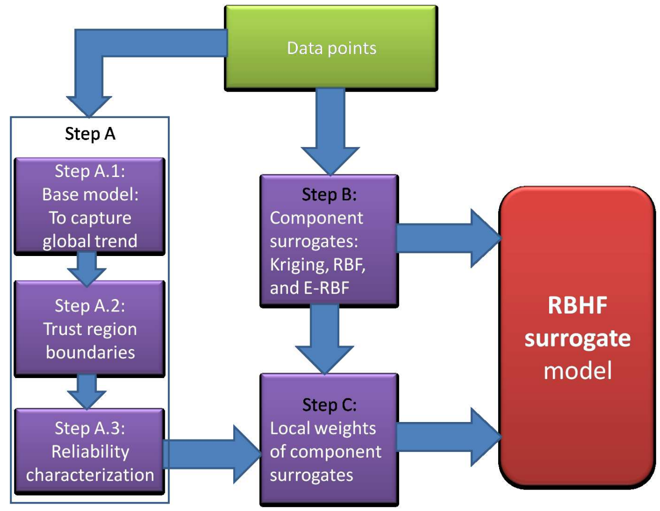

FIGURE 1. THE FRAMEWORK OF THE RBHF SURROGATE MODEL

probability, which can be expressed as

$$w_i(x) = \frac{P_i(x)}{\sum_{i=1}^{n_s} P_i(x)} \tag{11}$$

where $P_i(x)$ is the probability value of the i^{th} surrogate for point x. Details of the RBHF approach can be found in the paper by Zhang et al. [11].

Performance Criteria The overall performance of the surrogate can be evaluated using two standard performance metrics: (i) Root Mean Squared Error (RMSE) [27, 35], which provides a global error measure over the entire design domain, and (ii) Relative Accuracy Error (RAE), which is indicative of local deviations. The RMSE is given by

$$RMSE = \sqrt{\frac{1}{n_t}\sum_{k=1}^{n_t}\left(f(x^k) - \tilde{f}(x^k)\right)^2} \tag{12}$$

where $f(x^k)$ represents the actual function value for the test point x^k, $\tilde{f}(x^k)$ is the corresponding estimated function value. n_t is the number of test points chosen for evaluating the error measure. The RAE is evaluated at each test point, as given by

$$RAE(x^k) = \frac{|\tilde{f}(x^k) - f(x^k)|}{f(x^k)} \tag{13}$$

Cross-Validation Cross-validation technique is used to ensure that the developed response surface is robust and accurate. A cross-validation error is the error at a data point when the response surface is fitted to a subset of the data points not including that point, which is called *leave-one-out* strategy. For a set of q points, A vector of cross-validation errors, $\tilde{e}$, is obtained, when the response surfaces are fitted to all the other $p-1$ points. This vector is also known as the prediction sum of squares (the PRESS vector).

The *leave-one-out* strategy is computationally expensive for large number of points, which can be overcome by the q-fold strategy. Q-fold strategy involves (i) splitting the data randomly into q roughly equal subsets, (ii) removing each of these subsets in turn, and (iii) fitting the model to the remaining $q-1$ subsets. A loss function L can be computed to measure the error between the predictor and the points in the subset we set aside at each iteration; the contributions to L are then summed over the q iterations.

More formally, if a mapping $\zeta : 1,\cdots,n \rightarrow 1,\cdots,q$ describes the allocation of the n training points to one of the q subsets and $\hat{f}^{-\zeta(i)}(x)$ of the predictor obtained by removing the subset $\zeta(i)$ (i.e. the subset to which observation i belongs), the cross-validation measure is (by introducing the squared error in the role of the loss function) given by

$$PRESS_{SE} = \frac{1}{n}\sum_{i=1}^{n}\left[y^{(i)} - \hat{f}^{-\zeta(i)}(x^{(i)})\right]^2 \tag{14}$$

Hastie et al. [36] recommend compromise values of $q=5$ or $q=10$. In practical terms, using fewer subsets has an added advantage of reducing the computational cost of the cross-validation process by reducing the number of models that have to be fitted.

NUMERICAL EXAMPLES

In this paper, we explore two different scenarios in the wind potential evaluation of farm siting. We consider a fixed-size (land) rectangular wind farm that is comprised of a defined turbine-type. The different scenarios are

Case 1: Evaluating the wind power potential (maximum power generation, or farm efficiency) of a farm, comprised of four turbines;
Case 2: Evaluating the wind power potential (maximum power generation, or farm efficiency) of a farm, comprised of nine turbines.

Both of the cases present $2N$ design variables. The *GE-1.5MW-xle* [37] turbine is chosen as the specified turbine-type in both Cases 1 and 2. The features of this turbine is provided in Tab. 1.

TABLE 1. FEATURES OF THE *GE-1.5MW-XLE* TURBINE [37]

Turbine feature	Value
Rated power (P_{r0})	1.5MW
Rated wind speed (U_{r0})	11.5m/s
Cut-in wind speed (U_{in0})	3.5m/s
Cut-out wind speed (U_{out0})	20.0m/s
Rotor-diameter (D_0)	82.5m
Hub-height (H_0)	80.0m

The specified wind farm properties are given in Tab. 2. The farm is such oriented that the positive X-direction of the layout co-ordinate system points towards the South. The rectangular farm size/orientation corresponds to a array configuration, with a row-wise spacing of seven times the turbine rotor-diameter and a column-wise spacing of three times the turbine rotor-diameter.

TABLE 2. SPECIFIED WIND FARM PROPERTIES

Farm property	Value
Land size (length x breadth)	Case 1: $7D_0 \times 3D_0$ Case 2: $(2\times 7D_0)\times(2\times 3D_0)$
Orientation	North to South lengthwise
Average roughness	0.1m (grassland)
Density of air	1.2 kg/m^3

Response Surface Development

Case 1 investigates the wind potential by evaluating the maximum power generation of a wind farm with four turbines, for a particular distribution of wind velocity at the site. For the 100 differing wind velocity distributions generated in Subsection , we obtain the maximum power generation through UWFLO. These 100 sets of points are treated as the training points for the development of the following response surface. Table 3 shows a representation set of the selected training points.

Cross-validation technique is used to evaluate the performance of the response surface (RBHF) for various numbers of subsets. The $PRESS_{SE}$ values are listed in Tab. 4 and Fig. 2, which shows the accuracy of the response surface model. It can be seen that the maximum value of $PRESS_{SE}$ is 0.0816, which shows the accuracy the developed response surface.

Case 2 investigates the wind potential by evaluating the maximum farm efficiency of a farm with nine turbines. Same as the first case, the training points are shown in Tab. 3; the $PRESS_{SE}$

TABLE 3. SELECTED TRAINING POINTS

Point	Mean, μ_U speed	Mean, μ_U direction	Variance, σ_U speed	Variance, σ_θ direction	Correlation, ρ coefficient	Max. efficiency four turbines	Max. efficiency nine turbines
1	8.00	180.00	2.25	50.63	0.50	0.9005	0.9102
2	11.50	90.00	3.13	30.94	0.75	0.3456	0.4629
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
50	12.59	174.38	2.30	69.08	0.23	0.2515	0.2631
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
99	5.05	317.81	2.88	58.62	0.76	0.4524	0.5037
100	6.80	92.81	1.57	48.78	0.38	0.8675	0.8919

TABLE 4. PREDICTION SUM OF SQUARES

Subsets, q	$PRESS_{SE}$ (4 turbines)	$PRESS_{SE}$ (9 turbines)
2	0.0578	0.0721
4	0.0356	0.0583
5	0.0405	0.0643
10	0.0456	0.0802
20	0.0623	0.0821
25	0.0468	0.0951
50	0.0816	0.0724

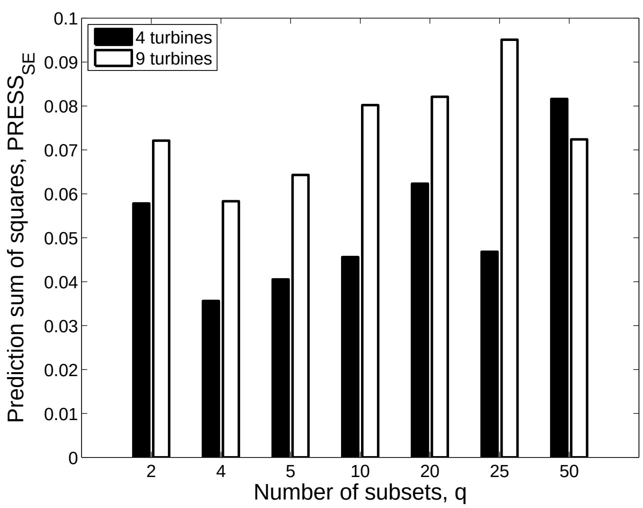

FIGURE 2. PREDICTION SUM OF SQUARES

values are listed in Tab. 4 and Fig. 2. We can see that the maximum value of $RPESS_{SE}$ is 0.0951.

Potential Power Evaluation

For any farm site, we can estimate the parameters of the bivariate normal wind velocity distribution using the recorded wind data. Subsequently we can predict the maximum power generation for specified farm size and capacity, using the WPPE model. Four locations are selected to evaluate their potential wind power. The wind data for these four locations is obtained from the *North Dakota Agricultural Weather Network* (NDAWN) [38]. The daily averaged data (wind speed and wind direction) in 2010 is measured and recorded at the four differing stations (Ada, Baker, Beach, and Bottineau). Table 5 shows the geographical coordinates and the elevation of the stations. The parameters of the bivariate normal distribution for the four stations are estimated using maximum likelihood estimators (Eqn.(6)), which are listed in Tab. 6.

The values of maximum farm efficiency and RAE are shown in Tab. 7. It can be seen that the maximum differences between the UWFLO estimation and the response surface estimation are 3.73% and 3.65%, for the four-turbine farm and the nine-turbine farm, respectively. The RMSE value evaluated using Eqn.(12) is 0.0053 for the four-turbine farm, and is 0.0070 for the nine-

TABLE 5. DETAILS OF NDAWN STATION [38]

Station	Ada, MN	Baker, ND	Beach, ND	Bottineau, ND
Latitude	47.321°	48.167°	46.789°	48.821°
Longitude	−96.514°	−99.648°	−103.966°	−100.760°
Elevation	277m	512m	893m	450m

TABLE 6. DISTRIBUTION PARAMETERS ESTIMATED FOR THE FOUR STATIONS

Station	Mean, μ_U speed	Mean, μ_U direction	Variance, σ_U speed	Variance, σ_θ direction	Correlation, ρ coefficient
Ada	3.89	197.45	1.89	101.04	0.10
Baker	3.94	195.51	1.83	103.74	0.07
Beach	4.00	219.24	1.44	85.97	0.13
Bottineau	3.91	196.38	1.78	103.49	0.15

turbine farm. We can see that: (i) Baker station is the best site for a four-turbine wind farm; and (ii) Beach station is the best site for a nine-turbine wind farm. This observation can be attributed to: (i) the variation of the wind conditions, and (ii) the wake effects in the farm. The wake of the nine-turbine farm is more complicated than that of the four-turbine farm. The wind direction variance value (103.74) at Baker station is larger than that at Beach station (85.97). Figure 3 shows the estimated bivariate normal distributions of wind speed and wind direction for Baker and Beach stations.

CONCLUSION REMARKS

This paper developed a Wind Power Potential Evaluation (WPPE) model, which would help decision makers in wind farm siting. This comprehensive method could characterize and predict the quality of a wind resource by considering the distribution of both wind speed and wind direction. The wind distribution was modeled using bivariate normal distribution. The farm power was maximized through layout design using the Unrestricted Wind Farm Layout Optimization (UWFLO) methodology. A response surface was then constructed, using the recently developed Reliability Based Hybrid Functions (RBHF), to represent the computed maximum power generation as a function of the parameters of the wind velocity (speed and direction) distribution. The wind power potentials at four stations in North Dakota are successfully evaluated and compared using the WPPE model. The case study illustrated the variation of wind conditions and subsequently the its influence on the quality of a wind resource.

In the future, the effect of differing distribution types on the wind power potential evaluation, will be investigated. Future research should also address the assumptions made in this model.

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REFERENCES

[1] Jamil, M., Parsa, S., and Majidi, M., 1995. "Wind power statistics and an evaluation of wind energy density". *Renewable Energy,* ***6***(5-6), pp. 623–628.

[2] Karsli, V., and Geçit, C., 2003. "An investigation on wind power potential of nurdagı-gaziantep, turkey". *Renewable Energy,* ***28***, pp. 823–830.

[3] Celik, A., 2003. "A statistical analysis of wind power density based on the weibull and rayleigh models at the southern region of turkey". *Renewable Energy,* ***9***, pp. 593–604.

[4] Kusiak, A., Zheng, H., and Song, Z., 2009. "Wind farm power prediction: A data-mining approach". *Wind Energy,* ***12***, pp. 275–293.

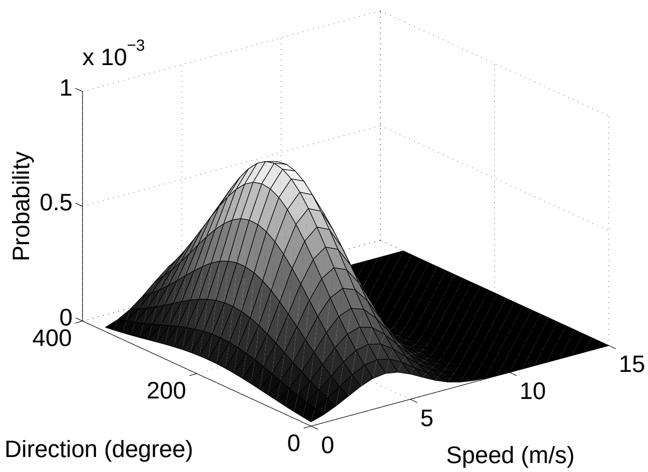
[5] Celik, A., 2003. "Assessing the suitability of wind speed probabilty distribution functions based on wind power density". *Renewable Energy,* ***28***(10), pp. 1563–1574.

[6] Lu, L., Yang, H., and Burnett, J., 2002. "Investigation on wind power potential on hong kong islands - an analysis of wind power and wind turbine characteristics". *Renewable Energy,* ***27***, pp. 1–12.

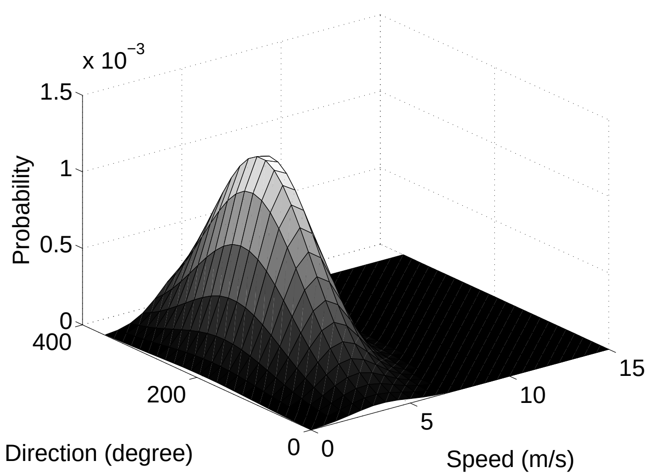
[7] Chowdhury, S., Zhang, J., Messac, A., and Castillo, L. "Unrestricted wind farm layout optimization (uwflo): Investigating key factors influencing the maximum power generation". *submitted to Renewable Energy*.

TABLE 7. ESTIMATED NORMALIZED MAXIMUM POWER GENERATION

Station	Four-turbine farm			Nine-turbine farm		
	UWFLO	Response surface	RAE	UWFLO	Response surface	RAE
Ada	0.4171	0.4188	0.40%	0.4837	0.4852	0.31%
Baker	0.4360	0.4240	2.75%	0.4918	0.4957	0.78%
Beach	0.4331	0.4169	3.73%	0.5116	0.4929	3.65%
Bottineau	0.4275	0.4234	0.96%	0.4832	0.4910	1.60%



(a) Baker



(b) Beach

FIGURE 3. DISTRIBUTIONS OF WIND SPEED AND WIND DIRECTION AT BAKER AND BEACH STATIONS

[8] Abramowitz, M., and Stegun, I., 1972. *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables*. Dover Publications.

[9] Sobol, I., 1976. "Uniformly distributed sequences with an additional uniform property". *USSR Computational Mathematics and Mathematical Physics,* ***16***(5), pp. 236–242.

[10] Chowdhury, S., Zhang, J., Messac, A., and Castillo, L., 2010. "Exploring key factors influencing optimal farm design using mixed-discrete particle swarm optimization". In 13th AIAA/ISSMO Multidisciplinary Analysis Optimization Conference.

[11] Zhang, J., Chowdhury, S., and Messac, A., 2011. "A hybrid methodology for surrogate modeling". In AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference.

[12] Burton, T., Sharpe, D., Jenkins, N., and Bossanyi, E., 2001. *Wind energy handbook*. Wiley.

[13] Manwell, J., McGowan, J., and Rogers, A., 2010. *Wind Energy Explained: Theory, Design and Application*, 2 ed. Wiley.

[14] Carta, J., Ramírez, P., and Velázquez, S., 2009. "A review of wind speed probability distributions used in wind energy analysis case studies in the canary islands". *Renewable and Sustainable Energy Reviews,* ***13***(5), pp. 933–955.

[15] Seguro, J., and Lambert, T., 2000. "Modern estimation of the parameters of the weibull wind speed distribution for wind energy analysis". *Journal of Wind Engineering and Industrial Aerodynamics,* ***85***(1), pp. 75–84.

[16] Dorvlo, A., 2002. "Estimating wind speed distribution". *Energy Conversion and Management,* ***43***(17), pp. 2311–2318.

[17] Morgan, E., Lackner, M., Vogel, R., and Baise, L., 2011. "Probability distributions for offshore wind speeds". *Energy Conversion and Management,* ***52***(1), pp. 15–26.

[18] Vega, R., 2008. "Wind directionality: A reliability-based approach". PhD thesis, Texas Tech University, Lubbock, TX, August.

[19] Carta, J., Ramírez, P., and Bueno, C., 2008. "A joint probability density function of wind speed and direction for wind energy analysis". *Energy Conversion and Management,* ***49***(6), pp. 1309–1320.

[20] Erdem, E., and Shi, J., 2011. "Comparison of bivariate distribution construction approaches for analysing wind speed and direction data". *Wind Energy,* ***14***(1), pp. 27–41.

[21] Kusiak, A., and Zheng, H., 2010. "Optimization of wind turbine energy and power factor with an evolutionary computation algorithm". *Renewable Energy,* ***35***(3), pp. 1324–1332.

[22] Bratley, P., and Fox, B., 1988. "Algorithm 659: Implementing sobol's quasirandom sequence generator". *ACM Transactions on Mathematical Software,* ***14***(1), pp. 88–100.

[23] Chowdhury, S., Messac, A., Zhang, J., Castillo, L., and Lebron, J., 2010. "Optimizing the unrestricted placement of turbines of differing rotor diameters in a wind farm for maximum power generation". In ASME 2010 International Design Engineering Technical Conferences (IDETC).

[24] Frandsen, S., Barthelmie, R., Pryor, S., Rathmann, O., Larsen, S., Hojstrup, J., and Thogersen, M., 2006. "Analytical modeling of wind speed deficit in large wind offshore wind farms". *Wind Energy,* ***9***(1-2), pp. 39–53.

[25] Katic, I., Hojstrup, J., and Jensen, N., 1986. "A simple model for cluster efficiency". In Proceedings of European Wind Energy Conference and Exhibition.

[26] Myers, R., and Montgomery, D., 2002. *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*. Wiley-Interscience; 2 edition.

[27] Forrester, A., and Keane, A., 2009. "Recent advances in surrogate-based optimization". *Progress in Aerospace Sciences,* ***45***(1-3), pp. 50–79.

[28] Wilson, B., Cappelleri, D., Simpson, T., and Frecker, M., 2001. "Efficient pareto frontier exploration using surrogate approximations". *Optimization and Engineering,* ***2***(1), pp. 31–50.

[29] Hardy, R. L., 1971. "Multiquadric equations of topography and other irregular surfaces". *Journal of Geophysical Research,* ***76***, pp. 1905–1915.

[30] Mullur, A., and Messac, A., 2005. "Extended radial basis functions: More flexible and effective metamodeling". *AIAA Journal,* ***43***(6), pp. 1306–1315.

[31] Messac, A., and Mullur, A., 2008. "A computationally efficient metamodeling approach for expensive multiobjective optimization". *Optimization and Engineering,* ***9***(1), pp. 37–67.

[32] Simpson, T., Peplinski, J., Koch, P., and Allen, J., 2001. "Metamodels for computer-based engineering design: Survey and recommendations". *Engineering with Computers,* ***17***(2), pp. 129–150.

[33] Basudhar, A., and Missoum, S., 2008. "Adaptive explicit decision functions for probabilistic design and optimization using support vector machines". *Computers and Structures,* ***86***(19-20), pp. 1904–1917.

[34] Yun, Y., Yoon, M., and Nakayama, H., 2009. "Multi-objective optimization based on meta-modeling by using support vector regression". *Optimization and Engineering,* ***10***(2), pp. 167–181.

[35] Jin, R., Chen, W., and Simpson, T., 2001. "Comparative studies of metamodelling techniques under multiple modelling criteria". *Structural and Multidisciplinary Optimization,* ***23***(1), pp. 1–13.

[36] Hastie, T., Tibshirani, R., and Friedman, J., 2001. *The Elements of Statistical Learning*. Springer-Verlag.

[37] GE, 2010. *GE Energy 1.5MW Wind Turbine Brochure*. General Electric, http://www.gepower.com/.

[38] NDAWN, 2010. The north dakota agricultural weather network. `http://ndawn.ndsu.nodak.edu/`.