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# Cluster Wind Power Uncertainty Model and Operation Simulation Method

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**Abstract.** The rational modelling of wind power uncertainty is the premise of relevant analysis and decision-making. The uncertainty, intermittent nature of cluster wind power and the spatial correlation between different wind farms are the key factors to determine the impact of cluster wind power on the power system. The rationality of the wind power uncertainty model will determine the validity of the wind power uncertainty analysis and decision-making model and the credibility of the analysis conclusions. The development of wind power in China is very rapid, but the accumulation of wind power and meteorological statistics is insufficient. The research on the uncertainty of cluster wind power output is not deep-going. For this reason, the wind power uncertainty model is taken as the entry point. This paper will establish the uncertain model of wind power and its simulation method. This method can generate time series of wind farm output in accordance with wind power uncertainty characteristics, and effectively analyze the overall output characteristics of large-scale cluster wind power to be planned in the future, which provides a new idea for studying the impact of wind power on future power systems.

## 1. Overview

The rational modelling of wind power uncertainty is the premise of relevant analysis and decision-making. The uncertainty, intermittent nature of cluster wind power and the spatial correlation between different wind farms are the key factors to determine the impact of cluster wind power on the power system. The rationality of the wind power uncertainty model will determine the validity of the wind power uncertainty analysis and decision-making model and the credibility of the analysis conclusions. The development of wind power in China is very rapid, but the accumulation of wind power and meteorological statistics is insufficient. The research on the uncertainty of cluster wind power output is not deep-going.

At present, there are three main problems in the analysis of cluster wind power uncertainty:

(1) The analysis stays at the level of actual data and does not deep into the height of the model and method. At present, the existing research on wind power uncertainty is based on the statistical analysis

of the collected wind power historical data, but does not propose a widely applicable model. When the object of analysis is changed, the reference and significance of it are limited.

(2) The detailed modelling of the spatial correlation of wind farms is less. For cluster wind power, the spatial correlation between wind farms is an important factor in determining its overall output characteristics and its impact on the power system. At present, the research on the spatial correlation of wind farms only stays in the qualitative analysis and the calculation of several simple indicators, and there is no mature theoretical support and sufficient empirical analysis.

(3) The perfect wind power operation simulation model is insufficiency. Many wind power research needs to use time series data of wind speed or wind power output, but these data are often difficult to obtain in practice: the wind farms studied may not have been fully put into operation or the wind tower is not built, resulting in insufficient accumulation of wind data; The dispatching operation of wind power farm may be affected by various factors, and its output cannot reflect its true random characteristics. At present, there is a lack of a time series output simulation method that comprehensively considers various operational factors of wind farms.

For this reason, the wind power uncertainty model is taken as the entry point. This paper will establish the uncertain model of wind power and its simulation method. A probabilistic sequence model of load and wind power dependence is established. At the same time, based on the study of wind power intermittent, a set of cluster wind power operation simulation methods [1] that can consider the random characteristics of wind speed, intermittent and spatial correlation are proposed. The relationship between the research content of this paper can be summarized in figure 1.

This paper uses the way of the combination of empirical analysis and mathematical modeling. Because of the wind speed and wind power prediction error time series data used in the analysis are not enough in China, the Wind Integration Datasets[2] of US National Renewable Energy Laboratory (NERL) is selected, which contains wind data from the US and offshore 30,000 wind towers from 2004 to 2006, meanwhile, the database also use the IEC wind power standard power characteristic curve to indicate the "predicted" output and "predicted" forecast output of wind farm, providing important data support for analyzing the uncertainty analysis and modeling of large-scale wind power output. This paper will select the corresponding time series data from the 10 wind towers on the East Coast of the United States in 2004 for an empirical analysis. The geographic locations and their coordinate IDs of the 10 wind towers are shown in figure 2. It should be noted that although the US wind power data is used in this paper, the proposed analytical methods and analytical conclusions are equally applicable to wind farms in China.

## 2. Probability sequence modelling of power system generation and load dependence

The core of power system uncertainty analysis is considering the model and calculation method of uncertainty. In the uncertainty analysis of power system considering wind power, the uncertainty of power generation and load is usually considered at the same time. To this end, this section will establish a probabilistic sequence model of power system generation and load dependence including wind power, load and generator, which will lay the foundation for the uncertainty analysis and decision-making method proposed in the following paper. Copula theory expresses the joint distribution of multiple random variables as the "join" of their respective edge distributions. Therefore, using this theory, the related multiple random variables can be modelled separately according to their edge distribution and dependent structure, which provides great convenience for studying multiple related random variables.

### *2.1. Univariate Edge Distribution Sequence Modeling*

Taking the uncertainty of the long-term output of a single wind farm as an example, taking the capacity discretization common factor as $\bar{C}$, the wind power output discretization sequence length is:

$$N_w = < C_w / \bar{C} > \tag{1}$$

$C_w$ in formula (1) is the installed capacity of the wind power farm. According to the theory of sequence operations, the wind power farm has a total of states of $N_w + 1$, wherein the available capacity of the $i$ state is $(i-1)\bar{C}$. In the process of serialization of wind power farm output, according to historical statistics, the frequencies of the output of each discretized interval wind power farm are separately counted as an estimate of the probability that the output of the wind farm falls into the discretization interval. Taking the statistical one-hour hourly output in one year as an example, the $P_w(j)$ is the output of wind power farm in the $j$ hour, the wind power output sequence $S_w(i)$ can be calculated by the following formula:

$$S_w(i)=\frac{\sum_{j=1}^{8760} I_i[<P_w(j)/\bar{C}>]}{8760}, i=0,1,\ldots,N_w \tag{2}$$

In equation (2), $<P_w(j)/\bar{C}>$ indicates discretization of wind power output data, $I_i(x)$ is an explanatory function.

The modelling principle of load sequence model is the same as the wind power output sequence model. The system load sequence can be generated by using the historical value of the statistical system load and formula (2). This method is also applicable to the serialization modelling of the node load.

In addition to the use of historical statistical values to generate a load sequence model, many studies tend to consider the load as a normal distribution [4-19]. Therefore, a sequence model of load can be established by load mean and variance information. Assume that the load mean value is $\mu$ and the variance is $\sigma^2$. Since the normal distribution is unbounded distribution, it needs to be truncated, and the probability distribution within the range of $\mu \pm 5\sigma$ is serialized. That is $i_{min}=<\mu-5\sigma>$, $i_{max}=<\mu+5\sigma>$, then the sequence model of the load $S_d(i)$ is:

$$S_d(i)=\begin{cases}\displaystyle\int_{-\infty}^{i\bar{C}}\frac{1}{\sqrt{2\pi\sigma^2}}e^{\frac{(x-\mu)^2}{2\sigma^2}}dx & i=i_{min}\\ \displaystyle\int_{(i-1)\bar{C}}^{\pi}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}dx & i=i_{min}+1, i_{min}+2,\ldots,i_{max}-1\\ \displaystyle\int_{(i-1)\bar{C}}^{+\infty}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}dx & i=i_{max}\end{cases} \tag{3}$$

In the uncertainty analysis of power system, the conventional generator set is generally modelled as a two-state model considering the forced outage rate (FOR). Assume that the installed capacity of the unit is $C_s$, the forced outage rate is $F_s$. The available capacity sequence length of the unit is $N_s=<C_s/\bar{C}>$. The available capacity sequence $S_s(i)$ of the unit can be expressed as:

$$S_s^{(0)}(i)=\begin{cases}F_s & i=0\\ 0, & i=1,2,\ldots,N_s-1\\ 1-F_s, & i=N_s\end{cases} \tag{4}$$

For hydroelectric units or thermal power units that consider the operating state of the falling force, they are often modelled as multi-state units[16], and their serialization methods are consistent with the above-described modelling principles.

It should be noted that in the process of serializing the above-mentioned conventional generator set, load, turbine generator system and virtual unit, a unified capacity discretization common factor $\bar{C}$ is required, which will affect the accuracy of the uncertainty analysis.

### *2.2. Dependent structure modelling*

Power system power generation and load-dependent structure refers to the complex relationship between the available capacity of different power generation components and the load of different nodes. It can be seen from the modelling process of the dependent probability sequence which the complex joint distribution function between random variables with different edge distributions can be transformed into the composite function form of their respective edge distributions and their dependent structures by Copula theory. Wherein, the dependent structure can be easily represented by the Copula function. Thus, the modelling process of the dependent structure is transformed into the fitting and parameter identification process of the Copula function, which is then transformed into the process of determining the coefficient of rank correlation between each random variable. Assume that the coefficient of rank correlation matrix between wind power and load is $C_D$. In this section, the modeling of the dependent structure is divided into two cases: the dependent structure modeling considering only active and the dependent structure modeling considering both active and reactive.

Only the active power of power generation and load is considered in the unit combination model and the DC power flow model. At this time, the rank correlation coefficient matrix $C_D$ of wind power and load can be expressed as:

$$C_D = \begin{bmatrix} C_{WP} & C_{WP-LP} \\ C_{WP-LP}^T & C_{LP} \end{bmatrix} \tag{5}$$

In the formula (5), the sub-blocks $\boldsymbol{C_{WP}}$ represent the rank correlation coefficients of the active outputs of different wind farms, and the magnitudes thereof can be estimated by the distance between the wind farms. $\boldsymbol{C_{LP}}$ indicates the correlation between load and active power of different nodes, and it is mainly determined by the type of load (industrial load, commercial load, etc.) supplied by the node and the power supply scale of the node. $\boldsymbol{C_{WP-LP}}$represents the correlation coefficient between wind power and load and is determined by the daily characteristics of the load and wind power. The identification of the above correlation coefficients and the selection of the Copula function can be implemented by the method.

*2.3. The dependent structure modelling of active and reactive power at the same time*

In the calculation of the AC tidal current model, it is necessary to consider both the active power and the reactive power of the power generation and the load. Therefore, the modelling of the dependent structure is more complicated than considering only the active power. In the dependent structures modelling considering active and reactive at the same time, the structure of the rank correlation coefficient matrix $\boldsymbol{C}_D$between load and wind power output is:

$$\boldsymbol{C}_D = \begin{bmatrix} \boldsymbol{C}_{WP} & \boldsymbol{C}_{WP-WQ} & \boldsymbol{C}_{WP-LP} & \boldsymbol{C}_{WP-LQ} \\ \boldsymbol{C}_{WP-WQ}^T & \boldsymbol{C}_{WQ} & \boldsymbol{C}_{WQ-LP} & \boldsymbol{C}_{WQ-LQ} \\ \boldsymbol{C}_{WP-LP}^T & \boldsymbol{C}_{WQ-LP}^T & \boldsymbol{C}_{LP} & \boldsymbol{C}_{LP-LQ} \\ \boldsymbol{C}_{WP-LQ} & \boldsymbol{C}_{WQ-LQ}^T & \boldsymbol{C}_{LP-LQ}^T & \boldsymbol{C}_{LQ} \end{bmatrix} \tag{6}$$

The meaning and calculation method of $\boldsymbol{C}_{WP}$, $\boldsymbol{C}_{WP-LP}$ and $\boldsymbol{C}_{LP}$in equation (6) are the same as it in the formula (5). The other sub-blocks in the matrix (6) are related to reactive power. In theory, these matrices can be obtained by analyzing the synchronized time series with the actual data. However, in practice, the data of wind power reactive power and reactive load are not easy to obtain. Therefore, the rank correlation coefficient sub-matrix related to reactive power can be estimated by.

$\boldsymbol{C}_{WQ}$ and $\boldsymbol{C}_{LQ}$ respectively indicate the rank correlation coefficient of reactive power between the different node loads and the different wind power farms, it can generally be considered to be the same as the corresponding active rank correlation coefficient $\boldsymbol{C}_{WP}$ and $\boldsymbol{C}_{LQ}$.

$\boldsymbol{C}_{WP-WQ}$indicates the rank correlation coefficient between the active output and the reactive output of different wind farms. The diagonal element indicates the co-correlation between the active output and the reactive output of a certain wind farm, which is related to the wind farm control strategy. Generally speaking, wind farms are all powered by a constant power factor, so the diagonal elements of $\boldsymbol{C}_{WP-Q}$ are often close to 1, and the non-diagonal elements of $\boldsymbol{C}_{WP-Q}$ indicate the correlation between the active output of one wind farm and the reactive power of another wind farm. Its' amount can be estimated indirectly by the active power output correlation of two wind power farms and the rank correlation coefficient between active and reactive power output of the wind farm. Assume that the element in $\boldsymbol{C}_{WP}$ is $c^{WP}$, the element in $\boldsymbol{C}_{WP-WQ}$is $c^{WP-WQ}$, then the non-diagonal element in $\boldsymbol{C}_{WP-WQ}$can be estimated by the following formula:

$$c_{ij}^{WP-WQ} = c_{ij}^{WP} c_{jj}^{WP-WQ} \tag{7}$$

That is, the rank correlation coefficient of the active output of the $i$ wind farm and the reactive power of the $j$ wind farm can be approximated as the product of corresponding element in $\boldsymbol{C}_{WP}$ and the corresponding diagonal element to the $j$ wind farm in $\boldsymbol{C}_{WP-WQ}$.

$\boldsymbol{C}_{LP-LQ}$ indicates the rank correlation coefficient of the active load and the reactive load between different nodes, and its' diagonal element indicates the rank correlation coefficient between the active load and the reactive load of the node. Generally, the number of users carried by the node is related to the load characteristic, and The fewer users carried by the node, the more single for the load type, then the stronger the correlation between the active load and the reactive load. The non-diagonal elements of $\boldsymbol{C}_{LP-LQ}$ represent the correlation between the active load of one node and the reactive load of another node, where the size of each element can be estimated indirectly by $\boldsymbol{C}_{LP}$ and $\boldsymbol{C}_{LP-LQ}$:

$$c_{ij}^{LP-LQ} = c_{ij}^{LP} c_{jj}^{LP-LQ} \tag{8}$$

$\boldsymbol{C}_{WQ-LQ}$ indicates the co-correlation between a wind power reactive output and a node reactive load. Generally, it can be considered that the corresponding active rank correlation coefficients are the same.

$\boldsymbol{C}_{WP-LQ}$ represents the correlation between the active output of a wind farm and the reactive load of a node. The size of each element can be estimated indirectly by $\boldsymbol{C}_{WP-LP}$ and $\boldsymbol{C}_{LP-LQ}$:

$$c_{ij}^{WP-LQ} = c_{ij}^{WP-LP} c_{jj}^{LP-LQ} \tag{9}$$

$\boldsymbol{C}_{WQ-LP}$ indicates the correlation between the reactive output of a certain wind farm and the active output of a certain node. The principle of is similar to determination of $\boldsymbol{C}_{WP-LQ}$, as follows:

$$c_{ij}^{WQ-LP} = c_{ii}^{WP-WQ} c_{ij}^{WP-LP} \tag{10}$$

## 3. Cluster wind power operation simulation model and method research

Effective cluster wind power operation simulation is of great significance for studying and planning the output characteristics of wind farms and their impact on the power system. The key to the simulation of cluster wind power operation is to consider the randomness of wind speed, the correlation of multiple wind farms and the volatility of wind speed at the same time. In addition, factors such as wind turbine reliability and wind farm wake effect should be considered.

Based on the study of wind power intermittent, this section uses the stochastic differential equation model introduced in [20] to establish a cluster wind power operation simulation model and method.

### *3.1. Intermittent analysis of wind power*

The intermittent nature of wind power comes from the volatility of wind speed. The effective way to characterize the volatility of wind speed is to use the autocorrelation function, which is the linear correlation coefficient of the sequence of time series and its own time shift. Set $v_t$ is a time series, $\bar{v}$ and $\sigma^2$ is its' mean and variance, then the autocorrelation function $\rho(k)$ of $v_t$ is:

$$\rho(k) = \frac{1}{T}\frac{\sum_{t=1}^{T}(v_t-\bar{v})(v_{t-k}-\bar{v})}{\sigma^2},\ k = 1,2,3\ldots \tag{11}$$

The autocorrelation function is a measure of the temporal correlation of time series, reflecting the magnitude of the volatility of the time series. In general, the value of the autocorrelation function is attenuated by increasing the time difference, and the more intense the time series fluctuation, the faster the autocorrelation function decays. Studies have shown that the autocorrelation function of wind speed can be numerically represented by a negative exponential function:

$$\rho(k) = e^{-\theta k},\ \theta>0, k = 1,2,3\ldots \tag{12}$$

In equation (12), the size of $\theta$ is determined by the speed of the autocorrelation function decay, which in turn can reflect the severity of wind speed fluctuations.

The wind speed time series of a wind tower is selected, and the time interval of the data is 1 hour. The autocorrelation function of the wind speed time series is fitted by the negative exponential function. The result is shown in figure 1. The fitting value $\theta$ of the attenuation coefficient of the wind speed autocorrelation function =0.0904

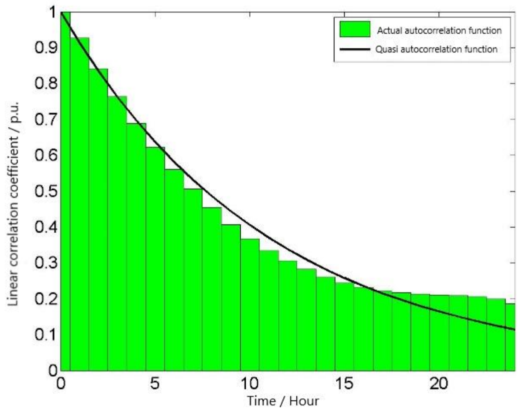


Figure 1. Autocorrelation function and its fitting result of the wind farm (attenuation coefficient =0.0904)

### 3.2. Single wind farm operation simulation model

The cluster wind power operation simulation method proposed in this section uses the stochastic differential equation model introduced in [20]. The model is capable of simulating a stochastic process that yields a given edge distribution and the autocorrelation function obeys exponential decay. Among them, the single wind farm operation simulation model can be briefly described as follows:

**Theorem 1** If the probability density function $f(x)$ is greater than zero, continuous and the variance is limited in its' domain of definition $(l, u)$, its mathematical expectation $E(x) = \mu$, the stochastic process $X_t$ satisfies the following stochastic differential equation:

$$dX_t = -\theta(X_t - \mu)dt + \sqrt{v(X_t)}dW_t,\ \ t \geq 0 \tag{13}$$

Wherein $\theta \geq 0, W_t$ is the standard Brownian motion, $v(X_t)$ is a non-negative function defined on $(l, u)$:

$$v(x) = \frac{2\theta}{f(x)} \int_l^x (\mu - y) f(y)\, dy,\ \ x \in (l, u) \tag{14}$$

Then there are the following conclusions:

(1) The stochastic process $X$ is the ergodic of each state and the corresponding edge probability density function $f(x)$ of its state at each moment.

(2) The stochastic process $X$ is mean-reverting and its autocorrelation function is consistent with:

$$corr(X_{s+t}, X_s) = e^{-\theta t},\quad s, t \geq 0 \tag{15}$$

A stochastic process model can be established by using the above theorem. The corresponding probability distribution of the state of the stochastic process at each moment (hereinafter referred to as the probability distribution of the stochastic process) obeys the Weibull distribution, and its autocorrelation function obeys the exponential decay. The sample with the fixed time interval of the random process is generated as the wind speed time series, and the running simulation of the single wind farm can be realized by combining the wind turbine standard power characteristic curve, the reliability model and the wind farm wake effect.

Set the wind speed meet the Weibull distribution with the scale parameter $c$ and the shape parameter $k$, then the average wind speed is $\mu$:

$$\mu = E(X) = c\Gamma\left(\frac{1}{k} + 1\right) \tag{16}$$

The expression of the Weibull distribution and the definition of the function $v(X_t)$ according to equation (1):

$$\upsilon(x) = \frac{2\theta}{f(x)}\int_l^x(\mu - y)f(y)\,dy = \frac{2\theta}{f(x)}\left(\mu F(x) - \int_l^x yf(y)\,dy\right)$$
$$= \frac{2\theta}{f(x)}\left(c\Gamma\left(\frac{1}{k}+1\right)\left(1 - exp\left[-\left(\frac{x}{c}\right)^k\right]\right) - c\Gamma\left(\left(\frac{x}{c}\right)^k, \frac{1}{k}+1\right)\right) \quad (17)$$

Wherein, $F(x)$ is the corresponding distribution function for$f(x)$, $\Gamma(a)$is a gamma function

$$\Gamma(a) = \int_0^{+\infty} y^{a-1}e^{-y}dy \quad (18)$$

$\Gamma(x,a), x \geq 0$ is incomplete gamma function

$$\Gamma(x,a) = \int_0^x y^{a-1}e^{-y}dy \quad (19)$$

In summary, a single wind farm output time series $\hat{v}_t$,$t = 1,2,\ldots,T$can be calculated iteratively by the following formula:

$$\hat{v}_t = \hat{v}_{t-1} + dX_t \quad (20)$$

The wind speed sequence of the wind farm is not a completely random process. For the weather reasons, the wind speed of the wind farm in different seasons is different and has certain regularity (such as small in winter and large in summer). In one day, the average wind speed at different times in the day is different (such as large at night and small during the day), due to the different surface temperatures of the wind farm. In order to consider the seasonality of the wind speed and the regularity in one day of the wind farm, the generated wind speed sequence $v_t$ is corrected as follows:

$$v_t = k_h k_m \hat{v}_t \quad (21)$$

Among them, $k_m(m = 1,2,\ldots,12)$ is the seasonal factor for wind speed, $k_h(h = 1,2,\ldots,24)$ is the daily characteristic factor for wind speed.

Using the corrected wind speed sequence$v_t$, considering the output characteristic curve of wind turbine generator, the wind farm wake effect and the wind farm wind turbine output reliability, the wind farm timing output curve can be generated by the following formula:

$$P_t = n_t(1-\eta)C(v_t k_h k_m) \quad (22)$$

Among them, $C(x)$ is the output characteristic curve of wind turbine generator,$\eta$ is the wind farm wake effect coefficient, which indicates that the wind farm loses its output due to the wake effect, which is usually 5%~10%, $n_t$is the number of units available for the wind farm, which is a random variable and is the number of wind turbines available in the wind farm. If it is assumed that the unit fault in the wind farm is subject to an independent exponential distribution, then for any time$t$, the available wind turbines in the wind farm is subject to Bernoulli distribution, which can be obtained by random sampling.

### *3.3. Cluster wind farm operation simulation model*

The key to the simulation of cluster wind farm operation is to generate wind speed sequences containing spatial correlation. According to the theorem and its properties of using multiple stochastic differential equations to generate multiple stochastic processes in [20], it is easy to prove that when$f(x)$ is a normal distribution and$W_t$is a non-independent multiple Brownian motion. Each dimension edge probability distribution corresponding to the time state in its' established multidimensional normal stochastic processes still satisfies the two conditions in the conclusion of Theorem 1, and at the same time, the linear correlation coefficient matrix of the joint probability distribution corresponding to the state of the multi-dimensional normal stochastic process at each moment is the same with the$dW_t$, and the specific proof process for the above conclusions is given in Appendix C. Using the above conclusions, it is possible to design a cluster wind farm operation simulation model similar to the principle of section 2. The cluster wind farm wind speed sequence $X_t = [X_t^{(1)}, X_t^{(2)}, \ldots, X_t^{(N)}]$ can be generated by a number of stochastic differential equations as follows:

$$X_t^{(1)} = -\theta^{(1)}(X_t^{(1)} - \mu^{(1)})dt + \sqrt{\upsilon^{(1)}(X_t^{(1)})}dW_t^{(1)}$$
$$X_t^{(2)} = -\theta^{(2)}(X_t^{(2)} - \mu^{(2)})dt + \sqrt{\upsilon^{(2)}(X_t^{(2)})}dW_t^{(2)}$$

$$\cdots$$
$$X_t^{(N)} = -\theta^{(N)}(X_t^{(N)} - \mu^{(N)})dt + \sqrt{\upsilon^{(N)}(X_t^{(N)})}dW_t^{(N)} \tag{23}$$

$\theta^{(1)}, \theta^{(2)}, \dots, \theta^{(N)}$ indicates the autocorrelation function attenuation coefficient of wind speed of each wind farm, $\mu^{(1)}, \mu^{(2)}, \dots, \mu^{(N)}$ indicates the average wind speed of each wind farm. The function$\upsilon^{(1)}(X_t^{(1)})$,, $\upsilon^{(2)}(X_t^{(2)})$,…, , $\upsilon^{(N)}(X_t^{(N)})$ is determined by the wind speed parameters of each wind farm by formula (24). $W_t^{(1)}, W_t^{(2)}, \dots, W_t^{(N)}$are 1-dimensional Brownian motions, whose linear correlation coefficient in increments $dW_t^{(1)}, dW_t^{(2)}, \dots, dW_t^{(N)}$per unit time is $\Sigma$.

It can be seen from Theorem 1 that the edge probability distributions of each dimension of $X_t^{(1)}, X_t^{(2)}, \dots, X_t^{(N)}$satisfy the two conditions in the conclusion of Theorem 1 respectively. Set the linear correlation coefficient of $X_t^{(1)}, X_t^{(2)}, \dots, X_t^{(N)}$in the joint probability distribution corresponding to each time state is $\Sigma'$. The conclusion in Appendix C is for$f(x)$ in normal distribution and therefore $\Sigma = \Sigma'$ cannot be derived. In fact, for the Weibull distribution, this conclusion is not strictly established. However, since the shape of the Weibull distribution is similar to the normal distribution, it can be inferred that $\Sigma'$ is approximately equal to $\Sigma$ in the numerical value. The actual example in this section shows that the linear correlation coefficient matrix $\Sigma'$ corresponding to the wind speed generated by equation (23) is very similar to $\Sigma$.

It should be noted that the matrix obtained when evaluating the spatial correlation of wind speed is the Kendall rank correlation coefficient matrix. When the simulation is performed by using equation (23), the input matrix is a linear correlation coefficient matrix. After obtaining the wind speed curves of the wind farms, the output curves of multiple wind farms can be generated by the same method as the single wind farm operation simulation.

## 4. Summary

When studying the problem of large-scale wind power consumption in the power system in the future, the actual wind power data is difficult to obtain, which makes it difficult to conduct research on the impact of wind power uncertainty on the power system. Therefore, establishing a reasonable and effective cluster wind farm operation simulation model is a necessary tool for subsequent research. To this end, this paper uses the autocorrelation function model to study the intermittence of wind power, on this basis, using a stochastic differential equation theory, a set of cluster wind power simulation methods that can consider the random characteristics of wind speed, intermittent and spatial correlation are proposed. This method can generate time series of wind farm output in accordance with wind power uncertainty characteristics, and effectively analyze the overall output characteristics of large-scale cluster wind power to be planned in the future, which provides a new idea for studying the impact of wind power on future power systems. This paper not only verifies the effectiveness of modelling of wind power using the theory of dependent probability sequence operation, but also reflects the necessity of considering wind power spatial correlation in uncertain analysis and decision-making of cluster wind power.

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## References

[1] Zhang N, Kang C, Duan C, et al. (2010) Simulation methodology of multiple wind farms operation considering wind speed correlation. International Journal of Power and Energy Systems, vol.30(4), pp.264-173.

[2] National Renewable Energy Laboratory (NERL). (2011) Wind Integration Datasets [2011-04-20], http://www.nrel.gov/wind/integrationdatasets/, webpage.
[3] Hannele H. (2005) Hourly wind power variations in the Nordic countries. Wind Energy,vol. 8(2), pp.173-195.
[4] Borkowska B. (1974) Probabilistic Load Flow. IEEE Transactions on Power Apparatus and Systems, PAS-93(3), pp.752-759 .
[5] Ding M, Li H, Huang K, (2001) Probabilistic Load Flow Analysis Based On Monte-Carlo Simulation, Power System Technology, vol.25(11),pp.10-14,22.
[6] Leite da Silva A M, Arienti V L. (1990) Probabilistic load flow by a multilinear simulation algorithm. IEE Generation, Transmission and Distribution, vol.137(4), pp. 276-282.
[7] Breipohl A, Lee F N, Huang J, et al. (1990) Sample size reduction in stochastic production simulation. IEEE Transactions on Power Systems, vol.5(3), pp. 984-992.
[8] Yu H, Zhong Z, Huang J, et al. (2009)_A Probabilistic Load Flow Calculation Method with Latin Hypercube Sampling, Automation Of Electric Power Systems, vol.33(21), pp.32-35,81.
[9] Li J, Zhang B, (2001) Probabilistic Load Flow Based on Improved Latin Hypercube Sampling With Evolutionary Algorithm, Proceedings of the CSEE, vol.31(25), pp.90-96.
[10] Rosenblueth E. (1981) Two-point estimates in probability. Applied Mathematical Modelling, vol.5, pp.329-335.
[11] Chun-Lien S. (2005) Probabilistic load-flow computation using point estimate method. IEEE Transactions on Power Systems, vol.20(4), pp.1843-1851.
[12] Harr M E. (1989) Probabilistic estimates for multivariate analysis. Applied Mathematical Modelling, vol.5(5),pp.313-318.
[13] Morales J M, Perez-Ruiz J. (2007) Point estimate schemes to solve the probabilistic power flow. IEEE Transactions on Power Systems, vol.22(4), pp.1594-1601.
[14] Hong H P. (1998) An efficient point estimate method for probabilistic analysis. Reliability Engineering & System Safety, vol.59,pp.261-267.
[15] Allan R N, Leite da Silva A M, Burchett R C. (1981) Evaluation Methods and Accuracy in Probabilistic Load Flow Solutions. IEEE Transactions on Power Apparatus and Systems, PAS-100(5),pp.2539-2546.
[16] Wang X, (1988) Optimal Planning of Power System, Hydropower and Water Conservancy Press. 1990.
[17] Wang X. (2013) Stochastic power flow analysis of power system, Journal of Xi'an Jiaotong University, vol.22(3), pp.87-97.
[18] Allan R N, Al-Shakarchi M R G. (1977)Probabilistic techniques in a.c. load-flow analysis. Proceedings of the Institution of Electrical Engineers, vol.124(2), pp.154-160.
[19] Tian W D, Sutanto D, Lee Y B, et al. (1989)Cumulant based probabilistic power system simulation using Laguerre polynomials. IEEE Transactions on Energy Conversion, vol.4(4), pp.567-574.
[20] Bibby B M, Skovgaard M, Sørensen M. (2005) Diffusion-type models with given marginal distribution and autocorrelation function. Bernoulli Journal, vol. 11(2), pp.191-220