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FAROW: A TOOL FOR FATIGUE AND RELIABILITY OF WIND TURBINES

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ABSTRACT

FAROW is a computer program that evaluates the fatigue and reliability of wind turbine components using structural reliability methods. A deterministic fatigue life formulation is based on functional forms of three basic parts of wind turbine fatigue calculation: (1) the loading environment, (2) the gross level of structural response given the load environment, and (3) the local failure criterion given both load environment and gross stress response. The calculated lifetime is compared with a user specific target lifetime to assess probabilities of premature failure. The parameters of the functional forms can be defined as either constants or random variables. The reliability analysis uses the deterministic lifetime calculation as the limit state function of a FORM/SORM (first and second order reliability methods) calculation based on techniques developed by Rackwitz [1]. Besides probability of premature failure, FAROW calculates the mean lifetime, the relative importance of each of the random variables, and the sensitivity of the results to all of the input parameters, both constant inputs and the parameters that define the random variable inputs. The ability to check the probability of failure with Monte Carlo simulation is included as an option.

INTRODUCTION

Fatigue is an insidious problem in structures of all types, but especially in wind turbines where severe environmental loadings combine with stringent cost requirements to produce an inevitable conflict between expense and durability. The best defense against fatigue problems is an accurate estimate of the fatigue life for candidate or prototype designs. The LIFE2 code [2] is one of a few useful tools for achieving that end. These methods share the characteristic of requiring specific values for all governing parameters and producing deterministic predictions of time to failure. FAROW builds on that foundation and provides even more valuable information for designers by using structural reliability methods.

Why Reliability Methods?

Every designer of fatigue sensitive structures would like to know the lifetime of the design with perfect accuracy. The design could then be fine tuned to eliminate needless costs while maintaining acceptable durability. Unfortunately, designers are often disappointed with fatigue life computation results. Not only are the techniques difficult to apply, requiring a daunting level of detail of the machine and its environment, but the results are highly sensitive to changes in the inputs [3]. Ranges of plausible answers from two months to ten years erode the value of the results and make the process frustrating. The knowledge that this sensitivity is inherent to the fatigue problem is of little comfort.

A good designer will therefore put appropriate safety factors on all the uncertain quantities that affect fatigue life. It would be beneficial, however, to provide a more quantitative measure of the design conservatism. The proper question may not be "what is the actual fatigue life of this component?" but rather "with what confidence will the component meet its target design life?" Such questions are naturally addressed by the theory of structural reliability.

The main result of a reliability analysis is the probability of failing to meet a specified target lifetime. This result alone provides a more accurate sense of the quality of a component design than a deterministic time to failure based on either qualitative safety factors or ad hoc measures such as maximum strain. But structural reliability methods provide much more information than just probability of failure. *Importance factors*, which indicate how much each random variable contributes to the total probability of failure, are also calculated. By focusing on the most *important* of the random variables in prototype testing and design refinement, the developers can efficiently work toward a more reliable design. The FAROW code also estimates the *sensitivity* of the reliability to each of the controlling parameters, both random and deterministic. Again, the wind turbine developer is provided direction as to which of the parameters have the greatest overall impact on fatigue durability. This kind of information is a natural byproduct of using structural reliability methods in the fatigue analysis of wind turbine components.

FAROW Overview

The FAROW code has been named to describe its function, calculating the Fatigue And Reliability Of Wind Turbines. It is based on a deterministic fatigue life formulation for the specific case of wind turbine components loaded by continuous operation in a typical (user specified) wind environment. This formulation is used by a reliability analysis engine to produce the desired probabilistic results.

The fatigue formulation is intended to capture uncertainty in environmental loading, gross structural response and local fatigue properties. Fatigue damage is modeled probabilistically using Miner's Rule and the effects of variable loads, mean stress, and stress concentration factors. Uncertainty in the fatigue properties themselves is included. A critical distinction here is between continuously varying quantities such as an environmental parameter (e.g., instantaneous wind speed V, applied stress amplitude S versus time, etc.) and fixed parameters which may be uncertain (e.g., fatigue law coefficients, distribution parameters of V, S given V, etc.). Continuously varying quantities are reflected here implicitly, through their average effect on fatigue damage. In contrast, parameter uncertainty doesn't "average out" over fatigue life, and is modeled here explicitly.

FAROW uses assumed functional forms for the controlling quantities of fatigue life. The functions are defined by parameters such as S-N coefficient and exponent, RMS stress level at a characteristic wind speed, average wind speed, etc (see Table 1). There is a trade-off between the level of generality and the ease of use; the restrictive assumptions catalogued in the user's manual [4] permit definition of the entire problem with a condensed data set. The emphasis has been on keeping the input simple and easy to use.

The probability of failure is calculated using the general purpose FORM/SORM (first and second order reliability methods) package developed by Rackwitz [1]. Enhancements to the way the basic algorithm treats correlation between random variables have been added [5]. Importance factors and sensitivities are calculated as well. The analysis is made specific to the wind turbine problem with an appropriate failure state function and by adding the necessary input and output coding.

Inputs are defined in a user edited file with comments included throughout. The intent is for the user to copy and edit the file for each new case to be analyzed. The name of the input file is the only interactive response requested by the code. There are two output files: One given a ".OUT" extension is for general use and one given a ".LOG" extension is for assistance if things go wrong.

FAROW Capabilities

As previously stated, calculating probabilities of failure is only one of the many results provided by FAROW that aid in understanding the fatigue reliability of a component and indicate how to improve it. The many capabilities alluded to above are listed here:

- Mean time to failure is estimated using median parameter values.
- The probability of failing to meet a lifetime target is determined.
- The evolution of the probability of failure is determined as a function of time.
- The relative importance of each source of uncertainty is calculated.
- The sensitivity of the reliability to each of the input quantities, both constant inputs and the parameters of the distributions of random variables, is estimated.
- Monte Carlo simulation for brute force estimates of the probability of premature failure is included as an option.
- The inputs are taken from a set of descriptive parameters in a user edited file.
- Random variables are selected from a library of distribution functions.

EXAMPLE

It may be simplest to illustrate FAROW by working through an example that shows how one might approach the fatigue reliability problem. This example should not restrict the user's creativity in applying this rather powerful tool for probabilistic analysis, but is intended to give some initial guidance.

An earlier example [6] produced with a precursor to FAROW illustrated the kind of analysis one might encounter in the final design stages of a machine where there has already been extensive testing and data analysis so that the uncertainty in many of the inputs is fairly small. Data was taken from the 34-m Test Bed in Bushland Texas, a machine designed and tested by Sandia National Laboratories. The results indicated that with a mean lifetime of 370 years the probability of failure in less than 20 years was still over 2%. Variability in the S-N coefficient was identified as the greatest source of this probability of failure. The wind speed distribution shape and stress concentration factor were also heavy contributors.

The following example represents an attempt to deal with the uncertainty in fatigue analysis of a typical fiberglass blade early in the design stages, before any test data is available, and while detailed analysis may be in progress. The number of uncertain parameters is therefore greater and some of the levels of uncertainty may be higher. The design is a HAWT blade built of a mostly unidirectional fiberglass composite material. Material testing has not been done on the specific blade material, but published data from similar materials are available. Stress levels have been predicted with relatively high confidence, at least in wind speeds below stall. The stall controlled machine operates at variable speed in low winds (fixed pitch) to optimize efficiency. The objective is to have a very low probability of failure within five years of installation.

There are five specific areas of information required to set up the fatigue analysis of this example component, assuming that fatigue damage only occurs during operation. The controlling parameters in each area are described below. Inputs are summarized in Table 1, which is an echo of the inputs taken from the FAROW output file.

1. Wind Speed Distribution

Wind speed is assumed to be Weibull distributed with both average, $\overline{V}$, and shape factor, α_V, permitted to be defined as random variables or constants. Here we assume $\overline{V}$ is normally distributed with a mean of 7.5 and a standard deviation of 0.5. α_V is taken to be Weibull distributed with a mean of 1.8 and a COV of 0.1 (COV = Coefficient of Variation = standard deviation divided by the mean). The Weibull distribution on α_V is chosen because it has a relatively "fatter tail" on the low side, which is the more damaging extreme for wind speed distribution shape factor.

2. RMS of the Instantaneous Stress at the Point

The root mean square (RMS = σ_g) of the instantaneous stress history is used to describe the nominal stress as a function of wind speed. The nominal stress is magnified by a detail dependent stress concentration factor, K. The functional form is taken to be

$$\sigma = K\sigma_g \ ; \ \sigma_g = \sigma_{char}\left(\frac{V}{V_{char}}\right)^p \tag{1}$$

where σ_{char} is the nominal RMS at the characteristic wind speed V_{char}, and p is an exponent that allows the user to specify a nonlinear RMS versus wind speed.

For our example, we assume a nominal flapwise-bending RMS stress of 400 psi in the blade root region for steady state operation at a characteristic wind speed of 10 m/s. The nominal uncertainty in stress predictions leads to assessment of a 10% COV on σ_{char}, which is taken to be normally distributed about the 400 psi mean value. Stresses have been predicted to increase linearly with wind speed. Because of the uncertainty of the stress predictions above stall, the parameter p is defined as a normally distributed random variable with mean 1.0 and 20% COV. Variations in this exponent have the effect of "wagging the tail" of the RMS stress vs wind speed curve at high wind speeds as illustrated in Figure 1. The highly uncertain stress concentration factor, K, is taken to be log-normally distributed with mean 1.5 and COV = 0.2.

3. Distribution of Stress Amplitudes

FAROW supports a general Weibull distribution function as the form for the distribution of stress amplitudes. The Weibull includes the exponential and Rayleigh distributions as special cases with shape factor, α_S in this case, equal to 1.0 and 2.0 respectively. All possible values of the shape factor are supported.

The rainflow counted stress amplitudes from flapwise loads on HAWT blade roots have at times been shown to be exponentially distributed. We assume that the analysis in this example supports this evidence. The parameter α_S is therefore taken to be narrowly distributed (COV of 0.05) about a mean value of 1.0.

4. S-N Curve

Materials data on mostly unidirectional fiberglass composites can be found in Mandell, et al. [7]. The S-N data in this report, however, are reported in the form of cycles to failure versus peak stress divided by ultimate strength, at a stress ratio (maximum divided by minimum) of $R = 0.10$. Cumulative damage assessment in FAROW and elsewhere is typically done using stress mean and amplitude. The data do not convert simply from one form to the other; a straight line log-log plot in one form will be curved in the other form. Mandell's data has been converted to mean and amplitude using Goodman's rule in the same way it is applied in the FAROW fatigue formulation. The two curves are shown in Figure 2. The resulting expression for fatigue life as a function of effective stress is

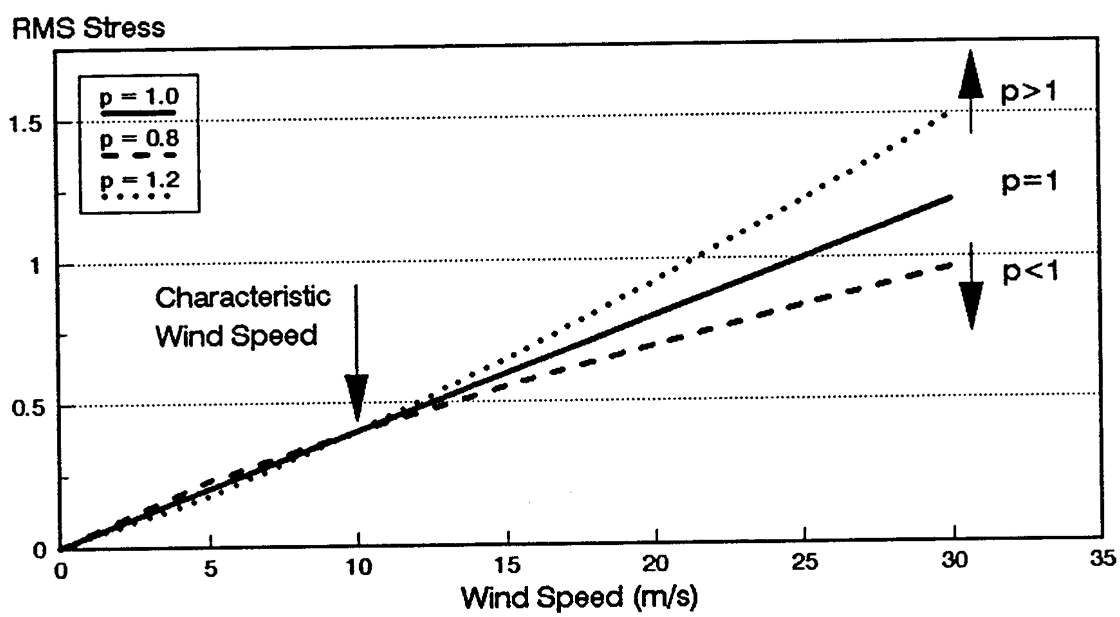

Figure 1. The RMS stress levels are defined as a function of wind speed using the value of the RMS stress at the characteristic wind speed and an RMS exponent, p.

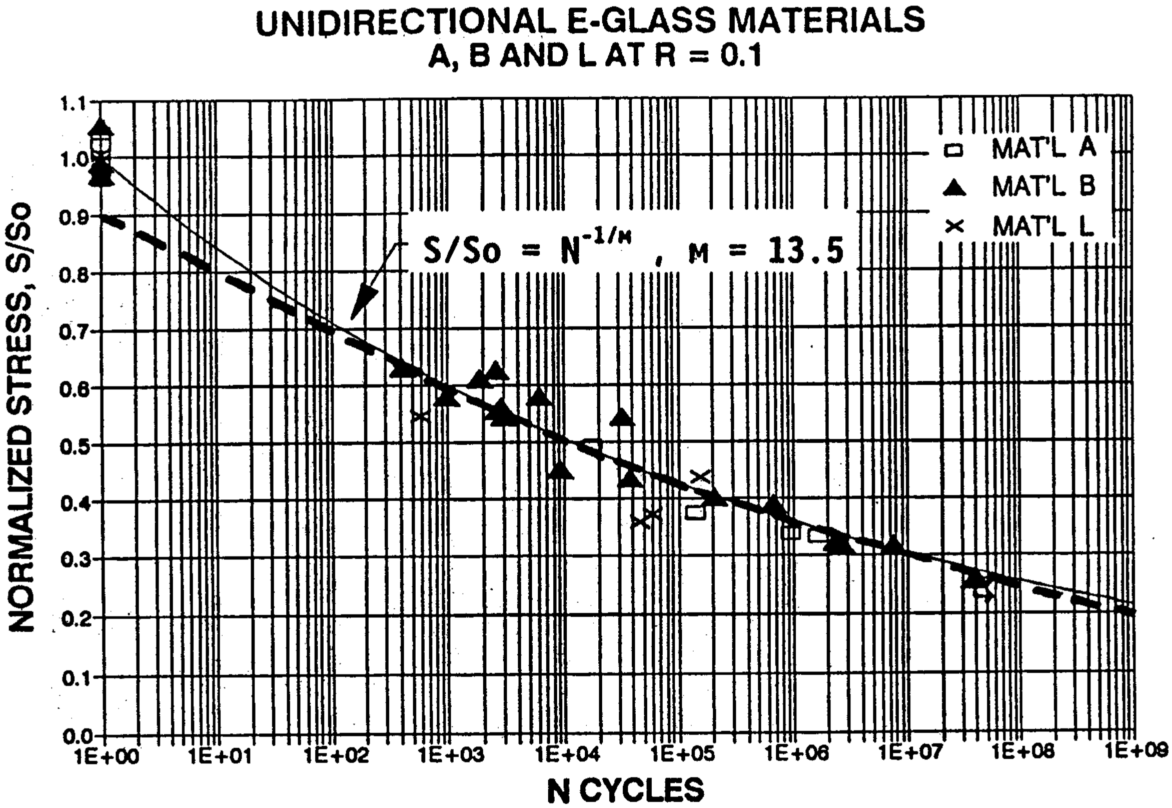

Figure 2. S-N curve for unidirectional fiberglass materials taken from Figure 9 of Reference 7. The added dashed line is the fit to the data from Equation 2.

$$N_f = CS_{eff}^{-b} \;\; ; \;\; C = \frac{S_u^{10}}{10} \;\; , \;\; b = 10 \qquad (2)$$

where S_u is the ultimate strength, S_{eff} is the effective stress amplitude, and C and b are the new material S-N properties.

As shown in the figure, this fit is almost indistinguishable from the original in the range of the test data, between 10^3 and 10^7 cycles to failure. It falls slightly below the Mandell fit at higher and lower lives. Notice that the change from peak stress to effective stress amplitude results in a slight reduction in the S-N exponent from Mandell's m = 13.5 to the effective formulation with b = 10.

The S-N coefficient, C, in this formulation is functionally related to the ultimate strength through Eq. 2. Given an ultimate strength of 85 ksi, the S-N coefficient will be 2 x 10^{18}, with the obscure units of: $(\text{ksi})^{10}$ cycles. C and S_u are assigned a correlation of 0.9 to simulate the functional dependence. The variance in C is used to represent not only the variation in material properties, which alone usually result in COVs > 0.50, but must also reflect the fact that the referenced S-N data used to estimate the material parameters are not based on the actual material to be used in the blade. The S-N coefficient is here chosen to be Weibull distributed with the above mean and a COV = 0.7. The exponent is fixed at b = 10.

5. Average Damage Rate

All of the remaining parameters that determine the average damage rate, except those controlling the cycle rate, are chosen to be constants. The cut-out wind speed is selected to be V_{max} = 25 m/s. The Miner's rule constant, Δ, the value at which the summation of damage is equated with material failure, is fixed at unity (although it might be good practice to assign some healthy uncertainty to this parameter when dealing with composite materials). The availability is also set to 100%.

The frequency versus wind speed relationship, $F(V)$, is modeled here in some detail to simulate loading on this variable speed rotor. Cycle rate is given in terms of V_{char} and f_0, f_1, and f_2: the constant, linear, and quadratic coefficients.

$$F = f_0 + f_1\left(\frac{V}{V_{char}}\right) + f_2\left(\frac{V}{V_{char}}\right)^2 \tag{3}$$

To achieve a cycle rate of 1 Hz at zero wind speed, 2 Hz at 10 m/s, and a maximum of 2.5 Hz in high winds, the cycle rate coefficients are given mean values of $f_0 = 1.0$, $f_1 = 1.25$, and $f_2 = -0.25$. All are assumed to be uncertain: f_0 is assigned a log-normal distribution with a COV of 0.20, while the others are assigned normal distributions with COVs of 0.10. The log-normal is used because it has a "fatter tail" on the high value side, which is the worst case for cycle rate. To keep the sum of the coefficients from wandering too far from the stated value of 2.0 Hz at the characteristic wind speed of 10 m/s, some negative correlation is assigned between f_1 and f_2. That way, a higher realization of one will more likely be coupled with a lower realization of the other, keeping the sum more steady. The constant coefficient is allowed to vary more freely to reflect the possibility of a poor over all prediction of the average cycle rate.

Table 1. Summary of the inputs to FAROW taken from the output file.

* * I N P U T   P A R A M E T E R S * *

KEYWORD	DESCRIPTION OF KEYWORD	DISTRIBUTION NUMBER/TYPE	INPUT PARAMETERS	
VBAR	MEAN WIND SPEED	1/NORMAL	MEAN 7.500	STD DEV .5000
ALPHAV	WIND SPEED SHAPE	7/WEIBULL	MEAN 1.800	COV .1000
SCF	STRESS CONCENTRATION FACTOR	6/LOG NORMAL	MEAN 1.500	COV .2000
VCHAR	CHARACTERISTIC WIND SPEED	5/NORMAL	MEAN 10.00	COV .0000
RMSC	RMS COEFFICIENT	5/NORMAL	MEAN .4000	COV .1000
RMSEXP	RMS EXPONENT	5/NORMAL	MEAN 1.000	COV .2000
ALPHAS	STRESS CYCLE DISTRIBUTION SHAPE	5/NORMAL	MEAN 1.000	COV .5000E-01
MEANST	MEAN STRESS	5/NORMAL	MEAN 3.500	COV .2000
ULTST	ULTIMATE STRESS	5/NORMAL	MEAN 85.00	COV .1000
C	S-N COEFFICIENT	7/WEIBULL	MEAN .2000E+19	COV .7000
B	S-N EXPONENT	1/NORMAL	MEAN 10.00	STD DEV .0000
F0	CYCLE RATE CONSTANT COEFFICIENT	7/LOG NORMAL	MEAN 1.000	COV .2000
F1	CYCLE RATE LINEAR COEFFICIENT	5/NORMAL	MEAN 1.250	COV .1000
F2	CYCLE RATE QUADRATIC COEFFICIENT	5/NORMAL	MEAN -.2500	COV .1000
VMAX	CUT-OUT WIND SPEED	1/NORMAL	MEAN 25.00	STD DEV .0000
DELTA	MINERS DAMAGE	1/NORMAL	MEAN 1.000	STD DEV .0000
AVAIL	AVAILABILITY	1/NORMAL	MEAN 1.000	STD DEV .0000
TARLIF	TARGET LIFETIME	1/NORMAL	MEAN 5.000	STD DEV .0000

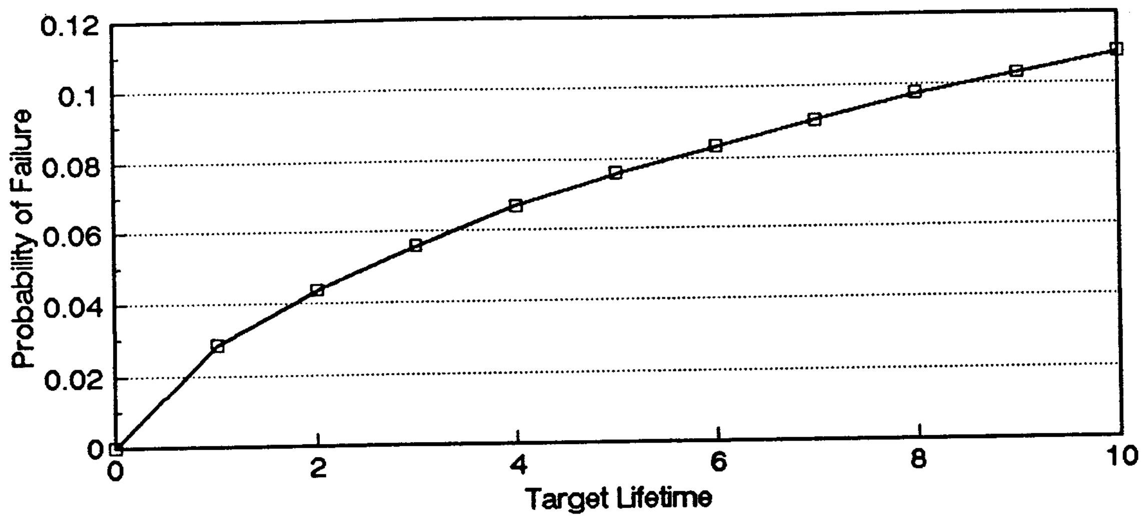

Figure 3. Plot of the evolution of probability of failure with increasing target lifetime for the Example presented here.

Results

Mean lifetime and Probability of Failure: By substituting the median values for all the random variables defined above, and using the constant values for all the other input parameters, a mean lifetime of 600 years is calculated. The probability of failing in less than the five year target, however, is estimated at 7.5%, illustrating both the uncertainty in the fatigue life calculation given reasonable uncertainty in the inputs and the sensitivity of fatigue life to parameter variation. In addition, FAROW prints out the probability of premature failure for a user specified range of target lifetimes, plotted in Figure 3.

Reliability Index: Because probabilities of failure can range over orders of magnitude as reliability increases and probability of failure approaches zero, a more well behaved "reliability index" is usually defined. The reliability index is the distance from the mean, measured in standard deviations, of the most likely failure point (the most likely combination of values that, when substituted into the deterministic analysis, produce failure at the target lifetime). For example, a "three sigma" probability of failure of 0.0013 would be associated with an index of 3.0. This keeps the index limited to small values and produces a measure that increases as reliability improves. The reliability index in this example is 1.44.

Importance Factors: FAROW also determines how much each of the uncertain inputs contributes to the probability of failure. Table 2 shows the FAROW output file segment that contains these "importance factors." Notice that importance factors only apply to inputs with nonzero variance, and not to parameters defined as constants. The values of the random variables at the most likely failure point are listed under the `PHYSICAL` column. Also printed are `GAUSSIAN` values, which are the number of standard deviations from the mean. A `GAUSSIAN` value near zero is associated with a low importance factor and means that the variable contributes negligibly to the probability of failure. It is interesting that the combination of random variable values that produce a five year lifetime, 120 times less than the mean lifetime, deviate less than one standard deviation from each mean value.

The random variable with the greatest importance in Table 2 is the stress concentration factor (K = `SCF`), with the RMS exponent (p = `RMSEXP`) and stress amplitude distribution shape factor (α_S = `ALPHAS`) next in line. Although the S-N coefficient (C = `C`) was assigned a large uncertainty of COV = 0.7, it is only tied for fourth among the random variables in this example. Recall that in the example of Ref. 6, where there were more data from stress measurements, S-N properties dominated the uncertainty.

Sensitivity Estimates: FAROW determines the sensitivity of the reliability to all input quantities, first to constants and mean values, and then to the variance of the random variables. The sensitivities are derivatives of the reliability index with respect to the input parameters. Thus linear estimates of how much the reliability can be increased by changes in the parameters are available. While there is insufficient room in this forum to reproduce the entire table of sensitivity calculations, a few of the sensitivities in this example bear examining.

Table 2. FAROW output file segment for importance factors.

KEYWORD	PHYSICAL VALUE	GAUSSIAN VALUE	IMPORTANCE FACTOR	IMPORTANCE GRAPH	IMPORTANCE BY FRACTION OF TOTAL VARIATION
VBAR	7.548E+00	9.685E-02	-.065	*.	.004
ALPHAV	1.795E+00	-2.298E-01	.153	.**	.024
SCF	1.784E+00	9.758E-01	-.652	*******.	.425
RMSC	4.176E-01	4.390E-01	-.293	***.	.086
RMSEXP	1.135E+00	6.755E-01	-.451	*****.	.203
ALPHAS	9.706E-01	-5.884E-01	.393	.****	.154
MEANST	3.554E+00	7.677E-02	-.051	*.	.003
ULTST	8.118E+01	-1.427E-02	.010	.	.000
C	1.137E+18	-4.741E-01	.317	.***	.100
F0	9.876E-01	3.619E-02	-.024	.	.001
F1	1.254E+00	3.195E-02	-.021	.	.000
F2	-2.505E-01	-1.253E-02	.008	.	.000

The greatest sensitivity to a mean value or constant is to the S-N exponent, *b*. But the stress amplitude distribution shape factor, α_S, is a close second. While the normalized sensitivity to *b* is 10 (meaning a 10% change in *b* will change in the reliability index by 10 times 10%, or 1.0), the sensitivity to α_S is 7.5. Several sensitivities are in the 2 to 3.5 range. Also, if the α_S =1.0 assumption in this example is changed to the opposite extreme of α_S =2.0 (a Rayleigh distribution), the resulting mean time to failure becomes 18 million years (!) and the probability of failure in less than 5 years is $3x10^{-6}$.

Sensitivity to the assumed variance (standard deviation or COV) in the uncertain parameters is less than sensitivity to the mean values or constants. Sensitivity to the variance indicates how much is to be gained by reducing the uncertainty in each input. The general trends follow that of the importance factors, but not exactly. In this example, the greatest increase in reliability can be gained by reducing the variance in stress concentration factor and RMS exponent, just as might be surmised by the importance factors. But reducing the uncertainty in the S-N coefficient is a close third, higher than its "importance" ranking. Sensitivities to these three variances are 0.53, 0.31 and 0.27.

SUMMARY

FAROW provides quantitative information on a component's fatigue reliability that reflects the state of knowledge of the component and its environment. While using this tool won't solve all turbine designers' fatigue problems, it can provide important information about the state of the design and about the value of additional data.

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