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A HYBRID MEASURE-CORRELATE-PREDICT METHOD FOR WIND RESOURCE ASSESSMENT

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ABSTRACT

This paper develops a hybrid Measure-Correlate-Predict (MCP) strategy to predict the long term wind resource variations at a farm site. The hybrid MCP method uses the recorded data of multiple reference stations to estimate the long term wind condition at the target farm site. The weight of each reference station in the hybrid strategy is determined based on: (i) the distance and (ii) the elevation difference between the target farm site and each reference station. The applicability of the proposed hybrid strategy is investigated using four different MCP methods: (i) linear regression; (ii) variance ratio; (iii) Weibull scale; and (iv) Artificial Neural Networks (ANNs). To implement this method, we use the hourly averaged wind data recorded at six stations in North Dakota between the year 2008 and 2010. The station Pillsbury is selected as the target farm site. The recorded data at the other five stations (Dazey, Galesbury, Hillsboro, Mayville and Prosper) is used as reference station data. Three sets of performance metrics are used to evaluate the hybrid MCP method. The first set of metrics analyze the statistical performance, including the mean wind speed, the wind speed variance, the root mean squared error, and the maximum absolute error. The second set of metrics evaluate the distribution of long term wind speed; to this end, the Weibull distribution and the Multivariate and Multimodal Wind Distribution (MMWD) models are adopted in this paper. The third set of metrics analyze the energy production capacity and the efficiency of the wind farm. The results illustrate that the many-to-one correlation in such a hybrid approach can provide more reliable prediction of the long term onsite wind variations, compared to one-to-one correlations.

Keywords: Energy, neural network, power generation, wind distribution, wind resource assessment

INTRODUCTION

In the past decade, there has been notable progress in developing renewable energy resources; among them, wind energy

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has taken a lead, and is currently contributing towards 2.5% of the worldwide electricity consumption [1]. However, the available energy from a wind resource varies appreciably over one year. The uncertainty in wind resource potential is partially responsible in restraining wind energy from playing a major role in the overall energy market. A determination and the forecasting of the long term wind condition would serve two important objectives: (i) Analyzing the quality of a wind farm site, and (ii) designing an optimum wind farm layout and selecting appropriate turbine types for the site.

Wind resource assessment has been playing an important role in a wind energy project. The accuracy of long term predictions obtained using MCP methods is subject to (i) the availability of a nearby meteorological station, (ii) the uncertainty associated with a specific correlation methodology [2], and (iii) the likely dependence of this correlation on physical features such as the topography, the distance between the monitoring stations, and the type of the local climate regime [3].

Measure-Correlate-Predict (MCP) Overview

Wind resource assessment is the process of estimating the power potential of a farm site. A wide variety of MCP techniques have been reported in the literature, such as: (1) linear regression [4,5]; (2) variance ratio [5,6]; (3) Weibull scale [6]; (4) Artificial Neural Networks (ANNs) [3,4,7]; (5) Support Vector Regression (SVR) [8,9]; (6) Mortimer [3]; and (7) wind index MCP [10].

The MCP methods were first used to estimate the long term annual mean wind speed [11, 12]. The linear regression method [13] was presented to characterize the relationship between the reference and target site wind speeds.

Rogers et al. [14] compared four MCP algorithms: (i) a linear regression model; (ii) a model using distributions of ratios of the wind speeds at the two sites; (iii) a vector regression method; and (iv) a method based on the ratio of the standard deviations of the two data sets. Perea et al. [5] proposed and evaluated three MCP methods based on concurrent wind speed time series for two sites. The three MCP methods are: (i) linear regression derived from bivariate normal joint distribution; (ii) Weibull regression; and (iii) approaches based on conditional probability density functions.

Given the unavoidable practical constraints, the overall reliability of the predicted long term wind distribution remains highly sensitive to the one-year distribution of the recorded on-site data. Quantifying and modeling the uncertainty in the MCP methods would provide more credibility to the wind resource assessment and farm performance estimation. Kwon [15] and Lackner et al. [16] presented different frameworks to analyze the uncertainty in MCP-based wind resource assessment. The wind resource-based uncertainty models proposed by Messac et al. [17] can be also applied to the long term data recorded at the meteorological stations when MCP methods are used.

Research Objectives and Motivation

The existing MCP methods estimate the wind data at the farm site using the recorded wind data at one reference station, without considering the topography, and distance and elevation difference between the two stations. Generally, the recorded wind data at more than one meteorologic stations nearby the targeted farm site is available. It would be more comprehensive if we use the recorded wind data from different reference stations to estimate/predict the wind conditions at the targeted farm site.

In this paper, we develop a hybrid Measure-Correlate-Predict method and apply it to different stations for wind resource assessment. The hybrid MCP method uses the recorded data of multiple reference stations to estimate the long term wind condition at the target farm site. The weight of each reference station in the hybrid strategy is determined based on: (i) the distance and (ii) the elevation difference between the target farm site and each reference station. The remainder of the paper is organized as follows:

1. The hybrid MCP method is developed in Section II.
2. The wind data used for the MCP development is summarized in Section III.
3. The performance metrics for evaluating the effectiveness of the MCP method are presented in Section IV.
4. Section V presents the results and discussion on the case study.

HYBRID MEASURE-CORRELATE-PREDICTION (MCP) METHOD

Measure-Correlate-Predict (MCP) algorithms are used to predict the long term wind resource at target sites using the short term (1 or 2 year) onsite data, and the co-occurring data at nearby meteorological stations (that also have long term data).

The hybrid MCP method developed in this paper correlates the wind data at the targeted farm site with that at multiple reference stations. This strategy accounts for the local climate and the topography information. Two types of hybrid strategies are proposed: (i) All component MCP estimations between the targeted farm site and each reference station use one single MCP method (e.g. linear regression, variance ratio, Weibull scale, or neural networks); and (ii) each component MCP estimation (between the targeted farm site and the reference station) uses different MCP methods. The final hybrid MCP estimation is a combination of each component MCP estimation based on the distance and elevation difference between stations. In this paper, the first strategy is implemented; and preliminary results are discussed and analyzed. The key components of the hybrid MCP methodology include:

1. Estimation of the long term wind condition using single MCP method. In this paper, we use four MCP methods:

(i) linear regression; (ii) variance ratio; (iii) Weibull scale; and (iv) Artificial Neural Networks (ANNs).
2. Determination of the weights of each reference site based on the topography that consists of: (i) the distance and (ii) the elevation difference between the target farm site and each reference site.
3. Weighted aggregate of the estimated long term wind conditions.

Determining The Weights of Stations

The weight of each reference station in the hybrid strategy is determined based on: (i) the distance and (ii) the elevation difference between the target farm site and each reference station. The hypothesis here is that the weight of a reference station is larger, when the reference station is closer (shorter distance and smaller elevation difference) to the target farm site. The weight of each reference station, w_i, is determined by

$$w_i = \frac{1}{2(n_{ref}-1)}\left(\frac{\sum_{j=1,j\neq i}^{n_{ref}}\Delta d_j}{\sum_{j=1}^{n_{ref}}\Delta d_j}+\frac{\sum_{j=1,j\neq i}^{n_{ref}}\Delta h_j}{\sum_{j=1}^{n_{ref}}\Delta h_j}\right) \tag{1}$$

where n_{ref} is the number of reference stations; Δd_j and Δh_j represent the distance and the elevation difference between the target farm site and j^{th} reference station, respectively.

Individual MCP Method

In this paper, four MCP methods are investigated: (i) linear regression; (ii) variance ratio; (iii) Weibull scale; and (iv) Artificial Neural Networks (ANNs). It is helpful to note that other MCP methods can also be used in conjunction with the hybrid strategy, because the weights determination strategy is independent with the MCP method.

The Linear Regression Method Linear regression is a common method to characterize the relationship between the reference and target sites wind speeds. The prediction equation is given as

$$\hat{y} = ax + b \tag{2}$$

where $\hat{y}$ is the predicted wind speed at the target site; x is the observed wind speed at the reference site; and a and b are the estimated intercept and slope of the linear relationship.

The Variance Ratio Method When using linear regression, the predicted mean wind speed at the target site will be close in value to the measured mean over the training interval. However, the predicted variance at the target site will be less than the measured variance. This can result in biased predictions of wind speed distributions.

The Variance Ratio method was proposed in response to the above limitations of linear regression. It involves forcing the variance of the predicted wind speed at the target site to be equal to the measured variance at the target site. The prediction equation is express as follows.

$$\hat{y} = \mu_y - \frac{\sigma_y}{\sigma_x}\mu_x + \frac{\sigma_y}{\sigma_x}x \tag{3}$$

where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of the two concurrent data sets.

The Weibull Scale Method The Weibull Scale method presumes that the relationship between the Weibull distribution parameters and the frequency follow the general relation:

$$k_{site}^{long} = \frac{k_{site}^{short}}{k_{reference}^{short}} \times k_{reference}^{long} \tag{4}$$

and

$$c_{site}^{long} = \frac{c_{site}^{short}}{c_{reference}^{short}} \times c_{reference}^{long} \tag{5}$$

where k and c are the shape and scale parameters of the Weibull distribution, respectively.

The Artificial Neural Networks (ANNs) Method ANNs have been used to correlate and predict wind data because of their ability to recognize patterns in noisy or otherwise complex data. A neural network generally contains an input layer, one or more hidden layers, and an output layer. Figure 1 shows a typical three layer feedforward neural network. An ANN is developed by defining the following three types of parameters:

1. The interconnection pattern between different layers of neurons;
2. The learning process for updating the weights of the interconnections; and
3. The activation function that converts a neuron's weighted input to its output activation.

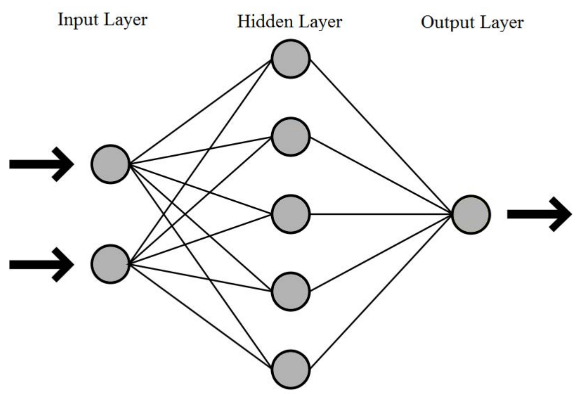


Figure 1. A GENERIC TOPOLOGY OF NEURAL NETWORKS

WIND DATA SUMMARY

The wind data used in this paper is obtained from the *North Dakota Agricultural Weather Network* (NDAWN) [18]. We use the hourly averaged data for wind speed and wind direction measured at six stations between the year 2008 and 2010. Table 1 shows the geographical coordinates and the elevation of each station. The measurement information is listed as follows.

1. Wind speed is measured at 3 meters above the soil surface with an anemometer.
2. Wind direction is the direction from which wind is blowing (degrees clockwise from north) measured at 3 meters above the soil surface ($N = 0°; NE = 45°; E = 90°; SE = 135°; S = 180°; SW = 225°; W = 270°; NW = 315°; etc.$) with a wind vane. The value is the average of all measured wind directions for a 24-hour period from midnight to midnight.

Table 1. DETAILS OF NDAWN STATIONS [18]

Station	Latitude	Longitude	Elevation (m)
Dazey	47.183	-98.138	439
Galesburg	47.210	-97.431	331
Hillsboro	47.353	-96.922	270
Mayville	47.498	-97.262	290
Pillsbury	47.225	-97.791	392
Prosper	47.002	-97.115	284

Generally, the Wind Power Density (WPD) is evaluated at 10 or 50 meters height. In the case of the atmospheric boundary layer, a similarity study can be performed to describe the vertical profiles of turbulence statistics, when fully developed conditions are reached [19]. Assuming neutral conditions (negligible thermal effects), the mean speed in the surface layer (for heights less than 100m) is commonly represented by the log profile [19]. For a known measured wind speed U_m at a height z_m, the log profile can be expressed as

$$\frac{U}{U_m} = \frac{\ln \frac{z}{z_0}}{\ln \frac{z_m}{z_0}} \tag{6}$$

where z_0 is the average roughness length (terrain dependent) in the farm region. In this paper, the wind speed data at the measured height is still used, which does not affect the distribution of wind conditions. However, wind speed data can be presented at any specific height for commercial wind turbines.

PERFORMANCE METRICS

Three sets of performance metrics are used to evaluate the performance of the MCP methods, which are: (i) statistical metrics; (ii) wind distribution metrics; and (iii) wind farm performance: power generation and farm efficiency metrics.

Statistics of MCP Estimating Accuracies

Mean long term wind speed is often used to characterize the potential of a farm site, which is an important measure of wind power potential. Four metrics are evaluated based on the estimated wind speeds by MCP methods and the reference wind speeds, which are: (i) the ratio of mean wind speeds [14]; (ii) the ratio of wind speed variances; (iii) Root Mean Squared Error (RMSE); and (iv) Maximum Absolute Error (MAE).

The ratio of mean wind speeds, R_μ, is expressed as

$$R_\mu = \frac{1/n_t \sum_{i=1}^{n_t} \tilde{v}(t^k)}{1/n_t \sum_{i=1}^{n_t} v(t^k)} \tag{7}$$

where $v(x^k)$ represents the measured hourly averaged wind speed at time t^k at the targeted farm site, $\tilde{v}(t^k)$ is the corresponding estimated wind speed value, and n_t is the total number of paired data points used in the analysis.

The ratio of wind speed variances, R_{σ^2}, is expressed as

$$R_{\sigma^2} = \frac{1/n_t \sum_{i=1}^{n_t} \left(\tilde{v}(t^k) - \tilde{\mu}\right)^2}{1/n_t \sum_{i=1}^{n_t} \left(v(t^k) - \mu\right)^2} \tag{8}$$

where $\tilde{\mu}$ and μ represent the mean the estimated and measured wind speeds of all test paired data points.

The RMSE is given by

$$RMSE = \sqrt{\frac{1}{n_t}\sum_{k=1}^{n_t}\left(v(t^k) - \tilde{v}(t^k)\right)^2} \tag{9}$$

The MAE is expressed as

$$MAE = \max_k \left| v(t^k) - \tilde{v}(t^k) \right| \tag{10}$$

Wind Distributions

Wind speed distributions are necessary to quantify the available energy (power density) at a site, and to design optimal wind farm configurations. Two types of distributions are adopted to evaluate the performance of the long term wind condition data predicted by the MCP method, which are: (i) Weibull distribution, and (ii) Multivariate and Multimodal Wind Distribution (MMWD). The 2-parameter Weibull distribution is one of the most widely used distribution for the characterization of wind speed [20, 21]. The Multivariate and Multimodal Wind Distribution (MMWD) model [22] can capture the joint variation of wind speed, wind direction and air density, and also allows representation of multimodally distributed data.

Weibull Distribution The 2-parameter Weibull distribution is the most widely accepted distribution for wind speed. The Weibull *pdf* and *cdf* are expressed as

$$f(u;\alpha,\beta) = \frac{\beta}{\alpha}\left(\frac{u}{\alpha}\right)^{\beta-1}\exp\left[-\left(\frac{u}{\alpha}\right)^{\beta}\right] \tag{11}$$

and

$$F(u;\alpha,\beta) = 1 - \exp\left[-\left(\frac{u}{\alpha}\right)^{\beta}\right] \tag{12}$$

where $x \geq 0$.

The estimated shape parameter $\hat{\beta}$ can be solved using an iterative procedure, given by

$$\hat{\beta} = \left[\frac{\sum_{i=1}^{n}\left(u_i^{\hat{\beta}}\ln u_i\right)}{\sum_{i=1}^{n} u_i^{\hat{\beta}}} - \frac{1}{n}\sum_{i=1}^{n}\ln u_i\right]^{-1} \tag{13}$$

The estimated scale parameter $\hat{\alpha}$ can be solved using

$$\hat{\alpha} = \left(\frac{1}{n}\sum_{i=1}^{n} u_i^{\hat{\beta}}\right)^{\frac{1}{\hat{\beta}}} \tag{14}$$

Multivariate and Multimodal Wind Distribution (MMWD) The MMWD model is developed based on the *Kernel Density Estimation* (KDE) method [22, 23]. For a $d-variate$ random sample $U_1, U_2, \cdots, U_n$ drawn from a density f, the multivariate KDE is defined to be

$$\hat{f}(u;H) = n^{-1}\sum_{i=1}^{n} K_H(u - U_i) \tag{15}$$

where $u = (u_1, u_2, \cdots, u_d)^T$ and $U_i = (U_{i1}, U_{i2}, \cdots, U_{id})^T$, $i = 1, 2, \cdots, n$. Here, $K(u)$ is the kernel that is a symmetric probability density function, H is the bandwidth matrix which is symmetric and positive-definite, and $K_H(u) = |H|^{-1/2}K(H^{-1/2}u)$. The choice of K is not crucial to the accuracy of kernel density estimators [24]. In this paper, $K(u) = (2\pi)^{-d/2}exp\left(-\frac{1}{2}u^T u\right)$ is considered, the standard normal throughout. In contrast, the choice of H is crucial in determining the performance of $\hat{f}$ [25]. In the MMWD model an optimality criterion, the Asymptotic Mean Integrated Squared Error [25], is used to select the bandwidth matrix.

Wind Distribution Metrics Besides the probability density function, the ratios of $\tilde{k}$ (and $\tilde{c}$) for the predicted wind speeds to k (and c) for the observed targeted wind speeds, R_k and R_c, are also evaluated.

$$R_k = \frac{\tilde{k}}{k}, \quad and \quad R_c = \frac{\tilde{c}}{c} \tag{16}$$

Wind Farm Power Generation

This power generation model is adopted from Chowdhury et al. [26]. The power generated by a wind farm is an intricate function of the configuration and location of the individual wind turbines. The flow pattern inside a wind farm is complex, primarily due to the wake effects and the highly turbulent flow. The power generated by a wind farm (P_{farm}) comprised of N wind turbines is evaluated as a sum of the powers generated by the individual turbines, which is expressed as [26]

$$P_{farm} = \sum_{j=1}^{N} P_j \tag{17}$$

Accordingly, the farm efficiency can be expressed as

$$\eta_{farm} = \frac{P_{farm}}{\sum_{j=1}^{N} P_{0j}} \tag{18}$$

where P_{0j} is the power that $turbine - j$ would generate if operating as a stand-alone entity, for the given incoming wind velocity.

Detailed formulation of the power generation model can be found in the papers [26].

The power generated by a wind farm with 9 turbines is evaluated in this paper. Two types of turbines are selected: (i) the *GE-1.5MW-xle* [27] turbine and (ii) the *GE-2.5MW-xl* [28] turbine. The features of this turbine are provided in Table 2.

Table 2. FEATURES OF THE *GE-1.5MW-XLE* and *GE-2.5MW-XL* TURBINES [27]

Turbine feature	1.5MW-XLE	2.5MW-XL
Rated power (P_{r0})	1.5 MW	2.5 MW
Rated wind speed (U_{r0})	11.5 m/s	12.5 m/s
Cut-in wind speed (U_{in0})	3.5 m/s	3 m/s
Cut-out wind speed (U_{out0})	20.0 m/s	25 m/s
Rotor diameter (D_0)	82.5 m	100 m
Hub height (H_0)	80.0 m	100 m

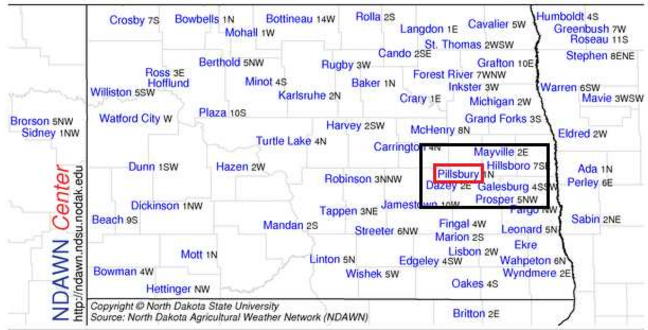


Figure 2. NDAWN STATION LOCATIONS [18]

Table 3. PARAMETERS SELECTION IN NEURAL NETWORK

Parameter	Value	Units
Training Algorithm	Levenberg-Marquardt	-
Training Size	80	%
Validation Size	20	%
Performance Function	Mean Squared Error	-

CASE STUDY

Selection of Stations

As discussed in the wind data summary section, the wind data is obtained from the *North Dakota Agricultural Weather Network* (NDAWN) [18]. The station locations are shown in Fig. 2; and the six stations inside the outer rectangle are used in this paper. The station Pillsbury is selected as the target farm site. The recorded data at the other five stations (Dazey, Galesbury, Hillsboro, Mayville and Prosper) are used as reference site data. The long term wind data at the target site is estimated using MCP methods, using the long term wind data at reference sites and the concurrent short term data. The distance between stations LOC1 and LOC2 is represented by the *great circle distance*. LOC1 and LOC2 are latitude and longitude coordinates.

Selection of Parameters

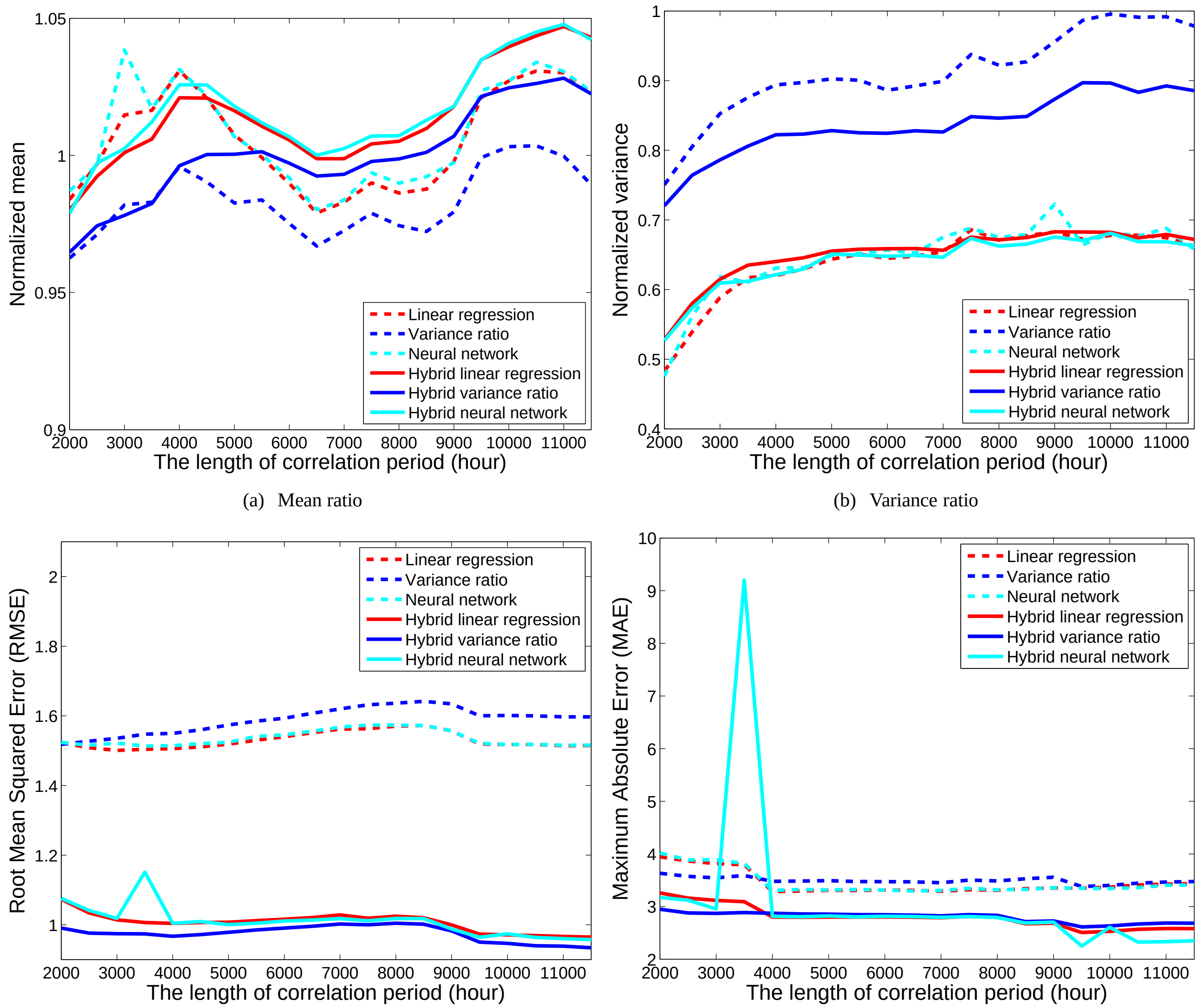
The MATLAB Neural Network Toolbox [29] is used in this paper. Table 3 lists the values of the neural network parameters. Levenberg-Marquardt algorithm is selected for neural network training. 80 percent data points are randomly selected as training points; and 20 percent points are used to validate the network. The Mean Squared Error (MSE) metric is used to evaluate the performance of the developed neural network.

Results and Discussion

We compare the performance of four hybrid MCP methods (using multiple reference stations) with that of individual MCP method (using one reference station version). The four hybrid MCP methods are: (i) hybrid linear regression; (ii) hybrid variance ratio; (iii) hybrid Weibull scale; and (iv) hybrid neural network. The performance of the hybrid MCP methods is shown in Figs. 3-5. The horizontal axis represents the length of the concurrent hours between reference stations and the targeted farm site. Figure 3 illustrates the statistical performance of the hybrid MCP method.

In Figs. 3(a) and 3(b), the closer the value of the ratio is to one, the more the estimated wind condition agrees with the observed data. It is observed from Fig. 3(a) that the three hybrid MCP methods perform better than the three individual MCP algorithms, when the correlation period is over approximately 4,500 hours. In Figs. 3(c) and 3(d), smaller values of RMSE and MAE indicate better estimation performance. We observe that: (i) the average RMSE value of hybrid MCP methods is approximately 35% smaller than that of traditional MCP methods; and (ii) the average MAE value of hybrid MCP methods is approximately 17% smaller than that of traditional MCP methods.

Figure 4 shows the wind distribution metrics for evaluating the hybrid MCP method. Figures 4(a) and 4(b) show the normalized parameters of Weibull distribution (k and c). The distributions of estimated wind speeds are plotted in Fig. 4(c). The distributions of the wind speeds estimated using Weibull scale and hybrid Weibull scale methods are plotted based on the k and c values. Other distributions are estimated using the Multivariate and Multimodal Wind Distribution (MMWD) method. In Fig. 4(c), the solid black line represents the wind speed distri-

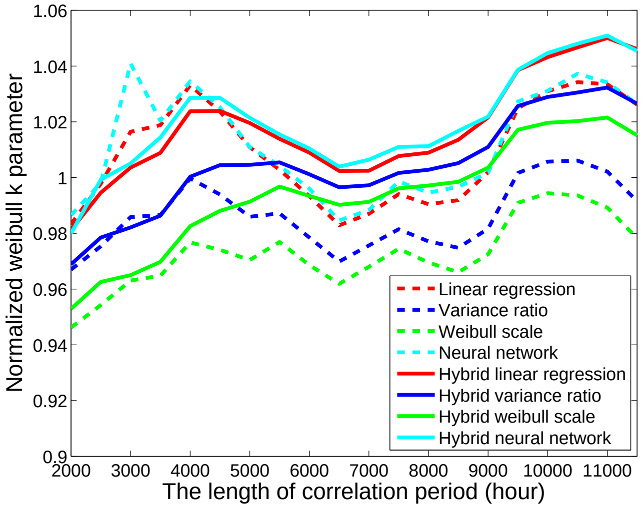


(a) Mean ratio (b) Variance ratio (c) RMSE (d) MAE

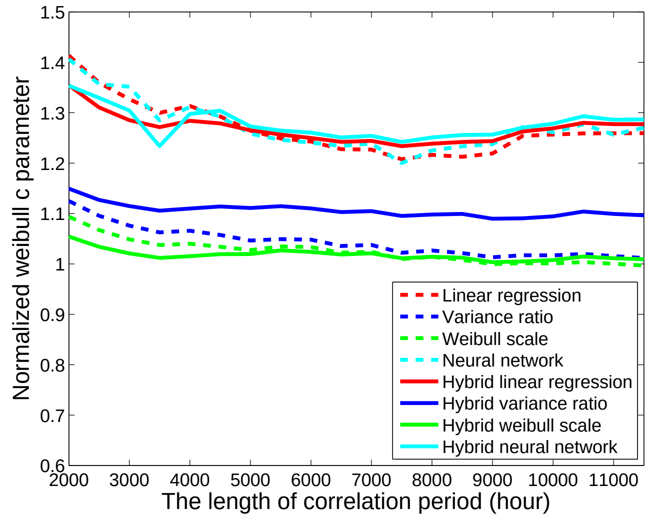
Figure 3. STATISTICAL PERFORMANCE METRICS TO EVALUATE THE HYBRID MCP

bution using the recorded wind data. It is observed that: (i) the solid red line (hybrid linear regression method) agrees more with the record data distribution (black line) than the dashed red line (linear regression method); and (ii) similarly, the hybrid neural network method with multiple reference stations performs better than the neural network method with single reference station.

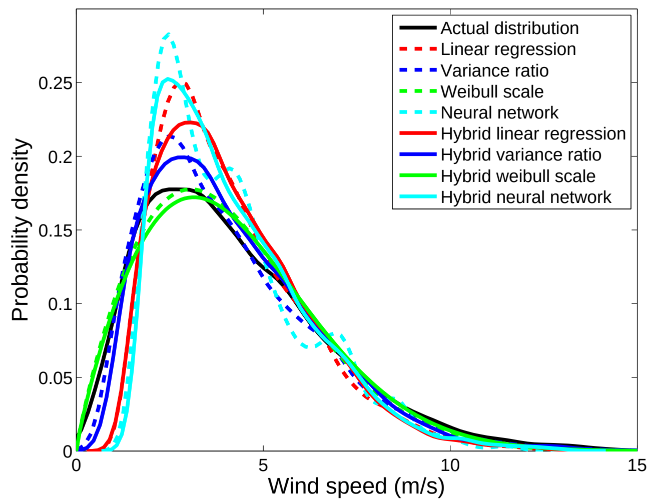
Figure 5 illustrates the power generation metrics for evaluating the hybrid MCP methods. The power generated by the wind farm with the *GE-1.5MW-xle* turbine is shown in Fig. 5(a); and Fig. 5(b) shows the power generation by the win farm with the *GE-2.5MW-xl* turbine. The layout of the wind farm is illustrated in Fig. 5(c); and the small squared points represent the locations of wind turbines. In Figs. 5(a) and 5(b), the black line represents the power generation estimated using the recorded wind data. Comparing the hybrid MCP methods with the traditional MCP methods (e.g., hybrid linear regression vs. linear regression; hybrid variance ratio vs. variance ratio), We observe that: (i) hybrid MCP strategies with multiple reference stations generally perform better than traditional MCP strategies with one reference station; (ii) in Fig. 5(b), the hybrid Weibull scale curve (solid green line) agrees more with the actual power generation curve (black line) than the Weibull scale curve (dashed green line); (iii) similar trends also apply to hybrid linear regression, hybrid variance ratio, and hybrid neural network methods; and (iv) in most cases, the power generation is overestimated when using the wind data predicted by MCP methods.



(a) Normalized Weibull k parameter



(b) Normalized Weibull c parameter



(c) Wind distribution

Figure 4. WIND DISTRIBUTION METRICS TO EVALUATE THE HYBRID MCP

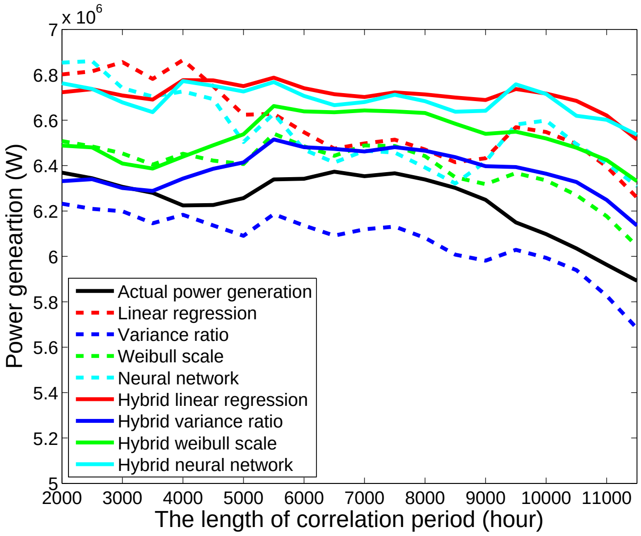
CONCLUDING REMARKS AND FUTURE WORK

This paper developed a hybrid MCP strategy to predict the long term wind resource information at a farm site. The hybrid MCP method uses the recorded data of multiple reference stations to estimate the long term wind condition at the target farm site. The weight of each reference station in the hybrid strategy is determined based on: (i) the distance and (ii) the elevation difference between the target farm site and each reference station.

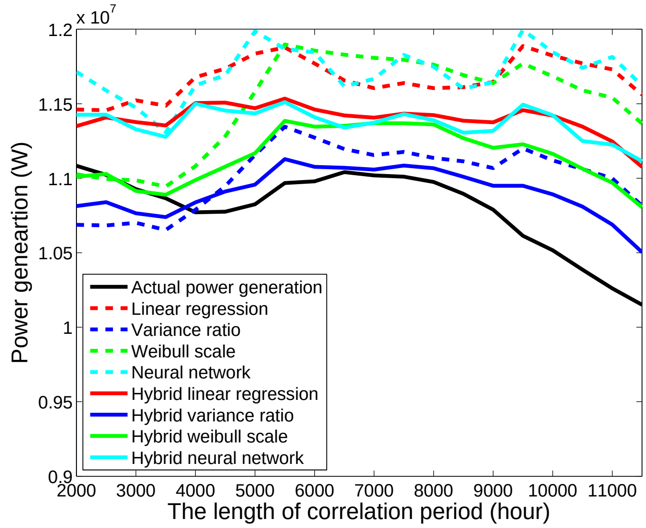
Three sets of performance metrics are used to evaluate the hybrid MCP method. The first set of metrics analyze the statistical performance, including the mean wind speed, the wind speed variance, Root Mean Squared Error (RMSE), and Maximum Absolute Error (MAE). The second set of metrics evaluate the distribution of long term wind speed; and Weibull distribution and Multivariate and Multimodal Wind Distribution (MMWD) are adopted. The third set of metrics analyze the wind farm performance which includes the power generation and the farm efficiency.

The results illustrate the promising potential of this hybrid MCP approach. We found that: (i) the hybrid MCP strategy using multiple reference stations can more accurately predict the long term wind condition at the targeted farm site; (ii) the power generation is generally overestimated using the data predicted by MCP methods.

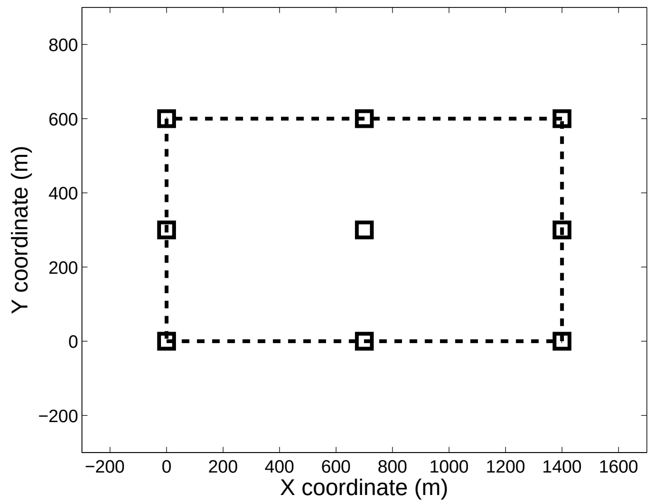
The preliminary hybrid strategy is developed based on the distance and elevation information. However, the correlation be-



(a) Power generation with *GE-1.5MW-XLE*



(b) Power generation with *GE-2.5MW-XL*



(c) Farm layout

Figure 5. POWER GENERATION METRICS TO EVALUATE THE HYBRID MCP

tween reference stations and targeted station will become more complex in real life wind resource assessment. A more comprehensive hybrid strategy should be investigated to include: (i) the local topography, and (ii) wind direction information.

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