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EFFECTS OF CYCLIC STRESS DISTRIBUTION MODELS ON FATIGUE LIFE PREDICTIONS¹

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ABSTRACT¹

The fatigue analysis of a wind turbine component typically uses representative samples of cyclic loads to determine lifetime loads. In this paper, several techniques currently in use are compared to one another based on fatigue life analyses. The generalized Weibull fitting technique is used to remove the artificial truncation of large-amplitude cycles that is inherent in relatively short data sets. Using data from the Sandia/DOE 34-m Test Bed, the generalized Weibull fitting technique is shown to be excellent for matching the body of the distribution of cyclic loads and for extrapolating the tail of the distribution. However, the data also illustrate that the fitting technique is not a substitute for an adequate data base.

INTRODUCTION

The analysis of component fatigue lifetime for a Wind Energy Conversion System (WECS) requires that the component load spectrum be formulated in terms of stress cycles. Typically, these stress cycles are obtained from time series data using a cycle identification scheme such as the "rainflow" counting algorithm. As discussed by many authors [e.g., see Sutherland and Butterfield (1994)], the matrix or matrices of cycle counts that describe the stresses on a turbine are constructed from relatively short samples of time series data. Thus, these cycle counts are representative samples of the cyclic loads on the turbine.

Several techniques are currently used to convert these representative samples to the lifetime cyclic loads on the turbine. Many designers simply scale the sample loads with time. They note that these limited time measurements or

simulations define the main body of the distribution, and assume that they capture all of the necessary loads on the turbine to define its service lifetime. Other designers note that the infrequent occurrences of high-stress events contained in the "tail of the distribution" are affected by the specific data set, and that the distribution tails fill in as more and more data are added to the record. They note that the existence of a "high stress tail" on the distribution has significant influence on the predicted service lifetime of the turbine, and they believe that it must be well defined for an accurate analysis. The latter group of designers typically extrapolate from the body of the cycle count distribution into this tail region.

The ability to correctly represent the long-term behavior of the distribution of stress cycles with only a representative sample of time series is of critical importance. This paper examines the effects of using various models for the distribution of stress cycles. The models are compared to one another based on fatigue life analyses that include the entire range of operating wind speeds. The analyses use the LIFE2 fatigue analysis code (Sutherland, 1987). There are basically three models to test: the histogram of the measured cyclic stress counts (Sutherland and Schluter, 1990), a Rayleigh distribution fitted to the measured RMS of the stress time series (Veers, 1987), and a generalized Weibull fit to the histograms with which we extrapolate the tail of the distribution (Winterstein and Lange, 1995).

Time series data from the Sandia/DOE 34-m Test Bed turbine are used for example calculations. These data were previously analyzed by Sutherland and Schluter (1990) using the direct scaling technique discussed above. In addition, simulated time series data synthesized from a frequency domain representation (Sutherland, 1992) are used as an example in which arbitrarily long data sets were generated to examine the development of the tail of the distribution as more and more

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data are "collected." The results for two different candidate materials are summarized and discussed.

GENERALIZED WEIBULL FITTING ALGORITHM

Assumed distribution types have been applied to wind turbine cyclic loads data in the past. Emphasis has been placed on exponential (Jackson, 1992) or Rayleigh (Malcolm, 1990) distributions. In fact, both the exponential and Rayleigh are just special cases of the more general Weibull distribution. Weibull distributions can model a wide range of behaviors with two parameters to describe the central tendency of the distribution (i.e., the body of the distribution) and the spread of the distribution (i.e., the tail of the distribution). The Rayleigh, for example, is a distribution that has about half the spread about its mean (as described by the ratio of the standard deviation over the mean) as the exponential. The spread of the distribution is particularly important in fatigue analyses.

Typically, the tails of distributions that are found in nature are difficult to infer from the body of the distributions, because the tails are often found to differ somewhat from the body of the distribution. The differences are due to behavioral changes that occur when the most severe environments are encountered (e.g., due to nonlinearities, or the initiation of a different mode of response). This causes a skewing, or distortion of the tail from what might be found in a standard distribution model.

Winterstein and Lange (1995) have introduced a technique that optimally retains the statistical information of the high-level response data. Their "generalized Weibull" fitting technique distorts a parent Weibull distribution to fit the first *four* statistical moments of the data. Most distribution models use only the first *two* moments. Fitting to the higher moments² of the distribution enhances the fit to the largest values in the data. Thus, this fitting technique distorts the parent distribution when the data indicate that tail behavior differs from the parent distribution.

EXAMPLE PROBLEM

Fatigue analyses of the Sandia 34-m Test Bed Vertical Axis Wind Turbine (VAWT) were conducted previously by Ashwill, Sutherland and Veers (1990) and Sutherland and Schluter (1990). The first analysis uses a narrow-band Gaussian approximation to model the turbine response to dynamic loading. This assumption results in a Rayleigh distribution of cyclic stress amplitudes. The second analysis uses rainflow counting techniques to convert measured time series data to fatigue cycles and uses histograms of these cycle magnitudes to define the long-term loading.

All of these analyses use the LIFE2 fatigue analysis code for wind turbines (Sutherland, 1987) to estimate service lifetime from the loading models.

The Sandia 34-m VAWT

As discussed by Ashwill, et al. (1987), Sandia National Laboratories erected a research-oriented, 34-meter diameter, Darrieus VAWT near Bushland, Texas. This variable speed turbine, commonly described as the 34-m Test Bed, has been operated at fixed speeds throughout its operating range of 28 to 38 rpm and in a true variable speed mode. The turbine blades are made from extruded aluminum. The turbine and its site are equipped with a large array of sensors that permit the characterization of the turbine under field conditions.³

Ashwill (1987) and Ashwill and Veers (1990) found the highest stressed region of the turbine blade, both in the flatwise and lead-lag directions, to be at the upper blade-to-tower joint (upper root), where the blade attaches to the tower. For this example, the flatwise stress in the blade at this joint will be analyzed for constant-speed operation at 28 rpm.

Rainflow Counting (Histogram) Analysis

Sutherland and Schluter (1990) analyzed measured time series data using a rainflow counting algorithm to predict the service lifetime of the 34-m Test Bed. In their analysis, the operational stress states of the turbine were divided into the six wind speed intervals (bins) summarized in Table I. To insure time series data sufficiently long for the rainflow analysis, each wind speed bin contained data from a minimum of 200 turbine rotations. To further insure that the total duration of the time series data was sufficiently long for this analysis, the distribution of the alternating stress cycle ranges was monitored as a function of the total time contained in the data segments. Each time series data record was chosen to have an average wind speed near the center of its respective interval and to have minimal excursions outside that interval.

Table I. Summary of Wind Speed Intervals

Wind Speed Interval (m/sec)	Total Time (sec)	Stress Summary (MPa)			
		Histogram		Long Term Bins	
		Mean	RMS	Mean	RMS
5-7	600	0.5	2.2	-1.1	2.2
7-9	750	-1.2	2.8	-1.1	3.1
9-12	445	-1.5	4.8	-1.1	4.5
12-15	700	-1.0	6.2	-1.1	6.6
15-18	680	-2.5	9.4	-1.1	8.9

² The *i*th moment of a distribution equals the average value of the difference between each value and the mean value of the distribution raised to the *i*th power.

³ Veers (1990) has put together a compendium of the technical papers written on this turbine.

A typical plot of the cycle count histogram of these data, for the 12 to 15 m/sec wind speed interval, is shown in Figure 1. In this figure, the cycle count histogram is divided into 2 MPa intervals. To allow direct comparison of the data counted over various time lengths, the cycle counts are normalized to a 100-second time duration.

Keeping all operational parameters constant, the service lifetime of the turbine blade based on the histogram representation of the cyclic loading was predicted to be 2250 years.

Narrow-Band Gaussian (Rayleigh) Analysis

A detailed parametric study of the fatigue life of the critical joint was conducted first by Ashwill, Sutherland and Veers (1990) using a narrow-band Gaussian assumption for the stress response of the turbine (Veers, 1987). In this approach, the RMS stress level of the time series is measured as a function of wind speed with a "bins" technique, and a Rayleigh distribution is assumed for the ranges of the cyclic stresses at each wind speed. Malcolm (1990) has suggested that this formulation is a good approximation of the distribution for flatwise stress cycles in this class of turbine blades.

The predicted lifetime for the blade, when the machine is operated in a constant speed mode at 28 rpm, is 950 years. This prediction is based on hundreds of hours of measured data. A complete set of the assumptions used to obtain these predictions is presented in a report by Ashwill, Sutherland and Veers (1990). The essential point for comparison here is that the stress cycles were assumed to be Rayleigh distributed with the magnitude of the distribution defined by the long-term RMS stress response at the critical location.

Comparison of Rayleigh and Histogram Analyses

Stress States Comparison. A statistical comparison of the measured stresses used in the histogram analysis and those from long-term RMS bins data (used in the Rayleigh analysis) are listed in Table I. As seen in the table, the relatively short duration histogram RMS (based on several hundred seconds of turbine operation) varies slightly from the "bins" RMS (based on hundreds of hours of turbine operation), while the mean of the rainflow counted data is in very good agreement with the bins data.

The histogram of the rainflow counted data for the 12 to 15 m/s wind speed interval is compared to a Rayleigh distribution in Figures 1 and 2. Figure 1 compares the two on a linear plot and Figure 2 compares the two on a Weibull scale.⁴ The cycles in both distributions are displayed in 2 MPa intervals. The low-amplitude stress counts in the histogram have been eliminated

⁴ In a plot of this form, a Rayleigh Distribution will plot as a straight line.

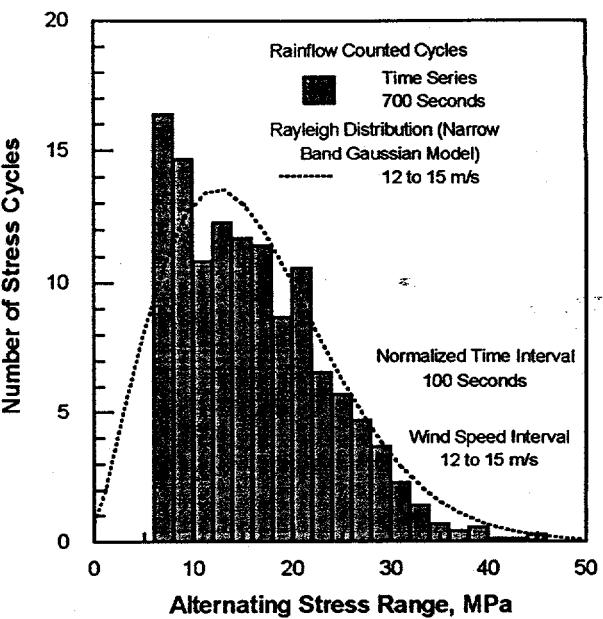


Figure 1. Rainflow Counted Stress Cycles.

from Figure 1 and are not modeled in this approximation because they do not contribute significantly to fatigue damage. Also, in Figure 1, the cycle counts have been normalized to a 100-second time interval to allow direct comparison of the data collected over various time lengths. As seen in these two figures, the distributions compare favorably.

The Rayleigh distribution is, however, displaced slightly from the rainflow counted data. Table I indicates that the RMS

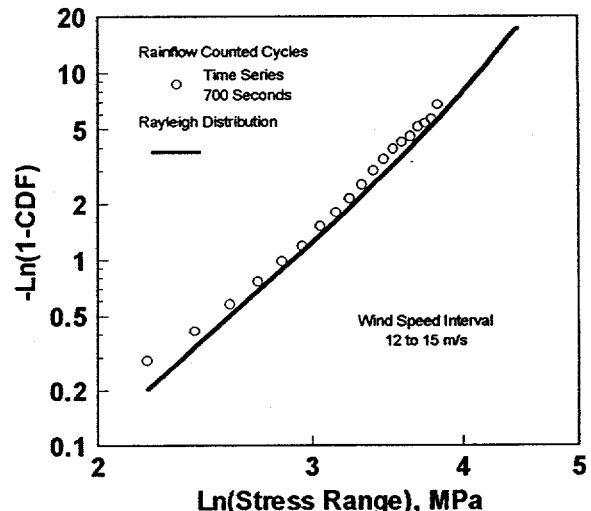


Figure 2. Comparison of Rainflow Counted Stress Cycles (Histogram Data) and the Rayleigh Approximation; Weibull Plot

values for the "Long Term Bins" and the "Histogram" differ slightly, sometimes higher and sometimes lower. This difference is attributed to the sample lengths for the two data sets. Namely, the "Bins" data is based on relatively long data records that have been developed over many hours of operation of the turbine (Ashwill and Veers, 1990), and the histogram data are based on relatively short data records of between 445 and 750 seconds.

Service Lifetime Comparison. The prediction of service lifetime based on the Rayleigh distribution is less than half that predicted by the rainflow counted histogram. As shown in Table I and in Figures 1 and 2, the differences between the two distributions are relatively slight. However, for the prediction of service lifetimes, the difference is significant. There are three possible sources of difference: (1) differences in distribution shape, (2) a shift in the entire distribution due to the different RMS levels listed in Table I, and (3) the longer tail on the Rayleigh distribution shown in Figure 2. In the tail region, the Rayleigh model predicts that the turbine will be subjected to some very high stress cycles over the course of its lifetime. The rainflow counted histogram data has a similar nominal distribution, although shifted to lower stress amplitudes, and the high stress tail is truncated.

The effect of the difference between the RMS values for the two distributions may be evaluated by artificially shifting the Rayleigh distributions to the RMS stress levels measured in the rainflow counted histograms. The resulting lifetime, using the histogram RMS levels from Table I, is 1900 years which compares favorably with the histogram analysis of 2250 years.

Normalization. We will use the histogram results to normalize all subsequent fatigue life predictions. Table II summarizes the results to this point. The shift in the RMS level results in a change in the normalized Rayleigh prediction from 0.42 to 0.84. It is a generally accepted truth that fatigue predictions within a factor of 2 are within the "noise" of prediction capability. Therefore, the difference between the Rayleigh and the histogram approaches is essentially accounted for by the differences in RMS levels obtained when short-term versus long-term data are used in the analysis.

TAIL SENSITIVITY

The previous example illustrates how, for one specific example of machine type, material, and environment the assumptions on cyclic loading distributions influence the predicted fatigue life. We now examine the issue of tail behavior and the ability to fit and extrapolate that behavior from finite data sets.

In our examination of the effect of distribution tails on fatigue lifetime calculation, two additional tools will be brought into play here. The first is the generalized Weibull fitting technique described above, and the second is the frequency domain techniques developed by Sutherland (1992). The former is applied to both the rainflow histogram data and the frequency domain simulations, and the latter will be used to generate arbitrarily long data sets.

TABLE II: Normalized Lifetime Predictions for the Upper Root: Histogram vs. Rayleigh

Loading Definition	Normalized Lifetime
Histogram	1.0
Rayleigh: Long Term RMS	0.42
Rayleigh: Short Term RMS (same as Histogram)	0.84

Frequency Domain Analysis

As noted by Akins (1990), the fatigue loads on a turbine may also be determined from the frequency-domain stress spectra. Simply stated, the technique converts frequency-domain stress data into time-series data (stress-time history) suitable for rainflow counting using a Fourier transform. This technique permits the synthesis of very long time series data to fill the population of the stress distribution in the high-stress region; thus, the technique simulates the effect of having longer data samples.

The Test Bed cycle count distribution was analyzed using the frequency domain representations of small data samples (Sutherland, 1992). In that analysis, Sutherland demonstrated that over 150,000 seconds of time-series data were required to achieve a stable, relatively smooth, and monotonically decreasing distribution of the cycle counts in the high-stress tail. The distribution of stress cycles, for synthesized time series of 10,200 seconds and 2,700,000 seconds, produced by this technique is shown in a generalized Weibull plot in Figure 3. The Rayleigh distribution, shown in Figures 1 and 2, is included in the figure for reference.

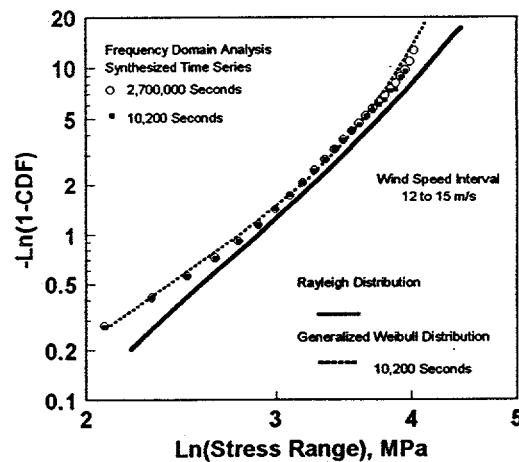


Figure 3. Comparison of Short-Time Generalized Data Fit

Generalized Weibull Fits

In the analysis presented here, the generalized Weibull fitting technique developed by Winterstein and Lange (1995) is used to fit the measured cycle count data from the Test Bed, presented above. The results will be compared and contrasted with the previous analyses. In addition, the generalized fits are artificially truncated to the highest cycle found in the histograms of the sample measurements to check the generalized fit to the histogram and to examine tail sensitivity.

Histograms. The generalized fit of the Test Bed histogram data is illustrated in Figures 4 and 5 (linear histogram and Weibull plot, respectively). It is difficult to see the difference between the histogram data, the Rayleigh distribution and the generalized Weibull fit in the linear plots, Figures 1 and 4. However, the differences are much clearer in the Weibull plots, Figures 2 and 5. As illustrated in the latter plots, the generalized Weibull fit is able to follow curvature in the body of the distribution and, more important, follows and extrapolates the tail of the distribution. The predicted service lifetime using the generalized fit is 2300 years. If the distribution is truncated at the level of the largest cycle in the histogram, the lifetime is extended to just 2450 years, virtually no change from the histogram analysis of 2250 years.

Frequency Domain. The frequency domain analysis of the Test Bed 12-15 m/s wind speed bin was evaluated with the generalized Weibull technique to examine its ability to extrapolate the tail of the distribution. The cyclic stress histogram for 10,200 seconds was fit using the generalized Weibull technique. Both the histogram from the synthesized time series data and the fit are shown in Figure 3. These results are compared to the histogram for over 2,700,000 seconds of synthesized time series data. As noted above, the Rayleigh distribution, shown in Figures 1 and 2, is included in the figure for reference. As illustrated in Figure 3, the curve fitting technique applied to the shorter data set fits the long-time synthesized results very well.

Service Lifetime Comparison. The service lifetime predictions using the long duration simulations to determine the long-term stress cycle distributions are very close the original histogram predictions. Table III summarizes the ratios of the "Spectral" simulations analyses to the original predictions. Notice that the RMS level of the spectral definition is identical to the measured histogram data of Table I. They are identical because the spectral representation of the stress response was determined from the histogram data. The "Generalized Curve

TABLE III: Normalized Service Lifetime Predictions for the Upper Root for Aluminum Blades.

Data Source	Analysis Technique		
	Histogram	Generalized Curve Fit	Truncated Generalized Curve Fit
Measured	1.0	1.02	1.09
Spectral	1.02	1.02	1.04

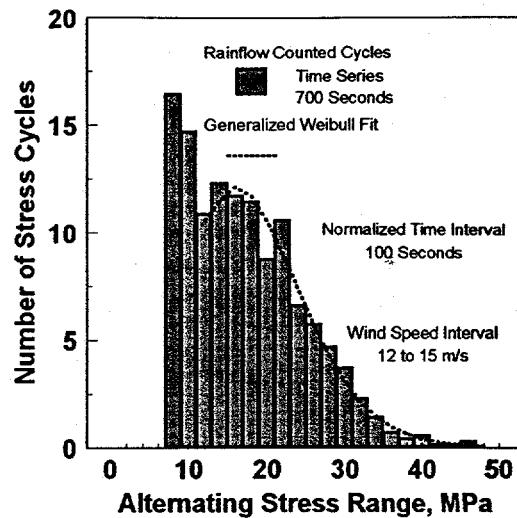


Figure 4. Comparison of Rainflow Counted Stress Cycles and the Generalized Weibull Fit

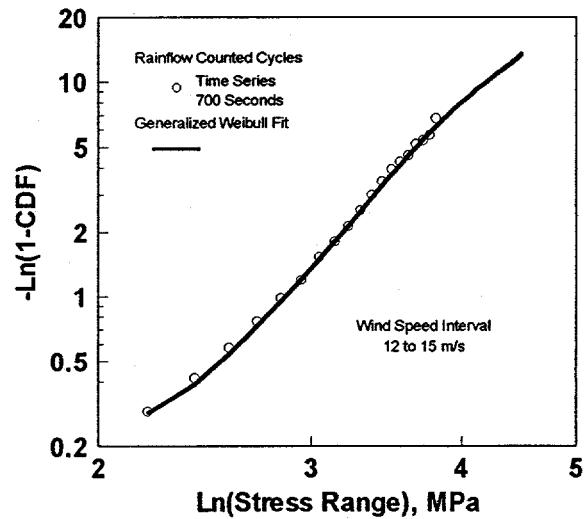


Figure 5. Comparison of Rainflow Counted Stress Cycles and the Generalized Weibull Fit, Generalized Weibull Plot

Fit" (generalized Weibull fit) predictions are also nearly identical to the histogram predictions, as expected because of the high fidelity of the distribution fit to the histogram data.

Truncating the tail of the distribution again provides no substantial increase in the fatigue life calculation.

The Material Property Influence

As was observed by Winterstein, see the discussion in Sutherland and Butterfield (1994), there is a direct link between material fatigue properties and the sensitivity of predicted

service lifetimes to the tail of the load distribution. The Test Bed example is based on the fatigue properties of the extruded aluminum blades. This aluminum has an S-N exponent (slope of the S-N curve) that is roughly mid-range (about 7) between welded steel (about 3) and fiberglass composites (greater than 10). The higher the exponent, the greater will be the tail sensitivity.

As an example, we replaced the aluminum material properties in the fatigue life calculations with the fiberglass composite properties obtained by Mandell, et al. (1993). The resulting normalized service lifetimes are summarized in Table IV. Two big differences are obvious. First, the spectral simulation predicts a lifetime approximately half of that predicted by the histogram data. Second, the extrapolation of the tail of the distribution using the generalized Weibull results in a 25% shorter lifetime, a much greater tail sensitivity than

TABLE IV: Normalized Service Lifetime Predictions for the Upper Root for Fiberglass Blades.

Data Source	Analysis Technique		
	Histogram	Generalized Curve Fit	Truncated Generalized Curve Fit
Measured	1.0	0.75	0.95
Spectral	0.57	0.57	0.83

the 2% increase in lifetime seen in the aluminum example.

Even Shorter Data Samples

Table I illustrated that sample lengths on the order of ten minutes can result in small difference in the level of response, as characterized by the RMS stress, when compared with long sample lengths of many hours. These differences, even though they may be relatively small, can produce large differences in predicted lifetimes. Here we examine the effect of using even shorter duration records to determine the cyclic stress distributions.

Six 100-second time series were extracted from the 15 to 18 m/s wind speed time series used in the Test Bed example. Each was rainflow counted. A cumulative damage calculation was then done on each time segment and a resulting "lifetime" (actually, the inverse of the damage in the 15 to 18 m/s bin) was compared with the same computation for the entire 680-second record. Ratios of the results are shown in Table V. It is clear that these short records cannot even guarantee an order of magnitude estimate of the fatigue damaging potential of operation in a particular wind speed. The difference between the most damaging and least damaging is a factor of 110. For this example, a VAWT blade root in Bushland, at least ten minutes of data is required, if only to get within a factor of 2 of the long term results. And in our example the short-term

TABLE V: Normalized Lifetime In 15-18 m/s Wind Speed Bin.

Data Length sec	Normalized Lifetime	
	Histogram	Generalized Curve Fit
680	1.00	1.07
	16.	9.5
	30.	33.9
	0.27	0.27
	0.99	.97
	3.1	2.1

response level was high in some bins and low in others. One could imagine possibilities where the difference would be significantly greater as when most of the wind speed bins are off in the same direction. Therefore, significantly longer time series are recommended to reduce the uncertainty in fatigue life estimates due to cyclic stress distribution.

DISCUSSION

Our examples in this paper, because they are taken from a single machine, focus on the nature of tail sensitivity and sample length for a particular class of problems. Specifically, the distributions of rainflow counted stress cycles are slight distortions of the Rayleigh distribution. Typical distributions describing wind turbine components are expected to be generally Weibull in nature (because they are always one-sided distributions) with the Rayleigh on one end of the range of possibilities and the exponential on the other. As stated earlier, the exponential distribution [which is also found in wind turbine applications (Jackson, 1992)] is a special case of the Weibull family of distributions that has twice the spread about its mean value as the Rayleigh. Exponential-like distributions will likely exhibit much greater tail sensitivity than we have seen in this nearly Rayleigh case. Here, we see a clear example of a type of loading that is not particularly tail sensitive.

It is also worth noting the facility of the generalized fitting technique in matching the rainflow counted distribution shape and extrapolating into the tail of the distribution. Comparing Figures 2 and 5 illustrates that the distortion of the parent Weibull distribution allows the generalized fitting technique to match very closely the field data. In the case of the frequency domain synthesis of long-time data, the fitting technique not only matched the body of the distribution from a shorter data sample, but the extrapolation into the tail of the distribution predicted the actual tail obtained by simulating orders of magnitude more time series.

There are caveats to blindly extrapolating limited data. First, the short sample often simply misses the long term *level* of response. No amount of fancy curve fitting to match the distribution shape will negate that error. Second, unlike the simulation example where the long-term response is forced to

be determined by the short-term spectral density, long-term data have the possibility of containing events where the turbine enters a different *kind* of response, a nonlinear response or just a fundamentally different response than anything seen in the short term. The examples here indicated none of this behavior, but it is always a possibility and a good motivation to continue data collection and analysis.

Service lifetimes, in the examples used here, are thousands of years. It is tempting to consider fatigue a non-problem and to move on the other issues when confronted with such results. A reminder is in order, that the lifetimes calculated here are based on *average* quantities for loading and material durability. Analyses that consider the complete range of possibilities (Veers, 1993) indicate that there can still be a substantial probability of early failure even with very long average lifetimes. The point of this paper is to examine the bias built into the lifetime calculation due to stress distribution effects.

SUMMARY

As the analyses presented here cover a rather large spectrum of variables, the results of this investigation warrant a concise summary. The following six comments summarize our results.

1. Fitting analytic distribution forms to rainflow counted stress data removes the artificial truncation of large amplitude cycles that is inherent in finite data samples.
2. Errors in determining the level of stress response as characterized by the RMS level can have a substantial effect on fatigue life estimates, even for sample lengths of over ten minutes.

3. Stress distribution tail truncation did not contribute significantly to differences in service lifetime predictions for the Test Bed VAWT in Bushland, Texas. The peculiarities of the response on this turbine are that the levels are generally low (average lifetimes are thousands of years), the blades are aluminum and the stress distributions have a nearly Rayleigh character.

4. Stress distribution tail truncation did contribute significantly to differences in service lifetime predictions for materials with relatively large fatigue exponents. When the Test Bed data example is applied to fiberglass composite material fatigue properties the tail sensitivity increased markedly (from no effect to a 25% effect on predicted lifetime).

5. The generalized Weibull fitting technique does an excellent job of both matching the body of the distribution and of extrapolating the tail of the distribution. This is demonstrated using a frequency domain simulation to generate relatively short and very long samples from the spectral content of measured data.

6. If time series samples are too short (e.g., 100 seconds), the lifetime prediction errors will be tremendous whether or not there is what we might call "tail sensitivity." The source of the errors is a combination of a wrong definition of the overall level of response (i.e., RMS level of the stresses on the turbine at that particular wind speed) and tail truncation.

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