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Copula-ARMA Model for Multivariate Wind Speed and Its Applications in Reliability Assessment of Generating Systems

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Abstract – The dependence between wind speeds in multiple wind sites has a considerable impact on the reliability of power systems containing wind energy. This paper presents a new method to generate dependent wind speed time series (WSTS) based on copulas theory. The basic feature of the method lies in separating multivariate WSTS into dependence structure and univariate time series. The dependence structure is modeled through the use of copulas, which, unlike the cross-correlation matrix, give a complete description of the joint distribution. An autoregressive moving average (ARMA) model is applied to represent univariate time series of wind speed. The proposed model is illustrated using wind data from two sites in Canada. The IEEE Reliability Test System (IEEE-RTS) is used to examine the proposed model and the impact of wind speed dependence between different wind regimes on the generation system reliability. The results confirm that the wind speed dependence has a negative effect on the generation system reliability.

Keywords: Multivariate wind speed model, Copulas, Reliability evaluation, Dependence

1. Introduction

Wind energy has attracted more and more attentions around the world due to its excellent economic and social benefits. Moreover, enhanced public awareness of the environment has promoted the further development of wind energy. With the extensive utilization of wind energy, there may be multiple wind farms integrated into power systems in a region. Due to the spatial and locational relationship between wind sites, there exists dependence between wind speed time series (WSTS) in different wind farms. The wind speed dependence has a considerable impact on reliability of power systems integrated wind energy and the impact will be more prominent when the quantity of wind farms and their installed capacity increase. Therefore, it is necessary to consider the dependence between WSTS in the reliability assessment model.

Considerable work has been done on the development of models and techniques for reliability assessment of generating systems incorporating multiple wind farms [1-7]. In [1], a simple probabilistic model based on stochastic transitional probability matrix is proposed in which the correlation between different wind regimes is considered. Based on capacity- probability tables, an approach to model a two-site wind energy conversion system is proposed [2]. In [3], a reliability evaluation model of wind farms considering the wind speed correlation using cross-correlation is presented and the impact of correlation is investigated. In [4, 5], a trial and error method (TEM) is used to search the appropriate initial number seeds of auto-regressive and moving average (ARMA) models. The method is capable of simulating correlated hourly WSTS with specified cross-correlation coefficients of two wind sites. However, this method can be difficult to find the appropriate initial seeds for multiple wind sites. Consequently, an improvement of this method by applying genetic algorithm methods is made to find the suitable initial number seeds for ARMA time series models [6]. Using time-shifting technique, a novel method for producing new WSTS with a given correlation between two wind sites is presented [7]. Most of the proposed methods are based on the linear correlation coefficient (LCC). However, it is a measure of linear dependence and cannot provide a complete representation of dependence between WSTS.

The multivariate distribution function (MDF) is the most comprehensive method to describe dependence between random variables. It contains all statistical properties of random variables. However, there exist some drawbacks in MDF method. For examples, it is only suitable for special marginal distributions such as normal, lognormal, and gamma distributions. The disadvantages limit the practical applications of this method.

The copulas technique can overcome these drawbacks. A copula is a function that couples marginal distributions and MDF. According to copulas, a MDF can be decomposed into two parts: n-marginal distribution functions and a dependence structure which can be described by a copula function. In the late 1990s, the copulas theory was rapidly developed and widely applied in financial [8, 9], hydrological [10, 11], and power systems [12, 13].

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This paper presents a technique for generating dependent WSTS using copulas and applies it to the reliability analysis of power systems containing multiple wind farms. The impacts of wind speed dependence on generation system adequacy (or reliability) are illustrated using the IEEE Reliability Test System (IEEE-RTS) [14]. The three basic reliability indices of the loss of load expectation (LOLE), the loss of energy expectation (LOEE) and loss of load frequency (LOLF) [15] are used to quantify the system reliability.

The rest of the paper is organized as follows. Section II gives a brief introduction to copulas theory. Section III presents the ARMA model for WSTS. The methodology to establish the multivariate wind speed model is described in Section IV. Section V presents the algorithm for the development of multivariate WSTS model. Case studies of the proposed model and impacts of wind speed dependence on the generation system reliability are given in Section VI and VII, respectively. Conclusions are stated in Section VIII.

2. Copulas Theory

The necessary concepts of copulas theory, the commonly used copulas, the methodology of model identification and the simulation technique for copulas are presented in this section. Interested readers are referred to [8] and [16] for detailed information.

2.1 Copulas and dependence

An N-dimensional copula is a multivariate cumulative distribution function (CDF) C with margins uniformly distributed in [0, 1] and with the following properties [16]:

1) C has a domain of $\mathbf{I}^N=[0, 1]^N$;
2) C is grounded and N-increasing;
3) C has margins C_k (k=1,2,…,N), which satisfy $C_k(u) = C(1,\ldots 1, u, 1, \ldots, 1) = u$ for all u in [0,1].

It is obvious that if $F_1, F_2, \ldots, F_N$ are univariate CDFs, $C(F_1(x_1), F_2(x_2), \ldots, F_N(x_N))$ is a multivariate CDF with margins $F_1, F_2, \ldots, F_N$.

Let F be an N-dimensional CDF of WSTS $\boldsymbol{X}=(X_1, X_2, \ldots, X_N)$ with continuous margins $F_1, F_2, \ldots, F_N$. According to Sklar's theorem [16], there exists the following unique copula representation:

$$F(x_1, x_2, \ldots, x_N) = C\left(F_1(x_1), F_2(x_2), \ldots, F_N(x_N)\right) \tag{1}$$

Sklar's Theorem is the basis of copulas theory and its application. It provides a way to analyze the dependence structure of multivariate distributions without studying marginal distributions.

The most widely used dependence index is LCC, which measures the degree of linear relationship between time series. However, this measure may create a misleading conclusion if the random variables do not meet the elliptical distributions or are obtained by nonlinear transformations. Therefore, the Kendall's tau, which is based on the rank of variables and reflects the concordance between variables, can be used as a more appropriate dependence measure. The Kendall's tau is superior to the LCC because of its invariance under strictly monotonic transformations and no restriction on wind speed distributions [8].

2.2 Commonly used copulas

There are many types of copulas, such as normal copulas, student-t copulas, and Archimedean copulas. The discussion of the paper will concentrate on normal copulas and Archimedean copulas.

1) Normal Copulas

An N-dimensional normal copula can be expressed as follows:

$$C(u_1, \ldots, u_N; \rho) = \Phi_\rho\left(\Phi^{-1}(u_1) + \ldots + \Phi^{-1}(u_N)\right) \tag{2}$$

where $\boldsymbol{\rho}$ is a correlation coefficient matrix, $\Phi_\rho(\cdot, \ldots, \cdot)$ is the standard multivariate normal distribution function, and $\Phi^{-1}(\cdot)$ is the inverse function of standard normal distribution function.

2) Archimedean copulas

The class of Archimedean copulas is an important class for which the construction of multivariate copulas can be performed quite generally. An N-dimensional Archimedean copula can be expressed as follows 0:

$$C(u_1, \ldots, u_N) = \varphi^{-1}\left(\varphi(u_1) + \ldots + \varphi(u_N)\right) \tag{3}$$

where $\varphi(\cdot)$ is the generator of Archimedean copulas.

Archimedean copulas are determined by generators. Commonly used Archimedean copulas include Gumbel copula, Clayton copula, and Frank copula. Table 1 gives their generators.

Table 1. Generators of Archimedean copulas

Copula	Generator	Range of parameter
Gumbel	$(-\ln u)^\theta$	$[1,+\infty)$
Clayton	$(u^{-\theta}-1)/\theta$	$[-1,0) \cup (0, +\infty)$
Frank	$\ln(e^{-\theta}-1) - \ln(e^{-\theta u}-1)$	$(-\infty, 0) \cup (0,+\infty)$

However, the Archimedean copulas generated from (3) are exchangeable and limited in describing various dependence structures among joint distribution. Hence, a more developed method is proposed in [17] for general extension by the following coupling scheme:

$$C(u_1, u_2, ..., u_N) = C_1(u_N, C_2(u_{N-1}, ..., C_{N-1}(u_2, u_1)) \quad (4)$$

It is possible that φ_i in C_i are generators of different types of Archimedean copulas.

According to Eq. (4), an N-dimensional Archimedean copulas can be constructed by N-1 bivariate Archimedean copulas.

2.3 Selection of the optimal copulas

Many methods can be used to select copulas 0. A shortest distance method (SDM) based on the empirical copula is used to select the optimal copula. The empirical copula can be expressed as the following formula:

$$C_e\left(\frac{i_1}{n}, ..., \frac{i_k}{n}, ..., \frac{i_N}{n}\right) = \frac{1}{n}\sum_{j=1}^{n} \mathrm{I}\left(x_{1,j} \le x_1^{(i_1)}, .., x_{k,j} \le x_k^{(i_k)}, .., x_{N,j} \le x_N^{(i_N)}\right) \quad (5)$$

where $x_k^{(i)}$ is the order statistics and $1 \le i_1, \ldots, i_N \le n$

The Euclidean distance between the empirical and theoretical copula is calculated using the following formula:

$$d(C, C_e) = \left\{ \sum_{i_1=1}^{n} ... \sum_{i_N=1}^{n} \left[C\left(\frac{i_1}{n}, ..., \frac{i_N}{n}\right) - C_e\left(\frac{i_1}{n}, ..., \frac{i_N}{n}\right) \right]^2 \right\}^{1/2} \quad (6)$$

The optimal copula is the one with the shortest distance.

2.4 Sampling copulas

A copula is a multivariate joint distribution function and therefore, conventional simulation methods can be used to generate samples from the copulas. The Marshall-Olkin method 0 is applied in this paper to simulate the Archimedean copulas and briefly described in the following steps:

Step 1 Generate a random number V for each distribution function $G(\cdot)$, where $G=L^{-1}[\varphi^{-1}(t)]$, L^{-1} stands for inverse Laplace transform;

Step 2 Generate N random numbers $x_1, x_2, x_3, \ldots, x_N$, each of which meets the (0,1) uniform distribution;

Step 3 Let $U_n=G(-\ln(x_n)/V)$, n=1, 2, …, N.

Following the above procedures, a vector $\boldsymbol{U}$ of random numbers whose generator $\varphi(\cdot)$ meets the distribution of Archimedean copulas can be formed.

3. ARMA Model for Univariate WSTS

An essential requirement in incorporating WECS in power system reliability analysis using sequential Monte Carlo simulation is to realistically simulate the hourly WSTS. Wind speed varies with time and location, and at a specific hour, it is related to the wind speeds of previous hours. The ARMA model, which has the advantage of containing a time-order feature, has been widely used to simulate the WSTS in the reliability study [3-6, 18]. The general expression for the ARMA (p, q) model is shown in the following equation:

$$x_t = \sum\nolimits_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t - \sum\nolimits_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad (7)$$

where x_t is the series value at time t, φ_i (i=1,2,…, p) and θ_j (j=1,2,…,q) are autoregression and moving average parameters, respectively, $\{\varepsilon_t\}$ is a normal white noise process with zero mean and a variance of σ_ε^2,ie. $\varepsilon_t \in NID(0, \sigma_\varepsilon^2)$ where NID denotes a normal independent distribution.

The hourly-simulated wind speed SW_t at time t is obtained from the mean speed μ_t, the standard deviation σ_t and the time series x_t as shown in (8).

$$SW_t = \mu_t + x_t \times \sigma_t \quad (8)$$

New values of x_t can be calculated using Eq. (7) from current random white noise at and previous values of x_{t-i}.

According to Eq. (7), the ARMA model is composed of two parts, the autoregressive (AR) model involving lagged terms in the time series itself, and the moving average (MA) model involving lagged terms in the white noise (independent standard normal errors), which determine the dependence between the different time series. It is, therefore, possible to adjust the wind speed dependence level between two or more different wind farms by generating a dependent N-dimensional vector of time series $\boldsymbol{\varepsilon_t} = (\varepsilon_{1t}, \varepsilon_{2t}, .., \varepsilon_{Nt})$ using copulas.

4. Copula-ARMA Model for Multivariate WSTS

A Copula-ARMA model composed of a copula function and ARMA model is proposed for multivariate WSTS in this section.

Assume that $\boldsymbol{x}= (x_{1t}, x_{2t}... x_{Nt})$ is an N-dimensional vector of time series and each marginal series can be described by ARMA (p, q), then the N-dimensional Copula-ARMA (p, q) model can be expressed as:

$$\begin{cases} x_{kt} = \sum\nolimits_{i=1}^{p} \varphi_{ki} x_{kt-i} + \varepsilon_{kt} - \sum\nolimits_{j=1}^{q} \theta_{kj} \varepsilon_{kt-j}, \ k = 1, .., N \\ (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{Nt}) \sim C_a\left(\Phi\left(\frac{\varepsilon_{1t}}{\sigma_1}\right), \Phi\left(\frac{\varepsilon_{2t}}{\sigma_2}\right), ..., \Phi\left(\frac{\varepsilon_{Nt}}{\sigma_N}\right)\right) \end{cases} \quad (9)$$

where $\boldsymbol{\varepsilon}= (\varepsilon_{1t}, \varepsilon_{2t},..., \varepsilon_{Nt})$ are the N-dimensional vector of normal white noise series, $(\sigma_1, \sigma_2,..., \sigma_N)$ are the standard deviations of corresponding univariate series, $\Phi(\cdot)$ is the standard normal distribution, and C_a is a N-dimensional copula function that describe the dependence structure between the univariate series.

According to Eq. (9), the dependence level between the WSTS depends on that between white noise series. If the white noise series are generated independently, then the WSTS obtained are also independent of each other. Therefore, the key factor to obtain dependent WSTS is to generate dependent white noise series.

Assume that the dependence structure between univariatetime series x_{it} can be described by an N-dimensional copula function C_b.

$$(x_{1t}, x_{2t}, ..., x_{Nt}) \sim C_b\left(F_1(x_{1t}), F_2(x_{2t}), ..., F_N(x_{Nt})\right) \quad (10)$$

where F_i are the CDFs of series x_{it}.

Study shows that copula functions are invariant under strictly increasing transformations of the random variables, which is an attractive property of copulas [8, 16]. It can be found from Eq. (7) that the partial derivative of x_{it} with respect to ε_{it} is 1, namely $\partial x_{it}/\partial \varepsilon_{it}=1$. Thus, the N-dimensional copula function C_b describing dependence structure among time series x_{it} is identical to the copula function C_a for the white noise series

$$\begin{aligned} &C_a\left(\Phi\left(\frac{\varepsilon_{1t}}{\sigma_1}\right), \Phi\left(\frac{\varepsilon_{2t}}{\sigma_2}\right), ..., \Phi\left(\frac{\varepsilon_{Nt}}{\sigma_N}\right)\right) \\ &\quad = C_b\left(F_1(x_{1t}), F_2(x_{2t}), ..., F_N(x_{Nt})\right) \end{aligned} \quad (11)$$

Copula function C_b can be easily estimated using the real WSTS.

5. Algorithm for Multivariate Wind Speed Model

From the description above, an algorithm for modeling multivariate WSTS using Copula-ARMA can be synthesized as follows:

Step 1 Determine the ARMA model for WSTS at each wind site;
- a) Transformed the wind speed data by the mean speed μ_{it} and the standard deviation σ_{it} at time t and obtain times series x_{it} ;
- b) Construct ARMA model for times series x_{it} based on the method described in [18].

Step 2 Indentify a copula function to describe the dependence structure among time series x_{it};
- a) Transform time series x_{it} into uniformly distributed time series u_{it} using corresponding CDF;
- b) Calculated the parameters of copula functions based on the series $(u_{1t}, u_{2t},.., u_{Nt})$;
- c) Choose the optimal copula functions for the multivariate WSTS using SDM;

Step 3 Construct the multivariate Copula-ARMA model of WSTS based on Eq. (9).

6. Case Studies –Verification of Copula-ARMA Model

The wind speed data in two sites, Regina and Swift Current in Saskatchewan, Canada are used in this paper to demonstrate the accuracy and the effectiveness of the model. Hourly WSTS for five years (from January 1, 1999 to December 31, 2003) obtained from Environment Canada were used are used for model identification. The main statistics of the historical data are listed in Table 2.

Table 2. Main statistics of real wind speed data

Statistics	Regina	Swift Current
Mean(m/s) μ	5.42	5.41
Standard deviation (m/s) σ	3.05	2.69
Linear correlation coefficient ρ	0.4901	
Kendall's tau rank correlation τ	0.3299	

The multivariate normal copulas and Archimedean copulas introduced above are used to capture the dependence structure between WSTS of the two sites. The dependence parameters of Archimedean copulas are calculated using the maximum likelihood estimation method 0. Table 3 gives the values of parameters of different copula functions and Table 4 shows the Euclidean distance between the empirical and theoretical copula.

Table 3. Values of copulas parameter

Copula	θ
Gumbel	1.4162
Clayton	3.1479
Frank	0.5633
Gauss	0.4904

Table 4. Euclidean distance between empirical and theoretical copulas

Copula	$d(C_e, C)$
Gumbel	0.0085
Clayton	0.1797
Frank	0.0266
Gauss	0.0190

It can be observed from Table 4 that Gumbel copula has the shortest Euclidean distance. Therefore, Gumbel copula is used to describe the dependence structure between WSTS of the two sites in this paper, as the following formula:

$$(\varepsilon_{1t},\varepsilon_{2t}) \sim C\left[\Phi(\varepsilon_{1t}),\Phi(\varepsilon_{2t})\right] = \exp\left[-\left(\left[-\ln\Phi(\varepsilon_{1t})\right]^{\theta}+\left[-\ln\Phi(\varepsilon_{2t})\right]^{\theta}\right)^{1/\theta}\right] \quad (12)$$

The ARMA models of WSTS for the two sites [18] are as follows:

Regina: ARMA (4, 3):

$$x_t = 0.9336x_{t-1} + 0.4506x_{t-2} - 0.5545x_{t-3} + 0.1110x_{t-4} + \varepsilon_t - 0.2033\varepsilon_{t-1} - 0.4684\varepsilon_{t-2} + 0.2301\varepsilon_{t-3}$$
$$\varepsilon_t \in NID(0, 0.4094^2) \quad (13)$$

Swift Current: ARMA (4, 3):

$$x_t = 1.1772x_{t-1} + 0.1001x_{t-2} - 0.3572x_{t-3} + 0.0379x_{t-4} + \varepsilon_t - 0.5030\varepsilon_{t-1} - 0.2924\varepsilon_{t-2} + 0.1317\varepsilon_{t-3}$$
$$\varepsilon_t \in NID(0, 0.5248^2) \quad (14)$$

Two hundred years of simulated wind speed were generated for the two sites using the proposed Copula-ARMA model and the TEM-ARMA method. Table 5 shows the main statistics of the simulated WSTS. It can be found that the Copula-ARMA model can preserve all the main statistics of real data well, while the TEM-ARMA product a recognizable difference for Kendall's tau rank correlation, in general, the Kendall's tau of the WSTS generated using TEM-ARMA method does not match the one of the real wind data satisfactorily.

In order to compare the probability distribution of the two models, the values of bivariate empirical cumulative distribution function (B-ECDF) of the wind data simulated from the models are plotted against those from the real wind data as shown in Fig. 1 and Fig. 2, respectively. The probability-probability (P-P) plot is a standard means of comparing probability distributions. If the simulated wind data and the real one are from the same distribution, then the P-P plot follows approximately a straight line with a unit slope. The values of B-ECDF at sample points $\{(x_{1i}, x_{2i}),\ t=1, 2, T\}$ can be calculated using the following formula:

$$F(x_{1i},x_{2i}) = \frac{1}{n+1}\sum_{t=1}^{n} \mathrm{I}(x_{1t} \le x_{1i}, x_{2t} \le x_{2i}) \quad (15)$$

Here, n is the sample size, **I** is an indicator function

Table 5. Main statistics of simulated wind speed data

Statistics	Copula-ARMA		TEM-ARMA	
	Regina	Swift Current	Regina	Swift Current
μ	5.45	5.46	5.46	5.44
σ	3.07	2.72	3.09	2.73
ρ	0.4896		0.4916	
τ	0.3294		0.3927	

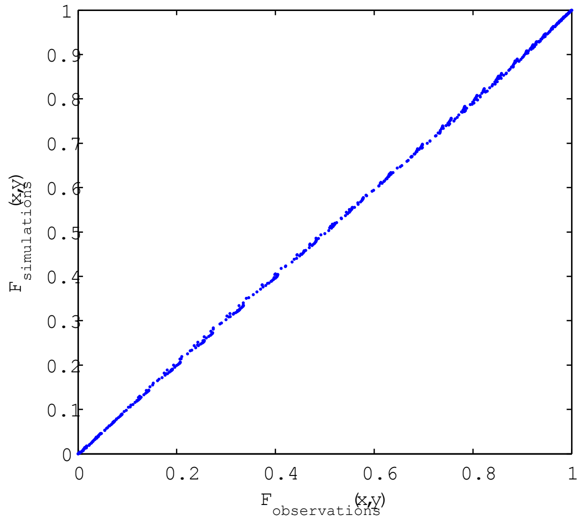

Fig. 1. P-P plot of Copula-ARMA-simulated wind data against real one

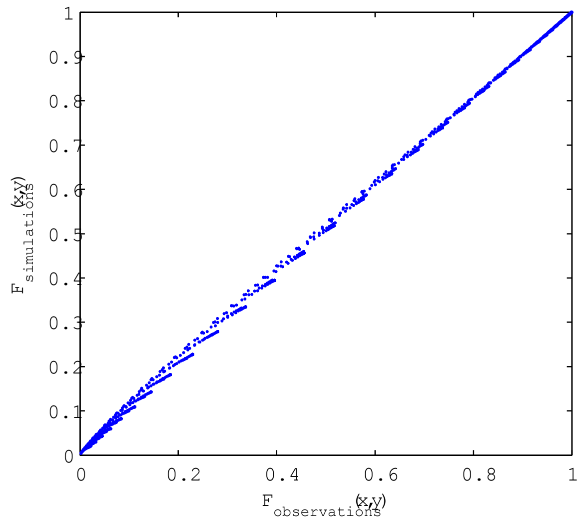

Fig. 2. P-P plot of TEM-ARMA-simulated wind data against real one

whose value is equal to one if the condition in the bracket is satisfied. Otherwise, it is zero.

It can be observed that the Copula-ARMA model can preserve the bivariate distribution of real data better than the TEM-ARMA method. The residual sum of squares between real and simulated wind data from the Copula-ARMA model and the TEM-ARMA method are 0.4493 and 1.0483, respectively. It shows that copulas-based model can represent the dependence between wind speeds more accurately than the LCC-based model.

7. Case Studies – Impacts of Wind Speed Dependence on Generation System Reliability

The IEEE-RTS has 32 traditional generating units with the rated capacities from 12 MW to 400 MW. The total rated capacity of the IEEE-RTS is 3405 MW and the system peak load is 2850 MW. The detailed generating unit capacities, reliability parameters and load data are given in [14].

To quantitatively assess the impacts of the wind power and the dependence between wind speeds on system reliability, the IEEE-RTS was modified to create a system designated as the Combined Test System (CTS) by the addition of the two wind farms with the capacity 300MW. The cut-in, rated, and cut-off wind speed of wind turbine generators are 3.3, 10.6, and 22.2 m/s, respectively.

The reliability indices of the IEEE-RTS and the CTS calculated using Sequential Monte Carlo simulation are shown in Table 6. The indices of CTS in the cases of independence and completely dependence are shown in Table 7.

It can be seen from Table 6 that the two-300MW wind farms have a significant impact on the IEEE-RTS reliability indices. From the comparison of Table 6 and 7, it can be found that the reliability indices for systems considering dependence are smaller than that without considering dependence. In other words, the wind speed dependence has a negative impact on generation system reliability. It is,

Table 6. Reliability indices for the IEEE-RTS and the CTS

Test system	LOLE (hr/yr)	LOEE (MWh/yr)	LOLF (occ./yr)
IEEE-RTS	9.3716	1197.4448	1.9192
CTS	4.2082	491.7470	1.2834

Table 7. Reliability indices of the CTS with two dependence levels

Dependence level	LOLE (hr/yr)	LOEE (MWh/yr)	LOLF (occ./yr)
Independent	4.0837	487.31	1.2090
Completely dependent	4.6996	551.83	1.4101

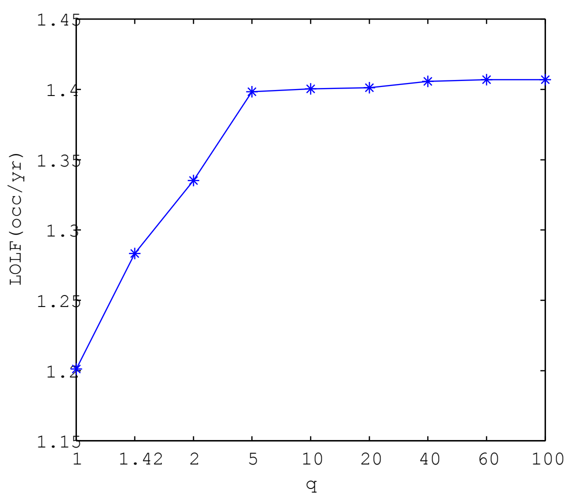

Fig. 3. LOLF index of the CTS with different dependence levels

therefore, necessary to consider dependence between WSTS in reliability analysis of power systems containing multiple wind farms.

Fig. 3 illustrates the variation of the LOLF index with different dependence levels. It can be observed that the system reliability decrease as the dependence level increases. Another interesting point observed from Fig. 3 is that the effect of wind speed dependence on the generation system reliability tends to be stabilized when the dependence reaches a certain level.

8. Conclusions

The dependence between wind speeds has a considerable impact on reliability of power systems containing multiple wind farms. The key factor of evaluating this impact is to generate wind speed samples considering the dependence. This paper presents a Copula-ARMA model for multivariate WSTS by combining the copulas and ARMA model. The main advantage of this approach is that the margins of wind speed can be defined separately from their dependence structure and this offer a great flexibility in building multivariate wind speed model. The case studies demonstrate that the Copula-ARMA model can preserve the statistical characteristics of historical WSTS better that LCC-based methods and thus can model dependence structure between them more accurately.

The IEEE-RTS is used to verify the applicability of the proposed model. The results show that generation system reliability will decrease as the wind speed dependence increases. Furthermore, the effect of wind speed dependence tends to be stabilized after a certain level.

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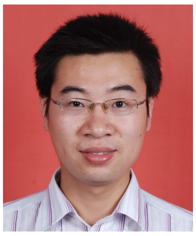

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