MODELING OF NON-STATIONARY WINDS IN GUST-FRONTS

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Abstract

The time-varying amplitude and frequency components embedded in random processes make the stationarity assumption inappropriate. Accordingly, non-stationarity of data during passage of hurricanes often precludes utilization of conventional analysis tools. In this study by invoking the Discrete Wavelet Transform (DWT) and empirical mode decomposition (EMD), non-stationary wind speed variations are modeled as a sum of a time-varying mean and a fluctuating component that can be described as a stationary random process. Wind speed data from Hurricane Lili, 2002 was utilized to obtain the turbulence intensity, gust factors, power spectral density and probability density function utilizing the non-stationary model and compared to traditional analysis. Discrepancies between the traditional approach and the new model were noted and discussed. The overall effectiveness of the proposed scheme based on DWT/EMD was demonstrated through detailed data analysis.

Introduction

The accurate estimation of turbulent wind characteristics during thunderstorms, hurricanes and tornados is difficult as these processes may not be stationary. Most traditional analysis tools are suited for stationary processes, which may not be always appropriate for the analysis of non-stationary data. Therefore, the performance evaluation of structures under transient conditions manifested by non-stationarity has been rather elusive. In order to fully understand the hurricane wind characteristics and their effects on structures, there is clearly a need for analysis tools to analyze non-stationary data.

There has been a number of approaches advanced to handle non-stationarity, e.g., parametric time series models with application to earthquake problems. However, with the recent developments in time-frequency analysis, e.g., the Wavelet transform and a combination of empirical mode decomposition and the Hilbert transform, new insights into the signal contents have offered new venues for analysis (Gurley and Kareem, 1999; Huang *et al*, 1998; Kareem and Kijewski, 2002). This study introduces a new approach based on a time-frequency perspective to analyze and model non-stationary events. An analysis framework that models non-stationary random process as a deterministic time-varying mean wind speed plus a stationary random process as fluctuating component is proposed. The time varying mean wind speed is extracted by two different approaches, i.e., discrete wavelet decomposition and empirical mode decomposition. The wind speed data recorded during Hurricane Lili, 2002 was analyzed to obtain the time-varying mean wind speed, turbulence intensity, spectral density function (psd), probability density function (pdf), gust factors and length scale. The results are then compared to those obtained through traditional approach based on the stationary wind model.

Non-stationary Wind Model

In the analysis of wind effects on structures, traditionally, the longitudinal wind speed is assumed to be a stationary random process, which can be expressed as

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

in which $\overline{U}$ is a constant mean wind speed, $u(t)$ is a longitudinal fluctuating wind speed component. The constant mean wind speed denotes an average over a time interval T, which is usually taken as one hour. In this study, the non-stationary wind speed is modeled as the sum of a deterministic time-varying wind speed and a zero-mean stationary random process as fluctuating component:

$$U(t) = \overline{U}(t) + u'(t) \tag{2}$$

where $\overline{U}(t)$ is the temporal trend of wind speed and $u'(t)$ is the fluctuating component which can be taken as a zero-mean stationary process. After a time-varying mean wind speed $\overline{U}(t)$ has been identified, the fluctuating wind speed $u'(t)$ can be acquired by subtracting the time-varying mean wind speed $\overline{U}(t)$ from the measured wind speed time history, $u'(t) = U(t) - \overline{U}(t)$. As the fluctuating wind speed $u'(t)$ is assumed to be a zero-mean stationary process, the standard deviation and the probability density distribution and the wind spectrum of the fluctuating component can be obtained by replacing $u(t)$ by $u'(t)$ in the traditional definition of these quantities.

For non-stationary wind speed time history with time-dependent mean, the turbulence intensity of non-stationary wind speed is proposed to be given by the expected value of the time-dependent turbulence intensity over the time interval T.

$$I_{u',T} = E[\frac{\sigma_{u',T}}{\overline{U}_T(t)}] \tag{3}$$

in which $E[\ ]$ denotes the expected value over the time interval T; $\sigma_{u',T}$ represents the standard deviation of the fluctuating wind speed over the time interval T. Accordingly, the gust factor is defined as the maximum ratio of time-varying mean wind speed over time t_1 to the corresponding hourly time-varying mean wind speed:

$$G(t_1) = max[\frac{\overline{U}_{t_1}(t)}{\overline{U}_{3600}(t)}] \tag{4}$$

in which t_1 is normally equal or less than 3600s. The integral length scale in the direction of the flow is defined as

$$L_{u'} = \overline{U}(t) \int_0^\infty \frac{R_{u'}(\tau)}{\sigma_{u'}^2} d\tau = \frac{\overline{U}(t)}{4\sigma_{u'}^2} S_{u'}(0) \tag{5}$$

where $R_{u'}(\tau)$ denotes the autocorrelation function of $u'(t)$, and $S_{u'}$ represents its Fourier transform. Utilizing the calculated length scale of longitudinal wind speed fluctuations, the commonly used von Karman spectrum is recast as:

$$\frac{nS_{u'}(n)}{\sigma_{u'}^2} = \frac{4nL_{u'}/\overline{U}(t)}{[1 + 70.8(nL_{u'}/\overline{U}(t))^2]^{5/6}} \tag{6}$$

The following section deals with data analysis involving wavelets and EMD to capture the time varying mean wind.

Wavelet Analysis

As a convenient tool to obtain time-frequency information of a process, the Wavelet transform has found a number of applications in engineering in recent years. Through a set of basis functions, the dilation and translation of the parent wavelet function, the Wavelet transform provides a bank of wavelet coefficients representing a measure of similitude between the basis function and the signal at time t and scale a (Kareem and Kijewski, 2002). The wavelet analysis decomposes a signal into components akin to the output of a dyadic filter bank. At each level, the low-frequency output of the previous level is decomposed into adjacent high- and low-frequency sub bands by a pair of high-pass (HP) and low-pass (LP) filters. Each of the two output sub-bands is half the bandwidth of the input to that level. The band-limited output of each filter is decimated by a factor of 2 to preserve the bit rate of the original signal. This process leads to a multi-resolution decomposition of the signal.

Empirical Mode Decomposition

The empirical mode decomposition (EMD) introduced by Huang *et al*. (1998) also facilitates the analysis of non-stationary signals. The upper and lower envelopes of the signal are fitted using a spline function and the mean of the two envelopes is subtracted from the signal. This is referred to a sifting process which is repeated until the signal becomes mono-component, i.e., when the number of zero crossings (or down-crossing) are equal to the number of peaks (or troughs). This mono-component signal is referred to as intrinsic mode function (IMF). Using EMD, without any pre-determined function, a signal can be decomposed into a series of IMFs and a residue. The IMFs believed to be band limited allow the Hilbert transform operation which yields instantaneous frequency information. The decomposition procedure is adaptive and applicable to any nonlinear and non-stationary process (Huang *et al*. 1998). The time-varying mean wind speed with an arbitrary highest frequency component can be derived by setting intermittency criterion.

Data analysis

Discrete Wavelet Decomposition

The set of hurricane data analyzed in this section was measured during Hurricane Lili, 2002. As shown in Fig. 1, nineteen consecutive hours of data was sampled at 1/3 Hz. Fig. 2(a) demonstrates the 5 levels of signal sub-components and residue of the signal decomposed by DWT at 10 levels. From the figure, it is obvious that as the level number increases, the frequency component decreases and the residue matches the trend of the corresponding time-averaged mean quite well. Figs. 2(b) demonstrates the comparison of constant hourly mean and the time varying hourly mean of the 11^{st} hour of the signal, in which the time-varying means were obtained by DWT. Obviously, the approximation reflects the trend of the signal, while the hourly mean is just a constant during the hour. Correspondingly, the fluctuating process is the original signal minus hourly mean, or the approximation in the case of DWT. Probability density functions of the corresponding fluctuating process derived from the constant mean, and 600s-mean of the 15^{th} hour data are shown in Figs. 2(c) together with the fitted Gaussian function to the data. It can be noted that the pdf derived from the constant mean deviates from the Gaussian, while that from the time-varying mean exhibits a better match with the Gaussian. It has been noted that often hurricane winds have been perceived as non-Gaussian by examining the pdf without any prior conditioning of the data. Nonetheless, this observation may still be valid in a strong convective region of a hurricane.

For the calculation of the integral length scale (Eq. 5), the low frequency component of $S_{u'}(n)$ is sensitive to the different time-averaged means, which influences the calculated value of the length scale. As the low frequency component increases in the time varying mean, the value of $S_{u'}(0)$ decreases, resulting in smaller integral scale. Using hourly mean, 1200s-mean, 600s-mean, 300s-mean, and 150s-mean, corresponding calculated length scales are 94m, 90m, 85m, 79m and 70m, respectively. Figs. 2(d) shows the power spectral density functions of the two fluctuating processes of the 18^{th} hour data using hourly mean given by DWT, together with a fitted von Karman spectrum. It is observed that the fluctuating component derived from the time-varying mean has lower energy at low frequencies than the corresponding process with a constant mean. This can be explained as the very low frequency components have already been filtered out of the fluctuating component. At high frequencies, there is no discernible difference. The von Karman spectrum was fitted using the respective value of the length scale. Using proposed Eqs. (3) and (4), wind characteristics such as turbulence intensity and gust factor are reported in Figs. 2(e) and 2(f), along with the traditional approach. It is observed in Fig. 2(f) that by using 1200s time-varying mean, the turbulence intensity is very similar to that given by the constant mean, with slightly reduced values. Gust factors obtained by the time-varying mean have a similar trend in comparison with the traditional method.

Empirical Mode Decomposition

The empirical mode decomposition was utilized to obtain the time-varying mean of the wind speed data. Fig. 3(a) shows some of the IMFs of the signal in which the bottom plot shows the residue, which gives the trend of the original signal. In this study, the residue was taken as the corresponding time-varying mean. Results are shown with the residue as time varying mean in Fig. 3(b). It can be noted that the time-dependent mean matches the trend of the signal. The pdf is shown in Fig. 3(c), and the power spectral density function is presented in Fig. 3(d) using 600s-mean, together with the corresponding von Karman spectrum. Using hourly mean, 600s-mean, and 150s-mean, corresponding turbulence length scales were found to be 96m, 90m, and 85m, respectively. Using Eq. 3 and Eq. 4, the turbulence intensity and gust factor were obtained. The results are compared to the traditional method in Figs. 3(e) and 3(f). It is observed that the gust factors and the turbulence intensity are similar to those by the traditional method with some exception.

Discussion and Conclusion

A new approach for analyzing non-stationary wind speed time histories has been presented here. The idea of decomposing wind speed into the sum of a deterministic time-varying mean wind speed plus a stationary fluctuating wind speed was realized by DWT, and EMD, which helps to eliminate the limitations of the stationarity assumption implied in the traditional approach. Field measurements of wind data recorded during Hurricane Lili, 2002 has been used to verify the proposed approach. The power spectral density of the fluctuating components obtained by DWT or EMD had lower amplitude in the low frequency range when compared to the traditional approach, while in the higher frequency range they were found to be very similar. This is due to the presence of low frequency trend in the wind fluctuations obtained traditionally, which is filtered out in the process of removing the time varying mean. Turbulence intensities obtained by the DWT and EMD are very close to those by the traditional approach with slightly reduced values. Intuitively, the results reflect reality as the constant mean process should yield higher intensity, albeit unrealistic. The gust factors obtained by the DWT and EMD are similar to those obtained by the traditional approach. It can be concluded that the concept of time-varying mean wind speed can be applied in the analysis of wind speed data through the application of DWT or EMD. From the above observations, one can draw the conclusion that while processing hurricane data, time-varying mean is a more appropriate quantity for separating the original signal into two categories than the constant hourly mean. It represents the trend of the wind speed, and the remaining fluctuating component complys with the Gaussian assumption. The proposed approach has the merit of becoming a method of choice for engineering applications in the near future.

Acknowledgments

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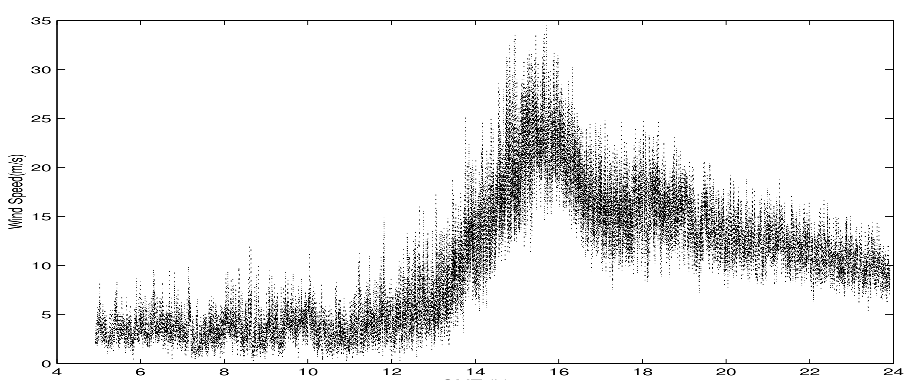

Fig. 1 Wind Speed Time History

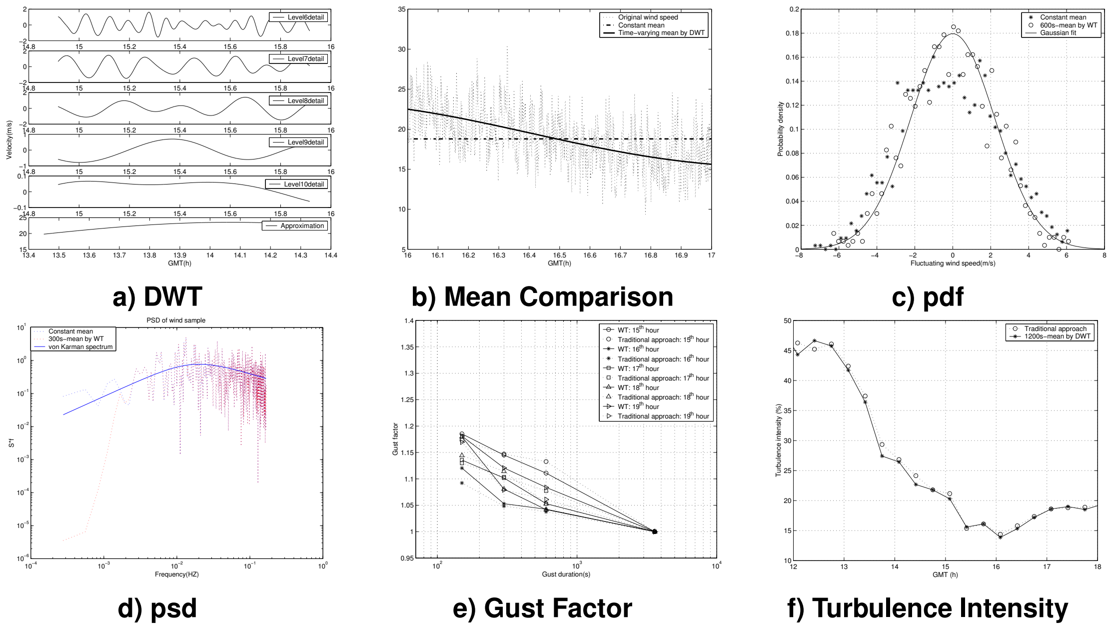

Fig. 2. Analysis based on Discrete Wavelet Decomposition

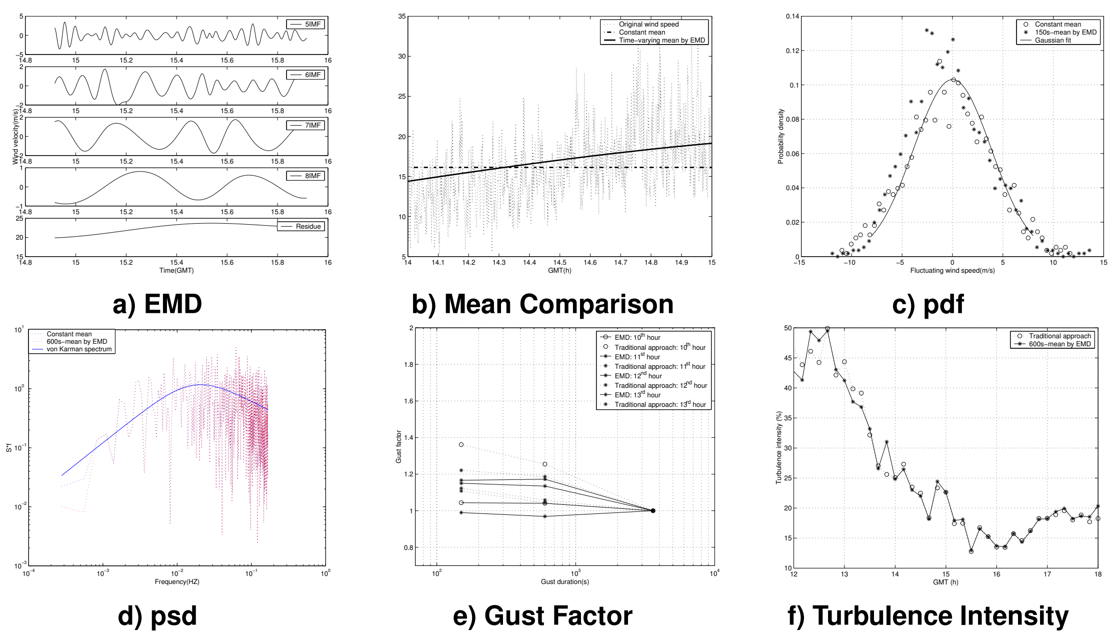

Fig. 3. Analysis based on Empirical Mode Decomposition