AIAA-2003-0866

PROBABILISTIC ANALYSIS OF LIST DATA FOR THE ESTIMATION OF EXTREME DESIGN LOADS FOR WIND TURBINE COMPONENTS*†

M.D. Pandey
Department of Civil Engineering
University of Waterloo
Waterloo, ON N2L 3G1 Canada
mdpandey@uwaterloo.ca

H.J. Sutherland
Wind Energy Technology Department
Sandia National Laboratories‡
Albuquerque, NM 87185-0708 USA
hjsuthe@sandia.gov

ABSTRACT

Robust estimation of wind turbine design loads for service lifetimes of 30 to 50 years that are based on field measurements of a few days is a challenging problem. Estimating the long-term load distribution involves the integration of conditional distributions of extreme loads over the mean wind speed and turbulence intensity distributions. However, the accuracy of the statistical extrapolation is fairly sensitive to both model and sampling errors. Using measured inflow and structural data from the LIST program, this paper presents a comparative assessment of extreme loads using three distributions: namely, the Gumbel, Weibull and Generalized Extreme Value distributions. The paper uses L-moments, in place of traditional product moments, to reduce the sampling error. The paper discusses the application of extreme value theory and highlights its practical limitations. The proposed technique has the potential of improving estimates of the design loads for wind turbines.

INTRODUCTION

The design of wind turbines depends on the robust estimation of long-term extreme loads from limited records of load measurements [1, 2]. The accuracy of the statistical extrapolation techniques used to estimate extreme values is fairly sensitive to both model and sampling errors. Modeling errors originate from fitting data that form an inconsistent distribution, whereas sampling (or statistical) errors are due to insufficient data used in the estimation analysis. Minimizing modeling and statistical errors has become an active area of research in extreme value estimation.

The determination of long-term extreme load distributions involves the integration of conditional distributions of extreme loads over the mean wind speed and turbulence distribution [2]. In this technique, a conditional extreme distribution is modeled as a Gumbel distribution that is fitted to a sample of 10-min maximum values corresponding to a fixed range (bin) of the mean wind speed. The Gumbel distribution is fit to the data using the method-of-moments. This fitting technique utilizes the mean and standard deviation of the data. Since this approach ignores higher-order moments, the fit of the Gumbel model to realistic data can be inadequate, especially in the tail of the distribution.

To improve modeling of the tail of the distribution, higher-order (greater than 2) statistical moments, such as skewness and kurtosis, have been advocated in the literature [3]. In particular, cubic and quadratic polynomials of Weibull-distributed random variables have been proposed to preserve the first three and four moments of the data set, respectively. These moment-based probabilistic models are particularly susceptible to the large sampling uncertainty that is associated with higher-order moments estimated from limited data. It is well known that skewness and kurtosis estimated from small samples tend to be highly biased and uncertain [4, 5]. Obviously, poor estimates of the higher-order moments lead to erroneous predictions of extreme design values.

The Long Term Inflow and Structural Test (LIST) program [6] has collected a long-term inflow and structural response data set for a wind turbine. This program has provided 1017 records of loads, each of

*This work was partially funded by the U.S. Department of Energy under contract DE-AC04-94AL85000.

‡ Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin company

Fig. 1. The Micon 65/13M turbine at the Bushland Test Site.

which are 10-minutes in duration. The records were classified in seven wind speed classes according to the mean wind speed and then the extreme value of the root bending moment in the flapwise and edgewise directions were determined. These data are used here to illustrate three techniques for estimating long-term, extreme loads.

The first technique uses a Gumbel distribution that is based on the mean and standard deviation of the data, to predict extreme values. The analysis of the LIST data confirms that in many instances, the Gumbel distribution leads to a poor fit of the tail of the distribution [6], which reduces the accuracy of the estimated extreme loads.

The second technique is a new approach to the modeling of extreme value distribution. This technique uses a generalized (3-parameter) Gumbel model. For the technique presented here, L-moments are used to determine the distribution parameters rather than conventional statistical moments. L-moments are based on the linear combination of data, which is in sharp contrast to the determination technique for ordinary statistical moments. The linearity of L-moment estimates increases their accuracy over conventional estimates, because conventional estimates of higher-ordered moments suffer from the effects of sampling uncertainty and the bias that is created by the squaring, cubing, etc. the data [8]. Experience suggests that highly accurate estimates of higher-order L-moments (order ≈ 3-6) can be obtained from fairly small samples (size ≈ 20) [4, 5]. This paper presents the Generalized Extreme Value (GEV) technique that preserves skewness of data distribution by using three L-moments in the fitting method.

The third technique uses a 3-parameter Weibull distribution that also accounts for the skewness of data [9]. This modeling technique uses conventional statistical moments to account for skewness in the data.

Numerical results presented in the paper provide a basis to examine the usefulness of extreme value theory for design load estimation for wind turbines.

THE LIST DATA SET

The LIST turbine is a three-bladed Micon 65/13M wind turbine that is being tested at a USDA site located near Bushland, Texas. The site is representative of most Great Plains commercial sites. For a complete description of the turbine, its instrumentation and the site, see Sutherland, et al. [6, 7]. Sutherland [10, 11] has reported on other analyses of these data. A short description of the turbine and the measurement campaign is included here.

The LIST Turbine

The LIST turbine, see Fig. 1, is a Micon 65/13M, a fixed-pitch turbine with a 3-phase 480V asynchronous generator rated at 115kW. The generator operates at 1200 rpm while the blades turn at a fixed 55 rpm (the standard Micon 65/13 turbine rotates at a fixed 45 rpm). It has a rated wind speed of approximately 15 m/s.

The turbine is fitted with Phoenix 8m blades that are based on Solar Energy Research Institute (SERI)** airfoils. These "SERI" blades are 7.9 m (312 in) long and are equipped with tip brakes.

Data

From the LIST program, data are recorded and stored as 10-min segments. The experiment was being

** SERI is now the National Renewable Energy Laboratory (NREL).

monitored using a total of 60 sensors: 19 sensors measure structural response and 34 sensors to measure atmospheric conditions. A total of 1998 10-min records are available in this data set. For this analysis, a subset of the data, the records with mean wind speeds greater than 5 m/s (1017 10-min records), is considered. Figure 2 shows a distribution of the records, classified according to the mean, hub-height horizontal wind speed of each 10-min record.

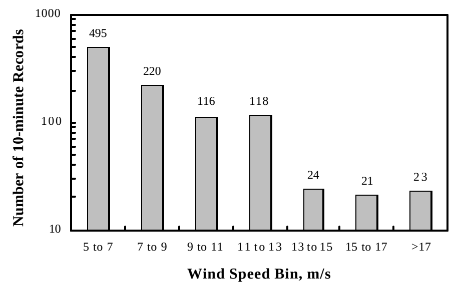

Fig 2. Distribution of the 10-min data records by hub-height mean wind speed.

Extreme Bending Loads

For this analysis, the extreme bending load, both in flap and edge bending, were extracted from each 10-min data record. These extremes were collected in various bins according to mean wind speed range. Statistical analysis of each sample of extreme loads was carried out, and results are presented in this paper.

PROBABILISTIC MODELS OF EXTREME LOAD

Basic Approach

The distribution of extreme loads that is conditional on the mean wind speed, denoted by $F(L|V)$, should be integrated over the probability density of mean wind speed, $f(V)$, to obtain an overall distribution $F(L)$:

$$F(L) = \int_V F(L\,|V)\,f(V)dV \quad . \qquad (1)$$

The dependence of extreme load on turbulence and other parameters can be handled in a similar way.

In the LIST data, mean wind speed is discretized into a total of 7 wind speed bins: six 2 m/s wide bins that range from 5 to 17 m/s and a seventh bin for wind speeds that exceeding 17 m/s. Therefore, 7 conditional distributions are required to be fitted to the load data. The selection of a representative conditional distribution of extreme loads, $F(L|V)$, is crucial from the point of view of minimizing the model error. The next section describes some possible candidates for this purpose.

Probabilistic Models

The Gumbel distribution is a classical model for extreme values that is characterized by an exponential tail. This distribution is the normal choice for modeling the distribution $F(L|V)$. The generic form of this distribution is given by:

$$F(x) = \exp[-e^{-y}] \quad , \qquad (2)$$

where y is the standardized variate given as

$$y = \left(\frac{x-u}{h}\right) \quad . \qquad (3)$$

Here, u and h denote the location and scale parameters, respectively. These parameters can be easily estimated from the method-of-moments using the mean and standard deviation of data. This form has been found suitable for modeling simulated values of extreme load [12].

The three-parameter Weibull distribution is more versatile then the Gumbel distribution, since it can incorporate the skewness of data. It is expressed as

$$F(x) = \exp[-y^k] \quad , \qquad (4)$$

where k is the shape parameter and y is defined in Eq.(3). The distribution parameters can be calculated by matching 3 moments of data: the mean, standard deviation and skewness. The shape parameter is calculated from a nonlinear function of skewness. Moriarty et al [9] applied this model to simulated load extremes and found that it predicted smaller design loads than those obtained from the Gumbel model.

This paper proposes a Generalized Extreme Value (GEV) distribution, which is a generalization of the Gumbel model. Similar to the Weibull model, it is capable of including the skewness of data. The distribution is given as:

$$F(x) = \exp[-e^{-z}] \text{ where } z = \frac{-1}{k}\log[1-ky] \quad . \qquad (5)$$

When the shape parameter $k = 0$, it reduces to the Gumbel distribution, Eq. (2). For positive values of the shape parameter ($k > 0$), the distribution has an upper bound value ($u + h/k$). There is no upper bound when $k < 0$; however, the distribution does have a lower bound of ($u + h/k$).

The GEV is an asymptotically correct distribution of extremes that are generated from a general non-exponential parent distribution. Therefore, this distribution is a conceptually correct model in the analysis of extreme load data. The distribution parameters are calculated from L-moments of data as discussed in the following section.

METHOD OF L-MOMENTS

Probability-Weighted Moments (PWMs)

Consider the definition of an i^{th} order statistical moment in terms of the density function, $f(x)$, and the quantile function, $x(p) = F^{-1}(p)$, as

$$E[X^i] = \int_R x^i f(x)dx = \int_0^1 [x(p)]^i dp \quad , \qquad (6)$$

where $dp=dF(x) = f(x)\ dx$. Note that $p=F(x)$ is a monotonic, strictly increasing, absolutely continuous and non-negative probability measure. The PWM of a random variable is defined as [8]:

$$b_m = \int_0^1 p^m x(p)dp \quad , \quad (m = 0, 1, . . . n) \quad . \qquad (7)$$

Alternatively, it can be defined in terms of the exceedance probability $q = (1 - p)$ as

$$a_m = \int_0^1 q^m x(q)dq \quad . \qquad (8)$$

Note that β_0 (= α_0) is the mean of the random variable.

A comparison of Eqs. (6) and (7) reveals that PWMs are essentially moments of the quantile function. The definition of PWMs involves only the linear combination of data, which contrasts with the definition of ordinary moments. Because of this linearity, the accuracy of PWM estimates suffers less from the effects of sampling uncertainty and bias. Highly accurate estimates of higher-order PWMs (order ≈ 4-6) can be obtained from fairly small samples (size ≈ 20) [4, 5].

An interesting property of β_k (or α_k) is that they are directly related to the average of the maximum (or minimum) values in a sample of size k. Using this property along with simple combinatorial arguments, Landwehr et al. [13] derived their unbiased estimates, b_k (maxima) and a_k (minima), respectively, as

$$b_k = \frac{1}{n}\sum_{i=1}^{n}\binom{i-1}{k}X_{i,n}\Bigg/\binom{n-1}{k} \quad , \text{ and}$$

$$a_k = \frac{1}{n}\sum_{i=1}^{n}\binom{n-i}{k}X_{i,n}\Bigg/\binom{n-1}{k} \quad . \qquad (9)$$

Note the definition $\binom{n}{r} = \frac{n!}{r!(n-r)!}$ and $X_{i,,n}$ denotes an i^{th} order statistics in a sample of size n.

L-Moments

Hosking [8] showed that certain linear combinations of PWMs, referred to as L-moments, can provide valid measures of dispersion, skewness and kurtosis analogous to ordinary moments. For example, measures of mean (λ_1), dispersion (λ_2) and third moment (λ_3) can be written as

$$l_1 = a_0, \qquad l_2 = a_0 - 2a_1$$

$$l_3 = a_0 - 6a_1 - 6a_2 \qquad (10)$$

The L-skewness is defined as l_3 / l_2, and l_2 / l_1 is analogous to the coefficient of variation. The "L" in L-moments emphasizes that it is constructed from a Linear combination of ordered data. The dispersion, λ_2, is denoted by L2 in this paper. An interesting property of L-skewness is that it is bounded between ±1.

In recent years, the use of L-moments (or PWMs) for parameter estimation has become very popular in hydrology and water resources engineering. L-moments and PWMs are synonymous in a practical sense, since they are uniquely related to each other.

Parameters of GEV Distribution

The first three L-moments of a GEV distribution in terms of its location (u), scale (h) and shape (k) parameters are given as [14]

$$l_1 = u + \frac{h}{k}\left[1 - \Gamma(1+k)\right] \qquad (11)$$

$$l_2 = (1 - 2^{-k})\frac{h}{k}\Gamma(1+k) \qquad (12)$$

$$\frac{l_3}{l_2} = t_3 = 2\frac{(1-3^{-k})}{(1-2^{-k})} - 3 \qquad (13)$$

Note that $\Gamma(x)$ denotes the Gamma function. By inverting these equations, the distribution parameters can be calculated directly. Hosking has proposed the following simple approximation for calculating the shape parameter:

$$k = 7.859c + 2.9554c^2 \text{ and } c = \frac{2}{3+t_3} - \frac{\log 2}{\log 3} \qquad (14)$$

The results of this approximation are in error less than 9×10^{-4} for L-skewness values within ±0.5. The other parameters can then be calculated as

$$h = \frac{l_2 k}{\Gamma(1+k)(1-2^{-k})} \qquad (15)$$

$$u = l_1 - \frac{h}{k}\left(1 - \Gamma(1+k)\right) \qquad (16)$$

The statistical accuracy of the method of L-moments is superior to other conventional methods of moments, maximum likelihood and the least squares, as demonstrated by Hosking et al. [14] through extensive simulations. For this reason, the use of this method to analyze LIST data is particularly important because sample size in high-speed bins (> 13 m/s) is fairly small which can amplify the sampling error.

RESULTS AND DISCUSSION

Probabilistic Characteristics of Data

Loads acting on turbine components are sensitive to wide ranging aerodynamic parameters among which the effects of mean wind speed and turbulence are predominant. To understand the influence of wind speed and turbulence on probabilistic characteristics of extreme loads, variations of their statistical moments and L-moments are studied here.

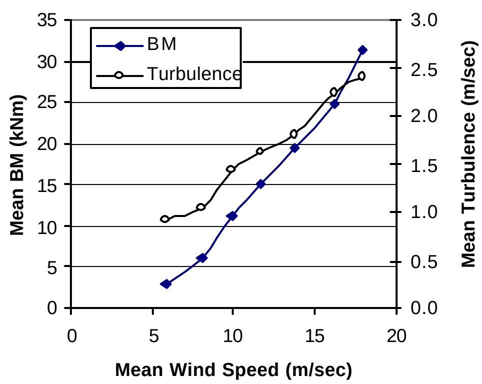

Figure 3. Mean flap bending moment versus wind speed and turbulence intensity.

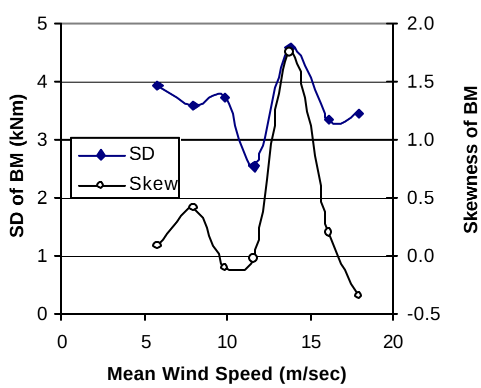

Figure 4. SD and skewness of flap BM versus mean wind speed.

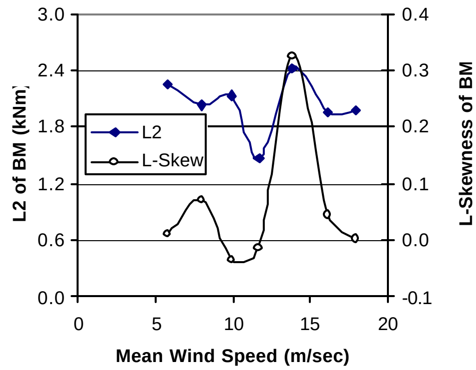

Figure 5. L2 and L-skewness of flap BM versus mean wind speed.

Flap Bending Moment

As shown in Fig. 3, both the mean of the flap bending moment (BM) and the turbulence increase almost linearly with mean wind speed. However, the variation of standard deviation (SD) and skewness of BM with mean wind speed is irregular, as shown in Fig. 4. Both the SD and skewness peak in the 13-15 m/s wind speed bin.

The L-dispersion (L2) and L-skewness also exhibit qualitatively similar trends in Fig. 5.

The probabilistic characteristics of the distribution of turbulence can have a strong influence over the extreme bending moment. To explore this point, the dispersion (L2) of BM and turbulence are plotted against mean speed in Fig. 6. Both curves are remarkably similar in shape. For example, both curves dip in the 11-13m/s bin at and sharply rise in the 13-15 m/s bin.

Figure 7 illustrates the relationship of the L-skewness of the flap BM to the L-skewness of the turbulence.

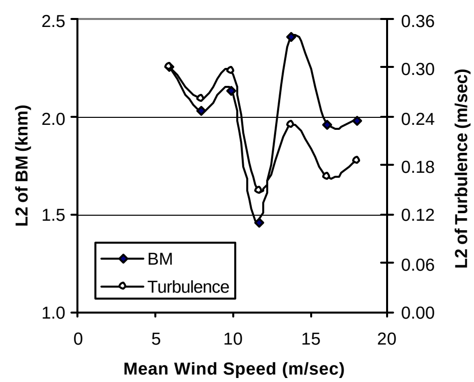

Figure 6. L2 of flap BM and turbulence versus mean wind speed.

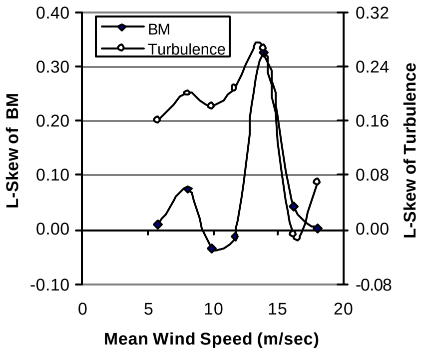

Figure 7. L-skewness of flap BM and turbulence versus mean wind speed.

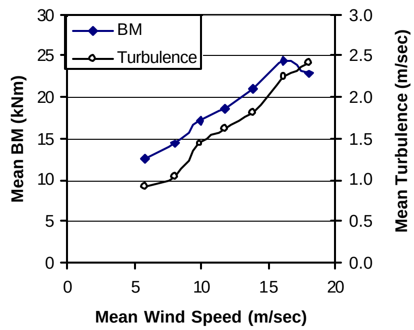

Figure 8. Mean edge BM ve rsus wind speed and turbulence.

The skewness of BM peaks in the 13-15 m/s bin, which also coincides with the peak in turbulence curve. A sharp decline in skewness of bending moment in the 15-17 m/s bin is consistent with the turbulence curve. It is evident that the dispersion and skewness of the extreme flap bending moment distribution are dependent on the respective properties of the turbulence distribution. This observation also confirms the results of an earlier simulation-based study [9].

Edge Bending Moment

Figures 8 through 11 present the variation of statistical properties of edge BM with mean speed and turbulence. The mean of both edge BM and turbulence increases with speed (Fig. 8). However, L2 and L-skewness of BM fluctuate considerably with speed (Fig. 9). Sharp peaks in dispersion and skewness plots for 13-15 m/s bin are noteworthy (Fig. 9).

Dispersion and skewness of edge BM are plotted along with that of turbulence in Figs. 10 and 11, respectively. Both parameters are strongly influenced by variation in turbulence properties. The dependence of edge BM on

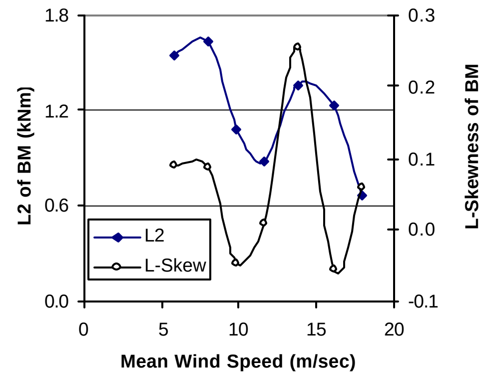

Figure 9. L-dispersion and L-skewness of edge BM versus mean wind speed.

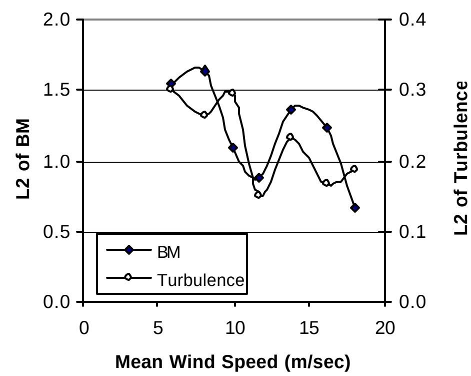

Figure 10. L-dispersion of edge BM and turbulence versus mean wind speed.

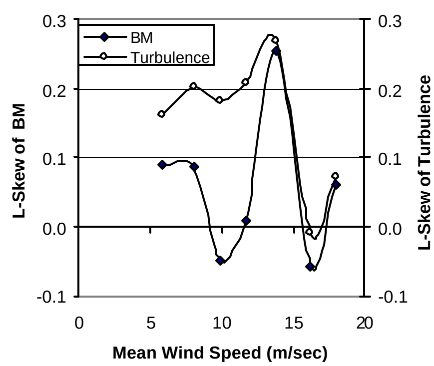

Figure 11. L-skewness of edge BM and turbulence versus mean wind speed.

turbulence is qualitatively similar to that of flap BM as shown previously.

Distributions of Extreme Flap Bending Moment

The Gumbel, Weibull and GEV models are fitted to maximum flap bending moment data, and results for the 7 wind speed bins are presented in Figs. 12 through

18. In all the figures, the Gumbel variate, –Log[–LogF(x)], is plotted on the vertical Y-axis against the bending moment on the X-axis. In this coordinate system, the Gumbel distribution plots as a straight line.

In general, GEV and Weibull models provide better fit than the Gumbel model, since they can incorporate the curvature of empirical (observed data) distribution. In most cases, the Gumbel model has a tendency to predict a larger design value, because it has a longer distribution tail than the Weibull or GEV distributions.

The shape parameter of the proposed GEV model is generally positive indicating that the extreme BM distribution has an upper bound (see Eq.5).

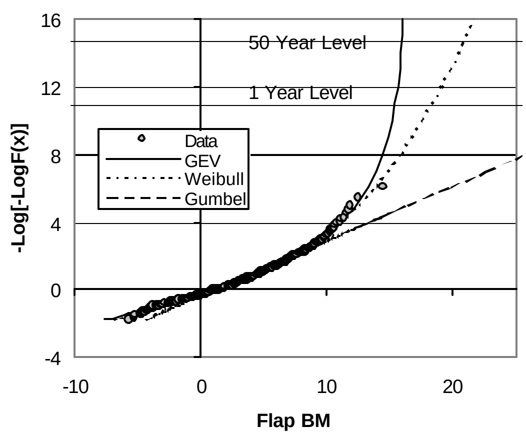

Figure 12. Probability distributions of flap BM for wind speed range of 5 – 7 m/s.

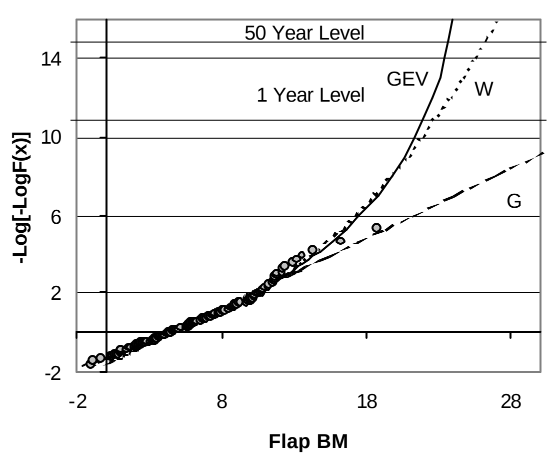

Figure 13. Probability distributions of flap BM for wind speed range of 7 – 9 m/s (W=Weibull, G=Gumbel).

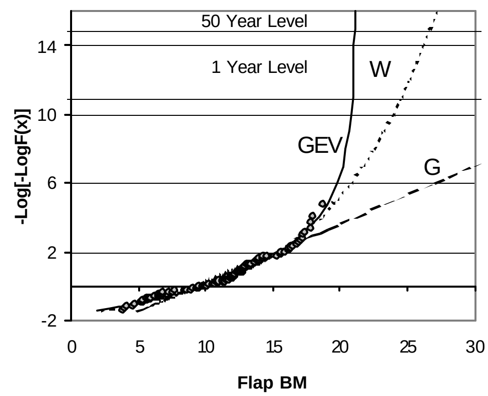

Figure 14. Probability distributions of flap BM for wind speed range of 9 – 11 m/s.

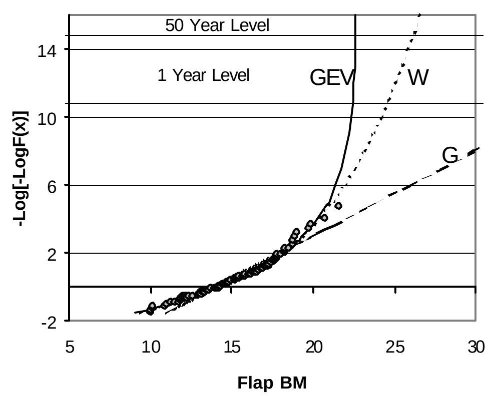

Figure 15. Probability distributions of flap BM for wind speed range of 11 – 13 m/s.

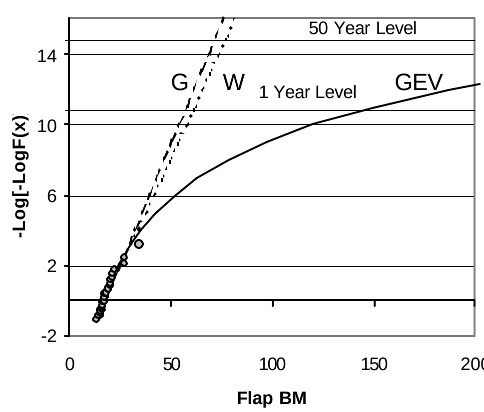

Figure 16. Probability distributions of flap BM for wind speed range of 13 – 15 m/s.

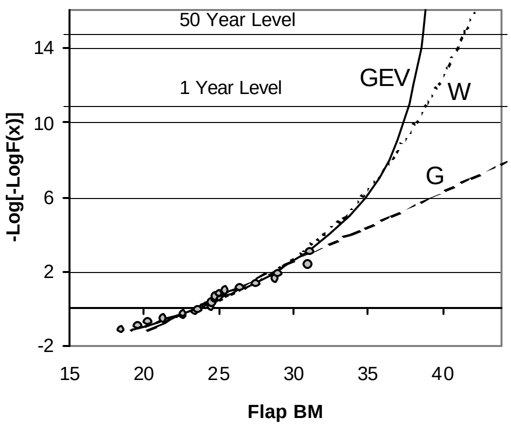

Figure 17. Distributions of flap BM for wind speed range of 15 – 17 m/s.

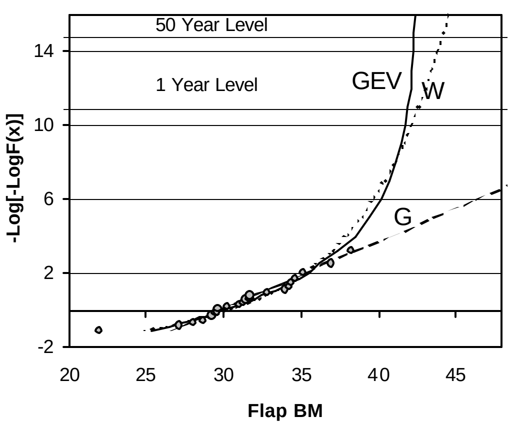

Figure 18. Distributions of flap BM for wind speed exceeding 17 m/s.

General Observations

In all the samples analyzed here, most of the data points are crowded near the sample mean, and only a few extremes are observed far beyond the mean value. This is reflected by fairly small values of skewness as shown in Fig. 5. As a result, the GEV fits lower sample values quite well, but its tail exhibits a sharp curvature that in some cases poorly fits the upper sample extremes, such as the cases shown in Figs. 12 and 13. This sharp curvature is also an indication of the fact that samples are not sufficiently large to ensure an asymptotic convergence of extreme values to GEV distribution. The Weibull tail is somewhat less sensitive to the irregularly spaced sample values. The goodness of fit can be improved by fitting GEV and the Weibull models to data chosen using threshold criteria.

The Weibull distribution, unlike GEV, has unbounded upper tail in all the cases. The tail length is mostly shorter than the Gumbel distribution, and it is inversely related with the shape parameter. The Weibull shape parameter is the smallest ($k=1$, exponential tail) for 13-15 m/s bin, which implies the longest tail among the set of 7 bin distributions. The shortest tail (k = 5.7) is seen for the last bin (speed > 17 m/s). The Weibull model predicts larger 50-year design values than the GEV model with the exception of 13-15 m/s bin (Fig. 16).

13-15 m/s Wind Speed Bin

An exception to the bounded GEV tail is seen in Fig. 16. In this case, skewness of data is very large, see Figs. 4 and 5, which results in a negative shape parameter and long distribution tail without an upper bound. The reason for an exceptionally large value of skewness can be understood by examining the data. This bin (13-15 m/s) consists of 24 observations of flap BM ranging from 13.7 to 34.4 kN-m with an average of 19.5 kN-m and a standard deviation of 4.6 kNm. The highest observation exceeds the mean value over 3 times the standard deviation. The other two prominent extremes are 27.33 and 27.37 kNm, and remaining 21 values range from 14 to 22 kN-m. The highest value, 34.4 kN-m, in a small sample results in a drastic increase of skewness that in turn increases the GEV shape parameter.

The large tail of GEV is a manifestation of sampling uncertainty resulting from large skewness observed in a small sample. Because of this GEV assigns higher probabilities of occurrence to larger extremes, whereas Weibull model provides extrapolation in line with lower sample values.

Distribution of Extreme Edge Bending Moment

The selected numerical results presented in Figs. 19 through 23 for edge BM distribution are largely similar in nature to those for flap BM. Namely, the crowding of the data near the sample mean implies that GEV fits lower sample value quite well, but its tail exhibits a sharp curvature that in some cases poorly fits the upper sample extremes. This is readily obvious in Fig. 21 when the predicted 50-year extreme is less than the observed maximum extreme.

The Weibull model is close to GEV in many instances. The use of the Gumbel model is likely to predict larger design loads. Once again in the case of 13-15 m/s, the GEV has an unbounded tail resulting from the relatively large skewness in the data.

The 13-15 m/s Bin

For both the flap and edge BM in the 13-15 m/s wind speed bin, the predicted 50 year extreme is physically

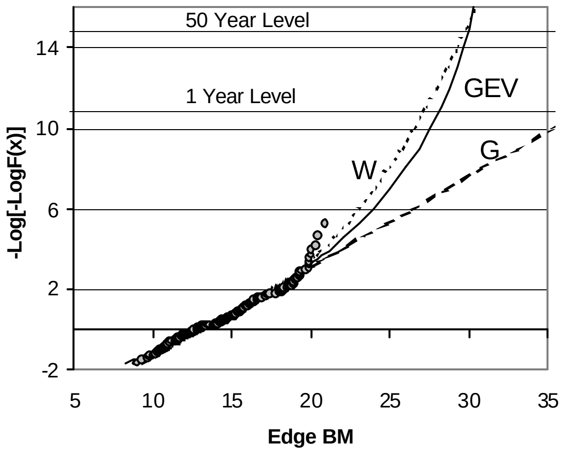

Figure 19. Distributions of edge BM for wind speed range of 7 – 9 m/s.

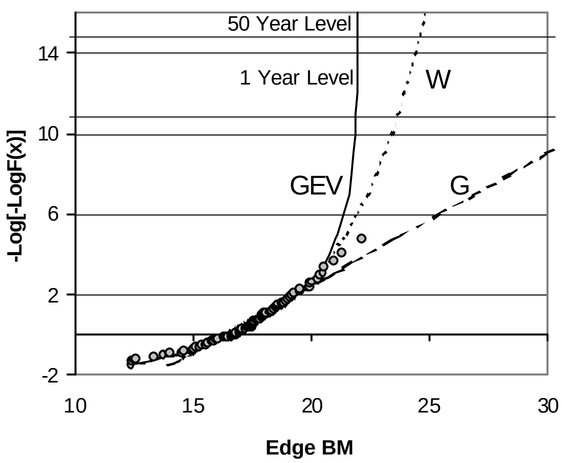

Figure 20. Distributions of edge BM for wind speed range of 9 – 11 m/s.

unrealistic. Namely, for the flap BM, the 50-year extreme predicted for the 13-15 bin is approximately an order-of-magnitude larger than any of the other 50-year extreme predictions. For edge BM, the prediction is approximately 3 times larger.

As discussed above, these extremely large predictions are based on 2 data points that deviated significantly from the other data. The first question that arises is whether or not these points are real. A close examination of the original time series data indicates that these data points are not the result of anomalies in the data collection system. Moreover, these data points are consistent with data contained in the 15-17 m/s bin. Thus, the fitting process must consider these two data points.

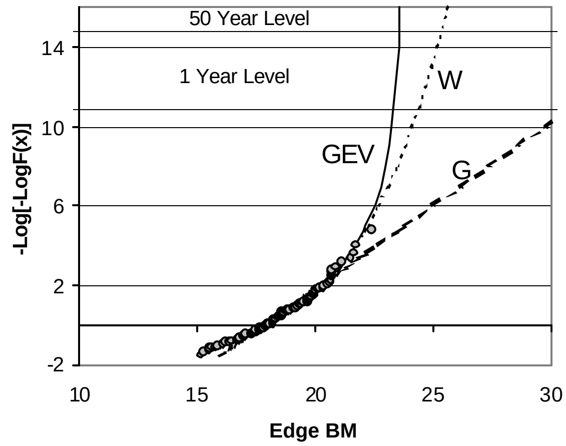

Figure 21. Distributions of edge BM for wind speed range of 11 – 13 m/s.

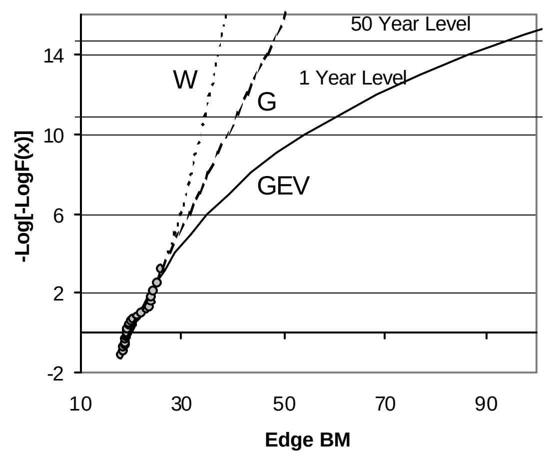

Figure 22. Distributions of edge BM for wind speed range of 13 – 15 m/s.

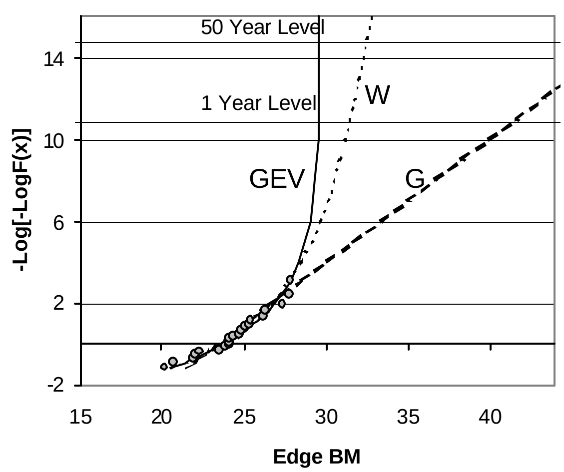

Figure 23. Distributions of edge BM for wind speed range of 15 – 17 m/s.

The high skewness in these data may be a result of the changing turbine aerodynamics as the inflow approaches the rated wind speed of the turbine. The rated wind speed for this turbine is approximately 15 m/s. Thus, with this stall-regulated turbine, the turbine blades will be going into and out of stall in this wind speed bin. The choice of 2 m/s wind speed bins (at even intervals) has probably resulting in a "modeling" error that yields an inconsistent distribution of the data. Maybe the bins should have been chosen based on the rated wind speed. Indeed, when the data are divided into only two bins, see Figs. 24 and 25, the anomaly is no longer present. For these two figures, the data was divided at 13 m/s to insure that all of the stalled-blade data was contained in a single fit.

Finally, the anomaly may be a result of the technique used for choosing the extreme from the time series data. For this analysis, only one extreme is taken from each 10-min record. This is in contrast to the technique used by Moriarty, et al [9] where multiple extremes (peak-over-threshold method) are taken from each 10-min record. Their technique provides significantly more extremes from a given data set, and, thereby, provides "better" measure of the statistical variables. Thus, our choice has probably resulted in a "sampling" (or statistical) error that is due to insufficient data.

Thus the application of the GEV technique to wind turbine loads is still a work in progress. The techniques for the choosing extremes from time series data and for dividing the data into wind speed bins have yet to refined to the point where the GEV will yield consistent, robust predictions.

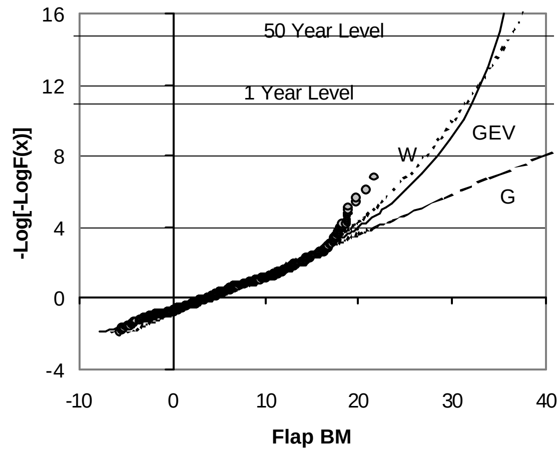

Figure 24. Distribution of flap BM for mean wind speeds below 13 m/sec.

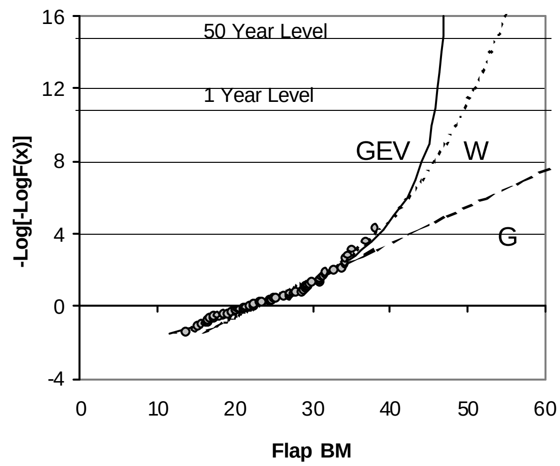

Figure 25. Distribution of flap BM for mean wind speeds above 13 m/sec.

CONCLUSIONS

The paper examines the application of extreme value distribution theory to the modeling of extreme flap and edge bending moment. The classical Gumbel and its generalized form, Generalized Extreme Value (GEV), are fitted to the data. A new method of L-moment is used for GEV distribution fitting purposes. The performance of extreme value distributions is compared with 3-parameter Weibull. In contrast with several simulation-based studies reported previously, the present results are more realistic due to use of actual field data contained in the LIST database.

General conclusions are as follows:

- The probabilistic characteristics of the bending moment (BM) extremes vary across seven bins of mean wind speed. The mean of bending moment increases with the mean of wind speed.
- The dispersion and skewness that affect the distribution tail are dependent on the dispersion and skewness of turbulence within a bin. It is interesting to observe that the skewness of bending moment varies in tandem with that of the turbulence.
- A major limitation of the Gumbel distribution is that it ignores the skewness of BM data, which can result in a significant overestimation of design loads. This emphasizes the need for including higher-order moments in the extreme value estimation.
- The GEV is an asymptotically consistent and more versatile form of extreme value distribution. GEV accounts for skewness of data, and provides better fit than the Gumbel model.
- Although GEV is an asymptotically consistent and versatile extreme value distribution, its practical application needs careful consideration. In some cases it has short bounded tail that can

underestimate extreme values, and also opposite of this can happen in highly skewed data. It is attributed to the lack of convergence of extreme values to their asymptotic form.

- The Weibull model is less sensitive to skewness of data than GEV. It provides reasonable fit in several cases with potential for further improvement.
- The use of peaks over threshold method to improve the modeling accuracy is currently under investigation.

In summary, this paper presents preliminary results of an investigation into the probabilistic modeling of extreme loads acting on wind turbine components. This paper discusses application of extreme value theory and highlights its practical limitations as well as potential for improvement.

REFERENCES

[1] Ronold, K.O., Wedel-Heinen, J. and Christensen, C.J., 1999, "Reliability-Based Fatigue Design of Wind Turbine Rotors," *Engineering Structures*, 21, pp. 1101-1114.

[2] Fitzwater, L.M. and Winterstein, S.R. (2001), "Predicting Design Wind Turbine Loads from Limited Data: Comparing Random Process and Random Peak Model." *2001 ASME Wind Energy Symposium*, AIAA/ASME, pp. 265-272.

[3] Winterstein, S.R. and Kashef, T., 2000, "Moment-Based Loads and Response Models with Wind Engineering Applications," *J. OMAE*, pp. 122-128.

[4] Pandey, M.D., 2001, "Extreme Quantile Estimation Using Order Statistics with Minimum Cross-Entropy Principle," *J. Probabilistic Engineering Mechanics*, 16(1), pp. 31-42.

[5] Pandey, M.D., 2002, "An Adaptive Exponential Model for Extreme Wind Speed Estimation," *Int. J. Wind Eng. Industrial Aerodynamics*, 90(7), pp. 839-866.

[6] Sutherland, H.J., P.L. Jones, and B. Neal, 2001, "The Long-Term Inflow and Structural Test Program," *2001 ASME Wind Energy Symposium*, AIAA/ASME, pp. 162-172.

[7] Sutherland, HJ., 2001, "Preliminary Analysis of the Structural And Inflow Data From the LIST Turbine," *2001 ASME Wind Energy Symposium*, AIAA/ASME, pp. 173-183.

[8] Hosking, J.R.M, 1990, "L-Moments Analysis and Estimation of Distributions Using Linear Combination of Order Statistics, *J. of the Royal Statistical Society*, Series B, 52, pp. 105-124.

[9] Moriarty, P.J., Holley, W.E. and Butterfield, S., 2002, "Effect of Turbulence Variation on Extreme Loads Prediction for Wind Turbines," *2002 ASME Wind Energy Symposium*, AIAA/ASME, pp.278-287.

[10] Sutherland, H.J., 2002, "Analysis of the Structural and Inflow Data from the LIST Turbine," *JSEE*, in publication.

[11] Sutherland, H., 2002, "Inflow and the Fatigue of the LIST Wind Turbine," *2002 ASME Wind Energy Symposium*, AIAA/ASME, pp. 427-437.

[12] Madsen, P.H., Pierce, K. and Buhl, M., 1999, "Predicting Ultimate Loads for Wind Turbine Design," Proc. *1999 ASME Wind Energy Symposium*, pp. 355-364.

[13] Landwehr, J.M., Matalas, N.C. and Wallis, J.R., 1979, "Probability Weighted Moments Compared with Some Traditional Techniques in Estimating Gumbel Parameters and Quantiles," *Water Resources Research*, 15(5), pp. 1055-1064.

[14] Hosking, J.R.M., Wallis, J.R and Wood, E.F., 1985, "Estimation of the Generalized Extreme Value Distribution by the Method of Probability-Weighted Moments," *Technometrics*, 27, PP. 251-261.