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Special Issue

A Method for Correlating Field Life Degradation with Reliability Prediction for Electronic Modules

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A methodology was developed to correlate field life with observed degradation for electronics modules. This procedure was developed by identifying common deterioration characteristics in field units, modeling observed trends and then developing a model to predict future deterioration trends. This particular method focused on the deterioration of solder joint strength due to solder fatigue and comparing these values with a threshold based on known electrical failures. A conditional probability density function was formulated and quantified for both random shear strength and the minimum shear strength within a module. The conditional probability density function characterized both the changing mean and variance for a normally distributed random shear strength. With this methodology, time or mileage (life) prediction is based on the probability that the minimum performance response is less than a defined failure threshold. The methodology described herein promises to be an effective product development tool as the effect of design changes on product life can be more quickly and easily evaluated. While the technique developed herein is applicable to all electronic designs, the method was developed with a particular focus on understanding these relationships for automotive (harsh environment) applications. ***Copyright © 2005 John Wiley & Sons, Ltd.***

KEY WORDS: degradation; reliability prediction; solder connection; electronic module

1. INTRODUCTION

A relatively quick and accurate technique to predict the useful life of electronic modules is a critical tool to assure that future, and existing, product designs are successful in meeting warranty requirements. This need is particularly true for harsh environment electronics, such as in the automotive industry. However, understanding the direct relationship between field needs and environmental testing has been an

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elusive target for many years. Current lifetime prediction techniques require test data obtained over extended periods that approach actual module life. Furthermore, available field failure data is sparse and collected under uncontrolled conditions.

For example, automotive electronic products must operate satisfactorily under stressful environmental conditions. Environmental exposures include large temperature changes, constant vibration, long dwells at high temperatures and exposure to contaminants (e.g. automotive fluids, salt spray, etc.).

Substantial environmental exposure variability in automotive electronic modules creates a distribution of degradation patterns. For example, automotive electronics controllers are now located in the passenger compartment, firewall and mounted on or integrated within the engine/transmission system. Throughout these different locations, many different temperature ranges exist, with no set standard for each environment. This problem is compounded by the fact that vehicles containing these modules are located in many different areas of the world with varying ambient environments. In addition, driving patterns (e.g. commercial fleet service versus recreation, highway versus city, etc.) contribute to the variable environmental exposure.

One solution to this problem is to study degradation patterns in a large sample of deployed assemblies returned from random field locations and compare the observed degradation with a failure threshold. The failure threshold is established from the behavior of a performance variable with a predictable response obtained from accelerated laboratory testing. The minimum value of any predictable performance variable could be used as a basis for lifetime prediction.

Previous research has shown that solder joints deteriorate over time due to fatigue and creep. This predictable deterioration provides a measurable parameter for performance degradation modeling and extrapolation.

2. DEGRADATION MODELING

In this study, degradation modeling was used as an efficient means to predict reliability. Operational electronic assemblies were taken from fielded units with differing operating periods and tested. These assemblies were still operating (unfailed) and were then destructively tested to provide empirical shear strength data that can be used to track and model degradation trends. Degradation modeling has already been successfully applied for other applications.

Reliability prediction based on degradation modeling can be an efficient method to estimate reliability for some highly reliable parts 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 conceptual monotonically decreasing 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. Note that in the figure the degradation measure has a larger variance as time increases. While this may not be representative of all failure mechanisms characterized by a decreasing 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 greater than a critical threshold value. Alternatively, if the degradation path was monotonically increasing, then the reliability would be estimated as the probability that the degradation measure is less than the critical threshold value.

To predict reliability based on degradation modeling, the failure mechanism must be clearly understood. The model parameters or coefficients can then be thought of as random variables for individuals within the population. Although the concept of reliability prediction based on degradation modeling is relatively recent, there have been several important and successful applications.

Lu and Meeker[1] presented one of the first successful applications of degradation modeling to predict reliability. They used a regression model for the analysis of degradation data at a fixed level of stress (i.e. no acceleration) 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. Degradation path models often include terms that are nonlinear in the parameters. The parameters are divided into two types: fixed-effects parameters

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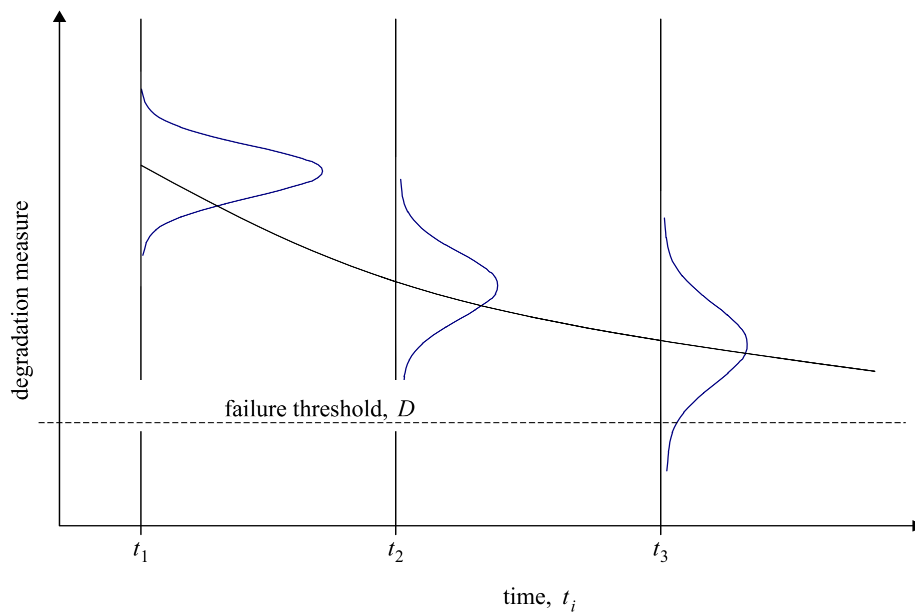

Figure 1. Degradation path example

ϕ that are common for all units; and random-effects parameters θ_i representing individual unit characteristics. A 'two-stage' method[1] was used to estimate the mixed-effect path model parameters. Monte Carlo simulation was then used to estimate the time-to-failure distribution function and they suggested bootstrap methods for estimating confidence intervals.

Other researchers have developed different perspectives and modeling approaches to this reliability prediction paradigm. Sethuraman and Young[2] developed a cumulative damage threshold crossing model. Under this model, an item consists of a large number of components that suffer damage at regular moments of time. Failure occurs as soon as the maximum cumulative damage to some component crosses a certain threshold. Time-to-failure data is used to estimate the model parameters. Zuo *et al.*[3] introduced three approaches for reliability modeling of continuous state devices. The three approaches are based on a random process model, the general path model and the multiple linear regression model, respectively. They also proposed a mixture model that can be used to model both catastrophic failures and degradation failures.

Lu *et al.*[4] developed a technique for predicting system performance reliability in real-time considering multiple failure modes. The technique includes on-line multivariate monitoring and forecasting of performance measures and conditional performance reliability estimates. The performance measures are treated as a multivariate time series and a state-space approach is used to model the multivariate time series. The predicted mean vectors and covariance matrix of performance measures are used for the assessment of system reliability. The technique provides a means to forecast and evaluate the performance degradation of an individual system in a dynamic environment in real-time.

There have also been other successful examples of degradation modeling. Abdel-Hameed[5] introduced failure models of devices subject to deterioration (degradation). He discussed the properties of different classes of life distributions (such as increasing failure rate, increasing failure rate average, etc.) under various threshold distributions. Pascual and Meeker[6] used a random fatigue-limit model to describe the variation in fatigue life and the unit-to-unit variation in the fatigue limit. Bogdanoff[7] presented an analysis of fatigue crack growth data. He investigated the impact of a *fixed* versus a *variable* initial crack length on the modeling of fatigue crack growth.

Applications of reliability prediction based on degradation modeling include reliability prediction of helicopter transmission systems (Place *et al.*[8]), optimal degradation process control (Kopnov[9]), distribution

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system reliability evaluation with aging equipment (Asgarpoor and Mathine[10]), reliability estimation of degraded structural components subject to corrosion (Ettouney and Elsayed[11]), real-time conditional reliability prediction from on-line tool performance data (Kim and Kolarik[12]) and others. In a new approach, Elsayed and Liao[13] used Brownian motion properties to model degradation and relate it to reliability.

3. RELIABILITY PREDICTION

A reliability prediction methodology was developed to maximize the use of available data for systems with scare field failure data. The solder joints deteriorate over time due to fatigue and solder creep. This deterioration causes the strength of the solder joints to be reduced during operation, thus providing a measurable parameter for performance degradation modeling and extrapolation. This deterioration can be measured in the shear strength of the solder joint. A solder connection failure will occur when the strength (measured by a shear strength test) reduces to a pre-defined critical threshold. The circuit card assembly fails when any of the solder connections deteriorates to the critical level. Therefore, reliability can be defined as the probability that the minimum shear strength, at a particular time or mileage, exceeds the critical value.

The reliability prediction methodology has several distinct steps. The reliability prediction methods are based on destructive shear testing of operational fielded units. The observed data is then used to quantify a conditional probability density function model that characterizes the distribution of shear strengths. For any particular time or mileage, an estimated probability density function for solder connection shear strength provides the mean and shape of the distribution. The method of maximization of a likelihood function was used to estimate the conditional probability density function model parameters. Then, a corresponding probability density function was developed for the *minimum* shear strength on a circuit board populated with multiple solder connections. Reliability was based on the probability that the minimum shear strength was less than a failure threshold.

Failure time of a circuit card, T, is the minimum of N individual solder connection failure times, T_i, for $i = 1, \ldots, N$, or,

$$T_i = \min\{t;\ X_i(t) \le D\}, \quad i = 1, 2, \ldots, N$$
$$T = \min\{T_1, T_2, \ldots, T_N\}$$

The reliability of the circuit card, $R(t)$, can be related to a trendline distribution and the cumulative distribution function of shear strength, $F_X(x|t)$, for time or mileage t, assuming that the individual solder connection failure times are independent.

$$\begin{aligned}
R(t) &= 1 - F_T(t) = \Pr\{T > t\} = \Pr\left\{\min_i T_i > t\right\} \\
&= \Pr\{T_1 > t \cap T_2 > t \cap \cdots \cap T_N > t\} \\
&= \Pr\{T_1 > t\}\Pr\{T_2 > t\}\cdots\Pr\{T_N > t\} \\
&= \Pr\{X_1(t) > D\}\Pr\{X_2(t) > D\}\cdots\Pr\{X_N(t) > D\} = \Pr\{X(t) > D\}^N \\
&= (1 - F_X(D|t))(1 - F_X(D|t))\cdots(1 - F_X(D|t)) = (1 - F_X(D|t))^N
\end{aligned}$$

$F_T(t)$ is the cumulative distribution function for circuit card time-to-failure, D is a defined failure threshold and $X_i(t)$ is the shear strength of the ith component. It is assumed that the shear strengths are independent and identically distributed with common cumulative distribution function, $F_X(x|t)$.

These reliability prediction methods are appropriate for a certain class of electronic assemblies. Specifically, the methodology is applicable to electronic assemblies meeting the following conditions:

- failure of the circuit board is due to failure of the solder connections;
- the assemblies are exposed to sufficiently harsh environmental conditions leading to solder connection deterioration;
- solder connection shear strength deterioration is an indicator of failure;

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- assembly failures occur when the minimum solder connection shear strength deteriorates to a failure threshold level;
- the shear strengths are normally distributed.

In practice, some of these conditions can be relaxed. If other independent component failures contribute significantly to the circuit card assembly failure probability, then this methodology is still applicable, but it will have to be modified by multiplying the assembly reliability (due to the multiple solder connections) to the reliability of the other components, which can be estimated from data, handbook values, etc. Also, if the solder connection strengths are not normally distributed, then an analogous methodology and likelihood function could be readily determined to reflect some other distribution.

The models and assumptions used in these analyses result in practical solutions to a difficult problem. However, the approach does involve some simplifications of a very complex reliability modeling problem. A more sophisticated and complex approach could have been to model the degradation pattern using a Brownian motion model. Elsayed and Liao[13] developed a degradation model that relies on the continuity and independent increments properties of Brownian motion to capture all sources of variation in a model. This could be a logical extension to the current model.

3.1. Shear strength testing and data

The first step is to physically test the boards. Circuit board assemblies are removed from their field operating environment. They are obtained with a range of operating time or mileage, which is known. These boards do not have failed solder connections, but are tested to determine their shear strength and to evaluate the relative aging or degradation. The boards are of the same design, but there are a different number of solder connections that are available to be tested.

To prepare a circuit board for testing, it was necessary to remove it from the rest of the module and then peel off the soft silicon covering which is over the components on the board. The residual silicon was then removed from the boards using solvent in an ultrasonic cleaner.

For the example analyses, the shear testing was performed at the Center for Advanced Vehicle Electronics (CAVE) of Auburn University. Since a shear test is a destructive test, it was very critical to calibrate the machine before each testing session. In addition, only one operator was used for testing and every machine setting, such as test speed and shear height, was kept constant from one test to the next. These steps ensured that all data would be tested under the same conditions so that all test variability was eliminated.

A special fixture was created to hold the circuit board securely during testing. Circuit boards were placed and locked into adjustable arms and a suction force was applied to hold the fixture in position. All shear testing was performed in the direction of the base of the fixture to eliminate any movement that might occur from pushing against one of the fixture arms.

A 10 kg testing module was used for the shear test of the resistors and the data that was recorded is in kilograms-force. This data provided a quantifiable means in which the comparison and successive correlation are based.

3.2. Determination of an expected minimum trendline

The observed shear strength data are then used to obtain a minimum trendline. This trendline depicts the minimum shear strength as it varies with time or mileage. To obtain estimates of reliability in the future, the established trend is extrapolated. This is depicted graphically in Figure 2. The point in time when the minimum trendline intersects with the failure threshold, D, represents the mean time to failure. The solder connection shear strength is a random variable and, therefore, it is prudent to also consider confidence bounds on the established trend. A $1-\alpha$ lower bound trendline is also indicated in the figure. For a particular time or mileage, it indicates the $1-\alpha$ lower bound on shear strength. The intersection of the failure threshold, D, and the $1-\alpha$ lower bound trendline represents a $1-\alpha$ lower bound on circuit card time-to-failure.

Determination of the minimum trendline requires several steps as described in the following paragraphs.

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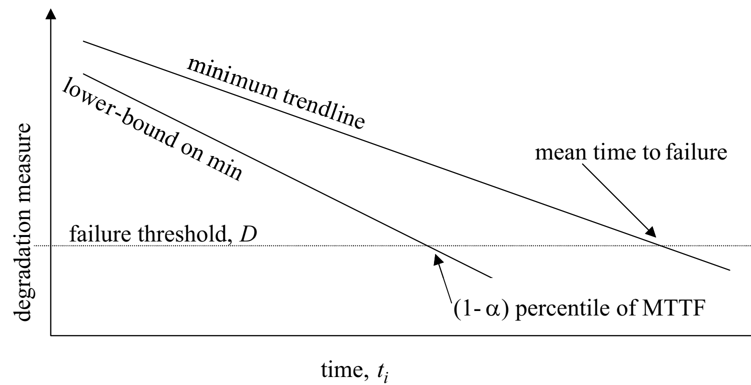

Figure 2. Minimum trendline

Step 1: Definition of a conditional probability density function for shear strengths, $f_X(x|t)$
Physical models often predict mean or nominal degradation based on design and operational conditions (e.g. stress cycles). However, to predict reliability, it is necessary to characterize the distribution of shear strength values for a specified time t. $f_X(x|t)$ is defined as the probability density function for random shear strengths, conditional on time or mileage. $f_X(x|t)$ is determined using all available shear strength test data (not just the minimum). X is the shear strength of a solder connection for a randomly selected resistor. For a normally distributed shear strength $f_X(x|t)$ and $F_X(x|t)$ are given by:

$$
\begin{aligned}
f_X(x|t) &= \frac{1}{\sqrt{2\pi}\sigma(t)} \exp\left(-\frac{1}{2}\left(\frac{x-\mu(t)}{\sigma(t)}\right)^2\right) \\
F_X(x|t) &= \int_0^x \frac{1}{\sqrt{2\pi}\sigma(t)} \exp\left(-\frac{1}{2}\left(\frac{u-\mu(t)}{\sigma(t)}\right)^2\right) \mathrm{d}u = \Phi\left(\frac{x-\mu(t)}{\sigma(t)}\right)
\end{aligned}
\tag{1}
$$

$\Phi(\cdot)$ represents the cumulative distribution function for a standard normal random variable. $\mu(t)$ and $\sigma(t)$ are the mean and standard deviation of shear strength as a function of time t.

For the electronic modules being studied, linear relationships for $\mu(t)$ and $\sigma(t)$ were selected based on physical considerations of degradation, preliminary graphical and curve-fitting analyses. They indicate that the mean shear strength is decreasing linearly with operating usage, but the variance is increasing. In practice, these relationships can be based on physical models or curve fitting. They may be nonlinear or linear and they can also be expressed as a function of other design or usage parameters. For this analysis, the following relationships were used for $\mu(t)$ and $\sigma(t)$:

$$
\begin{aligned}
\mu(t) &= a_1 - a_2 t \\
\sigma(t) &= a_3 + a_4 t
\end{aligned}
$$

For the normal distribution example, estimation of a_1, a_2, a_3 and a_4 completely determines the conditional probability density function and allows for the estimation of a minimum trendline and reliability prediction. For other applications where a normal distribution is not appropriate, the distributions of shear strength could be some other distribution (gamma, Weibull, log-normal) and this can be readily accommodated as well.

Step 1a: Determination of a likelihood function
Estimation of the conditional probability density function parameters, $\mathbf{a} = (a_1, a_2, a_3, a_4)$ is accomplished by maximization of a likelihood function. Given the available data, the likelihood function conveys how likely possible combinations of a_i values are. A suitable choice are those values of a_i that maximize the likelihood function. The likelihood function is a product of probability density functions evaluated where data

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was available. It is given by

$$L(\mathbf{a}|\mathbf{x}, \mathbf{t}) = \prod_{i=1}^{m} \prod_{j=1}^{n_i} f_X(x_{ij}|t_i) \tag{2}$$

where m is the number of different time or mileage levels with shear strength data, n_i is the number of different shear strength data entries at t_i, t_i is the ith time or mileage level, x_{ij} is the jth shear strength data entry at t_i.

For the normal distribution, $L(\mathbf{a}|\mathbf{x}, \mathbf{t})$ is given by

$$L(\mathbf{a}|\mathbf{x}, \mathbf{t}) = \prod_{i=1}^{m} \prod_{j=1}^{n_i} \frac{1}{\sqrt{2\pi}(a_3 + a_4 t_i)} \exp\left(-\left(\frac{x_{ij} - (a_1 - a_2 t_i)}{(a_3 + a_4 t_i)}\right)^2\right) \tag{3}$$

Step 1b: Determination of the conditional probability density function parameters
Coefficient vector **a** is estimated by maximizing the likelihood function. The maximum $L(\mathbf{a}|\mathbf{x}, \mathbf{t})$ can be found by taking partial derivatives of the log-likelihood function and setting them equal to zero *or* using a numerical search technique (e.g. Newton or pseudo-Newton search). For the sample data and likelihood function in this study, a numerical solver was used.

Step 2: Determination of a probability density function for the minimum shear strength
A particular circuit card has N solder connections, any which can lead to a failure. Therefore, of the N solder connections, the critical one is the minimum shear strength. The next step is to determine the probability density function for the *minimum* of N shear strength data entries, conditional on time or mileage t_i. N is pre-specified based on the construction of the board. For the particular problem being studied, it is the maximum number of resistors on a board. If Y is defined as the minimum of N data sentries, then,

$$\begin{aligned} F_Y(x|t) &= 1 - (1 - F_X(x|t))^N \\ f_Y(x|t) &= N(1 - F_X(x|t))^{N-1} f_X(x|t) \end{aligned} \tag{4}$$

where $f_X(x|t)$ is the probability density function for shear strength, conditional on t (Equation(1)), $F_X(x|t)$ is the cumulative distribution function for shear strength, conditional on t (Equation(1)), $f_Y(x|t)$ is the probability density function for the minimum of N shear strengths, conditional on t, $F_Y(x|t)$ is the cumulative distribution function for minimum of N shear strengths, conditional on t.

Step 3: Determination of the minimum and lower-bound trendline
The minimum and lower-bound trendline are found as follows.

- The minimum (of N) trendline is found by setting $F_Y(x|t) = 0.5$ (for symmetrical distributions where the mean and median are equal) and solve for x for each t_i. For example, if the original shear stress distribution was normally distributed with $N = 7$, then

$$\begin{aligned} F_Y(x|t) &= 1 - (1 - F_X(x|t))^N = 0.5 \\ F_X(x|t) &= 1 - 0.5^{1/N} = 1 - 0.5^{1/7} = 0.0943 \end{aligned}$$

  Therefore, the 0.0943 percentile of the original distribution for X is the expected minimum of $N = 7$ resistors.
- If the shear strength distribution is not symmetrical, then the expected trendline for the minimum shear strength is found by solving numerically,

$$\hat{y}_t = E[Y|t] = \int_0^{\infty} y f_Y(y|t)\, \mathrm{d}t \tag{5}$$

It is also often of interest to determine a $1 - \alpha$ lower-confidence bound on the minimum trendline. The lower-bound trendline is found by setting $F_Y(x|t) = \alpha$ and solving for x.

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3.3. Reliability prediction

Once the probability density trendline and probability density functions have been estimated, reliability predictions can be made for any time. Of course, the further the extrapolation is extended, the more uncertainty is introduced into the process. However, as more data are collected, sound trends are observed or based on physical models, there can be more confidence in the reliability predictions. Reliability prediction at time or mileage t is given by,

$$\begin{aligned}\hat{R}(t) &= \Pr\{Y > D\}\\ &= 1 - F_Y(D|t)\\ &= (1 - F_X(D|t))^N\\ &= \left(1 - \Phi\left(\frac{D - (\hat{a}_1 - \hat{a}_2 t)}{\hat{a}_3 + \hat{a}_4 t}\right)\right)^N \end{aligned} \tag{6}$$

where $\hat{a}_i$ is the maximum likelihood estimate of model parameter a_i.

This model can be used to model electronic module or assembly reliability and to make estimates for the warranty period and beyond. As more data are collected, the model is updated and improved. Decisions regarding the functional form for $\mu(t)$ and $\sigma(t)$ can be re-visited as the process evolves.

The testing is destructive. Statistically, this has some advantages because all samples are independent, but pragmatically there are disadvantages. Tested units have to be taken from fielded units and then, after testing, they can no longer be used. However, this is less of a limitation than it may seem. Automotive manufacturers need timely and accurate reliability predictions and they already pull electronic modules, based on opportunity and sampling, from fielded units to conduct various types of testing.

4. EXAMPLE

We now present an example to demonstrate the reliability prediction methodology. Consider a circuit card assembly with $N = 7$ soldered chip resisters. Fielded units were obtained on 39 circuit cards with different operating durations. It can be assumed that the operating conditions are diverse because the modules were used by actual consumers and, thus, reflect their diversity. For this example, the operating duration was measured as miles for an automotive application. Table I presents empirical data indicated shear strength. For many of the fielded units, it was not possible or desirable to perform shear tests on all solder connections. The data in Table I are simulated but typical based on the actual experimental results. The actual data collected were not available to be published in this paper.

The analysis was conducted on the data as described in Section 3. The likelihood function was defined and maximized using a standard numerical solver. Maximum likelihood estimates for the model parameters were found to be

$$\hat{a}_1 = 6.141, \quad \hat{a}_2 = 0.000\,0118, \quad \hat{a}_3 = 0.3479, \quad \hat{a}_4 = 0.000\,003\,06$$

The trendlines are presented in Figure 3. Three trendlines are given. The first represents $\mu(t)$, the mean of all shear strength data. The second trendline is the expected *minimum* shear strength for a circuit board with seven solder connections. The third line is a 90% lower bound on the minimum trendline.

Based on these results, reliability can be estimated for any mileage, t, by the following equation for a failure threshold of 4. Figure 4 depicts reliability as a function of mileage. The failure threshold of 4.0 was determined experimentally by examining failed modules.

$$\hat{R}(t) = \left(1 - \Phi\left(\frac{4 - (6.141 - 0.000\,0118t)}{0.3479 + 0.000\,003\,06t}\right)\right)^N$$

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Table I. Shear strength data

Board	t_i	x_{ij}	Board	t_i	x_{ij}	Board	t_i	x_{ij}	Board	t_i	x_{ij}
A1	91 392	5.98	A11	16 579	6.08	A20	35 233	5.04	A30	14 214	6.16
A1	91 392	5.57	A11	16 579	5.97	A20	35 233	5.90	A30	14 214	5.90
A1	91 392	5.71	A11	16 579	5.52	A20	35 233	5.28	A30	14 214	5.62
A1	91 392	4.51	A11	16 579	5.45	A20	35 233	5.84	A30	14 214	5.12
A1	91 392	4.81	A11	16 579	6.21	A20	35 233	5.99	A31	96 128	3.99
A1	91 392	4.03	A11	16 579	6.51	A20	35 233	6.47	A31	96 128	5.17
A2	34 155	5.73	A12	82 278	4.94	A21	52 757	5.12	A31	96 128	4.87
A2	34 155	5.56	A12	82 278	4.94	A21	52 757	5.15	A31	96 128	4.29
A2	34 155	5.69	A12	82 278	3.69	A21	52 757	5.17	A32	35 143	6.39
A2	34 155	4.40	A12	82 278	6.20	A21	52 757	5.48	A32	35 143	5.65
A2	34 155	5.73	A12	82 278	4.54	A21	52 757	5.37	A32	35 143	5.30
A2	34 155	6.42	A13	56 255	5.20	A22	78 878	5.15	A32	35 143	5.43
A3	44 654	5.94	A13	56 255	5.26	A22	78 878	6.24	A32	35 143	6.26
A3	44 654	5.80	A13	56 255	5.61	A22	78 878	5.14	A33	44 464	5.64
A3	44 654	6.31	A13	56 255	5.63	A22	78 878	4.67	A33	44 464	5.86
A3	44 654	5.57	A13	93 534	5.70	A22	78 878	5.40	A33	44 464	5.80
A3	44 654	5.53	A13	93 534	5.41	A22	78 878	4.74	A33	44 464	4.83
A4	43 284	5.60	A13	93 534	4.64	A23	14 811	5.48	A33	44 464	4.60
A4	43 284	5.56	A13	93 534	4.40	A23	14 811	5.86	A34	84 897	4.86
A4	43 284	5.31	A14	87 170	4.34	A23	14 811	6.01	A34	84 897	5.41
A4	43 284	5.82	A14	87 170	4.88	A23	14 811	6.27	A34	84 897	5.15
A5	72 641	5.22	A14	87 170	4.91	A23	14 811	6.23	A35	37 268	6.15
A5	72 641	6.29	A14	87 170	4.71	A24	40 351	5.15	A35	37 268	5.49
A5	72 641	5.97	A14	87 170	6.04	A24	40 351	5.86	A35	37 268	4.90
A5	72 641	5.67	A15	21 265	6.00	A24	40 351	5.39	A35	37 268	5.91
A6	38 830	5.34	A15	21 265	5.91	A24	40 351	5.46	A35	37 268	5.88
A6	38 830	5.50	A15	21 265	6.32	A24	40 351	5.30	A36	33 627	5.36
A6	38 830	5.31	A15	21 265	5.92	A24	40 351	6.22	A36	33 627	5.85
A6	38 830	6.17	A16	22 233	5.75	A25	78 689	5.20	A36	33 627	6.50
A6	38 830	5.75	A16	22 233	6.48	A25	78 689	6.25	A36	33 627	5.65
A7	47 913	5.37	A16	22 233	5.51	A25	78 689	6.40	A37	47 320	6.32
A7	47 913	4.82	A16	22 233	6.67	A25	78 689	5.58	A37	47 320	5.29
A7	47 913	6.28	A16	22 233	6.68	A25	78 689	5.11	A37	47 320	5.60
A7	47 913	5.66	A16	22 233	5.74	A26	68 171	5.88	A37	47 320	5.42
A7	47 913	6.12	A17	58 178	5.81	A26	68 171	5.68	A37	47 320	4.79
A7	47 913	5.24	A17	58 178	6.00	A26	68 171	3.97	A37	47 320	6.23
A7	47 913	6.26	A17	58 178	5.09	A26	68 171	5.10	A38	29 420	5.86
A8	35 855	5.91	A17	58 178	6.10	A27	26 170	6.17	A38	29 420	6.57
A8	35 855	5.92	A17	58 178	4.97	A27	26 170	5.61	A38	29 420	5.70
A8	35 855	5.65	A18	74 882	5.41	A27	26 170	5.36	A38	29 420	5.64
A8	35 855	5.42	A18	74 882	4.59	A27	26 170	5.84	A38	29 420	5.37
A9	91 898	6.25	A18	74 882	5.21	A28	34 648	4.98	A38	29 420	5.46
A9	91 898	5.13	A18	74 882	5.28	A28	34 648	6.35	A39	21 899	5.67
A9	91 898	4.49	A18	74 882	4.93	A28	34 648	5.68	A39	21 899	5.65
A9	91 898	4.68	A19	54 152	6.03	A28	34 648	5.66	A39	21 899	6.22
A10	50 917	5.66	A19	54 152	5.98	A29	34 949	6.18	A39	21 899	4.95
A10	50 917	5.47	A19	54 152	4.77	A29	34 949	6.73			
A10	50 917	4.88	A19	54 152	5.48	A29	34 949	5.39			
A10	50 917	6.03	A19	54 152	6.43	A29	34 949	5.33			

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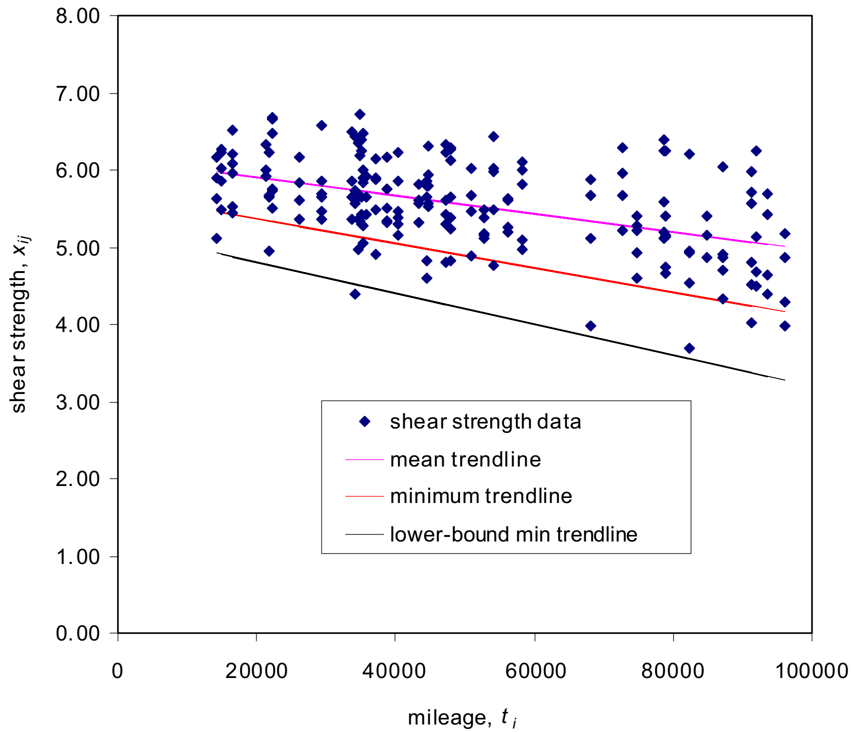

Figure 3. Shear strength data and trendlines

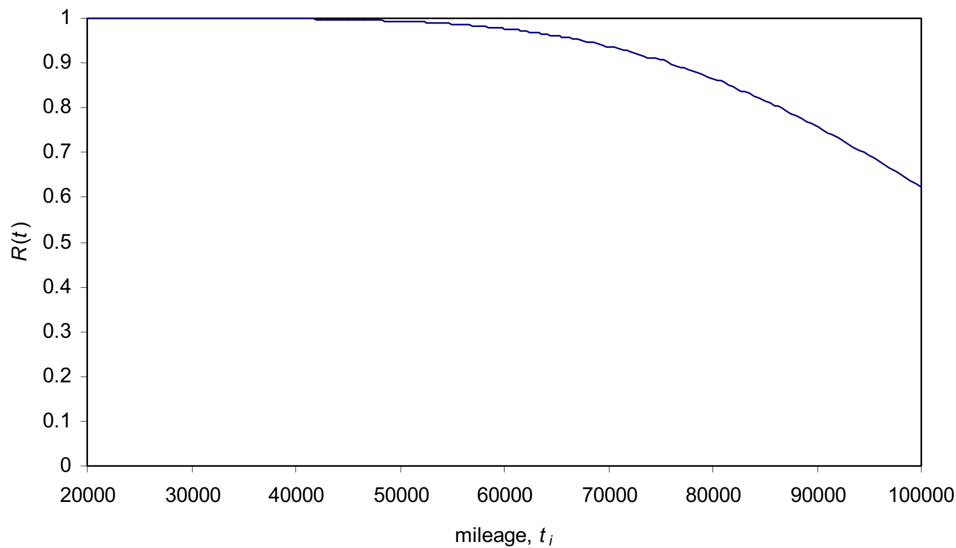

Figure 4. Reliability versus mileage

5. *ACCELERATED TESTING APPLICATIONS AND EXTENSIONS*

A primary motivation for this modeling is to assist in developing a link between field degradation and the corresponding degradation (and failure) observed during accelerated environmental testing. The models were developed to provide a mapping between field usage (miles) and the corresponding distribution of

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shear strengths. These models can then be used in interpreting the results of accelerated environmental testing and the associated shear strengths observed from that testing. In developing this correlation, the CAVE at Auburn University, along with DaimlerChrysler Huntsville Electronics, developed this research strategy to understand this relationship. Employing the help of the correlation relationship, the method was implemented during a three-year study. During this time, a collection of 200 field engine controller units were obtained and evaluated. These modules were exposed to vehicle mileage ranging from zero miles to over 150 000 miles. The resistor shear strength from a specific set of resistors was measured and compared with the shear testing of a large sample of similar resistors exposed to thermal cycle testing (−40 °C to +125 °C). The accelerated data (to be presented in an forthcoming publication) provided a clear relationship between vehicle miles and accelerated life testing. As expected, the field strength values contained a significant level of variance due to uneven driving conditions and, as noted previously, this variance increased in value as the vehicle mileage increased. However, the data provided an unambiguous relationship between the field units and the accelerated life tests when targeting a minimum acceptable reliability value.

6. CONCLUSIONS

This described correlation method provides the first clear correlation method for understanding the relationship for electronics under accelerated environmental and field conditions. The particular value is that it draws on measurable values (shear strength) to provide variable data necessary to correlate data with limited sample sizes with large variances. When applied to the actual field and accelerated life data, this method helped define a critical design characteristic (minimal thermal cycle requirements) previously missed within the automotive electronics community. For future work, a method for correlating these values with dissimilar field environments will be investigated. This is needed to help to specify requirements for modules exposed to harsher environmental conditions (i.e. mechatronic controllers) where no available field units are available.

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