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Time Series Model of Wind Speed for Multi Wind Turbines based on Mixed Copula

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Abstract. Because wind power is intermittent, random and so on, large scale grid will directly affect the safe and stable operation of power grid. In order to make a quantitative study on the characteristics of the wind speed of wind turbine, the wind speed time series model of the multi wind turbine generator is constructed by using the mixed Copula-ARMA function in this paper, and a numerical example is also given. The research results show that the model can effectively predict the wind speed, ensure the efficient operation of the wind turbine, and provide theoretical basis for the stability of wind power grid connected operation.

1 Introduction

With the continuous development of economic globalization, energy has gradually increased to a high degree of impact on national security. In order to achieve the sustainable development of human society, to actively develop new energy sources of clean and renewable energy, to seek and explore new energy technologies has become the world's most important strategic task [1], [2]. Compared to other sources of energy, wind power is the most clean energy sources, which will not bring the acid rain, fog and haze caused by traditional energy, and radiation and other hazards caused by nuclear energy [3], [4]. Because of the uncontrollable nature of wind energy, the output power of wind power is unstable, and the volatility and intermittent are obvious. This year, the wind power installed capacity continues to increase, and the security, stability and economy power of grid system will be affected to varying degrees by the impact of wind power [5], [6]. If there is a more objective understanding of the current China's wind power industry status, a scientific identification of influence factors of the intermittency of the wind power generation, and effective measure of stochastic process of large-scale wind power generation, these can provide a very valuable reference for the development of large-scale wind power industry in our country [7].

Wind power is intermittent mainly caused by the random fluctuation of wind speed [8]. Therefore, when study intermitten tdynamic stochastic process of large-scale wind power generation, we should focus on two things. One is that the universality of wind speed time series model for multi wind turbines, the other is why there is less study ontime series model of wind speed for multi wind turbines home and abroad at present [9], [10]. In this paper, we will use time series theory and Copula theory to build the time series model of wind speed for multi wind turbines to study the spatial and temporal correlation of them.

2 Establishment of wind speed time series model for multiple wind turbines

Copula function scientifically and effectively seperated marginal distributions of random variable from the correlation structure of it, and simulate the change of wind speed of wind turbine through the ARMA. Copula function can reflect the correlation of the wind speed time series of multi wind turbines. The process is as follows:

Multi dimensional standardized wind speed time Series $\left\{y=\left(y_{1,t},y_{2,t},......,x_{m,t}\right),t=1,2,......,T\right\}$, Its each one dimensional time series is represented by the ARMA time series model, and the wind speed time series model based on Copula-ARMA multi wind turbines can be expressed as:

$$\begin{cases} y_{z,t}=\sum_{i=1}^{p}\alpha_{z,i}\,y_{z,t-i}+\beta_{z,t}-\sum_{j=1}^{p}\varphi_{z,j}\,y_{z,t-j} \\ \left(y_{1,t},y_{2,t},......,y_{x,t}\right)\sim C_a\left(F_1\left(y_{1,t}\right),...,F_x\left(y_{x,t}\right)\right) \\ v_{z,t}=\mu_{z,t}+y_{z,t}\times\sigma_{z,t} \end{cases} \tag{1}$$

where C_a represents the Copula function describing the correlation structure between wind speed sequences. For the wind speed Copula-ARMA time series model, it not only reflects the time characteristics of the wind speed series, but also combines the spatial correlation of wind speed of the wind turbine, which can fit the actual wind speed well. A deterministic ARMA time series model is composed of a sequence and a sequence. The numerical value of the sequence is generated by the first few moments, and the numerical value is generated by the Gauss white noise in the sequence. The numerical values in the sequence which are generated by the Gauss white noise are generated by the numerical values of the first few moments according to the fixed expressions. So the uncertainty of ARMA sequence is mainly generated by Gauss white noise, and in every simulation, $\theta_{i,t}$ is the only uncertainty factor. Therefore, it can reflect the correlation of the whole wind speed time series through the correlation of Gauss white noise sequence. The correlation degree of the Gauss white noise time series can be expressed by the function:

$$(\theta_{1,t},...,\theta_{x,t}) \sim C_b\left(F\left(\frac{\theta_{1,t}}{\sigma_1}\right),...,F\left(\frac{\theta_{x,t}}{\sigma_x}\right)\right) \tag{2}$$

The $\left(\theta_{1,t},...,\theta_{x,t}\right)$ indicates the multidimensional Gauss white noise sequence; $\left(\sigma_1,\sigma_2,...,\sigma_x\right)$ indicates that the standard deviation of each one dimension $\left\{\theta_{i,t}\right\}$ sequence; $\Phi(\cdot)$ indicates the standard normal distribution function.

In the ARMA time series model, because the $AR(m)$ model is fixed by the first few numerical values, the perturbation is only related to the Gauss white noise $\theta_{i,t}$. According to the model expression: $\frac{\partial y_{i,t}}{\partial \theta_{i,t}} = 1 > 0$.

Due to the transformation invariance theorem of the Copula function, the Copula function is invariant when the multi-dimensional variable is changed unilaterally, so it has the following relations:

$$C_a\left(F_1(y_{1,t}),...,F_x(y_{x,t})\right)=C_b\left(\Phi\left(\frac{\theta_{1,t}}{\sigma_1}\right),...,\Phi\left(\frac{\theta_{x,t}}{\sigma_x}\right)\right) \tag{3}$$

The correlation structure between the multi dimensional wind speed sequence can be expressed by the correlation structure of the Gauss white noise sequence in the wind speed series.Thus, the formula (1) can be converted to:

$$\begin{cases} y_{z,t} = \sum_{i=1}^{p}\alpha_{z,i}\, y_{z,t-i} + \beta_{z,t} - \sum_{j=1}^{p}\varphi_{z,j}\, y_{z,t-j} \\ (\theta_{1,t},\theta_{2,t},......,\theta_{x,t}) \sim C_a\left(\Phi\left(\frac{\theta_{1,t}}{\sigma_1}\right),...,\Phi\left(\frac{\theta_{x,t}}{\sigma_x}\right)\right) \\ v_{z,t} = \mu_{z,t} + y_{z,t}\times\sigma_{z,t} \end{cases} \tag{4}$$

The wind speed time series model based on the hybrid Copula-ARMA is constructed, and the simulation process is as follows:

(1)The wind speed of the wind turbine is simulated by the ARMA time series model, and the standard wind speed sequence $\left\{x_{k,t}\right\}$ is obtained;(2)The generation of T Gauss white noise sequences which obey m-dimensional Copula function;(3)Combined with the standard wind speed sequence and the Gauss white noise sequence, the wind speed simulation sequence can be obtained according to the formula 4.

3 Example analysis

In this paper, the wind speed measured data of G provincial wind farm in China in March 2012 was analyzed. The installed capacity of the wind farm is 102MW, which is composed of 120 doubly fed wind generators with rated output of 850KW. The cut in wind speed, rated wind speed and cut out wind speed are 3m/s, 12m/s, 21m/s, and wind energy resource is good. Examples are analyzed for a total of 720 historical wind speed values in March. Sample a point every hour, and then do one hour ahead forecast of the 24 wind speed in March 31st through the model, and then compared with the actual value of the same day analyzing the curve fitting error. The wind speed curve of the area over the past period of time is shown in Fig. 1.

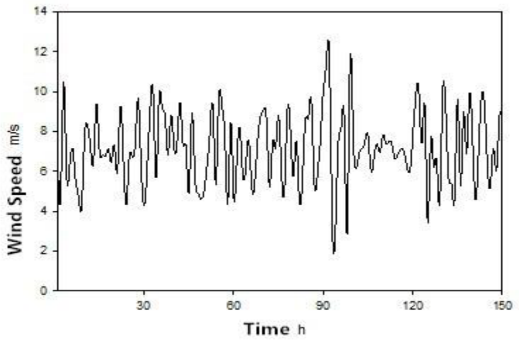

Figure 1. wind speed fluctuation curve of wind farm.

The wind speed data of A wind turbine and B wind turbine are selected, and the wind speed time series model is validated. The wind speed data of two wind turbines are analyzed, and the data are as follows:

Table 1. A and B wind turbine

statistical data	A wind turbine	B wind turbine
mean value(m/s)	7.193	7.543
Standard deviation(m/s)	1.973	2.341
Linear correlation coefficient	0.840	
Kendal	0.635	

Firstly, the ARMA model is validated by taking the A wind turbine as an example.

Because the wind speed sequence is a non stationary random sequence, its mean value is not zero. In the application of wind speed time series model, we first use the zero mean method to make the wind speed the standard sequence:

$$y_t = \frac{v_t - \mu_t}{\sigma_t} \tag{5}$$

where: v_t ——Original wind speed sequence of wind turbine generator; μ_t ——Mean value of wind speed unit; σ_t ——Variance of wind speed per year.

Then, the wind velocity ARMA time series model is made by using the AIC model,and the appropriate model order is selected at the same time. The AIC values of the model are shown in Table 2 under different orders.

Table 2. AIC value of different orders of ARMA time series model

R	M	AIC	R	M	AIC
1	1	47460.802127	3	4	44243.426530
1	2	47390.124775	3	5	44117.291021
1	3	47258.386528	4	1	47178.982975
1	4	47199.134515	4	2	44198.880355
1	5	47157.225788	4	3	47116.117534
2	1	47392.673425	4	4	44663.617039
2	2	47221.150570	4	5	47115.671914
2	3	47165.735587	5	1	47171.780603
2	4	47158.443695	5	2	47293.746394
2	5	47148.776002	5	3	47326.484630
3	1	47235.365075	5	4	47220.946265
3	2	47114.494617	5	5	47151.153943
3	3	44114.421911			

According to Table 2, when order number R=3,M=3, AIC reaches the minimum value of 44114.421911, then the wind speed simulation model can be expressed by ARMA (3, 3), that is:

$$P_t = 2.878P_{t-1} - 2.827P_{t-2} + 0.946P_{t-3} + \theta_t - \beta_1\theta_{t-1} - \beta_2\theta_{t-2} - \beta_3\theta_{t-3} \tag{6}$$

The parameters of the model are estimated by maximum likelihood, and the parameters of the model are obtained $a = \{2.878,-2.827,0.946\}^T$; moving average parameter $\beta = \{-1.978,1.092,-0.050\}^T$ .The first step wind speed sequence simulation model can be expressed as:

$$P_t = 2.878P_{t-1} - 2.827P_{t-2} + 0.946P_{t-3} + \theta_t + 1.978\theta_{t-1} - 1.092\theta_{t-2} + 0.050\theta_{t-3} \tag{7}$$

Among them $\theta \in NID\left(0,0.4181^2\right)$,and then the model parameters are re- calculated according to the obtained fitting values.

Fitting the obtained values as known wind speed for the parameter estimation, and thus the regression parameters and the moving average parameters per a simulation are gained. According to the formula (6) the standard sequence is converted into the actual wind speed sequence:

$$v_t = x_t \times \sigma_t + \mu_t \tag{8}$$

The comparison of the 1h actual wind speed and the fitting curve as shown in Fig. 2. The approximate wind speed values are obtained by the wind speed time series model, and compared with the actual wind speed. The result of wind speed fitting and its error are shown in Table 3.

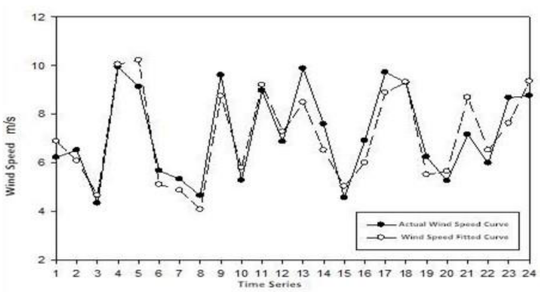

Figure 2. Comparison of the 1h actual wind speed and the fitting curve.

Table 3 shows that the maximum relative error of the model is 21.34%, the minimum relative error is 1.12%, the mean error is 9.39%, and the error standard deviation is 4.50%. Model fitting effect is good, suitable for the simulation of wind speed.

Secondly, the wind speed forecasting series of B wind turbine can be obtained by the same method:

$$P_t = 1.244P_{t-1} - 1.791P_{t-2} + 1.528P_{t-3} + \theta_t + 0.854\theta_{t-1} - 0.370\theta_{t-2} + 0.627\theta_{t-3} \tag{9}$$

where $\theta_t \in NID\left(0,0.5818^2\right)$, So that the velocity sequence of wind speed sequence based on Copula-ARMA is obtained. The wind speed data of A and B wind turbines are statistically analyzed, as shown in Table 4.

The wind speed sequence obtained by Copula-ARMA model is compared with the numerical value of the original wind speed sequence(comparison between Table 1 and Table 4). The mean error of A wind turbine is 1.14% and the standard deviation is 4.66%; the mean error of B wind turbine is 3.95%; the standard deviation error is 7.43%; the linear correlation coefficient error is 0.14%, and the Kendall rank correlation coefficient error is 2.13%. The comparison results show that the correlation index of the original wind speed series can be kept well.

In addition, some colour figures will degrade or suffer loss of information when converted to black and white, and this should be taken into account when preparing them.

4 Conclusion

In this paper, the wind speed time series model of a multi wind turbine generator is constructed. By using the mixed Copula function to describe the spatial correlation of wind speed between different wind turbines, and then the wind speed time series model of the hybrid Copula-ARMA is constructed and the numerical example is analyzed. The model can be applied to the power system to arrange the wind turbine maintenance and its plan reasonably. The peak generation scheme can be adjusted to avoid effective wind, so that the peak load capacity of power network can be improved and the efficient operation of the unit can be ensured . Also the waste wind and the power loss of the wind turbine can be reduced, and as a result, the efficiency of wind power generation is improveand and the power consumption of the grid electricity is increase.

Table 3. results of 1H wind velocity fitting

time series	actual value	predicted value	relative error	time series	actual value	predicted value	relative error
1	6.23	6.89	10.65%	13	9.88	8.49	14.08%
2	6.52	6.08	6.74%	14	7.60	6.52	14.13%
3	4.34	4.66	7.45%	15	4.56	5.04	10.43%
4	9.95	10.06	1.12%	16	6.91	6.00	13.20%
5	9.14	10.23	11.93%	17	9.73	8.90	8.58%
6	5.67	5.11	9.97%	18	9.31	9.33	0.24%
7	5.33	4.87	8.58%	19	6.25	5.51	11.76%
8	4.65	4.08	12.27%	20	5.26	5.64	7.38%
9	9.61	8.75	8.96%	21	7.16	8.69	21.34%
10	5.27	5.80	10.02%	22	5.99	6.52	9.00%
11	8.97	9.21	2.61%	23	8.68	7.63	12.06%
12	6.87	7.29	5.98%	24	8.76	9.36	6.84%
Mean of error is 9.39%				Mean of error is 4.50%			

Table 4. A and B wind turbine

	A wind turbine	B wind turbine
Mean value（m/s）	7.111	7.245
standard deviation（m/s）	1.881	2.167
Linear correlation coefficient	0.839	
Kendal	0.622	

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