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Research Article

Wind Velocity Field Simulation of the Large-Span Spatial Structure Based on the Wavelet Decomposition Method

Daming Zhang[1,2] **Fangjin Sun**[3,4,5] **and Zhonghao Xu**[6]

[1]Guangxi Key Laboratory of Embedded Technology and Intelligence, Guilin 541006, China
[2]College of Information Science and Engineering, Guilin University of Technology, Guilin 541006, China
[3]Guangxi Key Laboratory of New Energy and Building Energy Saving, Guilin University of Technology, Guilin 541004, China
[4]Guangxi Key Laboratory of Geomechanics and Geotechnical Engineering, Guilin University of Technology, Guilin 541004, China
[5]College of Civil Engineering and Architecture, Guilin University of Technology, Guilin 541004, China
[6]College of Civil Engineering, Liaoning Technical University, Fuxin 123000, China

Correspondence should be addressed to Daming Zhang; e_horse@163.com

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In this study, the wavelet decomposition method is combined with the vector AR model of the linear filter method to present a new method for simulating the fluctuating wind field of a large-span spatial structure. This method performs wavelet expansion on the autoregressive coefficients of the vector AR model in adequate space and adopts the least square method to estimate the autoregressive coefficients of the AR model. The implementation steps of this method are to simulate the wind field of large-span structures are given. The method is applied to the wind velocity field simulation of a large-span spatial structure, and the comparison between the simulation result and the target value and the comparison with the simulation result of the vector AR model are given. The results prove that the proposed method can reduce the information loss of wind velocity time-series analysis in the frequency domain, can accurately simulate the wind velocity time series of large-span spatial structures, and has high computational efficiency.

1. Introduction

Wind load is an important design load for large-span spatial structures. With the development of numerical simulation theory, computer simulation of wind velocity and wind load is increasingly applied. To study the wind load of long-span spatial structures, it is necessary to simulate the wind speed time history at a large number of points and consider the temporal and spatial correlation characteristics of the wind. At present, there are two main models widely used in wind field simulation: harmonic superposition method [1] and linear filter method [2]. The former is computationally intensive, especially when there are many simulated points, which is quite time-consuming. However, the AR model in the latter method simulates the stochastic process directly from the perspective of time domain, so it has less computation and faster simulation speed, especially in the wind field simulation of large complex structures, which is more widely used. AR models can be classified into two categories: AR models of scalar processes [3] and AR models of vector processes [4, 5]. The AR model of vector process is very commonly used in multivariate time series analysis due to its stationarity and simplicity of parameter interpolation, and the fluctuation of natural wind can be approximated as a stable Gaussian random process experienced by various states. If the wind field is regarded as the sum of random wind waves at discrete spatial points, it can be treated as a one-dimensional multivariable random process. However, the disadvantage of the vector AR model is that it is not suitable for random field simulation of nonuniform grids. Moreover, these processes are difficult to strengthen the local solution of random field samples, and wavelet transform is an appropriate method that has a nonuniform grid and can detect the local similarity of time series [6]. Wavelet decomposition is widely used in signal feature extraction in various fields [7–10]. Because of its good localization characteristics in both the time domain and frequency domain, it has broad application prospects in wind engineering applications [11].

At present, there are few studies about the specific application of wavelet analysis in wind field simulation. Zeldin and Spanos [12] simulated one-dimensional and multidimensional random fields with Daubechies orthogonal wavelets based on the principle of linear estimation. Chen and Wang [6] simulated the fluctuating wind velocity time series at a point with wavelet analysis and compared them with the measured results. Gao et al. [13] proposed an ultrashort-term wind speed prediction method based on neural network and wavelet analysis. Zhang et al. [14] proposed to use discrete biorthogonal wavelets with a distance-dependent threshold to denoise wind speed that has large dynamic range along the data profile, and wavelet analysis is adopted to improve the accuracy of the wind velocity derived from lidar backscattering. Cava et al. [15] applied the Euler autocorrelation function and Morlet continuous wavelet transform to study the turbulence of the boundary layer at night under low wind conditions. Zheng [16] considered the difference and predictability of the frequency series obtained after the decomposition of the actual wind speed series and proposed a combined forecasting method of ultrashort-term wind speed mixed model based on wavelet decomposition to improve the prediction accuracy. Chandra et al. [17] and Doucoure et al. [18] also applied wavelet analysis to wind speed prediction. Based on the wavelet extension of autoregressive coefficients, the estimation method of vector process AR model is presented in this paper so as to simulate the wind speed field of long-span roof.

In this study, a new method for simulating the fluctuating wind field of large-span structures is given by combining the vector process AR model in the linear filter method and applying the wavelet decomposition method. In this method, the autoregressive coefficients of the vector process AR model is spatially extended by wavelet, and the least square method is applied to estimate the autoregressive coefficients of the AR model, and the realization steps of the wind field simulation of the large-span structure are given. The method is applied to the simulation of wind velocity field of a large-span structure, and the simulation results are compared with the target value.

2. Methodology

The methodology is developed as follows.

2.1. Theory of Wavelet Decomposition. Wavelet is a special kind of waveform with fast decay or a small area with a finite length and a mean value of 0. In the early 20th century, the wavelet was first discovered and used by Haar, and this wavelet was also named as Haar wavelet. In the 1980s, French scholar Morlet proposed wavelet transform, a theoretical method of time-frequency analysis based on the Fourier transform [19]. French scientist Meyer successfully constructed a smooth function with a certain attenuation and constructed the normal orthogonal basis of the $L^2(R)$ space through scaling and translation. Daubechies, Coifman, and Wickerhauser have also made outstanding contributions to the development of wavelet theory and engineering applications. Wavelet transform not only has the nature of frequency analysis but also can represent the time of occurrence, which is convenient for analyzing and determining the phenomenon of time. Wavelet transform has been widely used in many fields [20] such as signal processing, pattern recognition, and image processing.

Wavelet transform is developed from Fourier transform. Compared with Fourier transform, wavelet transform emphasizes the local characterization of time and frequency. Fourier transform can only get the spectrogram of the signal but not the time of appearance, and even the same spectrogram may appear for two different nonstationary sequences. The wavelet transform can change adaptively, and the variable time window enables the wavelet transform to extract effective information from the signal and clearly shows the trend component and detail component of the signal, which is more advantageous than the Fourier transform [21].

Wavelet transform can be divided into three wavelet transforms: continuous wavelet transform, discrete wavelet transform, and dyadic wavelet transform [22].

If $\psi(t) \in L^2(R)$, its Fourier transform $\widehat{\psi}(\omega)$ satisfies the following formula:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\widehat{\psi}(\omega)|^2}{|\omega|} \mathrm{d}\omega < \infty, \tag{1}$$

where C_ψ is bounded and ψ is called a base wavelet or mother wavelet. Equation (1) is called the admissible condition of wavelet function.

After the mother wavelet is stretched and translated, the wavelet sequence can be obtained as

$$\psi_{a,b}(t) = |a|^{-1/2} \psi\left(\frac{t-b}{a}\right), \tag{2}$$

where a is the expansion factor and b is the translation factor.

The shape of the time-frequency window is determined by the value of the scaling factor a, and the position of the window is determined by the translation factor b. When both a and b take values continuously, $\psi_{a,b}(t)$ is called a continuous wavelet function. For $\forall f(t) \in L^2(R)$, when the function $f(t)$ is expanded under the continuous wavelet base $\psi_{a,b}(t)$, the expression is

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = |a|^{-1/2} \int_{-\infty}^{+\infty} f(t) \overline{\psi}\left(\frac{t-b}{a}\right) \mathrm{d}t. \tag{3}$$

Equation (3) is called continuous wavelet transform (CWT) on mother wavelet ψ. $\overline{\psi}(t-b/a)$ is the conjugate operation of $\psi(t-b/a)$.

Because the continuous wavelet transform needs to calculate the integral in the application, it is inconvenient to process digital signals, so it is mainly used for theoretical analysis and demonstration. In practical problems, the discrete form is usually used, namely, discrete wavelet transform (DWT). DWT can be obtained by discretizing the expansion factor a and the translation factor b in CWT. Usually, $a = a_0{}^m$ and $b = nb_0 a_0{}^m$; then, Equation (4) can be obtained as

$$\psi_{m,n}(t) = |a_0|^{-m/2}\psi(a_0{}^{-m}t - nb_0), m, n \in Z. \quad (4)$$

The wavelet function in equation (4) is a discrete wavelet. The discrete wavelet transform is

$$W_f(a,b) = \langle f, \psi_{a,b}\rangle = |a_0|^{-m/2}\int_{-\infty}^{+\infty} f(t)\overline{\psi}(a_0{}^{-m}t - nb_0)\mathrm{d}t. \quad (5)$$

Taking $a_0 = 2$ and $b_0 = 1$, the dyadic wavelet can be obtained as follows:

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n), m, n \in Z. \quad (6)$$

In practical applications, it is usually necessary to construct a wavelet function with orthogonality to make the calculation of wavelet transform more effective:

$$\langle \psi_{m,n}, \psi_{j,k}\rangle = \int_{-\infty}^{+\infty} \psi_{m,n}(t)\overline{\psi}_{j,k}(t)\mathrm{d}t = \delta_{m,j}\delta_{n,k}. \quad (7)$$

2.2. Wind Load Simulation of the Vector AR Model. The AR model is commonly used in wind load simulation. Here is only a brief introduction to the equation of vector process AR model, which lays the foundation for the subsequent analysis using the wavelet method.

N related fluctuating wind velocity time series $\mathbf{v}(t) = [v_1(t), v_2(t), \cdots, v_n(t)]^{\mathrm{T}}$ can be generated by the following equation:

$$\mathbf{v}(t) = \sum_{k=1}^{p} \boldsymbol{\psi}_k \mathbf{v}(t - k \cdot \Delta t) + \mathbf{N}(t), \quad (8)$$

where p is the regression order of the AR model, ψ_k is the $N \times N$ order autoregressive coefficient matrix, $\mathbf{N}(t) = [N_1(t), N_2(t), \cdots, N_N(t)]^{\mathrm{T}}$, and $N_j(t)$ is an independent random process with undetermined zero mean and covariance.

From the nature of the stationary random process, the regular equation of the AR model can be obtained as

$$\mathbf{R} \bullet \boldsymbol{\psi} = \begin{bmatrix} \mathbf{R}_N \\ \mathbf{O}_p \end{bmatrix}, \quad (9)$$

where $\psi = [I, \psi_1, \cdots \psi_p]^T$ is an $(p+1)M \times M$ order matrix, $\mathbf{I}$ is an M-order unit matrix, $\mathbf{O}_p$ is a $pM \times M$ order matrix with all zero elements, and $\mathbf{R}$ is a $(p+1)M \times (p+1)M$ order autocorrelation matrix.

The correlation function $\mathbf{R}(k\Delta t)$ is a square matrix of order $M \times M$, $k = 0, \cdots p$, determined by the Wiener–Khintchine equation:

$$R_{ij}(k\Delta t) = \int_0^{+\infty} S_{ij}(f)\cos(2\pi f k \Delta t)\mathrm{d}f, \quad (10)$$

where f is the frequency of fluctuating wind velocity and $S_{ij}(f)$ can be determined by the autospectral density function $S_{ii}(f)$ and coherence function $r_{ij}(f)$:

$$S_{ij}(f) = \sqrt{S_{ii}(f)S_{jj}(f)\bullet r_{ij}(f)}. \quad (11)$$

The large-span spatial structure has a relatively small span and little change in node height. Davenport wind velocity spectrum can be adopted [23] as

$$S_{ii}(f) = \frac{4kV_{10}^2}{f}\frac{x^2}{\left(1 + x^2\right)^{4/3}}, \qquad x = \frac{1200f}{V_{10}}, \quad (12)$$

where k is the surface resistance coefficient and V_{10} is the average wind velocity at a height of 10 m.

Considering the spatial correlation of wind velocity time series through $r_{ij}(f)$ [23], its three-dimensional expression is

$$r_{ij}(f) = \exp\left[\frac{-2f\sqrt{C_x^2\left(x_i - x_j\right)^2 + C_y^2\left(y_i - y_j\right)^2 + C_z^2\left(z_i - z_j\right)^2}}{\overline{V}(z_i) + \overline{V}\left(z_j\right)}\right]. \quad (13)$$

where C_x, C_y, C_z, respectively, represent the attenuation coefficients of left and right, up and down, and front and back of any two points in space, which are determined by experiment or actual measurement and $\overline{V}(z_i), \overline{V}(z_j)$, respectively, represent the average wind velocity at the ith point and the jth point.

2.3. AR Model Parameter Estimation Based on the Wavelet Method. The wavelet decomposition method is used to spatially expand the autoregressive coefficients of the above AR model. The wavelet expansion method is adopted to expand the vector process AR model coefficients in sufficient space. For any function $f(x) \in L^2$, it can be extended to

$$f(x) = \sum_{j=-1}^{\infty}\sum_{k=0}^{\infty} \beta_{j,k}\psi_{j,k}(x), \quad (14)$$

where $\psi_{j,k}(x)$ is the mother wavelet and $\beta_{j,k} = \langle f(x); \psi_{j,k}\rangle$.

Regarding the above multidimensional AR model as a function of time and belonging to L^2, here, we refer to the representation method in [24], and the model can be expressed as

$$v_t = \sum_{j=-1}^{J}\sum_{k=0}^{2j-1} \mathbf{u}_{j,k}\psi_{j,k}(t) + \sum_{l=1}^{p}\sum_{j=-1}^{J}\sum_{k=0}^{2j-1} \mathbf{A}_{j,k}^{(l)}\psi_{j,k}(t)x_{t-l} + \delta_t. \quad (15)$$

In the equation,

$$\delta_t = \sum_{jJ}\sum_{k=0}^{\infty}\mathbf{u}_{j,k}\psi_{j,k}(t) + \sum_{l=1}^{p}\sum_{jJ}\sum_{k=0}^{\infty}\mathbf{A}_{j,k}^{(l)}\psi_{j,k}(t)x_{t-l} + \eta_t = \zeta_t + \eta_t, \tag{16}$$

where $\mathbf{A}_{j,k}^{(l)}(l = 1, 2\cdots, j = 1, 2\cdots, k = 1, 2\cdots)$ is the matrix containing wavelet expansion coefficients, $\mathbf{u}_{j,k}$ is the intercept vector, $\mathbf{A}_{j,k}^{(l)}$ and $\mathbf{u}_{j,k}$ contain the coefficients to be estimated, η_t is the independent zero mean variable, and ζ_t is the truncation error. The above vectors are all functions of time.

The reliability and applicability of the time-varying model mainly depends on the accuracy of its parameter estimation. This study adopts the least square method to determine the autoregressive coefficient of the AR model; that is, the coefficients contained in $\mathbf{A}_{j,k}^{(l)}$ and $\mathbf{u}_{j,k}$. The commonly used estimation method for time-varying models is based on adaptive filter and window estimation, but this method is not accurate enough for the simulation of short-term time series because the window length should not be too large at this time. At this time, the method of function expansion in enough space can be used. This study adopts the expansion method based on wavelet.

First, assuming that the covariance matrix $\sum(t)$ is known, equation (15) can be rewritten as

$$v_t = \mathrm{H}[\mathbf{\Theta}\otimes\Gamma(t)]^{\mathrm{T}} + \delta_t, \tag{17}$$

where $\otimes$ represents the Kronecker product, Θ is the column vector containing v_t, $\Theta = [v_{t-1}, v_{t-2}, \cdots, v_{t-p}]^{\mathrm{T}}$, $\Gamma(t)$ is the 1×2^J order vector containing the wavelet function, $\Gamma(t) = [\gamma_{-1,0}(t), \gamma_{0,0}(t), \cdots, \gamma_{J,2^{J-1}}(t)]$, and H is the matrix containing all wavelet expansion coefficients.

Then, the p-order wavelet vector AR model can be expressed as

$$\mathbf{Z} = \lambda\mathbf{M} + \delta_t, \tag{18}$$

where λ is the generalized least squares estimation coefficient, and its value is determined by the following equation:

$$\lambda = \left(\mathbf{M}^{\mathrm{T}}\sum^{-1}\mathbf{M}\right)^{-1}\mathbf{M}^{\mathrm{T}}\sum^{-1}\mathbf{Z} = \left(\mathbf{C}^{\mathrm{T}}\mathbf{C}\right)^{-1}\mathbf{C}^{\mathrm{T}}\mathbf{V}. \tag{19}$$

Among them,

$$\mathbf{C} = \sum^{-1/2}M, \tag{20}$$

$$\mathbf{V} = \sum^{-1/2}\mathbf{Z}, \tag{21}$$

$$\mathbf{M} = \mathbf{I}_s\otimes\mathbf{K}, \tag{22}$$

$$\mathbf{K} = [\mathbf{I}_{N-P}\otimes\boldsymbol{\psi}, \mathbf{X}_{t-1}\otimes\boldsymbol{\psi}, \cdots, \mathbf{X}_{t-l}\otimes\boldsymbol{\psi}]^{\mathrm{T}}, \tag{23}$$

$$\mathbf{X}_{t-l} = \begin{pmatrix} x_{1,p-l+1} & x_{2,p-l+1} & \cdots & x_{s,p-l+1} \\ x_{1,p-l+2} & x_{2,p-l+2} & \cdots & x_{s,p-l+2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1,T-l} & x_{2,T-l} & \cdots & x_{s,T-l} \end{pmatrix}. \tag{24}$$

2.4. Implementation Steps of Wind Field Simulation for Large-Span Structures. In the previous steps, it is assumed that the covariance matrix $\sum(t)$ is known, but the covariance matrix is usually unknown in the actual use of the least square method. For this reason, we assume that η_t has zero mean and time-varying variance $\sigma^2(t)$; then, we obtain

$$E\left(\eta_t^2\right) = Var\left(\eta_t^2\right) + E(\eta_t)^2 = Var\left(\eta_t^2\right) = \sigma^2(t). \tag{25}$$

The reasonable estimation of $\sigma^2(t)$ is the squared residual [25], so the estimation of the covariance $\sigma_{lm}^2(t)$ of the two time series x_{lt} and x_{mt} that changes with time is obtained by the following wavelet expansion:

$$\sigma_l^2(t) = \sum_j\sum_k v_{j,k}\psi_{j,k}(x), \tag{26}$$

$$\sigma_{lm}(t) = \sum_j\sum_k c_{j,k}\psi_{j,k}(x), \tag{27}$$

where the coefficients $v_{j,k}$ and $c_{j,k}$ can be obtained by the classical wavelet smoothing of the squared residual [26], from which the estimation of the covariance matrix $\sum(t)$ is obtained.

The implementation steps of simulating spatial wind field based on wavelet method combined with the AR model are summarized as follows:

(1) Preliminarily, we assume that the covariance matrix $\sum = I$ and estimate the generalized least squares estimation coefficients by equations (19) to (24)
(2) We apply equations (26)~ (27) to obtain estimates of variance and covariance
(3) apply the covariance matrix obtained above and then use the least square method introduced above to estimate the autoregressive coefficients $\mathbf{A}_{j,k}^{(l)}$ and $\mathbf{u}_{j,k}$ of the AR model
(4) return to step 2 until the result converges

3. Case Analysis

The case analysis is explained in the following sections.

3.1. Simulation Results. The method mentioned above is applied to simulate the fluctuating wind field of a large-span rectangular flat roof structure. According to the above steps, a calculation program is compiled in MATLAB language. Through the analysis of the example, the simulation accuracy of the method in this paper is verified, and the accuracy and simulation efficiency of the vector process AR method are compared. There are 444 nodes on the roof, and the geometric dimensions of the roof are shown in Figure 1. The height of the roof above the ground is 20 m, the landform type is Class B, and the ground roughness $k = 0.03$. In the simulation, the regression order $p = 4$, the time step $\Delta t = 0.1$s, and the simulation time $t = 500$s. Wind velocity is taken as $V_{10} = 30$m/s, Davenport spectrum is taken as the target spectrum, db3 wavelet is adopted, and the function expansion of four wavelets (24 coefficients) is considered,

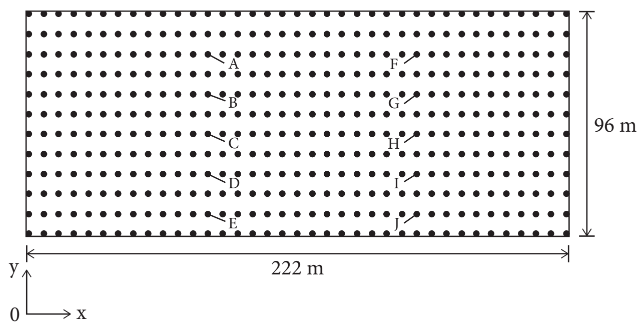


Figure 1: Location of the nodes on a flat roof.

and the wind velocity time series of all nodes on the structure considering time and space correlation is calculated. Here, only the horizontally correlated wind field is simulated, and the simulation of the vertical correlated wind field is the same. Only the simulated wind velocity time series of representative nodes A, D, G, and J are given here, as shown in Figures 2–5.

In order to verify the correctness of the proposed method, the comparison results of the simulated wind velocity time-series power spectrum of nodes A and G and the target spectrum are given, as shown in Figure 6, and the results show that the two methods are in good agreement. In order to verify the statistical characteristics of the sample, the wind velocity time-series autocorrelation and cross-correlation functions of nodes D and J are obtained through time average and compared with the corresponding objective correlation functions. The results show that the two are in good agreement, as shown in Figures 7 and 8.

At the same time, in order to verify the correctness of the AR model parameters estimated by the least square method in this paper, the estimated values of the parameters are compared with the theoretical values. Here, only the estimated average and theoretical values of the coefficients a_{11} and a_{22} in the matrix $\mathbf{A}_{j,k}^{(l)}$ and the coefficient u_{11} in the vector $\mathbf{u}_{j,k}$ are given. The comparison result is shown in Figure 9.

In order to further illustrate the accuracy and efficiency of the method proposed in this study, the comparison of the wind velocity time-series and the target spectrum at nodes A and G using the AR model is also shown in Figure 10. Table 1 shows the deviation statistics of the nodes A-J using the vector AR model and the method in this study to simulate the correlation function and the target value and the simulated wind speed mean square value and the target value. The total time spent using the vector AR model is 12684 s, and the total time using the method proposed in this study is 10247 s.

3.2. Results' Analysis. From the comparison between the simulated wind velocity time-series power spectrum obtained by the vector AR model and the target spectrum in Figure 10, it can be seen that the difference between the simulated wind velocity power spectrum value and the target wind spectrum value at the corresponding elevation is small, and the high frequency part is in good agreement. While the simulated wind velocity power spectrum has errors in the

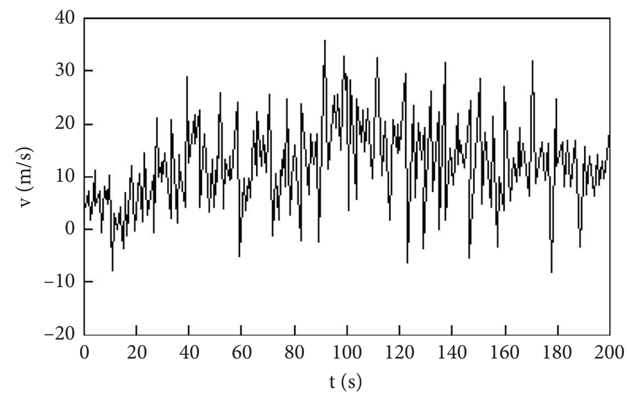


Figure 2: Wind velocity time series of node A.

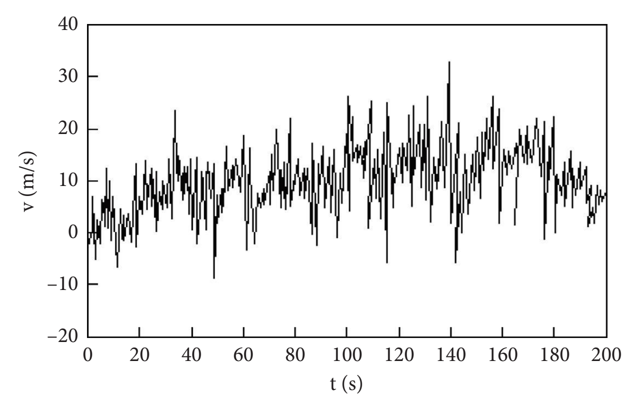


Figure 3: Wind velocity time series of node D.

low frequency part compared with the target spectrum, the calculation and simulation found that the wind velocity time series has higher accuracy in the time domain, but there is information loss in the frequency domain. The simulated wind velocity time series power spectrum in Figure 6 adopts the method proposed in this paper which is in good agreement with the target wind spectrum value. It can be seen that the proposed method reduces the loss of information in the time-frequency domain of wind velocity time series analysis and can more accurately simulate the wind velocity time series of a large-span structure. This can also be confirmed from the consistency between the simulation correlation function and the objective correlation function in Figures 7 and 8.

It can be seen from the comparison between the estimated average value of autoregressive coefficient and the theoretical value in Figure 9 that the estimated value is very consistent with the theoretical value, which proves the correctness of the wavelet spread function adopted in this paper and the least square method adopted in parameter estimation.

It can be seen from Table 1 that the correlation function deviation and wind speed mean square error deviation using this method have been greatly improved, and the correlation function deviation is 50% higher than the accuracy of the vector process AR model, and the wind speed mean square error deviation accuracy is improved by 69.4% on average,

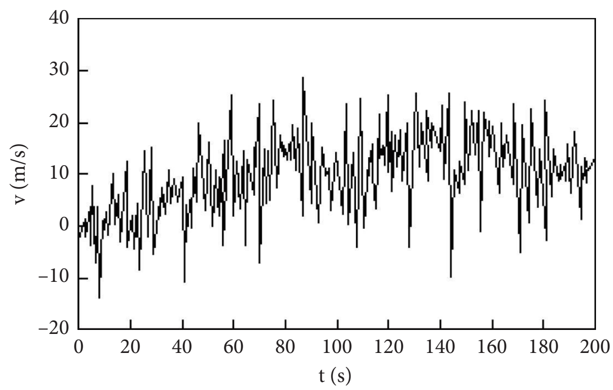


Figure 4: Wind velocity time series of node G.

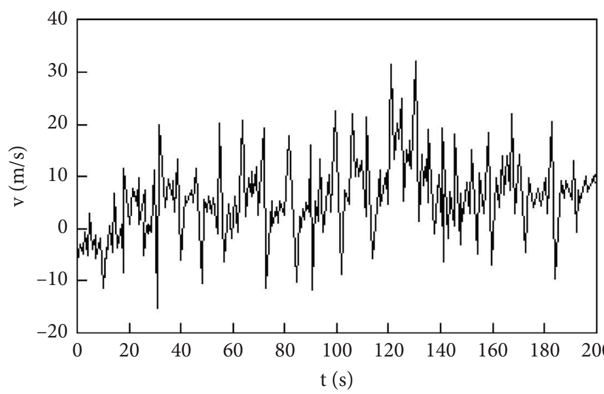


Figure 5: Wind velocity time series of node J.

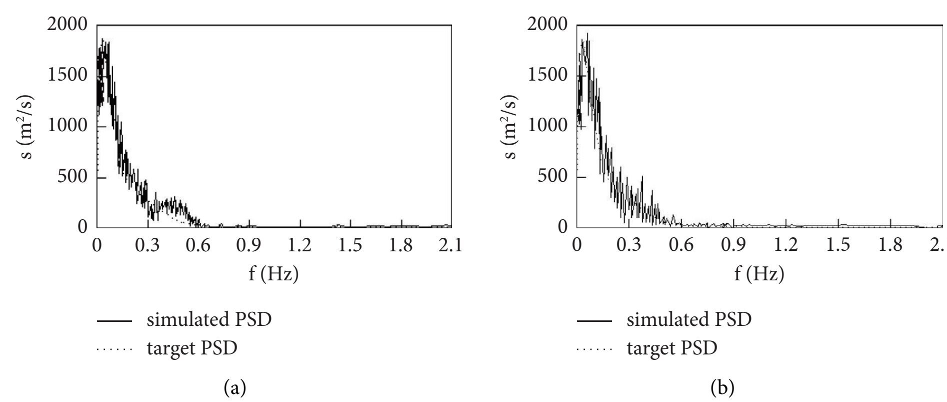


Figure 6: Comparison between simulated and target power spectral density (the method proposed). (a) Node A. (b) Node G.

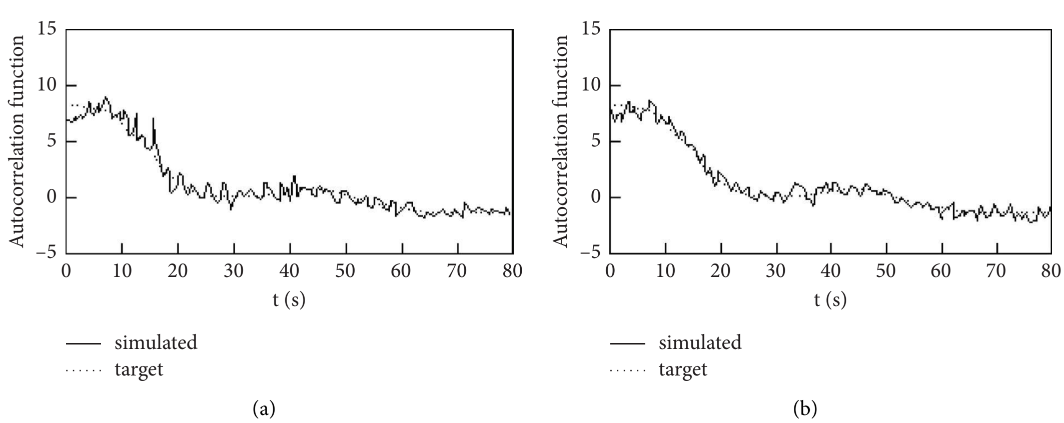


Figure 7: Comparison between the simulated and target autocorrelation function. (a) Node D. (b) Node J.

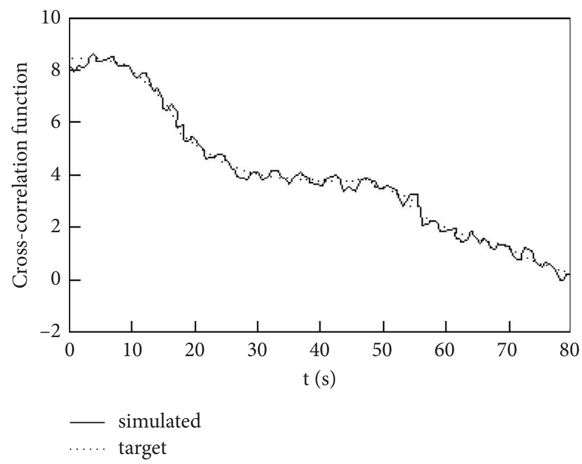


Figure 8: Comparison between the simulated and target cross-correlation function.

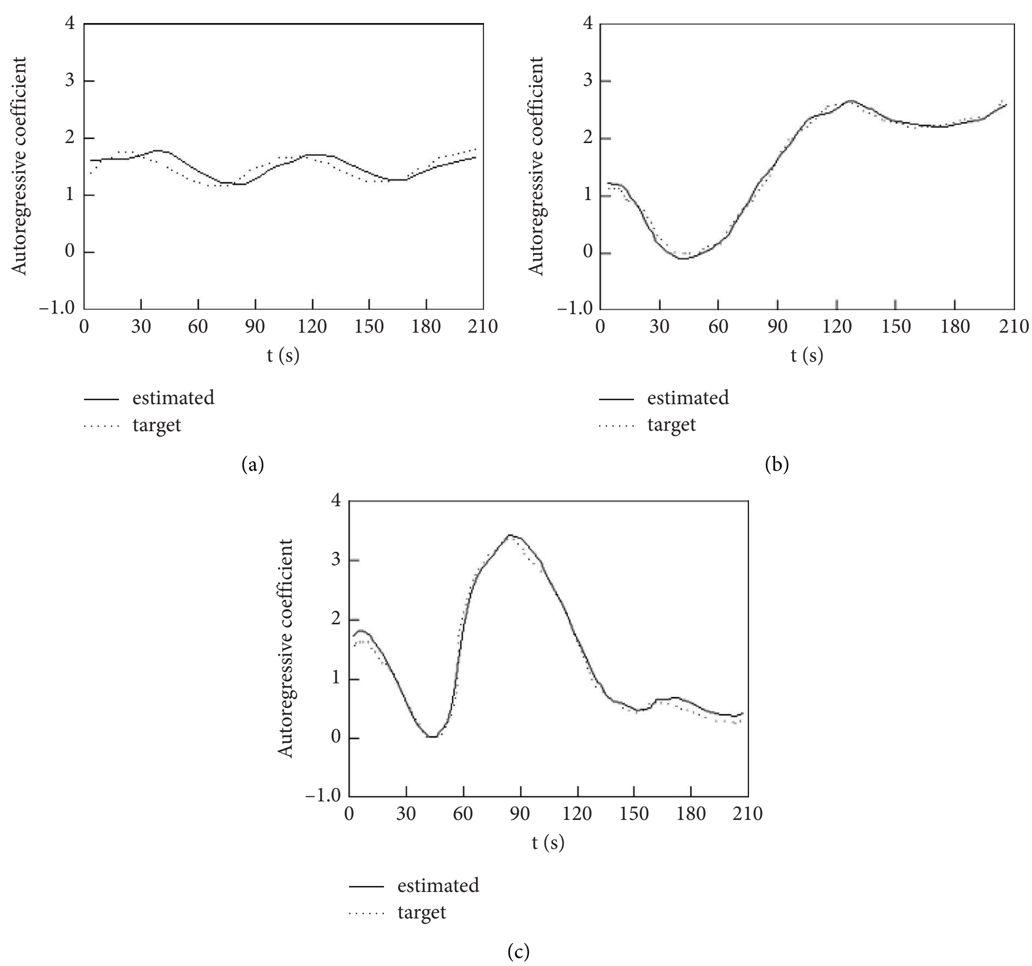
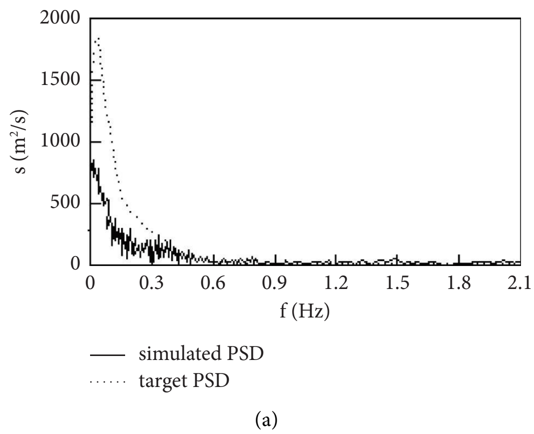


Figure 9: Comparison of autoregressive coefficients between the estimated and target function. (a) a_{11}. (b) a_{22}. (c) u_{11}.

indicating that the simulation accuracy of the proposed method is higher. In addition, from the perspective of the total simulation time, the method proposed in this paper requires less time than the AR model simulation, and the running time is reduced by about 20%, which shows that the efficiency of this method is higher.



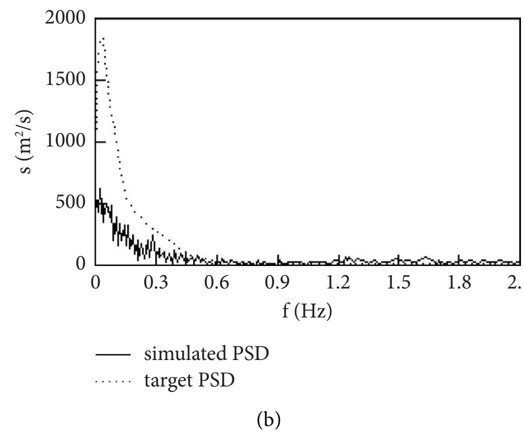


Figure 10: Comparison between simulated and target power spectral density (AR model). (a) Node A. (b) Node G.

Table 1: Comparison of statistic deviation of the correlation function and mean square value of wind velocity between the two methods.

Node	Statistic deviation of correlation function		Mean square value of wind velocity	
	Vector AR model	Method proposed in this study	Vector AR model	Method proposed in this study
A	0.148	0.052	0.591	0.186
B	0.112	0.043	0.615	0.204
C	0.227	0.164	0.474	0.139
D	0.185	0.091	0.537	0.193
E	0.166	0.082	0.658	0.235
F	0.197	0.103	0.493	0.137
G	0.173	0.098	0.472	0.108
H	0.184	0.085	0.574	0.164
I	0.203	0.110	0.523	0.209
J	0.167	0.093	0.461	0.120

4. Conclusions

In this study, a new method for simulating the wind field of long-span structures is presented by combining the vector process AR model of linear filter method and wavelet decomposition method. In this method, the autoregressive function of the AR model is extended by the wavelet function in sufficient space, and the least square method is applied to estimate the parameters of the AR model. The results of the numerical example in this study prove that the proposed method can reduce the information loss of wind speed time history analysis in the frequency domain and accurately simulate the wind speed time history of long-span spatial structure and has high computational efficiency. The specific conclusions are as follows:

(1) The AR model based on the wavelet method can reduce the information loss of wind velocity time-series analysis in the frequency domain, can better preserve the integrity of the simulated wind velocity time series in the frequency domain, and improve the accuracy of the wind field simulation

(2) The method of simulating spatial wind field proposed in this study has higher accuracy and higher computational efficiency for the simulation of short-term time series

(3) The expansion of the wavelet function in sufficient space can overcome the shortcomings of the time-varying model based on adaptive filters and window estimation methods that the window length should not be too large, which is an effective means to simulate short-term time series

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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