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Study on the Time-shifting Characteristics of Natural Wind with Multi Spatial and Temporal Scales

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ABSTRACT

The time-shifting property is an important parameter to characterize the fluctuation of natural wind at multiple temporal-spatial scales. Accurately grasping the time-shifting characteristics of natural wind can effectively reduce the impact of super-large-scale wind power grid integration on the power system. However, most of the existing methods are based on the ARMA model and time-shifting technology to generate wind speed time series with specified correlation coefficients. It is only the change of time to show that this time-shifting characteristic does exist, but there is no specific quantitative analysis on it. This paper will take the minimum Euclidean distance as the goal, and propose two evaluation indicators, time delay and speed offset, to quantitatively describe this time-shifting characteristics of natural wind associated with multiple time-space scales. First, combined with the empirical Copula function, select the optimal Copula function to describe the joint density distribution of the different wind speed time series, providing an important basis for the calculation of the correlation coefficient. Then analyze the time-shifting characteristics of natural wind based on different time scales (from 10 min to one month) to determine the optimal time analysis scale. Finally, based on the optimal time scale, the change law of the time delay and speed offset between natural wind sequences at different spatial points is studied.

Keywords: time-shifting characteristics, correlation coefficient, multiple temporal-spatial scales, time delay, speed offset

1. INTRODUCTION

Among wind turbines, wind farms, and wind farm groups, the wind speed at different points has a strong correlation [1-3], and there is a certain temporal and spatial correlation. At present, scholars at home and abroad have carried out some research on this spatio-temporal correlation, but the focus of the research is mostly on the correlation of wind speed, and the reference on the correlation research mainly focuses on two aspects: one is to directly calculate the correlation through time series. Coefficient to study the correlation between wind speeds. Xu et al. [5] reflects the linear correlation between wind speeds by calculating the Pearson linear correlation coefficient. Chen et al. [6] uses the correlation coefficient matrix to describe the correlation between the wind speed at different points. In fact, the linear correlation coefficient simply reflects the linear correlation between the variables, but when the linear correlation coefficient tends to 0, the variables cannot be simply regarded as uncorrelated. In fact, they may also have some kind of non-linear correlation, so some documents use nonlinear correlation coefficients to describe the correlation between wind speeds. For example, Pan et al. [7-9] uses the Nataf inverse transform technique to describe the nonlinear correlation between wind speeds. Zeng et al. [10] uses the detrended cross-correlation analysis (DCCA) coefficient method to study the temporal and spatial cross-correlation of wind speed. Zeng et al. [11] proposed to use the GP algorithm to calculate the saturation correlation dimension of the wind speed time series to study the correlation of near-surface wind speed. The wind speed at different spatial points must have a certain correlation, but the correlations obtained by using different description methods are also slightly different. The second is to analyze the correlation between wind speeds based on the Copula function [4]. Different Copula functions have different characteristics. Xie et al. [12-16] uses a single Copula function model to describe the correlation of wind speed; Ji et al. [17-19] constructs a mixed Copula function to analyze the correlation of two variables.

But time-shifting characteristic is not the same as correlation, and only a few scholars have carried out research on it. Li [20] is based on the continuous state Markov chain time series wind speed simulation method to characterize the dependence characteristics of different wind speed time series; Xie et al. [21-23] is based on the autoregressive moving average (ARMA) model and time-lapse technology to generate multiple A wind speed time series with a specified correlation coefficient. The above-mentioned documents are all based on the ARMA model and time-shift technology to generate wind speed time series with specified correlation coefficients. It is only the change of time to show that this time-shift characteristic does exist, but there is no specific quantitative analysis on it. This article will take the squared Euclidean distance as the optimization objective, and use two evaluation indicators, time delay and speed deviation, to quantitatively describe the time-shifting characteristics of natural wind at multiple time-space scales.

2. CORRELATION ANALYSIS BASED ON COPULA FUNCTION

2.1 Correlation coefficient

The correlation coefficient is mainly used to measure the correlation between variables. This paper mainly introduces three correlation coefficients, Pearson linear correlation coefficient, Kendall rank correlation coefficient, and Spearman rank correlation coefficient. Pearson's linear correlation coefficient is mainly used to describe linear random variables, and Kendall's rank correlation coefficient and Spearman's rank correlation coefficient are used to describe non-linear and non-normally distributed random variables.

(A) Pearson linear correlation coefficient

Suppose that $(X_i, Y_i), i = 1, 2, \cdots, n$ is a sample taken from the population (X, Y), and the Pearson linear correlation coefficient of the sample is

$$\rho = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}} \tag{1}$$

Among them, $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$, $\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$.

(B) Kendall's rank correlation coefficient

Suppose that (x_1, y_1) and (x_2, y_2) are two dimensional random vectors that are opposite to each other and have the same distribution as (X, Y). $P((X_1 - X_2)(Y_1 - Y_2) > 0)$ represents their harmony probability and $P((X_1 - X_2)(Y_1 - Y_2) < 0)$ represents their disharmony probability. The difference between these two probabilities is called Kendall rank correlation coefficient.

$$\begin{aligned}\tau = &P\left(\left(X_1 - X_2\right)\left(Y_1 - Y_2\right) > 0\right) \\ &-P\left(\left(X_1 - X_2\right)\left(Y_1 - Y_2\right) < 0\right)\end{aligned} \tag{2}$$

(C) Spearman's rank correlation coefficient

Suppose that $(X_i, Y_i), i = 1, 2, \cdots, n$ is a sample taken from the population (X, Y), R_i is used to represent the rank of X_i in $(X_1, X_2, \cdots, X_n)$, and Q_i is used to represent the rank of Y_i in $(Y_1, Y_2, \cdots, Y_n)$, then the Spearman rank correlation coefficient of the sample is

$$\rho_s = \frac{\sum_{i=1}^{n}\left(R_i - \overline{R}\right)\left(Q_i - \overline{Q}\right)}{\sqrt{\sum_{i=1}^{n}\left(R_i - \overline{R}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Q_i - \overline{Q}\right)^2}} \tag{3}$$

Among them, $\overline{R} = \frac{1}{n}\sum_{i=1}^{n} R_i$, $\overline{Q} = \frac{1}{n}\sum_{i=1}^{n} Q_i$.

2.2 Copula function

The Copula function is a connection function that connects the joint distribution function $F(x_1, x_2, \cdots, x_N)$ of the random vector $X_1, X_2, \cdots, X_N$ with the respective marginal distribution function $F_{X_1}(x_1), \cdots, F_{X_N}(x_N)$, that is, the function $C(u_1, u_2, \cdots, u_N)$, so that

$$F(x_1, x_2, \cdots, x_N) = C[F_{X_1}(x_1), F_{X_2}(x_2), \cdots, F_{X_N}(x_N)] \tag{4}$$

Commonly used Copula functions can be roughly divided into five types: Normal Copula function, t-Copula function and Gumbel Copula function, Clayton Copula function and Frank Copula function.

In order to select the optimal Copula function model, the empirical Copula function is introduced to evaluate the model.

Empirical Copula function: Let $(X_i, Y_i), i = 1, 2, \cdots, n$ be a sample taken from a two-dimensional population

(X,Y). Let the empirical distribution functions of X and Y be $F_n(x)$ and $G_n(y)$, respectively. The empirical Copula function of the sample is as follows:

$$\hat{C}(\mu,\nu)=\frac{1}{n}\sum_{i=1}^{n} I_{[F_N(x_i)\le\mu]} I_{[G_n(y_i\le y]} \tag{5}$$

Among them, $I_{[.]}$ is the indicative function, when $F_n(x_i)\le\mu$, $I_{[F_n(x_i)\le\mu]}=1$, otherwise $I_{[F_n(x_i)\le\mu]}=0$.

After having the empirical Copula function, the square Euclidean distance between the five kinds of Copula functions and the empirical Copula function is investigated. The calculation formula is as follows:

$$d_{Ga}^2=\sum_{i=1}^{n}\left|\hat{C}_n(\mu_i,\nu_i)-\hat{C}^{Ga}(\mu_i,\nu_i)\right|^2 \tag{6}$$

$$d_t^2=\sum_{i=1}^{n}\left|\hat{C}_n(\mu_i,\nu_i)-\hat{C}^{t}(\mu_i,\nu_i)\right|^2 \tag{7}$$

$$d_G^2=\sum_{i=1}^{n}\left|\hat{C}_n(\mu_i,\nu_i)-\hat{C}^{G}(\mu_i,\nu_i)\right|^2 \tag{8}$$

$$d_C^2=\sum_{i=1}^{n}\left|\hat{C}_n(\mu_i,\nu_i)-\hat{C}^{C}(\mu_i,\nu_i)\right|^2 \tag{9}$$

$$d_F^2=\sum_{i=1}^{n}\left|\hat{C}_n(\mu_i,\nu_i)-\hat{C}^{F}(\mu_i,\nu_i)\right|^2 \tag{10}$$

According to the square Euclidean distance criterion, the smaller the square Euclidean distance between the square Euclidean distance and the empirical Copula function is, the better the wind speed time series at two points can be fitted.

2.3 Correlation analysis based on Copula function

If the edge distribution of continuous random vector (X,Y) is set as $F(x)$ and $G(y)$ respectively, where $U=F(x)$ ~ $U(0,1)$, $V=G(y)$ ~ $U(0,1)$, the corresponding Copula function $C(\mu,\nu)$ and Kendall rank correlation coefficient(τ), Spearman rank correlation coefficient(ρ_s)

$$\tau=4\int_0^1\int_0^1 C(\mu,\nu)dC(\mu,\nu)-1 \tag{11}$$

$$\begin{aligned}\rho_s&=12\int_0^1\int_0^1 \mu\nu dC(\mu,\nu)-3\\&=12\int_0^1\int_0^1 C(\mu,\nu)d\mu d\nu-3\end{aligned} \tag{12}$$

2.4 Case study

2.4.1 Correlation analysis based on time series

This paper selects the wind speed and wind direction data at the 8# and 13# points of a wind farm for analysis. the time length of these data is one month, and the resolution is 30 seconds. The wind turbine of 13# is in the main wind direction, and the distance between them is about 6300m.

Table 1 is the correlation coefficient directly calculated based on the time series. The three correlation coefficients are all between [0.5, 1], which indicates that there is a certain correlation between the wind speeds at points 8# and 13#.

Table 1 The correlation coefficient between wind turbine 8# and 13#

	ρ	τ	ρ_s
13 #- 8#	0.7043	0.5119	0.7002

2.4.2 Correlation analysis based on Copula function

First, determine the edge distribution based on the two wind speed time series data, and then determine the binary frequency histogram based on the edge distribution. On this basis, the frequency distribution histogram can be drawn. Finally, the corresponding Copula function is selected according to the frequency histogram of the wind speed and the shape of the frequency histogram, as shown Figure 1.

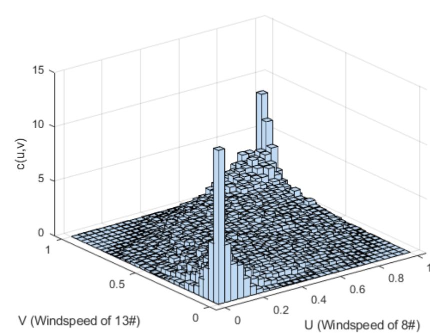


Fig 1 Frequency histogram of wind speed at 8# and 13#

Comparing and analyzing the frequency histogram of the two wind speed time series distributions and the five kinds of Copula function distribution graphs and density function graphs, it can be seen that the normal Copula function and the t-Copula function are closest to the frequency distribution of the two wind speed time series.

The squared Euclidean distance between the five Copula functions and the empirical Copula function is shown in the table 2. It can be seen that under the squared Euclidean distance standard, the squared

Euclidean distance between the t-Copula function and the empirical Copula function is the smallest.

Table 2 The square Euclidean distance of two wind speed time series (8# & 13#)

Type	d^2
Normal Copula	0.9242
t-Copula	0.9204
Gumbel-Copula	5.0992
Clayton-Copula	26.0219
Frank-Copula	8.6038

Combining the binary frequency histogram and frequency histogram of the two wind speed time series distributions and the squared Euclidean distance standard shows that the t-Copula function model can better fit the correlation between different wind speed time series.

The correlation coefficients of t-Copula function models are calculated based on the wind speed data at 8# and 13#, and the results are shown in table 3.

Table 3 The correlation coefficient based on the Copula function of two wind speed time series (8# & 13#)

	τ	ρ_s
t-Copula	0.5153	0.7053

3. STUDY ON TIME-SHIFTING CHARACTERISTICS OF NATURAL WIND IN MULTI-TIME SCALE

3.1 Quantitative evaluation index of time-shifting characteristics

The wind speed has the fluctuation randomness, the natural wind moves from one wind turbine to another wind turbine, from one wind farm to another wind farm, the wind speed must have a certain space-time change. In order to quantitatively describe the time-shift characteristics of natural wind at multiple spatial and temporal scales, two evaluation indexes, time delay and speed offset, are proposed. The shortest Euclidean distance between wind speed time series at different points is taken as the optimization objective to solve the optimal time delay and velocity migration.

The formula for calculating the shortest square Euclidean distance is:

$$D=\sqrt{\frac{\sum_{t=1}^{n}\left(V_1(t)-\left(V_2(t+\Delta t)+\Delta v\right)\right)^2}{n}} \tag{13}$$

Among them, D is the square Euclidean distance, V_1 and V_2 are the wind speed of the two wind turbines, Δt is the time delay, Δv is speed offset.

3.2 Analysis of time delay and velocity deviation under different time scales

Wind turbine 13# is in the main wind direction, so based on wind turbine 13#, 1 hour is reserved before and after the wind speed time series of 8# wind turbine to change the wind speed of wind turbine 8#. Based on the principle of the shortest squared Euclidean distance (considering the influence of wake), find out the wind speed data at point 8# that matches the 13# wind turbine, and get the optimal time delay and speed offset.

When the month is used as the time analysis scale, the optimal time delay obtained by calculation is 9 minutes, and the optimal speed deviation is 0.3m/s.

The correlation changes of the two wind speed time series before and after considering the time-shift characteristics are shown in Table 4. After considering the time-shifting characteristics, the correlation coefficient of the two wind speed time series becomes larger and the correlation becomes stronger.

Table 4 The correlation coefficient of two wind speed time series (time scale is one month)

	Original	Considering time-shifting
τ	0.5153	0.5188
ρ_s	0.7053	0.7098

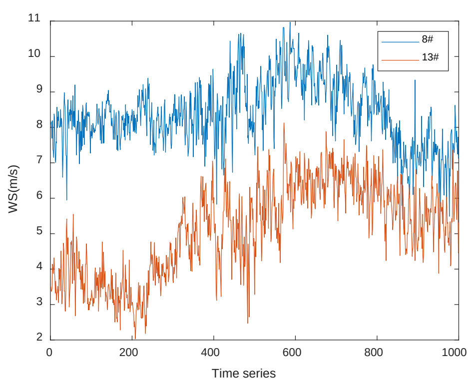
The time scale is too large, and the time-shifting characteristic changes insignificantly. Therefore, in order to accurately grasp the time-shifting characteristics of natural wind, the wind speed data needs to be segmented, with minutes as the time analysis scale. According to the measured results of wind speed characteristics made by Van der Hoven, the average wind speed is basically stable within 10 min-2 Hour. Therefore, when the wind speed data is segmented at 10 min intervals, it can be approximately considered that the wind speed is constant in this time range. So the time-shift characteristics were analyzed at the time scales of 10min, 20min, 30min, 40min, 50min, 1h, 2h, 3h, 4h, 6h, 12h, 24h, 15d and 30d, respectively. The results are shown in Table 5 and Figure 3.

It can be seen from Table 5 that as the time scale decreases, the correlation coefficient keeps increasing, and the squared Euclidean distance keeps decreasing.

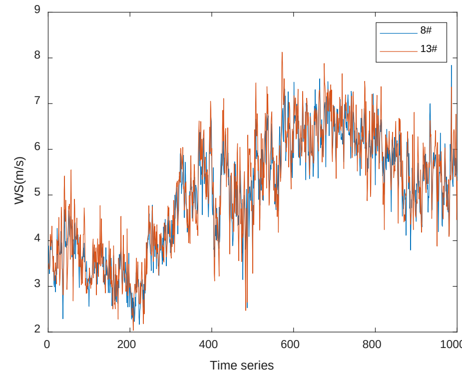
Table 5 The correlation coefficient of two wind speed time series in different time scales

	τ	ρ_s	D
30d	0.5129	0.7018	2.3380
15d	0.5328	0.7245	2.3904
2d	0.5729	0.7679	2.1222
1d	0.6005	0.7948	1.9882
12h	0.6461	0.8354	1.7182
6h	0.6870	0.8693	1.4857
4h	0.7143	0.8895	1.3644
3h	0.7383	0.9072	1.2357
2h	0.7601	0.9216	1.1177
1h	0.7983	0.944	0.9457
50min	0.806	0.9480	0.9100
40min	0.8174	0.9537	0.8607
30min	0.8032	0.9597	0.8056
20min	0.8482	0.9678	0.7125
10min	0.8821	0.9803	0.5662

As can be seen from Figure 3, when taking 10 minutes as the time analysis scale, the time series of wind speed at 8# and 13# have changed significantly. The wind speed at 13# is consistent with that at 8#. The time series of the two wind speeds basically coincide, only the speed is different.



a) Original



b) Consider time -shifting

Fig 3 Wind speed time series (time scale is 10min)

In summary, when the time analysis scale is 10 minutes, the correlation coefficient is the largest and the squared Euclidean distance is the smallest, so 10 minutes can be considered as the optimal time analysis scale.

4. STUDY ON TIME-SHIFTING CHARACTERISTICS OF NATURAL WIND IN MULTI-SPATIAL SCALE

4.1 Correlation analysis based on different spatial scales

The wind speed data of five wind turbines 3#, 19#, 20#, 21# and 24# from the same wind farm were selected for research. The wind turbine of 21# is in the main wind direction, and the distance between them is shown in table 6.

	Distance(m)
21#-20#	284
21#-19#	1822
21#-24#	2277
21#-3#	4212

Based on the optimal time scale, the correlation coefficient and square Euclidean distance between different wind speed time series are shown in table 7. After considering the time-shifting characteristics of natural wind, the correlation between different time series is enhanced, and the fluctuation characteristics of internal wind in different spatial domains can be simulated more accurately.

Table 7 Correlation coefficient and squared Euclidean distance between different wind speed time series

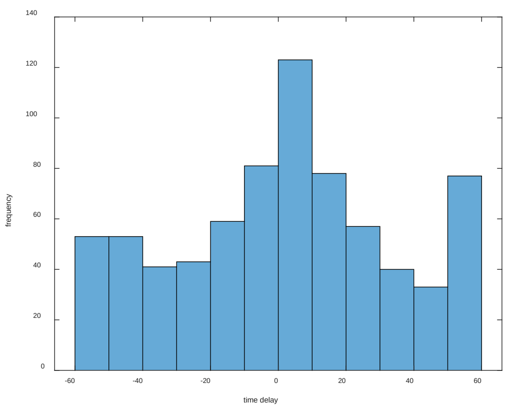
		21#-3#	21#-19#	21#-20#	21#-24#
Original	τ	0.7171	0.7475	0.8451	0.7546
	ρ_s	0.8923	0.9138	0.9654	0.9171
	D	1.3307	1.3175	0.8284	1.2156

Consider time-shifting characteristic	τ	0.9785	0.8778	0.9002	0.8810
	ρ_s	0.9814	0.9792	0.9859	0.9801
	D	0.5942	0.5983	0.5484	0.5934

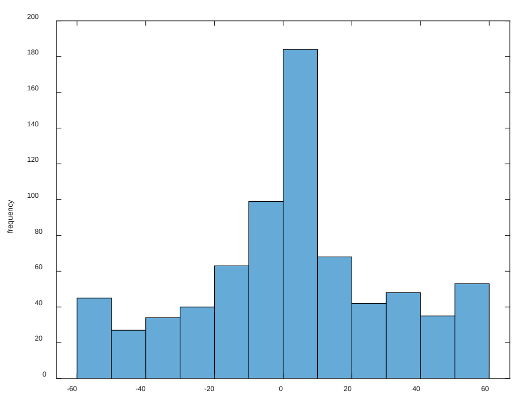
4.2 Time delay and speed offset distribution

4.2.1 Time delay

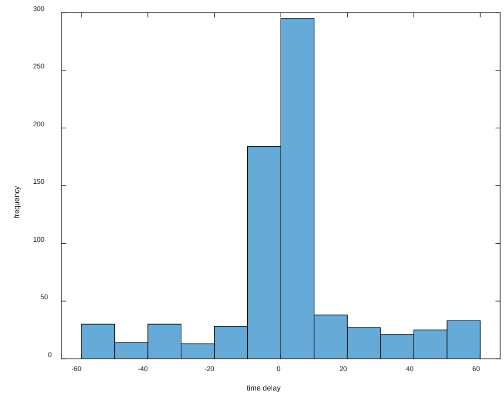
The frequency distribution histogram of the two wind speed time series is used to quantitatively describe the time-shifting characteristics of natural wind movement. It can be seen from Figure 4 that there is a certain time delay in wind speed between different wind turbines, and the delay time of most wind turbines is within 0 to 10 minutes. However, the time delay between the wind speed time series of wind turbine units 20# and 21# is relatively small. This may be because the units are close together, the natural wind moves fast, and the time delay is relatively small. Wind turbines 3# and 21# are far apart, and the time delays are approximately symmetrically distributed, but the overall time delay is still positive.



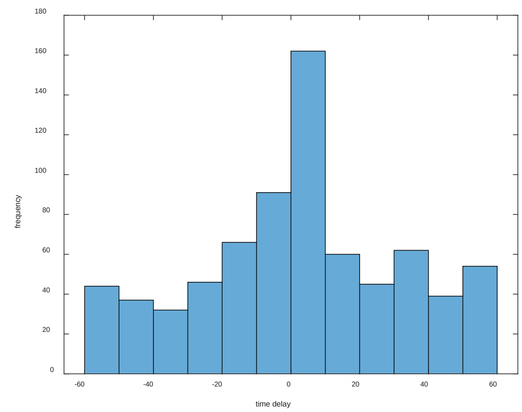
a) 3#-21#



b) 19# -21#



c) 20# -21#

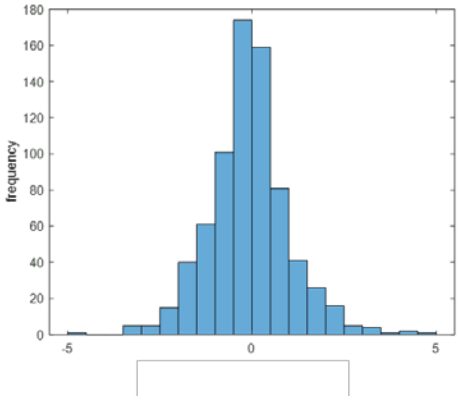


d) 24# - 21#

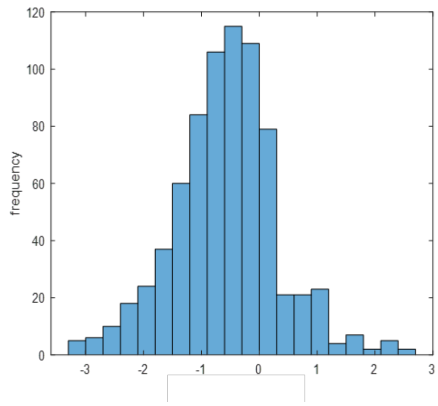
Fig 4 Histogram of time delay frequency distribution between different wind speed time series

4.2.2 Speed offset

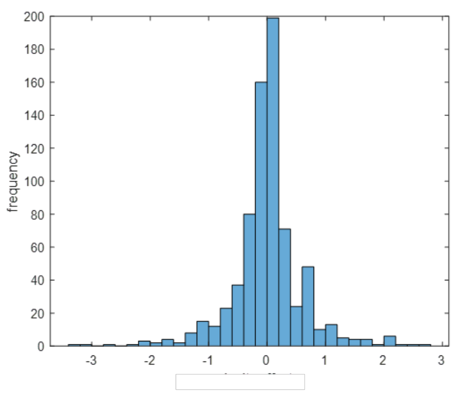
It can be seen from Figure 5 that the speed offset is distributed on the left, and the wind speed decreases when the natural wind moves from one point to another. Regardless of the distance between the wind turbines, the speed deviation is relatively small, which is mainly due to the close distance between them. However, the speed offset also shows more complicated characteristics. When the wind turbines are close together, the speed is usually attenuated due to wake factors; when the wind turbines are far apart, they are affected by factors such as terrain and temperature. The change situation is extremely complicated, and the regularity of velocity deviation is poor.



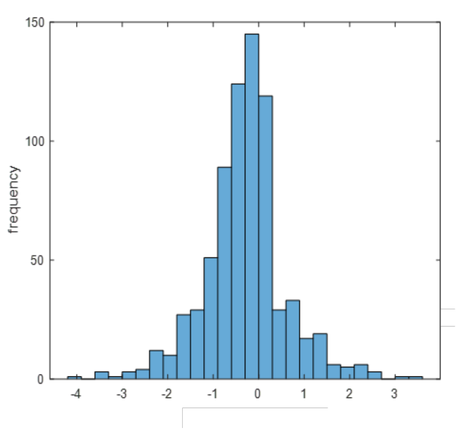
a) 3#-21#



b) 19#-21#



c) 20#-21#



d) 24#-21#

Fig 5 Histogram of speed offset frequency distribution between different wind speed time series

5. CONCLUSIONS

Taking the minimum Euclidean distance as the goal, this paper proposes two evaluation indicators of time delay and velocity deviation to quantitatively describe the time-shifting characteristics of natural wind at multiple time-space scales, and validates the proposed indicators based on correlation coefficients. The main conclusions are as follows:

1) When the t-Copula function is used to fit the wind speed time series at two points, the squared Euclidean distance is the smallest and the fitting effect is the best.

2)As the time analysis scale increases, the correlation between the two wind speed time series gradually decreases, and the Euclidean distance gradually increases. When the time analysis scale is 10min, the correlation coefficient is the largest, and the square Euclidean distance is the smallest. So the optimal time analysis is 10min.

3)The time delay of natural wind at different wind turbines increases with the increase of spatial distance, but the speed offset shows more complicated characteristics. When the wind turbines are close together, the speed is usually attenuated due to wake factors; when the wind turbines are far apart, affected by terrain, temperature and other factors, the changes are extremely complicated and the regularity is poor.

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