Reliability and Degradation Modeling with Random or Uncertain Failure Threshold

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SUMMARY & CONCLUSIONS

This paper developed extensions to the existing research so that reliability assessment based on degradation modeling can address new problem domains that previously did not meet the required assumptions and modeling constraints. Degradation modeling is based on probabilistic modeling of a failure mechanism degradation path and comparison of a projected distribution to a pre-defined failure threshold. Previous approaches to this problem required that the pre-defined failure threshold must be considered as a fixed deterministic value, which can be problematic for several reasons. Often, the designer and producer of a part or a system have many diverse users of their products. In practice, the critical threshold value can vary appreciably among users. In this case, a probabilistic, rather than a deterministic threshold value is more appropriate. For other applications, the designer may not know with certainty what explicit level of degradation will cause a failure. In this case, specification of a range of possible threshold values is more appropriate. This also can be accommodated by considering the threshold value as a random variable with some assumed distribution to reflect the variability. New modeling approaches are presented in this paper such that this limiting assumption is no longer required. This should allow systems with more varied usage conditions and failure mechanisms to be analyzed using degradation-based reliability assessment methods.

1. INTRODUCTION

Reliability prediction based on degradation modeling can be an efficient method to estimate reliability for some highly reliable components or systems when observations of failures are rare. Degradation modeling is based on probabilistic modeling of a failure mechanism degradation path and comparison of a projected distribution to a pre-defined failure threshold. Consider the monotonically increasing degradation path depicted in Figure 1. The failure mechanism is degrading probabilistically with time. At any specified time, there is a distribution of degradation measurements considering a population of similarly degrading parts. Notice in the figure that the degradation measure has a larger variance as time increases. While this may not be representative of all failure mechanisms characterized by an increasing degradation path, the increasing variance is often observed. For any specified time, reliability can then be estimated as the probability that the degradation measure is less than the critical threshold value. Alternatively, if the degradation path was monotonically decreasing, then the reliability would be estimated as the probability that the degradation measure is greater than the critical threshold value.

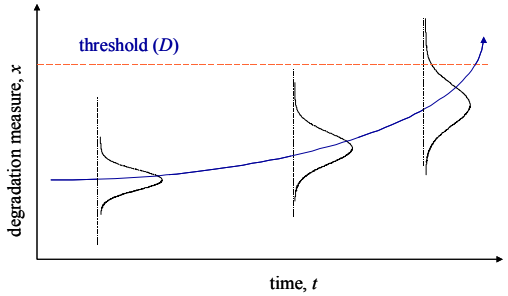

Figure 1: Degradation Path Example

To predict reliability based on degradation modeling, the failure mechanism must be clearly understood and there must be an underlying model or model form to characterize propagation of the degradation path. The model parameters or coefficients can then be thought of as random variables for individuals within the population. For many parts and systems, the specific failure mechanisms are unknown or there are many competing failure mechanisms. In these cases, degradation modeling would not be applicable as an approach to predict reliability.

There are many examples of failure mechanisms where there is some defined degradation path and reliability prediction based on degradation modeling is a viable approach. Typical degradation measures or examples include degraded light intensity, wear (measured by contaminants in lubrication), drug stability, crack propagation, resistance drift and loss of structural strength. In each instance, the failure mechanism is understood from a physical perspective and there are models to characterize average or typical degradation. However, the individual degradation paths may diverge significantly from the mean; thereby, creating the distributions depicted in Figure 1.

The primary advantage of degradation modeling is that multiple degradation measurements can be recorded on each individual within the population. Therefore, it is not necessary to wait until failure to obtain and analyze the data. Compared to traditional life testing, this yields more plentiful data. For highly reliable parts or systems, where failures are rare, this

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may be the only possible approach.

2. LITERATURE ON DEGRADATION MODELING

Sethuraman & Young [1] developed a cumulative damage threhold crossing model. Under this model, an item, fails as soon as the maximum cumulative damage to some component crosses a certain threshold. Zuo, Jiang & Yam [2] introduced three approaches for reliability modeling of continuous state devices. The three approaches are based on the random process model, the general path model, and the multiple linear regression model, respectively. They also proposed a mixture model which can be used to model both catastrophic failures and degradation failures. Meeker, Escobar & Lu [3] reviewed literature on accelerated degradation analysis and extend the approach of Lu & Meeker [4] to allow for acceleration. Crk [5] developed a methodology based on a multiple multivariate regression model which encompasses Lu & Meeker's [4] model and goes a step further by considering a component or a system performance degradation function whose parameters may be random, correlated and stress dependent. Chinnam [6] uses neural networks for modeling of degradation signals. In contrast to the methods in the literature that use degradation data to estimate a population characteristic(s), the approach in his paper focuses on on-line reliability estimation of individual components using degradation data. Eghbali & Elsayed [7] developed a new approach for the analysis of degradation data. This approach is based on a new concept called degradation hazard function. It is assumed that the degradation hazard function can be written in terms of two separable functions: time and degradation measure. The stress covariates can be incorporated in the model so that this approach could be used to model the results of Accelerated Degradation Tests (ADT). Other applications of reliability prediction based on degradation modeling include reliability prediction of helicopter transmission systems [8], optimal degradation process control [9], distribution system reliability evaluation with aging equipment [10], reliability estimation of degraded structural components subject to corrosion [11], real-time conditional reliability prediction from on-line tool performance data [12], investigations on the relation between a chosen degradation model and the resulting lifetime model [15], risk analysis related to the degradation mechanisms responsible for aging [16], multi-objective optimization using genetic algorithms in degradation test design [17], and acceptance sampling plan for degradation test of keyboard [18], etc.

Lu & Meeker [4] used a general degradation path model to estimate a time-to-failure distribution. They assumed that, for each unit in a random sample of n units, degradation measurements, x, will be taken at pre-specified times: $t_1, t_2, \ldots, t_s$, generally until x crosses a pre-specified critical level D or until time t_s, whichever comes first. The sample degradation path of i^{th} unit at time t_j is given by,

$$x_{ij} = f(t_j; \phi, \theta_i) + \varepsilon_{ij} \quad (1)$$

where ε_{ij} is measurement error.

Degradation path models often include terms that are nonlinear in the parameters. The parameters are divided into two types: fixed-effects parameters ϕ that are common for all units, and random-effects parameters θ_i representing individual unit characteristics. Lu & Meeker [4] assumed that the random-effects parameters are characterized by a multivariate distribution function $G(\cdot)$ which may depend on some unknown parameters that must be estimated from the data. They developed a 'two-stage' method to estimate the model parameters. They used Monte Carlo simulation to compute an estimate of the distribution function of the time-to-failure. Refer to the Appendix for a detailed description.

The next section discusses how Lu & Meeker's approach can be extended to a more general and practical class of degradation models.

3. DEGRADATION MODELING WITH RANDOM OR UNCERTAIN FAILURE THRESHOLD

Reliability prediction based on degradation modeling requires the user to specify a critical threshold value. When the degradation measure reaches this level, the assumption is that the part has failed due to the degradation failure mechanism. One example would be when the effective resistance of a 10 (+/- 10%) ohm drifts in either direction beyond 10%. The part is no longer functioning as intended, and thus, has failed. Another example would be the illumination of a display panel. As light intensity falls to 50% of the original (or design) level, the part should be considered a failure.

Previous degradation modeling approaches have required the user to specify a pre-determined deterministic critical value. For many problems, this is entirely valid and appropriate. However, for some other types of problems, this can be problematic for several reasons. Often, the designer and producer of a part or system have many diverse users of their product. In practice, the critical threshold value can vary appreciably among users. In this case, a probabilistic, rather than a deterministic threshold value is more appropriate. For other applications, the designer may not know with certainty what explicit level of degradation causes a failure. For instance, in structural reliability analysis fatigue crack length is often used as a degradation measure to evaluate the risk of structure fatigue failure. It is believed that the longer the crack length is, the more probable that the fatigue failure will occur. But the question is, at what specific crack length will the failure occur? A fixed threshold value may not always be appropriate. Other examples are automobile timing belts and tires. In these applications, a threshold could be determined based a measurable amount of tire wear. However, the applications and severity of stress may differ from user to user. In these applications, specification of a range of possible threshold values for the degradation failure thresholds is more appropriate. This also can be accommodated by considering the threshold value as a random variable with some assumed distribution to reflect the variability. The uncertainty caused by a random failure critical threshold value can be expressed as,

$$R(t|D) = f(\cdot|D), \quad E_D[R(t)] = \int_{all\ u} f(\cdot|u) g_D(u) du \quad (2)$$

where $f(\cdot)$ represents the reliability function, $g_D(u)$ represents

the probability density function of the critical failure threshold. An alternative valid approach to this problem would be to consider the conditional reliability at an expected threshold value with an associated confidence interval. This was not the approach we adopted; however, for some applications, it may be a preferable approach.

For previous approaches to the problem, users have been required to supply a deterministic threshold value without addressing the uncertainty. In general, when faced with uncertainty, there are two possibilities. Users may have supplied (1) an unbiased estimate of the mean of the threshold value, or (2) a lower-bound estimate for failure threshold (for increasing degradation paths) to be conservative. Both of these scenarios have been analyzed in detail as part of this paper, and Lu & Meeker's [4] approach has been extended to accommodate these cases.

In the estimation of $F_T(t)$, Lu & Meeker inverted the degradation path model, with the degradation measure set equal to the critical value, to solve for time-to-failure. Time-to-failure is a random variable because the model parameters are randomly selected from a multi-variate normal distribution. The resulting time-to-failure can be expressed as follows. (It is noted that $f(\cdot)$ is an arbitrary function describing degradation and not a probability density function in this context.)

$$\tilde{t} = f^{-1}(\tilde{\theta}, \hat{\phi}, D) \tag{3}$$

Cumulative distribution functions were determined by randomly sampling θ (model parameters) N times from the multi-variate normal distribution. The failure threshold, D, was always assumed to be a deterministic constant in all cases. To accommodate uncertainty, it can be considered as a random variable or an uncertain value.

Lu & Meeker analyzed crack propagation data. that had originally been reported by Ostergard & Hillberry [13] and Trantina & Johnson [14]. Crack propagation can be highly variable, but it is a failure mechanism that has been studied extensively. The Paris Law is a power-function that is often used to predict crack length as a function of stress cycles. For the case previously studied, the degradation measure is crack length, $a(N)$, and the degradation path is given by the following function.

$$a(N) = \frac{a(0)}{\left(1 - a(0)^{m-1} C(m-1)N\right)^{1/(m-1)}} \tag{4}$$

$a(0)$ is the initial crack length prior to exposure to stress cycles. $a(0)$ can also be considered as a random variable, although users of this model generally define $a(0)$ as the maximum crack length at time 0. C and m are empirically determined constants. N, the number of stress cycles, is considered as t. The θ variables described in the Appendix are determined from transformations of the $a(N)$ model. The failure criteria was defined to be when a crack reaches a length of 1.6.

If the failure threshold, D, is a random variable, it is reasonable to assume that it is independent of the random values, $\tilde{\theta}$, from the θ distribution. The distribution of θ is characterized by the random degradation paths within the population. Alternatively, a distribution for D is to characterize the uncertainty or the variability of the failure threshold among the population of users. This depends on the user's intended application, and not the random variations in the degradation path. If independent, then the previous approach can be extended by randomly sampling from an assumed distribution for D each time the random values of θ are selected within the simulation.

By modifying steps 2 and 3 of the approach described in the Appendix, the previous regression approach can be extended to consider uncertainty. $G_D(\cdot)$ is defined as the distribution for the random critical threshold value. The new proposed approach is:

1. Estimate the path-model parameters ϕ, μ_θ, and Σ_θ from the n sample paths by using the two-stage method.
2. Generate N simulated realizations $\tilde{\theta}$ of θ from a multivariate normal distribution, $Normal(\hat{\mu}_\theta, \hat{\Sigma}_\theta)$, where N is a large number (e.g., N=100,000).
3. For each sampled $\tilde{\theta}$, randomly select $\tilde{D}$ from $G_D(\cdot)$.
4. Compute the corresponding N simulated failure times $\tilde{t}$ from $\tilde{t} = f^{-1}(\tilde{\theta}, \hat{\phi}, \tilde{D})$ where $\tilde{D}$ is the critical value
5. Estimate $F_T(t)$ by

$$\hat{F}_T(t) = \frac{\#\ of\ \tilde{t} \le t}{N} \tag{5}$$

This approach was applied for numerous assumed $G_D(\cdot)$ distributions with the critical value assumed to be normally, uniformly and lognormally distributed (for the Lu & Meeker crack propagation data, D was always 1.6). Different cases were also considered by assuming that the previous deterministic estimate was a mean (median) or a lower-bound. Many different cases were considered with different distribution variance assumptions. When a lower bound assumption about the failure threshold D was made, it was to model the scenario where an uncertain user would select a conservative level. For example, if an analyst realized that product users had different failure thresholds (e.g., critical crack length), they may select the value for a user with a lower-limit. To conduct the analyses, it was assumed that the lower-limit was three standard deviations less than the mean.

Three sample reliability graphs are depicted as Figures 2, 3 and 4. In each figure, $R_o(t)$ is the reliability prediction ignoring the uncertainty with D, and $R(t)$ is the reliability prediction considering the uncertainty. For each, the x-axis,

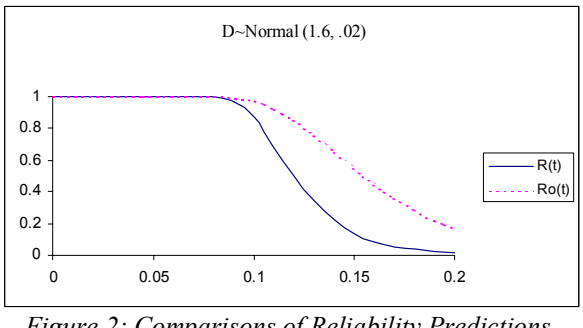

Figure 2: Comparisons of Reliability Predictions, $D \sim Normal(1.66, 0.02^2)$

time, is measured in units of 10^6 cycles. In Figure 2, D is normally distributed with mean of 1.66 and variance of $.02^2$, with a lower-bound for D of 1.6. As depicted in the figure, an incorrect deterministic assumption had little effect on the reliability prediction. In Figure 3, D is normally distributed with mean of 2.5 and variance of $.30^2$, with a lower-bound for D of 1.6. For this problem, consideration of the uncertainty leads to dramatically different results. It is interesting to note that ignoring uncertainty leads to under-estimated reliability by a significant amount. In Figure 4, D is normally distributed with mean of 1.6 and variance of $.02^2$. In this case, ignoring uncertainty leads to a large over-estimation of reliability.

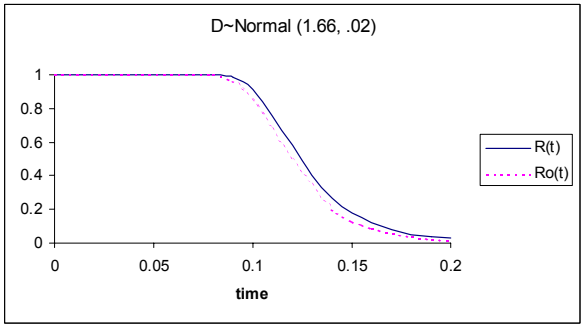

Figure 3: Comparisons of Reliability Predictions, D ~ Normal(2.5, 0.3^2)

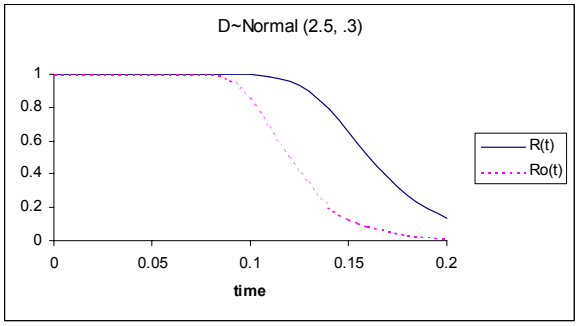

Figure 4: Comparisons of Reliability Predictions, D ~ Normal(1.6, 0.02^2)

4. CONCLUSIONS

Degradation modeling is an important analytical tool to serve as a basis for reliability prediction. Reliability predictions can be made based on observing degradation patterns prior to the observation of failures. Significant and important research has already been conducted by Lu & Meeker and others. This paper developed extensions to the existing research so that degradation modeling can address new problem domains that previously did not meet the required assumptions and modeling constraints. New applications addressed are variable or uncertain failure threshold, D. This extension can potentially broaden the use of degradation modeling methods. Many actual engineering problems, where degradation is observed and data is analyzed, have changing, variable failure thresholds. The extended approach presented here can be applied to these applications and can be used to make informed design decisions that will lead to more reliable and safer component and system designs.

APPENDIX
LU & MEEKER'S GENERAL PATH MODEL

The following are general assumptions about Lu & Meeker's (1993) general path model:

1. Sample units are randomly selected from a population or production process and random measurement errors are independent across time and units.
2. Sample units are tested in a particular homogeneous environment (e.g., the same constant temperature).
3. The measurement (or inspection) times are pre-specified. They are the same across all the test units, and may or may not be equally spaced in time. This assumption is used for constructing confidence intervals for the time-to-failure distribution via the bootstrap simulation method.

General Path Model

A general path model can be represented as

$$x_{ij} = f(t_j; \phi, \theta_i) + \varepsilon_{ij}$$

where,

X_{ij} observations of degradation measurement (i=1, 2, …, n, j=1, 2, …, m_i)

$f(t_j; \phi, \theta_i)$ degradation path

t_j time of j^{th} measurement

θ_i vector of the random-effect parameters for the i^{th} unit ~MVN (μ_θ , Σ_θ)

μ_θ mean vector of the random-effect parameters

Σ_θ varience-covarience matrix of the random-effect parameters

ϕ vector of fixed-effect parameters

n sample size

m_i number of measurements for unit i

Two-Stage Method

Estimation of reliability is based on a two-stage method. In the first stage, for each sampled unit, the degradation model is individually fit to the sample path to obtain n stage_1 estimates of the model parameters. Stage_1 estimates are transformed, if necessary, so that the random-effect parameters can be modeled with a multivariate normal distribution. In the second stage, estimates of ϕ , μ_θ , and Σ_θ are computed using stage_1 estimates of the model parameters.

Stage_1

In the first stage, for each unit i (i = 1, 2,…, n), the least squares estimates $(\hat{\phi}_i, \hat{\theta}_i)$ of (ϕ_i, θ_i) are the values of the path parameters that minimize the likelihood function $L(\phi,\theta)$, where,

$$L(\phi,\theta) = \sum_{j=1}^{m_\theta} \{x_{ij} - f(t_j; \phi, \theta)\}^2$$

An estimator of the error variance σ_ε^2 for the i^{th} unit is,

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{m_{\theta_i} - p} L(\hat{\phi}_i, \hat{\theta}_i)$$

where $p = p_\phi + p_\theta$

p_ϕ and p_θ are the dimensions of ϕ and θ, respectively. For large m_{θ_i}, the following asymptotic distributions are conditional on $\theta_i = \theta_i^*$.

$$\begin{pmatrix} \hat{\phi}_i \\ \hat{\theta}_i \end{pmatrix} \sim MVN\left(\begin{pmatrix} \phi \\ \theta_i^* \end{pmatrix}, \sigma_\varepsilon^2 [\dot{f}'(t_j;\phi,\theta_i^*)\dot{f}(t_j;\phi,\theta_i^*)]^{-1} \right)$$

$$\frac{(m_{\theta_i^*} - p)\hat{\sigma}_{\varepsilon_i}^2}{\sigma_\varepsilon^2} \sim \chi^2_{m_{\theta_i^*} - p}$$

where θ_i^* and $m_{\theta_i^*}$ are realizations of θ_i and m_{θ_i}, $\dot{f}(t_i;\phi,\theta_i) = \partial f(t_i;\phi,\theta_i)/\partial(\phi,\theta)$ and $MVN(\cdot)$ is the multi-variate normal distribution.

Stage_2

In the second stage, the multi-variate normal distribution parameters are estimated based on the unconditional estimators $(\hat{\phi}_i, \hat{\theta}_i)$, $i = 1, 2, \ldots, n$.

$$\hat{\phi} = \frac{1}{n}\sum_{i=1}^{n} \hat{\phi}_i$$

$$\hat{\mu}_\theta = \frac{1}{n}\sum_{i=1}^{n} \hat{\theta}_i$$

$$\hat{\Sigma}_\theta = \frac{1}{n-1}\sum_{i=1}^{n} (\hat{\theta}_i - \hat{\mu}_\theta)(\hat{\theta}_i - \hat{\mu}_\theta) - \frac{1}{n}\sum_{i=1}^{n} \hat{Var}_\varepsilon(\hat{\theta}_i)$$

$Var_\varepsilon(\hat{\theta}_i) = \sigma_{\varepsilon_i}^2 [\dot{f}'(t_j;\phi,\theta_i)\dot{f}(t_j;\phi,\theta_i)]^{p_\theta p_\theta}$ is the asymptotic variance-covariance matrix of $\hat{\theta}_i$ based on the sample path from the i^{th} unit, and $[\dot{f}'(t_j;\phi,\theta_i)\dot{f}(t_j;\phi,\theta_i)]^{p_\theta p_\theta}$ is the lower right $p_\theta \times p_\theta$ submatrix of $[\dot{f}'(t_j;\phi,\theta_i)\dot{f}(t_j;\phi,\theta_i)]^{-1}$.

Estimation of $F_T(t)$

When there is no closed-form expression for time-to-failure distribution, $F_T(t)$, one can use Monte Carlo simulation. This is done by generating a sufficiently large number of random sample paths from the assumed path model with the estimated parameters and using the proportion failing as a function of time to estimate $F_T(t)$. The following algorithm is used:

1. Estimate the path-model parameters ϕ, μ_θ, and Σ_θ from the n sample paths by using the two-stage method
2. Generate N simulated realizations $\tilde{\theta}$ of θ from $Normal(\hat{\mu}_\theta, \hat{\Sigma}_\theta)$, where N is a large number (e.g., $N = 100{,}000$)
3. Compute the corresponding N simulated failure times $\tilde{t}$ from $\tilde{t} = f^{-1}(\tilde{\theta}, \hat{\phi}, D)$ where D is the critical value
4. Estimate $F_T(t)$ by,

$$\hat{F}_T(t) = \frac{\#\ of\ \tilde{t} \le t}{N}$$

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