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Modeling wind-turbine power curve: A data partitioning and mining approach

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ABSTRACT

Model of a power curve allows to analyze performance of a wind turbine and compare it with other turbines. An approach based on centers of data partitions and data mining is proposed to construct such a model. Wind speed range is partitioned into intervals for which centers are computed. The centers are regarded as representative samples in modeling. A support vector machine algorithm is used to build a power curve model. Computational results have demonstrated that the model reflects dynamic properties of a power curve. In addition it is accurate and efficient to generate. The model accuracy has been tested with industrial wind energy data.

1. Introduction

Environmental concerns and a limited supply of fossil fuels have caused countries to pay attention to renewable energy. Wind energy is expanding at the fastest rate among all alternative forms of energy generation [1]. However, the large scale deployment of wind energy has brought challenges to performance assessment of wind turbines [2]. Fluctuating wind speed and power make it difficult to assess efficiency of a turbine. A turbine with a deteriorating performance may be prone to failures, including catastrophic failures. An early maintenance intervention may be warranted. The research presented in this paper offers a solution to performance evaluation of wind turbines.

Numerous approaches have been applied to model wind turbine power curves (WTPCs). The models presented in the literature are usually parametric or non-parametric [3]. Examples of parametric models include [4]: the piecewise linear model, polynomial power curve, maximum principle method, and dynamical power curve. In the piecewise linear model, the lines represent the data fitted according to the least square criterion [5,6]. More accurate WTPCs were modeled with polynomial equations, ranging from quadratic power curve models [7], to cubic and approximate cubic [3], exponential [7], and ninth degree polynomial models [8]. The maximum principle method was proposed in Ref. [9] to build a dynamic empirical power curve model. The main idea behind the dynamic power curve is to partition the wind power output into deterministic and stochastic components, for example the Langevin model was used in Ref. [9]. There are also probabilistic models, for example, the power curve model in Ref. [10] considered the dynamics and uncertainty of wind power generation. Logistic function models with four and five parameters were developed in Ref. [11].

Non-parametric models do not involve equations [4]. Examples of non-parametric models include, copula power curve model, cubic spline interpolation, neural network (NN), fuzzy models, and data derived models. Copula is a distribution function utilized to analyze dependence of random variables. The copula model in Ref. [12] considered the wind power curve as a bivariate joint distribution. Interpolation methods, generally used to determine values between two known data points, were utilized to model power curves. The cubic spline interpolation was successfully applied to model power curve in Ref. [3]. Neural network (NN) models are suitable for modeling WTPCs. Three different NNs, the generalized mapping regression (GMR), multi-layer perceptron (MLP), and general regression neural-network (GRNN) were applied to model WTPCs in Ref. [13]. Furthermore, fuzzy cluster center method, fuzzy c-means clustering, and subtractive

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clustering were used in Refs. [8,14] to model WTPCs. Since supervisory control and data acquisition (SCADA) systems collect large volumes of data, data mining algorithms were used to model power curves in Ref. [5].

In summary, parametric models have limitations in expressing dynamic characteristics of power curves [15], for example, at the area between two partitions. Non-parametric models are more accurate [16], however, they may come at higher computation and training cost. Development of a dynamics power curves at a low computational cost calls for a new approach. An approach to model power curve with cluster centers proposed in Ref. [17] reduced the computational cost. In this paper the partition centers are used as training examples to build a power curve model with the support vector machine (SVM) algorithm.

The paper is organized in three sections. In Section 2, the wind turbine power curve (WTPC) and a framework of the proposed method is presented. Section 3 discusses the data from an operating wind farm and the necessary data processing. Section 4 focuses on computation of partition centers and selection of a data mining algorithm. In Section 5, the proposed method is applied to the industrial data. Performance of the proposed model is also discussed. Section 6 concludes the paper.

2. The proposed approach

A wind turbine power curve (WTPC) model includes three main points: A, B, C (see Fig. 1). Point A represents the cut-in wind speed, point B reflects the rated power, and point C corresponding to the cut-out speed.

These three points divide power curve into four segments [18], each having a different distribution of wind power and wind speed. When the wind speed $v<v_A$ or $v>v_C$, wind power output is zero. In segment BC, the wind power output reaches the rated level. The theoretical performance of a wind turbine in segment AB is expressed in equation (1).

$$P = \frac{1}{2} C_p \rho \pi R^2 v^3 \quad (1)$$

where: C_p is the wind turbine power coefficient; ρ represents the air density; R is the radius of wind rotor, and v represents the wind speed.

As different segments of a power curve have different properties, segmented models are used, e.g., models composed of three and four segments were built in Ref. [19] (see Fig. 1). However, some points could not be well represented due to non-smoothness at a juncture of segments. Non-parametric models offer flexibility in dynamic models of power curves, but may come at a significant computational cost. The approach proposed in this paper allows to build a dynamic WPTC model at a low computational cost.

A framework of modeling wind turbine power curves is presented in Fig. 2. The published research (the blue dashed box at the left in Fig. 2) and the proposed one (the red dashed box at the right) are compared. First, the original wind data is preprocessed to eliminate abnormal data values. The approaches published in the literature favor use of segmented and non-parametric models. In this paper, the data is divided into equal size partitions. The centroids of the partitions serve as new data points. Based on the new data points, a dynamic WTPC is built by a support vector machine (SVM) algorithm. The power curve model is applied to assess performance of wind turbines.

3. Data source and preprocessing

The data (wind power and wind speed) used in this paper comes from a large wind farm located in the Midwest. The data set was collected at turbine at a sampling interval of 10 min. In total 57,025 data points were collected from June 1, 2014 to July 1, 2015. The unit of the active wind power is kW, and the value of power is normalized for air density of 1.18 kg/m^3.

Fig. 3 illustrates the power curve constructed from the industrial data. The black points are generally used to train the wind turbine power curve (WTPC). The red data points are defined in Ref. [20] as under-power points or stopping points pointing to abnormal behavior of a turbine. To reduce the modeling error, the under-the-power curve points are rejected at the pre-processing phase.

Assuming a wind power series $\{x_n\}$, the mean $\bar{x}$ and standard deviation σ are applied to determine abnormal values. The wind data may not be stationary at some periods due to wind speed fluctuation. Therefore, $\bar{x}$ is computed step-by-step based on exponential smoothing [21] according to equation (2).

$$\bar{x}_t = \alpha x_t + (1-\alpha)\bar{x}_{t-1} \quad (2)$$

where: $\bar{x}_t$ represents the computed mean at the tth step; α is the weight parameter; and $\bar{x}_0$ is chosen as x_0;. Based on equation (2),

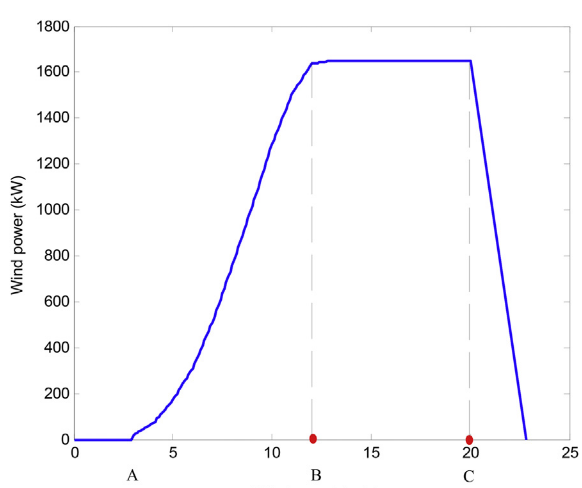

Fig. 1. An abstract power curve.

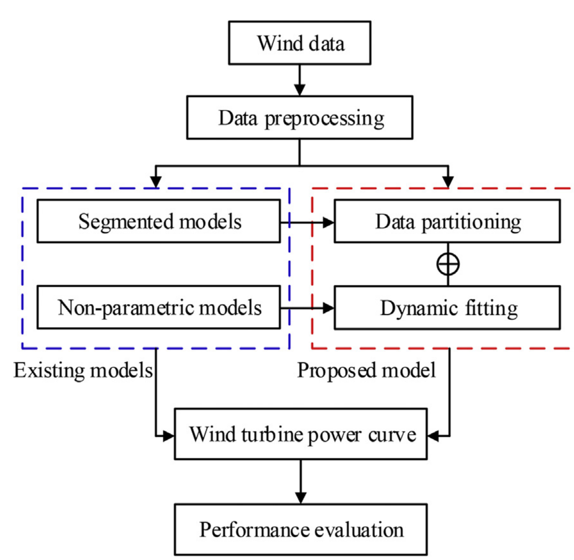

Fig. 2. A framework of the proposed modeling approach.

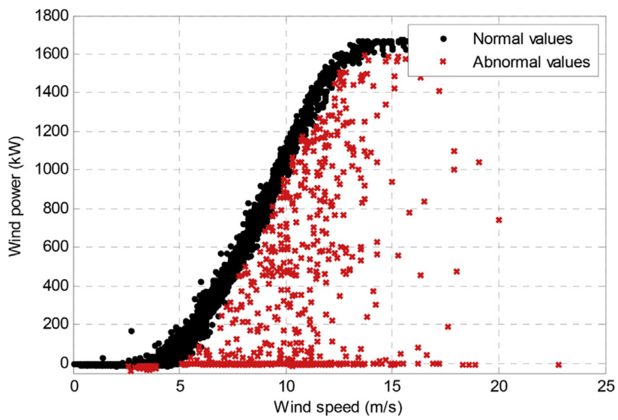

Fig. 3. Power curve of an industrial wind turbine.

the normal values are determined with equation (3), while the remaining vales are labeled abnormal.

$$\bar{x}_{t-1} - k\sigma < x_t < \bar{x}_{t-1} + k\sigma \quad (3)$$

where: k is a parameter determined from statistical analysis of small probability events. Given the values of k and α, the abnormal values are detected, and then deleted or revised. In this paper, the values of parameters are chosen as $\alpha = 0.2$ and $k = 3$, and the red points representing the abnormal values in Fig. 3 are deleted.

4. Wind turbine power curve modeling

The proposed modeling approach (Fig. 2) includes extraction of centroids and construction of a power curve model with a data-mining algorithm. The preprocessed data is first partitioned, and a data-mining algorithm is selected to build a dynamic WTPC.

4.1. Selecting partition centers

As illustrated in Fig. 2, the wind speed range is discretized into intervals, and the corresponding wind speed and power data make the partitions. Assuming the cut-out speed is v_{co}, the speed range [0, v_{co}] is divided into N equal length intervals. The data points in each interval are defined in equation (4).

$$S_i = \{(v, p) | v \le v_i, v \ge v_{i-1}\} \quad (4)$$

where: S_i represents the points set of the ith partition, v represents wind speed and p is the corresponding power, and $v_i = \frac{i}{n} * v_{co}$ is the demarcation speed between the ith and $(i+1)^{th}$ partition.

The set of points in partition i is denoted as $\{x_i\}$. Based on the k-means algorithm, the center of $\{x_i\}$ is determined from equation (5)–(6).

$$c(t+1) = c(t) - \eta(t) * (c(t) - x_i) \quad (5)$$

$$\eta(t) = 1/(t+1) \quad (6)$$

where: $c(t)$ represents the center point at the tth step, $\eta(t)$ is a coefficient. The value of $\eta(t)$ decreases with increasing t, i.e., more data points are considered (see equation (6)). For t=0, $\eta(0) = 1$ and $c(1) = x_0$, the initial partition center is randomly selected. Subsequently when t increases, a new point is computed and a new partition center is selected according to equation (5)–(6). If $t \to \infty$, the value of η is 0, which implies the partition center is determined.

Fig. 4 illustrates the wind speed partitions and centroids. All

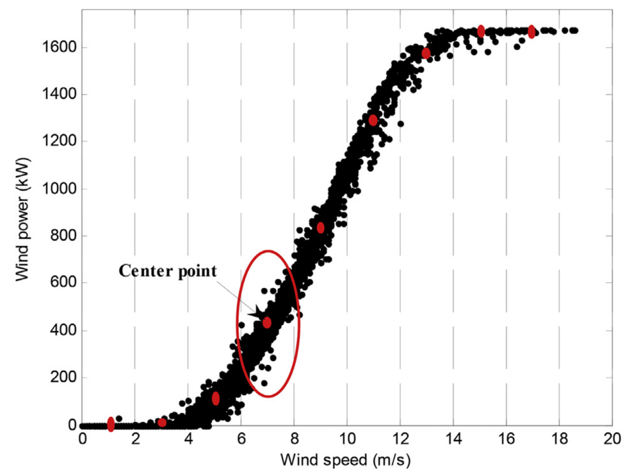

Fig. 4. Wind speed intervals, data partitions, and center points.

center points resemble the shape of an abstract power curve and they are used to model the WTPC.

4.2. Data mining modeling

A power curve model is a function $f(x)$ capturing the relationship between wind speed and wind power. In this paper, partition centers are used to reduce model complexity and computation cost. The partition centers are defined as $\{c_i | c_i=(v_i, p_i), i=1,2, \ldots,N\}$, where N is the number of partitions, v_i and p_i are the value of wind speed and wind power at the ith center, respectively. The WTPC model is expressed in equation (7).

$$p = f(v) \quad (7)$$

In parametric models, f in (7) is a mathematical expression, while in non-parametric modeling, f is not explicitly expressed. Data-mining algorithms are well suited for building non-parametric models. Neural network (NN), random forest, support vector machine (SVM), and k-nearest neighbor (k-NN) are frequently used data mining algorithms [22,23]. A support vector machine (SVM) algorithm utilizes support vectors to build the classification hyper-plane. It is suitable for modeling from small number of data points due to its strong generalization ability [24]. The SVM is applied to build a power curve model from the partition centers.

SVM was originally used in linear classification of data in categories. It gradually evolved into a support vector regression (SVR) algorithm [25]. Assume the training set is expressed in equation (8).

$$T_{set} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \cdots, (\mathbf{x}_l, y_l)\} \in (R^n \times Y)^l \quad (8)$$

where: x_i is the input, $y_i \varepsilon Y$ is the output, i=1,2, …, l, l is the number of the training points, and R^n and Y are the value domain of x and y, respectively. The SVR model is defined in equation (9)

$$f(\mathbf{x}) : y = <\omega, \mathbf{x}> + b \quad (9)$$

where: $\langle x,y \rangle$ represents the inner product of vector x and y, ω and b are the model parameters. To solve model equation (9), the principle of structural risk minimization (SRM) [20] results in the optimization model expressed in equation (10).

$$\min_{\omega,b} \quad \frac{1}{2}\|\omega\|2 + C\sum_{i=1}^{l}\left(\xi_i + \xi_i^*\right)$$
$$\text{s.t.} \quad \begin{aligned} & f(\mathbf{x}_i) - y_i \le \varepsilon + \xi_i \\ & y_i - f(\mathbf{x}_i) \le \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \ge 0, i = 1, 2, \cdots, l \end{aligned} \tag{10}$$

where: $\varepsilon \geq 0$ is an insensitive loss factor whose function is to keep the error between $f(\mathbf{x})$ and y less than ε. To take the random error into account, relaxation factors ξ_i, ξ_i^* and penalty factor C are introduced into the objective function of model equation (10). However, in most cases the model is non-linear and complex. The data is not expressed suitably by the linear model in equation (9), rather kernel functions are used to map the data points into a high dimension feature space [26], and the inner product $\langle \mathbf{x}_i, \mathbf{x}_j \rangle$ is often replaced by the kernel function $K(\mathbf{x}_i, \mathbf{x}_j)$.

In this paper, SVM is applied to build the power curve model with partition centers. Thus, input $\mathbf{x}$ represents wind speed and output y represents wind power, and $R^n = Y = R$. From the plot in Fig. 1, it is obvious that the power curve is non-linear, therefore a suitable kernel function needs to be selected. Performance of three kernel functions, polynomial, radial basis function (RBF), spline, is assessed in this paper. Fig. 5 illustrates the power curve models for these kernel functions.

The mean square error (MAE) and the standard deviation of mean absolute error (Std of MAE) are used to evaluate these three models of Fig. 5 (see Table 1). It is obvious that the spline kernel performs best, therefore it is considered in this paper for modeling. The spline kernel is expressed as a piece-wise cubic polynomial [27] in equation (11).

$$K(x,y) = 1 + xy + xy\min(x,y) - \frac{x+y}{2}\min(x,y)^2 + \frac{1}{3}\min(x,y)^3 \tag{11}$$

where: $K(x,y)$ represents the spline kernel function of vectors x and y.

4.3. Algorithm flow

Fig. 6 present the flow chart of the proposed approach that is outlined next:

Step 1: Preprocess the original data.

Step 2: Set the number of partitions to N, and decompose the wind speed range into N partitions. The data set corresponding to the ith partition is labeled S_i.

Step 3: Extract the centroid data points $\{c_i\}$ of partitions as a new data set, then SVM algorithms with different kernel functions to build a WTPC.

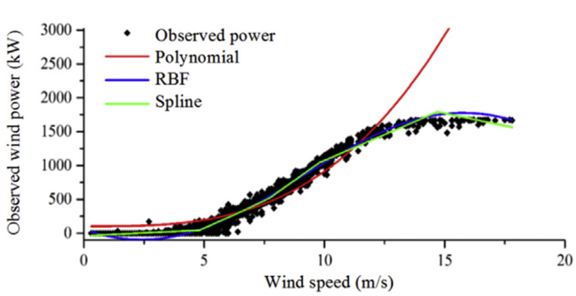

Fig. 5. Performance of power curve models with different kernel functions.

Table 1
Evaluation of models with three kernel functions.

	MSE	Std of MAE
Polynomial	125.05	144.34
RBF	44.849	54.454
Spline	15.98	9.88

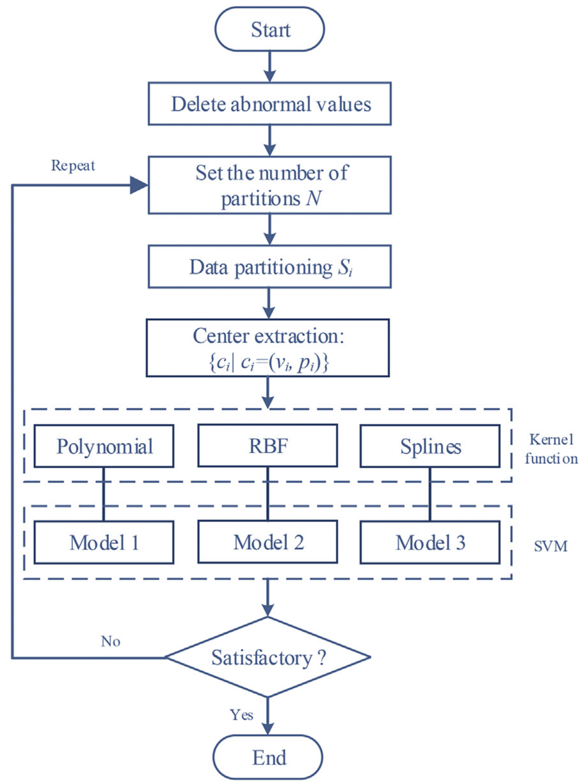

Fig. 6. The flow chart of the proposed modeling approach.

Step 4: Judging the performance of modeling WTPC. Stop when the model is satisfactory; otherwise, repeat from Step 2.

5. Results and discussion

5.1. Discussion of different models

The power curve model can be used to evaluate performance of a wind turbine. The number of partition centers determines the number of training data points. Assuming the number of partitions N, then the partition centers c_i, i=1,2, …, N of each partition are computed from equation (4)–(6). Using $\{c_i\}$ as the input variables, the WTPC model is built with the SVM algorithm in equation (8)–(10). Since different values of N may have different performance in modeling power curves, Fig. 7 illustrates performance and computation time of models as the function of N.

The wind speed range of [0, 20] is selected in Fig. 7 for the data from the industrial wind turbine (see Fig. 2). By increasing the number of partitions in increments of 1, several models are built. The green plot in Fig. 7 depicts the computation time of models with different partitions. The trend of computation time is increasing as more partitions are used in modeling. The blue plot depicts the performance of models fitting the actual wind power curve, the SSE (sum of square error) is used as the performance function. Note that the SSE value drops first (See Fig. 7), then

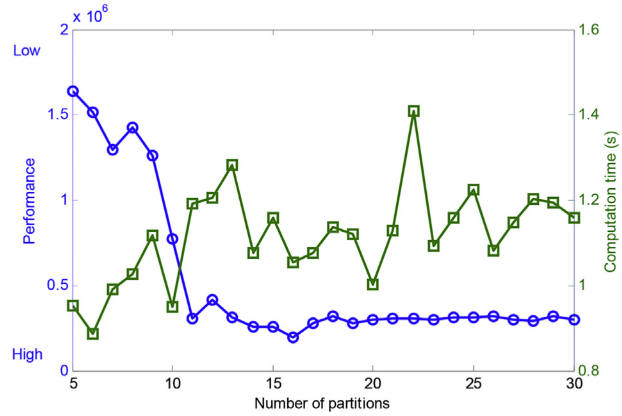

Fig. 7. Performance and computation time of power curve models with different number of partitions.

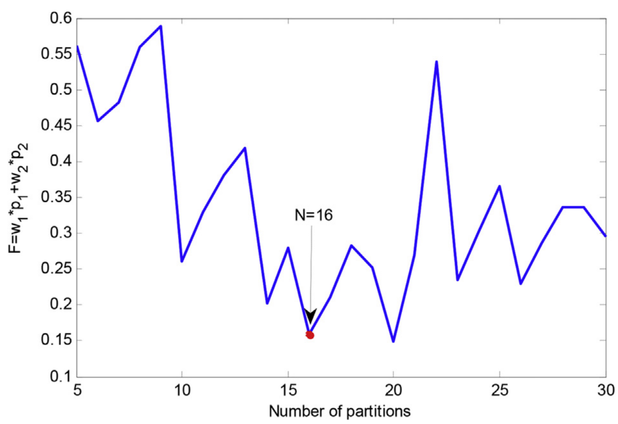

Fig. 8. The evaluation indicator *F*.

remains approximately constant in increasing *N*, which implies that it is feasible to find a reasonable number of partitions at low computational cost. To find the optimal number of partitions, an evaluation indicator synthesizing the two factors of Fig. 7 is defined in equation (12).

$$F = w_1 \cdot p_1 + w_2 \cdot p_2 \tag{12}$$

where: F is the evaluation indicator; p_1 and p_2 represent the normalized value of two factors (performance and computational cost) respectively; w is the weight of a factor.

Fig. 8 shows the values of F for different numbers of partitions. Given the weights $w_1 = w_2 = 0.5$, the optimal value of F is 16 and 20, which implies that 16 or 20 partitions are sufficient to obtain a high performance model. Three illustrative power curve models with 10, 20, and 30 partitions are illustrated in Fig. 9(a)-9(c).

The green points in Fig. 9 are the actual wind data; the red points represent the partition centers; the black curve represents the power curve; and the yellow region represents the 95% confidence zone. For comparison with the other models in Fig. 9, the model in Fig. 9(d) is built without data partitioning (using all data points). Most data points in Fig. 9 are located within the confidence zone. Deviations off the black curve are regarded as the model errors reflecting the wind power variability. There are some points outside the confidence zone due to the model's accuracy. Then the performance of a turbine is analyzed by combining all these factors. Generally, the random nature of wind impacts the model errors. The errors following the normal distribution are regarded as the random and are not considered in performance evaluation.

Fig. 10 provides the distribution of the errors of the power curves in Fig. 9. All errors follow a normal distribution, which implies that these models are valid for modeling WTPCs. The parameters of error distribution are provided in Table 2.

In Table 2, μ is the mean of error and σ is the standard deviation of error. Based on the results in Table 2, The model with 10 partitions has the largest value of the mean error μ, The model with all data points has the largest value of the standard deviation σ, which

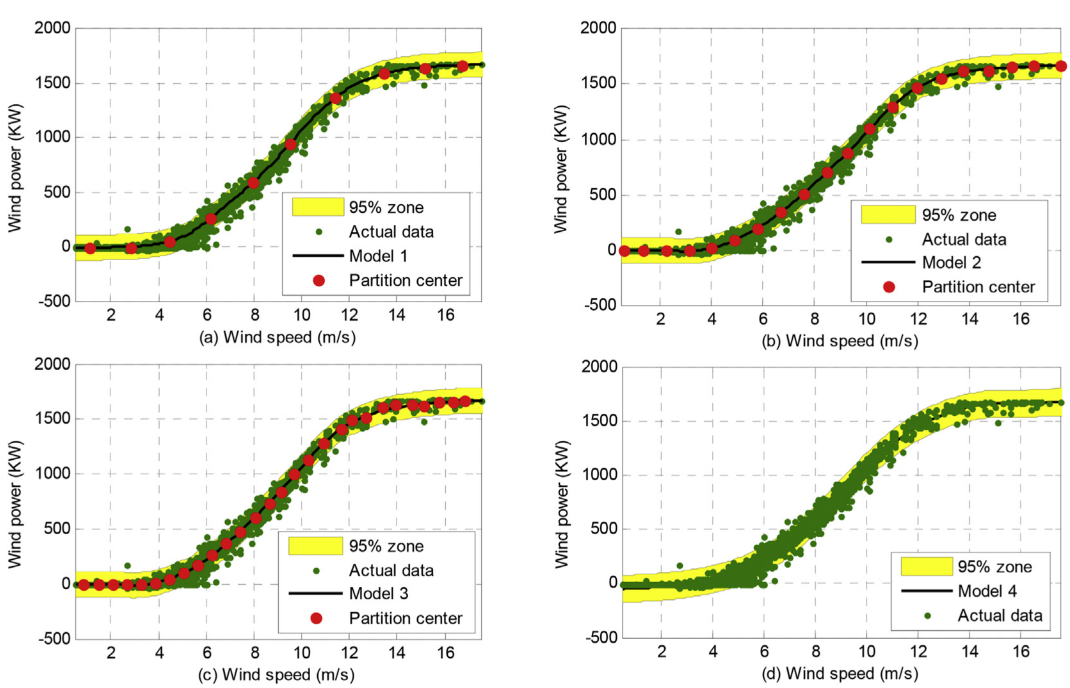

Fig. 9. Four power curve models for 10, 20, and 30 partitions.

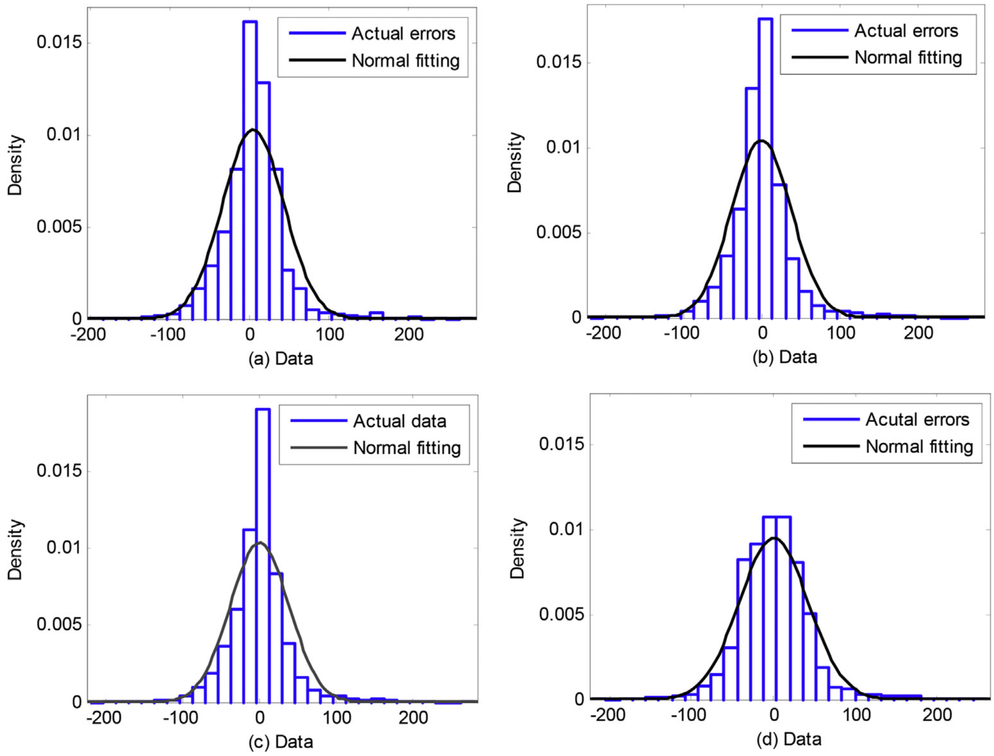

Fig. 10. Error distribution of the four models in Fig. 9.

Table 2
Parameters of the error distribution functions.

	10 partitions	20 partitions	30 partitions	All data points
μ	4.6789	−0.5109	0.5943	0.6790
σ	38.7523	38.2582	38.5236	42.1251

Table 3
Error statistics of four models.

	MAE	RMSE	R^2
10 partitions	26.5166	39.0280	0.9912
20 partitions	24.7002	38.2558	0.9915
30 partitions	25.0804	38.5224	0.9914
All data points	30.6594	42.1242	0.9897

implies that both models poorly model power curves. The model with 20 partitions captures the best WTPC model. The results in Table 2 indicates that a model built with all data points is inferior to the model built at lower computational cost with a smaller number of data points (the model with 20 partitions). The performance of these models is further analyzed in the next section.

5.2. Quantitative assessment of model performance

The mean absolute error (MAE) and the root mean squared error (RMSE) are used frequently in quantitative evaluation of models [28]. The two metrics presented in equation (13)–(14) will be used to evaluate the performance of the models in Fig. 9.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|p_i - \hat{p}_i| \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - \hat{p}_i)^2} \tag{14}$$

where: p_i is the actual wind power and $\hat{p}_i$ is the predicted wind power, and n is the number of test data points. In addition to metrics equation (13)–(14), the coefficient of determination R^2 in equation (15) is used.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(p_i - \hat{p}_i)^2}{\sum_{i=1}^{n}(p_i - \bar{p}_i)^2} \tag{15}$$

where: $\bar{p}_i$ is the mean value of the actual power. Table 3 provides the value of the three metrics for the four models.

The results in Table 3 show that models with 10, 20, 30 partitions have smaller values of MAE and RMSE than model with all data points, and their value of R^2 closer to 1, which implies that these models perform better than model with all data points. The data in Tables 2 and 3 point to the model with 20 partitions as the best performing. Therefore, it is used to evaluate performance of the wind turbine studied in this paper. A computational study was performed to compare the model built the approach presented in this paper and with the models presented in the literature. Table 4 shows the values of three indicators for different models.

Table 4
The evaluation indicators of three different models.

	SSE	Computational time	F
Model 1	7.93e+06	0.8185	2.6064
Model 2	3.08e+05	7.6098	6.4606
Model 3	3.01e+05	1.0330	0.1482

Model 1 is the segmented model with three piecewise functions. Model 2 is the non-parametric model built by SVM. Model 3 is built

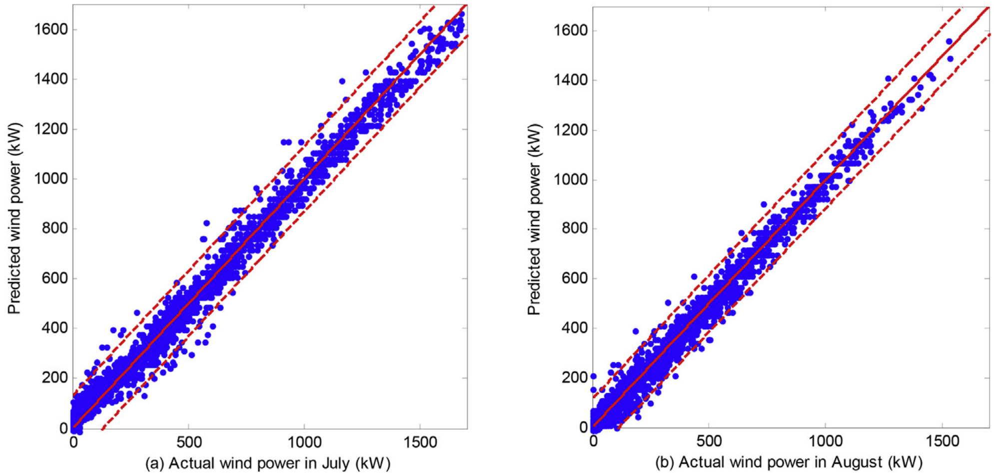

Fig. 11. Results of wind power prediction for a test data set.

using 20 partition centers. The segmented model dominates in the computational time, but its performance (SSE) is low. Comparing Model 2 with Model 3, a result similar to that of Table 3 is obtained. The value of indicator F demonstrates that the proposed approach prevails over the other two other models.

5.3. Performance evaluation of wind turbines

To evaluate performance of the wind turbine, Model 2 of Fig. 9 is used, the data of July and August are chosen as the testing set. Then power prediction results for two test data sets, July and August 2014, are shown in Fig. 11.

The red solid line in Fig. 11 indicates that predicted wind power equals to the measured wind power. The red dashed lines represent the confidence interval. Considering the fact that random errors exist, a confidence interval is needed to describe the performance of prediction. Fig. 10 and Table 2 analyze the error accord with the normal distribution, equation (16) is considered to apply to almost all of data.

$$\varepsilon \in [\mu - k\sigma, \mu + k\sigma] \tag{16}$$

where: ε is the prediction error, k is the proportionality coefficient, μ and σ are the mean and standard deviation of the error, respectively. When the value of coefficient $k=1$, 68.3% of errors conform to equation (16). For $k=2$ and 3, the probability values are 95.4% and 99.7% respectively. The two dotted lines in Fig. 11 represent the lower and upper boundary of 99.7% confidence interval based on the errors of Model 2. The results in Fig. 11(a) are for the month of July 2014 with the precision of 98.39%. Fig. 11(b) shows the prediction of wind power in August 2014 with the precision of 99.14%. The above presented results demonstrate validity of the proposed approach in performance evaluation of wind turbines.

6. Conclusion

In this paper, a model based on data partitioning and data mining was proposed for modeling power curves of wind turbines. Wind data from an industrial wind turbine was used in the study. First, abnormal values of the data set were deleted. Twenty-five data partitions (between 5 and 30) were considered and the center points of these partitions were extracted. An evaluation indicator F was defined to determine performance of power curves. The number of partitions, 16 and 20, were found to deliver a power curve at high performance and low computational cost. A support vector machine algorithm with three kernel functions was used to build power curve models. The model with 20 partitions performed best. Its performance was compared with the models published in the literature. The computational results demonstrated that there exists a data partition granularity leading to good performing model generated at a reasonable computational cost.

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