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Quantile based probabilistic wind turbine power curve model

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ABSTRACT

Accurate wind turbine power curves lay solid foundation for wind turbine performance evaluation and wind power forecasting, and then serve the planning and operating a low carbon energy system including renewables and electric vehicles. In order to improve the model accuracy, this paper presents the concept of quantile power curve and a quantile loss function based neural network algorithm, for establishing the proposed quantile power curve model. Based on the operational data of three wind turbines in a wind farm in China, a case study is carried out to validate the proposed model. The results show that the proposed quantile power curve model has good reliability.

Keywords: wind turbine, quantile power curve, quantile loss function, neural network

NONMENCLATURE

Symbols	
p	power output of a wind turbine
P_r	rated power output of a wind turbine
v、v_q	wind speed at hub height
θ	pitch angle
β_1、β_2	pitch angle thresholds
Prob	probability function
q	nominal quantile level
p_q	the q quantile of the power distribution at wind speed v_q
y	the actual power output
y^p	the simulated power output under a given quantile level
i	the data ordering
I	the set of data serial number
Q	the set of all quantile levels
$w_t^{(q)}$	power value on the q-quantile power curve at the time of t
$\vartheta^{(q)}$	binary indicating variable
$z^{(q)}$	number of data whose actual power falls below the q-quantile power curve at the quantile level of q
q_i'	actual quantile of corresponding to the power data point with the ordering of i in the data set
q^*	quantile corresponding to the nearest quantile-based power curve below the selected power data point
P	actual power data point
N	total number of data set

1. INTRODUCTION

The wind turbine power curve describes the relationship between wind speed and its power output, which is an important tool for converting the wind speed to its potential power generation as well as a good indicator for the wind turbine performance [1][2][3][4][5]. Therefore, a reliable power curve model is of great importance in many applications: (1) From the perspective of system operation, the wind turbine power curve is an important input for the wind power prediction and its uncertainty analysis [6][7][8][9][10] and optimal power flow calculation [11]. (2) From a

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planning perspective, a good wind turbine power curve can ensure a reliable estimation of the annual energy yield of a wind turbine, which is a crucial part of wind resource assessment and wind turbine deployment.

Many efforts have been made to improve the accuracy of wind turbine power curve model by using the real-world operational data to establish a one-to-one mapping relationship between wind speed and its corresponding power output, which can be divided into the following categories:

(1) The discrete method divides the wind speed into different intervals and obtains a power value in each interval by a given method. The Bin method used in the IEC-61400-12-1 standard is within this category. It divides the entire wind speed range into n bins with 0.5 m/s wind speed interval for each bin; pairs of (v, p) data are obtained by averaging the v and p values in each bin [12]. The advantage of the Bin method is that the modelling process is simple and clear, and does not use any mathematical function, which might distract from the actual situation. The disadvantage is a large amount of measured data is needed to improve accuracy [13].

(2) The parametric method uses a set of piecewise functions or a continuous mathematical expression to build a power curve model, including polynomial function [14][15][16], exponential equation [16], logic function [2][17], improved hyperbolic tangent function [18], the maximum method [19], etc. Camilo Carrillo et al. [14] used quadratic polynomial function to establish a power curve model with the cut-in wind speed, cut-out wind speed and rated power as the polynomial coefficient. M. S. Mohan Raj et al. [16] compared the accuracy of the power curve models based on the 4-degree, 7-degree and 9-degree polynomials; and the 9-degree polynomial model demonstrated the highest accuracy. Andrew Kusiak et al. [17] and Simon Gill et al. [2] established a power curve model based on four-parameter logic function and a five-parameter logic function-based model; logic function method improved the performance by considering the inflection point of a power curve comparing to polynomial fitting models.

(3) Different from the explicit mathematical function concerning the wind speed and the power output established by the parametric method, the nonparametric method does not have a specific function but tries to improve the fitting precision using a data mining algorithm and a large amount of SCADA data [20]. Nonparametric methods include k-Nearest Neighbor [17], Copula model [2], artificial neural network [21][22][23], fuzzy logic [16][24][25], cubic spline interpolation [15], support vector machine [26], adaptive neuro-fuzzy system model [27], etc. Francis Pelletier et al. [22] established a wind turbine power curve model using a multi-stage artificial neural network – a back-propagation algorithm with Multi-Layer Perception and six imported parameters; in the case study, this method outperformed the IEC Bin method and other newly developed methods. Bartolomé Manobel et al. [23] presented an automatic data filtering method based on Gaussian process and artificial neural network, which saved the computation time and reduced the root mean square error by 25%. Taner Üstüntaş et al. [24] proposed a fuzzy clustering center-based method with 4 or 5 cluster centers; and proved that this method is better than the least squares method. Lydia et al. [25] used Fuzzy c-means algorithm in the wind turbine power curve modelling. Andrew Kusiak et al. [17] used five data mining algorithms to establish the nonparametric wind turbine power curve models, namely Multi-Layer Perception, Random Forest, Boosting Tree, k-Nearest Neighbor algorithm; among the above methods, the k-Nearest Neighbor algorithm had the highest accuracy.

However, it is not easy to get an accurate wind power curve based on a deterministic model. The difficulty lies in the uncertainty during the power generation process of wind turbines, which can be visualized as that the hub height wind speed and power do not present a specific one-to-one relationship. This is because of the complex wind conditions, wind turbine conditions and the reaction of a wind turbine to the volatile wind. In fact, the actual power curve of a wind turbine has great uncertainty, and there is a big difference between the standard power curve provided by the manufacturer and the actual one.

To improve the uncertainty part in the model, some researchers have been shifting their attention to the probabilistic based power curve. Julia Gottschall et al. [28] proposed the Langevin dynamic power curve model by dividing the wind turbine power output into a deterministic part and a random part; the deterministic part is the average power corresponding to the wind speed, and the random part follows the Markovian property concerning other external factors, e.g. turbulence. Wang Bo et al. [6] also analyzed the uncertainty of the actual power curve. Simon Gill et al. [2] proposed a bivariate joint distribution-based wind turbine power curve using Copula model, which can estimate the power uncertainty, but the modelling complexity is high. Tongdan Jin et al. [29] proposed a power curve model by aggregating the average power and its variation within a wind speed bin as well as assuming the power output within a bin to follow a normal distribution with different mean and standard deviation. Lin Peng et al. [30] used nonparametric interval estimation to establish the probability density function of wind turbine power output corresponding to each wind speed level; the upper and lower power limits within each wind speed bin at a certain confidence level can be obtained to form two envelope curves; and therefore, improves the model reliability. Jie Yan et al. [31] proposed a probabilistic power curve model to generate a number of random powers within each wind speed bin according to the power distribution.

To sum up, most of the above probabilistic-based power curve models used a probabilistic distribution function or random power data points in each wind speed bin to represent the uncertainty of power generation process, which lost the usual form of a power curve and therefore is not always friendly to the practical application. And, some assumptions or simplifications are inevitably involved in the modelling process, which affects the model accuracy. Also, an index to quantify the uncertainty and efficiency of wind turbine generation from an uncertainty-based power curve is needed.

To quantify the uncertainty of wind power generation process in a more comprehensive and clear manner, this paper proposes a novel concept of wind turbine power curve termed as quantile wind turbine power curve as well as a wind turbine performance index based on the quantile power curve. To obtain the proposed quantile power curve, a quantile loss function based neural network algorithm is presented. The main contributions of this paper are as follows:

(1) The novel quantile power curve concept is a series of traditional power curve under any given confidence level. The purpose of this power curve is not to calculate a power value corresponding to each wind speed interval, instead it is to calculate a series of power and its corresponding probability according to the actual generation efficiency of the wind turbine.

(2) The quantile loss based multi-layer neural network algorithm is presented to establish the quantile power curve. The gradient descent method is adopted to optimize network parameters. The model is to learn the power distribution within a wind speed interval based on the historical wind speed and power output data.

2. DATA CLEANING

Wind farm operational data usually has a large amount of unreasonable data or data that cannot reflect the actual characteristics of the wind turbine, e.g. curtailment, maintenance and fault. If raw operational data is used, the obtained wind turbine power curve will be distorted, affecting the analysis of wind turbine performance. Similar to our previous work [31], the thresholds of the pitch angle, wind speed and wind power data are determined according to the wind turbine control strategy for filtering out the abnormal data. In this paper, the data filtering conditions are shown in equation (1). The parameters in the data cleaning conditions can be adjusted according to different wind turbines and specific control strategies.

$$\begin{cases} \text{Condition 1} = \left(0 \le p \le 0.8 \times P_r\right) \text{ and } \left(0 < \theta < \beta_1\right) \\ \text{Condition 2} = \left(0.8 \times P_r \le p < 0.95 \times P_r\right) \text{ and } \left(\theta \le \dfrac{\beta_2 \text{-} \beta_1}{0.2 \times P_r} \times (p - 0.8 \times P_r)\right) \\ \text{Condition 3} = p \ge 0.95 \times P_r \\ \text{Condition 4} = \left(p \ge 0\right) \text{ and } \left(0 \le v \le 3\right) \end{cases} \tag{1}$$

where p is the power output of a wind turbine; P_r is the rated power output of a wind turbine; v is the wind speed at hub height; θ is the pitch angle, and the pitch angle thresholds are set to be $\beta_1 = 1.5^{\circ}$, $\beta_2 = 8^{\circ}$.

If none of the above four conditions are met, the data would be deleted. If any of the conditions are met, the data can be retained. By using these data cleaning rules, the abnormal data can be deleted to reduce the negative effects of these data points in the following power curve modelling process. The remaining data represent the normal operation state and performance of the wind turbines.

3. MODELLING THE QUANTILE BASED PROBABILISTIC POWER CURVE

The actual power curve of a wind turbine is a stripping zone in the scatter plot of the wind speed and power output. At a given wind speed, the corresponding power output can be many power values rather than one value in a deterministic power curve, which indicates the uncertainty of the power generation process. The largest gap among these power values can reach to 40%-50% of the wind turbine capacity. The power output at a given wind speed v_q should be regarded as random variable p_q.

This section presents a quantile based probabilistic power curve model. The meaning of the quantile of the power distribution is that at certain wind speed, the ratio of the power below p_q to all the data points within this wind speed bin is q, as shown in equation (2).

$$\mathrm{Prob}(p \le p_q,\ \ v = v_q) = q \tag{2}$$

where Prob is the probability function; p is the power output generated by a wind turbine at a given wind speed v_q; p_q represents the q quantile of the power distribution at wind speed v_q.

Compared with a deterministic power curve, the proposed quantile based probabilistic power curve takes into account the uncertainty in the actual power generation process and provides the probabilistic distribution of power values pq within a given wind speed bin. The ratio of the data points below the quantile power curve to the total data set is *q*. To a large extent, it can reflect the dynamic characteristics of the actual operation process, and improve power curve accuracy.

To implement the proposed quantile power curve concept, this section introduces a quantile loss neural network algorithm. Different from traditional neural network using MAE or MSE as loss function [32], the quantile loss based neural network is able to generate a set of power output under various quantile levels at a given wind speed as model input. The quantile loss function is defined in equation (3).

$$L(y, y^p, q) = \sum_{i=y_i<y_i^p} (1-q)\cdot\left|y_i - y_i^p\right| + \sum_{i=y_i\geq y_i^p} q\cdot\left|y_i - y_i^p\right| \qquad (3)$$

where *y* is the actual power output; y^p is the simulated power output under a given quantile level; *q* is a given quantile level; *i* is the data ordering.

The quantile loss function imposes different degrees of penalties based on the quantile level and the fact that the analog value is greater or less than the actual value. For example, q=0.2 means that the penalty degree is larger when the analog value is larger than the actual value; vice versa.

To facilitate the programming, the quantile loss function is rewritten as shown in the equation (4). Given a set of quantiles, the neural network continuously optimizes the network parameters by learning the training samples. When the quantile loss function converges to its minimum value at the end of the optimization and iteration, the model output is the power value under the corresponding quantile level.

$$L(y, y^p, q) = \sum_{i\in I}\sum_{q\in Q}\left[q\max(0, y_i - y_i^p) + (1-q)\max(0, y_i^p - y_i)\right] \qquad (4)$$

where *I* is the set of data serial number; *Q* is the set of all quantile levels.

To establish a quantile power curve, operational data of many wind turbines are collected and combined. And, the wind speed and power data of these wind turbines are imported as the model input and model output. Meanwhile, at least one quantile level needs to be preset for defining the corresponding quantile loss function and training network. Modelling steps are introduced as follows.

1. Data Cleaning. To filter out the abnormal data by using the data cleaning rules introduced in Section 3.

2. Data Normalization. To avoid the influence of dimensional differences between wind speed and power, the data are normalized in the interval [0, 1].

3. Training the neural network model with quantile loss function. The wind speed is taken as the model input, the power is used as the model output. And, the quantile loss function is used to optimize the neural network model. The number of output neurons is determined by the number of quantiles. Each neuron corresponds to the power output under different quantiles at a given wind speed. To repeat the above steps for all wind speeds to obtain a set of power curves with different quantiles. Reverse Normalization of the model output.

4. CASE STUDY

To take three wind turbines in a Chinese wind farm as examples to validate the proposed quantile power curve model and the performance evaluation index. One-year operational data are used, including the hub height wind speed and power output. The time resolution of the data is 1 minute.

Fig 1 shows the proposed quantile power curves under all confidence levels (or called quantile levels). All normal data of three wind turbines after cleaning is normalized and divided into training set and test set. The given quantile levels are [0.1, 0.2, …, 0.8, 0.9] (quantile levels can be set according to the analysis needs, only need to ensure that the number of neurons of the output layer and the quantile levels are equal). For example, the power curve under 0.1 quantile level means that 10% of the power points are located below this curve. In the figure, the power curves of the nine different colors are the power curves at different quantile levels, and the corresponding quantiles increase from bottom to top. A larger quantile value represents a greater proportion of data points contained under the power curve to the total sample size and a larger probability of $P(p \leq p_q)$.

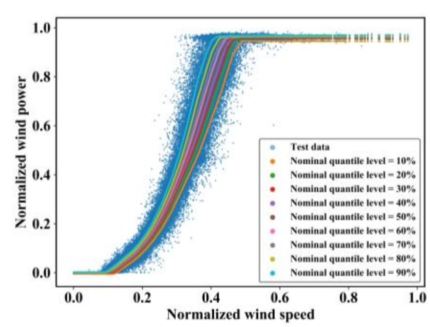

Fig 1 Results of the quantile based wind turbine power curves.

Fig 2 compares the results from the deterministic power curve from the traditional Bins method and the proposed quantile power curves. From the figure, the traditional Bins method generates similar power curve to

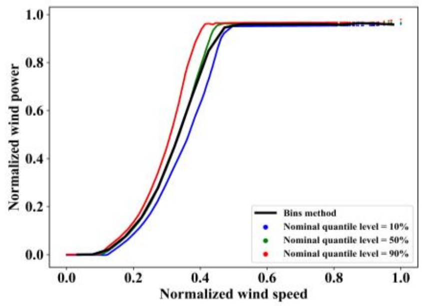

Fig 2 Comparison of Bins method and the proposed method

that of the 0.5-quantile and has large difference compared to the other quantiles. The difference validates the effectiveness of the proposed concept on quantile power curve and can be explained by the uncertainty of relation between wind speed and power output. Even for the Bins-based power curve and 0.5-quantile power curve, there is clear gap between these two power curves around the rated wind speed. This is because that the large uncertainty of the power generation process around the rated wind speed is larger than that under other wind speeds.

5. CONCLUSION

This paper introduces a new concept of quantile power curve and proposes a quantile loss function based neural network algorithm to establish the new quantile power curve. The feasibility and practicability of the proposed model and index are validated based on the real-world data.

(1) The new concept of power curve extends the traditional deterministic power curve and is more intuitive and convenient to apply than the traditional probabilistic power curve. The results show that the proposed model reaches the nominal level at all wind speed ranges and all quantile levels. Compared with the traditional power curve model, the wind power daily profiles can be obtained under different quantile levels, which provides comprehensive information for the decision making of the smart charging and planning of a sustainable electric transportation system.

(2) The proposed quantile power curve model can provide more comprehensive and reliable wind power output information, which is beneficial to the planning and operation of the renewables and electric vehicle charging. In this case study, the use of the quantile power curve in the wind power capacity optimization is also demonstrated. The results show that by using the conservative quantile level, the supply of wind power generation to the charging load can be improved.

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