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Validation and Error Quantification of Data-Informed Stochastic Wind Models for Performance-Based Wind Engineering Applications

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SUMMARY:

Performance-based wind engineering (PBWE) frameworks allow the propagation of uncertainties for a more accurate risk assessment of wind-excited systems. The simulation of multivariate stationary non-Gaussian wind processes can be obtained through stochastic wind models based on the translation process. The calibration of these models to wind tunnel data is advantageous as it enables the capture of the main aerodynamic phenomena. However, there is still a lack of recommendations for calibrating the model as well as detailed information on errors associated with its use, especially when calibrated using typical wind tunnel data. An experimental study on a rectangular building was conducted in this work with the aim of validating and quantifying the errors of such a wind tunnel-informed stochastic model. Errors associated with the variability of the wind tunnel dataset, calibration process, numerical model, and mode truncation are investigated and quantified. Recommendations and guidelines for calibrating and using the proposed wind model are provided.

Keywords: performance-based wind engineering, stochastic wind model, mixture model, error quantification

1. INTRODUCTION

Performance-based wind engineering (PBWE) frameworks have enabled the direct propagation of uncertainties during the probabilistic performance assessment of wind-excited building systems. For an accurate estimation of the local and global responses of building systems, an accurate representation of the wind loads is essential. Wind tunnel testing on bluff bodies has been used as the primary approach to effectively obtain realizations of wind loads acting on buildings. However, due to the cost and time constraints of experimental testing, stochastic simulation methods have emerged as a powerful tool for generating the large number of wind load realizations necessary for propagating uncertainty in PBWE applications.

Among the many stochastic wind load models that have been developed (e.g., Deodatis, 1996; Shinozuka and Deodatis, 1991), the proper orthogonal decomposition (POD)-based stochastic wind load model has gained popularity in wind engineering for the simulation of stationary Gaussian processes due to its computational efficiency and the possibility of mode truncation without significant loss of accuracy (Chen and Kareem, 2005). However, the assumption of modeling wind processes as Gaussian may not be appropriate for local responses such as the dynamic wind pressures acting on the envelope system, which can exhibit non-Gaussian characteristics, especially in the separated flow region (Tamura and Kareem, 2013). For the simulation of non-Gaussian processes, the translation model is a powerful method that can exactly match the target marginal distribution of the target process (Grigoriu, 1998; Zhao et al., 2019). Nevertheless, one of the challenges of using the translation process is the accurate modeling of the target marginal distribution for avoiding errors in the simulated process. Recently, the use of wind tunnel data to calibrate stochastic models has been explored as it enables the direct incorporation of the building- and wind direction-specific aerodynamic effects captured by the wind tunnel in the stochastic model (Ouyang and Spence, 2020; Suksuwan and Spence, 2018). Despite the potential of these wind tunnel-informed stochastic wind models, there is a lack of available guidelines for calibrating the translation process to wind tunnel data as well as a lack of information concerning the errors associated with the use of typical wind tunnel datasets during the calibration process.

This study aims to firstly validate the translation process-based wind tunnel-informed stochastic wind model outlined in Ouyang and Spence (2020) through quantifying the errors associated with calibrating the model to typical wind tunnel pressure data (e.g., a 32-second record) and secondly provide insight on the requirements for wind tunnel testing practice that are appropriate for modeling non-Gaussian wind processes. An extensive experimental dataset collected on a rectangular building for multiple wind directions is used to assess multiple sources of errors, including errors associated with using a typical wind tunnel record to calibrate the kernel-Pareto mixture model for describing the marginal distribution of the process, numerical errors associated with using the translation process to simulate non-Gaussian pressure time histories, and mode truncation errors. Requirements for accurately using wind tunnel data and mixture models for calibrating stochastic wind models are carefully investigated with the aim of providing future recommendations.

2. WIND TUNNEL-INFORMED STOCHASTIC WIND MODEL

To generate the vector-valued stationary wind process, $\mathbf{C}_p(t;\beta)$ (e.g., dynamic pressure coefficient time series), a wind tunnel realization of the process is used to calibrate the non-Gaussian stochastic model based on the translation process. Through this approach, the spectral POD-based stochastic wind model (Chen and Kareem, 2005) is first calibrated to match the second-order statistics of the wind tunnel process and then used to simulate a zero-mean Gaussian process, $\mathbf{C}_p^{GP}(t;\beta)$, for a given wind direction, β. The prescribed Gaussian process is transformed to a non-Gaussian process through the translation model (Grigoriu, 1998), which is a nonlinear memoryless transformation of stationary Gaussian process to a non-Gaussian process that matches the target marginal distribution exactly and covariance functions approximately. The translation process of the ith component of $\mathbf{C}_p(t;\beta)$ can be represented as:

$$C_{p,i}(t;\beta) = F_{C_{p,i}}^{-1} \cdot \Phi(C_{p,i}^{GP}(t;\beta)),\ i = 1,...,n \tag{1}$$

where $F_{C_{p,i}}$ is the corresponding non-Gaussian marginal distribution of $C_{p,i}(t;\beta)$, Φ is the standard Gaussian distribution function, $C_{p,i}^{GP}(t;\beta)$ is the Gaussian process simulated by the POD-based stochastic wind model, and n is the number of components. The kernel-Pareto mixture model was employed in this study to model the marginal distribution, $F_{C_{p,i}}$, of the target wind process, as it shows superior performance over other parametric distributions in modeling non-Gaussian wind processes (Zhao et al., 2019). The mixture model considers the extreme value distribution at the tails where there is a lack of data and uses kernel density estimator at the center where an adequate amount of data is available. The kernel-Pareto mixture model can be defined for the probability density function of $C_{p,i}$ as:

$$f_{C_{p,i}}(C_{p,i}) = f_i^l(C_{p,i}) l_{\{-\infty < C_{p,i} \leq nl_i\}} + f_i^c(C_{p,i}) l_{\{nl_i < C_{p,i} \leq nu_i\}} + f_i^u(C_{p,i}) l_{\{nu_i < C_{p,i} < \infty\}} \tag{2}$$

where $f_i^l(C_{p,i})$ and $f_i^u(C_{p,i})$ are the corresponding extreme value distribution of the lower and upper tail regions, respectively; $f_i^c(C_{p,i})$ is the central region represented by a kernel distribution; $l_{\{*\}}$ is the indicator function; nl_i and nu_i are the lower and upper tail thresholds.

3. ERROR QUANTIFICATION

To accurately estimate the marginal distribution and probabilistic properties of the underlying non-Gaussian process, a large sample size, i.e., a long-duration wind tunnel dataset, is usually required. However, typical wind tunnel records, which last between 30 seconds and 1 minute, may not capture adequate information for defining the kernel-Pareto mixture model, thus affecting the accuracy of the wind tunnel-informed stochastic wind model. To assess the adequacy of the mixture model calibrated to a typical wind tunnel dataset, the Kullback–Leibler (KL)-divergence measure is used. The discrepancy between a target distribution considering a long-duration wind tunnel dataset for the ith component and a distribution calibrated from a typical short-duration dataset is estimated as follows:

$$KL_{div,i}(f_{C_{p,i}} || f^T_{C_{p,i}}) = \int_{-\infty}^{\infty} f_{C_{p,i}}(x) \ln\left(\frac{f_{C_{p,i}}(x)}{f^T_{C_{p,i}}(x)}\right) \mathrm{d}x \tag{3}$$

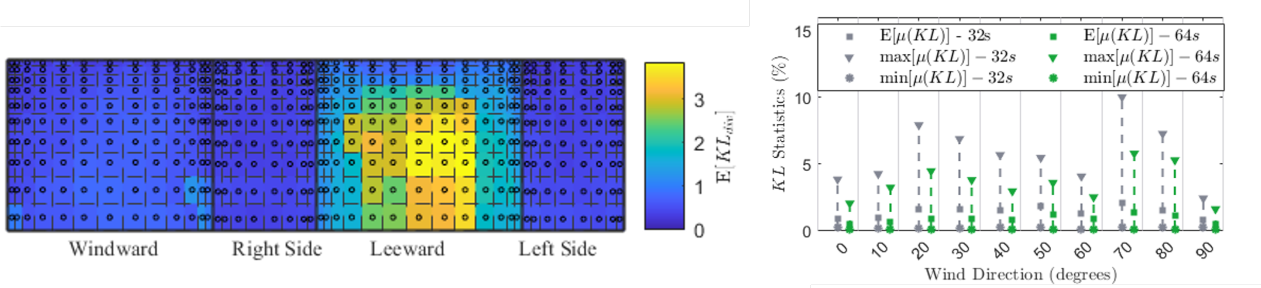
where $f_{C_{p,i}}$ represents the kernel-Pareto mixture distribution calibrated to the typical wind tunnel dataset and $f^T_{C_{p,i}}$ represents the target kernel-Pareto mixture distribution calibrated to a long-duration dataset.

4. EXPERIMENTAL SETTING

An extensive experimental study was carried out at the Natural Hazards Engineering Research Infrastructure Boundary Layer Wind Tunnel at the University of Florida to enable the validation of the wind tunnel-informed stochastic wind model and quantification of errors associated with the modeling of non-Gaussian processes. A total of 5 repetitions of length 15 minutes were conducted for wind directions from 0 to 90 degrees, in 10 degrees increments. The pressure acting on a 30cm×60cm×50cm rectangular rigid model with 512 built-in pressure taps distributed over 5 surfaces were simultaneously collected. To define the target distribution, a total of 50 minutes of data was assumed adequate. The remaining data was divided into 20 independent 32-second realizations representing typical wind tunnel records.

5. RESULTS AND DISCUSSION

Figure 1(a) shows the expected value of KL_{div} for each pressure tap on the vertical surfaces of the scale model, considering a total of 20 realizations of the 32-second wind record, $\beta = 0$ degrees, and $nu_i = nl_i = 5\%$ tail thresholds. A higher discrepancy between the target and calibrated distributions can be seen in the leeward surface of the model, which is expected since this is a region with significant flow separation and therefore an expected higher level of non-Gaussianity. The performance of the mixture model on realizations of different duration was also investigated. Results are demonstrated in Figure 1 (b) for $\beta = 0 - 90$ degrees, where the KL-Divergence statistics, estimated over 20 realizations, for 32-second and 64-second datasets are shown. It is evident that the calibrated mixture models improved when longer duration wind tunnel datasets were used for calibration, as more data provided a more accurate representation of the marginal distribution and statistical properties of the wind processes. In the next steps, various errors associated with the simulated wind pressure processes will be assessed including errors carried over from using a typical wind tunnel record for model calibration, numerical errors, as well as errors from mode truncation. The discrepancy between higher-order statistics, such as skewness and kurtosis, of the target and simulated wind processes will also be investigated.



(a) (b)

Figure 1. (a) Expected value of KL_{div} for a 32-second wind record for $\beta = 0$; (b) KL-Divergence statistics for 32-second and 64-second records for all wind directions.

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