An Accelerated Life Testing Model Involving Performance Degradation

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Key Words: Competing Risks, Degradation; Catastrophic Failure, Brownian Process, Accelerated Testing.

SUMMARY & CONCLUSIONS

Competing risk problems involving degradation failures are becoming increasingly common and important in practice. In this paper, we investigate the modeling of competing risk problems involving both catastrophic and degradation failures under accelerated conditions. By modeling the degradation process as a Brownian motion process for which the first passage time to a boundary is considered as the soft failure, and by modeling hard failures as a Weibull distribution enable us to model accelerated testing in a natural way, make inferences about the parameters of the degradation process and predict the reliability of products at the operating conditions. The methodology is demonstrated and validated using a real case study.

1. *INTRODUCTION*

The problem of competing risks encompasses the study of any failure process in which there is more than one distinct cause or type of failure. It is inherent and arises quite naturally in reliability area. Existing reliability methods for competing risk problem deal only with products operating at normal conditions subject to hard (catastrophic) failures, which imply the abrupt and complete cession of the product's function. Quality and reliability improvement has led to few or no hard failures at normal conditions, or even at accelerated conditions. On the other hand, most product performance may deteriorate continuously over time. As the important performance parameter gradually degrades to a critical threshold level, systems and its components are defined as soft (degradation) failure. Many products exhibit this failure mode, such as semiconductors, mechanical systems and microelectronics.

In recent years, the studies of performance degradation have attracted many interests and efforts because the degradation measurements contain fairly credible, accurate and useful information about product reliability. Lu and Meeker (1993), Tseng, Hamada and Chiao (1994), and Meeker, Escobar and Lu (1998) considered *general degradation path models*. Suzuki, Maki and Yokogawa (1993) used *linear degradation models* to study the increase in a resistance measurement over time. Meeker and Escobar (1998) used *concave degradation models* to study the growth of failure-causing conducting filaments of chlorine-copper compound in printed-circuit boards. Carey and Koenig (1991) used similar models to describe degradation of electronic components. Yang and Xue (1996) presented *random process* to model performance degradation and estimated the reliability of products. Eghbali (1999) developed the *degradation hazard function approach* for the analysis of degradation data.

A thorough review of the literature indicates that competing risk problems involving performance degradation, though commonly existing in industry, have not been investigated.

This paper intends to investigate the modeling of competing risk problems involving both catastrophic and degradation failures occurring under accelerated life testing. The remainder of this paper is organized as follows. Section 2 introduces definitions and assumptions about the model, and conducts reliability analysis of competing risk problems involving performance degradation. Section 3 develops a competing risk model and statistical inference under accelerated conditions. Section 4 presents a validation of the model.

2. *RELIABILITY AND FAILURE RATE PREPRESENTATION*

Notation

N	number of units in the test;
$f_{hi}(t)$	the *pdf* of time-to-failure for *i*th catastrophic failure mode
$Y_j(t)$	performance degradation measure for *j*th degradation failure mode
S_j	the critical threshold value for *j*th degradation failure mode
T_s	soft failure time
T_h	hard failure time
η	Weibull scale parameter
β	Weibull shape parameter

Assumptions

- N units are subjected to an accelerated tested.
- Testing units can fail in two types of failure modes: failure in one of k_1 hard failure modes and failure in one of k_2 soft failure modes; the component fails when the first of these k ($k = k_1 + k_2$) competing failure modes occurs.
- Two or more causes of failure may occur simultaneously. In the current framework such joint event may be taken as

defining additional failure types.

- For the j^{th} soft failure mode ($j=1,\cdots,\ k_2$), the related performance degradation measure $Y_j(t)$ is an increasing function in time t, and its *pdf* is $h_{sj}(y\mid t)$. When units or systems degrade to an unacceptable level S_j ($Y_j(t)\ge S_j$), system fails due to degradation *j*.

The competing risk problems involving degradation performance may be described using mathematical modeling as follows: For a given unit, let T_i be a random variable with cumulative distribution function $F_{hi}(t)$, $i=\{\ 1,2,\cdots,k_1\}$ (hard failure mode), T_j be a random variable with cumulative distribution function $F_{sj}(t)$, $j=\{\ 1,2,\cdots,k_2\ \}$ (degradation failure mode). We can observe the time of failure, $T\ge 0$, $T=\min(T_i,\ \ T_j)$, $i=\{1,\ 2,\ \cdots,\ k_1\}$, $j=\{1,\ 2,\ \cdots,\ k_2\}$ and the cause of the failure, J, among a finite set of possible causes, say $J\in\{\ 1,2,\cdots,\ (k_1+k_2)\ \}$, which may be censored. Regardless of component distributions, the component reliability can be expressed as

$$R_c(t)=\Pr(T_c>t)=\Pr(\min\{T_i,T_j\}>t)$$
$$=\left(\prod_{i=1}^{k_1}R_{hi}(t)\right)\cdot\left(\prod_{j=1}^{k_2}R_{sj}(t)\right) \tag{1}$$

and the failure rate function is

$$\lambda_c(t)=\sum_{i=1}^{k_1}\lambda_{hi}(t)+\sum_{j=1}^{k_j}\lambda_{sj}(t) \tag{2}$$

Where $R_{hi}(t)$ and $\lambda_{hi}(t)$ are the reliability and failure rate functions for the ith hard failure mode respectively, they can be written as

$$R_{hi}(t)=P\{T_{hi}>t\}=\int_t^{\infty}f_{hi}(t)dt \tag{3}$$

and

$$\lambda_{hi}(t)=\frac{f_{hi}(t)}{R_{hi}(t)} \tag{4}$$

$R_{sj}(t)$ and $\lambda_{sj}(t)$ are the reliability and failure rate functions for jth degradation failure mode respectively. These functions can be described by the degradation measure Y_j and its unacceptable level S_j.

$$R_{sj}(t)=P\{T_{sj}>t\}=P\{Y_j(t)<S_j\}=\int_0^{S_j}h_{sj}(Y|t)dY \tag{5}$$

and

$$\lambda_{sj}(t)=\frac{f_{sj}(t)}{R_{sj}(t)}=-\frac{\int_0^{S_j}\frac{\partial h_{sj}(Y\mid t)}{\partial t}dY}{R_{sj}(t)} \tag{6}$$

In the analysis of the failure times with competing risk, we also would like to know the probability that a product fails for a certain type of failure mode in a mission duration t, and the probability that a product fails for a certain type failure mode, these probability functions provide capabilities to predict which failure mode could cause a potential product failure in a certain operation time or during its entire life, thus give us some information which failure mode is more critical.

For this problem, the probability that the unit fails due to the ith hard failure mode in a mission duration t is as follows:

$$F_{C,\ hi}(t)=P\left\{\{T_{hi}\le t\}\cap\{\bigcap_{l=1,\ l\ne i}^{k_1}T_{hl}>t\}\cap\{\bigcap_{j=1}^{k_2}T_{sj}>t\}\right\}$$
$$=[1-R_{hi}(t)]\cdot\prod_{l=1,\ l\ne i}^{k}R_{hl}(t)\prod_{j=1}^{k_2}R_{sj}(t) \tag{7}$$

So, the probability that the product fails due to the ith hard failure mode can be expressed as

$$F_{C,\ hi}=\int_0^{\infty}\prod_{l=1,\ l\ne i}^{k}R_{hl}(t)\prod_{j=1}^{k_2}R_{sj}(t)\cdot f_{hi}(t)dt \tag{8}$$

Similarly, we can obtain the probability that the product fails due to the jth degradation failure mode in a mission duration t, and eventually the product fails due to the jth degradation failure mode respectively.

$$F_{C,\ sj}(t)=[1-R_{sj}(t)]\cdot\prod_{l=1,\ l\ne j}^{k_2}R_{sl}(t)\prod_{i=1}^{k_1}R_{hi}(t) \tag{9}$$

$$F_{C,\ sj}=\int_0^{\infty}\prod_{l=1,\ l\ne j}^{k_2}R_{sl}(t)\prod_{i=1}^{k_1}R_{hi}(t)\cdot f_{sj}(t)dt \tag{10}$$

3. *COMPETING RISK MODEL AND STATISTICAL INFERENCE*

In this section, we consider units or systems with two competing failure modes at an accelerated conditions with a stress covariate z: The first is soft failure mode due to degradation process $Y(t)$, the second one is catastrophic failure mode due to complete cession of the product's function.

Without lost of generality, we assume that the degradation process $Y(t)$ can be described by the following model

$$Y(t)=Y_0+\sigma W(t-t_0)+\mu(t-t_0),\quad t\ge t_0 \tag{11}$$

Where $W(t)$ is a standard Brownian motion on $[0,\ \infty)$, $\sigma>0$ is the variance parameter, μ is the drift parameter, and Y_0 is the initial degradation level at t_0. Suppose that the drift parameter $\mu=\mu(z)$ is dependent on the stress conditions, for a given critical threshold S. The lifetime T_s of the product is the instant of time at which the degradation process $Y(t)$ exceeds the level S for the first time.

$$T_s=\inf\{t\ge t_0:\ Y(t)\ge S\} \tag{12}$$

For $Y_0<S$, the lifetime T_s follows an inverse Gaussian distribution with the Lebesgue function.

$$f_{T_s}=\frac{S-Y_0}{\sqrt{2\pi\sigma^2(t-t_0)^3}}\exp\left(-\frac{(S-Y_0-\mu(t-t_0))^2}{2\sigma^2(t-t_0)}\right)\ I_{\{t>t_0\}} \tag{13}$$

The lifetime distribution depends on the parameters of the degradation process Y_0, t_o, μ, σ^2 and threshold level S.

Given n units under test, there are n independent degradation processes $Y_i(t)$ corresponding to these units. Let $t_{i1}, \cdots, t_{im_i}$ be m_i observation points of the realization of $Y_i(t)$ with $t_0 < t_{i1} < \cdots < t_{im_i} < \infty$, thus the censored observations in i^{th} realization has the form

$$\begin{aligned} x_i &= F(T_i,\ Y_i(t_{i1}),\ \cdots,\ Y_i(t_{im_i})) \\ &= (\min(T_h^{(i)},\ T_s^{(i)},\ t_{im_i}),\ F_{t_{i1}}(T_s^{(i)},\ Y_i(t_{i1})),\ \cdots,\ F_{t_{im_i}}(T_s,\ Y_i(t_{im_i}))) \end{aligned} \tag{14}$$

To obtain the likelihood function, we must find the *pdf* for a truncated Wiener process, since the surviving units have not reached the degradation threshold level S during test. Let Y_{j-1}, Y_j be degradation measure for time t_{j-1} and t_j respectively, and the *pdf* of $Y(t)$ conditional on $Y(\tau) < S$ for $t_{j-1} \le \tau \le t_j$ is given as follows:

$$\begin{aligned} f(Y_j,\ t_j) &= \left(\frac{1}{2\pi\ \sigma^2\ \ (t_j - t_{j-1})} \right)^{1/2} \exp\left\{ - \frac{((Y_j - Y_{j-1}) - \mu(t_j - t_{j-1}))^2}{2\ \sigma^2 (t_j - t_{j-1})} \right\} \\ &\times \left[1 - \exp\left\{ - \frac{2(S\ - Y_{j-1})(S - Y_j)}{\sigma^2 (t_j - t_{j-1})} \right\} \right] \end{aligned} \tag{15}$$

On the other hand, for the hard failure, we assume the time to a hard failure can be modeled as a Weibull distributed random variable, with probability density function $f(t)$ defined as follows:

$$f(t) = \frac{\beta}{\eta} (\frac{t}{\eta})^{\beta - 1} e^{-(\frac{t}{\eta})^{\beta}} \tag{16}$$

Where $t \ge 0$, $\beta > 0$, $\eta > 0$, scale parameter η is directly proportional to the mean time to failure, while shape parameter (or slope) β provides more information about the properties of failure mode, i.e. dictates the shape of failure rate function, making it decreasing function when $\beta < 1$, constant for $\beta = 1$ and increasing for $\beta > 1$. Thus likelihood function of the competing risk problem can be expressed as

$$\begin{aligned} L(x;\ \theta) &= \prod_{i=1}^{n} \left\{ \prod_{j=1}^{M_i} \left(\frac{1}{\sigma\ \sqrt{t_{ij} - t_{ij-1}}} \phi\left(\frac{(Y_{ij} - Y_{ij-1}) - \mu(t_{ij} - t_{ij-1})}{\sigma\sqrt{(t_{ij} - t_{ij-1})}} \right) \right) \right. \\ &\times \left[1 - \exp\left\{ - \frac{2(S\ - Y_{ij-1})(S - Y_{ij})}{\sigma^2 (t_{ij} - t_{ij-1})} \right\} \right] \\ &\times \left(\frac{S - Y_{iM_i}}{\sigma\sqrt{(\tau_i - t_{iM_i})}^3} \phi\left(\frac{(S - Y_{iM_i}) - \mu(\tau_i - t_{iM_i})}{\sigma\sqrt{(\tau_i - t_{iM_i})}} \right) \right)^{I_{\{M_i < m_i\}}\delta} \times \left(\frac{\beta}{\eta} (\frac{t_{iM_i}}{\eta})^{\beta-1} e^{-(\frac{t_{iM_i}}{\eta})^{\beta}} \right)^{\delta} \left. e^{-(\frac{t_{iM_i}}{\eta})^{\beta}} \right\} \end{aligned} \tag{17}$$

Where

$$\delta = \begin{cases} 1 & \text{if Hard Failure Occurs} \\ 0 & \text{if Soft Failure Occurs} \end{cases}$$

$\tau_i = \min(T_s^i,\ t_{iM_i})$ $M_i = \max\{k;\ t_{ik} < T_h^i \quad and \quad t_{ik} < T_s^i\}$

4. *MODEL VALIDATION*

In this section, we analyze an accelerated testing experiment that was conducted in the Quality and Reliability Engineering Laboratory, Rutgers University. The purpose of this experiment is to study the effect of stress on light emitting diodes (LEDs) and to predict their reliability under operating conditions.

The reliability of LEDs is strongly dependent on the degradation mode and device characteristics such as current versus optical output power and operating temperature. The influence of physical degradation on the degradation rate of the device characteristics is affected by the device characteristics themselves. The correlation between reliability and degradation modes is not so common. LED degradation modes are studied and rapid degradation is found to be related to the generation or growth of dark spot/line defects. At higher current density, voltage, or temperature, rapid power reduction due to dark spot/line defect generation occurs. Two primary causes for the dark spot/line defects are identified. They are precipitation of host atoms and the migration of electrode metal into the semiconductor. Solder and heat sink degradation is the cause of sudden failure (Fukuda, Fujita, and Iwane, 1983). We can consider this failure mode as a hard failure mode.

In our experiment, we assume that an LED fails when its performance reaches a specified rapid degradation level (degradation failure) that is defined by an additional test or suddenly due to the solder and heat sink (hard failure). This is a typical competing risk problem. To continuously record the failure times of testing units and to control the applied factors, an automatic accelerated testing environment is designed.

To continuously record the failure times of testing components and to control the applied factors, an automatic accelerated life testing environment is designed. Figure 1 depicts the layout of the experimental equipment.

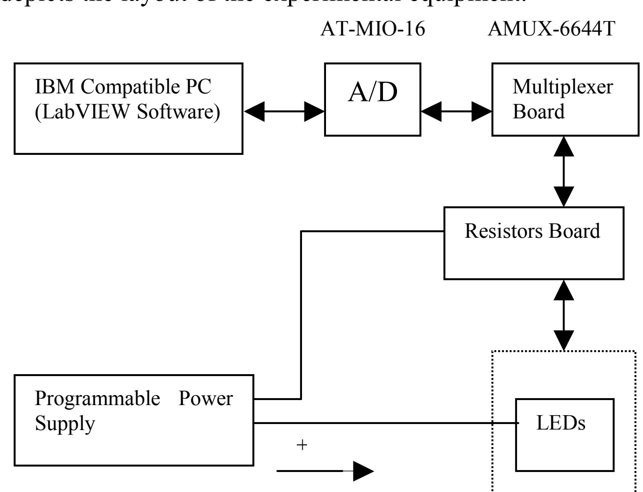

Figure 1. The Layout of Experimental Equipment

The AT-MIO-16 is a multifunction analog, digital, and timing I/O board. The AMUX-64T multiplexer board is a four to one multiplexer that can process single-ended inputs or 32 differential input. The data acquisition board is used to convert the information of the LED performance degradation to a voltage signal. Figure 2 and 3 are the samples of a LED test.

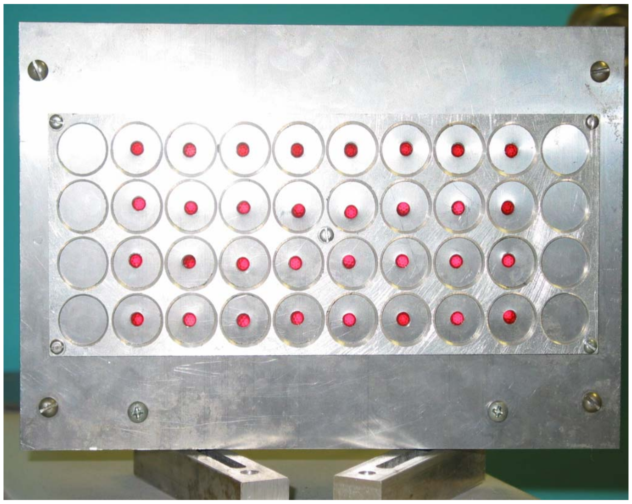

Figure 2. Samples of a LED Test

The experiment is conducted at three different stress levels 40mA, 35mA, and 28mA. We use data obtained from stress levels 40mA, 35mA to estimate the model, and then validate the model using 28mA data. At each stress levels we conduct six accelerated life testing experiments, for each experiment there are 32 samples for testing, so basically there are 192 samples for testing at each stress level; In each test a designed-circuit-board that contains 32 randomly chosen LEDs is placed in a temperature chamber where the temperature and current in the circuit are held constant. The light intensity of LEDs is then measured at room temperature every 50 hours. We utilize an inverse function to transform the original decreasing degradation (light intensity of LEDs) paths to monotonically increasing function of time. Table 1 shows the inverse LEDs light intensity and hard failure time for some samples.

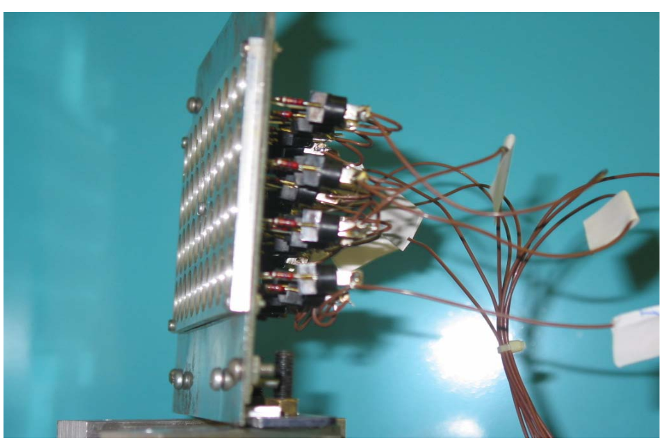

Figure 3. LEDs Testing Set

Table 1 Inverse LEDs Light Intensity and Hard Failure Time

Stress	Unit	T=50	T=100	T=150	T=200	T=250
40 mA	1	0.0091	0.0116	0.0128	0.0154	0.0185
	2	0.0104	0.0156	0.0217	0.0286	0.0417
	3	0.0102	0.0164	0.0238	0.0294	0.0357
	4	0.0112	0.0182	0.027	0.0333	0.0370
	5	0.0133	0.02	0.026	0.0370	0.0833
	6	0.0099	0.0139	0.0192	0.0256	0.0294
	7	0.020	0.0476	Hard failure at T=126		
	8	0.0139	0.0213	0.0385	0.05	T=203
	9	0.0145	0.0222	0.0312	0.04	0.0417
	10	0.0092	0.0189	0.0263	0.0333	0.0345
	11	0.0107	0.0222	0.0313	0.0357	0.0454
	12	0.0198	0.025	0.0357	0.0454	0.0510
	13	0.0207	0.0234	0.0354	0.0417	0.0634
	14	0.0126	0.0286	0.0294	0.0345	0.0560
	15	0.0136	0.0333	0.0353	T=193	
	16	0.0111	0.0355	0.0387	0.040	0.0516
	17	0.0178	0.0270	0.0454	0.0510	0.0609
	18	0.0177	0.0217	0.0294	0.0330	T=238
	19	0.0125	0.0238	0.0333	0.0387	0.0512
	20	0.0116	0.027	0.0355	0.0377	T=227
35 mA	1	0.0095	0.0128	0.0189	0.0333	0.05
	2	0.01	0.0123	0.0169	0.0233	0.0256
	3	0.0087	0.0103	0.0115	0.0137	0.0145
	4	0.0091	0.0118	0.0133	0.0156	0.0179
	5	0.0093	0.0115	0.0139	0.0159	0.0167
	6	0.0098	0.0149	0.0192	0.0286	0.0313
	7	0.0118	0.0178	0.0222	0.0333	0.0357
	8	0.0125	0.0185	0.025	0.0385	0.0454
	9	0.0115	0.0167	0.0204	0.0270	0.0294
	10	0.0072	0.0094	0.0112	0.0156	T=247
	11	0.0092	0.0126	0.0156	0.0230	0.0234
	12	0.0089	0.0136	0.0159	0.0222	0.0236
	13	0.0103	0.0131	0.0167	0.025	0.0291
	14	0.0099	0.0138	0.0178	0.0234	0.0250
	15	0.0102	0.0117	0.0177	0.0210	T=239
	16	0.0108	0.0120	0.0125	0.0217	0.0237
	17	0.0083	0.0113	0.0116	0.0187	0.0198
	18	0.0087	0.0157	0.0177	0.0202	0.0222
	19	0.010	0.0125	0.0165	0.0189	0.0204
	20	0.0120	0.0116	0.0181	0.0200	0.0207

The inverse power law (IPL) life-stress relationship is commonly used for non-thermal accelerated stresses and is given by $L(V)=\frac{1}{KV^n}$. Where L represents a quantifiable life measure, V represents the stress level, K, n are model parameters to be determined ($K>0$). In this particular competing risk problem, we use IPL to describe life-stress relationship, thus the IPL-Weibull-Brownian competing risk model can be derived by setting Weibull scale parameter

$\eta = L_1(I) = \frac{1}{K_1 I^{n_1}}$, and the drift parameter $\mu = L_2(I) = K_2 I^{n_2}$ (here I is the stress level (mA)), Yielding the following model.

$$L(x;\ \theta) = \prod_{i=1}^{n}\left\{\prod_{j=1}^{M_i}\left(\frac{1}{\sigma\ \sqrt{t_{ij}-t_{ij-1}}}\,\phi\left(\frac{(Y_{ij}-Y_{ij-1})-K_2 I^{n_2}(t_{ij}-t_{ij-1})}{\sigma\sqrt{(t_{ij}-t_{ij-1})}}\right)\right.\right.$$
$$\left.\times\left[1-\exp\left\{-\frac{2(S\ -Y_{ij-1})(S-Y_{ij})}{\sigma^2(t_{ij}-t_{ij-1})}\right\}\right]\right)$$
$$\times\left(\frac{S\ -Y_{iM_i}}{\sigma\sqrt{(\tau_i-t_{iM_i})}^3}\,\phi\left(\frac{(S-Y_{iM_i})-K_2 I^{n_2}(\tau_i-t_{iM_i})}{\sigma\sqrt{(\tau_i-t_{iM_i})}}\right)\right)^{I_{\{M_i<m_i\}}\delta}$$
$$\left.\times\left(\beta K_1 I^{n_1}(K_1 I^{n_1} t_{iM_i})^{\beta-1} e^{-(K_1 I^{n_1} t_{iM_i})^{\beta}}\right)^{\delta}\qquad e^{-(K_1 I^{n_1} t_{iM_i})^{\beta}}\right\}$$

Remark: Y_{ij} is ith LED's performance degradation measure at time t_j, S is the critical threshold value which we predetermine according, to the use's requirement, $\tau_i = \min(T_s^i,\ t_{iM_i})$, $M_i = \max\{k;\ t_{ik} < T_h^i \ \ and \ \ t_{ik} < T_s^i\}$, all these value are known, we can obtained these value from experiment data without any difficulty; $K_1, K_2,\ n_1,\ n_2,\ \sigma,$ and β are unknown, we need to estimate. Actually for data involving both catastrophic and degradation failures occurring under accelerated life testing, six parameters are reasonable especially for the competing risk problem.

In order to estimate the unknown parameters, we use a numerical method to maximize the log likelihood function. The resultant model is then used to estimate reliability at 28 mA using the accelerated testing data. The estimated values of reliability are then compared with the experimental one collected at the same level. Table 2 compares the reliability values obtained from our competing risk model and those obtained experimentally.

Table 2 Reliability of LEDs at 28 mA

Time	Estimated Reliability	Experimental Reliability
50 hrs	0.9998964	1
100 hrs	0.9998377	1
150 hrs	0.9985343	1
200 hrs	0.9975107	0.9947920
400hrs	0.9893241	0.9895830
550hrs	0.9866598	0.9843750
800hrs	0.9784455	0.9791670
900hrs	0.9757864	0.9739580
1000hrs	0.9633243	0.9687500
1100hrs	0.9608799	0.9583330
1150hrs	0.9543454	0.9531250
1200hrs	0.9503883	0.9479170
1300hrs	0.9432363	0.9375000
1350hrs	0.9374110	0.9322920
1440hrs	0.9284272	0.9270830

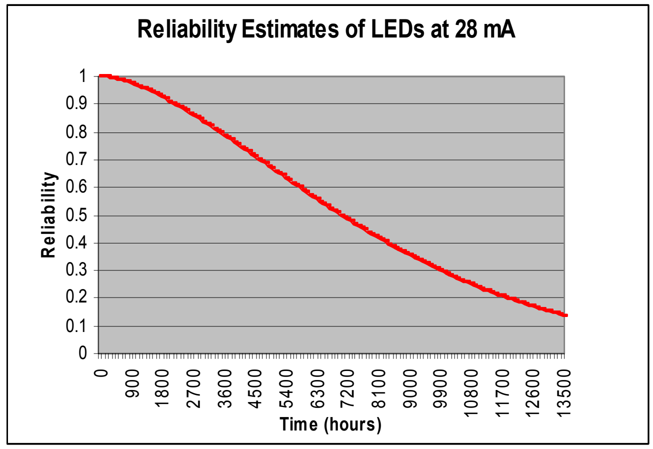

Figure 3

Based on Table 2 the estimated reliability matches closely the experimental reliability, implying that our model provides good estimates of the LEDs reliability. Figure 3 shows the reliability of LEDs at 28 mA.

Remark: we have develop a general model (17) for accelerated testing involving both catastrophic and degradation failures, if the accelerated stress is temperature or humidity, we can model the ALT by setting Weibull scale parameter and the drift parameter as Arrhenius or Eyring relationship, if the non-thermal is the accelerated stress, we can consider to use IPL like this particular case, if there are multiple stresses, we can use combination of Arrhenius, Eyring, and IPL to capture life-stress relationship.

5. *CONCLUSIONS*

In this paper, we develop an IPL-Weibull-Brownian model for analyzing competing risk data involving performance degradation and hard failures obtained at accelerated operating conditions. The model is also validated experimentally by conducting an accelerated testing on the LEDs subject to high test driving current. Three experiments are conducted at different operating conditions. The results of two experiments are used in estimating the parameters and subsequently, the reliability of the LEDs is estimated at the same stress conditions of the third experiment. Comparing the reliability estimates obtained by the proposed model with those obtained using the data form the third experiment indicates that the proposed model is valid and accurate.

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