Journal of Wind Engineering & Industrial Aerodynamics 170 (2017) 118–127

Contents lists available at ScienceDirect

Journal of Wind Engineering & Industrial Aerodynamics

journal homepage: www.elsevier.com/locate/jweia

Fast simulation of multivariate nonstationary process and its application to extreme winds

Ning Zhao, Guoqing Huang *

Research Center for Wind Engineering, School of Civil Engineering, Southwest Jiaotong University, Chengdu, Sichuan, 610031, China

ARTICLE INFO

Keywords:
Simulation
Nonstationary process
Time-varying coherence
Cholesky decomposition
Proper orthogonal decomposition
Fast Fourier transform

ABSTRACT

Simulation of the devastating excitations such as the ground motion and transient extreme winds is an important task in the structural response analysis when it comes to the nonlinearity, system stochasticity, parametric excitations and so on. Although the classic spectral representation method (SRM) is widely used in the nonstationary process simulation, it suffers from lower efficiency due to the unavailability of use of fast Fourier transform (FFT). In this study, the classic SRM is extended to the nonstationary process with the time-varying coherence. Then, the FFT-aided and almost accurate simulation algorithm for the nonstationary process with the time-varying coherence is developed with the help of the proper orthogonal decomposition (POD) which is used to factorize the decomposed evolutionary spectra. Especially, the more efficient simulation for the nonstationary process with time-invariant coherence is also proposed, where the spectral matrix decomposition, use of POD and execution of FFT can be reduced significantly. Two examples including downburst and typhoon winds are employed to evaluate the accuracy and efficiency of the proposed method. Results show that the method has the good performance in terms of the efficiency and accuracy.

1. Introduction

Devastating excitations such as the ground motions and transient extreme winds show nonstationary features and are typically modeled by nonstationary processes (e.g., Conte and Peng, 1997; Huang et al., 2015). The Monte Carlo simulation (MCS) of the nonstationary process is an important task in the structural response analysis when it comes to the nonlinearity, system stochasticity, parametric excitations and other certain stochastic problems (e.g., Deodatis, 1996a). Furthermore, MCS is the benchmark in order to evaluate the accuracy of other stochastic methods.

Generally, the ground motions and transient extreme winds can be further characterized by the oscillatory process defined by Priestley (1965). Accordingly, the evolutionary power spectral density function (EPSD) can be estimated (Priestley, 1965; Priestley and Tong, 1973). Compared with other approaches such as the time-varying time series model (e.g., Deodatis and Shinozuka, 1988) and wavelet-based spectra (e.g., Huang and Chen, 2009), EPSD is extensively applied in the engineering practice due to its physically meaningful description on the temporal and spectral energy distribution of the nonstationary process. With EPSD available, the spectral representation method (SRM) (e.g., Deodatis, 1996a) is the most popular tool to generate samples for the nonstationary excitation in engineering practice due to its accuracy and easy application. SRM-based simulations of nonstationary Gaussian processes are well developed in the literature (e.g., Shinozuka and Jan 1972; Deodatis, 1996a).

However, because EPSD is time-dependent, the simulation of nonstationary processes will suffer from lower efficiency if the cumbersome summation of the trigonometric items is directly used (e.g., Deodatis, 1996a). In order to take advantage of fast Fourier transform (FFT), which was introduced by Yang (1972) in the simulation of stationary processes, a few attempts have been conducted to expedite the simulation efficiency for nonstationary processes. Li and Kareem (1991) established FFT-aided SRM where polynomials including trigonometric and Legendre polynomial functions were used to fit the decomposed EPSD matrix. Huang (2014) developed a hybrid FFT-aided SRM where wavelets were used to decouple the time-dependent EPSD matrix. Huang (2015) adopted the proper orthogonal decomposition (POD) to factorize the decomposed EPSD matrix and utilized FFT to enhance the simulation speed. Compared with other FFT-aided approaches, POD-based approach achieves both of accuracy and straightforwardness in the simulation. Peng et al. (2017) proposed a new hybrid approach of stochastic wave and POD to generate multivariate nonstationary processes along a straight line, where the two dimensional FFT can significantly increase

* Corresponding author.
E-mail address: ghuang1001@gmail.com (G. Huang).

http://dx.doi.org/10.1016/j.jweia.2017.08.008
Received 11 February 2017; Received in revised form 8 August 2017; Accepted 8 August 2017

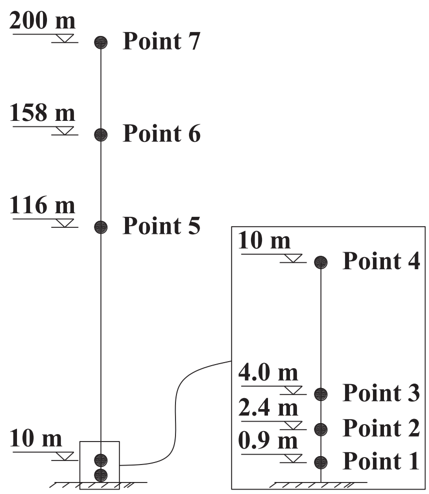

Fig. 1. Schematic diagram of the layout of anemometers.

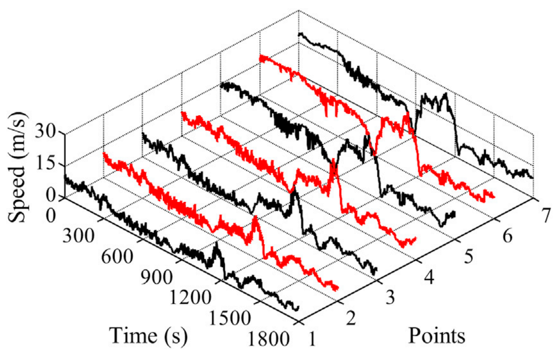

Fig. 2. Wind speed time histories.

the simulation efficiency. Apart from the application of FFT, the efficiency of EPSD matrix decomposition is also related to the simulation speed. Traditionally, the time-dependent EPSD matrix should be decomposed on both of time and frequency domains. Gao et al. (2012) and Huang et al. (2013) showed that the decomposition can be only conducted on the coherence matrix. If coherence matrix is time-independent, the decomposition efficiency will be noticeably improved. Further, Huang et al. (2013) separated the phase component of the coherence function to increase the decomposition efficiency. Although the great progress has been achieved, the need for improving the efficiency and applicability still exists, especially for many simulation points associated with modern colossal structures.

In the preceding literature review, the coherence function is assumed to be time-independent due to the limitation of original Priestley's evolutionary spectral theory (Priestley and Tong, 1973). Actually, the coherence function of the nonstationary excitations could have the noticeable time-varying feature. One example is the downburst wind, which can be found in section 4.1. To overcome this limitation on the coherence function, Battaglia (1979) proposed a concept of the sigma-oscillatory process. In this approach, the sigma-oscillatory process is the summation of a finite number of oscillatory processes. This concept has been adopted in the univariate nonstationary ground motions and extreme winds (Conte and Peng, 1997; Huang et al., 2015). Melard and Schutter (1989) adopted the Wold-Cramer decomposition model. This decomposition is similar to the Cholesky or eigenvector decomposition of stationary processes (e.g., Chen and Kareem, 2005). Both approaches can extend the Priestley's evolutionary spectral theory to consider the time-varying coherence function. Thus, it is desired to extend the simulation approaches to the nonstationary process with the time-varying coherence.

In this paper, an efficient and almost accurate simulation method is developed for the multivariate nonstationary process with the time-varying coherence, where the POD-based factorization originally introduced by Huang (2015) is significantly improved and adopted to enable the application of FFT. Firstly, the classic SRM is extended to the nonstationary process with the time-varying coherence. Secondly, the FFT-based fast algorithm is proposed for the nonstationary process with time-varying coherence. Especially, the more efficient algorithm for the nonstationary process with time-invariant coherence is provided. Furthermore, two examples including downburst and typhoon winds are employed to evaluate the accuracy and efficiency of the proposed method. Finally, concluding remarks are given.

2. Simulation of nonstationary process with time-varying coherence

Consider an n-component multivariate zero-mean nonstationary process $\mathbf{x}(t) = [x_1(t), x_2(t), \cdots, x_n(t)]^T$ with the time-varying coherence function, where T denotes transpose. Suppose this process has following EPSD matrix

$$\mathbf{S}(\omega, t) = \begin{bmatrix} S_{11}(\omega,t) & S_{12}(\omega,t) & \cdots & S_{1n}(\omega,t) \\ S_{21}(\omega,t) & S_{22}(\omega,t) & \cdots & S_{2n}(\omega,t) \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1}(\omega,t) & S_{n2}(\omega,t) & \cdots & S_{nn}(\omega,t) \end{bmatrix} \tag{1}$$

where ω is the circular frequency; $S_{jj}(\omega, t)$ is the auto spectra of $x_j(t)$, satisfying $S_{jj}(\omega, t) = S_{jj}(-\omega, t)$; $S_{jk}(\omega, t)$ is the cross spectra between $x_j(t)$ and $x_k(t)$, satisfying $S_{jk}(\omega, t) = S_{jk}^*(-\omega, t)$ and $S_{jk}(\omega, t) = S_{kj}^*(\omega, t)$ (Asterisk denotes the complex conjugate). Thus, $\mathbf{S}(\omega, t)$ is a Hermitian matrix with nonnegative definite property. The off-diagonal element of the EPSD matrix can be calculated by

$$S_{jk}(\omega, t) = \sqrt{S_{jj}(\omega, t) S_{kk}(\omega, t)}\gamma_{jk}(\omega, t) \tag{2}$$

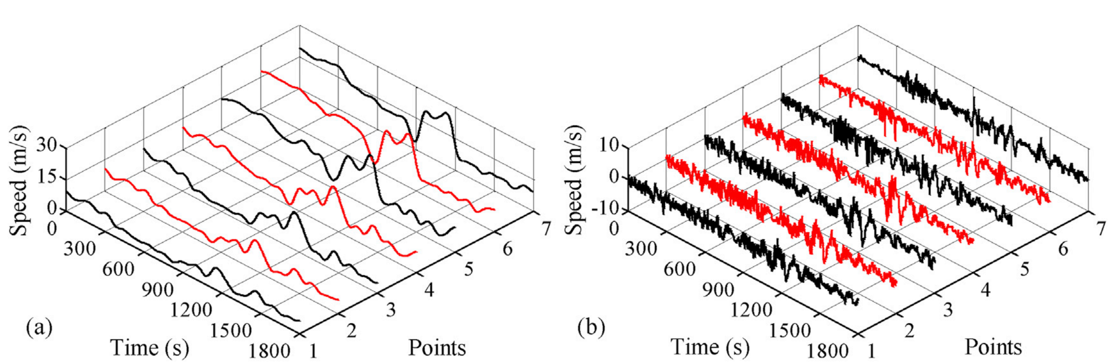

Fig. 3. Means and fluctuations of downburst: (a) Means (b) Fluctuations.