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Irregular distribution of wind power prediction

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Abstract Wind power is volatile and uncertain, which makes it difficult to establish an accurate prediction model. How to quantitatively describe the distribution of wind power output is the focus of this paper. First, it is assumed that wind speed is a random variable that satisfies the normal distribution. Secondly, based on the nonlinear relationship between wind speed and wind power, the distribution model of wind power prediction is established from the viewpoint of the physical mechanism. The proposed model successfully shows the complex characteristics of the wind power prediction distribution. The results show that the distribution of wind power prediction varies significantly with the point forecast of the wind speed.

Keywords Wind power prediction, Normal distribution, Irregular distribution, Distribution model

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1 Introduction

Wind power forecast error is one of the most challenging issues of dealing with wind in power system operations. There has been substantial research related to wind power prediction error [1–6]. Typical methods include probability distribution of the wind speed and its prediction error, as well as the wind power and its prediction error. A wind speed forecasting model is primarily divided into a time series prediction model and a probability distribution forecasting model. The time series prediction model primarily describes the changes of the wind speed between adjacent time periods, reflecting the correlation of wind speed during the adjacent time [7–9]. Typical time series prediction models include the autoregressive moving average model, neural network model [10], and support vector machine model [11–18]. The support vector machine model can be utilized for both point forecasting and probabilistic forecasting [19]. A probability distribution forecasting model describes the probability distribution characteristics of the wind speed, and the mean wind speed in a period of time. The Gamma, Weibull, normal and Beta distribution models are most often used in this area. Reference [20] statistically analyzes the wind speed in a region and fits the wind speed prediction error to the Weibull distribution. In [21], the authors develop a data-driven feature extraction procedure to utilize un-labeled numerical weather data, and the feature extraction procedure transforms extended numerical weather variables into supplementary input features which then can be used for supervised forecasting models. In [22], the authors give a comprehensive review on the basic approaches, typical patterns and key problems in the probabilistic forecasting of wind power. In [23], the probability distribution model of the wind power is established by a Gaussian mixture model. In [24], a wind power forecasting correction method considering wind speed prediction error is proposed, in which the wind speed prediction error meets the normal distribution.

Empirical distribution models such as normal distribution, Laplacian distribution, beta distribution and Cauchy distribution are suitable for different scenarios. References [25–27] analyze the wind power prediction errors. Reference [28] analyzes the day-ahead wind power forecast errors in Nordic countries. However, the normal distribution cannot accurately describe the error distribution, especially with large-scale wind power integration. According to the historical data, the statistical results show that the normal distribution model is unsuitable if the skewness of the wind power prediction is large. Reference [29] develops a versatile distribution representing forecast errors for all forecast timescales and magnitudes. Reference [30] proposes a piecewise exponential error distribution model. The probability distribution functions of different segments are derived respectively, and the parameters are estimated by the nonlinear least square method. Reference [31] derives the ultra-short-term wind power prediction errors according to their amplitudes and fluctuations, and combines the wind power prediction error model with the probability distribution fitting model to give a better analysis of the wind power forecast error. The authors previously proposed an irregular distribution of the wind power forecast considering the active control of the wind farms. With the active control of the wind farm, the distribution of the wind power is asymmetry [32]. In previous studies, some studies have considered turbine characteristics to model wind power prediction errors. Reference [33] analyzes the relationship between wind speed forecasting and wind power prediction. Assuming wind speed forecast error meets the normal distribution, the wind power forecast can be obtained through the wind turbine curve.

The main contributions of this paper can be summarized as follows.

1) The irregular distribution of wind power is explicitly described based on the relationship between wind speed and wind power of wind turbine.
2) The results show that there are multiple obvious peaks and impulses in the distribution of wind power.

This paper presents a wind power forecasting probability distribution model based on the relationship between wind speed and wind power. The distribution of the wind power can be expressed according to the distribution of the wind speed. The relationship between wind power and wind speed is nonlinear. The simulation results show that: ① the wind power prediction distribution can be obviously asymmetric or multimodal in some cases; ② the distribution shape and the number of the peaks are related with the point forecast of the wind power.

The remaining parts of this paper are organized as follows: the limitation of the regular distribution is detailed in Sect. 2; the model of wind power prediction is presented in Sect. 3; simulations and analysis are presented in Sect. 4; discussions on contribution are presented in Sect. 5. Concluding remarks are presented in Sect. 6.

2 Limitation of regular distribution based on statistical data

The traditional wind power forecasting error distribution types include the normal distribution and other mathematical distribution methods. The method based on historical data analysis describes the uncertainty of wind power in the long term, however, neglects the relationship between the distribution of the wind power prediction error and the expectation of the wind speed. This type of method will lose some relevant information on the wind speed distribution.

In the following, we take the normal distribution as an example and analyze its disadvantages. The output of wind power can be expressed by type (1):

$$P_w = P_w^{pre} + \varepsilon_w^{pre} \tag{1}$$

where P_w is the realistic wind power; P_w^{pre} is the wind power forecast; ε_w^{pre} is the wind power forecast error. Assuming that the wind power error satisfies the normal distribution, Laplacian distribution or beta distribution, the distribution can be shown in Fig. 1.

If the normal distribution is used to establish the probability distribution model of wind power, it is often assumed that the wind power prediction error obeys the normal distribution of a 0 expectation.

$$P = \mu_p + \varepsilon \tag{2}$$

where ε is the prediction error of wind power, and it is subjected to a normal distribution, that is to say, $\varepsilon \sim N\left(0, \sigma_p^2\right)$, its probability density function is:

$$f(P) = \frac{1}{\sqrt{2\pi}\sigma_p} e^{\frac{(P-\mu_p)^2}{2\sigma_p^2}} \tag{3}$$

where μ_p is the expectation of the random variable P; σ_p is the standard deviation of the random variable P; These distributions are obtained by statistical historical wind prediction error data over a long period of time.

The method based on historical data analysis describes the uncertainty of wind power in the long term, however, it neglects the relationship between the distribution of the wind power prediction error and the expectation of the

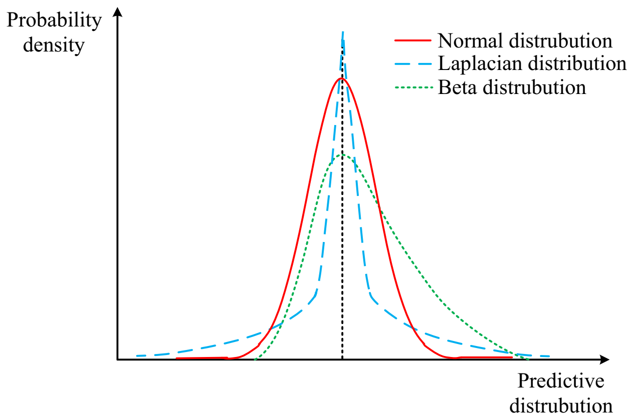

Fig. 1 Distribution of wind power forecasting error

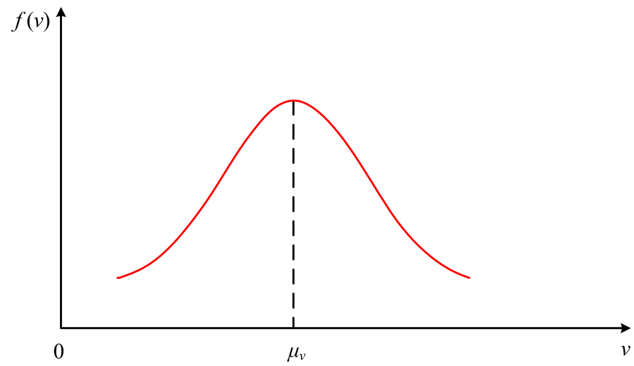

Fig. 2 Probability distribution of wind speed

wind speed. This type of method will lose some of the relevant information on the wind speed distribution.

3 Model of wind power prediction based on relationship between wind speed and wind power

3.1 Curve of "wind speed–wind power"

Based on the relationship between the wind speed and wind power, the distribution of the wind power forecast error considering the expectation of wind speed is deduced. The day-ahead wind speed prediction error is determined by using the numerical weather prediction (NWP) technology. Different prediction techniques will have different forecast errors of the wind speed forecast. The wind speed forecast error distribution is also affected by the location, altitude, geographical environment of the wind farms, as well as the prediction period. When the prediction period is relatively long, the prediction of wind speed tends to be a normal distribution under the influence of the central limit theorem. Therefore, it is assumed that the wind speed is a random variable v, and that the random variable satisfies the normal distribution $N\left(\mu_v, \sigma_v^2\right)$, which is shown in (4) and described by Fig. 2:

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} e^{\frac{(v-\mu_v)^2}{2\sigma_v^2}} \tag{4}$$

where μ_v is the expectation of wind speed and the standard deviation σ_v of the wind speed increases with the increase of the prediction period.

After the wind speed forecast error distribution is determined, the distribution of wind power can be indirectly obtained according to the conversion relationship of the wind turbine. Based on the relationship between the wind speed and wind power, the wind power distribution considering the expectation of wind power is shown in Fig. 3.

Wind power is primarily affected by the wind speed and air density, and the air density varies very little for a short time in the same area. Therefore, the influence of wind speed is primarily considered when fitting the wind power. Reference [28] shows that the relationship between wind speed and wind power can be described as shown in Fig. 4 where V_{in} is the cut-in wind speed; V_{out} is the cut-out wind speed; V_r is the rated wind speed; P_r is the power rating. When the wind speed is smaller than the cut-in wind speed, the wind machine cannot overcome the resistance of its operation, so there is no output power; when the wind speed is between the cut-in wind speed and the rated wind speed, the wind turbine speed increases as wind speed increases, thus the output power increases; when the wind speed reaches the rated wind speed, output power reaches the rated power; when the wind speed exceeds the cut-out speed, the output power is 0.

The scatter plot and the fitted curve of "wind speed–wind power" are given as follows.

The relationship between the wind power and the wind speed can be described by:

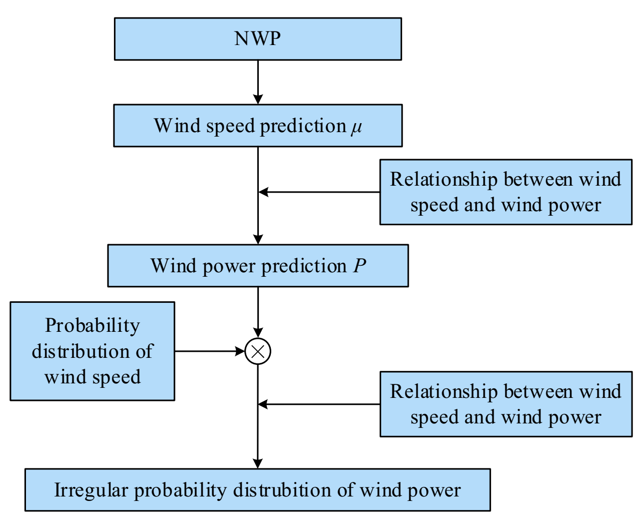

Fig. 3 Steps on modeling of wind power forecasting

$$P(v)=\begin{cases}0 & 0<v<V_{in}\\ a_0+a_1v+a_2v^2+a_3v^3 & V_{in}\le v<V_r\\ P_r & V_r\le v<V_{out}\\ 0 & v\ge V_{out}\end{cases} \tag{5}$$

From the historical data of wind power and statistical data of the wind speed, the curve of "wind speed–wind power" (5) is fitted by the least square method.

3.2 Wind power forecasting probability model

In [34], the probability distribution of wind speed is assumed to be the normal distribution $N(\mu_v,\sigma_v^2)$. Based on the hypothesis and the curve of "wind power-wind speed", the distribution of wind power can be derived as:

$$f(P,v)=\begin{cases}\left(\int_{-\infty}^{V_{in}}f(v)\mathrm{d}v+\int_{V_{out}}^{+\infty}f(v)\mathrm{d}v\right)\delta(P) & P=0\\ f(v) & P=a_0+a_1v+a_2v^2+a_3v^3\\ \left(\int_{V_r}^{V_{out}}f(v)\mathrm{d}v\right)\delta(P) & P=P_r\end{cases} \tag{6}$$

1) When the wind speed is less than the cut wind speed or greater than the cut wind speed, the value of the wind power is 0. So the probability of the wind power 0 is corresponding to the cumulative probability of wind speed $v\in(-\infty,V_{in})\cup(V_{out},+\infty)$.
2) When the wind speed is $v\in(V_{in},V_r)$, the probability of the wind power is immediately obtained from one to one mapping between the wind power and the wind speed.
3) When the wind speed is between the rated wind speed and the cut wind speed, i.e. $v\in(V_r,V_{out})$, the wind power is holding at the maximum value. Therefore, the probability value of wind power is the cumulative probability of wind speed $v\in(V_r,V_{out})$.

From the above derivation (6) and the normal distribution $N(\mu_v,\sigma_v^2)$ of wind speed, the distribution of the wind power can be given as:

$$f(P,v)=\begin{cases}\left(\frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{V_{in}}\exp\left(-\frac{(v-\mu_v)^2}{2\sigma^2}\right)\mathrm{d}V+\frac{1}{\sqrt{2\pi}\sigma}\int_{V_{out}}^{+\infty}\exp\left(-\frac{(v-\mu_v)^2}{2\sigma^2}\right)\mathrm{d}v\right)\delta(P) & P=0\\ \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(v-\mu_v)^2}{2\sigma^2}\right) & P=a_0+a_1v+a_2v^2+a_3v^3\\ \left(\frac{1}{\sqrt{2\pi}\sigma}\int_{V_r}^{V_{out}}\exp\left(-\frac{(v-\mu_v)^2}{2\sigma^2}\right)\mathrm{d}v\right)\delta(P) & P=P_r\end{cases} \tag{7}$$

Remark 1 There are many distribution models of wind speed. The above method can be applied in not only the normal distribution of the wind speed, but also in other distribution models. In Sect. 4, based on the normal distribution and the Weibull distribution, the simulation results will be given.

4 Case study

According to the historical data of the wind power and wind velocity as the average sample in [33], the overall wind power curve is fitted using the least square method. In this model, the cut-in wind speed is 3.07 m/s, the rated wind speed is 11.19 m/s, and the cut-out speed is 20 m/s. The relationship between wind power and wind speed is shown as:

$$P(v)=\begin{cases}0 & v<3.07\\ 36.14-25.53v+5.14v^2-0.21v^3 & 3.07\le v<11.19\\ 99.82 & 11.19\le v<20\\ 0 & v\ge 20\end{cases} \tag{8}$$

From the normal distribution of the wind speed and (8), the probability distribution of wind power is deduced as:

$$f(P,v)=\begin{cases}\left(\dfrac{1}{\sqrt{2\pi}\sigma}\displaystyle\int_{-\infty}^{3.07}\exp\left(-\dfrac{(v-\mu_v)^2}{2\sigma^2}\right)\mathrm{d}v+\dfrac{1}{\sqrt{2\pi}}\displaystyle\int_{20}^{+\infty}\exp\left(-\dfrac{(v-\mu_v)^2}{2\sigma^2}\right)\mathrm{d}v\right)\delta(P) & P=0, v\in(-\infty,3.07)\cup(20,+\infty)\\ \dfrac{1}{\sqrt{2\pi}\sigma}\exp\left(-\dfrac{(v-\mu_v)^2}{2\sigma^2}\right) & P=36.14-25.53v+5.14v^2-0.21v^3, v\in(3.07,11.19)\\ \left(\dfrac{1}{\sqrt{2\pi}\sigma}\displaystyle\int_{11.19}^{20}\exp\left(-\dfrac{(v-\mu_v)^2}{2\sigma^2}\right)\mathrm{d}v\right)\delta(P) & P=99.82,\quad v\in(11.19,20)\\ 0 \quad P>99.82 & \end{cases} \tag{9}$$

Case 1: Assuming wind speed is satisfying the normal distribution.

When the wind speed point forecast $\mu_v = 2$ m/s, the standard deviation $\sigma = 2$, the point forecast of the wind power is 0, and the distribution of the wind power forecast is shown in Fig. 5. When the wind speed point forecast μ_v=-10 m/s, the standard deviation $\sigma = 2$, the point forecast of the wind power is 84.84 MW, and the distribution of the wind power forecast is shown in Fig. 6. When the wind speed point forecast $\mu_v = 15$ m/s, the standard deviation $\sigma = 2$, the point forecast of the wind power is 99.82 MW, and the distribution of the wind power forecast is shown in Fig. 7.

From Figs. 5, 6 and 7, the distribution of the wind power cannot be expressed by the normal distribution. The detailed analysis is given as follows:

1) The range of wind power varies from 0 to a maximum of 99.8 MW, consisting of a smooth curve with a paragraph or two of impulse functions.
2) When the wind speed is lower than the cut-in wind speed or higher than the cut-out wind speed, the probability density of the wind power concentrates at 0, and the wind power is 0 MW with a higher impulse function.

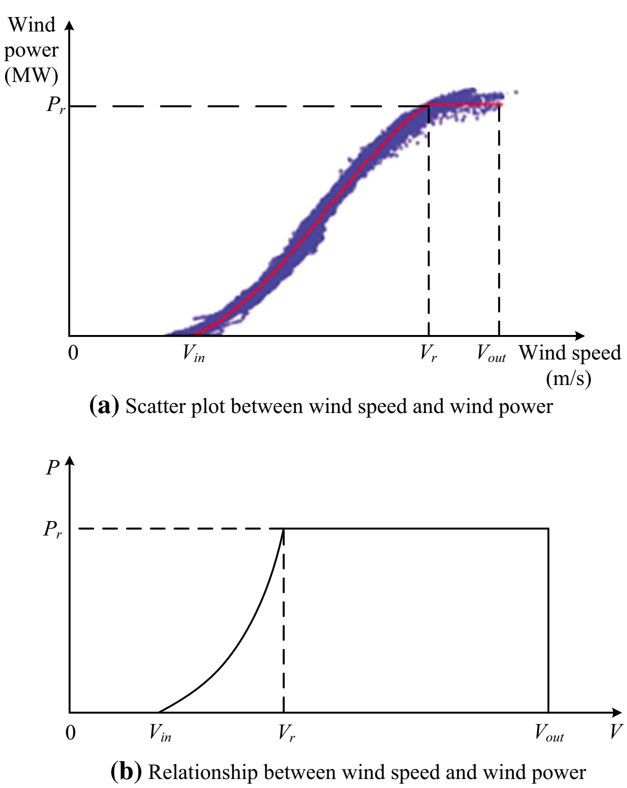

Fig. 4 Scatter plot and relationship between wind speed and wind power

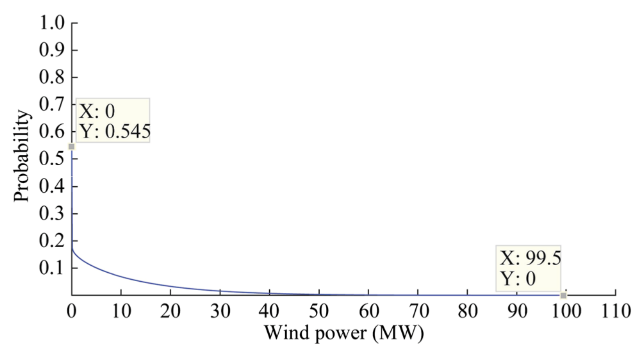

Fig. 5 Probability of wind power when $\mu_v = 2$ m/s

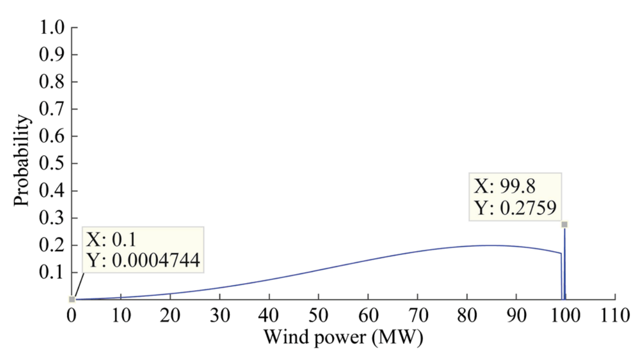

Fig. 6 Probability of wind power when $\mu_v = 10$ m/s

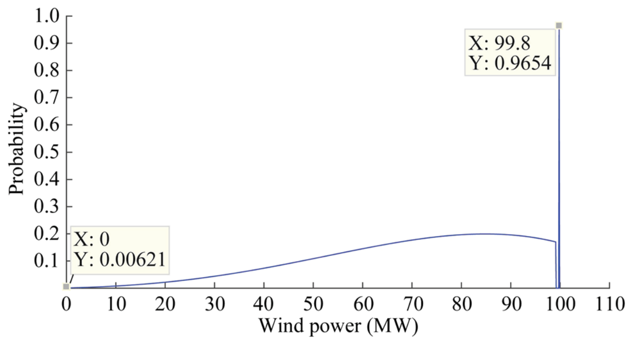

Fig. 7 Probability of wind power when μ_v = 15 m/s

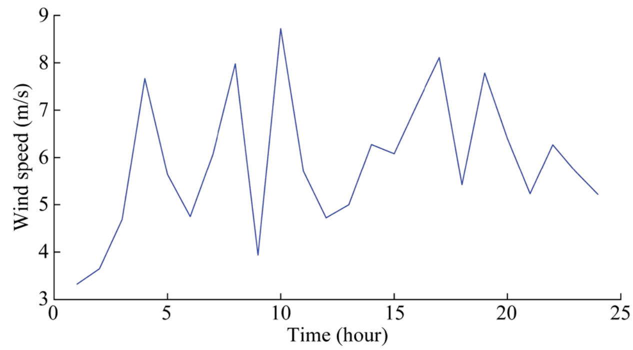

Fig. 8 Curve of μ_v

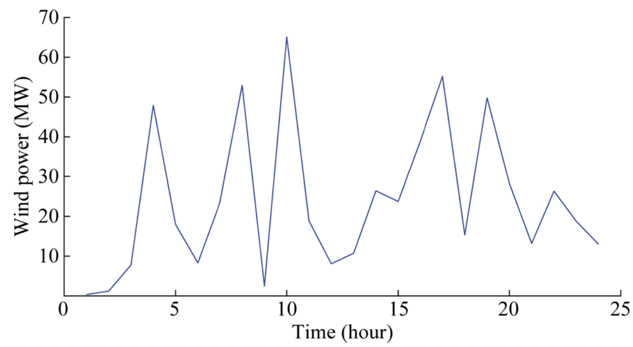

Fig. 9 Curve of $P(\mu_v)$

Table 1 24-hour (1 day) prediction of wind speeds

Time (h)	μ_v (m/s)	$v - \mu_v$ (m/s)	$P(\mu_v)$ (MW)
1	3.31982977	1.50	0.350436990
2	3.64722857	1.50	1.211501695
3	4.68761778	1.51	7.779282893
4	7.66592380	1.52	47.88348168
5	5.63812086	1.54	17.95354078
6	4.74832638	1.56	8.322456410
7	6.06583650	1.59	23.53265259
8	7.97647716	1.62	52.95451869
9	3.93715527	1.66	2.484125266
10	8.71997702	1.70	65.11388539
11	5.70904028	1.76	18.84107956
12	4.72256339	1.82	8.089998397
13	4.99874247	1.90	10.72727689
14	6.27414409	1.98	26.43060491
15	6.08094159	2.07	23.73908197
16	7.11252583	2.16	39.01984606
17	8.11065738	2.25	55.15461443
18	5.42167262	2.35	15.34541932
19	7.78314669	2.45	49.79261825
20	6.40350967	2.56	28.28291364
21	5.23277662	2.66	13.20087873
22	6.26860184	2.78	26.35211713
23	5.70305709	2.89	18.76559554
24	5.21316905	3.00	12.98566427

3) When the wind speed is between the rated wind speed and the cut out wind speed, wind power density focuses on the value of 99.8 at the maximum. Therefore, the wind power is 99.8 MW with a high impulse function.
4) When the wind speed is between the cut-in wind speed and the rated wind speed, the probability distribution of wind power can be described by the normal distribution.

In order to study the time variation of complex distributions of wind power, the following simulation is analyzed. The 24-hour (1 day) prediction data of wind speeds are shown in Table 1. The expectation of the wind speed is μ_v, and the error $v - \mu_v$ gradually increases. Based on the relationship between wind speed and wind power, the wind power $P(\mu_v)$ is calculated according to the different point forecasts of the wind speed.

The point forecast of wind speed μ_v and the point forecast of wind power $P(\mu_v)$ are different at different time points, which are shown in Figs. 8 and 9.

Case 2: Assuming a wind speed satisfying the Weibull distribution.

It is assumed that the wind speed is a random variable.

The random variable satisfies the Weibull distribution, which is shown in (10).

$$f(v) = \frac{b}{a}\left(\frac{v}{a}\right)^{b-1}\exp\left[-\left(\frac{v}{a}\right)\right]^{b} \tag{10}$$

where $a > 0$, $b > 0$. The cumulative distribution function is given in (11).

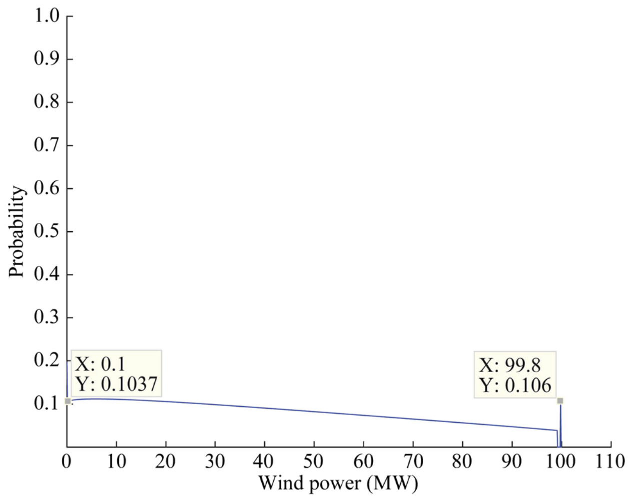

Fig. 10 Probability of wind power when a = 7.12, b = 1.77

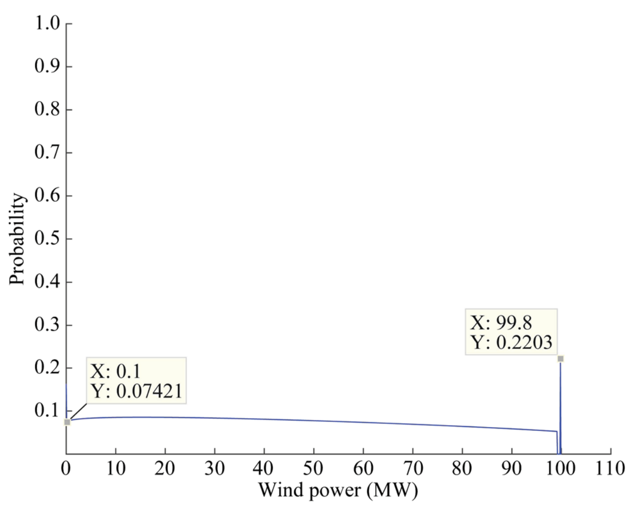

Fig. 11 Probability of wind power when a = 9.12, b = 1.7

$$F(v) = 1 - \exp\left[-\left(\frac{v}{a}\right)\right]^{b} \tag{11}$$

when a and b in (11) are with three different values (a = 7.12, b = 1.77; a = 9.12, b = 1.7; a = 5.27, b = 1.2), the prediction curves of wind power are shown in Figs. 10, 11 and 12 respectively.

Based on the wind power complex distribution, the variation curve of the wind power error distribution in the 24-hour period is obtained, as shown in Fig. 13. The blue part of the figure represents the probability density distribution under different wind power point forecasts. Deeper color indicates higher probability density. The red line represents the point forecast of the wind power. From Fig. 13, it can be determined that the accuracy of the day-ahead prediction will gradually decrease while the error gradually increases.

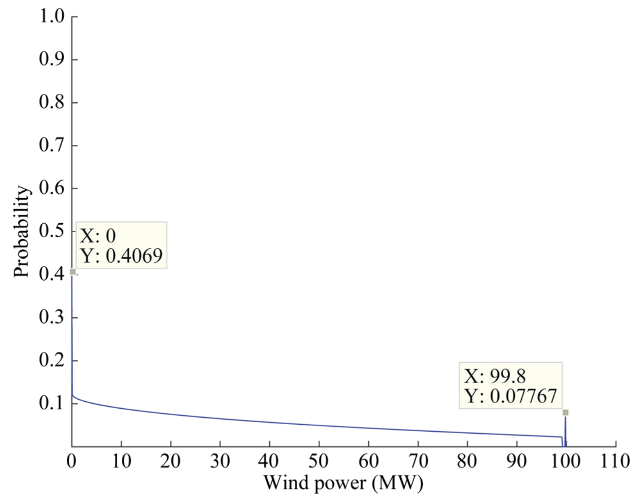

Fig. 12 Probability of wind power when a = 5.27, b = 1.2

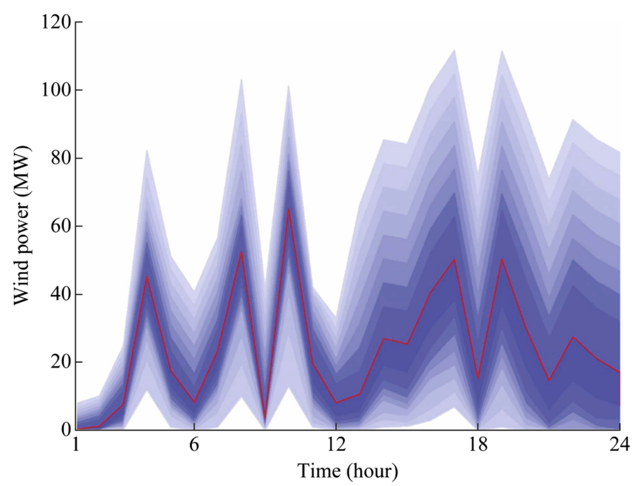

Fig. 13 Distribution of wind power forecasting

From the above simulation, the wind power prediction distribution shows its complexity, which is given as:

1) The distribution of the wind power forecast is asymmetry. The distribution can be a partial peak, and have different peak values.
2) The wind power prediction distribution varies with the wind speed prediction, and the numbers of the peak will change. When the wind speed forecast is low, the wind power is distributed in the left side in the forecast distribution, and the peak may appear at 0 MW, if it exists. When the wind speed forecast is high, the wind power is distributed in the right side in the forecast distribution, and the peak may appear at the maximum MW, if it exists.

There are three typical cases: ① When the wind speed is less than the cut-in wind speed or greater than the cut-out wind speed, the turbine does not produce the wind power. So the wind power will be 0 at the peak, while the rest value is with the smaller probability; ② When the wind speed is near the rated wind speed, the wind power will maintain its maximum with the maximum probability. So the wind power will be the maximum value at the peak; ③ When the wind speed is the cut-out wind speed, the distribution of the wind power output will peak at 0 MW and the rated power. Thus the distribution will peak at the 0 MW and the maximum power.

The wind power prediction error probability distribution is very complex due to the nonlinear relationship between the wind speed and wind power: when the wind speed is less than the cut-in wind, the wind power is 0; when the wind speed is between the cut-in wind speed and the rated wind speed, the wind power will be the smooth output; when the wind speed is between the rated wind speed and the cut-out wind, the wind power will maintain its maximum power; when the wind speed is greater than the cut-out wind speed, the wind power will be 0. Therefore, based on the nonlinear relationship between wind speed and wind power, the prediction distribution of wind power is complex.

5 Discussions on contribution

From the above research, it can be seen that the distribution of wind power is irregular. Compared with the related research, the main contribution of this paper is that the irregularity characteristics of wind power are derived based on a strict theoretical deduction. The existing work is primarily based on the analysis of historical data [17] or based on a supervised learning method, such as artificial neural networks [16, 34]. Based on the proposed method, the irregular distribution of wind power can be revealed in its essence, and then the results of this paper are extensive and easier to be understood.

Recently, our research team has applied the model proposed in this paper to solve a probabilistic unit commitment problem. Due to the limitation of space, detailed content will be introduced in another paper, and a brief introduction is given as follows.

1) Because the probability distribution of wind power is irregular, the analytical method is hardly applicable to the unit commitment problem, and the scenario-based method is an alternative.
2) The core of the scenario-based method is the selection of typical scenarios. One of the key issues is to select the most representative scenarios. For the irregular distribution model, we can select just one scenario in the peak point and use a traditional scenario selection method for other points in the distribution.
3) The selected scenarios are more representative than the ones which are selected by the traditional uniform method. Meanwhile, the selected scenes based on the irregular distribution are more suitable for the solution to the probabilistic unit commitment.

6 Conclusion

Based on the relationship between wind speed and wind power with the wind generator, the irregular distribution of wind power is explicitly described. Furthermore, the complexity of the proposed model is analyzed through simulation. The simulations demonstrate that there are obvious multiple peaks and impulses in the distribution of wind power. The results of this paper will be significant for understanding the uncertainty of wind power, and may further improve wind power forecasting, probabilistic load flow calculations and probabilistic unit commitment problems.

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