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A Novel Stochastic Cloud Model for Statistical Characterization of Wind Turbine Output

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ABSTRACT To overcome the problems of wind power forecast for the current deterministic wind power turbine output model cannot accurately describe the statistical characterization of wind turbine output, this article proposes a novel wind power stochastic cloud model. There are three steps to build this model. Firstly, it is necessary to analyze the power data and to filter out the disturbed data by utilizing the improved Bin method and data fitting. Secondly, it is available to obtain respectively two groups of the expectation, entropy and hyper entropy of the waist and upper data of stochastic cloud model by the known and unknown membership of backward cloud generators. Finally, the wind-speed data can be transformed into a stochastic cloud model, which is composed of X condition cloud generator and the positive cloud generator component. In short, the comparative data of the wind power cloud droplets and the measured data of wind power show that the line correlation coefficient of the wind power frequency of the proposed model reaches to 0.8868, which could simulate the statistical characterization of wind turbine output effectively.

INDEX TERMS Backward cloud generator, stochastic cloud model, positive cloud generator, X condition cloud generator, wind power forecast.

I. INTRODUCTION

Low carbon power production, high reliability of power equipment operation, and economy power transmission are the main directions of the future smart grid [1], [2]. Wind power forecast model is the basis of smart grid researches such as wind power simulation analysis, wind farm operating reliability evaluation, and system planning and dispatching operation decision of wind power integration [3], [4]. Currently, wind power can be directly forecasted by using historical data of wind power, and also can be forecasted by wind power model using forecasting wind speed [5], [6]. Accurate wind power model can not only provides the evidence for the safe and highly efficient operation of units, but also facilitates the electric power dispatch department to make dispatching plan [7]–[9]. Therefore, obtaining the forecasting wind-speed is very significant to establish an accurate model.

In this article, the wind turbine output of field operation is not strictly equal to the deterministic value obtained by wind power model, and such a phenomenon that fluctuates randomly in a certain area is called the statistical characterization of wind turbine output. The main reasons for this phenomenon are as follows: the wind turbine is affected by random factors, such as wind speed, air density, and wake effect [10]; there is a lag when the wind turbine adjusts to meet the wind according to the anemometer, which makes an angle between captured wind speed and real wind speed; the continuous dynamic conditions, abrasion, and aging situations of the power output would lead to the unstable power output of the wind turbine. However, wind power models can be roughly divided into fitting model [11], [12] and parameter model [13]–[16], which are based on deterministic mathematical theory. Since the two models that are mentioned above ignore the uncertainty of the statistical characterization of wind turbine output, they can only characterize the mean property of wind turbine output rather than accurately illustrate the statistical characterization of the wind turbine.

In response to these problems, this article introduces the cloud model theory [17]–[19] of uncertainty mathematics theory [20]–[24]. Cloud model, a cognitive model that is uncertain, based on probability theory researching qualitative and quantitative conversion. Unlike classic quantitative

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correlations [25], fuzzy model [26] and gray model [27], Cloud model can use cloud generator algorithm to implement bi-directional transformation between qualitative concept and quantitative data and establish the correlation between fuzziness and randomness [28]. Therefore, this article proposes a novel wind power stochastic cloud model, and defines the combined cloud model, which is described the statistical characterization of the discrete points of the wind turbine output power, as stochastic cloud model. There are four major steps to build this model—dividing the operation data, filtering out disturbed data, obtaining model parameters and making a model. Among them, the fitting curve, the envelope and the symmetrical envelope of the data maximum probability density center disturb data to be filtered out rapidly, and then obtain model parameters by using backward cloud generator, thus building a novel stochastic cloud model. Stochastic cloud model describes the mean property of wind turbine output power by parameter expectation and entropy. Besides, it uses parameter hyper entropy to describe the uncertainty of wind turbine output power under same wind speed. The comparison results of the wind power frequency correlation coefficient show that the proposed model takes full account of the mean and uncertainty of wind turbine output power and describes more accurately the statistical characterization of the wind turbine output.

II. FILTERING PRINCIPLE OF THE IMPROVED BIN

Taking maintenance and brownouts into account in the actual operating of wind turbines, the available wind power data exist so more interference data that cannot be filtered out using the traditional method Bin. Based on the relevant literature [29], an improved Bin is constructed as follow Figure 1.

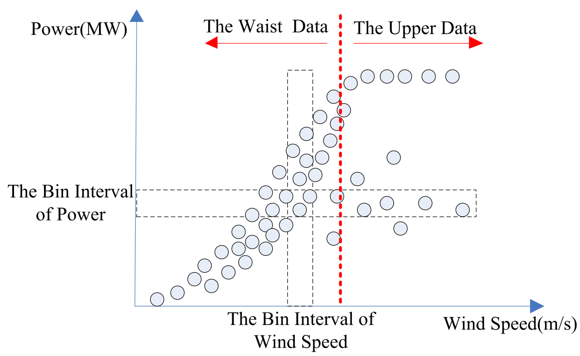

FIGURE 1. Filtering principle of the improved Bin.

As Figure 1 shown, the actual measuring data of the wind power built respectively the power Bin interval and wind-speed Bin interval, and the intersection of which formed a rectangular area. For further analysis, the interval of power is set as 0.05 MW, and the interval of wind speed is set as 0.5 m/s. The detailed procedures for obtaining the probability density center of wind power is as follows:

1) Dividing the wind power value into N intervals. Firstly, keeping the j-th Bin interval of power constant, and moving the Bin interval of wind power from 0 m/s of preliminary wind speed to the positive direction of X-axis, making the step to be 0.1 m/s. And calculating the frequency of power-data points in the rectangular area.

2) Selecting the area which has the maximum frequency of wind power points in step 1 and calculating the value of the probability density center. The relevant equations are shown in the following (1) and (2).

$$v_{m,j} = \frac{1}{S}\sum_{i=1}^{S} v_i \tag{1}$$

$$P_{m,j} = \frac{1}{S}\sum_{i=1}^{S} P_i \tag{2}$$

where, $v_{m,j}$ is the mean of wind speed in the j-th interval of power Bin. $P_{m,j}$ *is* the mean of power in the j-th interval of power Bin. S is the summation of power point in the rectangular area. v_i is the value of wind speed, and P_i is the value of power.

3) The probability density center of wind power can be got by repeating step 1) and 2).

III. THE THEORY OF CLOUD MODEL

A. THE DEFINITION OF CLOUD MODEL

Assuming U is a quantitative theory field of numerical representation, and C is a qualitative concept on U. If quantitative value $x \in U$ is a degree of certainty of qualitative concept C, that $\mu(x) \in [0, 1]$ is a random number with a stable tendency, μ: $U \rightarrow [0,1]$, $\forall x \in U$, $x \rightarrow \mu(x)$. The distribution of x on theory field U is called cloud, namely $C(X)$, and X is a set of quantitative value of x [28]. The cloud model describes the randomness and fuzziness of concept by expectation, entropy and hyper entropy.

B. INVERSE CLOUD GENERATOR

1) THE SITUATION OF KNOWN MEMBERSHIP GRADE

Among the wind power data, if membership grade of lumbar data is known, that lumbar parameters of stochastic cloud model could be calculated by the inverse cloud generator with membership grade. Specific steps are as follows:

1) Using cftool toolbox of Matlab to make Gaussian of maximum probability density center of lumbar data and get the fitting expression $y = a \times \exp\{-[(x-b)/c]^2\}$. The corresponding parameters are (a, b, c).

2) Making the encompassed data probability of both envelope expression $y' = a \times \exp\{-[(x-b)/c']^2\}$ and fitting expression reach 98% of the upper data of fitting curve by increasing the c value of fitting expression. Thus, c' is the one we requested and $\Delta c = c' - c$.

3) After the two steps above, lumbar parameters of stochastic cloud model would be: $Ex_w = b$, $En_w = c$, $He_w = Ex_U = c$.

2) THE SITUATION OF UNKNOWN MEMBERSHIP GRADE

In the proposed model, the upper data fluctuates near the rated power, power data is projected to the Y-axis, and membership grade of data is unknown. In this case, the upper data of stochastic cloud model can be determined by the following steps [28]:

1) When wind power is equal or belongs to $0.97P_r$(P_r is the rated power of wind turbine. $0.97P_r$ is the guaranteed value of wind turbine), wind speed has reached rated value. When the wind speed is higher than rated wind speed and less than cut-out wind speed at the same time, and wind power fluctuate near the rated power, the average power can be calculated by (3).

$$Ex_U = \frac{1}{M}\sum_{i=1}^{M} v_i \tag{3}$$

where, M is the amount of upper wind speed data; v_i is the wind-speed data of upper wind speed.

The second order center distance of wind power:

$$c_2 = \frac{1}{M-1}\sum_{i=1}^{M}(v_i - Ex_U)^2 \tag{4}$$

The fourth order center distance of wind power:

$$c_4 = \frac{1}{M-1}\sum_{i=1}^{M}(v_i - Ex_U)^4 \tag{5}$$

2) Entropy and hyper entropy of upper data of stochastic cloud model:

$$En_U = \sqrt[4]{\frac{9c_2^2 - c_4}{6}} \tag{6}$$

$$He_U = \sqrt{c_2 - \sqrt{\frac{9c_2 - c_4}{6}}} \tag{7}$$

3) THE CLOUD GENERATOR (CG) OF X CONDITION

Input: wind speed $v_{w,i}$ and the three Parameters of the lumbar data of stochastic cloud model Ex_w,En_w and He_w.

Output: Under specified wind speed circumstances, wind power value $P_{w,i}(i = 1, \ldots, n_w)$.

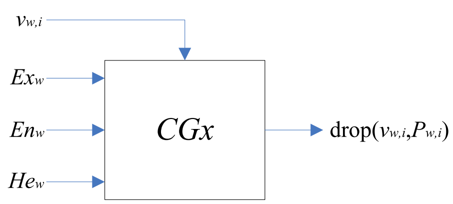

FIGURE 2. X condition cloud generator.

At the upper of statistics cloud model, there is a significant increasing relationship between wind speed and wind power before reaching the rated wind speed. Besides, this increasing relationship exists ambiguity. Thus, it is possible to obtain the uncertain cloud droplets of wind-electric power by X condition cloud generator with the wind speed data. The specific steps for determining cloud droplets of wind-electric power are as follow [17]:

1) First, forming a normal random entropy by the entropy and hyper entropy of the waist of the stochastic cloud model $E'_{nw} = N(E_{nw}, H_{ew}^2)$.

2) Secondly, obtaining droplets of wind-electric power in the setting wind-speed($v_{w,i}$):

$$P_{w,i} = a \times \exp\{-[(v_{w,i} - E_{xw})/E'_{nw}]^2\} \tag{8}$$

3) Repeating these two steps until all the desired droplets of wind-electric power are produced.

4) POSITIVE CLOUD GENERATOR

Input: the expectation, entropy and hyper entropy of the upper data of the stochastic cloud model.

Output: the output of wind power $P_{U,i}$ $(i = 1, \ldots, n_U)$.

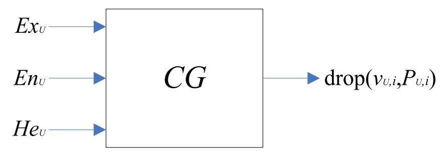

FIGURE 3. Positive cloud generator.

At the upper of statistics cloud model, wind speed has reached the rated wind speed, and there is no significant increasing or decreasing relationship between wind speed and wind power. However, they fluctuate near the rated power. In this case, we can generate the cloud droplets of wind-electric power with the forward cloud generator. The specific steps for determining cloud droplets of wind-electric power are as follow [30]:

1) First, generate a normal random entropy from the waist entropy (Enw) and hyper entropy (Hew) of statistics cloud model $E'_{nU} = N(E_{nU}, H_{eU}^2)$.

2) Secondly, generate clout droplets of wind-electric power $P_{U,i} = N(E_{xU}, E_{eU}'^2)$. The expectation is Ex_U and the standard deviation is E'_{nU}.

3) Repeating these two steps until all the desired cloud droplets of wind-electric power are produced.

IV. THE MODELING PROCESS OF STATISITCS CLOUD MODEL

A. MODELING PROCESS

Modeling the detailed circuit of stochastic cloud model from the measured data of the wind power, as shown in Figure 4.

According to the processes in Figure 4, establishing the stochastic cloud model of wind-electric power.

B. THE INTRODUCITON OF WIND FARM

To illustrate the process of the model building, we would analyze the wind power with measured operational data. Zhangjiakou Wind and Solar Power Energy Demonstration Station Co. Ltd. owned 177 wind turbines and it is subsidiary company XiaoDongLiang country Wind and Solar Power Energy Demonstration Wind Farm possess 24 wind turbines, with type of XuJi WT2000/86, and each wind turbine has

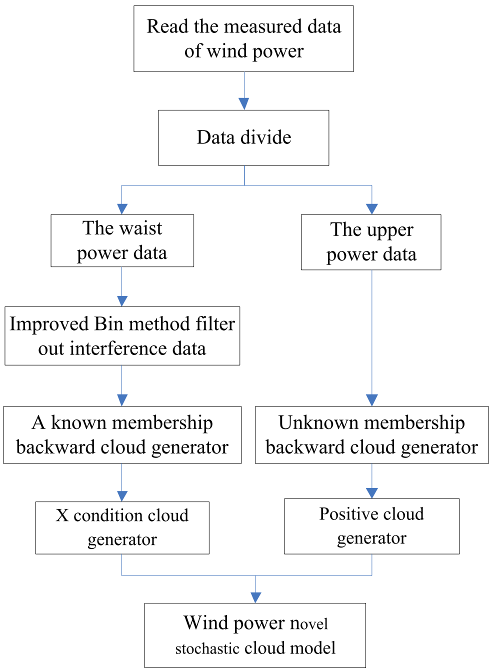

FIGURE 4. Statistics cloud model of wind-electric power.

2MW capability. The parameter of the wind turbine at cut-in speed is $v_{in} = 3.5$m/s, rated wind speed is $v_n = 11$m/s, and cut-out speed is $v_{out} = 25$m/s. With sampling interval of 10 minutes, the data analysis for the No.F001 wind turbine of XiaoDongLiang Wind Farm from October to December can make a distribution diagram of wind power that is shown in Figure 5.

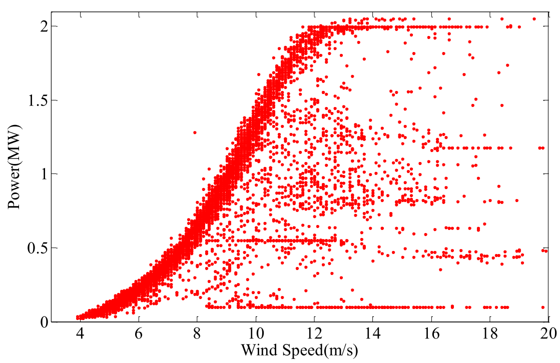

FIGURE 5. Distribution diagram of wind power.

By observing the Figure 5, the available wind power data exists much interference data, which is caused by the maintenance and brownouts in the actual operating of wind turbines. So, it is necessary to divide data and filter out disturbed data firstly.

C. DATA DIVIDING

Dividing the wind power data into two parts and the dividing principle is as follow:

1) Taking the wind-electric powers in the interval of $[0.05P_r, 0.97P_r]$ as waist data;

2) Taking the wind-electric powers in the interval of more than $0.97P_r$ as upper data.

After the proposed division of both above, two parts of power data are obtained as following Figure 6.

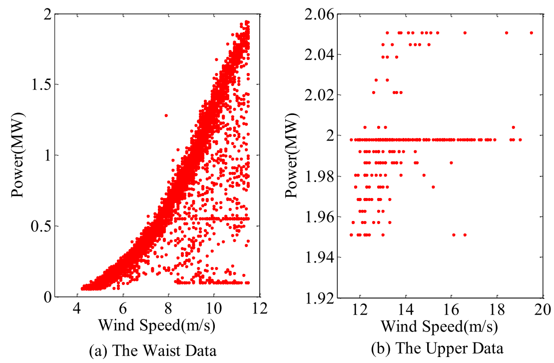

FIGURE 6. Division of power data.

According to the Figure 6 (a), there are huge amounts of disturbance data existed in waist data. And according to the Figure 6 (b), wind turbine power fluctuates around the rated power when the wind speed is equal to the rated wind speed. As the boundary wind speed of both two parts of power data is 11.4m/s, that the rated wind speed is corrected to $v_n = 11.4$m/s, while the cut-out speed is still $v_{out} = 25$m/s.

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D. THE FILTERING OF DISTURBED DATA

Before filtering the disturbed data in the waist, we use improved Bin method to find out the maximum probability of density center. The fitting curve of the maximum probability density center is shown in Figure 7 (a).

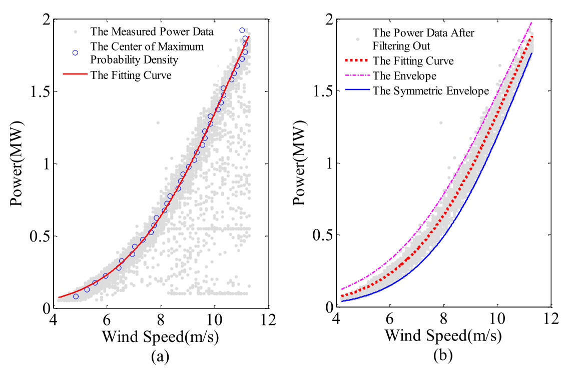

FIGURE 7. The filtering of disturbed data.

Using cftool toolbox in MATLAB to make Gaussian of the point of maximum probability density center in the waist and obtaining the parameters of fitting expression. "Fitting curve" is shown in Table 1.

TABLE 1. Fitting parameters.

Fitting parameters	*a*	*b*	*c*
Fitting curve	2.66 2	14.490 0	5.419 0
Envelope	2.66 2	14.490 0	5.859 0
Symmetric envelope	2.66 2	14.490 0	4.979 0

Wind-electric power fluctuates randomly around the fitting curve in the same wind speed. Obtaining the envelope of the wind power fitting curve by increasing fitting parameter c and getting the symmetric envelope of the fitting curve of wind-electric power by reducing the same amount of fitting parameter c to filter the disturbed data, which is shown in Figure 7 (b).

E. THE CALCULATION OF MODEL PARAMETERS

1) THE PARAMETERS CALCULATION OF THE *X* CONDITION CLOUD GENERATOR THAT DESCRIBE THE WAIST OF STOCHASTIC CLOUD MODEL

As what is shown in Figure 7 (b), the membership grade of the waist data of stochastic cloud model has been known, so it is possible to obtain the corresponding parameters by the solution procedures. The results are shown in Table 2.

TABLE 2. The waist parameters of stochastic cloud model.

Parameters of cloud mode	Ex_w	En_w	Δc	He_w
Values	14.490 0	5.419 0	0.440 0	0.146 7

2) THE PARAMETERS CALCULATION OF THE POSITIVE CLOUD GENERATOR THAT DESCRIBES THE UPPER PART OF THE STOCHASTIC CLOUD MODEL

The membership grade of the upper data of stochastic cloud model is unclear, and the wind-electric power value fluctuates randomly around the average power. By using the solution procedure, we can obtain the corresponding parameters. The results are shown in Table 3.

TABLE 3. The upper parameters of stochastic cloud model.

Parameters of cloud model	Ex_U	En_U	He_U
Values	1.993 6	0.020 8	0.007 7

F. STOCHASTIC CLOUD MODEL

The stochastic cloud model of wind-electric power can be built by using the braking situations of wind turbines, X condition cloud generator and the upper positive cloud generator component. Then, establishing the stochastic cloud model according to the corrected rated wind speed and cut-out speed, which is shown in Figure 8.

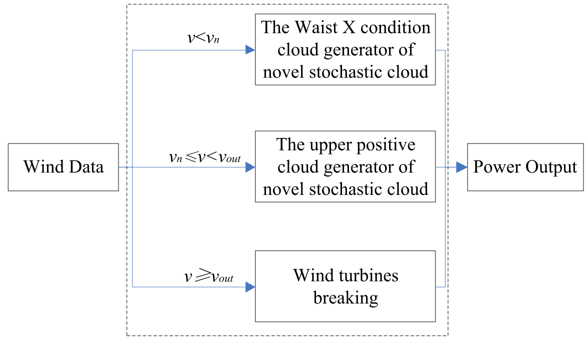

FIGURE 8. The combination chart of stochastic cloud model.

According to Figure 8, we generate the cloud droplets of wind-electric power by X condition cloud generator when the wind speed is less than the corrected rated speed; we generate the cloud droplets of wind-electric power by positive cloud generator when the wind speed is greater than rated speed and less than cut-out speed. The wind turbines that in the braked status do not work, and the wind-electric power is zero when the wind speed is greater than cut-out speed.

G. THE ANALYSIS AND DICUSSIONS OF RESULTS

To compare with the proposed model, we built respectively a wind-electric power parameter model based on the original parameters of the wind turbine and a wind-electric power fitting model based on the measured data of wind-electric power. The parameter solution of parameter model is achieved by formulas in reference [19], and the fitting model parameter is obtained by fitting of the maximum probability density center. The parameters are given in Table 4.

TABLE 4. The parameters of power curve model.

Parameter model	*A*	*B*	*C*	Rated power
Value	0.121 9	-0.084 4	0.014 2	2MW
Fitting model	waist			Average rated power
	a	*b*	*c*	Ex_U
Value	2.66 2	14.490 0	5.419 0	1.993 6MW

Mapping the parameter model and fitting model of wind-electric power according to the data given in Table 4, which is shown in Figure 9.

Transforming the measured data of wind speed into stochastic cloud model to generate the cloud droplets of wind-electric power and then comparing it with the measured data of wind-electric power. The result is shown in Figure 10.

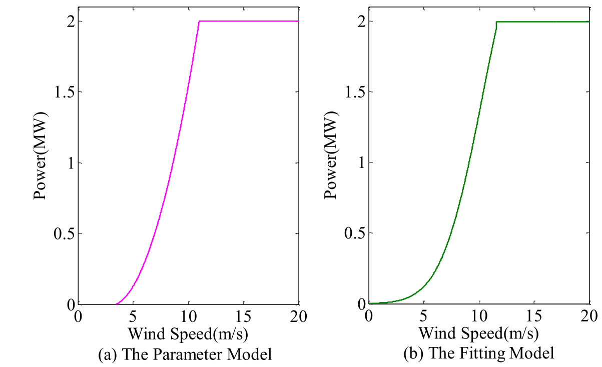

FIGURE 9. The wind-electric power model.

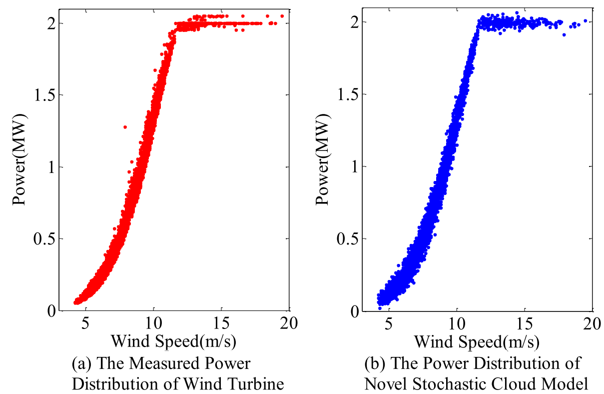

FIGURE 10. The scatter diagram of power.

As is shown in Figure 10, the cloud droplets of wind-electric power generated by stochastic cloud model and the discrete points of measured wind-electric power have similar statistical characterization.

According to the measured wind speed, the generated frequency distributions of wind-electric power of three models are described respectively in Figure 11.

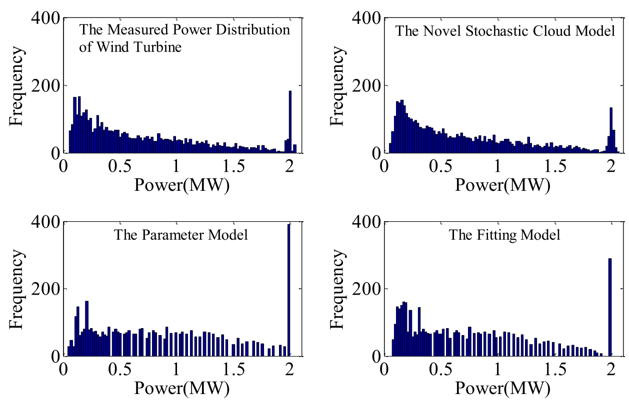

FIGURE 11. The distribution of power frequency.

The frequency distribution of wind-electric power represents the distribution character of wind turbine output. And correlation degree of power represents the similarity degree of the frequency distribution characteristic of the wind-electric power. To effectively contrast the difference of model frequency distributions of the wind-electric power, we respectively calculate the linear correlation coefficients [27] of the frequency distribution of wind-electric power from the three models and compare them with the measured data, which is shown in Table 5.

TABLE 5. Correlation of frequency distribution.

Model	Stochastic cloud model	Parameter model	Fitting model
Linear correlation coefficient	0.886 8	0.720 8	0.731 8

By observing Figure 11 and Table 5, there is a significant difference between the parameter model and measured data of the frequency distribution of wind-electric power, and the linear frequency correlation coefficients are respectively 0.7208 and 0.7318. On the other hand, the frequency distribution of wind-electric power generated by stochastic cloud model is similar to the measured data of frequency distribution of wind-electric power. The maximum linear correlation coefficients of stochastic cloud model reach to 0.8868 when compared with that of parameter model and fitting model, which has better efficiency. Thus, the stochastic cloud model turns out to be a more effective way to illustrate the overall operating characteristics of the wind turbine.

Assuming that there is no power limitation, maintaining or wake flow of the 24 wind turbines of Xiaodong Liang Wind Farm, and the value of wind speed is the same. In this case, applying the same wind speed sequence to three models respectively and generating sequences of wind-electric power respectively, which are shown as follow Figure 12.

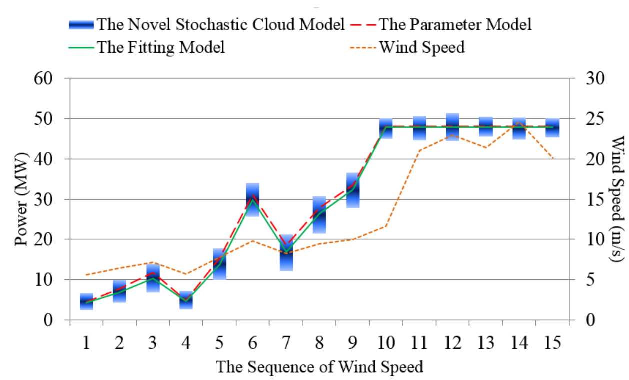

FIGURE 12. The power of wind farm.

As is shown in Figure 12, the parameter model and fitting model of wind-electric power value exist certainty, while stochastic cloud model has uncertainty. The fluctuation range of wind-electric power is indicated by a gradient rectangular, and the parameter model and fitting model of wind-electric power are approximately equal. Meanwhile, the fitting model of wind-electric power goes through the center of the gradient rectangular of the stochastic cloud model. The darker the color of gradient rectangular of stochastic cloud model, the more likely to appear the corresponding value of wind-electric power. With the increase of the distance away from the rectangular center, the color fades gradually, which, indicate that the corresponding value of wind-electric power is less likely to appear, and this value is defined as the center to be a downward trend.

V. CONCLUSION

By the cloud model theory, this article details the processes for establishing a stochastic cloud model of wind-electric power. Besides, a Matlab program has been written to verify the validity of this model. Compared with other models, the maximum linear correlation coefficients of stochastic cloud model can reach to 0.8868 and has better efficiency. The calculation draws follow conclusions:

1) The stochastic cloud model solved the uncertainty of wind-electric power and takes full account of the uncertainty of wind turbine output characterization. So we can describe the overall operating characteristics of wind turbine more accurately.

2) The proposed model can provide a more accurate model for the output of wind farm, and which is located in a power band. It is possible to provide a reference for the system dispatching in the future.

3) The hyper entropy of this model characterizes the uncertainty of wind power in the same wind speed, and which is correlated with the characteristics of local wind speed and the control system operation of the wind turbine. Therefore, the hyper entropy can be applied to illustrate the operation stability of the wind turbine.

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