Research on Correlation Between Wind Power and Load in Different Weather Conditions

Zixin Chen, Han Wang, Jie Yan, Yongqian Liu, Shuang Han and Li Li

Abstract The wind power and load are both affected by the meteorological factors. Studying on the correlation between wind power and load in different weather conditions is beneficial to reduce the double uncertainties on the sides of source and load, and significant to the planning, dispatching, safe and stable operation of the electric power system. First, the improved algorithm of traditional K-means clustering algorithm—X-means is adopted to divide the daily meteorological factors of wind speed and temperature, which mainly affect the wind power and load. Then, the Pearson, Kendall and Spearman correlation coefficients are used to analyze the correlation between wind power and load variables in different weather conditions. Finally, the optimal Copula function is selected from four commonly-used Copula functions to describe the joint distribution of wind power and load in each weather condition. Furthermore, the data in another place is used to verify the correlation between wind power and load with the weather condition. The conclusions are as follows: (1) the X-means algorithm can realize the effective classification of weather conditions. (2) The positive correlation between wind power and load is mainly concentrated in summer or near summer, the negative correlation between them is mainly concentrated in winter or near winter. (3) The correlation between wind power and load is quite varying in different weather conditions, but the joint distributions are basically consistent with the Archimedes Copula functions, and the tail correlation coefficients of their distribution are zero under most weather conditions. (4) There is a repeated rule between wind power and load with the weather condition.

Keywords Different weather conditions · Wind power · Load · Correlation · Copula function

Z. Chen
Chifeng Branch of China Datang Corporation, Inner Mongolia Autonomous Region, 024000 Chifeng, China

H. Wang · J. Yan (✉) · Y. Liu · S. Han · L. Li
School of Renewable Energy, North China Electric Power University, 102206 Beijing, China
e-mail: yanjie_freda@163.com

Y. Xue et al. (eds.), *Proceedings of PURPLE MOUNTAIN FORUM 2019-International Forum on Smart Grid Protection and Control*, Lecture Notes in Electrical Engineering 585, https://doi.org/10.1007/978-981-13-9783-7_3

1 Introduction

In the source side, with the high proportion of wind power integration, the volatility and intermittency of its output have a significant adverse impact on the reliability of power system and the power quality [1]. In the load side, as the proportion of activity load rises yearly, its uncertainty also increases greatly [2]. The double uncertainties of source and load sides pose huge challenges to the planning, scheduling, safe and stable operation of the electric power system [3, 4]. However, the wind power and load are both affected by the meteorological factors, studying on the correlation relationship between them under different weather conditions is beneficial to reduce the double uncertainties on the sides of source and load, improve the joint forecasting accuracy, and arrange the reserve capacity in advance, etc. [5].

Some scholars have already researched on the correlation between wind power and load at present. Li et al. [6] studied the correlation between wind power and load time series through the spatial transformation of probability distribution. The results show that the correlation relationship could impact the overload risk of the transmission line. Lin et al. [7] analyzed the linear correlation between the wind power time series and typical daily load, and proposed a new method to calculate the peak regulation capacity of wind power by considering the correlation between them. It is suggested from researches that the presented method shows great advantages when the wind power capacity of the regional power grid is more than 10% of the maximum load. Zhao et al. [8] researched on the correlation between wind power output and load change in a provincial power grid at the time scale of month and day, respectively. It can be seen that the monthly average output of wind power is negatively correlated with the load change of the power grid.

Some other scholars have considered the correlation between wind power and load in making investment decisions, calculating operation costs and assessing the adequacy of electric power system, etc. Baringo et al. [9] proposed two methodologies to generate the wind power and electric load time series which considered their uncertainty and the correlation between them. The results show that the scenario selection has a significant impact on the investment decision. Ak et al. [10] presented a multi-layer perceptron artificial neural network for interval forecasting of wind power and load, which accounting for the associated uncertainties of them simultaneously. Mazidi et al. [11] implemented a two-stage stochastic objective function which aiming at the minimization of the expected operation cost, and the reserve requirement in this function is provided by a combination of responsive load and renewable energy. Korkas et al. [12] presented a novel control algorithm for joint the demand response load, renewable energy and energy storage which considered the correlation between the source side and the load side. Liu et al. [13] proposed a two-stage robust security-constrained unit commitment method by considering the correlation of wind power and load, which could eliminate the undesirable scenarios and further limit the level of conservatism of the robust solution.

However, the above researches still have the following deficiencies. When the correlation between wind power and load is analyzed, the weather conditions are not taken into account and the correlation of them are not further studied in different scenarios. When the correlation between wind power and load is applied to the actual situation, the correlative differences between them in different scenarios are considered, but the correlation relationships are not stated. Therefore, the correlation between wind power and load is specific researched in different weather conditions in this paper. First, the improved algorithm of traditional K-means clustering algorithm—X-means is adopted to divide the daily meteorological factors of wind speed and temperature, which mainly affect the wind power and load. Then, the correlation between wind power and load variables in different weather conditions is studied based on the Pearson, Kendall and Spearman correlation coefficients, and the monthly distributions of different correlations are analyzed. Finally, based on the Euclidean distance, the optimal Copula function is selected from four commonly-used Copula functions, including t-student Copula function, Gumbel Copula function, Clayton Copula function and Frank Copula function to describe the joint distribution of wind power and load in each weather condition. The correlation between them is further studied on the basis of the optimal Copula function. Furthermore, the data in another place (Portland) is used to validate the correlation between wind power and load with the weather condition.

The remainder of this paper is organized as follows. In Sect. 2, the weather conditions are classified by using the X-means clustering algorithm according to the meteorological factors of wind speed and temperature. Section 3 studied the correlation between wind power and load in different weather conditions in Providence, and verified the obtained correlation in Portland. Section 4 concludes this paper.

2 Classification of Weather Conditions

The data used in this study is from two places, one is the Providence area of Rhode Island, USA, and the other is the Portland area of Maine, USA. The data in Providence is employed to analyze the correlation between wind power and load in different weather conditions, and the data in Portland is employed to validate the correlation with the weather condition. The wind power data, including the wind speed and output data, is derived from the grid integration data of National Renewable Energy Laboratory (NREL) [14]. The length and temporal resolution of the data is 6 years (from 2007 to 2012) and 5 min, respectively. The load and temperature data are the real time data of ISO New England electricity market, the dataset is publicly available on the official website of the ISO New England Incorporation [15]. The length and temporal resolution of the data is 8 years (from 2008 to 2015) and 1 h, respectively. Therefore, the data used in this study is from 2008 to 2012, and the temporal resolution is 1 h. Note, the data of Feb. 29 in 2008 and 2012, and Dec. 31 in these five years is missing.

First of all, the Pearson linear correlation coefficient, Kendall rank correlation coefficient and Spearman rank correlation coefficient are employed to analyze the correlation between wind power and load variables. The calculation method of each correlation coefficient is as follows.

(1) Pearson linear correlation coefficient (r)

Pearson linear correlation coefficient is the quotient of covariance and standard deviation between two variables and the calculation formula is shown in Eq. (1).

$$r = \frac{\mathrm{cov}(\bar{P}, \bar{L})}{\sigma(\bar{P})\sigma(\bar{L})} = \frac{E(\bar{P}\bar{L}) - E(\bar{P})E(\bar{L})}{\sigma(\bar{P})\sigma(\bar{L})} \tag{1}$$

Pearson correlation coefficient reflects the linear correlation relationship between the wind power time series $\bar{P}(t)$ and load time series $\bar{L}(t)$. The closer absolute value of r is to 1, the linear correlation between two variables is stronger.

(2) Kendall rank correlation coefficient (τ)

$$\tau = P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(j)) > 0) - P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(j)) < 0) \tag{2}$$

where, $P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(j)) > 0)$ and $P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(j)) < 0)$ represents the probability of harmony and disharmony, respectively, between the wind power and load at time of i and j. The difference of them is the Kendall rank correlation coefficient.

(3) Spearman rank correlation coefficient (ρ_s)

$$\rho_s = 3\{P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(k)) > 0) - P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(k)) < 0)\} \tag{3}$$

where, $P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(k)) > 0)$ and $P((\bar{P}(i) - \bar{P}(j))(\bar{L}(i) - \bar{L}(k)) < 0)$ represents the probability of harmony and disharmony, respectively, between $(\bar{P}(i), \bar{L}(i))$ and $(\bar{P}(j), \bar{L}(k))$.

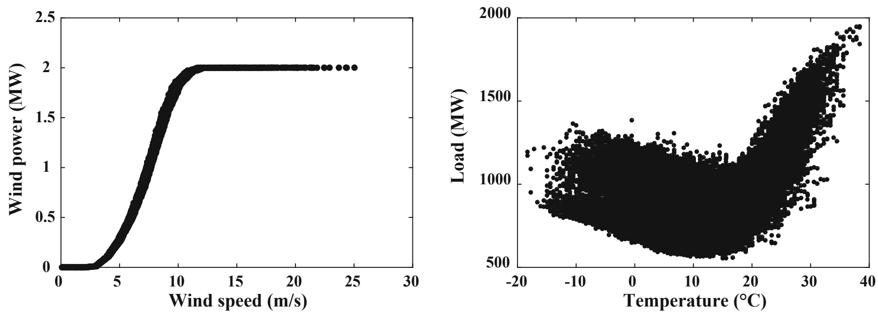
The correlation coefficients between wind power and load time series from 2008 to 2012 can be calculated according to the above formulas, the results are as follows: r = 0.012, τ = 0.023, ρ_s = 0.035. It can be seen that, the correlation relationship between wind power and load variables at the time scale of year, including the linear and nonlinear correlation, is extremely weak, i.e. the wind power and load are basically irrelevant if all data is used to analyze without filtering. Therefore, the correlation between wind power and load should be further studied in different scenarios.

The data used for analysis should be in the same magnitude, so the wind speed, temperature, wind power and load time series are normalized, respectively. The calculation formula is as follows.

$$\bar{X}(t) = \frac{X(t) - X_{\min}}{X_{\max} - X_{\min}} \quad (4)$$

The correlation between wind speed and wind power, temperature and load is analyzed, respectively, to illustrate the reasonableness of dividing the weather conditions based on meteorological factors of wind speed and temperature. As can be seen from Fig. 1, there is a cubic relationship between the wind speed and wind power when the wind speed is between the cut-in speed and the cut-off speed. The temperature and load is negatively correlated when the temperature is less than about 18 °C, and positively correlated when the temperature is larger than about 18 °C. Therefore, the wind speed and temperature variables are chosen as the main meteorological factors to classify the weather conditions in this study. The improved algorithm of traditional K-means clustering algorithm—X-means [16] is adopted to classify the weather conditions. Compared with the K-means algorithm, the X-means algorithm only need to give the range of clustering number (k) in advance, not the specific value of k. The clustering results will more scientific and effective with the X-means algorithm.

The daily normalized wind speed and temperature data are clustered by X-means algorithm and the weather condition in this area can be divided into 24 categories. In order to further verify the effective of X-means algorithm, the traditional K-means algorithm is adopted to cluster the daily normalized wind speed and temperature data, and the clustering number is set from 1 to 50. The clustering error of K-means is represented by the average Euclidean distance of each sample data to its cluster center. The clustering error of K-means algorithm under different clustering numbers is shown in Fig. 2. As can be seen that, with the increase of clustering number, the clustering error of K-means is decreased and the descent rate is gradually slow down. When the clustering number reaches 24, the descent rate is basically near to zero. The clustering error only reduced by 0.046 when the clustering number changes from 24 to 50. The results further illustrate the validity of X-means clustering algorithm.



(a) Wind speed and wind power

(b) Temperature and load

Fig. 1 Correlation between meteorological factors and wind power or load

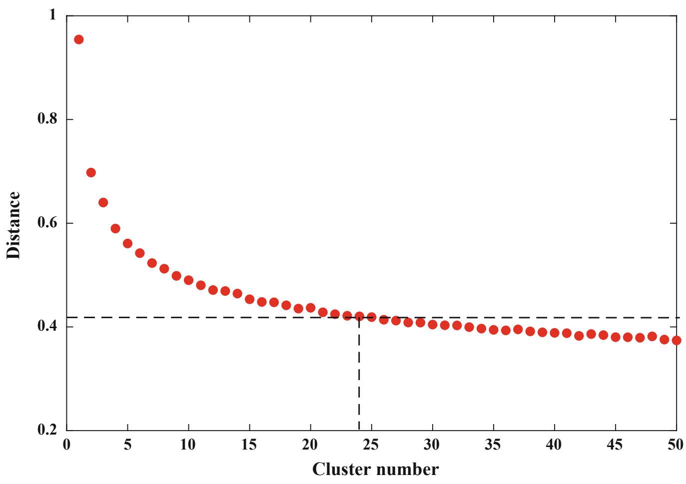


Fig. 2 Clustering error of K-means algorithm under different clustering numbers

3 Correlation Between Wind Power and Load in Different Weather Conditions

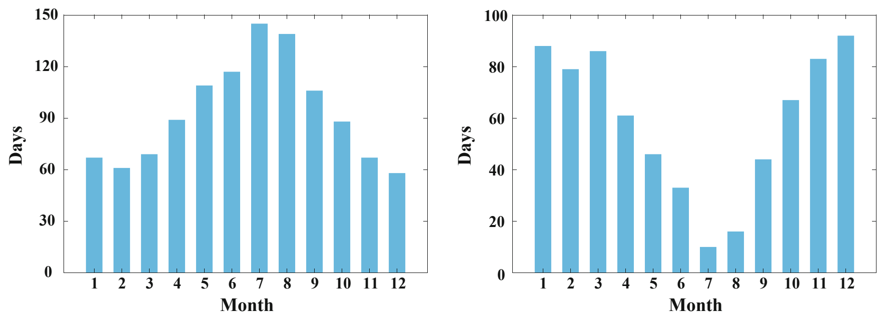
3.1 Linear and Rank Correlation Coefficients

In this section, Pearson linear correlation coefficient is used as an example to analyze the correlation between wind power and load variables in different weather conditions first. The Pearson correlation coefficients of wind power and load in the above 24 weather conditions (referred to as types in this paper) are calculated and listed in Table 1. It can be seen that, the correlation between wind power and load varies greatly in different weather conditions. The linear positive correlation coefficient can be up to 0.500 and the linear negative correlation coefficient can be low to 0.572.

Then, the monthly distribution of positive and negative linear correlation between wind power and load is calculated, respectively, according to the results of Pearson correlation coefficients in different weather conditions, as depicted in

Table 1 Pearson correlation coefficients in different weather conditions

Type	1	2	3	4	5	6	7	8
r	0.465	0.036	−0.082	0.333	0.128	0.402	−0.399	−0.227
Type	9	10	11	12	13	14	15	16
r	0.014	0.258	0.450	−0.084	0.355	0.442	−0.172	−0.092
Type	17	18	19	20	21	22	23	24
r	−0.572	0.250	−0.351	0.500	−0.491	0.473	0.243	−0.221



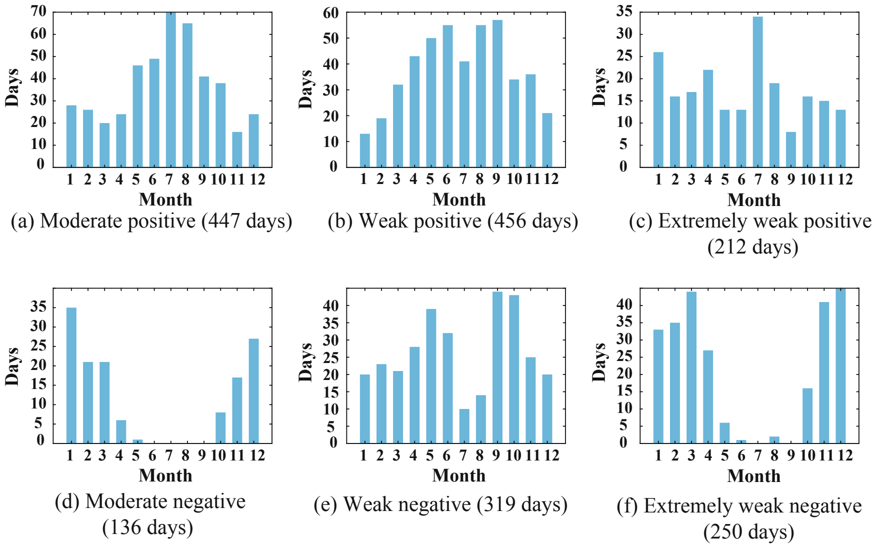
(a) Positive (1115days) (b) Negative (705 days)

Fig. 3 The monthly distributions of positive and negative linear correlations

Fig. 3. It can be seen that, (1) the frequency of positive correlation between wind power and load is higher than the negative correlation in these 5 years. The number of days with positive and negative correlation accounted for 61.3 and 38.7% of the total number of days, respectively. (2) The positive correlation between them is mainly concentrated in summer or near summer, and the negative correlation is mainly concentrated in winter or near winter.

In order to further analyze the linear correlation between wind power and load variables in different weather conditions, the monthly distributions of different degrees of linear correlation (moderate positive, weak positive, extremely weak positive, moderate negative, weak negative and extremely weak positive) are shown in Fig. 4. The discriminant basis is as follows, when $0.4 < |r| \leq 0.6$, the correlation is moderate; when $0.2 < |r| \leq 0.4$, the correlation is weak; when $|r| \leq 0.2$, the correlation is extremely weak. As can be seen from Fig. 4, (1) the weak correlation accounted for the largest proportion, followed by the moderate correlation, and the extremely weak correlation accounted for the smallest proportion among three degrees of the linear correlation. (2) The distributions of positive and negative correlation in different degrees are almost the same in each month. And the probability that a positive correlation occurs in summer or near summer, a negative correlation occurs in winter or near winter both increase with the correlation degree.

Then, the Kendall and Spearman correlation coefficients are used as the evaluation indexes to further study the nonlinear correlation between wind power and load variables in different weather conditions, as shown in Fig. 5. It can be seen that, the variation trend of the linear and rank correlation between wind power and load is basically the same in different weather conditions, the positive and negative correlations between random variables do not vary with the correlation coefficients. Therefore, the monthly distributions of nonlinear correlation are basically the same as Figs. 3 and 4.



(a) Moderate positive (447 days)
(b) Weak positive (456 days)
(c) Extremely weak positive (212 days)
(d) Moderate negative (136 days)
(e) Weak negative (319 days)
(f) Extremely weak negative (250 days)

Fig. 4 The monthly distributions of different linear correlation degrees

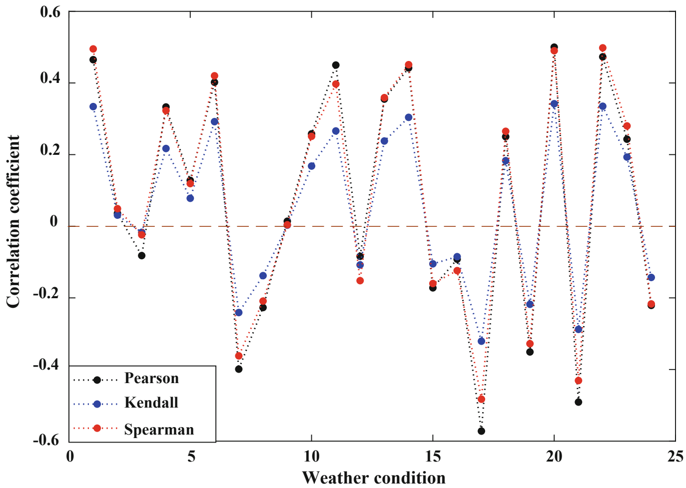


Fig. 5 Linear and rank correlation coefficients in different weather conditions

3.2 *Joint Distributions Based on Optimal Copula Functions*

Variables which with the same correlation coefficient may exhibit completely diverse characteristics due to the different correlation structures between them. For the research on the correlation between wind power and load, the real situation may not be fully reflected if the relevant structure of them is ignored, which will lead to the inaccurate or even incorrect correlation analysis results. Therefore, the joint distributions of wind power and load are further analyzed in different weather conditions in this section.

Firstly, four commonly-used Copula functions [17, 18], including t-student Copula function, Gumbel Copula function, Clayton Copula function and Frank Copula function are employed to fitted the joint distribution of wind power and load in each weather condition. Among four Copula functions, Gumbel Copula function, Clayton Copula function and Frank Copula function are the commonly-used Copula functions of Archimedes. The four binary Copula distribution functions and their respective characteristics are as follows.

(1) Binary t-student Copula distribution function

$$C^t(u, v; \rho, k) = \int_{-\infty}^{t_k^{-1}(u)} \int_{-\infty}^{t_k^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left[1 + \frac{s^2 - 2\rho st + t^2}{k(1-\rho^2)}\right]^{-\frac{k+2}{2}} dsdt \quad (5)$$

where, u, v is the marginal distribution function of wind power time series and load time series, respectively; ρ is the linear correlation coefficient between two variables; k is the degree of the freedom of binary t-student Copula.

(2) Binary Gumbel Copula distribution function

$$C(u, v; \alpha) = \exp\left(-[(-\ln u)^\alpha + (-\ln v)^\alpha]^{1/\alpha}\right) \quad (6)$$

where, $\alpha \in [1, \infty]$.

(3) Binary Clayton Copula distribution function

$$C(u, v; \alpha) = \max\left([u^{-\alpha} + v^{-\alpha} - 1]^{-1/\alpha}, 0\right) \quad (7)$$

where, $\alpha \in [-1, \infty]\backslash\{0\}$.

(4) Binary Frank Copula distribution function

$$C(u, v; \alpha) = -\frac{1}{\alpha}\ln\left(1 + \frac{(e^{-\alpha u} - 1)(e^{-\alpha v} - 1)}{e^{-\alpha} - 1}\right) \quad (8)$$

where, $\alpha \in (-\infty, \infty)\backslash\{0\}$.

Binary t-student Copula function has a thick symmetrical tail and is sensitive to the tail-related changes between random variables, so it can capture the symmetrical tail correlation between variables. Binary Gumbel Copula function and binary

Clayton Copular function have an asymmetrical tail. The Gumbel Copula function can capture the upper tail correlation between variables, and the lower tail correlation coefficient of this Copula function is 0. The Clayton Copula function can capture the lower tail correlation between variables, and the upper tail correlation coefficient of this Copula function is 0. Binary Frank Copula function has an independent and symmetrical tail, and the tail correlation coefficients of this Copula function are both 0.

The more suitable Copula function which can describe the joint distribution of wind power and load is selected from the above four commonly-used Copula functions in each weather condition, according to the Euclidean distance among the four Copula distributions and the empirical Copula distribution, respectively, as depicted in Fig. 6 and listed in Table 2. The Kendall and Spearman rank correlation coefficients, upper and lower tail correlation coefficients are calculated based on the optimal Copula function, as listed in Table 2. The calculation formulas of the correlation coefficients based on the Copula function are shown from Eqs. (9) to (12).

$$\tau = 4\int_0^1\int_0^1 C(u,v)dC(u,v) - 1 \tag{9}$$

$$\rho_s = 12\int_0^1\int_0^1 C(u,v)dudv - 3 \tag{10}$$

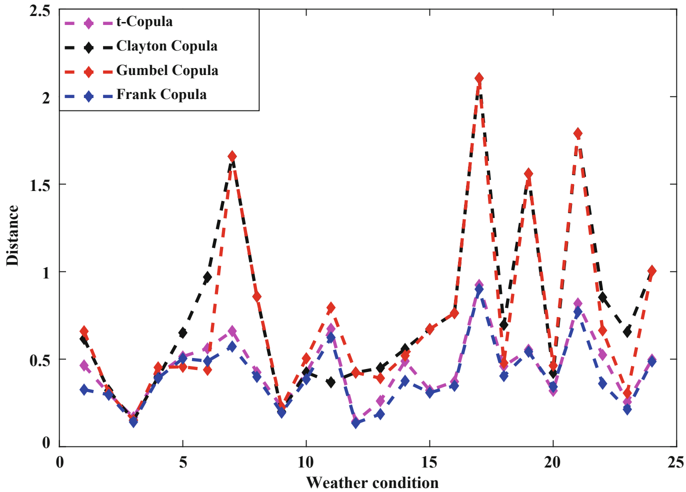


Fig. 6 Selection of Copula functions in different weather conditions

Table 2 Correlation of wind power and load in different weather conditions

Type	Optimal fitting					Type	Optimal fitting				
	Copula function	τ	ρ_s	λ_{up}	λ_{low}		Copula function	τ	ρ_s	λ_{up}	λ_{low}
1	Frank	0.349	0.506	0	0	13	Frank	0.242	0.357	0	0
2	Frank	0.032	0.048	0	0	14	Frank	0.321	0.467	0	0
3	Frank	−0.022	−0.034	0	0	15	Frank	−0.111	−0.165	0	0
4	Frank	0.224	0.331	0	0	16	Frank	−0.078	−0.117	0	0
5	Gumbel	0.080	0.119	0.107	0	17	Frank	−0.347	−0.502	0	0
6	Gumbel	0.276	0.400	0.348	0	18	Frank	0.186	0.276	0	0
7	Frank	−0.258	−0.380	0	0	19	Frank	−0.227	−0.336	0	0
8	Frank	−0.145	−0.217	0	0	20	t-student	0.375	0.536	0.001	0.001
9	Frank	0.004	0.006	0	0	21	Frank	−0.308	−0.450	0	0
10	Frank	0.175	0.260	0	0	22	Frank	0.352	0.510	0	0
11	Clayton	0.285	0.414	0	0.420	23	Frank	0.197	0.292	0	0
12	Frank	−0.109	−0.163	0	0	24	Frank	−0.151	−0.225	0	0

$$\lambda_{up} = \lim_{u \to 1^-} \frac{1 - 2u + C(u,u)}{1 - u} \tag{11}$$

$$\lambda_{low} = \lim_{u \to 0^+} \frac{C(u,u)}{u} \tag{12}$$

As can be seen from Fig. 6 and Table 2,

(1) when the wind power is positively correlated with load, the optimal Copula function which can describe the joint distribution between them is different with the weather condition. For example, Type 5 and Type 6 are more consistent with the Gumbel Copula function, Type 11 is more consistent with the Clayton Copula function, Type 20 is more consistent with the t-student Copula function, the remaining weather conditions are more consistent with the Frank Copula function. In addition, although the Euclidean distance between t-student Copula distribution function and the empirical Copula distribution function is smallest in Type 20, the upper and lower tail correlation coefficients are both only 0.001. It can be considered that the joint distribution of wind power and load is basically independent in the tail under this weather condition. When the wind power is negatively correlated with load, the optimal Copula function which can describe the joint distribution between them is more consistent with the Frank Copula function in each weather condition.

It can be concluded that the joint distributions of them are basically independent in the tail under most weather conditions, and only under a few weather conditions, the joint distributions of wind power and load show the upper tail correlation or the lower tail correlation.

(2) The correlation coefficients which calculated according to the wind power and load variables are basically the same as the correlation coefficients which calculated based on the optimal Copula function in different weather conditions, which further verifies the rationality of the selected optimal Copula functions.

Type 20, Type 6, Type 11, Type 17 and Type 22 are selected according to the results in Table 2 which is more consistent with the t-student Copula function, Gumbel Copula function, Clayton Copula function and Frank Copula function, respectively. The daily variation curves, actual frequency distributions and joint density distributions based on four Copula functions of wind power and load in these five typical weather conditions are depicted in Fig. 7, and the Euclidean distances among four Copula distributions and the empirical Copula distribution are also listed in Fig. 7. It can be intuitively seen from the figure that the selected optimal Copula function in each weather condition can better fit the frequency distribution between wind power and load, and can describe the tail correlation of the joint distribution between them accurately.

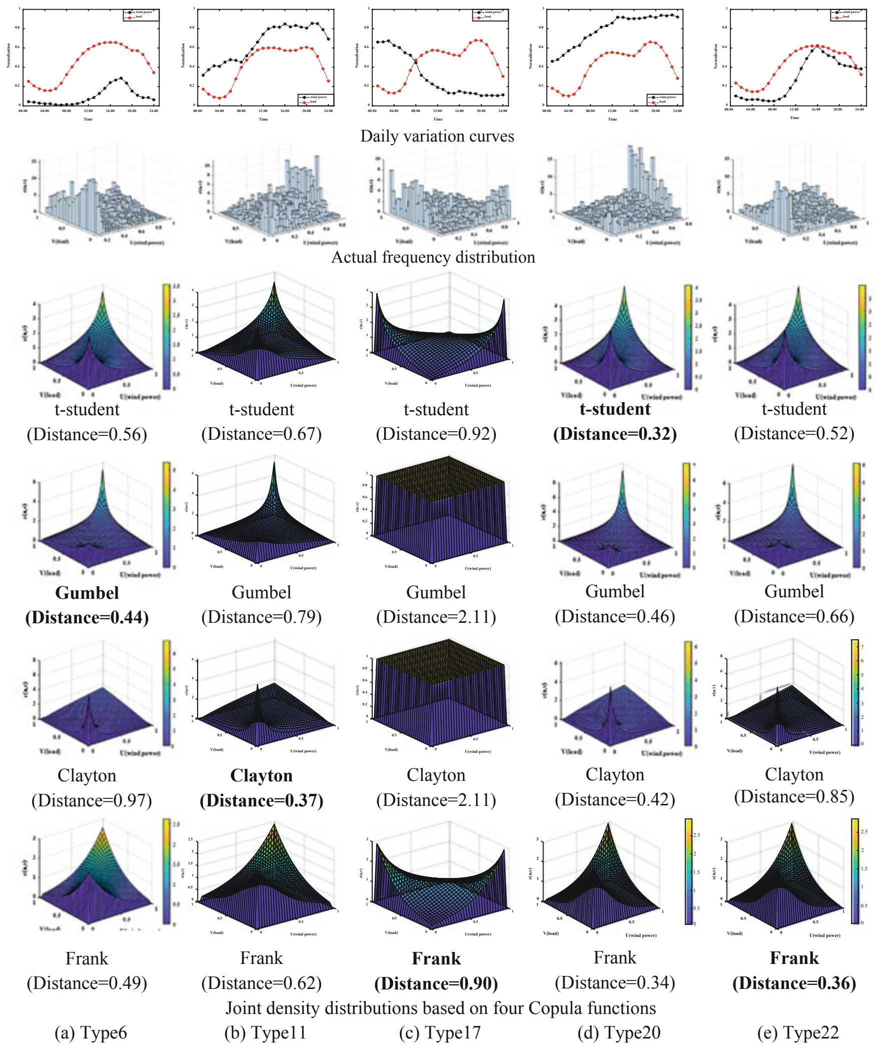
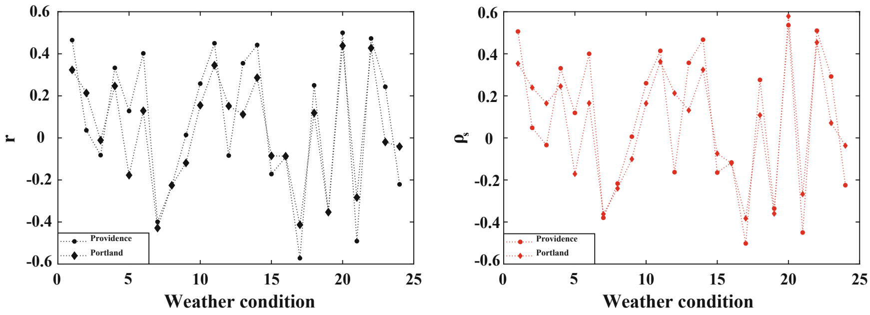


Fig. 7 Joint distributions of wind power and load in five typical weather conditions

3.3 Correlation Verification in Another Place

In this section, the data in Portland area of Maine, USA is used to validate the correlation between wind power and load in different weather conditions which is obtained above in Providence area of Rhode Island, USA. First, the daily normalized wind speed and temperature data in Portland is classified into 24 categories according to the cluster centers of wind speed and temperature in Providence based on the evaluation index of Euclidean distance. Then, the Pearson correlation coefficient is



(a) Pearson correlation coefficients based on variables

(b) Spearman correlation coefficients based on the optimal Copula functions

Fig. 8 Correlation between wind power and load under different weather conditions in two places

employed to analyze the linear correlation between wind power and load variables in 24 weather conditions in Portland, and compared with the results in Providence, as shown in Fig. 8a. Finally, the joint distribution between wind power and load in each weather condition in Portland is also fitted based on four commonly-used Copula functions, including t-student Copula function, Gumbel Copula function, Clayton Copula function and Frank Copula function, and the optimal Copula function is selected according to the Euclidean distance among the four Copula distributions and the empirical Copula distribution. The Spearman rank correlation coefficients are calculated based on the optimal Copula functions in 24 weather conditions, and compared with the results in Providence, as shown in Fig. 8b.

As can be seen from Fig. 8, the variation trend of correlation between wind power and load in different weather conditions is basically the same in these two different places, i.e., there is a repeated rule between wind power and load with the weather condition. The results further illustrate the necessity and validity of studying the correlation between wind power and load in different weather conditions, rather than based on all the data directly.

4 Conclusion

The correlation between wind power and load in different weather conditions is systematically studied based on the correlation coefficients and Copula functions in this paper. The main work and corresponding conclusions are as follows.

(1) The improved algorithm of traditional K-means clustering algorithm—X-means is adopted to divide the daily meteorological factors of wind speed and temperature, and the weather condition is classified into 24 types. The rationality and effectiveness of X-means algorithm are verified according to the clustering error of K-means algorithm under different clustering numbers.

(2) The correlation between wind power and load variables in different weather conditions is analyzed based on the Pearson, Kendall and Spearman correlation coefficients. The results show that, the correlation between wind power and load is quite different with the weather condition. The positive correlation between them is mainly concentrated in summer or near summer, the negative correlation between them is mainly concentrated in winter or near winter, and the probability of occurrence is increase with the correlation degree. The positive and negative correlations between wind power and load variables do not vary with the correlation coefficients.
(3) Four commonly-used Copula functions, including t-student Copula function, Gumbel Copula function, Clayton Copula function and Frank Copula function are employed to describe the joint distribution of wind power and load in each weather condition. The results show that, the joint distributions of wind power and load are more consistent with Frank Copula function, and the tail correlation coefficients of their distribution are zero under most weather conditions. Only in a few weather conditions, the joint distributions of wind power and load are more consistent with Gumbel Copula function (Type 5 and Type 6) and Clayton Copula function (Type 11).
(4) The data in another place (Portland) is used to validate the correlation between wind power and load in different weather conditions. The results show that, there is a repeated rule between the wind power and load with the weather condition.

The research results of this paper can be applied for the planning and dispatching of the electric power system, which with the double uncertainties of source and load sides.

Acknowledgements This work was supported in part by the project of the National Natural Science Foundation of China funded project (51707063), and the project of China Datang Corporation Ltd.

References

1. Lu Z, Huang H, Shan B et al (2017) Morphological evolution model and power forecasting prospect of future electric power systems with high proportion of renewable energy. Autom Electr Power Syst 41(9):12–18
2. Sun Y, Wang Y, Wang B et al (2018) Multi-time scale decision method for source-load interaction considering demand response uncertainty. Autom Electr Power Syst 42(2):106–113 + 159
3. Rakipour D, Barati H (2019) Probabilistic optimization in operation of energy hub with participation of renewable energy resources and demand response. Energy 173:384–399
4. Deng T, Lou S, Tian X et al (2019) Optimal dispatch of power system integrated with wind power considering demand response and deep peak regulation of thermal power units. Autom Electr Power Syst 43
5. Jin H, Sun H, Niu T et al (2019) Coordinated dispatch method of energy-extensive load and wind power considering risk constraints. Autom Electr Power Syst 43

6. Li X, Zhang X, Wu L et al (2015) Transmission line overload risk assessment for power systems with wind and load-power generation correlation. IEEE Trans Smart Grid 6(3):1233–1242
7. Lin L, Zhou P, Wang S et al (2016) Analysis impact on regional wind power to peak regulation capacity by considering the correlation. Mod Electr Power 33(6):21–26
8. Zhao L, Xu D, Li P (2018) Study on wind power output characteristics and correlation between load of region power system. In: 2018 37th Chinese Control Conference (CCC). IEEE, Wuhan, China, pp 8982–8984
9. Baringo L, Conejo A (2013) Correlated wind-power production and electric load scenarios for investment decisions. Appl Energy 101(1):475–482
10. Ak R, Li Y, Vitelli V et al (2018) Adequacy assessment of a wind-integrated system using neural network-based interval predictions of wind power generation and load. Int J Electr Power Energy Syst 95:213–226
11. Mazidi M, Zakariazadeh A, Jadid S et al (2014) Integrated scheduling of renewable generation and demand response programs in a microgrid. Energy Convers Manag 86 (10):1118–1127
12. Korkas C, Baldi S, Michailidis I et al (2016) Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. Appl Energy 163:93–104
13. Liu X, Zhang Z, Wang W et al (2018) Two-stage robust optimal dispatch method considering wind power and load correlation. In: 2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2). IEEE, Beijing, China, pp 1–6
14. Draxl C, Clifton A, Hodge B et al (2015) The Wind Integration National Dataset (WIND) Toolkit. Appl Energy 151:355–366
15. ISO New England Web Page of Pricing Reports, http://www.iso-ne.com/isoexpress/web/reports
16. Pelleg D, Moore A (2000) X-means: extending K-means with efficient estimation of the number of clusters. In: Intelligent Data Engineering and Automated Learning—IDEAL 2000, Data Mining, Financial Engineering, and Intelligent Agents. Morgan Kaufmann Publishers, Hong Kong, China, pp 308–313
17. Ji F, Cai X, Wang J (2014) Wind power correlation analysis based on hybrid copula. Autom Electr Power Syst 38(2):1–5 + 32
18. Han S, Qiao Y, Yan J et al (2019) Mid-to-long term wind and photovoltaic power generation prediction based on copula function and long short term memory network. Appl Energy 239:181–191