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Analytical Models for Nonstationary Winds

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ABSTRACT

Nonstationary extreme winds, including the typhoon (or hurricane), thunderstorm downburst and tornado, are responsible for many structural damages and attracting the ever-increasing attention from the meteorological and wind engineering communities (e.g., Fujita 1985; Holmes and Oliver 2000; Xu and Chen 2004). Modeling their fluctuation is very complex. Usually, they can be characterized by the evolutionary power spectra density (EPSD) functions (e.g., Priestley 1965). However, the empirical models based on EPSD are not available for these winds mainly due to difficulties in mathematical treatments.

In this study, based on the estimated EPSD, transient features of nonstationary winds are examined and results show that the spectral variations in the nonstationary wind fluctuations including two downburst samples are relatively weak. Also, validity of the nonstationary wind spectrum models directly extended from the stationary wind spectra is evaluated. Furthermore, two analytical models are suggested to characterize the nonstationary wind fluctuations, including a fully nonstationary process model and a simplified uniformly modulated process model. They will be helpful in the Monte Carlo simulation and structural dynamic analysis.

1. Introduction

Scholars from the meteorological and wind engineering communities pay more attentions to the extreme winds, including the typhoon (or hurricane), thunderstorm downburst and tornado, due to the wind-induced destructive damage on the buildings and other structures (e.g., Fujita 1985; Holmes and Oliver 2000; Xu et al. 2014). These winds often display the nonstationary characteristics. The mean component is typically characterized by a time-varying deterministic function. On the other hand, modeling the fluctuation is more complex. The fluctuation speed of the typhoon (or hurricane) is regarded to be stationary (e.g., Xu and Chen 2004; Wang and Kareem 2005), while that of the thunderstorm downburst wind is characterized by the nonstationary process (e.g.,

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Huang and Chen 2009). Recently, Xu et al. (2014) have modeled the wind fluctuation around the typhoon eye as the nonstationary process. These nonstationary processes can be described by the evolutionary power spectra density (EPSD) functions (e.g., Priestley 1965). EPSD portrays the energy distribution over both of the temporal and spectral domains and hence has more physical meanings over other approaches, such as the time-varying time series model and wavelets-based spectra (e.g., Huang and Chen 2009). Especially, when it comes to stochastic structural dynamics, EPSD functions render possible the frequency domain analysis, which is more efficient and physically meaningful over the time domain counterpart. Therefore, EPSD plays an essential role in structural dynamics under nonstationary excitations, which is similar to the power spectral density (PSD) for stationary excitations.

The nonstationary wind fluctuation shows non-ergodic characteristics. Hence, as limited samples, usually one sample, are available, the estimation of the EPSD is pretty tricky. Due to the existence of the uncertainty principle, the genuine spectra cannot be estimated for one sample and only averaged spectra both on time and frequency can be obtained. In addition, limited field measurement data are available, especially, for thunderstorm downburst and tornado (actually, no field measurements exist for the tornado although it may have the strongest nonstationarity) because of small temporal and spatial scales, and random occurrences. Furthermore, the understanding of physical mechanism of these extreme winds still needs the improvement. These obstacles lead to the significant challenges in modeling the nonstationary fluctuation, especially via the empirical nonstationary spectrum, which is different from the well-developed boundary layer winds where many wind spectra have been widely used.

Recently, the attempts have been made to characterize and model the nonstationary wind fluctuations. Chen and Letchford (2004) proposed the deterministic-stochastic hybrid model for thunderstorm downbursts where the nonstationary fluctuation is regarded as the uniformly modulated process. Chen (2005) developed the time-varying vector AR model for the nonstationary fluctuation using Kalman filter to estimate the model coefficients. Huang and Chen (2009) studied the transient characteristics of thunderstorm downbursts based on the estimated EPSD via wavelets. Huang et al. (2013) proved that treating the nonstationary downburst fluctuation as the uniformly modulated process was appropriate for the tall building response analysis. Wang et al. (2013) adopted wavelet

To develop an empirical model for nonstationary wind fluctuation, Li (2012) directly extended the existing stationary wind spectra to nonstationary winds and also derived the corresponding modulation functions. However, the physical mechanism of nonstationary extreme winds, especially that of thunderstorm downburst, is different from that of the traditional stationary boundary layer winds. The validity of such the direct extension should be examined. Also developing physically meaningful spectrum models for the nonstationary winds is critical to the structural dynamic analysis under extreme winds.

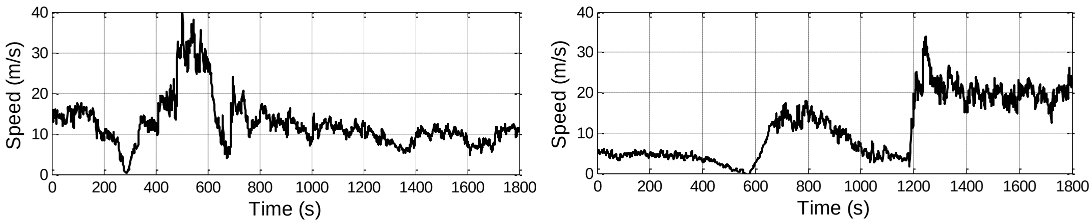
When it comes to the coherence function of nonstationary winds, it is even more difficult to be estimated based on one sample. Hence, mathematically, it is a very tough task to obtain an empirical model for the coherence function of nonstationary wind fluctuations. Currently, Davenport's exponential coherence function is adopted in nonstationary winds for convenience (e.g., Chen and Letchford 2005; Chen 2008;

Huang et al. 2013). Clearly, the coherence is assumed to be time-independent in this application. Such treatment should be evaluated.

This study is organized as follows. Firstly, the inference of time-varying mean and variance of nonstationary extreme winds, including two sets of thunderstorm downbursts from field measurements, will be discussed. Then EPSDs of these winds will be estimated and their transient features will be discussed. Also EPSDs will be used to evaluate the validity of the nonstationary wind spectrum models directly extended from current stationary wind spectra. Furthermore, two analytical models will be proposed to characterize the nonstationary wind fluctuations, including a fully nonstationary process model and a simplified uniformly modulated process model. Based on estimated EPSDs, the time dependence of the coherence function of nonstationary downbursts will be also discussed. Finally, the concluding remarks will be given.

2. Full-scale nonstationary wind records

Two sets of the full-scale observations of thunderstorm downburst winds measured near Reese Technology Center, Lubbock, Texas will be studied, where one is the outflow of a real-flank downdraft (RFD) and another one is derecho (Gast 2003). The RFD rotates around the backside of the mesocyclone and plays an integral part in tornadogenesis, while derechos are widespread convective windstorms and often produced by squall lines, linear storm systems with multiple discrete updrafts (Chen and Letchford 2005). The observations have a duration of 1800s and sampling frequency of 1 Hz. The downburst wind time histories at height of 15 m for both of RFD and Derecho are shown in Figure 1, respectively.



(a) RFD (b) Derecho

Figure 1 Time histories of thunderstorm downbursts (height 15m)

3. Inference of time-varying mean and variance

Nonstationary wind time history at height *z* can be modeled as the summation of the time-varying mean and fluctuating component, and given by

$$U^t(t) = U(t) + u(t) \tag{1}$$

where $U(t)$ is regarded as a deterministic function and $u(t)$ is characterized to be a nonstationary evolutionary process. Evidently, the variation of $U(t)$ can be assumed to be much slower compared to the lowest frequency embedded in $u(t)$. Hence, the structural response introduced by the time-varying mean of wind speed can be performed by the quasi-static analysis. Usually, the mean is can be estimated by the smoothing or filtering operations, such as the moving average (MA), low-pass filter and polynomial curve fitting. Because moving average usually cannot track the rapidly varying mean, the wavelet transform (WT) and empirical mode decomposition (EMD) are widely used in the derivation of the time-varying mean (e.g., Chen and Letchford 2005; Xu and Chen 2004; Huang et al. 2013; Wang et al. 2013). In this study, discrete WT will be used for the derivation. It has the capacity to decompose the univariate data as well as multivariate data. It should be noted that the estimated mean is generally biased. If the bias error in mean value estimation is reduced, the random error will be increased. Hence, there is a compromise between the bias and random errors (Bendat and Piersol 2010), which is similar the EPSD estimation based on one sample.

Analogous to the inference of time-varying mean, the determination of instantaneous variance of the nonstationary wind fluctuation based on the single sample also involves challenges. Chen and Letchford (2005) adopted a two stage weighted moving-average method developed by Nau et al. (1982) to evaluate the variance. Huang and Chen (2009) inferred the variance by integrating the estimated EPSD.

In this study, a straightforward method based on kernel regression will be used to estimate the variance. The proposed model can be expressed as

$$U^t(t) = U(t) - \sigma(t)\varepsilon_t \tag{2}$$

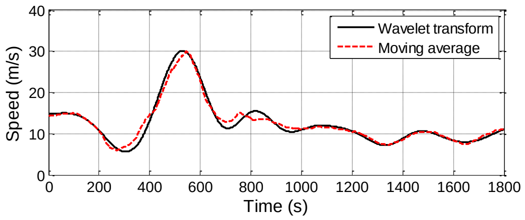
where $\sigma(t)$ is standard error for the model at time t and also the standard deviation of wind fluctuation; ε_t follows the standard Gaussian distribution. $U(t)$ can be estimated by WT or EMD, and $\sigma(t)$ can be estimated by using the kernel method (e.g., Nadaraya 1964).

$$\sigma^2(t) = \frac{1}{K_b}\sum_{i=1}^{T}\left[U^t(t) - U(t)\right]^2 K\left(\frac{t_i - t}{b}\right) \tag{3}$$

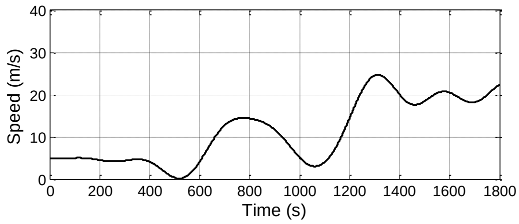
where $K(x) = \frac{1}{\sqrt{2\pi}}\exp(-x^2/2)$ is the standard normal function; $K_b = \sum_{i=1}^{T} K\left(\frac{t_i - t}{b}\right)$, and *T* is total number of time points in data and *b* is the bandwidth or window.

3.1 time-varying mean

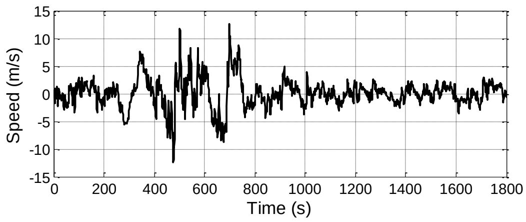
Both of downburst records are used as the examples to illustrate the effectiveness of the proposed method. The estimated mean speeds using the discrete wavelet are displayed in Figure 2 (a) and (b). Here the wavelet is chosen as Daubechies wavelet (e.g., Daubechies 1992) of order 20 with the decomposition levels of 7 (also equivalent to window size of 128 s). Accordingly, the frequency range embedded in the mean is less than 0.0078Hz, which is smaller than the fundamental frequencies of the majority of structures devastated by the thunderstorm downbursts. For the comparison, the time-varying mean via the moving average (window of 128 s) is also evaluated for RFD and shown in Figure 2 (a). It is observed that the corresponding mean is jagged, which indicates the moving average cannot track the fast-varying trend of wind speed very well. The fluctuation speeds for both of thunderstorm downbursts via WT are shown in Figure 2 (c) and (d).



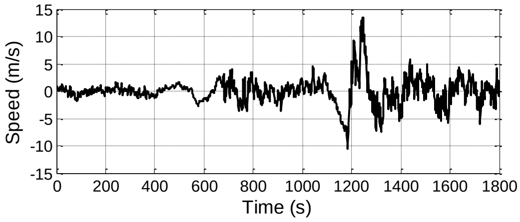
(a) Mean of RFD



(b) Mean of derecho



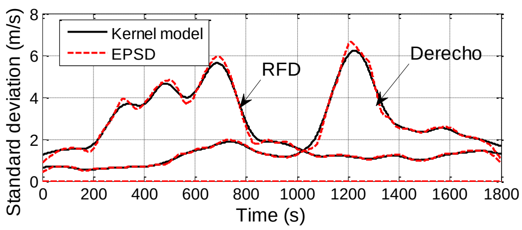
(c) Fluctuation of RFD



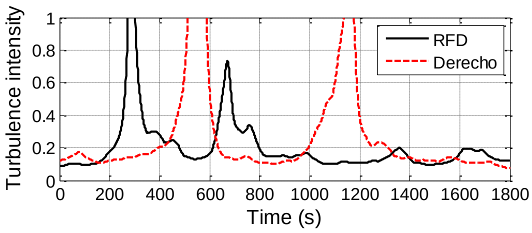
(d) Fluctuation of derecho

Figure 2 Mean and fluctuation of thunderstorm downbursts (height 15m)

3.2 Variance



(a) Standard deviations



(b) Turbulence intensities

Figure 3 Standard deviations and turbulence intensities of downbursts

With the proposed kernel regression model, the time-varying variance can be obtained. Figure 3 shows the standard deviations and turbulence intensities for downbursts. The time-varying turbulence intensity is defined as

$$I(\mathrm{t}) = \frac{\sigma(\mathrm{t})}{U(\mathrm{t})} \tag{4}$$

It can be seen that turbulence intensities for downbursts are around 0.12 expect few instants. Note the standard deviations estimated by kernel regression method are close to those based on the integration of EPSD as shown in Figure 3 (a).

4. EPSD estimation

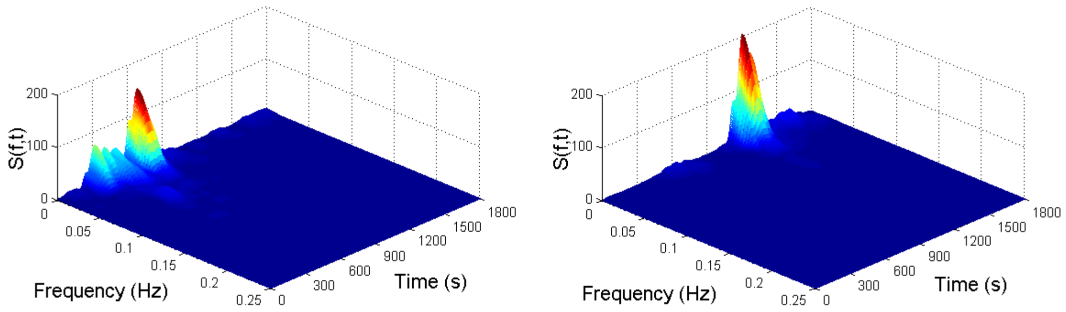
Except the EPSD estimation method developed by Priestley and his associates (e.g., Priestley 1965; Priestley and Tong 1973), a series of new methods have been proposed for EPSD estimation of nonstationary process, such as short-time Thomson’s multiple-window approach (Conte and Peng 1997), wavelet transform-based approach (Spanos and Failla 2004; Huang and Chen 2009) and time-varying AR model (Chen 2005). These new methods have some limitations for spectral estimation. Currently, the multiple-window scheme is only developed for the univariate process. Although the wavelet approach performs well for multiple samples, it may introduce few negative spectral contents for single sample if the wavelet parameters are not carefully chosen. On the other hand, it is hard to determine the order and the time-varying model coefficient for the time-varying AR model. Hence, Priestley’s classic EPSD estimation method is still widely used (e.g., Xu et. al 2014) due to its straightforwardness and wide applicability. In this study, this method will be used to evaluate the nonstationary spectra of extreme winds.

4.1 Downburst winds

The estimated and normalized EPSD (Normalization is based on instantaneous variance, which is estimated via the integration of EPSD) for RFD and derecho at height of 15 m (Only 0-0.25Hz shown) are displayed in Figures 4 and 5. Because the 3-dimensional illustrations may not clearly depict the detailed contents of EPSD, the contours for normalized EPSDs are also displayed in Figure 6. Based on these figures, it can be seem that spectra obviously show the time-dependent characteristics.

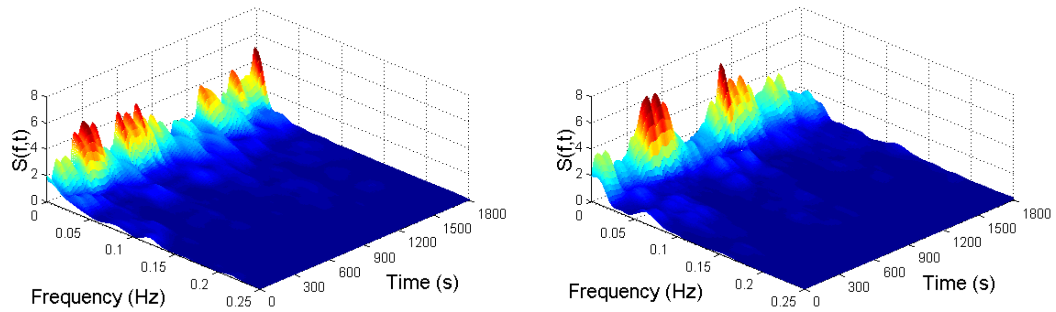
Figure 5 (a) shows that there exist significant energy evolutions around 500s and 700s for EPSD of RFD, which corresponds to the large variation of wind fluctuations at these time instants. On EPSD of derecho, there is a peak around 1200s, which is also related to the large fluctuations around that time instant. In addition, it can be roughly observed that there exist three plateaus on EPSD of derecho, including 0s-600s, 600s-1100s and 1100s-1800s, which are consistent with the three ranges of wind fluctuations with different amplitudes.

Figures 5 and 6 show that the spectral evolution along the time axis is rather slight, especially for RFD where spectral content has little variation with the time. Similar to stationary wind spectrum, the trend of the spectrum at each time instant is decaying with the increase of the frequency. The dominant frequency can also be found from Figure 6, which is located around 0.0125 Hz. This observation is validated by PSDs of downburst fluctuations, shown in Figure 7.



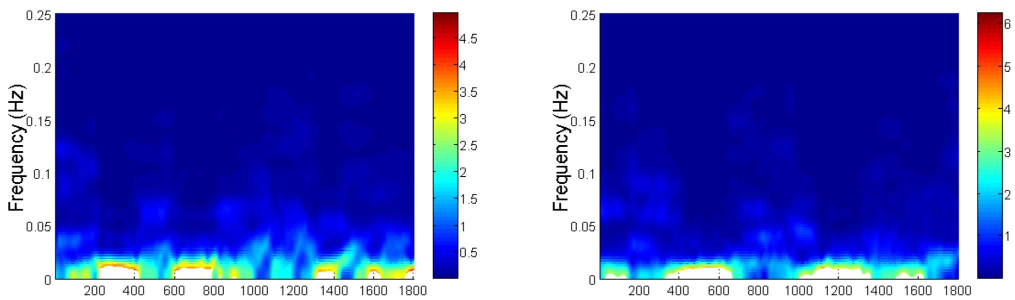
(a) RFD (b) Derecho

Figure 4 EPSDs for Downbursts (height 15m)



(a) RFD (b) Derecho

Figure 5 Normalized EPSDs for Downbursts (height 15m)



(a) Normalized EPSD for RFD (b) Normalized EPSD for derecho

Figure 6 Normalized EPSDs for thunderstorm downbursts (height 15m)

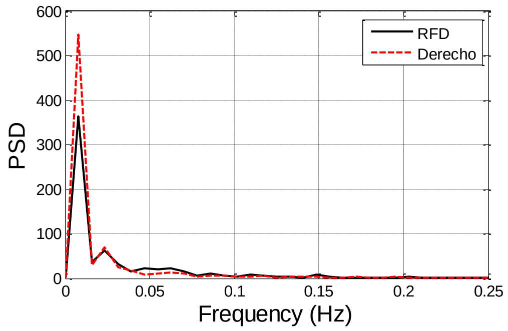


Figure 7 PSDs for thunderstorm downbursts (height 15m)

5. Validity of a class of analytical models for nonstationary wind fluctuations

Due to the lack of the empirical model for the nonstationary wind, the extension of available stationary wind spectra seems pretty natural. By dividing the duration of wind fluctuation into infinitely small intervals and regarding the PSD in each interval following existing stationary wind spectrum with varying mean wind speeds, Li (2012) claimed the nonstationary wind spectrum could be obtained by combining these time-varying PSDs. Actually, the stationary wind spectrum is valid for the well-developed storms and it may not be meaningful for extremely small interval. Hence, the validity of such extension should be examined.

Some widely used spectra, such as Kaimal's, von Karman's and Davenport's spectrum, may be directly adapted to nonstationary winds. Due to similarity among these spectra, Kaimal's spectrum at height *z* will be scrutinized as the example in this section and this spectrum is expressed as

$$\frac{nS(n)}{u_*^2} = \frac{200f}{(1+50f)^{5/3}} \tag{5}$$

where n is frequency in Hz; $S(n)$ is the wind spectrum at height of z above the ground; u_* is friction velocity and defined as $u_* = \dfrac{kU}{\ln(z/z_0)}$ in which $k \approx 0.4$, U is mean wind speed at height z and z_0 is roughness length; f is reduced frequency and defined as $f = \dfrac{nz}{U}$. By introducing the time-varying mean wind speed, the stationary Kaimal's spectrum could be extended to describe the nonstationary wind fluctuation, which is given by

$$S(t,n) = u_*^2(t)\frac{z}{U(t)}\frac{200}{[1+50f(t,n)]^{5/3}} \tag{6}$$

where $u_*(t) = \dfrac{kU(t)}{\ln[z/z_0]}$ and $f(t,n) = \dfrac{nz}{U(t)}$.

However, the spectra of nonstationary strong winds may not follow famous Kolmogorov's '$-5/3$' law. Hence, a more general model may be required. For stationary boundary layer winds, Olesen et al. (1984) proposed a general expression, which is given as

$$\frac{nS(n)}{u_*^2} = \frac{Af^{\gamma}}{(1+Bf^{\alpha})^{\beta}} \tag{7}$$

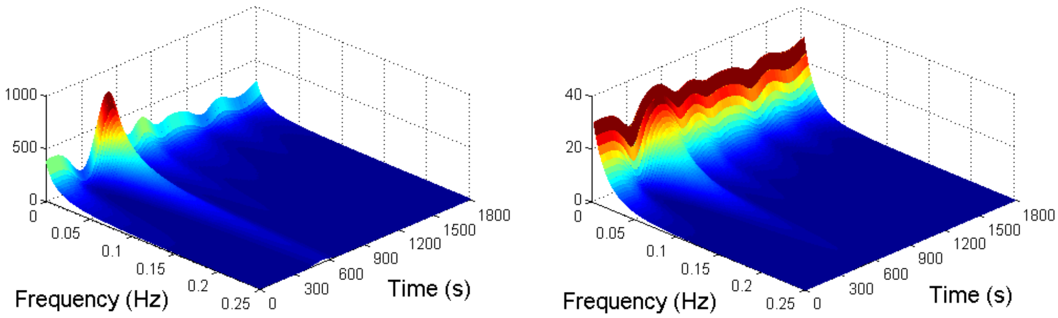
where A, B, α, β and γ are constants to be determined by the atmospheric conditions. The slope of this spectrum model is characterized by γ for the low-frequency range and by $\gamma-\alpha\beta$ for high-frequency range. Similar to the possible nonstationary Kaimal's spectrum, the general spectrum in Eq. 7 can also be adapted for nonstationary case, which is expressed as

$$S(t,n) = \frac{Af(t,n)^{\gamma}}{[1+Bf(t,n)^{\alpha}]^{\beta}} \tag{8}$$

where $u_*^2(t)/n$ has been included in numerator. All parameters in Eqs. (6) and (8) can be evaluated by nonlinear fitting.

To evaluate the validity of the aforementioned two models in the estimation of EPSD, the wind fluctuation of RFD downburst is used as the example. Figure 8(a) shows the estimated nonstationary spectra based on Eq. (6), where roughness length z_0 is taken as 0.2 m corresponding to flat terrain. It can be observed that the model in Eq. (6) cannot capture the dominant frequencies in the nonstationary winds, although the evolutionary characteristics of the wind fluctuation can be found. Furthermore, the amplitude of estimated EPSD shown in Figure 8(a) is also significantly deviated from that via Priestly's method. Figure 8(b) shows the fitted EPSD based Eq. (8), where the parameters $A=$ 15.7886, $B=$ 102.4225, $\alpha=$ 1.3674, $\beta=$ 2.0921 and $\gamma=$ -0.1198. Obviously, the model based on Eq. (8) performances poorly. Compared with Eq. (6) where the time-varying mean approximately works as the amplitude modulation function, Eq. (8) does not have the fast-varying amplitude modulation function. Also it cannot characterize the dominant frequencies and multiple peaks in the spectra.

Similar observations can be found for the derecho downburst sample. Obviously, both models derived directly from stationary counterparts are not appropriate for the nonstationary winds due to the different physical mechanism. The analytical models with sound physical meaning should be developed, which will be discussed in following section.



(a) Based on Eq. (6) (b) Based on Eq. (8)

Figure 8 Estimated EPSDs based on two nonstationary spectra models

6. Proposed analytical models for nonstationary wind fluctuations

Based on the discussion in previous section, the direct extension of stationary wind spectrum models is not appropriate. Hence, the appropriate nonstationary wind spectrum models are desired for better representing the nonstationary winds and facilitating the subsequent structural dynamic analysis excited by nonstationary winds. In following representation, two models will be proposed to model nonstationary winds.

6.1. Fully nonstationary model

Analogous to the nonstationary wind fluctuation, the ground motion often exhibit strong nonstationarity (e.g., Lin and Yong 1987). To describe the nonstationary ground motion, Conte and Peng (1997) proposed a fully nonstationary analytical model. The essence of this approach is to use the generally nonstationary analytical model to match the estimated spectra. Due to its versatility, this model will be adapted to represent the nonstationary wind fluctuation.

Nonstationary wind fluctuation $u(t)$ can be expressed as the summation of zero-mean, independent, uniformly modulated Gaussian processes, i.e.,

$$u(t) = \sum_{k=1}^{p} X_k(t) = \sum_{k=1}^{p} g_k(t) Y_k(t) \tag{9}$$

where p is the total number of component processes; $X_k(t)$ is k th uniformly modulated component process; $g_k(t)$ is the time-modulated function and $Y_k(t)$ is the zero-mean stationary Gaussian process. $g_k(t)$ is given by the modified gamma function

$$g_k(t) = \eta_k^{-1}\left(\frac{t-\zeta_k}{\lambda_k}\right)^{\delta_k} e^{-\frac{(t-\zeta_k)}{\lambda_k}} H(t-\zeta_k) \tag{10}$$

where η_k and λ_k are positive constants; ζ_k is 'arrival time' for k th component process; δ_k is the positive integer; and $H(t)$ is Heaviside step function. $Y_k(t)$ is represented by the one-sided PSD function

$$S_{Y_kY_k}(n) = \frac{n^{\gamma_k}}{(1+B_k n^{\alpha_k})^{\beta_k}} \tag{11}$$

Note that the natural frequency is used in the preceding equation because the reduced frequency is not meaningful for nonstationary winds. Accordingly, the EPSD of wind fluctuation $u(t)$ is obtained as

$$S_{uu}(t,n) = \sum_{k=1}^{p} g_k^2(t) S_{Y_kY_k}(n) \tag{12}$$

and the mean square value is given by

$$E[|u(t)|^2] = \int_0^\infty \sum_{k=1}^{p} g_k^2(t) S_{Y_kY_k}(n) dn \tag{13}$$

In this model, the product of the power and exponential functions in Eq. (10) make the modulation function $g_k(t)$ increase firstly and then decrease after a particular time instant, which can create the amplitude nonstationarity. On the other hand, the spectral nonstationarity can be obtained by summing up a series of uniformly modulated items as shown in Eq. (9). Hence the proposed model is pretty general in modeling both of amplitude and frequency nonstationarities. Also, the nonstationary wind fluctuation can be regarded as the superposition of several uniformly modulated component processes, which are characterized by the arrival time, spectral content and amplitude intensity. These component processes can arrest the local time-frequency resolution, thus this model can be used to describe the complex and general nonstationarity embedded in the wind fluctuation. Each component process can be interpreted as a class of eddies with similar statistical characteristics. For instance, the thunderstorm downburst can be decomposed into different types of vortexes. This model has many applications, such as the nonstationary wind speed simulation and the nonstationary wind-induced structural dynamic analysis.

Nonlinear least square method can be used to estimate the parameters in the model. However, when the number of components *p* is large, it's not easy to optimize the least square function since the total number of parameters is relatively large and the objective function may not be convex. The iterative algorithm is employed in the study. The estimated parameters for both of downbursts RFD and derecho are summarized in Tables 1 and 2, respectively. It can be seen that the estimated parameters are in reasonable range although fitting is complicated. For example, '$\gamma-\alpha\beta$' varies around -3~-2 for most items.

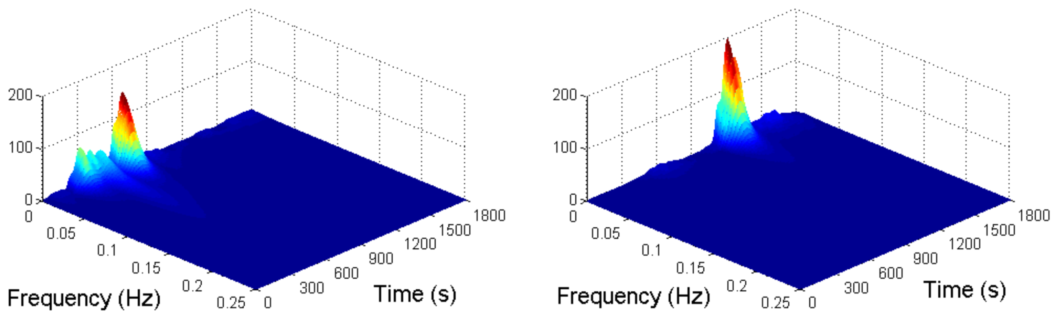
Figure 9 shows the fitted EPSDs for both downbursts. Comparison with Figure 4 shows that the proposed model fits the two sets of data very well. Figure 10 displays the spectra at the typical time instants for both downbursts, which further demonstrates the fitted results approach the estimated EPSD satisfactorily. EPSD of RFD peaks around time instant of 680s, while that of derecho has largest energy around time instant of 1200s. In this illustration, $p=9$ is used for both cases. It can be expected that the better fitting resolution can be achieved if the more items are included in the model.

Table 1 Estimated parameters for the fully nonstationary model (RFD)

p	η	κ	λ	ζ	γ	B	α	β
1	909.0824	11.982	31.353	-38.764	2.305	3.184	0.501	27.217
2	41.00603	7.042	28.843	291.274	0.399	29.613	1.125	3.854
3	0.000095	3.370	121.722	147.371	5.283	55.670	1.538	7.466
4	0.011492	6.288	30.370	-92.449	1.667	4.011	0.295	14.721
5	0.001032	7.340	33.236	417.071	0.836	12.804	0.277	15.942
6	491.8764	13.085	1170.74	48.844	31.487	0.003	1.035	32.357
7	67.49465	8.209	28.778	445.592	0.826	44.903	1.233	8.566
8	0.009593	2.764	382.729	686.969	0.992	10.432	0.582	6.603
9	0.003245	0.276	188.111	857.229	1.130	10.099	0.633	7.196

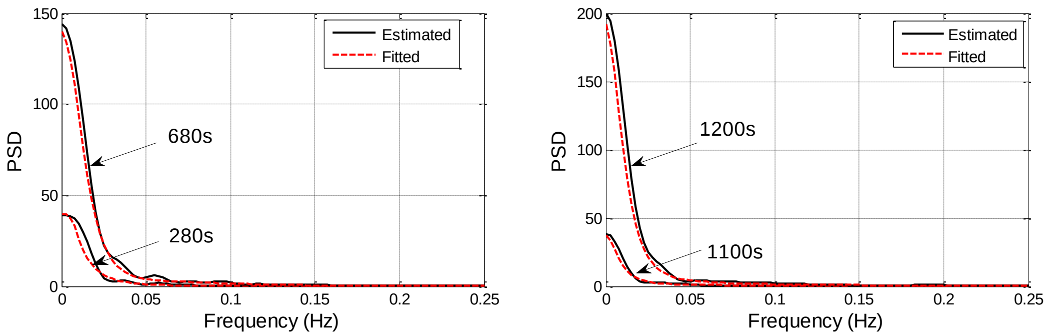
Table 2 Estimated parameters for the fully nonstationary model (derecho)

p	η	κ	λ	ζ	γ	B	α	β
1	0.00044	4.003	71.682	341.348	2.294	16.882	0.675	11.061
2	751.4678	8.182	29.104	980.385	-0.083	54.295	1.278	5.694
3	19.6117	9.449	43.027	1129.222	1.921	16.961	0.618	9.055
4	0.01494	9.208	24.331	1474.044	5.052	33.187	0.861	12.796
5	2155.5082	12.431	24.652	910.819	3.166	49.993	1.079	13.085
6	1419.2143	12.815	36.941	792.090	4.581	17.525	0.770	10.367
7	373.4885	12.823	7.063	1025.375	3.224	23.909	0.683	14.406
8	0.00136	2.990	441.487	-329.583	0.824	1.811	0.197	16.837
9	0.00044	4.003	71.682	341.348	2.294	16.882	0.675	11.061



(a) RFD (b) Derecho

Figure 9 Estimated EPSDs based on fully nonstationary model



(a) RFD (b) Derecho

Figure 10 Spectra at typical time instants

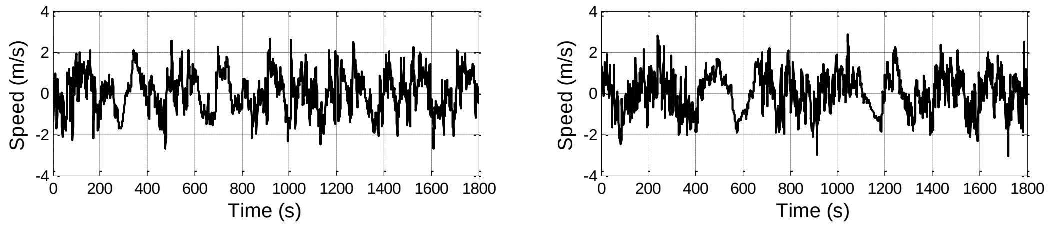
6.2. Simplified model

From the discussion in section 4, it is concluded that the frequency contents in normalized EPSDs of wind fluctuations of the downbursts evolve very slightly with the time. Therefore, it is reasonable to assume the normalized wind fluctuation is the uniformly modulated process. Similar modeling has been discussed by (Chen and Letchford 2005; Huang et al. 2013). However, no analytical model has been discussed previously, which will be presented below.

A simplified nonstationary wind spectrum model can be suggested as

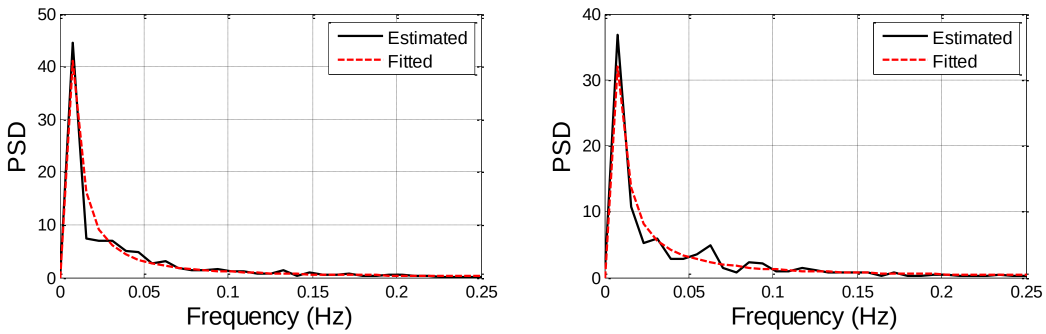
$$S(n,t) = \sigma^2(t)\tilde{S}(\mathrm{n})\ ;\quad \tilde{S}(n) = \frac{An^{\gamma}}{(1+Bn^{\alpha})^{\beta}} \tag{14}$$

In this model, the wind spectrum of the normalized wind fluctuation can be fitted. Note that the integration of $\tilde{S}(n)$ is unity. The normalized wind fluctuations for downbursts are shown in Figure 11. The estimated and fitted spectra of these normalized fluctuations are illustrated in Figure 12. It can be seen that the fitted spectra match the estimated ones well. Table 3 summarized the estimated parameters for the simplified models of the nonstationary wind fluctuations. It can be found that '$\gamma-\alpha\beta$' is in the range of -1.33~-1.67 for these normalized fluctuations, a little larger than '$-5/3$'. Also note that $\gamma \approx 0$ for all normalized wind fluctuations.



(a) RFD (b) Derecho

Figure 11 Normalized fluctuation (height 15m)



(a) RFD (b) Derecho

Figure 12 Comparison between PSDs for normalized downburst fluctuations

Table 3 Estimated parameters for the simplified model

	A	B	α	β	γ
RFD	992.077	529.346	0.9210	1.6289	8.487e-12
Derecho	1991.314	394.498	0.7629	1.7403	1.427e-13

7. Concluding Remarks

Based on the field measurements of downburst winds, the nonstationary wind characteristics and analytic models were studied. The major contributions were summarized as:

(1), The kernel regression method was proposed to infer the time-varying variance of the nonstationary extreme wind. This method had the good performance.

(2), Based on the estimated EPSD via Priestly's method, the spectral variations in the nonstationary downbursts were found weak. This indicated that the uniformly modulated process could be used to model these winds.

(3), The direct extension from the current stationary wind spectra was not suitable for nonstationary winds due to different physical mechanisms between boundary layer winds and nonstationary extreme winds.

(4), Two analytical models including the fully nonstationary and simplified ones were proposed. The fully nonstationary model was expressed as the summation of a train of uniformly modulated processes, while simplified one was the uniformly modulated process. Both models had more physical meaning than the direct extension visions and facilitated the wind speed simulation and structural dynamic analysis.

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