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Estimates of extreme wind effects and wind load factors: influence of knowledge uncertainties

Fabio Minciarelli[a,b], Massimiliano Gioffrè[c], Mircea Grigoriu[d], Emil Simiu[b,*]

[a]University of Perugia, Perugia, Italy
[b]Building and Fire Research Laboratory, National Institute of Standards and Technology, Building 226, Gaithersburg, MD 20899-8611, USA
[c]University of Perugia, Perugia, Italy
[d]Cornell University, Ithaca, NY 14853, USA

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Abstract

We propose a probabilistic methodology for developing improved load factors in standard provisions for wind loads, and use it to examine: the cause of the discrepancy noted in the 1980s between estimates of safety indices for wind and gravity loads; the relative magnitude of load factors for hurricane and non-hurricane regions; and the effect of the length of wind tunnel pressure records on the estimation of peak wind effects. According to our calculations, (1) the discrepancy between estimates of safety indices for gravity and wind loads is an artifact that can be removed by using current knowledge on probability distributions of extreme wind speeds; (2) the disregard in the ASCE 7-98 Standard of (a) knowledge uncertainties, and (b) errors inherent in the limited number of climatological data on which hurricane wind speed simulations are based, leads to incorrect wind load factor estimates; and (3) increasing beyond 30 min or even 20 min the length of pressure records used for the estimation of fluctuation peaks appears to have a relatively small effect on estimates of overall wind effects. We outline future research on wind directionality, sampling errors in the estimation of peak wind effects, and the use of probabilistic descriptions of wind effects and structural capacity to estimate probabilities of occurrence of nonlinear limit states, including structural collapse.

Keywords: Building technology; Hurricanes; Load factors; Monte Carlo simulation; Reliability; Structural engineering; Wind effects

1. Introduction

The estimation of wind loads and of the reliability of wind-excited structures has been investigated extensively during the last few decades. However, a number of important issues remain unsolved and warrant examination and debate:

1. According to the methods used by Ellingwood et al. [1], estimates of safety indices for structures designed in accordance with the ASCE 7 Standard and its predecessors are considerably lower for wind than for gravity loading. One of the aims of this paper is to consider this issue and propose a correction to those methods.
2. In the ASCE 7-95 Standard and its predecessors, wind load factors specified for hurricane effects are the same as those specified for extratropical storm effects. According to statistical analyses in which estimation uncertainties were not accounted for, risk consistency requires that wind load factors be significantly larger for hurricane winds than for extratropical winds [2]. This finding was taken into account in the ASCE Standard 7-98 [3]. However, in that Standard load factors are calculated as the ratio between point estimates of 500 and 50-yr wind loads, without accounting for knowledge uncertainties. In this paper, we perform estimates of load factors that take such uncertainties into account.
3. Wind load peaks are based in the ASCE 7-98 Standard and its predecessors on records taken in the wind tunnel over periods equivalent to 1 h in full scale. Wind tunnel operators sometimes specify peaks based on records longer than 1 h — in some instances as long as tens of hours. However, it may be the case that record lengths of 1 h or even less, say 30 or 20 min, are sufficient, at least for codification purposes. It is therefore in order to examine the extent to which the record length affects the estimates of wind effects when knowledge uncertainties are duly accounted for.

* Corresponding author. Tel.: +1-301-975-6076; fax: +1-301-869-6275.
E-mail address: simiu@nist.gov (E. Simiu).

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In this paper, we discuss these issues within a probabilistic framework. It is not our intention to present definitive results: some parameters and models require additional research and should be based on a consensus yet to be established. Rather, we wish to develop an investigation tool — with an attendant set of computer programs — that is transparent and simple to use, and to present results that, in our opinion, shed useful light on reliability issues related to wind loading. The main motivation for this work is to achieve standard provisions for wind loads that are more realistic and risk-consistent than current provisions.

Our investigation is limited to structures that do not experience significant wind-induced dynamic amplification effects. In Section 2 we describe the physical and probabilistic framework used in our investigation. We then use this framework for the following purposes. First, we wish to examine the finding by Ellingwood et al. [1] that their estimates of the safety indices inherent in the ASCE Standard and its predecessors are significantly lower for wind than for gravity loads. We do so by investigating the role of the assumed distribution of the extreme wind speeds in the estimation of load factors. Second, we report estimates of hurricane wind load factors that take knowledge uncertainties into account, and show that they reinforce earlier findings that, to ensure risk-consistency, wind load factors must be significantly larger for hurricane-prone regions than for regions not subjected to hurricanes. Third, we examine the role of the length of the wind tunnel record of fluctuating wind effects on the estimated magnitude of estimated peak wind effects. Fourth, we examine the sensitivity of our load factor estimates to changes in the variabilities of the uncertainty parameters on which the estimates are based. Fifth, we briefly discuss three topics for which further research is needed: the use of simulations to estimate peaks and sampling errors in the estimation of peaks, the role of wind directionality, and the use of probability distributions of wind effects and structural capacities to estimate probabilities of structural collapse and other limit states involving structural nonlinearities. The paper ends with a set of conclusions.

2. Probabilistic modeling of extreme wind effects

2.1. *Wind effect model*

We denote by $F_{\rm pk}(\tau, N)$ the peak wind load effect with an N-yr nominal mean recurrence interval, occurring in the prototype subjected to the action of a storm with duration τ. The time interval τ can be, say, 20, 30 min, 1 h or longer, and the storm is assumed to induce wind loads that may be assumed to be a statistically stationary process. The nominal mean recurrence interval can be, say, 50, 500 or 10,000 yr, and corresponds to wind speeds estimated without accounting for wind directionality effects (these are briefly discussed in Section 6). We use the model

$$F_{\rm pk}(\tau, N) = \tfrac{1}{2}\rho C_{\rm pk}(\tau) abc V^2(\tau, H_{\rm aero}, z_{\rm o}, N) \quad (1)$$

where ρ is the air density, which is sufficiently well known that no uncertainty is usually associated with its value; $C_{\rm pk}(\tau)$ is the peak factor for the fluctuating wind effect (e.g. bending moment, shear force, axial force, displacement) induced by the storm. It is associated with the largest peak wind effect occurring during time τ. The peak factor is a random variable that will be discussed subsequently; $V(\tau, H_{\rm aero}, z_{\rm o}, N)$ is the wind speed at reference height $H_{\rm aero}$, averaged over the time interval τ. The nominal mean recurrence interval of the wind speed is N, in years, and the roughness of the terrain that characterizes the site upwind of the building is $z_{\rm o}$. $H_{\rm aero}$ is commonly, but not necessarily, chosen to be the top of the building or the eave height; a, b, c are random variables associated with imperfect knowledge ('epistemic uncertainties'), as opposed to randomness inherent in a variable ('aleatory uncertainties'). For example, the terrain roughness is usually known with some uncertainty, whereas the wind speed and the peak value of a fluctuating random process are inherently random variables. Unless otherwise indicated, all uncertainty variables, including a, b, c will be assumed to have truncated normal distributions with mean unity. The parameters a, b and c are defined as follows:

a reflects aerodynamic errors inherent in the wind tunnel being used (results of wind tunnel tests may depend upon the specific wind tunnel facility in which the tests are conducted);
b reflects aerodynamic errors due to (a) the use of wind tunnel rather than full-scale measurements, and (b) the imperfect calibration of wind tunnel to full-scale data;
c reflects errors in the transformation of aerodynamic effects into stresses or other structural effects.

2.2. *Wind speed model*

The wind speed is estimated by using:

- measured or simulated wind speed data at the standard meteorological elevation $H_{\rm met}$ (e.g. 10 m above ground) in open terrain with standard roughness $z_{\rm o1}$ (e.g. $z_{\rm o1} = 0.05$ m). The averaging time T for the wind speed data varies. In the ASCE 7-98 Standard the interval $T =$ 3 s is used. Simulated hurricane wind speed data available in NIST public files (accessible as indicated in Ref. [4]) and based on the work of Batts et al. [5] are averaged over one minute. From these observed or simulated wind speed data, point estimates can be made of wind speed data with various mean recurrence intervals. The estimation methods are described subsequently, as are estimation methods for the sampling errors corresponding to winds with N-yr mean recurrence intervals. The estimates are also affected by *observation* *errors*, modeled by the uncertainty factor q, which, as noted earlier, is assumed to be normally distributed with mean unity.

- conversion factors r to account for wind speed averaging time. To obtain wind speeds averaged over time τ, wind speeds averaged over time T are multiplied by the factor $r(T, \tau)$. While, like all our uncertainty variables, we assume r to be normally distributed, its mean is not unity. Rather, the means of the variable $r(T, \tau = 1\,\text{h})$ are obtained from [6] as functions of T (see also Ref. [7], Chapter 2). For example, for $T = 3$ s, Mean$[r(T = 3\,\text{s}, t = 1\,\text{h})] \approx 0.65$, that is, the 1-h average is 0.65 times the 3 s peak. If $\tau = 20$ min and 30 min, the information provided by Durst yields the following means of r:

$$\text{Mean}[r(T = 3\,\text{s}, t = 20\,\text{min})] \approx 0.66$$

$$\text{Mean}[r(T = 3\,\text{s}, t = 30\,\text{min})] \approx 0.655.$$

- Factors converting wind speeds averaged over 1 h (or, e.g. 30 or 20 min) say, over open terrain with roughness z_{o1} at the standard meteorological elevation H_{met} to mean hourly wind speeds at the aerodynamic reference elevation H_{aero} over the terrain with roughness z_o upwind of the building. These factors are yielded by (a) the logarithmic law and (b) the relation between wind speeds in different roughness regimes ([7], pp. 42, 48), and are functions of the roughness lengths z_{o1} and z_o. (Effects of terrain fetch that may be insufficient for the full development of the boundary layer upwind of the building, or of escarpments or hills, are not dealt with in this paper). We denote by u and s the random variables, again assumed to be normally distributed with mean unity, that reflect the uncertainties with respect to the actual values of z_{o1} and z_o. The following approximate expression is obtained:

$$V(\tau, H_{aero}, z_o, N) = u_H[(sz_o)/(uz_{o1})]^{\delta} qr(\tau, T) V(T, H_{met}, z_{o1}, N) \times \{\ln H_{aero}/(uz_{o1})\}/\{\ln H_{met}/(sz_o)\} \quad (2)$$

where the exponent $\delta = 0.0706$ in the relation between wind speeds in different roughness regimes may be assumed to have negligible variability, and $V(T, H_{met}, z_{o1}, N)$ denotes the estimated wind speed with a mean recurrence interval N, averaged over time T, at elevation H_{met} above open terrain with roughness length z_{o1}. The factor u_H in **Eq.** (2) reflects the uncertainty with respect to the applicability of this model to hurricane wind speeds, which differ to some extent from extratropical wind speeds. For extratropical storm winds the factor u_H is, by definition, unity; for hurricane wind speeds its mean and coefficient of variation are assumed to be unity and 0.05, respectively.

It is assumed throughout that, the quantities involved in the calculation of wind effects are estimated on the basis of sound information, for example, information obtained from wind tunnels that meet standard performance criteria and are calibrated against dependable full-scale test results; or information obtained from certified weather stations. Gross errors or information based on substandard sources of information are not accounted for in our uncertainty model.

2.3. Estimation of wind speeds $V(T, H_{met}, z_{o1}, N)$ with a mean recurrence interval N

Denote the mean and the standard deviation of the sample of extreme wind speeds by $E(X)$ and $s(X)$, respectively. The Extreme Value Type I distribution and its inverse (the variate corresponding to a mean recurrence interval N in years) are

$$F_I(x) = \exp\{-\exp[(x - \mu)/\sigma]\},$$
$$\sigma = [(6)^{1/2}/\pi] s(X), \quad \mu = E(X) - 0.5772\sigma. \quad (3)$$

$$x_I(N) = \mu - \sigma \ln(-\ln(1 - 1/N)). \quad (4)$$

The reverse Weibull distribution and its inverse are

$$F_{III}(x) = \exp\{-[(\mu - x)/\sigma]^{\gamma}\}, \ \mu = E(X) + \sigma\Gamma(1 + 1/\gamma);$$
$$\sigma = \sigma s(X)/[\Gamma(1 + 2/79 - \Gamma^2(1 + 1/\gamma)]^{1/2}; \quad \gamma = -1/\kappa. \quad (5)$$

$$x_{III}(N) = \mu - \sigma[\ln(1 - 1/N)]^{1/\gamma}. \quad (6)$$

In **Eq.** (5), γ (or κ) is the distribution's tail length parameter.

2.4. Sampling errors in the estimation of extreme wind speeds

The mean $E(x)$ and the standard deviation $s(x)$ must be estimated from an n-yr record $\{x_1, x_2, \ldots, x_n\}$ of the extreme wind speeds. For example,

$$[\hat{s}(x)]^2] = \frac{1}{n}\sum_{k=1}^{n}(x_k - \hat{E}(x))^2 \quad (7)$$

The resulting estimate of the wind speed of average return period N yr is

$$\hat{x}_N = \hat{E}(x) + a(N)\hat{s}(x). \quad (8a)$$

where

$$a(N) = -0.779697\ln(-\ln(1 - 1/N)) - 0.450053 \quad (8b)$$

for the E.V. Type I distribution, and

$$a(N) = \Gamma(1 + 1/\gamma)\ln(1 - 1/N)]^{1/\gamma}/[\Gamma(1 + 2/\gamma) - \Gamma(1 + 1/\gamma))]^{1/2} \quad (8c)$$

for the reverse Weibull distribution (**Eqs.** (4) and (6)).

The value of $\hat{x}_N$ is uncertain because the estimates $(\hat{E}(x), \hat{s}(x))$ of $(E(x), s(x))$ are random variables whose variance depends on the sample size n. The mean and variance of $\hat{x}_N$ can be approximated by [8,9]

$$\text{Mean}[\hat{x}_N] \approx E(X) + s(X)a(N)[(n-1)/n]^{1/2} \tag{9}$$

$$s[\hat{x}_N] \approx \{1 + \sqrt{2}\gamma_3 a(N)[[(1-1/n)(\gamma_4-1)/2 + 1/n)]/[\gamma_4 - 1 + 2/(n-1)]] + a(N)^2[(1-1/n)(\gamma_4-1)/2 + 1/n)]/2\}^{1/2} s(X)/n^{1/2} \tag{10}$$

where γ_3 and γ_4 denote the coefficients of skewness and kurtosis of the distribution F_{I} or F_{III} (Eq. (3) or **Eq.** *(5))*.

For *hurricane-prone regions,* the estimates of extreme wind speeds are obtained by using the peaks over threshold approach. Sampling errors are estimated on the basis of the numbers of data that exceed the respective thresholds. However, it should be remembered that the data themselves are obtained by Monte Carlo simulation on the basis of information on relevant climatological parameters: pressure differences between the edge and the center of the hurricane, the radius where hurricane wind speeds are highest and the translation velocity of the hurricane. This climatological information is based on records of about 100 yr, corresponding to a total number of hurricanes at a particular location of about 50 (depending upon geographical location). Therefore, the climatological information on which the simulated hurricane data is based, is itself subjected to sampling errors. The effect of these climatological sampling errors on the estimated extreme wind speeds based on simulated data was studied in Ref. [10]. According to those studies, the coefficient of variation of the sampling errors in the estimation of the 50-yr wind speeds is typically of the order of 0.10. For 500-yr wind speeds, we assume that the coefficient of variation of the climatological sampling errors is 0.125. The total sampling error therefore depends upon the threshold, and is obtained in all cases by noting that the total variance of the sampling error is equal to the sum of the variance associated with the size of the simulated data sample used in the analysis, and the variance associated with climatological parameter uncertainties.

2.5. Peak factors C_{pk}

Consider a non-Gaussian process

$$X(t) = F_{\text{IF}}^{-1}(\Phi(Z(t))) = g(Z(t)), \qquad 0 \le t \le \tau. \tag{11}$$

where F_{IF} denotes the marginal distribution of the process, $\Phi(Z)$ denotes the distribution of a Gaussian variable with zero mean and unit variance and $Z(t)$ is a stationary Gaussian process with zero mean, unit variance and covariance function $\zeta(w) = E[Z(\tau)Z(\tau + w)]$.

Denote the peak value of the internal force during the interval $(0, \tau)$ by

$$C_{\text{pk}}(t) = \max_{0 \le t \le \tau} X(t) \tag{12}$$

The distribution of the peak value $C_{\text{pk}}(\tau)$ can be approximated as follows:

$$F_{\text{IF},\tau}(x) = P(C_{\text{pk}}(t) \le x) \approx \exp(-\nu(x)\tau), \tag{13}$$

$$\nu(x) = [\sigma_{\dot{z}}/(2\pi) \exp[-(1/2)(g(x)^{-1})^2] \tag{14}$$

is the upcrossing rate of the threshold x per unit time, $\sigma_{\dot{z}}$ is the standard deviation of the process $\dot{z}$, the symbol $\cdot$ denotes differentiation with respect to time, and -1 denotes 'inverse of'. The distribution $F_{\text{IF},\tau}$ can be used to calculate the mean and variance of C_{pk}.

If $X(t)$ represents an internal force (e.g. the bending moment at a particular cross-section of a frame), its marginal distribution and covariance function can be estimated from a wind-tunnel record of that force. These two properties define completely the model of Eq. (11), since they determine the memoryless transformation $g(Z(t))$ and the covariance function $\zeta(w)$ ([9], pp. 44–53).

Because the peak load effect given by Eqs. (12)–(14) depends on the marginal distribution and the covariance function of $X(t)$, C_{pk} will depend on the particular sample considered in the analysis and on its size. In general, no closed form expressions are available for the estimation of the sampling errors in the estimation of C_{pk}. It is, however, possible to estimate these errors from numerical simulations. This topic will be briefly discussed in Section 6.

The calculations performed in this paper were based on a 42-h record of wind-induced bending moments at the knee of a typical low-rise industrial building steel frame, provided by Dr M. Kasperski of Bochum University. The largest peak normalized with respect to the r.m.s. for the 42-h record was 6.5. The normalized mean of the peaks for the 1-h records was 5.00, with a c.o.v. = **0.09.** For the 30 and 20-min records, the mean and c.o.v. were 4.6, 0.10 and 4.4, 0.11, respectively.

3. Wind load factors

All results in this section were obtained by Monte Carlo simulation, the number of samples in each simulation being $n_s = 2{,}000$.

3.1. Regions not subjected to hurricane winds

The wind load factor is defined in the **ASCE 7-98** Standard as the square of the ratio between the point estimate (the 50 percentile) of the 500-yr wind speed and the point estimate of the 50-yr wind speed, both estimates being based on the assumption that the extreme wind speeds are best fitted by the Extreme Value Type I distribution. The ASCE **7-98** Standard further specifies that the structural member experience the state associated with strength design under the wind effect consisting of the 50-yr wind effect times the load factor so defined (see **ASCE 7-98** Standard Commentary, p. 114).

Table 1
Basic set of means and standard deviations of the uncertainty parameters, assumed to be normally distributed

Uncert. param.	*a*	*b*	*c*	*s*	*u*	*q*	*r*
Mean	1	1	1	1	1	1	**See Section 2**
Coeff. of var.	0.05	0.05	0.025	0.1	0.1	0.025	0.05

The ASCE 7-98 definition does not account for the errors and uncertainties in the estimation of the various quantities that determine the wind effect (terrain roughness, peak wind speed, factor converting of peak wind speed to reference hourly wind speed used in aerodynamic testing and so forth). These errors and uncertainties are considerable, and disregarding them results in unrealistic estimates. In fact, Ellingwood et al. [1] specifically accounted for errors and uncertainties in their estimates of safety indices. If it is assumed that wind speeds are more realistically described by a finite-tailed than by an infinitely-tailed model, it might then be argued that using an infinitely-tailed probabilistic model for the wind speeds instead of a finite-tailed model compensates for the failure to account for errors and uncertainties. However, there is no scientific reason to support the view that this is ***consistently*** the case.

We therefore define wind load factor as follows. As in the ASCE 7-98 Standard, we assume that the wind effect for strength design (corresponding, e.g. to the attainment of the yield stress by a cross-section's most stressed fiber) is induced by a wind speed with a 500-yr mean recurrence interval (ASCE 7-98 Standard Commentary, p. 114). Owing to errors inherent in the estimates of wind effects, we do not consider the point estimate of the 500-yr wind effect in our definition of the load factor, since there is a chance of approximately 50 percent that the true 500-yr wind effect would be larger than the point estimate. We consider instead a higher than 50 percentile. Noting that, in the development work for the ANSI A58 Standard, the predecessor of the ASCE 7 Standard, Ellingwood et al. [1] considered the 90 percentile for the estimates of 50-yr wind effects, we choose to define the wind load factor as follows:

$$\mathrm{LF} = F_{\mathrm{pk}}(N = 500\text{-yr}, 0.9)/F_{\mathrm{pk}}(N = 50\text{-yr}, 0.5)$$

where 0.9 and 0.5 denote the 0.9 percentage point and the 0.5 percentage point, respectively. In other words, multiplying the point estimate of the 50-yr wind effect by the estimated load factor LF yields the 90 percentile of the 500-yr wind effect. This definition is reasonable and useful for the purpose of our investigation; it is not normative, however, and consensus might be reached on alternative definitions.

The load factor estimates depend upon the probability distribution of the extreme wind speeds assumed in their estimation. The Type I distribution of the largest values (the Gumbel distribution) was until relatively recently universally believed to be a correct probabilistic model of the extreme wind speeds. A significant body of research conducted following the development in the 1970s of modern extreme value theory and approaches, including peak-over-threshold methods, strongly suggests that extreme wind speeds are better fitted by Type III distributions of the largest values (reverse Weibull distributions) which, unlike the Type I distribution, have bounded upper tails [11–13]. We performed Monte Carlo simulations for estimating load factors LF by using first the Extreme Value Type I distribution and then the reverse Weibull distribution, all other assumptions and parameters being the same. Sampling errors in the estimation of the extreme wind speeds, and peak values and sampling errors in their estimation, were estimated as indicated in Sections 2.4 and 2.5. The basic set of parameter values used in the calculations is listed in Table 1.

In addition, in our basic calculations it was assumed that the roughness lengths are $z_o = 1.00$ m and $z_{o1} = 0.07$ m (For other values used in the calculations, see Section 5.)

In our opinion, the assumption that the uncertainty parameters are normally distributed, though not exact, is reasonable, as are the values of the means and standard deviations listed in Table 1. A calibration of these values against the value of the load factor believed to be reasonable on the basis of past practice can be performed, depending on the results of the calculations.

First, we discuss briefly the influence on the results of the calculations of the assumed probabilistic of the extreme wind speeds. The results showed that estimated load factors are significantly larger if an infinite-tailed model (EVI), rather than a finite-tailed model (RW), is used for the distribution of the largest wind speeds. For example, for the parameters of Table 1, if the sample coefficient of variation of the extreme wind speed data is c.o.v = 0.15, then LF = 1.55 under the assumption that the reverse Weibull distribution with tail length parameter $\kappa = -0.2$ is valid, and LF = 1.90 under the assumption that the Extreme Value Type I distribution is valid. (The tail length parameter $\kappa = -0.2$, while not universally valid, is usually a reasonably conservative approximation for most stations — see Ref. [12].) These results are typical.

Under the assumption that the extreme wind speeds have a reverse Weibull distribution (see Refs. [11–13]), it follows from our results that load factors based on the Type I Extreme Value distribution are significantly overestimated. Therefore, in our opinion, the reason for the low safety index estimates for wind loading obtained by the procedure used in [1] is the use in that procedure of the assumption that extreme wind speeds are best fitted by the Extreme Value Type I distribution — an assumption consistent with the 1970s state of the art in extreme value applications to wind speeds. We note that, using this assumption for the estimation of wind speeds with relatively short mean recurrence intervals (50 yr, say) is, by and large, acceptable. The assumption becomes onerous if it is used for long mean recurrence intervals, such as those associated with strength design or ultimate structural capacity.

Note that the load factor specified in the ASCE 7-95 Standard for non-hurricane winds is 1.3, after multiplication by the wind direction reduction factor, assumed in the Standard to be 0.85; before reduction the load factor is 1.3/0.85 = 1.53 (i.e. close to our calculated value corresponding to the reverse Weibull assumption, LF = 1.55). The ASCE 7-95 value of the load factor was based on engineering judgment and experience, rather than on safety index calculations reported by Ellingwood et al. [1] (as was mentioned earlier, these were performed before modern extreme value distribution theory became widely applied – see, e.g. Ref. [14]). We note the agreement of our estimated value with the ASCE 7-95 value. We also note that the value 1.53 was augmented in the ASCE 7-98 Standard (p. 4, Section 2.3.2) to 1.36/0.85 = 1.6 (rather than being 1.5, as is indicated erroneously in the Commentary to the Standard, see ASCE 7-98, p. 114). This augmented value is still approximately consistent with our calculated value LF = 1.55. The reason for this consistency lies in our choice of uncertainty parameters, which as we suggested earlier, appear to be reasonable. However, should it be considered necessary to use different uncertainty parameters, the estimated value of the load factor would change to some extent. The sensitivity of the results to parameter changes is discussed in Section 5.

3.2. Regions subjected to hurricane winds

We performed simulations with the basic set of uncertainty parameters of Table 1, using the 999 simulated $T = 1$ min hurricane wind speeds for a northwestern Florida coast location, developed by Batts et al. [5] and available in a public electronic file (the identifier of the data set in the electronic file is 'milepost 1100'). Simiu and Heckert [12] and Simiu, Heckert and Whalen [2] reported that hurricane wind speeds are best fitted by reverse Weibull distributions for which it is reasonable to assume tail length parameter $\kappa \approx -0.2$, say, and that estimates of coastal hurricane wind speeds with mean recurrence intervals of 50 to 2,000 yr based on this assumption are consistent with estimates obtained independently by other authors (e.g. Refs. [7], p. I 17. For this reason, in our simulations, the distribution fitted to the extreme wind speeds was reverse Weibull with tail length parameter $\kappa = -0.20$. The distribution parameters were found by using Eq. (5) and the peaks over threshold method. Sampling errors in the estimation of the extreme wind speeds, and peak values and sampling errors in their estimation, were estimated as indicated in Sections 2.4 and 2.5, respectively. The basic set of parameter values used in the calculations is listed in Table 1.

For the mean hourly wind speed thresholds 19.4, 21.4, 23.3, 25.3 and 27.2 m/s (sample sizes 233, 172, 136, 100 and 77, respectively), the load factors obtained by simulation were, respectively, LF = 2.14, 2.13, 2.13, 2.15, and 2.21. The hurricane load factor LF ≈ 2.14, say, should be compared with the load factor LF ≈ 1.55 obtained, with the same set of uncertainty parameters, for extratropical wind speeds with coefficient of variation cov = 0.15, assumed to be best fitted by the reverse Weibull distribution with $\kappa = -0.20$. (Note that the Extreme Value Type I distribution, which as indicated earlier, has been assumed to be an appropriate distributional model for wind speeds in non-hurricane regions, has to our knowledge never been considered applicable to hurricane wind speeds.) As was indicated earlier, the result that load factors for hurricane-prone regions are larger than for non-hurricane regions is not new, and was taken into account in the development of the ASCE 7-98 Standard. The methodology presented in this paper allows, in our opinion, a more realistic estimation of the load factors, which takes into account the various uncertainties discussed in this section. As is the case for non-hurricane regions, uncertainty parameters that differ from those chosen here can be used in the estimates.

The mean and standard deviation of the data sets that exceed the 20.7 m/s threshold are 25.3 and 4.87 m/s; for the 22.8, 24.87, 26.95 and 29 m/s thresholds, they are (27, 4.5 m/s), (28.3, 4.25 m/s), (29.8, 3.9 m/s) and (30.9, 3.8 m/s). Results of sensitivity studies are presented in Section 6.

4. Influence of length τ of time series of pressures recorded in the wind tunnel

Estimates of wind effects depend upon the length τ of the time series of the pressures recorded in the wind tunnel. This dependence is of interest insofar as unduly long recording periods might create data storage problems for aerodynamic databases on buildings with a large number (say, hundreds) of pressure taps — see Ref. [2]. On the one hand it is desirable that the length of the time series τ of the pressures recorded in the wind tunnel be as short as possible. This would be convenient for both data storage and data processing reasons. On the other hand, a length τ that would be too short would cause unacceptable sampling errors in the estimation of extreme wind effects.

We performed simulations for three cases: $\tau = 1$ h, $\tau = 30$ min and $\tau = 20$ min. As mentioned in Section 2.5, the respective means and standard deviations of the peaks were taken to be equal to their averages over 42 1 h sets, 84 30 min sets and 126 20 min sets of time histories extracted from the 42-h long records of the wind-induced fluctuating moment at a frame knee mentioned earlier. For $\tau = 1$ h, $\tau = 30$ min and $\tau = 20$ min the mean and standard deviation of the peak factor were (in non-dimensional units), 5.00 and 0.45, 4.6 and 0.46, 4.4 and 0.48, respectively. We conducted two sets of calculations for wind speeds in non-hurricane regions. In the first set, it was assumed that the probability distribution of the peaks is normal. In the second set, it was assumed that the distribution of the peaks is Extreme Value Type I.

For non-hurricane extreme winds with cov = 0.15, and the basic set of uncertainty parameters (Table 1), under the simplifying assumption that the peaks are normally distributed, and the assumption that the extreme wind speeds are best fitted by a reverse Weibull distribution with tail length parameter $\kappa = -0.2$, we obtained, for $\tau = 60$, 30 and 20 min, respectively, load factors LF = 1.54, 1.55 and 1.57, and estimates of $F_{pk}(N = 500, 0.90)$ of 805, 800, and 793 (non-dimensional units), respectively; under the assumption that the wind speeds have an Extreme Value Type I distribution, the results were $LF = 1.90$, 1.90, 1.93; and of $F_{pk}(N = 500, 0.90) = 1084, 1077, 1067$. If it was assumed that, rather than being normally distributed, the peaks have Extreme Value Type I distribution, the results obtained differed insignificantly from those corresponding to a normal distribution of the peaks. The reason for these small differences lies in the 'drowning' of the larger extreme values of the peak factor C_{pk} yielded by the Type I distribution in the numerous errors and uncertainties involved in estimation of F_{pk}.

Therefore, for peak statistics comparable to those used in our calculations, that is, statistics typical of internal forces in frames of low-rise buildings, 30-min records would be adequate for codification purposes. However, in our opinion this issue should be further investigated by considering other statistics of fluctuating time histories.

Wind tunnel operators commonly conduct tests over periods longer than 1 h and recommend for design the largest peak recorded during those periods. To evaluate this practice we consider the largest peak of the 42-h Bochum record. We assume that the variability of this peak is negligible, that is, that largest peaks of 42-h records would differ little from record to record. For the 42-h record, the largest non-dimensional peak is 6.0; using the basic set of uncertainty parameters (Table 1), a coefficient of variation of the extreme speeds cov = 0.15, and the assumption that the reverse Weibull distribution is an appropriate model of the extreme wind speeds, we obtain LF = 1.50, instead of the value LF = 1.55 obtained by using the statistics for the 1-h record, and $F_{pk}(N = 500, 0.90) = 914$ instead of 805. Using the statistics corresponding to a 42-h record instead of a 1-h record thus results in a reduction of the estimated load factor by about 3 percent. However, the estimate of $F_{pk}(N = 500, 0.90)$ increases by almost 15 percent. Adopting this larger value of $F_{pk}(N = 500, 0.90)$ would be unrealistically conservative, however, since powerful storms whose highest mean speeds may be assumed to be uniform over durations exceeding 15–60 min rarely occur in nature.

5. Estimates of load factors with and without consideration of knowledge uncertainties: sensitivity studies

5.1. Non-hurricane wind regions

Having investigated in Section 4 the role of the record length τ we assume throughout this section that $\tau = 1$ h. In addition, we assume that the sample size of the set of extreme wind speed data is $n = 40$, and that the averaging time of the recorded extreme wind speeds is $T = 3$ s.

Influence of coefficient of variation of the extreme wind speeds for non-hurricane winds assumed to have a *reverse Weibull distribution* with tail length parameter $\kappa = -0.2$, the load factor corresponding to a coefficient of variation cov = 0.15 of the sample of extreme wind data is LF = 1.55. For a cov = 0.12, the corresponding estimated load factor is LF = 1.5. If the extreme wind speeds are assumed to be best fitted by *an Extreme Value Type I distribution*, the respective values are LF = 1.9 and LF = 1.8. Henceforth, we list in this section only load factors for cov = 0.15.

Influence of variabilities associated with (1) testing in different wind tunnels, (2) wind tunnel testing versus full-scale testing, (3) terrain roughness, (4) observation errors, (5) conversion of aerodynamic pressures into structural effects, (6) and conversion from wind speed averaged over interval T to mean hourly, 30, or 20-min wind speeds. Results on calculations based on various values of the standard deviations of the uncertainty parameters listed in Table 1 are shown in Table 2. In all calculations, the sampling errors in the estimation of extreme wind speeds were taken into account by assuming the sample size to be $n = 40$. We noted earlier that the calculations were performed by assuming the terrain roughness lengths to be $z_o = 0.07$ m, $z_{o1} = 1.00$ m. In addition, we performed calculations, in which, we assumed $z_o = 0.05$ m, $z_{o1} = 1.00$ m, and $z_o = 0.05$ m, $z_{o1} = 0.35$ m, and $z_o = 0.07$ m, $z_{o1} = 0.35$ m. While, as expected, the influence of these assumptions on the 50 and 500-yr load estimates can be significant, the influence on the load factors was found to be negligible (about 1%).

Additional information on the effect of various uncertainties is contained in Table 2.

Table 2 shows, for example, that if all variabilities of the uncertainty parameters listed in Table 1 are zero, rather than having the values of Table 1, assuming the wind speeds have a reverse Weibull distribution, the load factor is LF = 1.36 (case 2), rather than LF = 1.54 (case 1), and the estimate of $F_{pk}(500, 0.90)$ is 698, rather than 805. (Assuming the wind speeds have an Extreme Value Type I distribution, the load factor is LF = 1.75, rather than LF = 1.90). We conclude that neglecting all these uncertainties, as has been done for the development of load factors in the ASCE 7-98 Standard, would be inappropriate.

Table 2 also shows that, if instead of the variabilities listed in Table 1, we use variabilities augmented by 50 percent with respect to those of Table 1, the load factors increase by about 10 percent for the reverse Weibull case, and slightly less for the Extreme Value Type I case (case 3).

The influence of changing individual, pairs of, and three variabilities is also shown in Table 2. We note that, according to Table 2, the single most important variability among those listed in Table 1 is the variability of the ratio r between

Table 2
Calculated values of load factor LF corresponding to various sets of uncertainty parameters *a*, *b*, *c*, *s*, *u*, *q*, *r*. (The symbols sa,sb,sc,sq,sr,ss,su used in the first column of the table denote standard deviations of the variates *a*, *b*, *c*, *q*, *r*, *s*, *u*, respectively)

	LF(RW)	LF(EV1)	F_{pk}.9-500 (RW)	F_{pk}.9-500 (EV1)
1. Basic set (see Table 1)	1.54	1.9	805	1084
2. sa = sb = sc = su = sq = sr = ss = 0	1.36	1.75	698	983
3. Basic set increased by 50%	1.69	2.06	896	1198
4. sa = sb = sc = su = sq = ss = 0; sr = 0.05	1.48	1.85	767	1044
5. sa = sb = sc = sq = sr = su = 0; ss = 0.1	1.39	1.76	718	995
6. sa = sb = sc = su = sq = 0; sr = 0.05, ss = 0.1	1.51	1.86	784	1059
7. sa = sb = sc = sq = sr = 0; ss = su = 0.1	1.37	1.75	703	981
8. sa = sb = sc = sq = 0; su = ss = 0.1	1.41	1.77	725	1000
9. Basic set, except ss = 0	1.52	1.87	790	1062
10. Basic set, except su = 0	1.53	1.89	800	1084
11. Basic set, except sq = 0	1.54	1.89	801	1081
12. Basic set, except sr = 0	1.44	1.81	746	1028
13. Basic set, except ss = su = 0	1.51	1.87	785	1068
14. Basic set, except ss = sr = 0	1.42	1.79	730	1012
15. Basic set, except sa = sb = sc = 0	1.54	1.89	798	1078
16. Basic set, except sr = 0.025	1.45	1.82	756	1040
17. Basic set except su = 0.2	1.54	1.91	803	1093
18. Basic set except ss = 0.2	1.59	1.96	848	1141

the peak 3-s gust speed and the corresponding mean hourly speed (cases 12 and 16 versus case 1). We also note that the influence of the terrain roughness upwind of our low-rise structure is modest (cases 9 and 18 versus case 1). According to our results, it appears that seeking the greatest possible precision in the determination of that roughness may not be worthwhile from a designer's viewpoint. This is even more so the case for the terrain roughness at the meteorological site (cases 10 and 17 versus case 1).

5.2. Hurricane wind regions

Results of calculations on the influence of uncertainties affecting the estimation of load factors and of extreme wind speeds for hurricane winds are summarized in Table 3.

Table 3
Estimated load factors LF for various wind speed thresholds under consideration of various types of errors

Threshold (m/s)	Clim. error[a]	Sampl. Error	suh[b]	Basic errors[c]	LF
19.4	y	y	0.05	y	2.14
19.4	y	y	0	n	1.99
19.4	n	y	0.05	y	1.96
19.4	n	y	0	n	1.65
19.4	y	n	0.05	y	2.13
19.4	y	n	0	n	1.98
19.4	n	n	0.05	y	1.96
19.4	n	n	0	n	1.64
27.2	n	y	0	n	1.7
27.2	n	n	0	n	1.69

[a] See Section 2.4 following Eq. (10)
[b] suh = standard deviation of parameter u_H, see Eq. (2).
[c] y indicates that all the errors from the basic set (Table 1) are accounted for; n indicates that all those errors are disregarded.

Note in Table 3 that if the basic set of parameters is taken into account the load factor is LF = 2.14, whereas if those parameters are disregarded LF = 1.99. This suggests that the ASCE 7-98 failure to account for those parameters appears to be in need of correction. According to Table 3, the contribution to the sampling errors due to the uncertainty with respect to the climatological parameters (i.e. to the limited number of data on the basis of which hurricane wind speeds are simulated) is also significant. If this uncertainty is taken into account, the basic set of parameters yields a load factor LF = 2.14; if it is disregarded, that same set yields LF = 1.96. Because the number of simulated wind speed data used in the analysis is relatively large, the contribution of the sampling errors associated with the wind speed sample size is negligible. Therefore, it appears that simulating large numbers of data (e.g. 10,000), rather than, say, about 1000 (as in Refs. [5,10]) has limited, if any, usefulness for practical purposes. Finally, we note that the dependence of the load factors upon the wind speed threshold is weak (about 3% for the cases of Table 3; similar results were obtained for other cases).

6. Future research

To complement the research reported in this paper the following research topics are suggested:

1. The development of a catalog of estimates of the mean and standard deviation of the peak C_{pk}. A possible approach to this task is to simulate time series with typical marginal distributions and spectral densities, and obtain the requisite statistics on peaks from the time series.
2. Accounting for directionality effects. Recent research

(Rigato et al. [4]) has shown that the directionality reduction factor C_{dir}, that is, the ratio between wind effects with a mean recurrence interval N estimated by taking wind direction into account, and wind effects with a nominal mean recurrence interval N estimated without accounting for wind direction, increases as N increases. For example, for $N = 50$ yr, it is reasonable to assume $C_{dir} = 0.85$. However, for $N = 500$ yr, the value of the reduction factor can be $C_{dir} = 0.95$. This variation is not currently accounted for in the ASCE 7-98 Standard.
3. Estimating probability distributions of wind effects covering very long mean recurrence intervals. This can be achieved by using the computer program developed for this paper. The availability of such distributions will make it possible to estimate failure probabilities for structures with nonlinear behavior, including structures close to the collapse limit state.

7. Conclusions

In this paper we presented a probabilistic framework for the estimation of load factors that accounts for knowledge uncertainties. Our estimates showed that reasonable assumptions and estimation procedures lead to load factors LF $\approx$ 1.55, which are comparable to those validated by experience for regions not subjected to hurricanes. These load factors may be reduced for wind directionality effects, which remain to be incorporated in the calculations. Load factors for hurricane-prone regions should be considerably larger, that is, LF $\approx$ 2.15, again before reduction for wind directionality effects. These values are tentative, and their use would depend upon consensus on the appropriate descriptions of the uncertainty parameters used in the calculations.

It was assumed throughout the paper that the quantities involved in the calculation of wind effects are estimated on the basis of sound information, for example, information obtained from wind tunnels that meet standard performance criteria, and calibrated against dependable full-scale test results; or information obtained from certified weather stations. Gross errors or information based on substandard sources of information are not accounted for in our uncertainty model.

Based on the calculations presented in the paper, we conclude that:

1. Parameter uncertainties that are neglected in the ASCE 7-98 Standard can contribute significantly to the estimated magnitude of the load factor.
2. Estimates of load factors for hurricane winds must account for sampling errors in the estimation of climatological parameters such as pressure defect, radius of maximum hurricane wind speeds, and hurricane translation velocity, which are used in Monte Carlo simulations on which current estimates of hurricane wind speeds are based. These errors far outweigh errors due to the limited size of the simulated hurricane wind speed data sets.
3. Earlier estimates of load factors and reliability indexes, according to which structures calculated in accordance with conventional standard provisions are less reliable under wind than under gravity loads, depended upon the assumption that extreme wind speed distributions have infinitely long tails. Recent statistical analyses of extreme wind speeds strongly suggest that this assumption is not warranted, and that extreme wind speeds are better modeled by reverse Weibull distributions of the largest values, which have finite upper tails. The use of this distribution in lieu of the Extreme Value Type I distribution results in a considerable reduction of the magnitude of the estimated load factor corresponding to a nominal 500-yr wind effect, and helps to bring in line reliabilities (safety indices, load factors) under wind loads and under gravity loads.
4. For any given mean and standard deviation of the peaks of the wind effect fluctuations, the assumed probability distribution of the peaks appears to have a negligible effect upon the overall estimated wind effects.
5. For low-rise buildings, increasing wind tunnel pressure record lengths beyond 20 or 30 min to obtain better estimates of peaks does not appear to improve significantly estimates of overall wind effects.

The computer programs used in this work are to be assembled and made public by NIST and the Department of Civil Engineering, Texas Tech University.

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