Wind Characteristics of a Tropical Storm from Stationary and Nonstationary Perspectives

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ABSTRACT

Inherent time-varying trends of wind records are frequently captured in recent field measurements of tropical storms. That means the extreme wind speed is a nonstationary process which is deviated from the traditional stationary assumption. In this study, a tropical storm recorded at Sutong Bridge site in 2008 is taken for stationary and nonstationary analyses. Two categories of fluctuating wind speeds are obtained by subtracting constant or time-varying means from original wind samples. Based on the traditional stationary model and two kinds of nonstationary models, stationary and nonstationary turbulent wind characteristics are comparatively investigated and compared with the recommendations in Chinese code and ASCE7-10. Meanwhile, the evolutionary power spectral density (EPSD) of fluctuating wind velocity is analyzed with emphasis on the verification of a derived time-frequency turbulence spectrum based on short-term stationary assumption.

1. INTRODUCTION

Tropical storm is an extreme wind event that makes destructive effects on engineering structures. In recent few decades, damages to property with attendant economic losses and casualties are frequently reported by public media during storms (Kareem 1985). For wind-sensitive structures, e.g., high-rise buildings and long-span bridges, the associated fluctuations in storms are dominated elements for the wind effects on these structures, which emphasize the demand to deeply understand and accurately describe their wind characteristics.

Since the famous analytical theory called Alan G. Davenport Wind Loading Chain (Davenport 1961; Isyumov 2012) is proposed, the conventional approach used to deal with wind characteristics is in fact based on an underlying stationary assumption. This approach assumes that the fluctuating component of wind speed can be treated as a zero-mean stationary Gaussian random process by subtracting a constant mean from

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the wind data (Wang and Kareem 2004; Chen et al. 2007). Accordingly, some pioneering theories or methods on the analysis of boundary layer winds associated with its effects on structures are proposed and successfully applied in engineering practices (Simiu and Scanlan 1996). However, recent field measurements have captured strong nonstationary features in the measured wind records during tropical storms (Xu and Chen 2004). The nonstationarity existing in wind samples mainly reveals itself as the time-dependent changes in the mean value, variance, frequency components, or their combinations. In this situation, the measured wind records may naturally deviate from the traditional stationary hypothesis, which means the commonly used stationary model is not suitable for the analysis of extreme wind characteristics. To deal with this problem, there are some models about the nonstationary wind characteristics proposed to characterize nonstationary features. The models mainly can be classified as two categories according to the research groups. One is the Kareem group in University of Notre Dame in the USA (Wang and Kareem 2004; McCullough et al. 2014), the other is the Xu Group in the Hong Kong Polytechnic University in China (Xu and Chen 2004; Chen and Kareem 2007). Though there are some differences between two nonstationary wind models, but their recognition to the nature of nonstationary winds is consistent. In the nonstationary wind cases, the wind speed is treated as the superposition of a time-varying mean, which is known as an underlying trend, and a stationary turbulent component.

Some researches have been conducted on the nonstationary characteristics of extreme wind events, e.g., tropical cyclones including both typhoons and hurricanes. However, the wind characteristics heavily depend on the geographical location, topography and local terrains (Wang, et al. 2015). The accumulated data is still not enough for the establishment of a nonstationary database that can be utilized for design. Also, the efficiency of the two nonstationary models has never been comparatively evaluated. Hence in this paper, A tropical storm called Fung-Wong is selected to characterize the nature of both stationary and nonstationary gust values. Based on the measured wind records at Sutong Bridge site, the wind characteristics are emphatically analyzed based on the traditional stationary model and the two kinds of nonstationary models. The analyzed wind characteristics mainly include the mean wind speed, turbulence intensity, gust factor, turbulence integral scale as well as turbulence PSD. During the analytical procedure, a comparative study on the efficiency of the two nonstationary models, which are respectively named as Kareem model and Xu model in the following sections, for characterizing nonstationary wind characteristics is also investigated.

2. DATA SOURCE AND DESCRIPTIONS

2.1 Anemometer for field measurement

An anemometer is included in the field measurement of Fung-Wong at Sutong Bridge site. As shown in Fig. 1, it was installed on the midspan of Sutong Bridge with 76.9m above the ground and on the wind-coming side to eliminate the interference of the main girder. The anemometer is a three-axis ultrasonic anemometer made by Gill Instruments Limited in Britain. The wind speed ranging from 0m/s to 65m/s can be
accurately recorded with a resolution of 0.01 m/s, while the wind direction in the range between 0° and 359.9° can be measured with a resolution of 0.1°. The anemometer can steadily work in a temperature environment from -40 °C to 70 °C. During the measurement, the sampling frequency of the anemometer is set as 20 Hz. In the horizontal plane, the due north is defined as 0° with a positive direction rotating clockwise. The wind towards the horizontal plane from downward is defined as the positive direction of the attack angle.

WindMaster Pro 3D ultrasonic anemometer

Fig. 1 Layout of the anemometer installed on Sutong Bridge

2.2. Description of the tropical storm Fung-Wong

Fung-Wong was the 8th tropical storm in 2008. It was born as a tropical depression on the surface of the Pacific Ocean and moved towards west on 24th July. It was evolved into a tropical storm in the next day. On 26th July, the intensity of Fung-Wong was further developed and achieved the same level of a strong tropical storm. In the same day, it was upgraded to a typhoon and turned towards northwest. On 28th July, it entered the main continent of China from Fujian Province. After that time, it moved towards the north and the corresponding intensity began to decrease. On 5:00 29th July, the maximum wind speed near surface was 23m/s which means it had downgraded as a tropical storm. The moving routine of Fung-Wong is shown in Fig. 2.

Fig. 2 Moving routine of Typhoon Fung-Wong

3. STATIONARY AND NONSTATIONARY WIND MODELS

In traditional stationary wind model, the wind speed is treated as a constant mean plus a zero-mean stationary random process, detailed as following.

\[ U(t) = \bar{U} + u(t) \] (1)
where $U(t)$ is the wind speed; $\bar{U}$ is the constant mean over a time interval $T$; $u(t)$ is the fluctuating component.

In the nonstationary wind model, a deterministic time-varying trend is captured in the wind speed. So the wind speed is treaded as the superposition of a time-varying mean and a residual zero-mean stationary random process, as presented in Eq. (2).

$$U(t) = \bar{U}^*(t) + u^*(t)$$ (2)

where $\bar{U}^*(t)$ is the time-varying mean; $u^*(t)$ is the turbulence in a nonstationary model.

Based on the two basic models presented by Eq. (1) and Eq. (2), the stationary and nonstationary models for the wind characteristics can be accordingly defined. In the Xu model, an equivalent mean wind speed is defined as the mean value of the time-varying mean over the time interval $T$, detailed as Eq. (3).

$$\bar{U}^* = \frac{1}{T} \int_{0}^{T} \bar{U}^*(t) dt$$ (3)

3.1 Turbulence intensity

Turbulence intensity is a key parameter in the determination of wind-induced dynamic loads on structures. In the traditional wind model, it is defined as the ratio of the standard deviation of turbulence and the mean wind velocity in a given time interval (Simiu and Scanlan 1996; Wang et al. 2013), as expressed in Eq. (4a). In order to make the nonstationary turbulence intensity have the same physical meaning as the stationary one, the nonstationary turbulence intensities in Xu model and Kareem model are separately defined as Eq. (4b) and Eq. (4c).

$$I_\| = \frac{\sigma_\|}{\bar{U}} \quad I_\perp = \frac{\sigma_\perp}{\bar{U}} \quad I_\wedge = \frac{\sigma_\wedge}{\bar{U}}$$ (4a)

**Xu model**

$$I_\| = \frac{\sigma_\|}{\bar{U}} \quad I_\perp = \frac{\sigma_\perp}{\bar{U}} \quad I_\wedge = \frac{\sigma_\wedge}{\bar{U}}$$ (4b)

**Kareem model**

$$I_\| = E\left[\frac{\sigma_\|}{\bar{U}(t)}\right] \quad I_\perp = E\left[\frac{\sigma_\perp}{\bar{U}(t)}\right] \quad I_\wedge = E\left[\frac{\sigma_\wedge}{\bar{U}(t)}\right]$$ (4c)

where $I_\|$, $I_\perp$ and $I_\wedge$ are along-wind, cross-wind and vertical turbulence intensities in the stationary model, respectively. $\sigma_\|$, $\sigma_\perp$ and $\sigma_\wedge$ are corresponding standard deviations in stationary wind model; Variates with * as the superscript are parameters in the nonstationary model. $E[\cdot]$ represents the mean value over the time interval.

3.2 Gust factor

Traditionally, gust factor is the ratio of the peak gust wind speed in a gust duration $t_g$ to the mean wind speed over the time interval $T$, as denoted in Eq. (5a). Actually, it represents a crucial parameter that can convert the mean wind speed to wind maxima in gust duration. This parameter has been widely accepted in related specifications.
(Professional Standard PRC 2004; ASCE7-10 2010) and utilized to estimate the maximum wind actions on structures. For nonstationary gust factor, there is a unified description in the Xu model and Kareem model, as indicated in Eq. (5b). The nonstationary gust factor takes the underlying trend into account and appears as the maximum ratio of the \( t_g \)-averaged original wind speed to \( t_g \)-averaged time-varying mean.

\[
G_s(t_g,T) = \max \left( \frac{U(t_g)}{\bar{U}} \right) = 1 + \max \left( \frac{u(t_g)}{\bar{u}} \right) \tag{5a}
\]

\[
G_s^*(t_g,T) = \max \left( \frac{U(t_g)}{\bar{U}^*} \right) \tag{5b}
\]

where \( G_s(t_g,T) \) is the stationary gust factor; \( U(t_g) \) is the mean wind speed over a gust duration \( t_g \); \( \bar{U}^* \) is the mean value of the time-varying mean over the duration \( t_g \).

### 3.3 Turbulence integral scale

Turbulence integral scale is the average size of turbulent eddies in the flow (Simiu and Scanlan 1996). In the traditional stationary model, turbulence integral scale is mathematically defined as Eq. (6a) based on Taylor hypothesis. Keeping the physical meaning unchanged, the nonstationary model of turbulence integral scale is naturally presented as Eq. (6b) and Eq. (6c).

\[
L_i = \frac{\bar{U}}{\sigma_i^f} \int_0^\infty R_i(\tau)d\tau \quad i = u, v, w \tag{6a}
\]

**Xu model**

\[
L_i^* = \frac{\bar{U}^*}{(\sigma_i^f)^2} \int_0^\infty R_i^*(\tau)d\tau \quad i = u, v, w \tag{6b}
\]

**Kareem model**

\[
L_i^* = E \left[ \frac{\bar{U}(t)}{(\sigma_i^f)^2} \right] \int_0^\infty R_i^*(\tau)d\tau \quad i = u, v, w \tag{6c}
\]

where \( L_i \) and \( L_i^* \) are stationary and nonstationary turbulence integral scales, respectively; \( R_i \) and \( R_i^* \) are corresponding auto-covariance functions of the stationary and nonstationary fluctuations; \( \tau \) is the lag time.

### 3.5 Turbulence PSD

Turbulence PSD is a crucial parameter that directly influences the precise prediction of buffeting responses. A number of spectral descriptions have been advanced primarily in strong tropical winds, and the commonly used Kaimal spectrum (Kaimal 1972) in the wind-resistant design specification for highway bridges in China (Professional Standard PRC 2004) is employed for comparison in longitudinal direction while Panofsky spectrum is adopted for vertical turbulence. Taking Kaimal spectrum as an example, these spectra including both stationary and nonstationary cases are given in Eq. (7). As there is no recommendation about the frequency-domain spectral expression in Kareem model, an extension has been made on the Kaimal spectrum in the view of mathematical expectation, as indicated in Eq. (7c).
\[
S(n) = \frac{200(z/l\bar{U})(u^*)^2}{[1+50(nz/l\bar{U})]^{5/3}} \quad (7a)
\]

Xu model

\[
S^*(n) = \frac{200(z/l\bar{U}^*)(\bar{u}^*)^2}{[1+50(nz/l\bar{U}^*)]^{5/3}} \quad (7b)
\]

Kareem model

\[
S^*(n) = E\left[\frac{200(z/l\bar{U}^*(t))(\bar{u}^*)^2}{[1+50(nz/l\bar{U}^*(t))]^{5/3}}\right]_T \quad (7c)
\]

where \( S(n) \) and \( S^*(n) \) are stationary and nonstationary turbulence PSDs, respectively; \( z \) is the altitude of the wind speed; \( n \) is the natural frequency of turbulence; \( u^* \) and \( \bar{u}^* \) are stationary and nonstationary friction wind speeds, respectively. The friction wind speed is related to the standard deviation of turbulence, which can be presented as

\[
\sigma^2 = 6(u^*)^2 \quad (8a)
\]

\[
(\sigma^*)^2 = 6(\bar{u}^*)^2 \quad (8b)
\]

4. MEAN WIND CHARACTERISTICS

4.1 Measured wind samples

The anemometers on Sutong Bridge successfully recorded the wind data of Fung-Wong. Among the measurements, the wind record from 23:31:00 on 29th July to 08:21:00 on 30th July is selected for analysis. The full wind record is shown in Fig. 3.

Fig. 3 Measured wind samples during the moving of Fung-Wong
4.2 Stationary evaluation and time-varying mean extraction

In the application of nonstationary model, a crucial step is to preferentially extract the time-varying mean wind speed. A variety of methods have been developed to derive the slowly varying trend for nonstationary winds, among which empirical mode decomposition (EMD) and discrete wavelet transform (DWT) are two popular and efficient approaches. For example, Chen and Letchford (2005) employed db4 wavelet to estimate the time-varying mean for downbursts with five-level decomposition, while db20 and 7 levels were selected to acquire the mean of a downburst wind data by Wang et al. (2013). However, the number of decomposed levels is usually determined by experience. Huang et al. (2015) has provided some recommendations about the selection of the appropriate approach and time window size to derive a reasonable time-varying mean, but the procedure involves the estimation of EPSD and structural response computation so that is comparatively complex. In this paper, a self-adaptive approach which makes use of the functions of both stationary test and DWT is proposed to extract a reasonable time-varying mean. The general framework for this approach is shown in Fig. 5. Following the presented scheme, a time-varying mean can be derived automatically according to the signal stationarity.

Fig. 5 General framework for self-adaptive approach to determine time-varying mean
The principle of this self-adaptive approach can be described as the following four main steps. Under the guidance of this framework, the inherent time-varying mean in a wind record can be derived according to the signal stationarity. Once the underlying trend is removed, the residual turbulent wind speed will be stationary.

Step 1: Determine the maximum level that can be decomposed by DWT as Eq. (11), which is derived from the decomposition mechanism of Mallat algorithm (Mallat 1989). Then set the initial number of decomposed levels $N$ as $N_0$.

Step 2: Conduct a wavelet decomposition of the wind record $U(t)$ with $N$ levels. Then reconstruct the low-frequency content $L(t)$ at the $N^{\text{th}}$ level according to the wavelet coefficients. Thus the turbulent wind speed $u(t)$ can be obtained by subtracting $L(t)$ from $U(t)$.

Step 3: Conduct a stationary test on the turbulent wind speed $u(t)$. The stationary test can be realized by a run test or a reverse arrangement method. In this study, the run test method is employed. If $u(t)$ is judged as stationary, go directly to the final step. Otherwise, take $N$ as $N-1$ and then go to Step 2.

Step 4: The time-varying mean existing in $U(t)$ is determined as $L(t)$.

$$N_0 = \log_2(T \cdot s)$$ (11)

In Eq. (11), $N_0$ is the maximum decomposed level for DWT; $T$ is the time interval; $s$ is the sampling frequency of a wind record.

With the presented self-adaptive method, the time-varying trends of the wind records are successfully extracted for Fung-Wong. Some typical samples are shown in Fig. 6. It is easy to find that the time-varying mean is almost the same as the constant mean for stationary records. The minor discrepancies are attributed to the side effects existing in the wavelet transform of discrete time series. But for nonstationary wind records, the time-varying mean deviates much from the constant mean, which means the stationary assumption will be untenable.
5. TURBULENT WIND CHARACTERISTICS

5.1 Turbulence intensity

Based on the stationary and nonstationary models, the turbulence intensities of Fung-Wong are estimated, as shown in Fig. 7. It is noted that the nonstationary turbulence intensity is lower than the stationary one for each case. Among the three events, the discrepancy in the longitudinal case is the most obvious while the nonstationary turbulence intensities are all quite close to stationary intensities in the vertical case. For the lateral turbulence, the nonstationary turbulence intensity approaches to the stationary one for stationary wind samples and behaves lower than the stationary tendency at many points due to the inherent signal nonstationarity. Generally, the nonstationarity in longitudinal wind is stronger than that in lateral wind and performs the weakest in the vertical wind.

When comparing the two nonstationary models, the tendencies of the turbulence intensities by Xu model and Kareem model are almost the same. In a micro view, the nonstationary turbulence intensity characterized by Xu model is slightly smaller than that by Kareem model. The maximum, minimum and mean values of nonstationary turbulence intensities are presented in Table 1. As described in Fig. 7 and Table 1, Xu model and Kareem model are consistent with each other as supported by the unification between Eq. (4b) and Eq. (4c) in a statistical view.
The longitudinal turbulence intensity profile for categories B, C and D exposure in ASCE7-10 is given by

\[ I_u = c \left( \frac{10}{z} \right)^{1/6} \]  

(12)

where \( c \) equals to 0.15 for category D exposure. Hence at an altitude of 76.9m, the longitudinal turbulence intensity is recommended as 0.108 by ASCE7-10. In Chinese code (Professional Standard PRC 2004), a ratio between longitudinal, lateral and vertical turbulence intensity is suggested as 1:0.88:0.50 and the value for longitudinal turbulence is recommended as 0.110 within the altitude between 70m and 100m. The recommendations of turbulence intensity in ASCE7-10 and Chinese code are plotted in Fig. 7 and also listed in Table 1.

It can be seen in Fig. 7 and Table 1 that both ASCE7-10 and Chinese code provide a good estimate of longitudinal turbulence intensity for Fung-Wong as the mean of measured values is only slightly larger than the recommendations. The suggested lateral turbulence intensity by Chinese code is a bit smaller than the measured value, but the discrepancy is still within 15%. However for the vertical case, the recommended value is five times of the measured value which indicates that the recommendation gives a too high estimation for the vertical turbulence intensity.

<table>
<thead>
<tr>
<th>Event</th>
<th>Stationary model</th>
<th>Xu model</th>
<th>Kareem model</th>
<th>Chinese Code</th>
<th>ASCE7-10</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>Min</td>
<td>Mean</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>( u )</td>
<td>0.203</td>
<td>0.083</td>
<td>0.119</td>
<td>0.141</td>
<td>0.035</td>
</tr>
<tr>
<td>( v )</td>
<td>0.179</td>
<td>0.085</td>
<td>0.111</td>
<td>0.145</td>
<td>0.083</td>
</tr>
<tr>
<td>( w )</td>
<td>0.028</td>
<td>0.011</td>
<td>0.017</td>
<td>0.027</td>
<td>0.008</td>
</tr>
</tbody>
</table>

5.2 Gust factor

Gust factor is reported to be strongly related to the longitudinal turbulence intensity. The stationary and nonstationary gust factors with 3s gust duration versus the corresponding turbulence intensities are plotted in Fig. 8. It is easy to find that there is a positive relationship between the gust factor and the turbulence intensity. Also, the nonstationary gust factor is more concentrated around the tendency than the stationary case, which means the extraction of time-varying mean can decrease the dispersion of the stationary gust factor.
The relationship between gust factor and the longitudinal turbulence intensity has been studied for many years. The specific expressions are separately suggested based on the linear model (Ishizaki 1983) and the nonlinear model (Choi 1983; Cao 2009), which can be combined into one equation as follows,

\[
GF(t,T) = 1 + k_1 I_u^k \ln \left( \frac{T}{t_g} \right)
\]

where Ishizaki suggested \( k_1 = 0.5, \) \( k_2 = 1.0 \) for typhoons; Choi (1983) suggested \( k_1 = 0.62, \) \( k_2 = 1.27 \) and Cao (2009) suggested \( k_1 = 0.5, \) \( k_2 = 1.15 \) for Typhoon Maemi. Cook (1985) presented a similar equation for flat-terrain in a 1h interval as follows,

\[
GF(t,3600) = 1 + 0.42 I_u \ln \left( \frac{3600}{t_g} \right)
\]

The relationships between gust factor and turbulence intensity in the investigated cases are also fitted for comparison, where the stationary case suggests \( k_1 = 0.2232, \) \( k_2 = 0.8430 \) and the nonstationary case suggests \( k_1 = 0.2594, \) \( k_2 = 0.9118. \) The fitted relationships together with the empirical models are also shown in Fig. 8. It can be found that all the empirical models except Cook model cannot well describe the measured relationship between gust factor and turbulence intensity. The two fitted stationary and nonstationary expressions are quite close to each other and similar to the Cook model, especially in the effective region where the turbulence intensity ranges from 0.05 to 0.15. Hence, it is reasonable to suggest that the relationship between gust factor and turbulence intensity is consistent in stationary and nonstationary cases.

Fig. 8 Stationary and nonstationary gust factors versus the turbulence intensity

For another part, the gust factor heavily depends on the gust duration \( t_g \) and the time interval \( T. \) Fig. 9 presents stationary and nonstationary gust factors versus the gust duration in two time intervals. It is noted that the gust factor decreases with increase of the gust duration for a given time interval. The nonstationary gust factor are generally lower than stationary ones, which implies the traditional stationary method...
overestimates the gust wind speed and will lead to a conservative result. As shown in Fig. 9, the stationary curve is almost a straight line for the two cases in a linear-logarithmic coordinate system, while the nonstationary curve can be described with a third-order polynomial. The relationship between gust factor and gust duration is fitted for the two cases, which are shown as Eq. (15) and Eq. (16). A comparison in Fig. 9 shows that the fitted model matches well with the measured values for Fung-Wong.

**Case 1:** $T=600s$,

- **Stationary** \( GF(t) = 1.313 - 0.1138x \)  
  \( \text{(15a)} \)
- **Nonstationary** \( GF(t) = 1.247 - 0.0515x - 0.0788x^2 + 0.0236x^3 \)  
  \( \text{(15a)} \)

**Case 2:** $T=3600s$,

- **Stationary** \( GF(t) = 1.424 - 0.1245x \)  
  \( \text{(16a)} \)
- **Nonstationary** \( GF(t) = 1.367 - 0.0695x - 0.0541x^2 + 0.0125x^3 \)  
  \( \text{(16a)} \)

where \( x = \log_{10}(t) \) for Eq. (15) and Eq. (16).

![Fig. 9 Stationary and nonstationary gust factors versus the time duration](image)

**5.4 Turbulence integral scale**

Fig. 11 presents the stationary and nonstationary turbulence integral scales in longitudinal, lateral and vertical cases. It can be found that the nonstationary turbulence integral scales are totally smaller than stationary ones, which mainly attributed to the extraction of the time-varying mean. In the mathematical theorem, Eq. (6) is equivalent to Eq. (17) which is derived from Von Karman spectrum (Von Karman 1948).

\[
L_i = \frac{C_i}{4(\sigma_i)^2} \cdot \delta_i (0) \quad i = u, v, w \tag{17}
\]
where $S_i'(0)$ represents the Fourier transform of the auto-correlation function of turbulence in nonstationary wind model. With the extraction of the time-varying mean, the spectral value at zero point will decrease due to the separation of low-frequency components.

Comparing turbulence integral scales by Xu model and Kareem model, they are consistent with each other in all the three cases, which mainly results from the linear relationship between turbulence integral scale and time-varying mean in Eq. (7c) before doing the average. In Eq. (7b), an average has been done before the calculation of turbulence integral scales, and thus Eq. (7c) is in nature identical to Eq. (7b). In such a view, both the Xu model and Kareem model are suitable for the evaluation of nonstationary turbulence integral scales.

More specific comparisons between stationary and nonstationary turbulence integral scales can be found in Table 2. A ratio between the turbulence integral scales in three directions for stationary case is given as $L_u : L_v : L_w = 1 : 0.537 : 0.423$ while the mean value $L_u = 212.4$. This finding is well accorded with the empirical expression proposed by Counihan (1975), in which the corresponding ratio is $1 : 0.500 : 0.333$. For the nonstationary turbulence integral scale, the ratio in three directions is $1 : 0.943 : 0.895$ with $L_u' = 48.8$. There are two main differences between stationary and nonstationary turbulence integral scales. One is that the nonstationary turbulence integral scales are smaller than stationary ones since the estimates of turbulence scales depend significantly on the degree of stationarity of the record being analyzed (Simiu and Scanlan 1996). As there is a stronger nonstationarity existing in longitudinal turbulence, the turbulence integral scale descends rapidly while the other two cases only have a little decrease. The other obvious phenomenon is that the nonstationary longitudinal,
lateral and vertical turbulence integral scales are close to each other, which means the average size of turbulent eddies in the flow is almost equivalent in three directions by the nonstationary wind model.

The longitudinal turbulence integral scale profile for categories B, C and D exposure in ASCE7-10 is given by

$$L_u = l \left( \frac{z}{10} \right)^{\varepsilon}$$

(12)

where $l$ is equals to 198.2 and $\varepsilon$ is equals to 1/8 for category D exposure. At the 76.9m observation height, the longitudinal turbulence integral scale is recommended as 255.8 by ASCE7-10. The longitudinal and vertical turbulences are two main concerns in the wind-resistant design of bridges. Hence in Chinese code (Professional Standard PRC, 2004), the turbulence integral scales within the altitude between 70m and 100m are suggested as 140m and 70m for longitudinal and vertical directions, respectively. The recommendations of turbulence integral scale in ASCE7-10 and Chinese code are also plotted in Fig. 11. And specific comparisons between measured turbulence integral scales and recommended values by codes are given in Table 2.

It is noted in Fig. 11 that ASCE7-10 provides a good estimate of longitudinal turbulence integral scale for Fung-Wong as measured values fluctuate around the recommended one. In Table 2, the recommended longitudinal turbulence integral scale is a bit larger than the measurement, but the error is still within 20% and thus reasonable for estimation. In respect of the Chinese code, the recommended longitudinal value is totally smaller than the measured turbulence integral scales, indicating an improvement is required for this parameter in specification. The measured value matches well with the recommendation for the vertical turbulence integral scale by Chinese code with a 10.6% deviation.

<table>
<thead>
<tr>
<th>Event</th>
<th>Stationary model</th>
<th>Nonstationary model</th>
<th>Chinese Code</th>
<th>ASCE7-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u$</td>
<td>Max 532.6</td>
<td>Min 62.6</td>
<td>Mean 212.4</td>
<td>Max 100.2</td>
</tr>
<tr>
<td>$v$</td>
<td>Max 268.5</td>
<td>Min 33.6</td>
<td>Mean 79.7</td>
<td>Max 95.7</td>
</tr>
<tr>
<td>$w$</td>
<td>Max 292.5</td>
<td>Min 26.5</td>
<td>Mean 62.6</td>
<td>Max 193.9</td>
</tr>
</tbody>
</table>

5.5 Turbulence PSD

Two categories of wind samples characterized with strong and weak nonstationarities are selected for the PSD analysis. The measured stationary and nonstationary PSDs for longitudinal turbulence accompanied by the stationary and nonstationary Kaimal descriptions are presented in Fig. 12. And the measured spectra for vertical turbulence with comparison to Panofsky spectrum are also given in Fig. 13.

In longitudinal turbulence with strong nonstationarity, the turbulent energy sharply decreases in the low-frequency range due to the filtering of low-frequency contents while it keeps unchanged in the other frequency ranges. The reduction of spectral amplitude in the low-frequency range may affect the wind-induced dynamic response of
super long suspension bridges, which deserves for further studies. The stationary Kaimal spectrum generally can well satisfy with the measured stationary spectrum in most ranges except the high-frequency parts, but it is incapable of describing the measured nonstationary spectrum due to the inherent non-monotonicity. The Xu model is identical to Kareem model, but neither of them can match the measured nonstationary spectrum well since the governing equation for spectrum is only a monotonic function of the natural frequency.

In longitudinal turbulence with weak nonstationarity, only a little decrease can be found in the low-frequency range of the nonstationary spectrum. The stationary and nonstationary spectral models appear overlapped within the overall frequency regions due to the satisfaction of the stationary assumption. Comparing the appearances between Case 1 and Case 2, Xu model and Kareem model are still only suitable for stationary cases. They both in nature are not strictly nonstationary models which can characterize the energy distribution of turbulence. Similar features can also be captured in the vertical turbulence, as shown in Fig. 13. Hence, new models are still needed for the spectral descriptions of nonstationary winds.

![Fig. 12 PSD analysis of the longitudinal turbulence](image)

![Fig. 13 PSD analysis of the vertical turbulence](image)
In recent few decades, attempts have been made to capture the transient features of a signal via time-frequency analysis tools, e.g. Short-Term Fourier Transform and Wavelet Transform. On this occasion, the energy distribution of a nonstationary wind record can be naturally characterized in the terms of time-varying spectra. The EPSD, which is derived from traditional PSD, is defined with definite physical meanings by Priestley (1981) and has been widely accepted in the time-frequency description of nonstationary signals. The existing researches mainly concentrate on the EPSD estimation of measured random processes, and pioneering achievements have been made in this aspect (Spanos and Failla 2004; Huang and Chen 2009). However, an empirical time-frequency model is urgently needed in engineering practice when there are no field measurements. Hence, a time-frequency expression for the EPSD of nonstationary winds is deduced as following based on existing stationary spectral models.

According to the Kolmogrov theory, the PSD of the stationary turbulence can be described in a general form, which is given by

\[
S(n(t)) = \frac{A f^{\gamma}}{(1 + B f^{\alpha})^{\beta}}
\]

where \( f \) is the Monin coordinate and equals to \( n_{\varepsilon} / \bar{U} \); \( A \) and \( B \) are both multiplying factors for the Monin coordinate and can be determined through parameter fitting; \( \alpha, \beta \) and \( \gamma \) are power exponents and should follow the rule \( \gamma - \alpha \beta = 2/3 \).

Assuming the turbulence in short time duration \( \Delta t \) is a stationary random process and the energy in each segment can be described with the same spectral expression. Hence, the spectral expression at time instant \( t_1 \) is suggested as Eq. (14) with a reshaping of Eq. (13).

\[
S(n, t_1) = \frac{A n^{-1} \left( \frac{z}{U(t_1)} \right)^{\gamma/2} u^2_0(t_1)}{1 + B \left( \frac{n_{\varepsilon}}{U(t_1)} \right)^{\beta}}
\]

where \( u_0(t_1) \) is the friction wind speed during \( \Delta t \) around the time instant \( t_1 \) and defined as \( u_0(t_1) = k U(t_1) / \ln(z / z_0) \) in which \( k=0.4 \), \( U(t_1) \) is the mean wind speed in the given duration \( \Delta t \) at height \( z_1 \), and \( z_0 \) is the roughness length.

As the time duration \( \Delta t \) is very small, the mean wind speed can be treated as an instantaneous velocity which also corresponds to a piece of the time-varying trend. Taking all the segments together into account when \( \Delta t \) approaches zero, Eq. (14) can be recast into a more general form at any time instant \( t \), which is given by

\[
S(n, t) = \frac{A n^{-1} \left( \frac{z}{U(t)} \right)^{\gamma/2} u^2_0(t)}{1 + B \left( \frac{n_{\varepsilon}}{U(t)} \right)^{\beta}}
\]
With a stationary spectral expression taken out, Eq. (15) can be rewritten as Eq. (16) in the premise that the stationary friction speed is defined as $u_* = k\bar{U} / \ln(z / z_0)$.

$$S(n,t) = \left[ \frac{\bar{U}}{U(t)} \right]^{-2} \left[ 1 + B \left( \frac{n_z}{U(t)} \right)^\alpha \right]^{\beta} \left[ 1 + B \left( \frac{n_z}{U(t)} \right)^\gamma \right] \left( A(n,t) \right)^\gamma S(n)$$  \hspace{1cm} (16)

The EPSD of an arbitrary nonstationary process is mathematically defined as

$$S(n,t) = |A(n,t)|^\gamma S(n)$$ \hspace{1cm} (17)

where $A(n,t)$ is slowly varying time- and frequency-dependent modulating function and $S(n)$ is the PSD of a zero-mean stationary process as expressed in Eq. (13).

Hence, an empirical model for the EPSD of nonstationary turbulence can be suggested as Eq. (16). And the modulating function in the general form is presented as

$$A(n,t) = \left[ \frac{\bar{U}}{U(t)} \right]^{-2} \left[ 1 + B \left( \frac{n_z}{U(t)} \right)^\alpha \right]^{\beta} \left[ 1 + B \left( \frac{n_z}{U(t)} \right)^\gamma \right]$$ \hspace{1cm} (18)

Since Kaimal spectrum fits well with the measured spectrum in Fig. 12(a), it is taken for a numerical example here. When Kaimal spectrum is adopted, the modulating function is deduced as Eq. (19), which is consistent with the results by Li et al. (2015).

$$A(n,t) = \left[ \frac{U(t)}{U} \right] \left[ 1 + 50 \frac{n_z}{U} \right]^{\alpha/\gamma} \left[ 1 + 50 \frac{n_z}{U(t)} \right]$$ \hspace{1cm} (19)

To verify the availability of the general empirical model for the EPSD of nonstationary winds, the EPSD of the nonstationary turbulence in Fig. 12(a) is estimated based on wavelet transform as well as the Kaimal EPSD calculated by Eq. (16) and Eq. (19). The comparison of the measured EPSD and the Kaimal EPSD are shown as Fig. 14. It is easy to find that the general distribution of the measured EPSD is almost the same as that of Kaimal EPSD although many discrepancies are observed due to the fluctuations existing in the measured case. The positions where peaks or valleys occur nearly keep consistent in the two cases. For a more explicit comparison, two slices when $t=300s$ and $t=500s$ are picked out to present the similarities between measured EPSD and Kaimal EPSD in Fig. 15. As shown in Fig. 15, Kaimal EPSD generally matches well with the measured EPSD, which indicates the empirical model presented by Eq. (16) provides a good estimation of the measured EPSD in both frequency domain and time domain. Therefore, this empirical model can be further extended in engineering applications.
6. CONCLUSIONS

Based on the wind data of Fung-Wong, the wind characteristics characterized by stationary and nonstationary models are comparatively investigated. During the analysis, a self-adaptive approach which can automatically extract the time-varying mean is proposed and a general empirical EPSD is deduced for nonstationary turbulence. Some conclusions are summarized as below.

(1) The proposed self-adaptive approach makes use of the functions of both stationary test and DWT. Following the presented scheme, the time-varying mean in a given nonstationary wind record can be automatically and efficiently extracted according to the signal stationarity.

(2) The nonstationary turbulence intensity is obviously lower than stationary one for the longitudinal case, while they are quite close to each other in the lateral and vertical cases. This implies the longitudinal wind speed shows a much stronger nonstationarity than the other two cases.

(3) Both ASCE7-10 and Chinese code provide a good estimate of stationary longitudinal turbulence intensity for Typhoon Fung-Wong. Comparing the two nonstationary models, the tendencies of the turbulence intensities are almost the same as the two models are consistent with each other in a statistical view.

(4) All the empirical models except Cook model cannot well describe the measured
relationship between gust factor and turbulence intensity. For the relationship between gust factor and gust duration, the stationary curve is almost a straight line in a linear-logarithmic coordinate system, while the nonstationary curve can be described with a third-order polynomial.

(5) In nonstationary cases, the turbulent energy sharply decreases in the low-frequency range due to the filtering of the time-varying mean. The presented nonstationary spectral models are still only suitable for stationary cases and are not strictly nonstationary models which can characterize the energy distribution of turbulence.

(6) An empirical EPSD model is deduced from the general spectral description in frequency domain based on short-term stationary assumption. It provides a rather good estimate of the measured EPSD in both time domain and frequency domain, which verifies the efficiency and availability of this model so that it can be further extended in engineering applications.

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