Analysis and model on space-time characteristics of wind power output based on the measured wind speed data

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Abstract: Most of the existing studies on wind power output focus on the fluctuation of wind farms and the spatial self-complementary of wind power output time series was ignored. Therefore the existing probability models can't reflect the features of power system incorporating wind farms. This paper analyzed the spatial self-complementary of wind power and proposed a probability model which can reflect temporal characteristics of wind power on seasonal and diurnal timescales based on sufficient measured data and improved clustering method. This model could provide important reference for power system simulation incorporating wind farms.

1. Introduction

With the installed capacity of wind power increasing, the pattern of large-scale and centralized integration of wind power in China is a big challenge for safe and economic operation and power balance of power system [1-5]. Since wind energy source is affected by temperature, air pressure, topography, altitude, latitude, and so on, wind source is very stochastic. So, building an appropriate model on wind energy source or wind power is beneficial for understanding the randomness, fluctuation and intermittence of wind energy resource itself.

Most of the existing studies on wind power output focus on the fluctuation of wind farms. The method in reference [6] and reference [7] at first filters and idealizes wind power time series, then divides wind power time series into wind process and fragment and counts the transition probability of wind processes and probability distribution of fragments, at last samples sequentially wind processes and fragments to acquire simulated wind power time series. Reference [8] presents a new method for wind speed modeling of multiple time scales based on Weibull distribution, which uses the maximum likelihood method to estimate the parameters of Weibull distribution on multiple time scales uses the improved fuzzy c-means cluster method to classify these parameters. Reference [9] adjusts the historical data according to the change of installed wind capacity, and uses the adjusted data to power system analysis. Reference [10] uses diffusion process based on stochastic difference equation to simulate wind power time series. In reference [11], wind power time series are studied by spectral analysis method and wind speed time series are obtained through inverse wavelet transform. The method in reference [11] cannot simulate the randomness and fluctuation of wind speed. The method in reference [12] uses Markov Processing to simulate wind power output time series and doesn't

consider the correlation of wind source of large time scale. Reference [13] builds a wind speed forecasting model based on the seasonal periodicity and time continuity of wind speed and considers the wind power output of a day as a unit. In the researches mentioned above, spatial self-complementary of wind power output time series was ignored and the probabilistic analysis models cannot reflect temporal characteristics of wind power.

In view of the above problems, this paper analyzed the spatial self-complementary of wind power. The characteristics of wind power output change rates every 15 min, maximum simultaneity rate of the wind power output, and the gap between peak load and valley load in different areas are studied. And the paper proposes a probability model which can reflect temporal characteristics of wind power on seasonal and diurnal timescales based on improved clustering method. This model could provide important reference for power system simulation incorporating wind farms.

2. Space-time characteristics of wind power output

Wind power is fluctuant and space-time characteristics of wind power output analysis is the foundation of large-scale wind power integration for power system. To accommodate the wind power as much as possible, spatial self-complementary of wind power should be analyzed from the point of renewable energy resources self-complementary. Wind energy resources in China are mostly in northwest and coastal areas and because of the pattern of large-scale and centralized integration, wind power has the self-complementary characteristic in the same wind area.

2.1. spatial characteristics

The smoothing effect on output fluctuation of distributed wind turbines could be expected for a large area [14]. With the increase in size, the ratio of fluctuation of distributed wind turbines and total capacity decreases and the impact of stochastic wind power on power grid declines, which is contributed to dispatching.

2.1.1. Self-complementary As shown in figure 1, the maximum simultaneity rate of the wind power output of Beijing-Tianjin-Tangshan power grid (BTT) is 65% based on the measured data and that of state grid is only 49%, which shows that the maximum simultaneity rate of wind power output decreases and the smoothing effect on output fluctuation of distributed wind turbines could be expected with the increase in size. The spatial self-complementary of wind power output is expected. Analyzing the spatial self-complementary of wind power output is important to increase the credible capacity.

2.2. Analysis of fluctuation of wind power and frequency regulation of power grid based on self-complementary

With the example of Xinjiang power grid, spatial self-complementary is illuminated and ability of frequency regulation of power grid is calculated to check whether it can satisfy the fluctuation of wind power or not.

The probability of wind power output change rates in every 15 minutes in Mayitasi wind farm(49.5MW), Tacheng wind farm(297MW), wind farms in northwest area of Xinjiang power grid(841.5MW), and wind farms over the whole Xinjiang power grid(3232.25MW) are shown in figure 2.

According to the above figure, probability of that wind power output change rates every 15 min in Mayitasi wind farm is bigger than 1% is 50%, that in Tacheng wind farm is 26%, in northwest area is 12% and in Xinjiang power grid is 8%. That is to see, wind power output change rates every 15 min decrease with the increase in size. Probability of that wind power output change rates every 15 min in Xinjiang power grid is bigger than 10% (259MW) is 0.003%. The larger the wind farm, the more smoothing effect could be expected and the smaller wind power output change rates every 15 min is.

The main generators in Xinjiang power grid are thermal power units and hydroelectric units. The installed thermal capacity is 20715.8MW and installed hydroelectric capacity is 2614.5MW. The

speed of frequency regulation of thermal generators whose capacity is bigger than 300MW is 2% of capacity every min, and those of thermal generators whose capacity is smaller than 300MW is 1% of capacity every min and of hydroelectric generators is 20% of capacity every min. Considering that some small hydropower and small thermal power don't take part in frequency regulation, the speed of frequency regulation in Xinjiang power grid is 689.3MW every min and can satisfy the fluctuation of wind power.
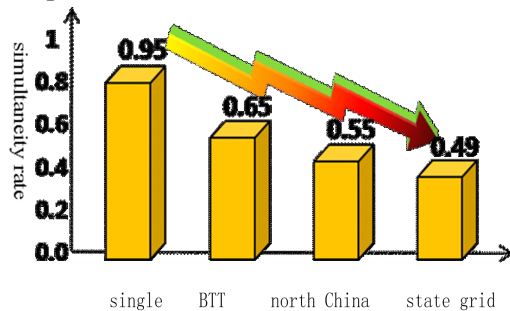
Figure 1. Maximum simultaneity rate of the wind power output on different spatial scales
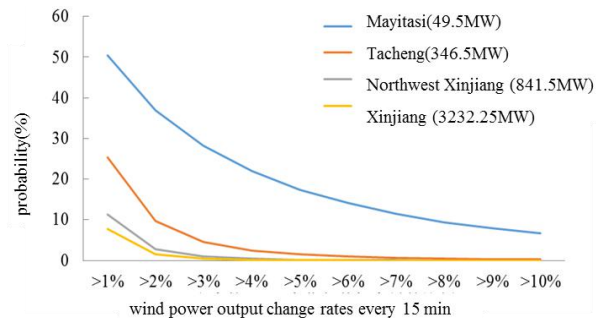
Figure 2. The probability of wind power output change rates in every 15 min in different areas

2.3. Analysis of self-complementary scales

Maximum simultaneity rate of the wind power output on different spatial scales and in different season and distribution of the gap between peak load and valley load on different spatial scales of eight wind farms in Xinjiang power grid are calculated and analyzed to find the appropriate self-complementary scale.

The time horizon of wind power in these wind farms is from 2010-1-1 to 2010-12-31, and the temporary resolution is 15 minutes. Parameters are calculated in the scope of 50km, 100km, 400km and 500km with the center of Guodiantianfeng wind farm. Information of wind farms in Xinjiang province is shown in table 1.

**Table 1.** Information of wind farms in Xinjiang province.

distance	name	capacity(MW)
50km	Guodiantianfeng	159
	Shuiliting	40
	Zhongjieneng	100.5
100km	Xiaocaohu	99
	Baiyanghe	99
400km	Mayitasi	49.5
500km	Buerjintianrun	49.5
	Wulandabusen	99

Maximum simultaneity rate of the wind power output of single wind farm, all wind farms in the scope of 50km, 100km, 400km and 500km are calculated one by one. As shown in figure 3, maximum simultaneity rate of the wind power output decreases with the increase in scales.

The distribution of the gap between peak load and valley load of single wind farm, all wind farms in the scope of 50km, 100km, 400km and 500km are calculated one by one. As shown in figure 4 and figure 5, the maximum and average value of gap between peak load and valley load decreases with the increase in scales.
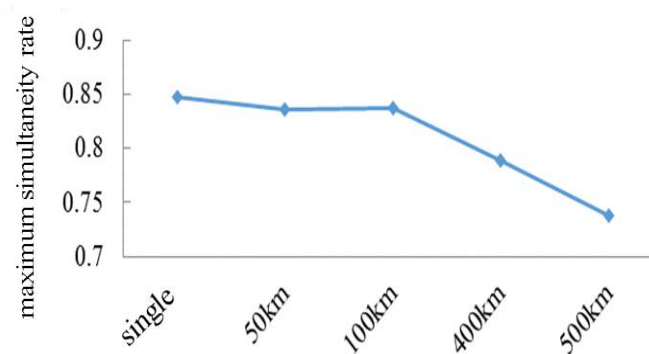
Figure 3. Maximum simultaneity rate of the wind power output on different spatial scales.
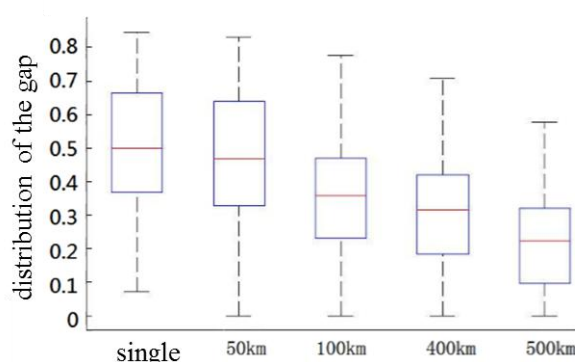
Figure 4. The distribution of the gap between peak load and valley load on different spatial scales
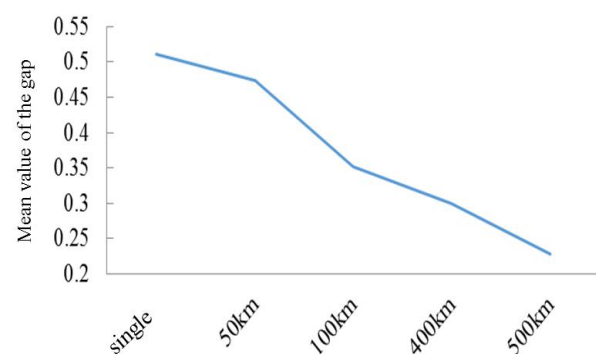
Figure 5. The average value of the gap between peak load and valley load on different spatial scales

The appropriate self-complementary scale of different scope is determined by maximum simultaneity rate and gap between peak load and valley load of the wind power output. According to the above analysis, maximum simultaneity rate and gap between peak load and valley load decrease with the increase in size.

2.4. Temporal characteristics

2.4.1. Fluctuation of wind power output
The extent and discipline of fluctuation of wind power output are different in different time scales [15]. Using the wind power data of a wind farm in Shangdong province, the fluctuation of wind power output in temporal scale is analyzed. Where the installed capacity is 49.5MW and sampling period of data is 0.2s. The curves of wind power output in 12h, 1h, 15min, and 1min are shown in figure 6,figure 7, figure 8 and figure 9. Results shown that the maximum fluctuation of wind power output in 12h, 1h, 15min and 1min is 55.4%, 41.6%, 23.7% and 6.8% of rated capacity. Besides, the curve of wind power output in 1s is almost straight. So, researchers can choose appropriate temporal scale for different research.

The probability distributions of the largest wind power output change rates are shown in figure 10. From the figure, we can see that the probability of that largest wind power output change is smaller than 10% of rated capacity in 1min, 15min and 1h is 99.74%, 76.16% and 8.8%. Fluctuation of wind power output in short period is bigger than in long period. It is important to study the fluctuation of wind power output in short period.
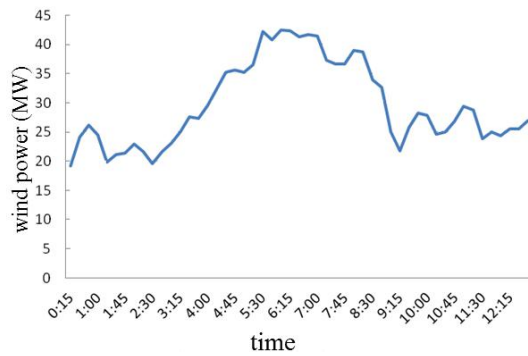
Figure 6. Wind power output in 12h
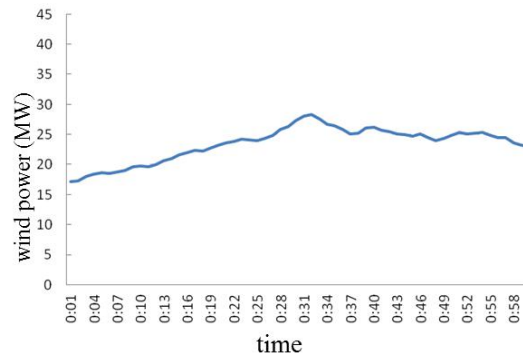
Figure 7. Wind power output in 1h
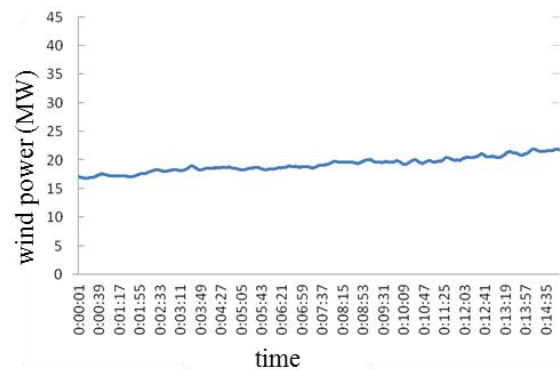
Figure 8. Wind power output in 15min
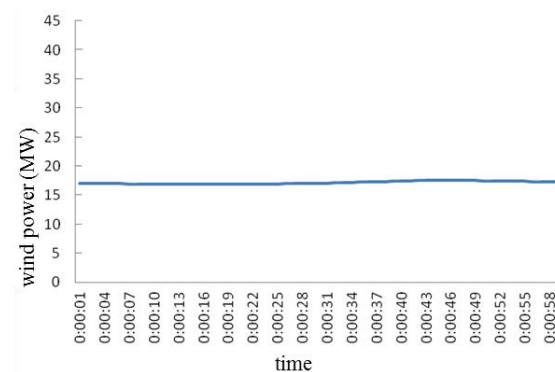
Figure 9. Wind power output in 1min
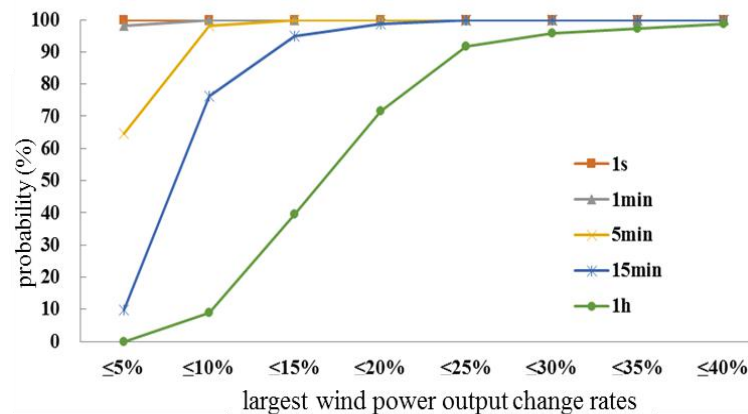
Figure 10. The probability of the largest wind power output change rates

2.4.2. Fluctuation characteristics on different temporal scales
A large number of studies have been published which propose the probability distribution functions to describe wind speed, such as Rayleigh distribution, Lognormal distribution, Weibull distribution, etc. Weibull distribution is by far the most adopted one among them because it can give a good fit to the measured data. The probability density function of Weibull distribution can be mathematically as follows:

$$f(v) = k / c(v/c)^{k-1} \exp[-(v/c)^k] \tag{1}$$

Wind speed, which can be described by Weibull distribution, are analyzed on horizontal and vertical time scale.

In different wind area, wind energy resources present different features, such as seasonal rhythms, diurnal patterns of a day, etc. Where v is the wind speed value in m／s ; k is the shape factor representing the slope of the distribution; c is the scale factor representing average speed.
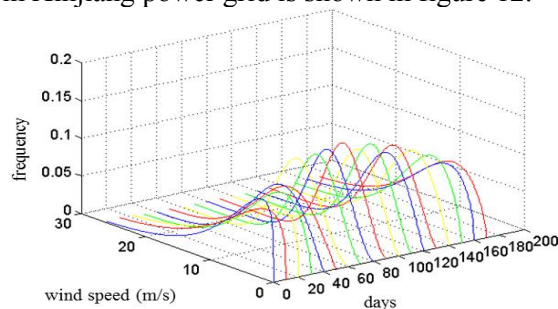
　　a）Horizontal time scale

The probability model on horizontal time scale is obtained through the sliding of sliding window. 18 Weibull distributions can be fitted through wind speed data of a year. Where the length of sliding window is 30 days and the step of sliding is 20 days.

The Weibull distribution model on horizontal time scale of a wind farm in Xinjiang power grid is

shown in figure 11. The peak and skewness of Weibull distribution change as time passes.

　　b）Vertical time scale

Vertical time scale takes wind speed data at the same time every day of a year to fit the distribution. More specifically, 365 or 366 points of the same time every day are used to fit the distribution. As the temporal resolution of wind speed data is 10 minutes and there're 144 wind speed data each day, 144 Weibull distributions can be fitted on this time scale. For the vertical time scale, it shows changes of wind speed from hour to hour in a day. The Weibull distributions on vertical time scale of a wind farm in Xinjiang power grid is shown in figure 12.

Figure 11. Weibull models on the horizontal time scale
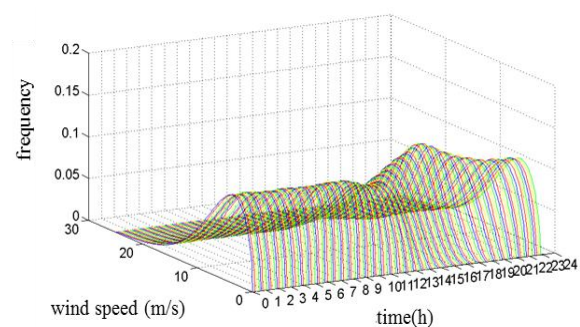
**Figure 12.** Weibull models on the vertical time scale

Through the comparison of models on horizontal time scale and vertical time scale, the change of model on horizontal time scale is bigger, which accords with the actual situation in Xinjiang.

3. Probability model on wind power

The parameters of Weibull distribution on horizontal time scale and vertical time scale can be classified into clusters according to their similarity by improved fuzzy c means clustering method [16].

Clustering is an unsupervised classification process based on the characteristics of the samples generally [17], [18]. Fuzzy c means clustering method (FCM) achieves classification by searching the minimum of the objective function and modifying cluster center matrix and membership matrix repeatedly. The convergence of the algorithm is proved. But as FCM is a local search algorithm, it is very sensitive to the selection of initial values. If the selection of the initial cluster centers is improperly, it is easy to converge to a local minimum point. And the speed of clustering will decreases because of a large number of iterations. Moreover FCM is also very sensitive to outlier data [19].

To solve these issues, the density clustering algorithm, subtractive clustering method (SCM) is employed to obtain the initial cluster centers. The initial cluster centers are adopted to participate in the iteration of FCM, and the impact of isolated points on the final clustering results can be reduced in this way. To ensure that each iteration approach towards the global optimum direction, the algorithm can be optimized by correcting the membership matrix and the cluster center matrix to accelerate the speed of the convergence [18]. The flow chart of the cluster-based Weibull model is shown in figure 13.
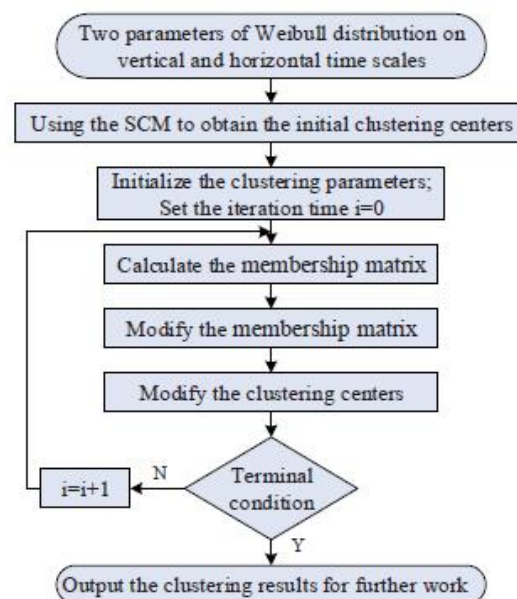
Figure 13. Clustering flow diagram

And the final clustering results can be obtained by iterations. After the clustering results are obtained, making the maximum value of membership as a particular type to stand the class. And its cluster center can represent the shape factor and the scale factor of the traditional two-parameter Weibull distribution of this class, which correspond to a period of time. The model on the horizontal time scale can be mapped to different seasons of a year and the model on the vertical time scale can correspond to different periods of a day.

Using the models on multiple time scales and improved fuzzy c means clustering method, the models on wind speed of a wind farm in Xinjiang is built.

3.1. Model on horizontal time scale
The model on horizontal time scale shown in figure 14 represents the seasonal rhythms of a year. The figure shows the parameters on horizontal time scale are unimodal. The deeper the color is in the figures, the stronger the average wind speed is and the richer the wind energy resources are.
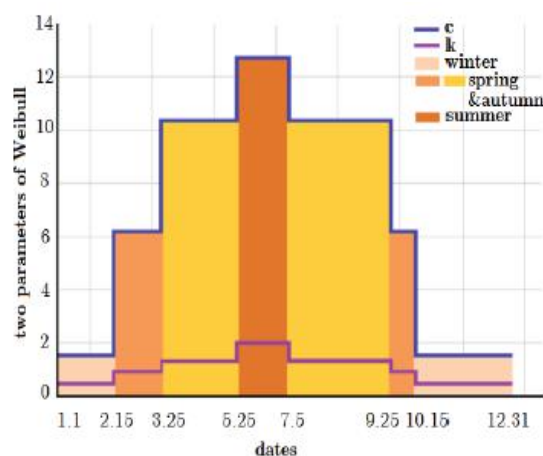
Figure 14. The models on the horizontal time scale
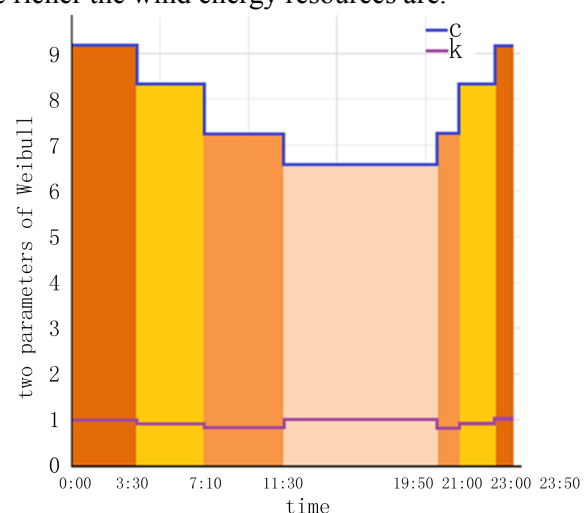
Figure 15. The models on the vertical time scale

The figure shows out obviously seasonal rhythms in a year. The models are divided into seven periods by eight dates of a year. And these periods correspond to the four seasons in a year. And the c and k representing wind in winter is 1.4865 and 0.4178. The c and k representing wind in spring and autumn is 6.1459, 0.8979, 10.3009, and 1.2785. The c and k representing wind in summer is 12.6799 and 1.9603. The figure shows the parameters on horizontal time scale are unimodal. The parameters in summer are larger than that in winter. The wind resources in summer is the richest and the wind resources in winter is the most poor.

3.2. Model on vertical time scale

The model on vertical time scale shown in figure 15 represents the diurnal patterns of a day. The model is divided into seven periods by eight time points of a day. The parameters are shown in table 2. The parameters in the afternoon are larger than that in the morning. There are obviously diurnal patterns in a day. The wind resources from 23:00 to 3:30 is the richest and the wind resources in the noon is the most poor.

Table 2. The Parameters of the models on the vertical time scale.

range	c	k
	7.2442	0.8214
	9.1808	0.988
	6.5754	0.985
	8.3331	0.9079

At last, the probability model on wind speed can be converted to the probability model on wind power by the function of wind power and wind speed. The wind power model is the foundation of power system analysis.

4. Conclusion

This paper analyzes the smoothing effect on spatial scale and fluctuation characteristics of wind power output on temporal scale. The research shows that the proportion of fluctuation of wind power output and rated capacity decreases with the increase in size. According to analyzing the maximum simultaneity rate of the wind power output and distribution of gap between peak load and valley load, the appropriate self-complementary scale can be evaluated. The probability of wind power output on temporal scale is concerned with the length of time. Besides, the paper builds the models of wind speed on horizontal and vertical time scale based on the Weibull distribution and improved fuzzy c means clustering method. The results of clustering of horizontal Weibull distribution parameters show out obviously seasonal rhythms in a year. The models are divided into seven periods by eight dates of a year. And these periods correspond to the four seasons in a year. The parameters in summer are larger than that in winter. Therefore, we can see that the wind resources in summer is the richest and the wind resources in winter is the most poor. The results of clustering of vertical Weibull distribution parameters show out the diurnal patterns of a day. The models are divided into five periods by six time points of a day. The parameters in the afternoon are larger than that in the morning. The horizontal and vertical models are more rational and practical than the traditional Weibull distribution and are the foundation of power system simulation.

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