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Influence of dependence of directional extreme wind speeds on wind load effects with various mean recurrence intervals

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ABSTRACT

This study offers an improved understanding of the influence of statistical dependence between directional extreme wind speeds when estimating the wind load effects with various mean recurrence intervals (MRIs). Existing multivariate approaches that concern the wind directionality effect are first reviewed. Several factors that influence the prediction with and without consideration of the statistical dependence between directional extreme wind speeds are discussed by using Gaussian copula model. The influence of wind speed masking on the wind effect estimation is discussed. The influence of use of different joint probability distribution models for directional extreme wind speeds is illustrated through a comparison between multivariate Gaussian and Gumbel copula models. The necessity of using multivariate approach is discussed and a simplified method is proposed to account for directional dependence, which not only provides accurate prediction but also reduces calculation effort. Examples with real wind climate model and generic wind tunnel test results are shown to illustrate the influences brought by directional dependence, model difference, and wind speed masking. Also discussion is made on the partition of directional sectors which concerns the balance of number of sectors and modeling uncertainty.

1. Introduction

Estimation of wind load effects with various mean recurrence intervals (MRIs) requires consideration of uncertainty and directionality of wind climate, aerodynamics and structural dynamics. Without consideration of directionality, probabilistic methods have been developed to integrate the probability distributions of yearly maximum wind speed and wind load effect (response) conditional on wind speed (Cook and Mayne, 1979, 1980; Harris, 1982, 2005; Chen and Huang, 2010). Other probabilistic models have also been addressed in literature to account for various uncertainties (e.g., Kareem, 1987, 1988, 1990; Diniz et al., 2004; Diniz and Simiu, 2005; Hanzlik et al., 2005). On the other hand, to address the directionality effects of wind climate, aerodynamic and structural dynamics, several approaches have been developed. Some of these approaches are based on parent distribution of wind speed (e.g., Davenport, 1977; Lepage and Irwin, 1985; Irwin et al., 2005), and the others on extreme wind speed data or wind storm passage data (e.g., Simiu and Filliben, 1981; Simiu and Heckert, 1998, Isyumov et al., 2003, 2014). All these approaches treat the wind load effect conditional on wind speed and direction as a deterministic quantity. Furthermore, there is a lack of consensus in the estimated design wind loads and responses for specified MRIs using different methods given that the dynamic wind loads derived by different experienced laboratories are in general very consistent. For instance, the wind-induced responses of the World Trade Center (WTC) towers estimated by two recent independent studies from two world leading wind engineering laboratories in North America differ from each other by about 40%-difficult for many structural engineers to accept as normal variability (Sadek, 2005).

A directionality factor is often used in building codes and standards to consider the wind load effect reduction from the worst case estimation (e.g., ASCE, 2010). However, the directionality factor is generally associated with many other factors such as characteristics of directional wind speed and aerodynamics, and the MRI of target response. The adequacy of the directionality factor specified in design standards has been reexamined in literature (Simiu and Heckert, 1998; Rigato et al., 2001; Laboy-Rodriguez et al., 2014; Isyumov et al., 2014; Zhang and Chen, 2015).

Recently, Zhang and Chen (2015) introduced a unified approach for estimating probabilistic wind effect with consideration of both directionality and uncertainty, where the joint probability distribution of directional extreme wind speeds was modeled by using multivariate extreme value theory with Gaussian copula. The Gaussian copula is the same as the multivariate Gaussian translation model (Grigoriu, 2007, 2009), which was used as a basis for

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generating directional extreme wind speeds (Yeo, 2014). Multivariate extreme wind speed models have also been addressed in literature in terms of bivariate Gumbel distribution model (Simiu et al., 1985), and multivariate Gumbel distribution model (Itoi and Kanda, 2002). It is reported that during a synoptic storm passage, the wind direction may vary about 200 degrees on average (e.g., Cook, 1982). Therefore, the extreme wind speeds in neighboring sectors often have certain level of correlation. The conservatism of using the independent assumption was proved and the underestimate from fully correlated assumption was also recognized (Simiu et al., 1985; Irwin et al., 2005).

This study addresses a number of issues related to the modeling of multivariate distribution of directional extreme wind speeds and its influence on the predicted wind effects with various MRIs. The influence of correlation coefficient between directional extreme wind speeds on the estimated wind effects is investigated. The results from the two variants of sector-by-sector method that assume full-correlation and independence of directional wind speeds are compared. Due to current data recording and analysis mechanism, some directional wind speed data are often masked (Coles and Walshaw, 1994; Vega-Avila, 2008). The masking issue affects not only the statistics of directional wind speeds but also their dependence. This study further discusses the influence of masking issue on the predicted wind load effects. A simplified procedure with consideration of the dependence of only a small number of important directional wind speeds is proposed for computational efficiency. This study also compares the multivariate Gumbel and Gaussian copula models which sheds insight on the model selection. Finally,this study examines the influence of the partition number of directional wind speeds on the prediction, which provides information on the modeling uncertainty.

2. Estimation of probabilistic yearly maximum wind effects

2.1. Approaches based on multivariate directional extreme wind speed model

The probabilistic extreme response for the i-th wind direction $(i=1,2,\ldots,n)$ with a given time duration, say, one hour, is often expressed as a function of mean wind speed:

$$X_i=\frac{1}{2}\rho V_i^2 C_i(V_i) \tag{1}$$

where V_i is hourly mean wind speed at the i-th direction; and $C_i(V_i)$ is normalized extreme response (load effect coefficient within one hour or simply termed as wind load coefficient and can be represented as

$$C_i(v_i)=v_i^{\,b-2}C_{0i}c_{\alpha i} \tag{2}$$

where C_{0i} is generally a random quantity with a unit mean, which reflects the uncertainty of extreme response coefficient in the i-th direction; $c_{\alpha i}$ is a deterministic value for the i-th direction, which reflects the directionality characteristics of extreme response coefficient, and $\max\{c_{\alpha i}, i=1,2,\ldots,n\}=1$; b is a power law exponent indicating the growth rate of the extreme response with wind speed. In the case of rigid structures, the wind load coefficient $C_i(v_i)$ can be independent of mean wind speed, i.e., $b=2$. On the other hand, it is a function of mean wind speed for flexible structures due to dynamic amplification effect, i.e., $b>2$.

When extreme response conditional on given wind speed and direction is considered as a deterministic quantity, i.e., C_{0i} is deterministic, the cumulative distribution function (CDF) of extreme response considering directionality can be determined as:

$$\Psi_X(x)=P(X_1\le x, X_2\le x,\ldots,X_n\le x)=P(V_1\le v_{x,1},V_2\le v_{x,2},\ldots,V_n \le v_{x,n})=H(v_{x,1},v_{x,2},\ldots,v_{x,n}) \tag{3}$$

where x is a given wind effect level; $v_{x,i}=\sqrt{2x/\rho C_i(v_{x,i})}$ is the corresponding wind speed in the i-th direction causing response level x; $H(v_1,v_2,\ldots,v_n)$ is the joint CDF (JCDF) of directional extreme wind speeds.

When C_{0i} thus C_i is a random variable, under the assumption that largest extreme response in a year for a given wind direction is always the result of the strongest wind speed (Cook and Mayne, 1979, 1980), Eq. (3) becomes (Zhang and Chen, 2015):

$$\Psi_X(x)=\int\ldots\int \mathrm{H}(v_{x1}|c_1,\ldots,v_{xn}|c_n)f(c_1,\ldots,c_n)dc_1\ldots dc_n \tag{4}$$

where $f(c_1,\ldots,c_n)$ is the joint probability density function (JPDF) of $C_i(V_i)(i=1,2,\ldots,n)$. In general, $C_i(V_i)(i=1,2,\ldots,n)$ are mutually independent, thus $f(c_1,\ldots,c_n)=f_1(c_1)f_2(c_2)\ldots f_n(c_n)$, where $f_i(c_i)$ is the PDF of $C_i(V_i)$. Technically, Eq. (4) can be evaluated through Monte Carlo simulation, i.e., by first generating samples of $c_i(v_i)=c_i$ $(i=1,2,..,n)$, and then calculating $H(v_{x1}|c_1,\ldots,v_{xn}|c_n)$, followed by ensemble average of these estimations. From $\Psi_X(x)$, the wind load effect for MRI=R-year, x_R, can be determined as $\Psi_X(x_R)=1-1/R$. It is noted that Eq. (4) can also be given in terms of JCDF of $C_i(V_i)(i=1,2,\ldots,n)$ and JPDF of directional extreme wind speeds, which can be computationally more efficient through Monte Carlo simulation when $C_i(V_i)(i=1,2,\ldots,n)$ are mutually independent (Zhang and Chen, 2015).

It should be noted that the full-order method (Harris, 1982, 2005; Chen and Huang, 2010), which accounts for the probability of the largest wind effect in a year for a given wind direction caused by second or high-order strongest wind speeds, results in improved estimations of wind effects with relatively lower MRIs as compared to the first-order method introduced by Cook and Mayne (1979, 1980). As pointed in Chen and Huang (2010), such an improvement is negligibly small for wind effects with large MRIs. Therefore, Eq. (4) is considered as adequate to address both directionality and uncertainty when the focus is placed on the wind effects with large MRIs.

The above approach combines the consideration of directionality and uncertainty in a unified framework with an analytical formulation which facilitates a systematic parametric study. Moreover, the work of statistical modeling of wind climate information, i.e., determination of $H(v_1,v_2,\ldots,v_n)$ and the work of wind tunnel testing, i.e., the determination of $C_i(v_i)$, can be separately conducted yet integrated through this framework. Also, the use of statistical model of directional extreme wind speeds makes the estimation for multiple responses under the same wind climate condition more efficient by avoiding the interpretation of extreme wind effect samples from the original wind speed data.

2.2. Modeling of multivariate directional extreme wind speeds

As introduced previously, now the problem of estimating the probabilistic wind load effect with consideration of directionality is converted to the modeling of the JCDF of directional extreme wind speeds which falls into the concerns of multivariate extreme value theory. For any multivariate extreme problem, the first step is to determine the extreme value distributions of univariate variables, i.e., marginal distributions. The extreme wind speed in the i-th sector is assumed to follow Gumbel (Type I) distribution and its CDF is expressed as:

$$F_i(v_i)=\exp\left[-\exp\left(-\frac{v_i-m_i}{\delta_i}\right)\right] \tag{5}$$

where m_i and δ_i are location and scale parameters. The mean and standard deviation (STD) of the Type I distribution are $m_i+\gamma\delta_i$ and $\delta_i\pi/\sqrt{6}$, respectively, where $\gamma=0.5772$ is Euler constant.