Research Article

Peak Factor Deviation Ratio Method for Division of Gaussian and Non-Gaussian Wind Pressures on High-Rise Buildings

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The reasonable division of Gaussian and non-Gaussian wind pressures of building structure is beneficial to study the mechanism of wind load and adopt a reasonable peak factor estimation method. In this study, a pressure measurement wind tunnel test of a square high-rise building was conducted to study the division method for Gaussian and non-Gaussian wind pressures. Firstly, the skewness and kurtosis of wind pressures were analyzed, and then a normalized kurtosis-skewness linear distance difference ($\delta$) was proposed. Moreover, the Gaussian and non-Gaussian criticality of wind pressure was discussed in combination with the wind pressure guarantee rate, and a peak factor deviation ratio (that is the deviation ratio between the complete probability peak factor with 99.95% guarantee rate and the Davenport peak factor) was proposed as the basis for Gaussian and non-Gaussian division. Subsequently, the functional relationships between the deviation ratio and the skewness and kurtosis as well as the $\delta$ were proposed, and then two classification criteria for Gaussian, weak non-Gaussian, and strong non-Gaussian regions were provided. Finally, the building surface wind pressures were divided into regions according to the classification criteria. The results show that the two Gaussian and non-Gaussian region division methods are reliable.

1. Introduction

The structures immersed in the atmospheric boundary layer are inevitably attacked by the wind, which would cause the main structure to vibrate strongly and the envelope structures to suffer damage for strong extreme wind pressures. With the development of wind engineering research for decades, a relatively complete theory system for the wind resistance of high-rise buildings has formed [1]. At present, the detailed researches on the nonstationary, non-Gaussian, unsteady, and nonlinear (aeroelastic effect) of structural wind load and wind vibration effect have attracted extensive attention [2–11]. The latest wind tunnel test on the cable-supported glass facades provided the expected impact research for the surface wind action of the flexible system represented by the facade of high-rise buildings [12]. At present, the determination method of extreme wind pressure on the structural cladding in most codes and standards [13–15] is based on the Gaussian assumption. However, numerous studies show that the structural surface wind pressures do not all obey Gaussian distribution, especially in separation flow, wake, and high turbulent wind field. The wind pressure at these locations shows strong non-Gaussian characteristics; that is, it shows the significant asymmetric distribution in the time domain with intermittent large amplitude pulses [16–20]. Jeong [21] showed that the wind pressure pulse is related to the organized and highly correlated large-scale vortex caused by the influence of the structure shape. At this point, if the Gaussian hypothesis is directly adopted in the design, the structure will have a great potential safety hazard. At present, the researches on non-Gaussian wind pressure on structural surface mainly involve the distribution characteristics and mechanism of non-Gaussian wind pressure on various structures, the
classification criteria for non-Gaussian and Gaussian wind pressures, the simulation method of non-Gaussian wind pressure, and the peak factor estimation methods for non-Gaussian wind pressure. In this study, the classification criteria for non-Gaussian and Gaussian wind pressures will be focused on.

The traditional peak factor (Davenport [22]), which has been widely adopted by most codes and standards, is often underestimated in non-Gaussian wind pressure extreme estimation. To overcome this shortcoming, over the past several decades, several methods have been proposed for determining the peak factors of fluctuating non-Gaussian wind pressures, which can be summarized into four types: the Hermit polynomial model (HPM), Johnson transformation model (JTM) and shifted Generalized Lognormal distribution (SGLD) model based on the transformation from Gaussian space to non-Gaussian space [23–29], the cumulative probability function (CPF) mapping (also called translated-peak-process, TPP) methods based on Gaussian space to non-Gaussian space [30, 31], the estimation methods based on extreme value theory represented by the extreme value type I distribution (Gumbel method), generalized extreme value distribution (GEV method) and generalized Pareto distribution (POT method) [32–34], and the complete probability method with different guarantee rate [16, 35–37]. The wind pressures at different locations on the structure show different degrees of non-Gaussian characteristics at different wind angles, which is closely related to its flow mechanism. Moreover, different peak factor estimation methods have different adaptability to Gaussian and non-Gaussian wind pressures [31, 34]. Therefore, the study of the reasonable division standard for Gaussian and non-Gaussian wind pressure regions is beneficial for understanding the mechanism of non-Gaussian wind pressure and adopting an appropriate peak factor estimation method in different regions. In current studies, there are a few criteria for the classification of non-Gaussian wind pressure and Gaussian wind pressure. Peterka et al. [38] first distinguished Gaussian distribution from non-Gaussian distribution by the positive and negative of average wind pressure, but the results are not always convincing. Kumar and Stathopoulos [17] presented that the skewness coefficient absolute value greater than 0.5 and the kurtosis coefficient greater than 3.5 can be used as the dividing boundary between Gaussian and non-Gaussian regions. Zou et al. [39] applied the aforementioned standard to the wind pressure division of a trough concentrator and obtained detailed results. Lou et al. [40] made reference to the conclusion of Kumar and Stathopoulos [17] and set the classification criteria for Gaussian and non-Gaussian wind pressures based on the experimental results: when the absolute value of skewness coefficient was greater than 0.2 and the kurtosis coefficient was greater than 3.5, and it was divided into non-Gaussian region. Han and Gu [41] proposed a qualitative classification criterion for Gaussian and non-Gaussian wind pressures of high-rise buildings based on the approximate linear correlation between the skewness coefficient and a normalized kurtosis as well as the probability density curves of the wind pressures.

At present, most of the researches on the division criteria of Gaussian and non-Gaussian wind pressures are only based on the qualitative results of skewness, kurtosis, and their correlation. There is no quantitative analysis method, which can not only reflect the reliability of the division of Gaussian and non-Gaussian wind pressures but also discriminate the degree of non-Gaussian characteristic. Therefore, in this study, a typical square-section super high-rise building was taken as an example to conduct a wind tunnel test of rigid model for pressure measurement to study a quantitative division method and criteria. First, a concept of normalized kurtosis-skewness linear distance difference was proposed and its calculation method was given. Subsequently, a peak factor deviation ratio was proposed to divide the Gaussian and non-Gaussian wind pressures (i.e., Gaussian and non-Gaussian wind pressure regions were divided based on the deviation ratio of the complete probability peak factor with 99.95% guarantee rate and Davenport peak factor). Moreover, the relationship function between the peak factor deviation ratio and the higher-order statistics (absolute value of the skewness coefficient and the kurtosis coefficient) and the normalized kurtosis-skewness linear difference was obtained by statistical analysis. Finally, a concept of strong non-Gaussian region was proposed, and the specific values of the skewness and kurtosis coefficients as well as the normalized kurtosis-skewness linear difference corresponding to different reliability were determined by using the aforementioned relationship function. Moreover, the distribution characteristics of the non-Gaussian and Gaussian regions based on the two kinds of indexes were compared.

2. Basic Principles

2.1. Properties of Higher Order Statistics. The Gaussian signal is shown in Figure 1(a), which is symmetrically distributed about the mean in the time domain and its amplitude distribution characteristics can be described by the first two order statistics (mean and standard deviation). However, for the wind pressure with non-Gaussian characteristics, as shown in Figure 1(b), it shows a very significant negative pressure pulse, which needs to be described by higher-order statistics (skewness and kurtosis). To compare with the standard Gaussian distribution, the original signal should be standardized as follows:

$$x(t) = \frac{X(t) - \mu_X}{\sigma_X},$$

(1)

where $x(t)$ represents the normalized signal of wind pressure, $X(t)$ represents the original signal of wind pressure, $\sigma_X$ is the standard deviation of $X(t)$, and $\mu_X$ is the average of $X(t)$.

The skewness is a digital feature of the degree of asymmetry in the distribution of statistical data, and the kurtosis is a statistic used to describe the steepness and slowness of the data distribution. To eliminate the influence of different variable value levels and the units of measurement, the ratios of the 3rd and 4th order central moments to
the variance of aforementioned normalized signal are defined as the skewness and kurtosis coefficients, which are hereinafter abbreviated as skewness and kurtosis, respectively. The specific calculation is as follows:

\[ \gamma_3 = \frac{k_3}{k_2^{3/2}}, \]
\[ \gamma_4 = \frac{k_4}{k_2^2}, \]

where \( \gamma_3 \) and \( \gamma_4 \) represent the skewness and kurtosis coefficients of the normalized wind pressure signal, respectively; \( k_2, k_3, \) and \( k_4 \) respectively represent the 2nd, 3rd, and 4th order central moments, which are determined as follows:

\[ k_2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu_x)^2, \]
\[ k_3 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu_x)^3, \]
\[ k_4 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu_x)^4, \]

where \( n \) represents the number of samples of the normalized wind pressure signal \( x(t) \), \( x_i \) represents the \( i \)th component of \( x(t) \), and \( \mu_x \) is the average of \( x(t) \).

Probability density function is usually used to reflect the probability distribution characteristics of a random signal. Figures 2(a), 2(b) show the probability density functions of some typical Gaussian and non-Gaussian processes. In the figures, the skewness of the normalized Gaussian distribution is 0, and its kurtosis is 3.0. In this case, the tail length of the probability density curve on both sides is symmetric and the steepness is moderate. While the skewness is less than 0, the distribution shows a positive deviation; that is, the mass of the distribution is concentrated on the right and the left tail of the curve is very long. Conversely, while the skewness is greater than 0, the distribution shows a negative deviation.

So, it can be seen that the skewness can test the normality of the distribution. Moreover, when the kurtosis is greater than 3.0, the distribution shows a sharp peak compared with the normal distribution. When the kurtosis is less than 3.0, the distribution shows a flat peak compared with the normal distribution.

2.2. Davenport Peak Factor Estimation. The peak factor estimation of Davenport [22] for Gaussian process was derived from the probability density function (PDF) and the cumulative distribution function (CDF) of extreme value [42] as well as the extreme crossing theory [43].

For a standard Gaussian process \( Y(t) \), assuming its extreme value \( Y_p \) obeys the extreme value type I distribution, the CDF in time period \( T \) is shown as follows:

\[ F_{Y_p}(y_p) = \exp\left[-\nu(y_p)T\right] \]
\[ = \exp\left[-\nu_0 T \exp\left(-\frac{y_p^2}{2}\right)\right], \]

where \( y_p \) is the specific value of \( Y_p \) at a certain time in the period \( T \). \( \nu(y_p) \) is the mean upcrossing rate at level, which can be estimated according to the Poisson assumption, and \( \nu_0 \) is the zero-mean crossing rate, which can be solved by the following equation:

\[ \nu_0 = \sqrt{\frac{m_2}{m_0}} = \sqrt{\frac{\int_0^\infty n^2 S_Y(n)dn}{\int_0^\infty S_Y(n)dn}}, \]

where \( m_i \) is the \( i \)th spectral moment, \( m_2 = \int_0^\infty n^2 S_Y(n)dn \), \( S_Y(n) \) is the unilateral power spectrum (PSD) of the standard Gaussian process, and \( n \) is the frequency in Hz. If \( \xi = \nu_0 T \exp(-y_p^2/(2)) \) is introduced, then \( y_p = \sqrt{2 \ln(\nu_0 T) - 2 \ln \xi} \). Through Taylor’s principle, it can be obtained as follows:
The expected and standard deviation of the extreme value can be deduced as follows:

\[
\mu_{y_p} = \int_0^\infty y_p dF_{Y_p}(y_p) = \int_0^\infty y_p \exp(-\xi)d\xi, \tag{7}
\]

\[
\sigma_{y_p} = \sqrt{\int_0^\infty (y_p - \mu_{y_p})^2 \exp(-\xi)d\xi}. \tag{8}
\]

Ignoring the lower order terms of \( \beta^{-3} \) and the power of \( \beta \) less than \(-3\) in equation (6), and substituting equation (6) into equations (7) and (8), the Davenport peak factor and its standard deviation of the standard Gaussian process can be obtained as follows:

\[
g_{sg,\beta} = \mu_{y_p} = \beta + \frac{\gamma}{\beta^3} \tag{9}
\]

\[
\sigma_{sg,\beta} = \sigma_{y_p} = \frac{\pi}{\sqrt{6}\beta} \tag{10}
\]

where \( \gamma \) is the Euler’s constant (\( \gamma \approx 0.5772 \)).

2.3. Complete Probability Peak Factor Estimation. The complete probability peak factor estimation method (CP method) was proposed by Davenport [35], and it has strong adaptability to not only the Gaussian process but also the non-Gaussian process. Moreover, it can be related to reliability through different guarantee rate.

The complete probability expression is shown as follows [35]:

\[
P\left[ |X(t) - \mu_X| \leq |X_p - \mu_X| \right] = P_{Obj}, \tag{11}
\]

where \( X(t) \) represents the non-Gaussian processes, \( \mu_X \) is the mean value of wind pressure, \( \sigma_X \) is the standard deviation of wind pressure, \( X_p \) is the extremum of wind pressure, and \( P_{Obj} \) is the target guarantee rate.

The overview of the complete probability method is shown in Figure 3. In the Figure, \( r \) is a coefficient to construct the initial threshold \( r\sigma_X \), which is advised to be set from 1 to 5. \( \delta \) is the increment, which can be set to \( 10^{-3} \) of the RMS of wind pressure. \( \epsilon \) is a set accuracy index, which can be set to \( 10^{-4} \) to satisfy the accuracy.

It can be seen from equation (10) and Figure 3 that the corresponding peak factor can be obtained when the target guarantee rate is given.

3. Overview of Wind Tunnel Tests

3.1. Test Overview. The pressure test was carried out in the wind tunnel of the National Engineering Laboratory of High-speed Railway Construction Technology at Central South University, China (Figure 4(a)). The high-speed test section is \( 3 \text{ m} \times 3 \text{ m} \times 15 \text{ m} \) (width \( \times \) height \( \times \) length) with wind speed ranging from 0 to 94 m/s and turbulent intensity is less than 0.5%. The test object is a square cross-section super high-rise building. Its rigid body pressure measurement model is shown in Figure 4(a), the total height is 1.4 m, the wind tunnel blocking rate caused by the model is about 2.5%, and the blocking effect caused by the model is very small and can be ignored. In this experiment, according to the Chinese Load Code GB50009-2012 [13], the passive simulation method is adopted to simulate the flow field of class C atmospheric boundary layer in a wind tunnel. The geometric scale ratio of the model is \( \lambda_L = 1/350 \). The height of the reference point was 1.3 m, about 0.5 m away from the side wall of the wind tunnel. The experimental wind speed of the reference point was 14 m/s. The wind profile characteristics of the wind field and the wind speed spectrum of the reference point are shown in Figures 4(b)–4(d).
Figure 3: Overview of the complete probability method.

Figure 4: Wind tunnel test model, wind field simulation, and tap arrangement. (a) Rigid model in wind tunnel. (b) Mean wind speed profile. (c) Turbulent intensity profile. (d) Along-wind velocity spectra. (e) Hierarchical layout of measurement taps. (f) Measurement taps layout (unit: mm).
“theoretical results” in Figures 4(b) and 4(c) are based on the definition of wind profile and turbulent intensity of the class C wind field in the national standard of China GB50009-2012. Where $Z_c$ and $U_c$ are the height and the wind speed at the reference point, respectively. $Z$, $U_z$, $u^*$, and $J_u$ mean the measurement height, the along-wind mean wind speed at $Z$ height, the shear wind speed at the ground surface, and the along-wind turbulence intensity, respectively. Assuming that the actual wind speed corresponding to the reference point is $54 \, \text{m/s}$, then the wind speed ratio is $\lambda_u = 0.26$. The time ratio is $\lambda_t = \lambda_u / \lambda_v = 0.011$ based on dimensional analysis. The characteristic size of the model section and the arrangement of surface pressure taps are shown in Figures 4(e) and 4(f). There are a total of 120 taps in this test, which are divided into 6 layers with 20 taps in each layer. In this study, $L_i$ is used to represent each tap, where $L$ represents the number of layer, $i$ represents the $i$th tap of this layer; for example, tap 3_13 represents the 13th tap of the third layer. In this test, the PSI scanning valve was used to measure the pressure. The sampling frequency was 330 Hz, the sampling number of each channel was 372,000, and the sampling time was about 20 min (corresponding to the actual sample length was 196 min). In other words, 170 standard samples were collected for all 120 taps of the model in the same working condition (one standard sample corresponds to the actual sample length of 10 min).

3.2. The Data Processing. In this study, the time history of wind pressure coefficient of a tap can be represented as a random process $X(t)$, then the time history of the wind pressure coefficient of the $i$th tap on the $j$th layer of the model surface can be written as follows:

$$X_{i,j}(t) = \frac{P_{i,j}(t) - P_{\infty}}{0.5\rho U_{\infty}^2},$$

where $P_{i,j}(t)$ is the wind pressure time history of the $i$th tap on the $j$th layer of the model surface, $P_{\infty}$ is static pressure of incoming flow, $\rho$ is the air density, and $U_{\infty}$ is the wind speed of incoming flow at the reference point.

As discussed in Section 2.1, the non-Gaussian characteristics of wind pressure have a significant correlation with the skewness and the kurtosis; therefore, Figure 5 shows the cloud diagrams of the skewness and kurtosis of the normalized wind pressure coefficients on the model by taking $0^\circ$ wind attack angle as an example.

Figures 5(a) and 5(b) show that the skewness of the windward face B are approximately 0 and the kurtoses are approximately 3.0, which shows significant Gaussian distribution characteristics. However, the skewness and kurtoses of the wind pressures on the side faces A and B as well as the leeward face D show significant negative deviation and sharp peak characteristics like as non-Gaussian process. The aforementioned results are consistent with the previous researches [18, 31, 33], which indicates that the experimental data are reliable.

Taking tap 3_3 as an example, Figures 6(a), 6(b) show the time history and the probability density function of its normalized wind pressure coefficient at $0^\circ$ wind attack angle, respectively. It can be seen that the time history presents significant intermittent pulses and the probability distribution shows a negative deviation, which reflects the typical non-Gaussian characteristics of the wind pressure at tap 3_3.

4. Division Methods for Gaussian and Non-Gaussian Wind Pressures

4.1. Non-Gaussian Reflection Based on High Order Statistics of Wind Pressure. In present studies, the boundary between Gaussian and non-Gaussian wind pressures is usually qualitatively divided by skewness and kurtosis [17, 18, 39]. Figures 7(a) and 7(b) show the correlations between the skewness as well as its absolute value and the kurtosis under all wind attack angles in the test, respectively. It can be seen from Figure 7 that there is a nonlinear monotonic relationship between the kurtosis and the absolute value of skewness, indicating that the skewness absolute value and the kurtosis are consistent to a certain extent in the description of an index of wind pressures. In view of this, Han and Gu [41] put forward a normalized kurtosis index, which can be determined as follows:

$$NK = \frac{(y_4 - |y_3|)}{y_4},$$

(12)

By comprehensively analyzing the correlation between the skewness and the kurtosis, the correlation between normalized kurtosis index and the skewness, as well as the probability density function of wind pressures, Han and Gu [41] finally qualitatively proposed a non-Gaussian characteristic discrimination standard for high-rise buildings: $|y_3| > 0.25$ and $|y_4| > 3.2$, or $|y_3| > 0.45$, or $|y_4| > 4.0$.

However, further analysis is required to obtain reasonable zoning criteria for the Gaussian and non-Gaussian wind pressures quantitatively. Figure 8 shows the relationships between the normalized kurtosis $NK$ and the absolute value of skewness $(|y_3|)$ of each building face at $0^\circ$ wind attack angle. It can be seen from Figure 8 that the absolute value of skewness $|y_3|$ of the wind pressure coefficients on the windward face B is significantly concentrated at 0 and the NK has an extremely significant linear correlation with $|y_3|$; however, this feature does not appear in the sides faces of A and C as well as the leeward face of D. Combined with the common knowledge that the wind pressures on the windward face basically conform to Gaussian distribution [18, 33], it can be assumed that NK and $|y_3|$ of Gaussian wind pressure process meet a linear relationship. Therefrom, the corresponding expression can be obtained by line fitting of the data of the windward face B in Figure 8(b):

$$NK = -0.322|y_3|+0.999.$$  

(13)

Equation (13) is very close to the linear expression obtained by Han and Gu [41] based on their experimental data, indicating its good applicability.

However, equation (13) can only judge the Gaussian wind pressure region qualitatively (such as face B) but
cannot quantify the classification basis of Gaussian and non-Gaussian wind pressure regions according to a certain reliability (such as faces of A, C, and D). Therefore, the fitting line (equation (13)) in Figure (8(b)) is further drawn on other surfaces (Figures 8(a), 8(c), and 8(d)), and it can be found that each point deviates from the line to varying degrees. In order to analyze the relationship between deviation degree and non-Gaussian degree, a normalized kurtosis-skewness linear distance difference \( \delta \) is defined as follows:

\[
\delta = \frac{-0.322 |y_3| - NK + 0.999}{\sqrt{(-0.322)^2 + (-1)^2}}
\]  

Figure 5: Cloud diagrams of skewness and kurtosis of wind pressure coefficient on each surface of building model at 0° Wind attack angle. (a) Skewness. (b) Kurtosis.

Figure 6: Time history and probability density function of normalized wind pressure coefficient of tap 3_3 at 0° wind attack angle. (a) Time history. (b) Probability density function.
Figure 7: Relationships of higher-order statistics under all wind attack angles in test. (a) $\gamma_4$ and $\gamma_3$. (b) $\gamma_4$ and $|\gamma_3|$.

Figure 8: Relationships between $NK$ and $|\gamma_3|$ of each building face at $0^\circ$ wind attack angle. (a) Face_A. (b) Face_B. (c) Face_C. (d) Face_D.
The representation of \( \delta \) is shown in Figure 8(a). In addition, Figure 9 shows the relationships between \( \delta \) and high-order statistics of each tap at 0° wind attack angle. It can be found that \( \delta \) keeps increasing with the increase of \( |\gamma_3| \) and \( \gamma_4 \). In addition, when \( |\gamma_3| < 0.28 \) and \( \gamma_4 < 3.5 \), \( \delta \) is significantly smaller and close to 0, indicating that \( \delta \) can represent the combination form of \( |\gamma_3| \) and \( \gamma_4 \) to reflect the non-Gaussian or Gaussian attribute of wind pressure.

4.2. Probability Theory Basis for the Methods of Peak Factor Estimation. The limit state design method based on probability theory is an advanced method for extreme value estimation, which has been adopted into the Chinese standard GB50153-2008 [44] for reliability design. This design method regards the design parameters as random variables and measures the reliability of structural components with structural failure probability or reliability index determined by statistical analysis. Similarly, the degree of deviation of the actual wind pressure distribution from the Gaussian distribution can be used to identify Gaussian and non-Gaussian regions. It can be seen from the aforementioned analysis that the non-Gaussian characteristics of wind pressure can be reflected either from the higher-order statistics \( (|\gamma_3| \) and \( \gamma_4) \) or from the normalized kurtosis-skewness linear distance difference \( \delta \). However, the critical values of skewness and kurtosis in Gaussian and non-Gaussian region division in previous studies are mostly obtained by the qualitative analysis [17, 38, 39]. Therefore, the Gaussian and non-Gaussian criticality of wind pressure will be discussed in this section to make theoretical preparations for the quantification of wind pressure partitioning in the following.

It is a good idea to discuss the division of Gaussian and non-Gaussian regions from the probability and statistics theory of wind pressure extreme value. For a normalized wind pressure time history \( x_i(t) \) of the \( i \)th tap on the model in the wind tunnel test, the probability that the extreme value of \( x_i(t) \) falls within the range of \( g \sigma_x \) can be obtained by integrating the probability density function of \( x_i(t) \), that is,

\[
P^g_i = \int_{-g}^{g} f(x_i)dx_i,
\]

where \( i \) represents the number of measuring tap, \( f(x_i) \) represents the probability density function of the normalized wind pressure time history \( x_i(t) \), and \( P^g_i \) represents the probability that the extremum of \( x_i(t) \) falls at \((-g, g)\) when the peak factor is \( g \).

Figure 3 is actually an automated implementation process of equation (15). By the way, the peak factor adopted in the Chinese Load Code GB50009-2012 [13] is 2.5, and the Davenport peak factor is routinely taken as 3.5 in engineering practice [24].

To discuss the relationship between the value of peak factor and the transcendence probability, a normalized non-Gaussian signal, such as the normalized wind pressure process of tap 3_3 at 0° wind attack angle, and the standard Gaussian signal are selected for comparative study. Figure 10 shows the probabilistic characteristics of these two kinds of signals. In the figure, G is the abbreviation of the standard Gaussian signal, and NG corresponds to the normalized non-Gaussian signal of tap 3_3. When \( g = 3.5 \), the probability of the calculated extreme value of the standard Gaussian process falling in the shadow of Figure 10(a) is 99.95%, while that of the normalized non-Gaussian wind pressure of tap 3_3 falling in the shadow of Figure 10(b) is only 99.44%. Therefore, when the wind pressure is non-Gaussian, it is necessary to take the peak factor greater than 3.5 to meet the probability of 99.95%. It should be pointed out that when the exceedance probability of the wind pressure extremum is less than or equal to 0.05%, it can be considered as an unlikely small probability event.
Figure 10(c) shows the incidences of the extreme value of normalized non-Gaussian process $x_{3_3}(t)$ (wind pressure on tap 3_3) and standard Gaussian process ($x_G(t)$) in different integration range $[-g, g]$. In the figure, the peak factors of 5.0, 3.5, and 2.5 are labeled as $g_{ng,C}$, $g_{ng,D}$, and $g_{ng,St}$ respectively, and the latter two are consistent with the peak factors of Davenport and Chinese Load Code GB50009-2012 [13] respectively. It can be found that at peak factor $g_{ng,C} = 5.0$, $x_{3_3}(t)$ approximately meets the occurrence probability of 99.95%, while the peak factor of standard Gaussian process $x_G(t)$ corresponds to $g_{ng,D} = 3.5$ with the same occurrence probability, which can be expressed as follows:

$$P_{g_{ng,C}=5} = \int_{-5}^{5} f(x_{3_3})dx_{3_3} \approx 0.9995$$

$$= \int_{-3.5}^{3.5} f_{Gaussian}(x_G)dx_G.$$  \hspace{1cm} (16)

The above analysis also shows that the greater the $g_{ng,C}$ deviated from the $g_{ng,D}$, the stronger the non-Gaussian degree of wind pressure is. At this point, if the peak factor of non-Gaussian wind pressure is still taken according to the assumption of Davenport Gaussian distribution, the extreme value would be underestimated. It can be summarized from Figure 10 and the aforementioned analysis that
(1) The peak factor \((g_{ng,St} = 2.5)\) recommended by the GB50009-2012 [13] and the Davenport peak factor \((g_{ng,D} = 3.5)\) based on the Gaussian distribution assumption are significantly lower than the peak factor estimated by the complete probability with 99.95% guarantee rate \((g_{ng,C} \approx 5.0)\), that is, \(g_{ng,St} < g_{ng,D} < g_{ng,C}\).

(2) The occurrence probability difference of peak factor estimated by the complete probability with 99.95% and 99.44% guarantee rate is \((P_{S,3}^{0.0} - P_{S,3}^{3.5}) = 0.51\%\). It indicates that if the peak factor estimation is consistent with Davenport peak factor based on Gauss hypothesis \((g_{ng,C} = g_{ng,D} \approx 3.5)\), 0.51% will be added to the acceptable exceedance probability of 0.05%, which may affect the safety and reliability of cladding structure to a certain extent.

Therefore, the division of Gaussian and non-Gaussian regions based on the deviation degree of \(g_{ng,C}\) relative to \(g_{ng,D}\) has credibility and theoretical basis.

4.3. Non-Gaussian Reflection Based on Peak Factor. In the aforementioned discussion, the peak factor estimation by the Davenport method is based on the Gaussian assumption, which is close to the result of standard Gaussian process by the complete probability method with 99.95% guarantee rate. However, the peak factor estimation of non-Gaussian process by the complete probability method with 99.95% guarantee rate is more suitable for actual wind pressures. In this section, a comparison of the differences between the two methods for estimating the peak factors of wind pressure is performed.

Figure 11 shows the peak factors of the wind pressures on the taps at 3rd layer of the model at different wind attack angles based on the Davenport method and the complete probability (CP) method with 99.95% guarantee rate. In the figure, the peak factors estimated by the Davenport method are approximately 3.5. Moreover, the CP peak factors of the wind pressures on the windward regions (e.g., windward face B of the model at 0° wind attack angle, as well as the smaller windward regions at 15°, 30°, and 45° wind attack angle) are consistent with the Davenport peak factors; however, the CP peak factors of the wind pressures on the regions immersed in separation flow, vortex shedding, and wake (e.g., side faces of A and C and leeward face D of the model at 0° wind attack angle, as well as most regions at 15°, 30°, and 45° wind attack angle) are significantly greater than the Davenport peak factors. The lower estimation of peak factor using the Davenport method will bring safety risks to the design of building cladding structure.

4.4. Method and Standard for Division of Gaussian and Non-Gaussian Wind Pressures. In summary, the deviation ratio between the CP peak factor with a guarantee rate of 99.95% and the Davenport peak factor is used as the basis for judging whether the wind pressure obeys Gaussian or non-Gaussian distribution. The deviation ratio of peak factor is defined as follows:

\[
DR(i) = \frac{|g_{ng,C}(i) - g_{ng,D}(i)|}{g_{ng,D}(i)},
\]

where \(i\) is the tap number of the model, \(g_{ng,C}\) represents the complete probability peak factor with 99.95% guarantee rate, and \(g_{ng,D}\) represents the Davenport peak factor.

As can be observed from Figure 11, it is generally believed that \(g_{ng,C}(i)\) and \(g_{ng,D}(i)\) are extremely close on the windward regions, and \(g_{ng,C}(i)\) is significantly larger than \(g_{ng,D}(i)\) in the rest. Based on the discussion in Section 4.2, \(DR_{cr}\) is set as the critical value for the division of Gaussian and non-Gaussian regions. When \(0 < DR(i) \leq DR_{cr}\), \(g_{ng,C}(i)\) deviation from \(g_{ng,D}(i)\) of wind pressure at measuring tap \(i\) is relatively small, which can be divided into Gaussian region. When \(DR(i) > DR_{cr}\), \(g_{ng,C}(i)\) deviation from \(g_{ng,D}(i)\) of wind pressure at tap \(i\) is relatively large, which is divided into non-Gaussian region.

Statistics are important characteristic parameters of random signals. A large number of studies have shown that the peak factor (or extreme value) of non-Gaussian signals has a significant correlation with higher-order statistics [26, 37, 45]. Therefore, Figures 12 and 13 show the correlations between the peak factor deviation ratios (\(DR\)) of wind pressures and \(|\gamma_3|\) as well as \(\gamma_4\) for faces A to D of the model at 0° wind attack angle and four different wind attack angles (0°, 15°, 30°, 45°), respectively. It can be seen from the figures that there is a significant linear positive correlation between \(DR\) and \(|\gamma_3|\), and there is a nonlinear positive correlation between \(DR\) and \(\gamma_4\), which follows a certain rule. Therefore, by performing the linear and nonlinear fittings on the data of Figures 12(b) and 13(b), the correlation expressions reflecting the deviation ratio (\(DR\)) and the two higher-order statistics (\(|\gamma_3|\) and \(\gamma_4\)) can be obtained respectively:

\[
DR = -0.445|\gamma_3| - 0.0239,
\]

\[
DR = -2.111 - 0.285\gamma_4 + 0.00316\gamma_4^2 + 1.725\gamma_4^{0.5}.
\]  

The monotonicity of the analytical equations (equation (18)) in the effective range reflects the one-to-one correspondences between \(DR\) and \(|\gamma_3|\) as well as \(\gamma_4\). Reverse solving the above equations and combining with Figures 12 and 13, it is found that when \(DR = 0\), the results of the corresponding high-order statistics are approximately \(|\gamma_3| \approx 0\) and \(\gamma_4 \approx 3.0\), which corresponds to the standard Gaussian distribution in Figure 2. It can be seen that \(DR\) is essentially the degree of deviation between the actual peak factor and the Davenport peak factor based on the Gaussian assumption.

According to the relationships between the normalized kurtosis-skewness linear distance difference \(\delta\) and the higher-order statistics (\(|\gamma_3|\) and \(\gamma_4\)), as shown in Figure 9, it can be found that there are good correlations between them, which also indicates that there is a certain correlation between \(DR\) and \(\delta\). Figures 14(a) and 14(b) show the scatter diagrams between \(DR\) and \(\delta\) for each face at 0° wind attack angles and for four different wind attack angles (0°, 15°, 30°, and 45°), respectively. It can be found that there is a significant monotonic positive correlation between the two variables mentioned above, which further indicates that \(\delta\)
can well reflect the strength of the non-Gaussian attribute of wind pressure. By performing the nonlinear fitting of the data in Figure 14(b), the expression reflecting the correlation between $DR$ and $\delta$ can be obtained as follows:

$$DR = 0.0364 + 0.496\delta - 1.0198^{0.5}. \tag{19}$$

The monotonicity of the analytical equation (equation 19) in the effective range reflects the one-to-one correspondence between $DR$ and $\delta$.

After obtaining the relational expressions between $DR$ and the higher-order statistics ($|\gamma_3|$ and $\gamma_4$) as well as $\delta$ respectively, the key problem is to obtain the critical value $DR_{cr}$ for judging the Gaussian and non-Gaussian regions of wind pressure. It can be seen from Figure 9 that when $|\gamma_3|$ and $\gamma_4$ are small ($|\gamma_3| < 0.28$ and $\gamma_4 < 3.5$), $\delta$ is basically distributed near 0, and these taps basically belong to the windward face B except only a few taps on the side faces. Thus, it can be determined as Gaussian region when the conditions of $|\gamma_3| < 0.28$ and $\gamma_4 < 3.5$ are satisfied. Taking $|\gamma_3| = 0.28$ and $\gamma_4 = 3.5$ and substituting them into equations (18), it is found that $DR$ is approximately equal to 0.15. Therefore, taking $DR_{cr} = 0.15$ is acceptable. As can be seen in Figure 14, the $DR$ of wind pressures on the windward face B at 0° wind attack angle is almost less than 0.15, while $\delta$ is basically concentrated near 0. By substituting $DR_{cr} = 0.15$ into equation (19), $\delta = 0.0111$ can be inversely calculated.

In summary, $DR_{cr} = 0.15$ can be used as the division standard to distinguish Gaussian and non-Gaussian regions. When the $DR$ of the wind pressure is greater than 0.15, its corresponding position of measuring tap can be divided into

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure11.png}
\caption{Peak factors of wind pressures on taps at the 3rd layer of the model under different wind attack angles based on Davenport and CP methods. (a) 0° wind attack angle. (b) 15° wind attack angle. (c) 30° wind attack angle. (d) 45° wind attack angle.}
\end{figure}
non-Gaussian region; conversely, when the DR of the wind pressure is less than or equal to 0.15, its corresponding position can be divided into Gaussian region. In addition, for the regions of vortex shedding and flow separation, obvious strong non-Gaussian characteristics appear. To observe the non-Gaussian intensity distribution characteristics of wind pressure clearly, DR = 0.45 is set as the division boundary of mild and strong non-Gaussian regions in this study (corresponding to this criterion, the number of corresponding pressure taps in the strong non-Gaussian region accounts for about 25% of all non-Gaussian pressure taps and 10% of all taps). In the strong non-Gaussian region, the extreme value of wind pressure needs special attention in the design of structural cladding. Similarly, by substituting DR = 0.45 into equations (18) and (19), the corresponding $|\gamma_3|$ and $\gamma_4$ as well as $\delta$ can be inversely calculated.

Table 1 lists the corresponding values of $|\gamma_3|$ and $\gamma_4$ as well as $\delta$ when the deviation ratios DR are 0.15 and 0.45, respectively. That is, the corresponding red horizontal dotted lines in Figures 12(b), 13(b), and 14(b) divide the tap pressures into Gaussian, weak non-Gaussian, and strong non-Gaussian, respectively. In this way, Gaussian and non-Gaussian regions, as well as weak non-Gaussian and strong non-Gaussian regions can be distinguished according to the corresponding relationship between representative DR and $|\gamma_3|$ and $\gamma_4$ or $\delta$, as listed in Table 1.
4.5. Division Results of Test Data Based on Two Types of Indexes. In summary, two types of indexes can be used for the division of Gaussian, weak non-Gaussian, and strong non-Gaussian regions for wind pressures on a building, as listed in Table 1 and equations (18) and (19). The details are as follows:

**Method 1.** Based on the skewness and kurtosis of wind pressure, when it meets the conditions of $|c_3| \leq 0.28$ and $c_4 \leq 3.47$, it belongs to the Gaussian region; otherwise, it belongs to the non-Gaussian region. In addition, when the wind pressure meets the condition of $|c_3| > 0.95$ and $c_4 > 5.40$, it belongs to strong non-Gaussian region.

**Method 2.** Based on the normalized kurtosis-skewness linear difference, when the wind pressure meets the condition of $\delta \leq 0.011$, it belongs to the Gaussian region; otherwise, it belongs to the non-Gaussian region. In addition, when the wind pressure meets the condition of $\delta > 0.120$, it belongs to strong non-Gaussian region.

In this study, the Gaussian and non-Gaussian wind pressures at all 120 taps of the square column are distinguished by the aforementioned two methods. The results of regional division on each surface of the model at different wind attack angles are shown in Figures 15–18. In the figures, the hollow dots indicate that these locations are divided into Gaussian wind pressure regions, while the solid dots belong to the non-Gaussian wind pressure regions, in which blue and red indicate the weak non-Gaussian region and the strong non-Gaussian region, respectively.

It can be seen from Figure 15 that at the 0° wind attack angle, the distributions of the Gaussian and non-Gaussian regions divided by the two methods are basically consistent (the results of the windward face B and leeward face D are complete consistent). Moreover, it can be intuitively observed from Figure 15 that the strong non-Gaussian regions (red) are mainly distributed in the trailing edge regions of the side faces and the middle and lower regions of the leeward face D of the square column.

It can be seen from Figure 16 that at the 15° wind attack angle: (1) Gaussian and non-Gaussian regions divided by the two methods are roughly the same; (2) compared with that at 0° wind attack angle, the wind pressures on the center region of face C of the model tend to Gaussian distribution while the wind pressures over a wider trailing edge positive triangle region of the face A appear strong non-Gaussian for the flow separation phenomenon on the surface of the model is greatly changed.

It can be seen from Figure 17 that at the 30° wind attack angle: (1) the difference between the two division methods is slightly larger than that at the aforementioned two wind attack angles, especially on the faces C and D. It shows that method 1 is more conservative in the division of Gaussian region and non-Gaussian region, while method 2 is more conservative in the division of general non-Gaussian region and strong non-Gaussian region; (2) compared with the 15° wind attack angle, the Gaussian distribution region of face C turns from the central region to the trailing rear.

It can be seen from Figure 18 that at the 45° wind attack angle: (1) the results of the two methods are similar; (2) the wind pressures on windward faces B and C basically belong to the Gaussian region, while the wind pressures on the leeward faces A and D mostly belong to the non-Gaussian region and only a small part of the region on the upper leading edge of the two faces become Gaussian region. Furthermore, the strong non-Gaussian regions are also mainly concentrated in the lower triangle of the trailing edges of the faces A and D.
Figure 15: Divisions of Gaussian and non-Gaussian regions by two methods at 0° wind attack angle.

Figure 16: Divisions of Gaussian and non-Gaussian regions by two methods at 15° wind attack angle.

Figure 17: Divisions of Gaussian and non-Gaussian regions by two methods at 30° wind attack angle.
It can be shown in Figures 15–18 that the regional di-

vision results at the above-mentioned wind attack angles 

using the two methods are generally similar. Comparatively 

speaking, method 1 is slightly conservative in the division of 

Gaussian region and non-Gaussian region, while method 2 is 

slightly conservative in the division of weak non-Gaussian 

region and strong non-Gaussian region. In general, both the 

two methods can reasonably predict the distribution char-

acteristics of Gaussian and non-Gaussian wind pressures on 

building surfaces.

5. Conclusions

In this study, based on the rigid model wind tunnel test of a 

square building for pressure measurement, an index of 

normalized kurtosis-skewness linear distance difference ($\delta$), 

as well as the indexes of skewness ($|c_3|$) and kurtosis ($c_4$) for 

distinguishing the Gaussian and non-Gaussian wind pres-

sures, was investigated. Then, a deviation ratio (DR) of the 

complete probability (CP) peak factor to the Davenport peak 

factor for the division of Gaussian and non-Gaussian regions 

of wind pressure quantitatively was proposed. The main 

conclusions are drawn as follows:

1. The normalized kurtosis-skewness linear distance 

difference ($\delta$) is sensitive to the absolute value of 

skewness ($|y_3|$) and kurtosis ($y_4$). When $|y_3| < 0.28$ and 

$y_4 < 3.5$, $\delta$ has a significant positive correlation 

with $|y_3|$ and $y_4$; moreover, in the regions with 

significant Gaussian characteristics, $\delta$ fluctuates near 

zero. $\delta$ as well as $|y_3|$ and $y_4$ can all represent the 

intensity of non-Gaussian wind pressures.

2. The deviation ratio (DR) of the complete probability 

(CP) peak factor with 99.95% guarantee rate to the 

Davenport peak factor is positively correlated with 

the higher-order statistics of $|y_3|$ and $y_4$, as well as $\delta$. 

The analytical expressions proposed in this study can 

be used as the basis for dividing the Gaussian and 

non-Gaussian regions of wind pressure and judging 

its non-Gaussian degree.

3. $DR_{CP} = 0.15$ can be used as the critical value for 

dividing the Gaussian and the non-Gaussian wind 

pressure regions, which is corresponding to 

$|y_3| \leq 0.28$ and $y_4 \leq 3.47$ or $\delta \leq 0.011$. Moreover, 

$DR_{CP} = 0.45$ can be used as the critical value for the 

division of the weak non-Gaussian region and the 

strong non-Gaussian region, which is corresponding to 

$|y_3| > 0.95$ and $y_4 > 5.40$ or $\delta > 0.120$. The results 

show that the regional division methods on the basis 

of $|y_3|$ and $y_4$ and $\delta$ can reasonably reflect the dis-

tribution characteristics of Gaussian and non-

Gaussian wind pressures on the building surface in 

detail.

Data Availability

The data that support the findings of this study can be 

obtained from the corresponding author upon reasonable 

request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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