AIAA-2001-0047

# PARAMETRIC MODELS FOR ESTIMATING WIND TURBINE FATIGUE LOADS FOR DESIGN

Lance Manuel[1]
Paul S. Veers[2]
Steven R. Winterstein[3]

[1]Department of Civil Engineering, University of Texas at Austin, Austin, TX 78712
[2]Sandia National Laboratories, Wind Energy Technology Department, Albuquerque, NM 87185-0708
[3]Department of Civil and Environmental Engineering, Stanford University, Stanford, CA 94305-4020

## ABSTRACT

International standards for wind turbine certification depend on finding long-term fatigue load distributions that are conservative with respect to the state of knowledge for a given system. Statistical models of loads for fatigue application are described and demonstrated using flap and edge blade-bending data from a commercial turbine in complex terrain. Distributions of rainflow-counted range data for each ten-minute segment are characterized by parameters related to their first three statistical moments (mean, coefficient of variation, and skewness). Quadratic Weibull distribution functions based on these three moments are shown to match the measured load distributions if the non-damaging low-amplitude ranges are first eliminated. The moments are mapped to the wind conditions with a two-dimensional regression over ten-minute average wind speed and turbulence intensity. With this mapping, the short-term distribution of ranges is known for any combination of average wind speed and turbulence intensity. The long-term distribution of ranges is determined by integrating over the annual distribution of input conditions. First, we study long-term loads derived by integration over wind speed distribution alone, using standard-specified turbulence levels. Next, we perform this integration over both wind speed and turbulence distribution for the example site. Results are compared between standard-driven and site-driven load estimates. Finally, using statistics based on the regression of the statistical moments over the input conditions, the uncertainty (due to the limited data set) in the long-term load distribution is represented by 95% confidence bounds on predicted loads.

 Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin company, for the U.S. Department of Energy under contract DE-AC04-94AL85000.

## INTRODUCTION

Design constraints for wind turbine structures fall into either extreme load or fatigue categories. In the case of extreme load design drivers, the load estimation problem is limited to finding a single maximum load level against which to assess the structural strength. For design against fatigue, however, loads must be defined over all input conditions and then summed over the distribution of input conditions weighted by the relative frequency of occurrence. While this might seem to be a more daunting task, it is in many ways quite similar to the extreme load problem, as can be seen by comparing with Fitzwater and Winterstein[1]. In both cases, the loads must be determined as functions of wind speed (or other climatic conditions).

Parametric models define the response, statistically, with respect to input conditions. Such models fit analytical distribution functions to the measured or simulated data. The parameters of these distribution functions can be useful in defining the response/loads as a function of the input conditions. The end result, then, is a full statistical definition of the loads over all input conditions.

In the most prevalent alternative to parametric modeling, an empirical distribution of loads (i.e., a histogram describing frequency of occurrence of the modeled response quantity) is used to define the turbine response at the conditions of the measurement or simulation. When using simulations, a ten-minute time series is generated at specified environmental conditions using an aeroelastic analysis code. The time series is rainflow-counted and the number of ranges in specified intervals is summarized in histograms. The histograms serve as empirical distributions that are taken to be representative of the response of the turbine at those particular conditions. The full lifetime distribution is then obtained by summing the distributions after weighting by the frequency of occurrence of the wind speed associated with each simulated data segment included in a histogram interval. In the case of measured data, a similar approach has been described by McCoy et al.[2] but with an innovative weighting scheme to account for the irregular input conditions of field measurements.

The empirical approach uses only the measured or simulated data without any fitting of distributions or extrapolation to higher values that would be seen if more data were obtained. One of the disadvantages of using a purely empirical approach is, therefore, that the loading distribution may not be representative. Perhaps a subtler shortcoming is that the uncertainty in the loads is almost impossible to characterize.

With regard to uncertainties in loads and how they might be dealt with in design, one might expect that these uncertainties could be covered by the use of standard specifications of characteristic loads (derived from a specified high turbulence level) and safety factors. However, current standard load definitions use safety factors that do not depend on the relative uncertainty in the load estimates. Either the margins are larger than they need to be when load estimates are reasonably well established (i.e., exhibit low uncertainty), or they fail to cover the uncertainty when load estimates are based on limited data (i.e., large uncertainty cases).

Parametric load distribution models offer significant advantages over empirical models; they provide a means to (1) extrapolate to higher, less frequent load levels, (2) map the response to the input conditions, and (3) calculate load uncertainty. For example, Ronold et al.[3] have published a complete analysis of the uncertainty in a wind turbine blade fatigue life calculation. They used a parametric definition of the fatigue loads, matching the first three moments of the wind turbine cyclic loading distribution to a quadratic (transformed by a squaring operation) Weibull distribution.

Veers and Winterstein[4] described a parametric approach, quite similar to that employed by Ronold et al.[3], that can be used with either simulations or measurements, and have shown how it may be used in an uncertainty evaluation. Although Reference 4 describes how to use the statistical model to estimate the complete load spectrum, it does not indicate how these models compare with the design standards[5]. It is critical that the load distributions generated by any statistical methodology be adaptable for use in existing design standards. Moreover, it is arguably even more important that the load model provide insight into how the design standards might be improved in future revisions. The standards should require an accurate reflection of the load distribution with sufficient conservatism to cover the uncertainties caused by the limited duration of the sample, whether based on simulation or field measurements. Only then can design margins be trimmed to the point of least cost while still maintaining sufficient margins to keep reliability levels high.

The approach to load modeling is not uniform across the wind community by any measure. This lack of commonality in approach was reflected in the working group that produced IEC's Mechanical Load Measurement Technical Specification[6]. No consensus could be obtained on how to use measured loads to either create or substantiate a fatigue load spectrum at the conditions specified in the Safety Standard[5]. All that is offered are several examples of differing approaches in an annex of the specifications[6].

Here, we present a methodology for using measured or simulated loads to produce a long-term fatigue-load spectrum at specified environmental conditions and at desired confidence levels. To illustrate, example measurements of the two blade-root moments (flap and edge) from a commercial turbine in complex terrain are used. The ten-minute distributions of rainflow ranges are modeled by a quadratic Weibull distribution function based on three statistical moments of the ranges (mean, coefficient of variation, and skewness). The moments are mapped to the wind conditions by a two-dimensional regression over ten-minute average wind speed and turbulence intensity. Thus, the "short-term" distribution of ranges may be predicted for any combination of average wind speed and turbulence intensity. The "long-term" distribution of ranges is, then, easily obtained by integrating over the annual distribution of input conditions. Results are compared between standard-driven and site-driven load estimates. Finally, using statistics based on the regression of the statistical moments over the input conditions, the uncertainty (due to the limited data set) in the long-term load distribution is represented by 95% confidence bounds on predicted loads.

## IEC LOAD CASES

The loads specified by IEC 61400-1 Wind Turbine Generator Safety Requirements for design must be defined for a specified combination of mean wind speed and turbulence intensity known as the Normal Turbulence Model[5]. The standard provides an equation for the standard deviation of the ten-minute wind speed, $\sigma_1$, that depends on the hub-height wind speed and two parameters, $I_{15}$ and $a$.

$$\sigma_1 = I_{15}(15\text{m/s} + aV_{hub})/(a+1) \qquad (1)$$

Equation 1 is based on wind speed standard deviation data gathered from around the world and aggregated into a common data set. The equation was created to be "broadly representative of sites with reasonable international marketing interest,"[8] and does not represent any single site. $\sigma_1$ is intended to represent a *characteristic value* of wind-speed standard deviation. Certification guidelines are provided for high (A) and moderate (B) turbulence sites. $I_{15}$ defines the characteristic value of the turbulence intensity at an average wind speed of 15 m/s, and $a$ is a slope parameter when $\sigma_1$ is plotted versus hub-height wind speed. The values of these parameters for each category are shown in Table 1.

| CATEGORY | A (HIGH) | B (MODERATE) |
|---|---|---|
| $I_{15}$ | 0.18 | 0.16 |
| $a$ | 2 | 3 |

Table 1: Parameters for IEC turbulence categories.

The Category B moderate turbulence specification is intended to roughly envelope (i.e., be higher than) the mean plus one sigma level of turbulence for all the collected data above 15 m/s. Similarly, Category A envelopes all collected values of turbulence intensity (with the exception of one southern California site) for mean wind speeds above 15 m/s and is above the overall mean plus two sigma level in high winds[8]. Clearly, the IEC Normal Turbulence Model is intended to be conservative for all but the most turbulent sites.

It is a relatively straightforward matter to create a loading distribution that meets the standard criteria when using an aeroelastic simulation code. Input winds can be generated for any combination of wind speed and turbulence intensity. Representative loadings can, in theory, be generated by simulating repeatedly until sufficient data are produced to drive the uncertainty to an arbitrarily small level. Practically, however, it would be beneficial to generate a loading distribution with small, or at least known, uncertainty from a smaller data set. This is where the parametric approach provides significant value. By means of regression of load statistics (e.g., moments) over the entire range of wind speeds and turbulence levels, the uncertainty in the values of the parameters defining the short-term distributions at any specified turbulence condition can be estimated.

In the case of measured loads, it may be simply impossible to gather data at the specified turbulence conditions because of the limitations of the test site. In that case, the parametric approach provides a method to interpolate to a specified turbulence level using all of the data collected (thus adding to the confidence of the interpolation), or to extrapolate beyond the limits of the measurements. In either case, the parametric approach simplifies the generation of fatigue loads to Standard specifications.

## EXAMPLE DATA SET

An example data set taken from the copious measurements of the MOUNTURB program[7] is used to illustrate the parametric modeling process. The data are comprised of 101 ten-minute samples of rainflow-counted flap-wise and edge-wise bending-moment ranges at the blade root. The test turbine is a WINCON 110XT, a 110kW stall-regulated machine operated by CRES (the Centre for Renewable Energy Systems, Pikermi, Greece) at their Lavrio test site. The terrain is characterized as complex.

The original time series of the loads and winds were not available for further analysis; thus, only the rainflow-counted ranges were employed. The number of cycle counts was tallied in 50 bins ranging from zero to the maximum range in each sample. A single ten-minute sample is categorized by the mean wind speed and the raw turbulence intensity at hub height. The average wind speeds are limited to the range between 15 and 19 m/s and thus reflect response in high wind operation. Turbulence intensities cover a wide range of operating conditions as can be seen in Figure 1. The measured loads are summarized by frequency of occurrence in Figure 2a for flap moment ranges and in Figure 2c for edge moment. Plots showing exceedance counts for specified flap and edge loads are shown in Figures 2b and 2d, respectively.

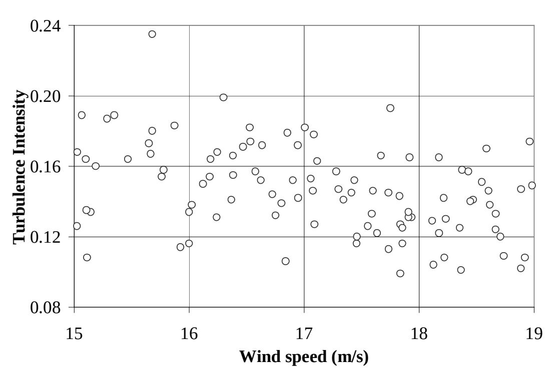



Figure 1 Wind speed and turbulence intensity values for the 101 10-minute data samples.

## ESTIMATING UNCERTAINTY IN LONG-TERM LOADS

To review, the parametric load modeling proposed here proceeds by (1) modeling loads by their statistical moments $\mu_i$ ($i$=1,2,3) and (2) modeling each moment $\mu_i$ as a parametric function of $V$ and $I$ (Eq. 6). The moment-based model in step (1) is in principle independent of the turbine characteristics (although the optimal choice among such models may be somewhat case-dependent). Hence, in this parametric approach, the turbine characteristics are reflected solely through the moment relations in Eq. 6; specifically, the 9 coefficients $a_i$, $b_i$, $c_i$ ($i$=1,2,3). For clarity, we organize these here into a vector,

$\boldsymbol{\theta} = \{a_1, b_1, c_1, a_2, b_2, c_2, a_3, b_3, c_3\}$ .

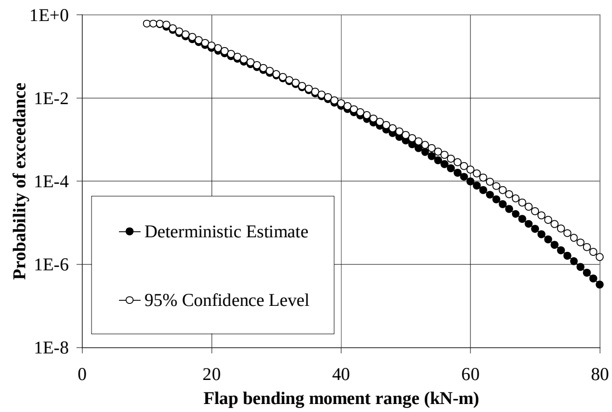
Simpler 2-moment models would require only 6 coefficients.

The preceding section has shown one benefit of this parametric model. Because it permits load statistics to be estimated for arbitrary $V$ and $I$, the results can be weighted to form the long-term loads distribution as in Eqs. 7-8 (and Figs. 9a-b). Symbolically, we rewrite Eq. 7 here, noting explicitly its dependence on the vector θ.

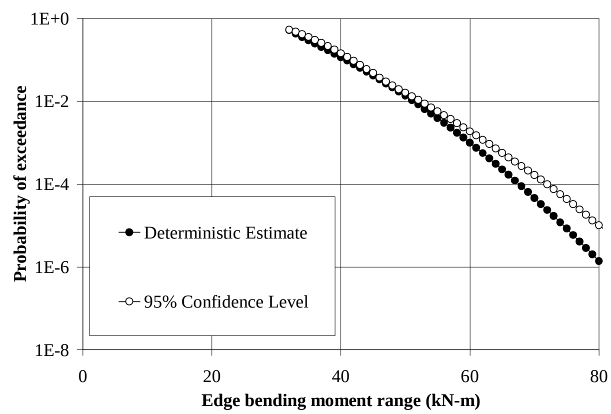
$$F(r\,|\,\boldsymbol{\theta}) = \int F(r\,|\,V, I, \boldsymbol{\theta})\, f(V)\, dV \qquad (9)$$

(Eq. 8 can be rewritten analogously.) The foregoing results (Figs 9a-b) have used our best estimates for the entries of θ; i.e., the mean values of each entry in **θ.** These are the values of $a_i$, $b_i$, and $c_i$ cited in Table 2.

A further advantage of the parametric model lies in its usefulness in estimating the effects of statistical uncertainty. To clarify, it is useful to distinguish between the various terms in Eq. 9. The quantities $V$ and $I$ are "random variables;" that is, their future outcomes will show an intrinsic randomness that cannot be reduced by additional study of past wind conditions. In contrast, the 9 coefficients in θ are in principle fixed (under the model's assumptions). We may, however, be uncertain as to their values due to limited response data. This "uncertainty" (as opposed to "randomness") can be reduced through additional sampling. The consequence of having only limited data can be reflected through 95% confidence levels, for example, on the exceedance probability 1-$F(r)$. These are conceptually straightforward to establish by simulation. Assuming the entries of θ are each normally distributed, for example, one may (1) simulate multiple outcomes of θ; (2) estimate $F(r)$ for each θ as in Eq. 9; and (3) sort the resulting $F(r)$ values (at each fixed $r$ value) to establish confidence bands; e.g., in which 95% of the values lie.




(a) Flap-wise banding




(b) Edge-wise Bending

Figure 11 95% Confidence levels on the exceedance probability of fatigue loads for the Lavrio site with turbulence set to the average value for each wind speed.

Figures 11a and 11b show the 95% confidence level on the exceedance probability, 1-F(r), which result from the simulation procedure described above. Each of the 9 coefficients in Eq. 9 were generated as statistically independent, normally distributed random variables, with means and standard deviations given by Tables 2 and 3, respectively. (Correlation among these variables can also be included; however, this was not done here.) All of these results adopt the site-specific mean turbulence model; i.e., the results labeled "Average I at each wind speed" in Figs. 9a-b. These results from Figs. 9a-b are repeated in Figs. 11a-b, and referred to there as "deterministic" results. Also shown are 95% confidence results; i.e., probability levels below which 95% of the simulations fall.

The increase in probability, over the deterministic results in order to achieve 95% confidence, is found to be relatively modest. This reflects the benefit of having as many as 101 10-minute samples. If the same mean trends had resulted from fewer samples, the resulting 95% confidence results would be correspondingly higher than the mean results. Note also that, at least for flap-wise loads, the conservatism induced by the IEC turbulence models exceeds that required to cover our statistical loads uncertainty, based on the data at hand. Of course, as noted earlier, this IEC conservatism may be desirable to cover other sources of uncertainty. Finally, we caution again that these long-term load results are intended for example purposes only; accurate numerical values would require data across a broader range of wind speeds.

## SUMMARY

Fatigue load spectra are generated for arbitrary site conditions (wind speed and turbulence intensity distributions) by using parametric models to fit the short term load spectrum to the first three moments of the truncated rainflow range distributions and regressing the moments over wind speed and turbulence intensity. The spectra are generated to specified IEC conditions for wind speed Class and turbulence Category. The spectra are also generated for as-measured scatter in the turbulence levels across all wind speeds. The comparison of the two approaches reveals the level of conservatism that results from assumed high turbulence levels written into the current standards. The selected confidence level can be calculated using the statistics from regression analysis. Since the confidence interval depends on the uncertainty in the load characterization, it could provide a better margin of safety on the loads than can be accomplished with an inflated turbulence level. The parametric approach presented here illustrates how statistically based standards may be able to reflect the uncertainty in the loading definition caused by finite-length data records.

## ACKNOWLEDGMENTS

The authors would like to extend a special debt of gratitude to the Centre for Renewable Energy Sources (CRES), Pikermi, Greece and especially to Fragiskos Mouzakis who found time in a busy schedule to supply the portion of the MOUNTURB data set used in the examples. The authors also gratefully acknowledge the efforts of LeRoy Fitzwater, of Stanford University, who provided the uncertainty analysis described in the final section of this paper.

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