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A hybrid measure-correlate-predict method for long-term wind condition assessment

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ABSTRACT

This paper develops a hybrid measure-correlate-predict (MCP) strategy to assess long-term wind resource variations at a farm site. The hybrid MCP method uses recorded data from multiple reference stations to estimate long-term wind conditions at a target wind plant site with greater accuracy than is possible with data from a single reference station. The weight of each reference station in the hybrid strategy is determined by the (i) distance and (ii) elevation differences between the target farm site and each reference station. In this case, the wind data is divided into sectors according to the wind direction, and the MCP strategy is implemented for each wind direction sector separately. The applicability of the proposed hybrid strategy is investigated using five MCP methods: (i) the linear regression; (ii) the variance ratio; (iii) the Weibull scale; (iv) the artificial neural networks; and (v) the support vector regression. To implement the hybrid MCP methodology, we use hourly averaged wind data recorded at five stations in the state of Minnesota between 07-01-1996 and 06-30-2004. 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, wind speed variance, root mean square error, and mean 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 models are adopted. The third set of metrics analyze the energy production of a wind farm. The best hybrid MCP strategy from 256 different combinations of MCP algorithms and reference stations is investigated and selected. The results illustrate that the many-to-one correlation in such a hybrid approach can provide a more reliable prediction of long-term on-site wind variations than that provided by the one-to-one correlations. The accuracy of the hybrid MCP method is found to be highly sensitive to the combination of individual MCP algorithms and reference stations used. It is also observed that the best combination of MCP algorithms is influenced by the length of the concurrent short-term correlation period.

1. Introduction

During the past decade, notable progress has been made in developing renewable energy resources; among them, wind energy has taken a lead, and currently contributes approximately 4% of worldwide electricity consumption [1]. However, the available energy from a wind resource varies appreciably during one year. The uncertainties in the wind resource potential and in the operation timeframes are partially responsible for restraining wind energy from playing a major role in the overall energy market. Determining and forecasting long-term wind conditions would serve two important objectives: (i) analyzing the quality of a wind farm site, and (ii) designing an optimum wind farm layout, including selecting appropriate turbine types for the site.

Wind resource assessment is the process of estimating the power potential of a wind plant site. This plays an important role in a wind energy project. In general, wind resource assessment includes (i) on-site wind condition measurement; (ii) correlations between on-site meteorological towers to fill in missing data; (iii) correlations between long-term weather stations and short-term on-site meteorological towers; (iv) analysis of the wind shear and its variations; (v) modeling of the distribution of wind conditions; and (vi) prediction of the available energy at the site. Measure-correlate-predict (MCP) algorithms are used to assess the long-term wind resource at target sites using short-term (one- or two-year) on-site data and concurrent data at nearby meteorological stations (which also have long-term data). The accuracy of

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long-term predictions obtained using MCP methods is subject to the (i) availability of a nearby meteorological station; (ii) uncertainty associated with a specific correlation methodology [2]; and (iii) likely dependence of this correlation on physical features such as the topography, distance between monitoring stations, and type of local climate regime [3].

A wide variety of MCP techniques have been reported in the literature, such as: (i) linear regression [4,5]; (ii) variance ratio [5,6]; (iii) Weibull scale [6]; (iv) artificial neural networks (ANNs) [3,4,7]; (v) support vector regression (SVR) [8,9]; (vi) Mortimer [3]; and (vii) wind index MCP [10]. MCP methods were first used to estimate long-term annual mean wind speed [11,12]. Linear regression [13] was presented to characterize the relationship between the reference and target sites wind speeds. Rogers et al. [14] compared four MCP algorithms: (i) a linear regression model; (ii) a model using distributions of ratios of 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: (i) linear regression derived from bivariate normal joint distribution; (ii) Weibull regression; and (iii) approaches based on conditional probability density functions. Xydis [15] adopted MCP methods to refill gaps in the wind speed and wind direction measures for four coastal mountainous areas. Carta et al. [16] proposed a Bayesian networks based methodology for long-term estimation of wind speed and wind power generation. Carta et al. [17] also reviewed a wide range of MCP methods used for estimating long-term wind conditions at a target farm site. Ishihara and Yamaguchi [18] recently developed a method to predict the extreme wind speed at an offshore site based on Monte Carlo simulation and MCP. Weekes and Tomlin [19] used MCP methods to assess wind resource for small-scale wind farms, and found that MCP approaches could be a valuable addition to the wind resource assessment toolkit for small-scale wind developers.

Given the unavoidable practical constraints, the overall reliability of the predicted long-term wind distribution remains highly sensitive to the one-year distribution of recorded on-site data. Quantifying and modeling the uncertainty in the MCP methods would better establish the credibility of wind resource assessment and wind plant performance estimation. Kwon [20] and Lackner et al. [21] presented different frameworks to analyze the uncertainty in MCP-based wind resource assessment. The wind resource–based uncertainty models proposed by Messac et al. [22] can be applied also to the long-term data recorded at meteorological stations when MCP methods are used.

1.1. Research objectives and motivation

The existing MCP methods estimate wind data at a farm site using recorded wind data at one reference station without considering the topography, distance, and elevation differences between the two stations. Generally, recorded wind data is available from multiple meteorological stations near the target farm site. It is more comprehensive to use recorded wind data from different reference stations to estimate and predict wind conditions at the targeted farm site.

In this paper, we developed a *hybrid MCP* method and applied it to different stations for wind resource assessment. The hybrid MCP method used recorded data from multiple reference stations to estimate long-term wind conditions at the target farm site. The weight of each reference station in the hybrid strategy was determined based on the (i) distance and (ii) elevation differences between the target farm site and each reference station. The hybrid MCP methodology also (i) considered both wind speed and direction as the components of the hybrid MCP methodology, and (ii) investigated the best combination of different MCP methods and reference stations. The remainder of the paper is organized as follows:

1) The hybrid MCP method is developed in Section 2.
2) The performance metrics for evaluating the effectiveness of the MCP method are presented in Section 3.
3) Section 4 presents the results and discussion on the case studies.

2. Hybrid MCP method

2.1. Overview of the hybrid MCP method

MCP algorithms are used to predict the long-term wind resource at target sites using short-term (one- or two-year) on-site data and concurrent data at nearby meteorological stations (which also have long-term data). The hybrid MCP method developed in this paper correlates the wind data at the target farm site with that at multiple reference stations. This strategy accounts for the local climate and topography. Two types of hybrid strategies are proposed: (i) all component MCP estimations between the target farm site and each reference station use one MCP method (e.g., linear regression, variance ratio, Weibull scale, or artificial neural networks); and (ii) each component MCP estimation (between the target farm site and the reference station) uses different MCP methods, and the best combination of MCP methods among reference sites are determined. The final hybrid MCP estimation is a combination of each component MCP estimations based on the distance and elevation difference between stations. Fig. 1 illustrates the overall structure of the proposed hybrid MCP methodology. The key components of the hybrid MCP method include:

1) Selecting reference sites based on the correlations between the measured short-term wind speeds at the reference sites and the target wind farm site.
2) For each reference site, long-term wind speeds at the target farm site are predicted using a single MCP method. The MCP method can be selected from the following five MCP methods: (i) linear regression; (ii) variance ratio; (iii) Weibull scale; (iv) ANNs; and (v) SVR.
3) Determining the weights of each reference site based on the physical parameters, including the (i) distance and (ii) elevation differences between the target farm site and each reference site.

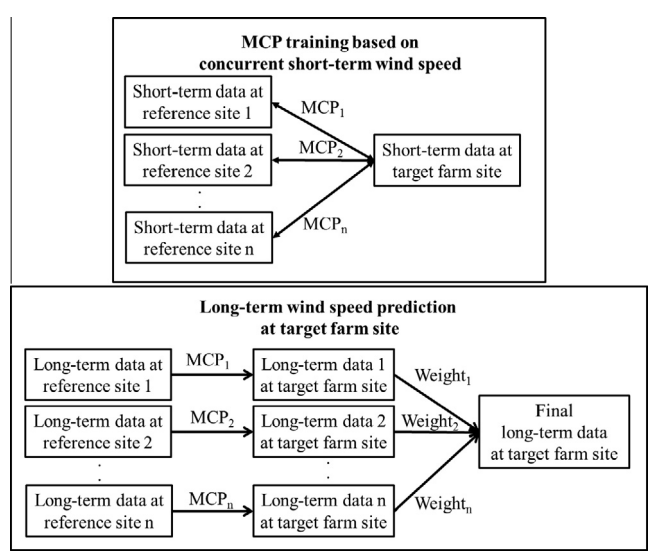


Fig. 1. Overall structure of the hybrid MCP method.

4) The final long-term wind speeds are determined though a weighted aggregation of the long-term wind speeds estimated by each reference site.

The weight of each reference station in the hybrid strategy is determined based on the (i) distance and (ii) elevation differences 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

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

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

2.2. Modeling the impact of wind direction on the hybrid MCP performance

The wind direction binning method is widely used for MCP methods in the wind industry or in the scientific literature [10,14,23]. In this paper, each wind data point was allocated to a bin according to the wind direction sector measurement at the target wind plant site. We investigated four cases by choosing to bin into different numbers of sectors: (i) 4 sectors; (ii) 8 sectors; (iii) 16 sectors; and (iv) 32 sectors. At the multiple reference stations, the concurrent wind speed and direction measurement was allocated to the corresponding bin. Within each sector, the long-term wind speed was predicted by applying the hybrid MCP strategy based on concurrent short-term wind speed data within that sector. A wind rose is a graphical tool used by meteorologists to provide a succinct illustration of how wind speed and wind direction are distributed at a location. Fig. 2 shows a wind rose diagram with 16 direction sectors.

By combining the wind speed data from all sectors, we obtained the set of long-term wind data at the target wind plant site. The quality of the predicted long-term wind data was evaluated using the performance metrics described in Section 3.

2.3. Component MCP methods

In this research, five MCP methods were investigated: (i) linear regression; (ii) variance ratio; (iii) Weibull scale; (iv) ANNs; and (v) SVR. It is helpful to note that other MCP methods can also be used in conjunction with the hybrid strategy, because with the MCP method the weights determination strategy is independent of the methods utilized.

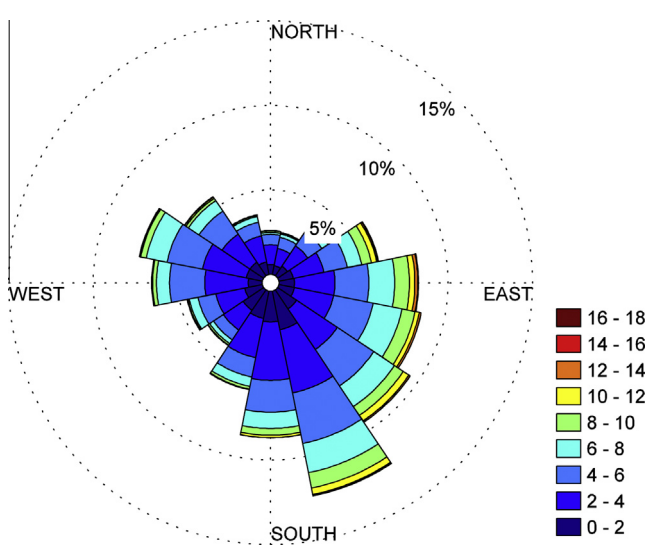


Fig. 2. Wind rose diagram with 16 sectors (each color represents a different range of wind speed, m/s).

2.3.1. 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 [14]

$$\hat{y} = ax + b \quad (2)$$

where $\hat{y}$ is the predicted wind speed at the target site; x is the observed wind speed from one reference site; a and b are the estimated intercept and slope of the linear relationship using the concurrent short-term wind speed, respectively.

2.3.2. 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 during 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 [14]

$$\bar{y} = \mu_y - \frac{\sigma_y}{\sigma_x}\mu_x + \frac{\sigma_y}{\sigma_x}x \quad (3)$$

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

2.3.3. The Weibull scale method

The Weibull scale method was developed based on the two-parameter Weibull distribution which is one of the most widely accepted distribution models [24,25]. The Weibull probability density function and cumulative distribution function are respectively expressed as

$$f(x;c,k) = \frac{k}{c}\left(\frac{x}{c}\right)^{k-1}\exp\left[-\left(\frac{x}{c}\right)^{k}\right] \quad (4)$$

and

$$F(x;c,k) = 1 - exp\left[-\left(\frac{x}{c}\right)^{k}\right] \quad (5)$$

where $x \geqslant 0$, and k and c are shape parameter and scale parameter, respectively. The parameters k and c are estimated using the maximum likelihood estimators. The Weibull scale method presumes that the relationship between the Weibull distribution parameters and the frequency follow the general relation:

$$k_{site}^{long} = \frac{k_{site}^{short}}{k_{reference}^{short}} \times k_{reference}^{long} \quad (6)$$

and

$$c_{site}^{long} = \frac{c_{site}^{short}}{c_{reference}^{short}} \times c_{reference}^{long} \quad (7)$$

where k and c are the shape and scale parameters of the Weibull distribution, respectively. Superscript *long (short)* refers to the long-term (concurrent short-term) wind speed, while subscript *site (reference)* refers to the target (reference) site.

2.3.4. The ANNs method

ANNs have been used to correlate and predict wind conditions 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. An ANN is developed by defining the following 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.

The weights of the interconnections and biases of the network are tuned to optimize network performance, based on mean squared error (MSE), which is defined by

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{8}$$

where a and t represent the network outputs and the target outputs, respectively. In this paper, the Levenberg–Marquardt optimization is adopted to update the weights and bias values in the network training process. The input and output of the ANNs are the wind speed at one reference site and the wind speed at the target site, respectively. The ANNs is trained using the concurrent short-term wind speed at both the reference site and the target site. The long-term wind speed at the target site is predicted based on the long-term wind speed at one reference site.

2.3.5. The SVR method

SVR has gained popularity within the statistical learning community, engineering optimization community, and renewable energy community [26–29]. The SVR approach provides a unique way to construct smooth and nonlinear regression approximations by formulating the surrogate model construction problem as a quadratic programming problem. The SVR approach can be expressed as [30]

$$\tilde{f}(x) = < w, \emptyset(x) > + b \tag{9}$$

where $\langle\cdot,\cdot\rangle$ denotes the dot product; w is a set of coefficients to be determined; and $\varnothing(x)$ is a map from the input space to the feature space. To solve the coefficients, we allow a predefined maximum tolerated error ε (with respect to the actual function value) at each data point, given by [30]

$$|\tilde{f}(x_i) - f(x_i)| \leqslant \varepsilon \tag{10}$$

where $f(x)$ is the actual function to be approximated. The flatness of the approximated function can be characterized by w. By including slack variables ξ to the constraint and a cost function, the coefficient w can be obtained by solving a quadratic programming problem given by [30]

$$\min_{w,\xi,\xi^*} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n_p}(\xi_i + \xi_i^*) \tag{11}$$

$$\begin{aligned} \text{subject to} \quad & f(x_i) - \tilde{f}(x_i) \leqslant \varepsilon + \xi_i \\ & f(x_i) - \tilde{f}(x_i) \leqslant \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geqslant 0 \end{aligned} \tag{12}$$

where n_p is the number of sample points. The parameter $C > 0$ is user-specified and represents the trade-off between flatness and the amount up to which errors larger than ε are tolerated. The above formulation is the primal form of the quadratic programming problem. In most cases, the dual form with fewer constraints is easier to solve, and is widely used to define the final form of the approximation.

In this paper, the input and output of the SVR are the wind speed at one reference site and the wind speed at the target site, respectively. The SVR is trained using the concurrent short-term wind speed at both the reference site and the target site. The long-term wind speed at the target site is predicted based on the long-term wind speed at one reference site.

3. Performance metrics for evaluating the MCP method

Three sets of performance metrics were proposed to evaluate the MCP methods: (i) statistical metrics; (ii) wind distribution metrics; and (iii) wind plant performance: power generation and capacity factor metrics.

3.1. Statistical metrics

Mean long-term wind speed is often used to characterize the potential of a wind plant site. It is an important measure of wind power potential. Four metrics were evaluated based on the wind speeds estimated by MCP methods and the reference wind speeds: (i) the ratio of mean wind speeds [14]; (ii) the ratio of wind speed variances [14]; (iii) root mean square error (RMSE); and (iv) mean absolute error (MAE).

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

$$R_\mu = \frac{1/n_t\sum_{i=1}^{n_t}\tilde{v}(t^k)}{1/n_t\sum_{i=1}^{n_t}v(t^k)} \tag{13}$$

where $v(t^k)$ represents the measured hourly averaged wind speed at time t^k at the target wind plant 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

$$R_{\sigma^2} = \frac{1/n_t\sum_{i=1}^{n_t}[\tilde{v}(t^k) - \tilde{\mu}]^2}{1/n_t\sum_{i=1}^{n_t}[v(t^k) - \mu]^2} \tag{14}$$

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

The RMSE is given by

$$\mathrm{RMSE} = \sqrt{\frac{1}{n_t}\sum_{k=1}^{n_t}[v(t^k) - \tilde{v}(t^k)]^2} \tag{15}$$

The MAE is expressed as

$$\mathrm{MAE} = \frac{1}{n_t}\sum_{k=1}^{n_t}|v(t^k) - \tilde{v}(t^k)| \tag{16}$$

3.2. Wind distribution metrics

Wind speed distributions are necessary to quantify the available energy (power density) at a site and to design optimal wind plant configurations. The Multivariate and Multimodal Wind Distribution (MMWD) model [31,32] can capture the joint variation of wind speed, wind direction, and air density, and also allows representation of multimodally distributed data.

3.2.1. Multivariate and multimodal wind distribution (MMWD)

The MMWD model was developed based on kernel density estimation (KDE) [31,32]. For a d-variate random sample $U_1, U_2, \cdots, U_n$ drawn from a density f, the multivariate KDE is defined as

$$\hat{f}(x;H) = \frac{1}{n}\sum_{i=1}^{n} K_H(u - U_i) \tag{17}$$

where $u = (u_1, u_2, \cdots, u_d)^T$, $U_i = (U_{i1}, U_{i2}, \cdots, U_{id})^T$, and $i = 1, 2, \cdots, n$. 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 $K_H(u) = |H|^{-1/2}K(H^{-1/2}u)$. In the MMWD model, $K(u) = (2\pi)^{-d/2}\exp(-1/2u^Tu)$ is considered throughout; an optimality criterion, the asymptotic mean integrated squared error, is used to select the bandwidth matrix H. The details of the MMWD model can be found in Ref. [31].

3.2.2. Wind distribution metrics

In addition to 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, were also evaluated.

$$R_k = \frac{\tilde{k}}{k}, \text{ and } R_c = \frac{\tilde{c}}{c} \tag{18}$$

3.3. Wind plant performance metrics

The power generation model was adopted from Chowdhury et al. [33,34]. The power generated by a wind plant is an intricate function of the configuration and location of the individual wind turbines. The flow pattern inside a wind plant is complex, primarily because of the wake effects and the highly turbulent flow. The power generated by a wind plant (P_{plant}) consisting of N wind turbines is evaluated as a sum of the powers generated by the individual turbines, which is expressed as [33]

$$P_{plant} = \sum_{j=1}^{N} P_j \tag{19}$$

Accordingly, the wind plant efficiency can be expressed as

$$\eta_{plant} = \frac{P_{plant}}{\sum_{j=1}^{N} P_{0j}} \tag{20}$$

where P_{0j} is the power that turbine-j would generate if operating as a stand-alone entity for the given incoming wind velocity. The power generation model (i) uses the wake growth model proposed by Frandsen et al. [35]; (ii) implements the wake superposition model developed by Katic et al. [36]; and (iii) includes the estimated distribution of the wind speed and wind direction. Detailed formulation of the power generation model can be found in the papers [33,34].

The power generated by a wind plant with nine turbines was evaluated in this paper. Two types of wind turbines were selected: (i) the GE 1.5-MW XLE [37] and (ii) the GE 2.5-MW XL [38]. The features of these turbines are provided in Table 1.

Table 1
Features of the GE 1.5-MW XLE and GE 2.5-MW XL wind turbines [37,38].

Turbine feature	1.5-MW XLE	2.5-MW 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

Table 3
Correlation coefficient between two sets of speed data.

Station	Chandler	Brewster	Currie	Marshall	Luverne
Chandler (30 m)	1	0.84	0.87	0.79	0.85
Brewster (30 m)	0.84	1	0.86	0.75	0.84
Currie (30 m)	0.87	0.86	1	0.86	0.77
Marshall (30 m)	0.79	0.75	0.86	1	0.69
Luverne (30 m)	0.85	0.84	0.77	0.69	1

4. Case study: assessing the wind resource potential at a wind plant site

4.1. Wind data summary

To implement the advanced hybrid MCP methodology, we used the hourly averaged wind data recorded at five stations in the state of Minnesota between 07-01-1996 and 06-30-2004 (including 8-years of data). The wind data was obtained from the University of North Dakota Energy & Environmental Research Center [39]. Quality control steps were taken so that bad data (e.g., bad sensors, icing events, tower shadowing, failed voltage test, and failed range test) was removed from the data sets. Table 2 shows the geographical coordinates and elevation of each site. The distance between sites LOC1 and LOC2 is represented by the great circle distance. LOC1 and LOC2 are latitude and longitude coordinates. The measurement information is listed as follows:

1) Wind speed is measured at both 30 m and 70 m above the soil surface.
2) Wind direction is the direction from which wind is blowing (degrees clockwise from north) measured at both 30 m and 70 m 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 correlation coefficient matrix for the five sets of 30 m data is shown in Table 3. The minimum correlation coefficients between Chandler, Brewster, Currie, Marshall and Luverne stations and the other four stations were 0.79, 0.75, 0.77, 0.69, and 0.69, respectively. The station of Chandler had the largest minimum correlation coefficient, and was selected as the target wind plant site. The recorded data at the other four stations (Brewster, Currie, Marshall and Luverne) was used as reference station data. The long-term wind data at the target site was estimated with MCP methods using the long-term wind data at the reference sites and concurrent short-term data. Table 4 shows the correlation coefficients between the 70 m data at the Chandler site and the 30 m data at

Table 2
Details of sites [39].

Site	Latitude	Longitude	Elevation (m)	Distance between two sites (km)			
				Brewster	Currie	Marshall	Luverne
Chandler	43.888	−95.928	555	49.11	37.33	62.41	22.70
Brewster	43.729	−95.357	427	–	44.25	95.36	57.25
Currie	44.098	−95.564	471	–	–	52.63	59.06
Marshall	44.446	−96.012	445	–	–	–	81.85
Luverne	43.711	−96.069	472	–	–	–	–

Table 4
Correlation coefficients between the Chandler site (70 m data) and other reference sites (30 m data).

	Station	Brewster (30 m)	Currie (30 m)	Marshall (30 m)	Luverne (30 m)
Chandler (70 m)	Hourly average winds	0.77	0.83	0.77	0.77
	Daily average winds	0.61	0.60	0.56	0.56
	Monthly average winds	0.70	0.39	0.35	0.45

Table 5
Parameter selection in neural networks.

Parameter	Value	Units
Training algorithm	Levenberg–Marquardt	–
Training size	80	%
Validation size	20	%
Performance function	Mean squared error	–

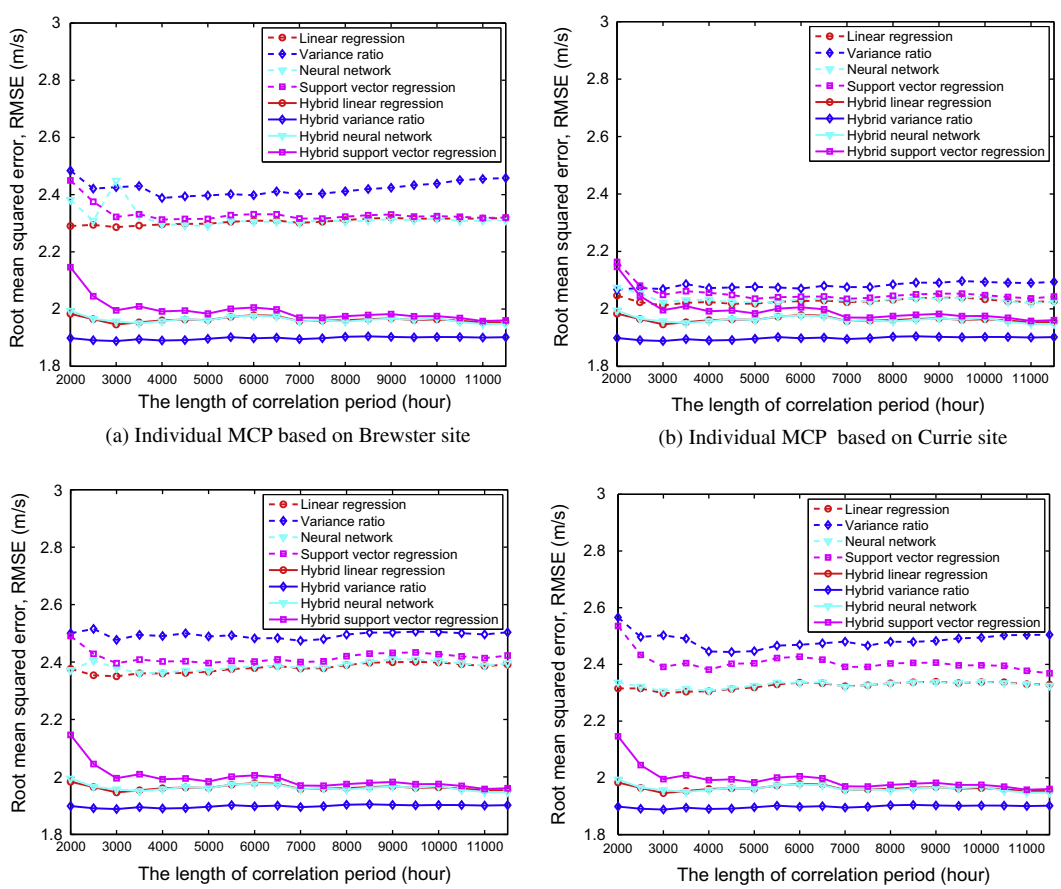
other reference sites. Three different timescales are analyzed, including hourly, daily and monthly average wind speeds.

4.2. Parameter selection

The MATLAB Neural Network Toolbox [40] was used in this paper. Table 5 lists the values of the neural network parameters. The Levenberg–Marquardt algorithm was selected for neural network training. Eighty percent data points were randomly selected as training points, and 20% points were used to validate the network. The mean squared error metric was used to evaluate the performance of the developed neural network. For the SVR method, we used an efficient SVM package, LIBSVM (A Library for Support Vector Machines), developed by Chang and Lin [41]. The epsilon-SVR and the radial basis function kernel are adopted in this paper. The parameters are selected based on cross-validation to achieve a desirable training accuracy.

4.3. Results and discussion

Three scenarios were analyzed in the case study. In the first scenario, we compared the performance of five hybrid MCP methods (using multiple reference stations) with that of an individual MCP method (using one reference station version). In the second scenario, the hybrid MCP strategy was implemented without binning wind data points to different sectors. The objective of the second scenario was to investigate the performance of the hybrid MCP method with combinations of multiple MCP algorithms and multiple reference stations together. In the third scenario, we evaluated the hybrid MCP performance, including consideration of both wind speed and direction. For each scenario, the length of the concurrent short-term data ranged from 2000 h to 11,500 h (approximately 3 months–16 months), in 500 h intervals. The remainder of the



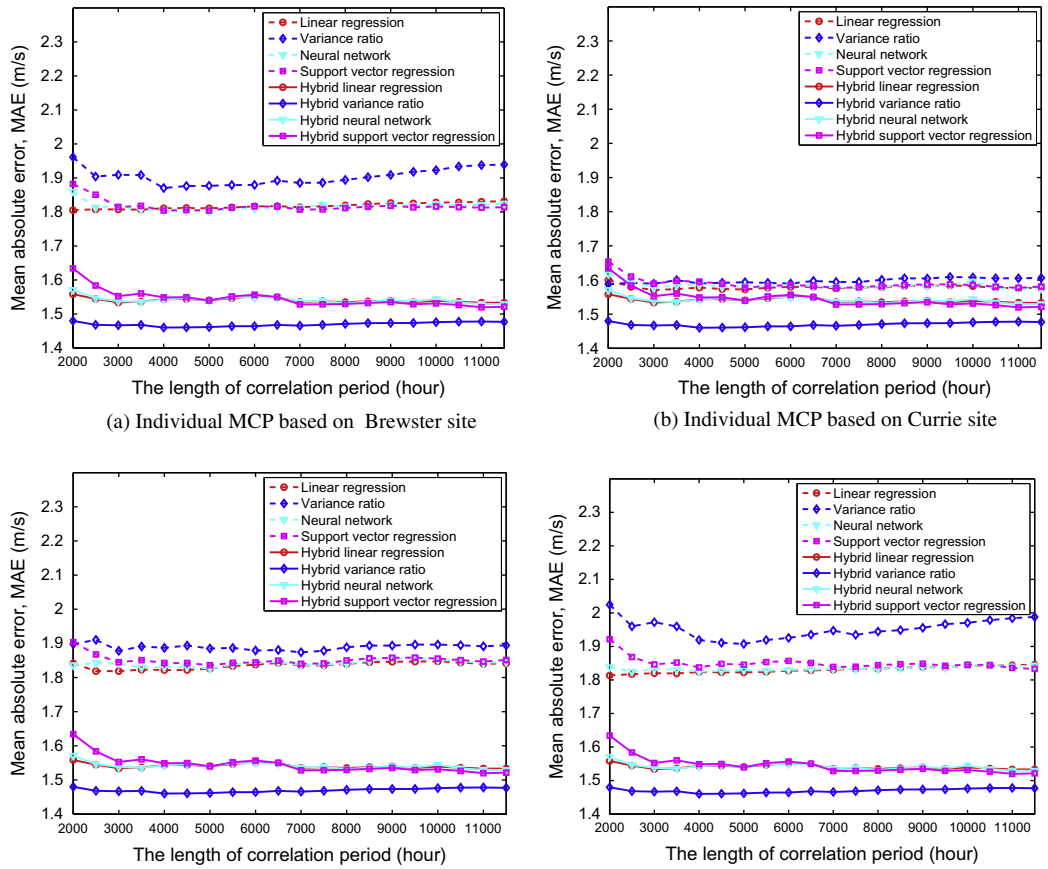
(a) Individual MCP based on Brewster site

(b) Individual MCP based on Currie site

(c) Individual MCP based on Marshall site

(d) Individual MCP based on Luverne site

Fig. 3. RMSE comparison for different reference sites: hybrid MCP vs. individual MCP.



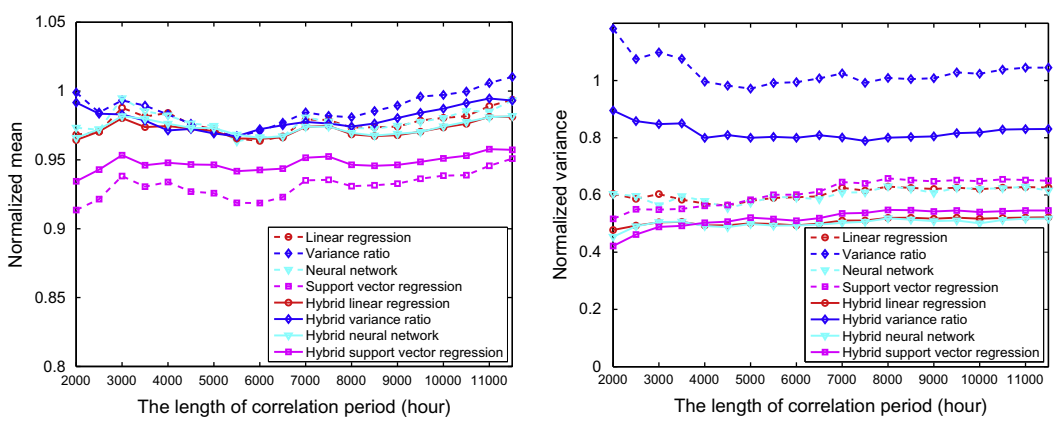
(a) Individual MCP based on Brewster site

(b) Individual MCP based on Currie site

(c) Individual MCP based on Marshall site

(d) Individual MCP based on Luverne site

Fig. 4. MAE comparison for different reference sites: hybrid MCP vs. individual MCP.



(a) Mean ratio, hybrid MCP *vs.* Luverne site

(b) Variance ratio, hybrid MCP *vs.* Luverne site

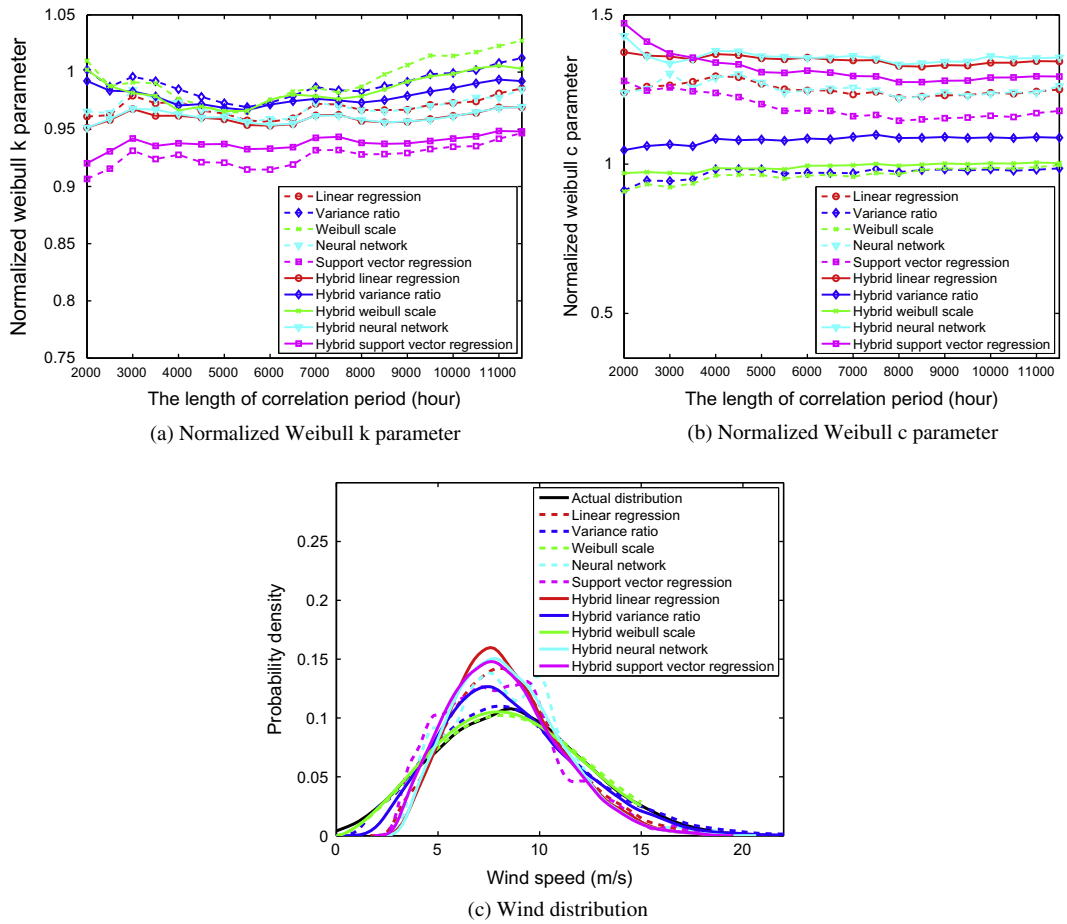
Fig. 5. Statistical performance metrics to evaluate the hybrid MCP.

data (approximately 7 years) was used as test data to evaluate the performance of MCP methods. However, this paper discussed wind direction primarily related to the prediction of wind speed. The prediction of the long-term wind direction at the target wind plant site was not within the scope of this paper.

4.3.1. Scenario I: hybrid MCP methods

We compared the performance of five hybrid MCP methods (using multiple reference stations) with that of an individual MCP method (using one reference station version). The five hybrid MCP methods are (i) hybrid linear regression; (ii) hybrid variance ratio; (iii) hybrid Weibull scale; (iv) hybrid ANNs; and (v) hybrid SVR. For each hybrid MCP method, the same single MCP algorithm is used for all reference stations. The performance of the hybrid MCP methods is shown in Fig. 3 through Fig. 7. The horizontal axis represents the length of the concurrent short-term hours between reference stations and the target farm site. Figs. 3–5 illustrate the statistical performance of the hybrid MCP method.

Figs. 3 and 4, respectively, show the RMSE and MAE metrics of hybrid MCPs and individual MCP based on different reference sites.



(a) Normalized Weibull k parameter

(b) Normalized Weibull c parameter

(c) Wind distribution

Fig. 6. Wind distribution metrics to evaluate the hybrid MCP (hybrid MCP vs. Luverne site); see online version for color.

Table 6
Kullback–Leibler divergence between the actual distribution and the distributions estimated by MCP methods.

MCP	Linear regression	Hybrid linear regression	Variance ratio	Hybrid variance ratio	Weibull scale	Hybrid Weibull scale	ANNs	Hybrid ANNs	SVR	Hybrid SVR
Actual distribution	0.4952	0.5981	0.0190	0.0714	0.0054	0.0050	1.0068	0.7747	0.8145	0.6890

Table 7
RMSE between the actual power generation and the power generation estimated by MCP methods.

MCP	Linear regression	Hybrid linear regression	Variance ratio	Hybrid variance ratio	Weibull scale	Hybrid Weibull scale	ANNs	Hybrid ANNs	SVR	Hybrid SVR
Nine 1.5-MW turbines	1.01e6	1.03e6	1.86e6	1.79e6	1.39e6	1.31e6	0.97e6	0.80e6	3.82e6	2.41e6
Nine 2.5-MW turbines	1.75e6	1.78e6	2.78e6	2.80e6	2.19e6	2.10e6	1.71e6	1.41e6	6.34e6	4.02e6

Smaller values of RMSE and MAE indicate better estimation performance. We observe that: (i) the hybrid MCPs have smaller RMSE and MAE values than traditional individual MCP based on all four reference sites; (ii) the average RMSE values of hybrid MCP methods in Fig. 3(a)–3(d), respectively, are approximately 16.57%, 4.58%, 19.16%, and 18.00% smaller than those of traditional MCP methods; and (ii) the average MAE values of hybrid MCP methods in Fig. 4(a)–(d), respectively, are approximately 17.05%, 3.98%, 17.78%, and 18.24% smaller than those of traditional MCP methods. Overall, the hybrid MCP performs better than any individual MCP strategy considered in this paper.

Table 2 shows that the Luverne reference site has the shortest distance to the target Chandler site. In the following sections, the hybrid MCP predictions are compared with individual MCP predictions based on the Luverne site. Fig. 5(a) and (b) shows the mean ratio and variance ratio, respectively. The closer the value of the ratio is to one, the more the estimated wind condition agrees with the observed data. As shown in Fig. 5(a), (i) the hybrid SVR method

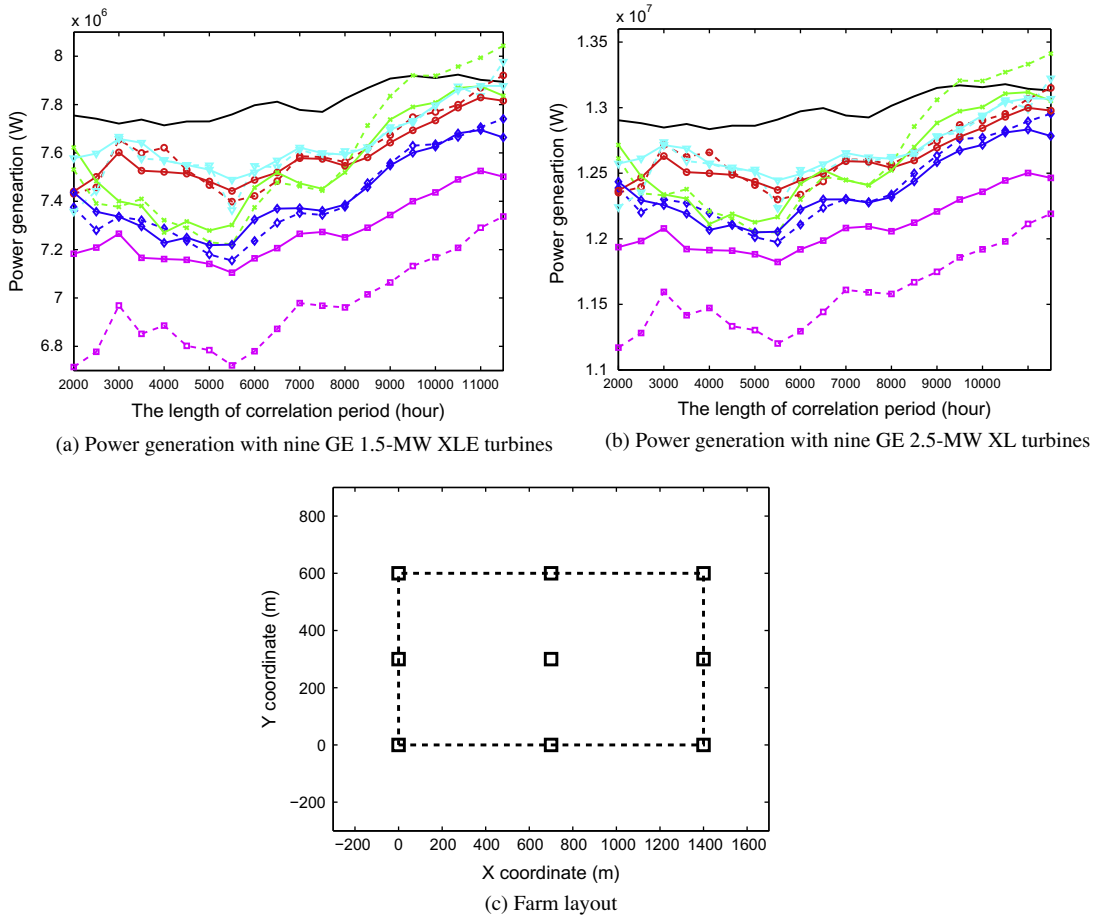


Fig. 7. Power generation metrics to evaluate the hybrid MCP (hybrid MCP vs. Luverne site); the black line represents the power generation estimated using the recorded wind data; other curves in (a) and (b) follow the legend in Fig. 6(a).

performs better than the individual SVR method throughout all different short-term correlation periods; and (ii) the other three hybrid MCP methods perform better than the three individual MCP algorithms when the correlation period is approximately 5000–6000 h. Fig. 5(b) shows that variance values in the hybrid MCP predictions generally deviate more than those in individual MCP methods, from the actual variance values in the long-term wind speeds.

Fig. 6 shows the wind distribution metrics for evaluating the hybrid MCP method. Fig. 6(a) and (b) shows the normalized parameters of Weibull distribution k and c, respectively. The distributions of estimated wind speeds are plotted in Fig. 6(c). The distributions of wind speeds estimated using the Weibull scale and hybrid Weibull scale methods are plotted based on the k and c values. Other distributions are estimated using the MMWD method. In Fig. 6(c), the solid black line represents the wind speed distribution using the recorded wind data. It is observed that (i) the solid green line (hybrid Weibull scale method) agrees more with the record data distribution (black line) than other curves; and (ii) oscillations are observed in the distributions of long-term wind speeds estimated by SVR and ANNs, whereas distributions estimated by hybrid SVR and hybrid ANNs present smooth characteristics, which agree more with the actual distribution (black line).

The Kullback–Leibler divergence is adopted to further compare the wind speed distributions. The Kullback–Leibler divergence is a metric to measure the difference between two probability distributions [42]. In this paper, the Kullback–Leibler divergence measures the difference between (i) the actual wind speed distribution fitted to the recorded wind data and (ii) the distributions fitted to the wind speed data predicted by the MCP methods. A smaller Kullback–Leibler divergence indicates a relatively more accurate distribution of predicted wind speeds. Table 6 lists the Kullback–Leibler divergence between the actual wind distribution and the predicted wind distributions. It is observed that the hybrid Weibull scale, the hybrid ANNs, and the hybrid SVR have smaller Kullback–Leibler divergence values than the corresponding single MCP methods. Among all 10 MCP methods (single and hybrid MCPs), the hybrid Weibull scale is observed to have the smallest Kullback–Leibler divergence.

Fig. 7 illustrates the power generation metrics for evaluating the hybrid MCP methods. The power generated by the wind farm with the GE 1.5-MW XLE turbines is shown in Fig. 7(a). Fig. 7(b) shows the power generation by the wind farm with the GE 2.5-MW XL turbines. The layout of the wind farm (with GE 1.5-MW XLE or GE 2.5-MW XL turbines) is illustrated in Fig. 7(c); the small squared points represent the locations of wind turbines. In Fig. 7(a) and (b), the solid line represents the power generation estimated using 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) the hybrid SVR curve (solid line with square points) agrees more closely with the actual power generation curve (solid line) than the SVR curve (dashed line with square points); and (ii) the power generation is generally under-estimated when using the wind data predicted by MCP methods.

To further explore the difference between the actual power generation and the power generation predicted by MCP methods, Table 7 lists the RMSE between the actual power generation and

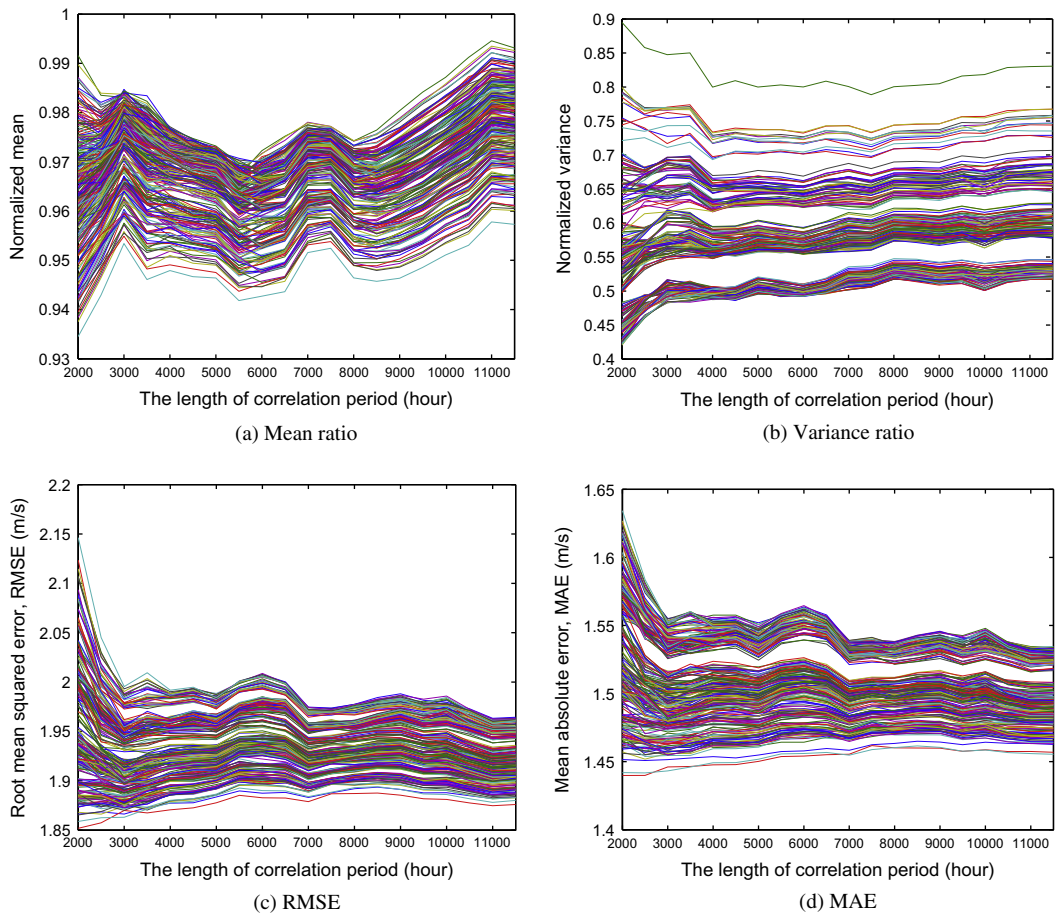


Fig. 8. Statistical performance metrics to evaluate the hybrid MCP with 256 combinations.

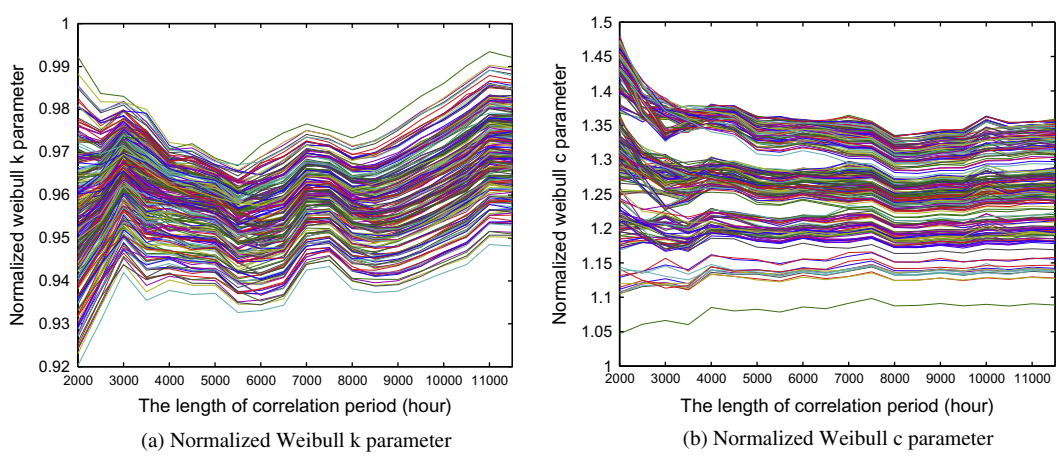
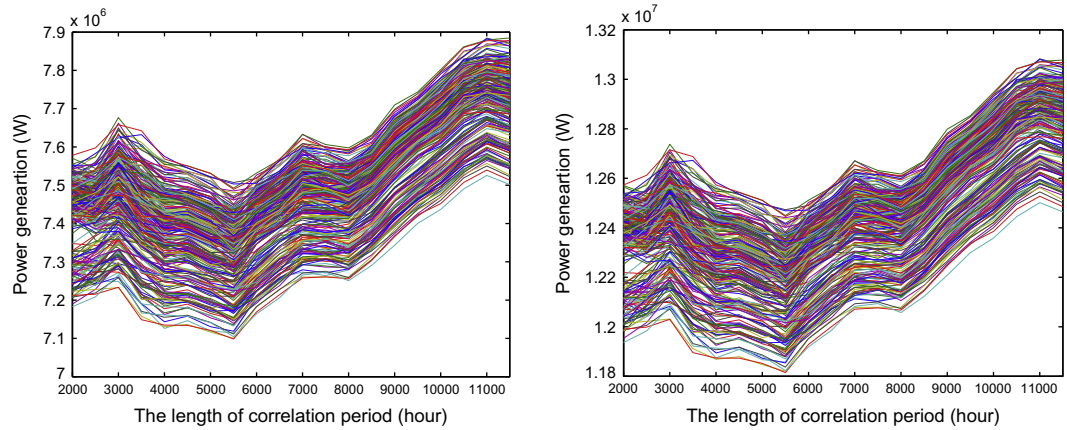


Fig. 9. Wind distribution metrics to evaluate the hybrid MCP with 256 combinations.

Table 8
Best combination of MCP algorithms and reference stations based on RMSE.

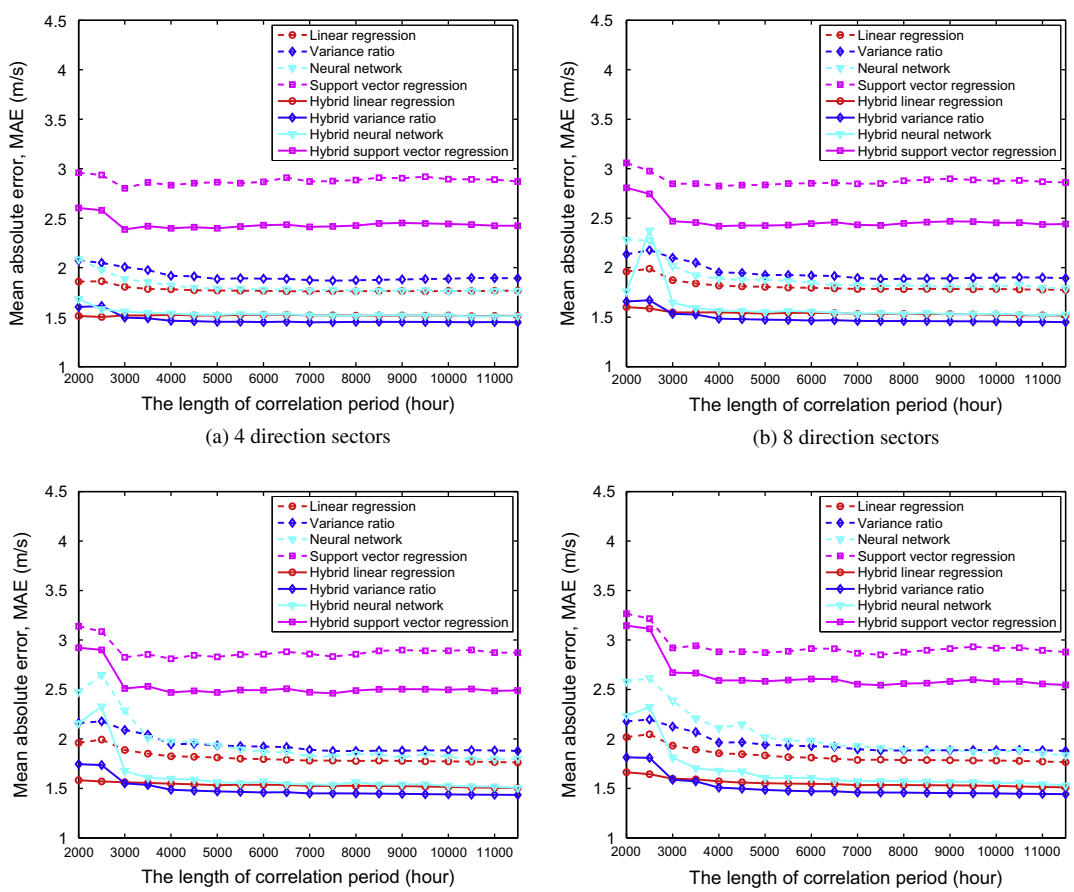
Stations	2000–3000 (h)	3000–3500 (h)	3500–11,500 (h)
Brewster	ANNs	SVR	ANNs
Currie	Ratio	Ratio	Ratio
Marshall	Ratio	Ratio	Ratio
Luverne	Ratio	Ratio	Ratio

the power generation estimated by MCP methods. It is observed that, (i) the linear regression has a smaller RMSE value than the hybrid linear regression for both the 1.5 MW and 2.5 MW turbines; (ii) the hybrid variance ratio has a smaller RMSE than the variance ratio for the 1.5 MW turbines; and (iii) the hybrid Weibull scale, the hybrid ANNs, and the hybrid SVR have smaller RMSE values than their corresponding single MCP methods for both the 1.5 MW and 2.5 MW turbines. Overall, hybrid MCP strategies with



(a) Power generation with nine GE 1.5-MW XLE turbines (b) Power generation with nine GE 2.5-MW XL turbines

Fig. 10. Power generation metrics to evaluate the hybrid MCP with 256 combinations.



(a) 4 direction sectors (b) 8 direction sectors

(c) 16 direction sectors (d) 32 direction sectors

Fig. 11. MAE comparison with different direction sectors.

multiple reference stations perform better than traditional MCP strategies with one reference station.

4.3.2. Scenario II: hybrid MCP methods with mixing combinations

A comparison of the hybrid MCP method (using multiple reference stations) with the individual MCP method (using one reference station) was investigated in Scenario I. However, the hybrid MCP methods used a single MCP technique for all four reference stations, which might not be optimal. Each reference station has the flexibility to use any of the available MCP techniques. In Scenario II, the same four stations were selected as reference stations. In addition, each station can be combined into the hybrid MCP method with one of the four following MCP algorithms: (i) linear regression; (ii) variance ratio; (iii) ANNs; and (iv) SVR. Therefore, a total of 256 (which is equal to 4^4) combinations were investigated to formulate the hybrid MCP strategy.

Fig. 8 through Fig. 10 illustrate the three sets of performance metrics. Each line in the figures represents one specific combination of reference stations and MCP algorithms. It is observed that the performance of the hybrid MCP technique varies significantly.

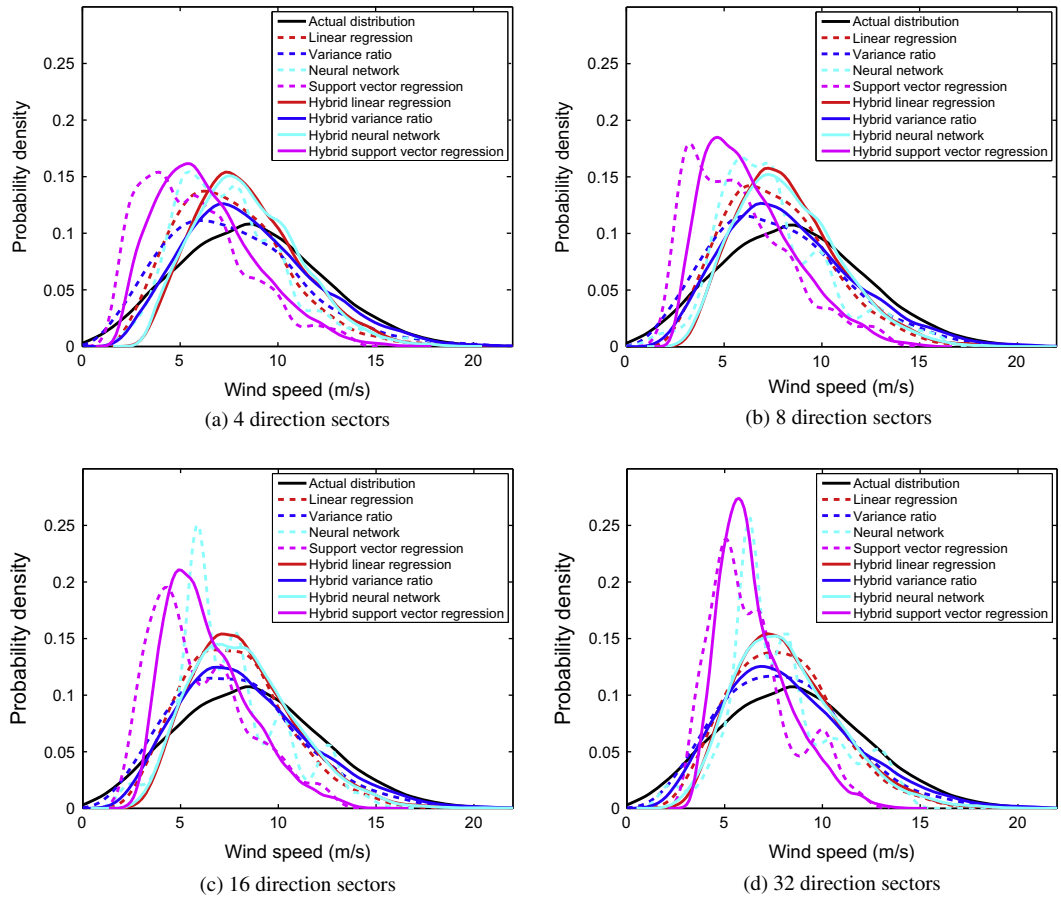


Fig. 12. Wind distribution metrics with different direction sectors; see online version for color.

For instance, the average value of RMSE during the length of correlation period (Fig. 8 (c)) varies up to 6.26% during the 256 hybrid MCP models.

The smaller the RMSE value, the more accurate the estimated wind pattern. Based on the RMSE values, we found the best combination of MCP algorithms and reference stations, shown in Table 8. In the table, "Ratio" represents variance ratio. Three combinations were observed based on the length of the correlation period. Table 8 shows that: (i) the variance ratio algorithm is chosen at the Currie, Marshall, and Luverne reference stations for all three correlation periods; and (ii) at the Brewster reference station, different MCP algorithms are selected based on the length of the correlation period; the ANNs algorithm is selected for two correlation periods: 2000–3000 h and 3500–11,500 h; the SVR is selected for the third correlation period: 3000–3500 h.

Fig. 9 shows 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, for the total 256 combinations. In this figure, R_k and R_c are named normalized Weibull k and c parameters, respectively. The closer the value of the R_k (or R_c) is to one, the more accurate the estimated long-term wind condition. The average values of R_k and R_c varies 4.40% and 25.65%, respectively, throughout the 256 different combinations. The above observation indicates that the scale parameter (c) is more sensitive to the MCP strategies than the shape parameter (k).

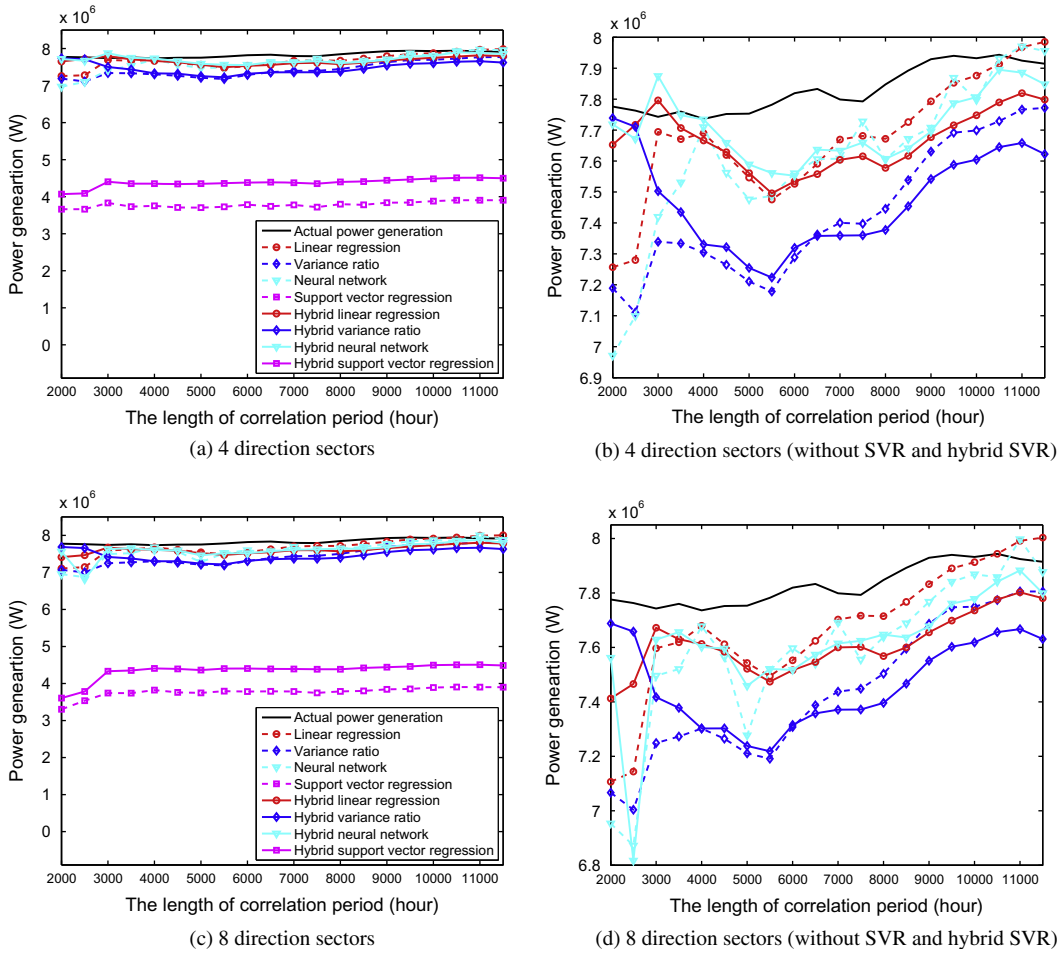
The power generation of the nine-turbine wind plant is shown in Fig. 10. Fig. 10(a) and (b) shows the 256 wind power generations of wind plants with 1.5-MW and 2.5-MW turbines, respectively. We observe that (i) the average value of the power generation with GE 1.5-MW XLE turbines during the length of correlation period (Fig. 10 (a)) varies 3.13% during the 256 hybrid MCP models; and (ii) the average value of the power generation with GE 2.5-MW XL turbines during the length of correlation period (Fig. 10(b)) varies 5.12% during the 256 hybrid MCP models.

4.3.3. Scenario III: hybrid MCP methods considering wind speed and direction

Each wind data point was allocated to a bin according to the wind direction sector measurement at the target plant site (Chandler station). In Scenario III four cases were investigated: (i) 4 sectors; (ii) 8 sectors; (iii) 16 sectors; and (iv) 32 sectors. For the four reference stations (Brewster, Currie, Marshall, and Luverne), the concurrent wind speed and direction measurement was allocated to the corresponding bin. Within each sector, the long-term wind speed was predicted by applying the hybrid MCP strategy based on concurrent short-term wind speed data within that sector. The hybrid MCP strategy used a single MCP technique for all four reference stations. For the single MCP technique applications, the Luverne reference site was used.

Fig. 11 shows the MAE with the four different direction sectors. It is observed that (i) the hybrid MCP method performs better than the corresponding individual MCP method for all four direction sectors; and (ii) the hybrid SVR algorithm perform relatively worse than the other three hybrid MCP methods.

Fig. 12 shows the wind speed distributions with the four different direction sectors. The closer the predicted distribution curve is to the actual distribution curve (the black line in the figure), the more accurate the estimated wind pattern. It is observed that (i) for all four direction sectors in Fig. 12(a)–(d), the hybrid variance ratio method (solid blue line) agrees more with the actual distribution curve (solid black line) than other MCP methods; and (ii) for



(a) 4 direction sectors

(b) 4 direction sectors (without SVR and hybrid SVR)

(c) 8 direction sectors

(d) 8 direction sectors (without SVR and hybrid SVR)

Fig. 13. Power generation of nine 1.5 MW turbines for evaluating the hybrid MCP with 4 and 8 direction sectors; the legend in (a) is also applicable to (b) and (d).

all four direction sectors, the hybrid SVR and hybrid ANNs perform significantly better than the individual SVR and ANNs, respectively.

Fig. 13 shows the wind power generation of the wind plant with nine GE 1.5-MW XLE turbines. The closer the predicted power generation curve to the actual power generation curve (the solid line in the figure), the more accurate the estimated wind pattern. The predicted power generation of the wind plant was estimated using the long-term wind data predicted by the hybrid MCP method; the actual wind plant power generation was estimated using the measured long-term wind data. Fig. 13(a) and (c) shows the power generation for the 4 and 8 direction sectors, respectively. It is observed that the power generation estimated by the hybrid SVR and individual SVR methods is relatively less than that estimated by other MCP methods. For better visualization, Fig. 13(b) and (d) compares the MCP methods without the hybrid SVR and the single SVR methods. We observe that: (i) in most cases, the power generation is under-estimated when using the wind data predicted by MCP methods; (ii) the hybrid ANNs and hybrid linear regression methods perform relatively better when the correlation period is between 4000 h and 6500 h (approximately 5.5 months–9 months); and (iii) the linear regression method has relatively better power generation estimations when the correlation period is between 8000 h and 11,000 h (approximately 11 months–15 months).

5. Conclusion

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 a target farm site. The weight of each reference station in the hybrid strategy is determined based on the (i) distance and (ii) elevation difference between the target farm site and each reference station.

Three sets of performance metrics were used to evaluate the hybrid MCP method. The first set of metrics analyzed the statistical performance, including the mean wind speed, wind speed variance, RMSE, and MAE. The second set of metrics evaluated the distribution of long-term wind speed; in this case, the Weibull distribution and MMWD were adopted. The third set of metrics analyzed the wind farm performance.

Three scenarios were analyzed using the hybrid MCP methodology, and interesting results were observed and discussed. The results illustrated the promising potential of this hybrid MCP approach. In the first scenario, we found that (i) the hybrid MCP strategy using multiple reference stations can more accurately predict the long-term wind condition at the target farm site, and (ii) the power generation was generally under-estimated using the data predicted by MCP methods. In the second scenario, each reference station used one of the following MCP algorithms: (i) linear regression; (ii) variance ratio; (iii) ANNs; and (iv) SVR. Therefore, a total of 256 (which is equal to 4^4) combinations were investigated to formulate the hybrid MCP strategy. The best combination of the hybrid MCP strategy and reference stations was determined. We found that the accuracy of the hybrid MCP method was highly sensitive to the combination of individual MCP algorithms and reference stations. We also found that the best hybrid MCP strategy varied based on the length of the correlation period. In the third

scenario, both wind speed and direction were considered in the application of the hybrid MCP strategy. For the nine-turbine wind plant, the power generation was generally under-estimated by most MCP methods.

Quantifying and modeling the uncertainty in the MCP methods would better establish the credibility of wind resource assessment and wind plant performance estimation. Modeling the propagation of uncertainty through the MCP process would allow quantification of the expected uncertainty in on-site wind conditions and wind plant power generation. In addition, an investigation of how the uncertainties in the annual distribution of wind conditions interact with the uncertainties inherent in the MCP correlation methodology is also necessary. This investigation is an important topic for future research.

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