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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.

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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.

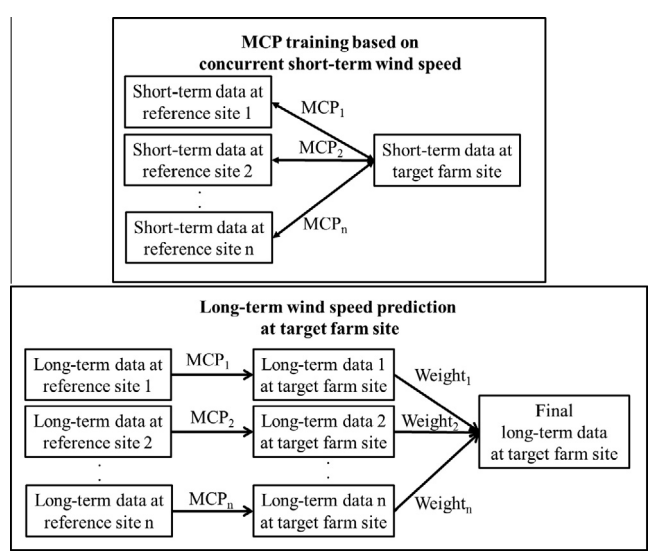


Fig. 1. Overall structure of the hybrid MCP method.

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

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

where n_{ref} is the number of reference stations, and $\mathrm{D}d_j$ and $\mathrm{D}h_j$ 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.

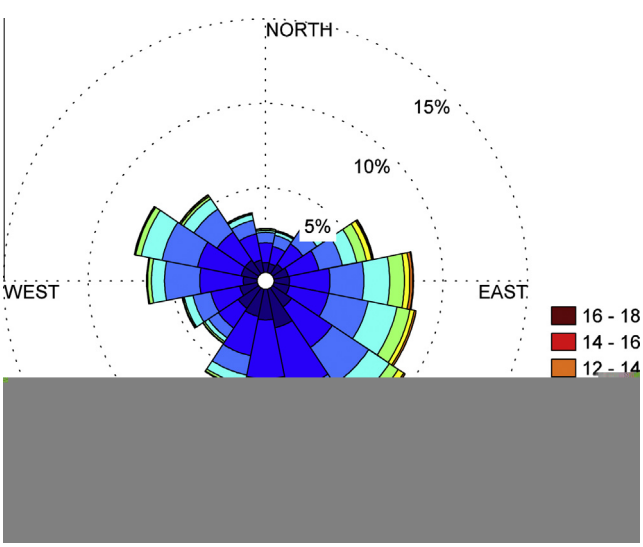


Fig. 2. Wind rose diagram with 16 sectors (each color represents a different range of wind speed, m/s).

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.

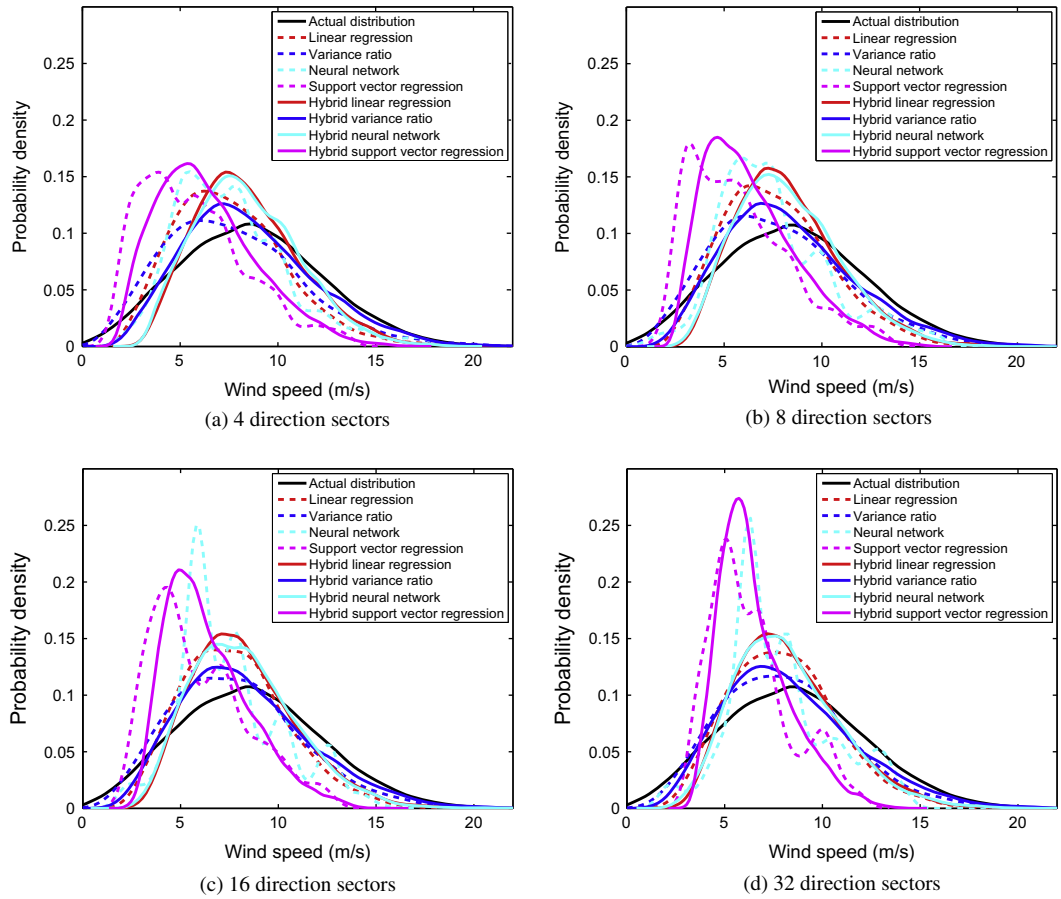


Fig. 12. Wind distribution metrics with different direction sectors; see online version for color.

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).

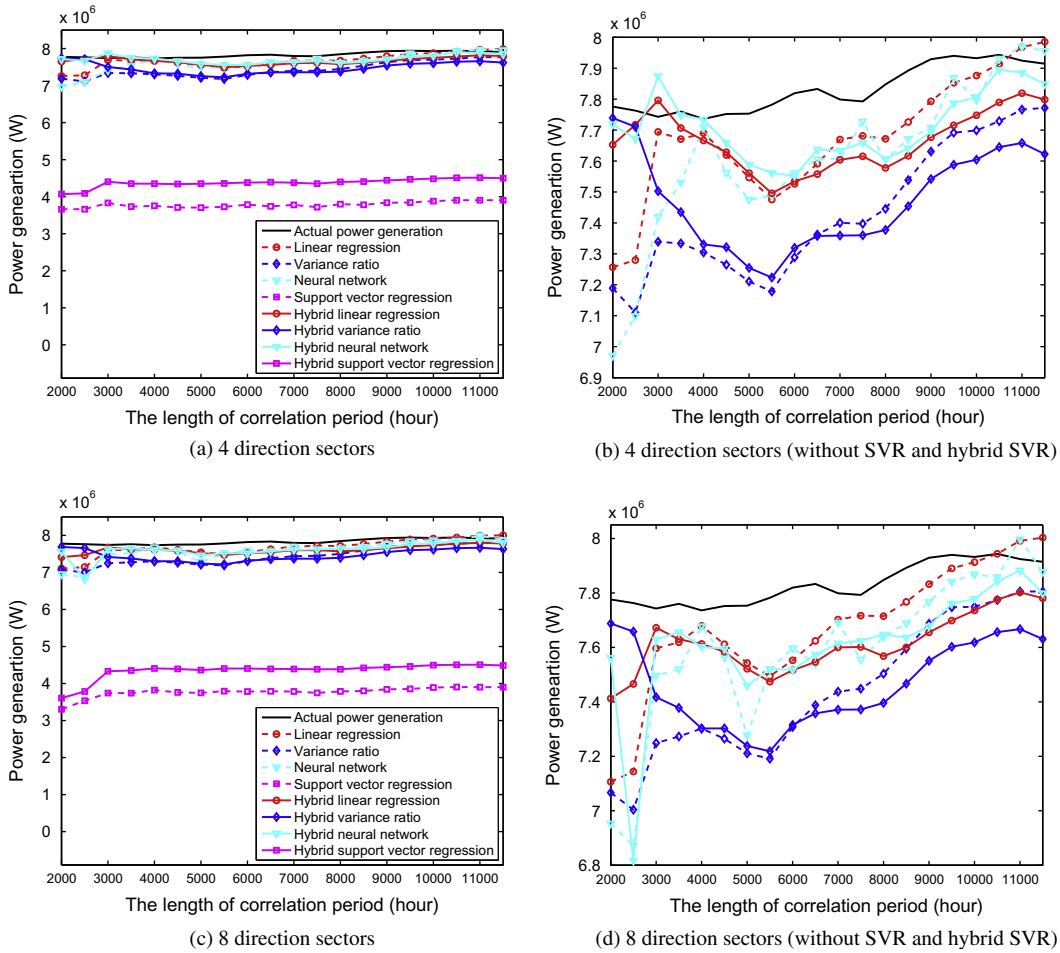
The power generation of the nine-turbine wind plant is shown in Fig. 10. Fig. 10(a) and (b) shows the 256 wind power generations of wind plants with 1.5-MW and 2.5-MW turbines, respectively. We observe that (i) the average value of the power generation with GE 1.5-MW XLE turbines during the length of 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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