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Discussion

Discussion of “Revisiting moment-based characterisation for wind pressures” by G. Huang, Y. Luo, K.R. Gurley and J. Ding

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1. Introduction

The paper by Huang et al. (2016) (HLGD) is the latest in a series of papers promoting the Hermite polynomial model (HPM) to transform non-Gaussian data into a Gaussian process so that the Davenport peak factor method can be used to estimate peak wind pressures of a given risk. HLGD revisits the theory given the earlier paper by Yang et al. (2013) (YGP), then compares the HPM method against the standard Gaussian process using a set of research-quality long-duration pressure coefficient (*Cp*) data from the University of Western Ontario (UWO). HLGD conclude that the HPM method performed well as a whole, but not for *Cp* outside of its effective region, and even underperformed in some cases within the effective region. What HLGD did not do was calibrate HPM-Davenport against direct extreme-value analysis (EVA) methods.

This discussion contribution includes a calibration the HPM-Davenport method against direct EVA using high-quality *Cp* data from the same source as HLGD. It investigates the various problems associated with the HPM-Davenport method and shows that it will perform poorly more often than has been admitted, and that is not possible to determine when it will perform poorly without additional analysis. Issues with direct EVA methods are also discussed. Finally it will be shown that XIMIS – an alternative method that operates on the upper tail of the distribution of local peaks, instead of the parent distribution of all values – avoids all the problems evident in both HPM-Davenport and EVA methods and is efficient and economical to implement.

2. Supporting data

The data supporting this discussion are from two taps in the same series of tests at UWO as the data used by HLGD. Fig. 1 shows the location of these two taps and the wind direction: Tap A corresponds to the permanently separated-flow region behind the ridge in the gable corner, while Tap B corresponds to a generally attached flow region with transient separations. The pressure coefficient data had been sampled at 40 Hz for 30 h, equivalent full-scale, giving 4,320,000 values for each tap. The extreme length of these data makes them particularly suitable for calibrating analysis methods. The relevant overall statistics computed from the data are given in Table 1. The first four parameters are required to implement HPM, while the mean crossing rate (MCR) is required to implement the Davenport peak factor method.

3. Direct extreme-value-analysis

The datum 78% percentile of the distribution of peak values corresponds to the reduced variate $y=1.4$ and stems from the simplified Cook-Mayne method (Cook and Mayne, 1980) which accounts for the joint statistics of wind speed and pressure coefficient. (Note that the value $y=1.4$ was derived for the wind climate of the UK and may not be suitable for other climates.) This methodology demands that the datum epoch, T, for the peak *Cp* is matched to the averaging time of the design wind speed: e.g. hourly-max/min *Cp* with hourly-mean wind speeds. Economy in wind tunnel testing demands that the epoch is as short as possible while still encompassing the full spectrum of the simulated ABL turbulence, thus the minimum epoch is typically equivalent to ten minutes at full scale, and this is the value adopted by HLGD. A characteristic of the FT1 distribution is that extremes measured for one epoch may be translated to another epoch by applying the

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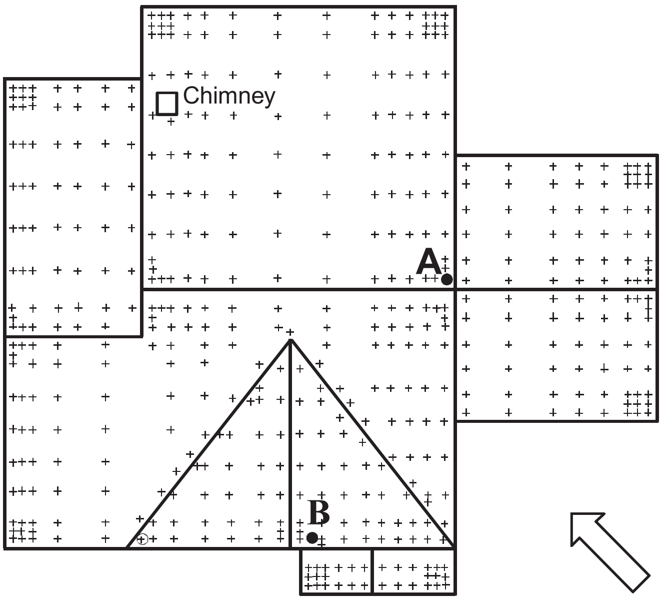

Fig. 1. Location of taps and wind direction.

Table 1
Overall statistics of supporting data.

	Tap A	Tap B
Mean	−1.69	−0.286
StdDev	0.899	0.312
Skew	−1.34	−2.27
Kurtosis	5.68	15.57
MCR	8176 h^{-1}	11,528 h^{-1}

"Poisson shift", $\Delta y = \ln(T_1/T_2)$, so that 10 min extremes are translated to 1 h extremes using $\Delta y = \ln(6)$, as in the previous calibration exercise of Cook (1982b). Economy also demands the smallest number of extremes consistent with the desired accuracy and the extremes from 16 ten-minute epochs is typical in commercial wind tunnel tests, corresponding to 160 min equivalent full scale. Following the procedure adopted by HLGD, the UWO data was split into 180 ten-minute segments, permitting EVA analysis of one trial of 30 one-hour extremes, one trial of 180 ten-minute extremes, and 11 independent trials of 16 ten-minute extremes: the latter simulating a typical commercial test repeated 11 times.

Fig. 2 displays the fits for the two single-trial cases for both taps: a least-mean-square fit on Gumbel axes using the Gringorten plotting positions to eliminate bias errors (Cook and Harris, 2003).

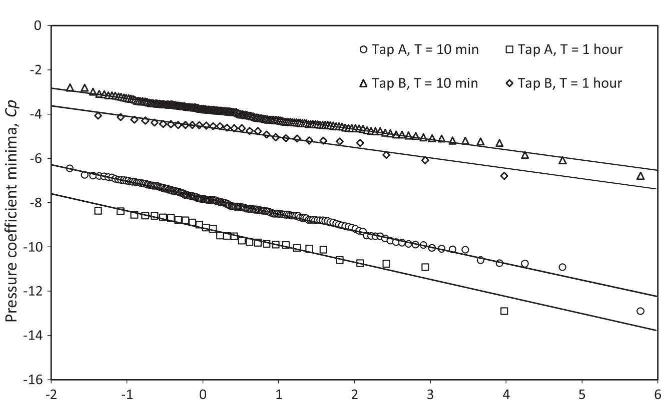

Fig. 2. Direct extreme-value analysis of hourly-maximum peak suctions on Gumbel axes.

It is clear that the 10 min epoch is sufficient to achieve good convergence to the FT1 distribution as, for each tap, the fitted straight line lies parallel to the 1 h epoch, separated by $\Delta y = \ln(6)$. To allow direct comparison between methods, the datum epoch of $T = 1$ h is used to report results, with values obtained at other epochs Poisson-shifted to this datum value. Results are given in Table 2 for: case (a) 11 trials of $N = 16$ epochs of $T = 10$ min; (b) 1 trial of $N = 180$ epochs of $T = 10$ min; and (c) 1 trial of $N = 30$ epochs of $T = 1$ h. Cases (b) and (c) correspond to Fig. 2.

Fig. 3 displays the ensemble average and standard deviation of 11 trials for Tap A using 16 ten-minute epochs – case (a). A single of trial of case (a) corresponds to typical commercial practice and require 96 s of data at 1/100 time scale. The principal reasons that this case is optimal are that: 16 is the minimum number of epochs for a reliable Gumbel (1958) analysis; ten minutes is the shortest epoch that encloses the micro-meteorological wind spectrum; and the design value of $y = 1.4$ lies just within the data range so that no extrapolation is needed.

4. Hermite polynomial method

The HPM transformation method is attributed to Winterstein (1988) who proposed it to impose orthogonality on the components of narrow-band processes. The Hermite polynomials, H_n, are no "magic bullet": they merely relate the standard Normal distribution, $\phi\{x\}$, to its derivatives, $\phi^{(n)}\{x\}$:

$$\phi^{(n)}\{x\} = (-1)^n H_n \phi\{x\} \tag{1}$$

which is possible because of the persistence of the exponential term in $\phi\{x\}$ when differentiated. Hence HPM is merely a Taylor series expansion about the mean, truncated after the fourth term, where the coefficients are determined directly from the first four overall moments: in practice, from the mean, standard deviation, skewness and kurtosis. Here, where the concern is to define the 78% percentile of the extreme distribution, which lies well into the tails of the parent distribution, four terms may not be sufficient. But including higher terms results in transformations which may not have unique closed-form inversions. Hence, the claim that only the first four moments are required to implement HPM makes a virtue out of a necessity. An additional issue is that surface pressures are broad-band, not narrow-band and this has implications for the later application of the Davenport peak factor method. The HPM coefficients h_3 and h_4 in HLGD, c_3 and c_4 in YGP, are determined by solving a pair of non-linear equations (YGP, Eqs. (7) and (8)). The skew and kurtosis of both Taps A and B, lie outside the zone of validity and the resulting values fail the Choi and Sweetman test (HLGD, Eq. (20)). Implementation of the HPM equations with these values leads to square-root of negative value errors. The papers promoting HPM fudge this issue by adjusting the values of skew and kurtosis onto the boundary of the valid zone. YGP's approximation formulas (YGP, Eqs. (11) and (12)) include this fudge, so the corresponding HPM coefficients are valid for both taps. However, as is seen in Fig. 4, the resulting HPM model denoted by "HPM YGP" is a very poor fit for both taps. In these circumstances Ding and Chen (2014) advocate an empirical fit to the PDF in order to represent the tails more accurately. So as to preserve the HPM form for comparison of the parameters, the coefficients h_3 and h_4 were optimised to give the best fit to the PDF in terms of the least-mean-square error in $\log(p)$ – that is, for the best linear fit on the semi-log axes of Fig. 4. This gives good representation of the tails, denoted by "HPM best fit", but not in the body. The HPM scaling factor, κ in Eq. (17) of HLGD, is needed to preserve unit variance of the Gaussian process – it is another fudge factor, but its value is indicative of the proportion of the data