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Uncertainty propagation of turbulence parameters for typhoon and non-typhoon winds in buffeting analysis of long-span bridges

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SUMMARY:
Turbulence-induced buffeting vibration will affect the serviceability of the structure and lead to fatigue problems. Traditional deterministic methods cannot reproduce discrete random buffeting responses of structures. In this paper, a probabilistic buffeting analysis framework based on multi-point estimation, dimension reduction and the principle of maximum entropy, is proposed. The proposed algorithm is applied to Xihoumen Bridge accounting for the uncertainties of turbulence parameters in power spectral density functions. The comparison with Monte Carlo simulation shows that great consistency and low computational costs can be achieved using the proposed method. Based on the proposed algorithm, the probability density evolution of buffeting response along with mean wind speed can be readily obtained. And the predicted probability density evolution is compared with the observational deck vibration acceleration. Furthermore, by introducing the parent distribution of typhoon and non-typhoon mean wind speed, the exceeding probability of vibration in a given period can be easily obtained.

Keywords: Power spectrum density function, Buffeting analysis, Uncertainty propagation

1. INTRODUCTION

Unavoidable buffeting is a random vibration induced by wind turbulence, and may bring about structural fatigue problems, as well as affect the normal use during its service life. Great efforts have been put in estimating the buffeting vibration of structures thanks to the fundamental works (Jain, 1997), which are usually based on deterministic inputs. However, turbulence winds, as one of the decisive external loads for buffeting response evaluation, exhibit strong variability, which has been proved in many measured data thanks to the advances in field observation techniques (Liu et al., 2022). And the power spectral density (PSD) is adopted to describe the distribution of fluctuating wind energy at different frequencies in wind engineering community. These commonly-used spectrum, recommended by many standards and codes, show inconsistency with recent observations, especially for typhoon winds due to its internal complex circulation and thermodynamics. And using the code-recommended wind PSD is unable to reproduce the scattered structure response (Fenerci and Oiseth, 2017). Thus, it is necessary to consider the uncertainties of typhoon and non-typhoon's turbulence parameters in PSD, respectively, to achieve the closer-to-reality wind loads.

Based on long-term structural health monitoring data, this paper establishes a statistical correlation model between mean wind speed and wind spectrum parameters of typhoon and non-typhoon winds. The uncertainty propagation, based on dimension-reduction method, point estimation method and maximum entropy principle, of turbulence parameters to buffeting response is introduced. The proposed method in this paper provides a forward step towards the conversion of structure design from the conventional uniform-hazard method to the uniform-risk method in wind engineering. Moreover, it allows the estimation of structural response at different reliability levels which is helpful to the development of the performance-based wind engineering.

2. UNCERTAINTY PROPAGATION THEORY

Considering a system with random independent inputs $\boldsymbol{X} = \{X_1, X_2, \dots, X_N\}$, and let $Y = g(\boldsymbol{X})$ represents the desired response. The lth moment of Y can be approximated by dimension-reduction method (DRM):

$$m_l(Y) = \int_{\mathbb{R}^N} g^l(\boldsymbol{X}) f_{\boldsymbol{X}}(\boldsymbol{X}) d\boldsymbol{X} \cong [g(\mu_1, \dots, \mu_N)]^{l(1-N)} \prod_{i=1}^{N} E\{[g(\mu_1, \dots, \mu_{i-1}, X_i, \mu_{i+1}, \dots, \mu_N)]^l\} \quad (1)$$

Where, $E[\cdot]$ is the expectation operator, $f_{\boldsymbol{X}}(\boldsymbol{X}) = f_{X_1, X_2, \dots, X_N}(X_1, X_2, \dots, X_N)$ donates the joint probability density function (PDF) and $\mathbb{R}^N$ is the multi-dimensional integral space. $g(\mu_1, \dots, \mu_{i-1}, X_i, \mu_{i+1}, \dots, \mu_N)$ is the random response of subsystem corresponding to ith variable and $g(\mu_1, \dots, \mu_N)$ is a deterministic response while every variables are fixed at their mean values. And the moments of univariate subsystems can be estimated with multi-point estimation method. For m-point estimation, the lth moment can be approximated by:

$$m_l(\mathrm{Y}) \cong \sum_{i=1}^{m} w_i [\mathrm{g}(z_i)]^l \quad (2)$$

where w_i is the weight coefficient corresponding to the normal space estimating point z_i. As for a system with arbitrary input x, it can be transferred from standard normal space by:

$$x = F^{-1}[\Phi(z)] \quad (3)$$

in which $\Phi(\cdot)$ and $F(\cdot)$ are the cumulative probability density function of the standard normal distribution and input variable x. Then the distribution of a continuous random variable can be approximated by maximizing the entropy H, and the moments are the constraints of optimization:

$$\max H = -\int p(x) \ln[p(x)]\, dx \quad (4)$$

$$s.t. \int_{-\infty}^{+\infty} x^l\, p(x) dx = \mathrm{m}_l, l = 0,1,2, \dots, N \quad (5)$$

3. RANDOM TERBULENCE WIND FIELD

The along and cross wind random spectrum models are:

$$S_i(\omega) = \frac{\sigma_i^2 A_i z}{U\left(1+1.5A_i\frac{\omega z}{2\pi U}\right)^{\frac{5}{3}}}, i = u, w \tag{6}$$

in which, A_i is the undetermined non-dimensional parameters, σ_i is the standard deviation (Std) of fluctuating winds and z is the height above the surface of water. To perform the DRM, the independence requirement of the wind field parameters should be satisfied. Herein, imitate the idea of Rosenblatt technique, two new indexes are introduced:

$$\alpha_w = \frac{\sigma_w}{\sigma_u}, \beta_w = \frac{A_w}{A_u} \tag{7}$$

The wind data measured by Structural Health Monitoring System (SHMS) of Xihoumen Bridge is utilized to quantify the uncertainty of turbulence wind field. Nine typhoon records collected during 1st May 2011 and 31st December 2015 and non-typhoon records of years 2011 and 2012 are utilized. Different turbulent parameter bins are separated by setting different mean wind speeds with increment of 1m/s for mean wind speed below 18m/s, and the mean wind speeds above 18m/s are assigned into one bin, which guarantees the minimum number of 70 recordings in each speed interval for the apparent probability distribution. The lognormal distribution is adopted to fit every bins through maximum likelihood estimation, and the fitted relationship between the estimated distribution parameters and mean wind speed are summarized in Table 1.

Table 1. Relationship between the estimated distribution parameters and mean wind speed.

Parameters	$\hat{\sigma}$		$\hat{\mu}$	
	Non-typhoon	Typhoon	Non-typhoon	Typhoon
σ_u	0.357	0.394	$0.042U - 0.467$	$0.035U - 0.214$
A_u	0.997	0.872	$U^{0.446} - 0.573$	$U^{0.352} - 0.069$
α_w	0.207	0.191	-0.555	-0.617
β_w	0.981	0.894	$-0.047U - 0.452$	$-0.045U - 0.499$

4. APPLICATION EXAMPLE

The proposed probability buffeting algorithm is employed to examine the effect of random turbulence wind field on Xihoumen Bridge. The buffeting responses, computed through the proposed method along with the Monte Carlo simulation (MCS) results, at mean wind speed 30m/s are shown in Fig. 1.

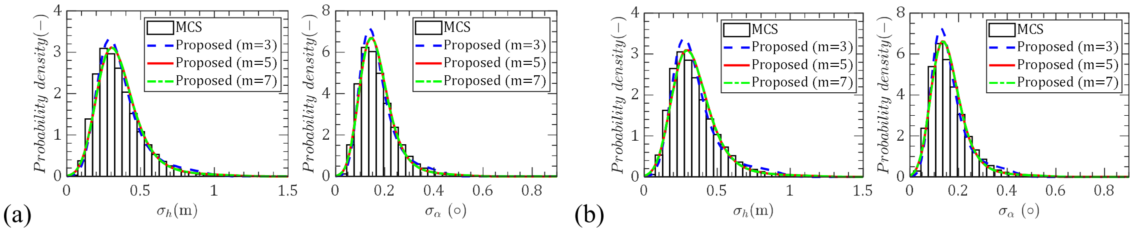

Figure 1. Probability density of vertical and torsional RMS: (a) non-typhoon; (b) typhoon

Fig. 2 shows the buffeting response probability density evolution estimated by 5 points and the most probable value (MPV) along with the mean wind speeds.

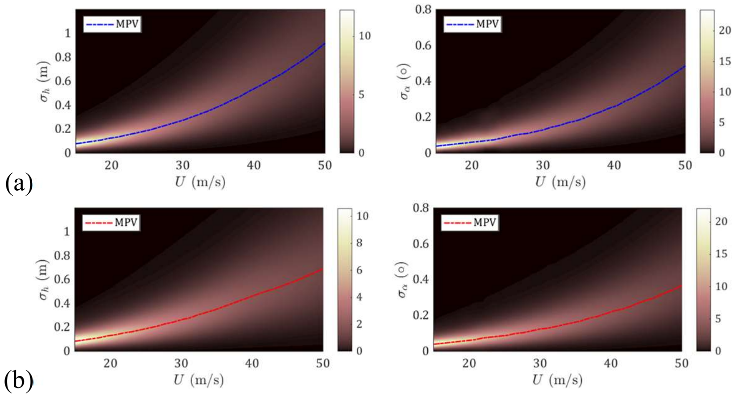

Figure 2. Probability density evolution of vertical and torsional RMS with wind speed: (a) non-typhoon; (b) typhoon

Fig. 3 illustrates the comparision between the acceleration captured by SHMS of Xihoumen bridge and the predicted probability density evolution.

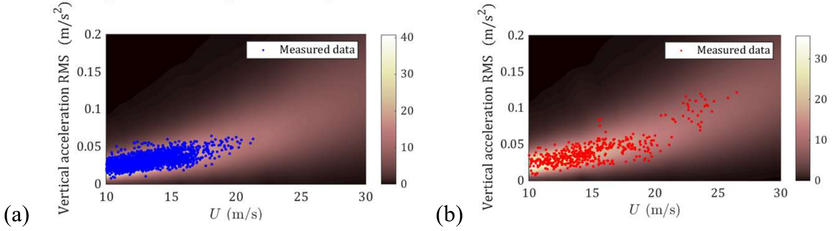

Figure 3. Measured data and probability density evolution of vertical acceleration RMS: (a) non-typhoon; (b) typhoon.

5. CONCLUSIONS

Based on long-term observation data, a wind speed dependent stochastic model of typhoon and non-typhoon wind spectrum is established. The random buffeting response of long-span bridges considering the uncertainty of turbulence parameters is calculated through uncertainty propagation, and the probabilistic buffeting analysis considering the real wind field environment is established. It can provide reference for achieving uniform risk design of bridge wind resistance.

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REFERENCES

Fenerci, A., Oiseth, O., 2017. Measured Buffeting Response of a Long-Span Suspension Bridge Compared with Numerical Predictions Based on Design Wind Spectra. Journal of Structural Engineering 143.

Jain, A., 1997. Multi-mode aeroelastic and aerodynamic analysis of long-span bridges. Ph.D. Dissertation, Johns Hopkins University, Baltimore, Maryland, USA.

Liu, Z., Fang, G., Hu, X., Xu, K., Zhao, L., Ge, Y., 2022. Stochastic power spectra models for typhoon and non-typhoon winds: A data-driven algorithm. Journal of Wind Engineering and Industrial Aerodynamics 231, 105214.