Useful lifetime analysis for high-power white LEDs

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ABSTRACT

An accelerated degradation test is used to analyze the useful lifetime of high-power white light-emitting diodes (HPWLEDs) as the point at which the light output declines to 70% of the initial flux in lumens, called TL0. In this study, the degradation-data-driven method (DDDM), including the approximation should be fitted to a bi-exponential extrapolation model and the extrapolation algorithm for the degradation curve of HPWLEDs. The estimation of the model parameters are easily obtained by using the nonlinear least square method. Through numerical examples, the results show that the bi-exponential model performs better than the exponential model based on the two-staged method. The extrapolation algorithm for TL0 should be fitted to a bi-exponential extrapolation model and two-staged method.

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1. Introduction

Lighting systems play a significant role in life, affecting visual conditions, comfort, health, well-being, and work performance [1–3]. Light-emitting diodes (LEDs) were developed in 1993 and have been continuously improved. LEDs have attracted increasing interest in the field of lighting systems owing to their having superior characteristics to conventional light sources in terms of guaranteed longer lifetime, lower power consumption, higher brightness and being less harmful [4]. These merits of LEDs forced them to be used for high-power applications, such as general lighting, back lighting (small to large size), strobe lighting (cell phones and cameras), automotive, and large outdoor displays [5].

In recent years, LEDs have been increasingly used in display back lighting, communications, medical services, signage, and general illumination [6–9] due to their small exterior outline dimensions, often less than 10 mm × 10 mm. LEDs, when designed properly, offer higher energy efficiency that results in lower power consumption (energy savings) with low voltage (generally less than 4 volts) and low current operation (usually less than 700 mA). LEDs can have a longer lifetime (50,000–100,000 h) [10] with better thermal management than conventional lighting sources (e.g., fluorescent lamps and incandescent lamps). LEDs provide high performance, such as ultra-high-speed response time (microsecond-level on–off switching), a wider range of controllable color temperatures (4500–12,000 K), a wider operating temperature range (20–85 °C), and no low-temperature startup problem [11].

As LEDs may have a much longer lifetime, and it is not practical to gather data for such long periods of time it is important to develop some rapid reliability assessment techniques and methods to predict LED light data accurately. Traditional reliability assessment techniques, like the failure mode mechanism and effect analysis (FMMEA), fault tree analysis (FTA), lifetime test or accelerated lifetime test (ALT), are always time and cost consuming during operation [12,13]. However, with highly reliable products, few failures may have occurred during reliability tests, meaning that we could not obtain enough lifetime data in short and reasonable time by using traditional reliability assessment techniques or ALT [14].

In this situation, collecting degradation data can overcome this problem and provide information to perform the reliability assessment. The degradation data can be collected under higher levels of stress and allow extrapolation of the reliability information under use conditions. This is called an accelerated degradation test (ADT). Therefore, using ADT is more attractive to alternative traditional reliability assessment techniques in processing failure time data, such as more reliability information and benefits in identifying the degradation path and providing effective maintenance methods before failures happen [15].

In general, LEDs do not fail catastrophically. However, their light output slowly decreases with operating time. The useful lifetime of...
an LED component or system is defined as the operating time (\(L\), in hours) for the component or system to reach two performance criteria: time to 70% lumen maintenance (\(L_{70}\)) and time to 50% lumen maintenance (\(L_{50}\)) [16]. That is, the failure criterion can be defined as the 50% or 70% decrease in the emitted optical power, when compared with the initial level. The failure time is, accordingly, the time required to achieve that failure criterion. For general lighting applications, \(L_{70}\) is considered and \(L_{50}\) is used in other applications.

In this paper, we analyze the test data of LUXEON Rebel White LED devices from LUMILEDS, PHILIPS. The LUXEON Rebel White LED devices are one type of high-power white LEDs (HPWLEDs) with high luminous flux [17]. A typical high-power LED has a built-in heat sink, or slug, on which the GaN-based LED chip is placed and connected with two wires with the cathode and anode leads. In the case of HPWLEDs, the chip is uniformly coated with a layer of phosphor. The chip is then covered by a silicone gel and a lens is placed on top of it. The constructional details of the LUXEON Rebel White LED are showed in Fig. 1. We compare two different models to fit the data from luminous flux degradation testing based on the degradation-data-driven method (DDDM). Section 2 presents degradation models. Section 3 presents a general procedure for ADT to predict the lifetime of LUXEON Rebel White LEDs. Section 4 discusses the lifetime analysis of the two different models. Finally, Section 5 outlines the conclusions and discusses further research.

2. Degradation models

Accurate lifetime estimates for a high brightness LED operating in specified conditions is a very important task for LED manufacturers. The current practice of LED manufacturers is to measure the light output after a certain number of hours, such as 6000 h in an ADT [18–22]. The procedure of the IES TM-21-11 method can be found in TM-21 working group [22]. The useful lifetime \(L_{70}\) is defined as the point at which the LED light output has declined to 70% of its initial flux in luminos. The extrapolation algorithm for lumen maintenance testing ignores data from the first 1000 h, and uses data from the last 5000 h of the test. The data are then fit to a model using a least square curve method. However, Fan, Yung, and Pecht [14] reported that by applying the “6 times rule” required in IES TM-21–11, both projecting results exceed the 6 times limitation (like \(L_{70}\) (6 k) > 36,000 h). Therefore, more test time and more lumen maintenance data are required to estimate lumen lifetime under these test conditions for the LUXEON Rebel White LED device. Another drawback of IES TM-21–11 is that as it does not consider the variance of each test unit, so little reliability information for this device, including mean time to failure (MTTF), confidence interval (CI), and reliability function and so on, could be obtained.

Levada et al. [23] presented the accelerated life tests of GaN LEDs under two different packaging schemes (plastic transparent encapsulation and pure metallic) using a Weibull-based statistical model. The results show that metal packaged devices exhibit a longer lifetime than lamp devices. Shen et al. [24] investigated an accelerated life test for HPWLEDs based on spectroradiometric measurement using an exponential model. Ishizaki et al. [25] developed a robust high-power LED module that could operate at junction temperatures of up to 140 °C. The failure time, defined as a 50% decrease from the initial light level, was longer than 40,000 h. Jeong et al. [26] performed an accelerated life test of an InGaN LED backlight module for the front display of a refrigerator. Han and Narendran [27] presented an accelerated life test method for LED drivers that used electrolytic capacitors at the output stage by monitoring the output current ripples at different elevated operating temperatures. Pan and Crispin [15] investigated the degradation process of LEDs used as a light source in DNA sequencing machines. The degradation path is based on a nonlinear model proposed by Fukuda [28]. Wang and Chu [29] reported that the exponential model is better than the nonlinear model as the fit for the degradation path of light bars as a light source in laptops.

However, several failure mechanisms for LEDs can be categorized into temperature dependent packaging (e.g. epoxy and phosphor), semiconductor (e.g. growth of dislocation and metal diffusion), and stress (e.g. thermal overload and electrostatic). Therefore, other models might be suitable to fit the degradation data. In addition, the parameter estimates of the model can be obtained using evolutionary algorithms, such as the genetic algorithm, particle swarm optimization, and differential evolution.

Fukuda [28] reported that the degradation modes can be classified as several types such as dislocations that affect the inner region, metal diffusion and alloy reaction that affect the electrode, solder instability (reaction and migration) that affects the bonding parts, separation of metals in the heat sink bond, and defects in buried hetero-structure devices. Models based on the current flow during ambient temperature operations can be used to predict the LED lifetime in different accelerated degradation stress tests.

For the degradation life test of LEDs, the extrapolation function uses an exponential model, which is called model-1 and is given by

\[
D(t_j) = \beta_1 e^{-\beta_1 t_j} + \varepsilon(t_j)
\]

(1)

where \(D(t_j)\) is the actual degradation path of a LED at \(j\) test time referred to as \(t_j\), \(\beta_1\) is a fixed effect parameter that describes population characteristics, \(\beta_2\) is a random effect parameter that describes the decaying characteristic according to the diversity of the raw materials, production processes, component dimensions, and \(\varepsilon(t_j)\) is a normal distribution with zero mean and unknown variance \(\varepsilon(t_j) \sim N(0, \sigma^2)\).

The extrapolation function, using a bi-exponential model proposed by Bae et al. [30], is called model-2 and is given by

\[
D(t_j) = \phi_1 e^{-\gamma_1 t_j} + \phi_2 e^{-\gamma_2 t_j} + \varepsilon(t_j)
\]

(2)

where \(D(t_j)\) is the actual degradation path of a LED at \(j\) test time referred to as \(t_j\), \(\phi_1\) and \(\phi_2\) are parameters of fixed effects that describe population characteristics, and \(\gamma_1\) and \(\gamma_2\) are parameters of random effects associated with the diversity of the raw materials, production processes, component dimensions, \(\varepsilon(t_j)\) is a normal distribution with zero mean and unknown variance \(\varepsilon(t_j) \sim N(0, \sigma^2)\).

The estimates of the parameters in Eqs. (1) and (2) can be determined by the nonlinear least square method (NLS) and standard particle swarm optimization (SPSO) from the R Development Core Team [31].

3. A general procedure for ADT

In this section, the DDDM is briefly presented, including three methods: the approximation method, the analytical method, and
the two-staged method. Then, a general procedure for lifetime prediction for high-power LED degradation data under several stress levels and samples is discussed. In order to ensure high-test accuracy, the stress interval between the maximum stress and minimum stress should be large. Further, the maximum stress should not be larger than the limit stress that the product can bear, so as not to bring in new failure mechanisms. According to reliability theory, the number of accelerated stress levels should not be less than 3; the number of devices under each stress level should not be less than 10 [32]. Therefore, we will consider the principle to develop the procedure for ADT based on DDDM.

The failure at time $t$ can define that the degradation measurement $y_i$ exceeds (or is lower than) the critical threshold $D_j$ by time. Thus, the distribution of the time-to-failure $T$ for degradation path models and the cumulative probability of failure function $F(t)$ can be expressed as follows:

When the degradation measurements are increasing and decreasing with time, we have

$$F(t) = P(t \leq T) = P(D(t) \geq D_j)$$  (3)  

and

$$F(t) = P(t \leq T) = P(D(t) \leq D_j)$$  (4)  

In order to estimate the time to failure distribution $F(t)$ based on degradation data, several statistical methods have been proposed, the approximation method, the analytical method, and the two-staged method [33]. After reviewing these three methods, it can be concluded that, briefly, two basic steps are involved: (1) estimating the parameters for the degradation model, (2) evaluating the time to failure distribution $F(t)$.

3.1. Approximation method

The approximation method predicts the time to failure for each unit based on two different degradation models and projects the useful lifetime when the unit will reach the critical degradation level ($D_j$). It consists of the following steps:

1. Select $m$ stress levels ($S_1, S_2, \ldots, S_m$).
2. At each level, $n$ devices are randomly selected for testing.
3. For the degradation data at each stress level, two different degradation models are used to fit the data for estimating the parameters by using the NLS method. Then, we can obtain the values of sum of square errors (SSE) based on exponential model and bi-exponential model. The value of SSE is used to verify the goodness of fit of the two models. It is a measure of the discrepancy between the data and an estimation model. A small value of SSE indicates a good fit of the model to the data.

$$SSE = \sum_{i=1}^{n} c_i^2 = \sum_{i=1}^{n} (y_i - D_j)^2$$  (5)  

where $c_i$ is the error term, $y_i$ is the observed data, and $D_j$ is the estimated data based on degradation path model.
4. Extrapolate the degradation model of each unit to the critical degradation level. The failure threshold of the LEDs under different stress levels is defined as 50% or 70% of the initial value of the time of lumen maintenance. When $D(t) = D_j$, the useful lifetime for each unit can be obtained.
5. Fit the probability distribution for these useful lifetimes. Some distributions are used to fit the useful lifetimes, such as Weibull, lognormal, and exponential [14–16,19,23,24,29,32]. The best-fit distribution can be determined by the Anderson–Darling test statistic. A small value of the Anderson–Darling test statistic indicates a good fit of the distribution to the data.

(6) Assess the reliability, MTTF, and CI. A response model based on an inverse power (exponential) law for the lifetime which depends on the stress values, junction temperature $T_j$, is fitted [34]. Here, the model is given by: $\text{Life} = A_x e^{-\theta D}$, where $A_x$ and $\theta$ are constants. Finally, the lifetime prediction under operating conditions can be obtained from the response model.

However, to obtain accurate and believable prediction results for the approximate method the following are required: the degradation model $D(t)$ has to be relatively simple, the degradation model has to be sufficiently appropriate, there has to be enough degradation data, the magnitude of the errors has to be small, the magnitude of the extrapolation needs to predict that the failure time is small [35].

Furthermore, the approximate method still has some problems: (1) it ignores the errors term in the prediction of the useful lifetimes; (2) the distribution of the estimated useful lifetime does not generally correspond to the one that would be indicated by the degradation model; and (3) the degradation rate should be sufficient to estimate the parameters of degradation model. Therefore, we may consider another statistical method to predict the useful lifetime.

3.2. Analytical method

Regarding the degradation models, Meeker and Escobar [35] reported that there might be some relationships between the random effect parameters of the degradation models and the cumulative probability of the failure distribution: in the degradation models $b_1$, $\phi_1$, and $\phi_2$ are fixed effect parameters, and $b_2, \gamma_1$, and $\gamma_2$ are random effect parameters. Then, the reliability information can be obtained by analyzing the random effect parameters. Therefore, the following steps of the analytical method have some differences in approximation consisting of the following steps:

The steps (1)–(3) are the same as steps (1)–(3) of the approximation method.

(4) Use the Anderson–Darling test statistic to find the best-fit distribution of the fixed effect parameter. The mean of the fixed effect parameter can be obtained by using the maximum likelihood estimation (MLE) method.

(5) Assume the random effect parameter varies from unit to unit according to some distributions, such as two-parameter Weibull, two-parameter lognormal, and two-parameter exponential. Then, we use the Anderson–Darling test statistic to find the best-fit distribution of the random effect parameters. The scale, location, shape, and threshold parameters can be estimated by using the MLE method.

(6) Use the mean of the fixed effect parameter and the probability distribution of the random effect parameter to infer the cumulative probability of failure distribution $F(t)$.

(7) This step is the same as the step (6) of the approximation method.

If $\beta_2 \sim \text{Weibull}(\delta_2, \lambda_2)$, then

$$F(t) = P(t \leq T) = P\left[ t \leq \ln(D_j / \beta_1) / \beta_2 \right] = 1 - \exp \left[ - \left( \ln(D_j / \beta_1) / -\lambda_2 \right)^{\gamma_2} \right]$$  (6)  

where $\gamma_2$ is the shape parameter, $\lambda_2$ is scale parameter. In this situation, $1/T \sim \text{Weibull}(\delta_2, \lambda_2 / \ln(\beta_1 / D_j))$ the reciprocal of time to failure is an exponential distribution. So the time to failure distribution can be inferred from the probability distribution of the random effect parameter. The MTTF can be
obtained as follows: \( \text{MTTF} = \left[ \left( \frac{1}{\pi \sqrt{2 \pi}} \right) \times \Gamma \left( 1 + 1/\delta \right) \right] ^{-1} \),

where \( \Gamma \) is the Gamma function.

If \( \beta_2 \sim \text{Lognormal}(\mu_{\beta_2}, \sigma_{\beta_2}) \), then

\[
F(t) = P(t \leq T) = P \left[ \frac{\ln(D_t/\beta_2)}{\sigma_{\beta_2}} \leq -\frac{1}{\Gamma(1 + 1/\delta)} \right] = \Phi \left[ \frac{\ln\left( \frac{\beta_2}{D_t} \right) - \ln \left( \frac{\beta_2}{D_0} \right)}{\sigma_{\beta_2}} \right]
\]

(7)

where \( \Phi \) is the cumulative distribution function, \( \mu_{\beta_2} \) is location parameter, and \( \sigma_{\beta_2} \) is scale parameter. In this situation, \( 1/\Gamma \sim \text{lognormal}(\mu_{\beta_2} - \ln(|\beta_2/D_0|), \sigma_{\beta_2}) \) the reciprocal of time to failure is an exponential distribution. So the time to failure distribution can be inferred from the probability distribution of the random effect parameter. The MTTF can be obtained as follows:

\[
\text{MTTF} = \left\{ \exp \left[ \mu_{\beta_2} - \ln(\beta_2/D_0) + \sigma_{\beta_2}^2 \right] \right\}^{-1}.
\]

(8)

If \( \beta_2 \sim \text{exponential}(\theta_{\beta_2}, \eta_{\beta_2}) \), then

\[
F(t) = P(t \leq T) = P \left[ \frac{\beta_2}{D_0} \leq -\frac{1}{\Gamma(1 + 1/\delta)} \right] = 1 - \exp \left[ -\left( \frac{\beta_2}{D_0} \right) \eta_{\beta_2}/\theta_{\beta_2} \right]
\]

where \( \theta_{\beta_2} \) is threshold parameter, \( \eta_{\beta_2} \) is scale parameter. In this situation, \( \ln(\beta_2/D_0) \sim \text{exponential}(\theta_{\beta_2}, \eta_{\beta_2}) \) so the time to failure distribution can be inferred from the probability distribution of the random effect parameter. The MTTF can be obtained as follows:

\[
\text{MTTF} = \left\{ \exp \left[ \mu_{\beta_2} - \ln(\beta_2/D_0) + \sigma_{\beta_2}^2 \right] \right\}^{-1}.
\]

When the random effect parameters are independently distributed, as in some distributions such as Weibull, lognormal, and exponential, the reliability information can be inferred from the probability distribution of the random effect parameters. In addition, the mean of the fixed effect and random effect parameters under different distributions can be obtained as followings:

If parameter \( \sim \text{Weibull}(\delta, \lambda) \), then

Mean of parameter = \( \lambda \times \Gamma \left( 1 + 1/\delta \right) \)

where \( \delta \) is shape parameter, \( \lambda \) is scale parameter.

If parameter \( \sim \text{Lognormal}(\mu, \sigma) \), then

Mean of parameter = \( \exp(\mu + \sigma^2/2) \)

where \( \mu \) is location parameter, \( \sigma \) is scale parameter.

If parameter \( \sim \text{exponential}(\theta, \eta) \), then

Mean of parameter = \( \theta + \eta \)

where \( \theta \) is threshold parameter, \( \eta \) is scale parameter.

We then use the mean of fixed effect and random effect parameters to infer the useful lifetime when \( D(t) = D_0 \) by Eq. (2). However, the analytical method still ignores the error \( \epsilon(t) \).

3.3. Two-stage method

Meeker and Escobar [35] proposed a two-stage method to solve this problem. It consists of the following steps:

(1) In the first stage, steps (1)–(3) of the two-stage method are the same as the approximation and analytical methods. The difference between this method and the three methods mentioned above is that the measurement error, \( \epsilon(t) \), is taken into consideration and the error variance, \( \sigma^2 \), is estimated by

\[
\sigma^2_i = \frac{1}{n} \sum_{i=1}^{n} \left( y_i - D(t_i) \right)^2
\]

(12)

where \( q = p + k, p \) and \( k \) are the number of estimated fixed effect parameters and the random effect parameters, respectively.

(2) Then by some appropriate reparameterization (e.g., using a Box-Cox transformation) transfer the distribution of the random effect parameters into a multinormal distribution with asymptotic mean \( \mu_R \) and variance covariance matrix \( \Sigma_R \). This step is the same as the step (6) of the approximation method.

(3) In the second stage, estimate the parameters, including \( \alpha, \mu_R \) and \( \Sigma_R \)

\[
\alpha = \frac{\sum_{i=1}^{n} \text{fixed effect parameters}(x_i)}{n}
\]

(13)

\[
\mu_R = \frac{\sum_{i=1}^{n} \varphi_i}{n}
\]

(14)

\[
\Sigma_R = \frac{\sum_{i=1}^{n} \left( \varphi_i - \mu_R \right) \times \left( \varphi_i - \mu_R \right)^T}{n-1} - \left( \frac{\sum_{i=1}^{n} \text{var}_R(\varphi_i)}{n} \right)
\]

(15)

where \( \varphi_i \) could be \( \beta_1, \varphi_1 \) and \( \varphi_2 \).

(4) Randomly generate \( N \) (normally 100,000) simulated realizations \( \phi' \) of \( \phi \) from Normal(\( \mu_R, \Sigma_R \)) and the corresponding \( N \) simulated realizations \( \beta' \) of \( \beta \) from \( H^{-1}(\phi) \).

(5) Calculate the simulated failure time \( t \) by substituting the \( \beta' \) into the \( D(t) = D(t; \beta) \)

(6) Using Monte Carlo simulation [36,37], the time to failure distribution \( F(t) \) can be expressed by:

\[
F(t) = \frac{\text{Number of simulated first crossing times} \leq t}{N}
\]

(16)

and the CI can be calculated by the bootstrap method [38].

(7) This step is the same as the step (6) of the approximation method.

4. Analysis results and discussions

We analyzed the test data of the LUXEON Rebel White LED devices from LUMILEDS, PHILIPS published in the document [DR03:

Table 1

The degradation testing conditions for the LUXEON Rebel White LED devices.

<table>
<thead>
<tr>
<th>Stress level</th>
<th>Conditions</th>
<th>Samples</th>
<th>Ambient temperature(°C)</th>
<th>Case temperature(°C)</th>
<th>Junction temperature(°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>350 mA, 55 °C</td>
<td>15</td>
<td>64</td>
<td>60</td>
<td>68</td>
</tr>
<tr>
<td>S2</td>
<td>700 mA, 55 °C</td>
<td>30</td>
<td>73</td>
<td>69</td>
<td>81</td>
</tr>
<tr>
<td>S3</td>
<td>350 mA, 85 °C</td>
<td>16</td>
<td>84</td>
<td>85</td>
<td>98</td>
</tr>
<tr>
<td>S4</td>
<td>700 mA, 85 °C</td>
<td>30</td>
<td>87</td>
<td>92</td>
<td>111</td>
</tr>
</tbody>
</table>
Temperature and forward current are the two major factors that lead to the degradation of an LED’s light output. The LED can be described as a thermal layer module in which the layers consist of thermal resistance from junction to slug, slug to board, and board to ambient. The junction temperature, which directly affects the lifetime of the die, is a function of ambient temperature, forward current, forward voltage and the total resistance from junction to ambient. In this ADT experiment, the light sources test was under different combinations of temperature and forward current are shown in Table 1. Here, we removed the initial data (0-500 h) to reduce the noise from the nonchip decay failure mechanisms (like encapsulant decay); and then normalize

Table 2
The SSE values of two models under different stress levels.

<table>
<thead>
<tr>
<th>Sample No.</th>
<th>Stress level</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S1</td>
<td>S2</td>
<td>S3</td>
<td>S4</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0003514</td>
<td>0.0003502</td>
<td>0.000286</td>
<td>0.000345</td>
<td>0.000323</td>
</tr>
<tr>
<td>2</td>
<td>0.0006563</td>
<td>0.0004966</td>
<td>0.001182</td>
<td>0.000172</td>
<td>0.00094</td>
</tr>
<tr>
<td>3</td>
<td>0.0003238</td>
<td>0.000128</td>
<td>0.000099</td>
<td>0.001029</td>
<td>0.000924</td>
</tr>
<tr>
<td>4</td>
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<td>0.0003606</td>
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<td>0.000366</td>
<td>0.000260</td>
<td>0.000570</td>
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<td>0.0002344</td>
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<td>0.000302</td>
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<td>0.000375</td>
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</tr>
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<td>0.000375</td>
<td>0.001138</td>
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<tr>
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all data to 1 at time zero test point. Its light outputs were measured at several time points. Then, we calculate the relative light output 
\[ \frac{\text{luminous flux at time } t}{\text{initial flux in lumens}} \times 100\% \] 
to present light output depreciation for each LED (see Fig. 2).

In this study, the estimation of the model parameters is easily obtained by using the NLS method. We can obtain the SSE values based on different models, such as exponential model and bi-exponential model (see Table 2). The smaller value of SSE indicates that the model provides a good fit to the data. The comparative results of the proposed models are shown in Table 2. It appears that model-2 fits the degradation data to all four stress levels better than model-1 in term of SSE. Thus, we can conclude that the analysis of the degradation model for the LUXEON Rebel White LED devices should be based on the bi-exponential degradation model for improving fitting accuracy.

Based on the proposed procedure, the approximation method was used to estimate the LED’s lifetime. According to the IES LM-80-08 standard [40], lumen degradation failure is defined as the degradation of luminance to 70% of its initial value, which is also called the lumen lifetime. Therefore, the useful lifetime \( L_{70\%} \) is defined as that where LED light output has declined to 70% of the initial flux in lumens.

Here, we consider three distributions, such as Weibull, lognormal, and exponential. The Anderson–Darling test statistic was used to compare three probability distributions to find the best-fit distribution of the useful lifetime for two degradation models under different stress levels. A small value of the Anderson–Darling test statistic indicates a good fit of the probability distribution to the useful lifetime. The test statistics are shown in Table 3.

The analytical method is similar to the approximation method. Steps (1–3) are the same as the approximation method. The difference between the three methods is the replacement of the extrapolation step as the probability analysis for the fixed effect and random effect parameters. Three distributions, such as the Weibull, lognormal, and exponential distribution, are considered. The Anderson–Darling test statistic was used to compare three distributions to find the best-fit distribution of the parameters under different stress levels for the degradation models. A small value of the
Table 7
MTTF and 95% confidence interval using analytical method (unit = hours).

<table>
<thead>
<tr>
<th>Model</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
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</thead>
<tbody>
<tr>
<td>Model-1</td>
<td>122497 (105504, 140108)</td>
<td>90176 (83520, 96935)</td>
<td>71713 (68204, 75230)</td>
<td>60213 (56873, 63583)</td>
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<tr>
<td>Model-2</td>
<td>134176 (121687, 149788)</td>
<td>102666 (94916, 108418)</td>
<td>74557 (72044, 77298)</td>
<td>69344 (65847, 74973)</td>
</tr>
</tbody>
</table>

Note: () indicates the confidence interval.

Table 8
MTTF and 95% confidence interval using Two-stage method (unit = hours).

<table>
<thead>
<tr>
<th>Model</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model-1</td>
<td>129571 (129441, 129764)</td>
<td>93260 (93174, 93355)</td>
<td>72332 (72298, 72368)</td>
<td>61426 (61385, 61476)</td>
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<tr>
<td>Model-2</td>
<td>140854 (140717, 141035)</td>
<td>107105 (106949, 107202)</td>
<td>75691 (75648, 75731)</td>
<td>74489 (74367, 74601)</td>
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</tbody>
</table>

Note: () indicates at 95% confidence interval.

Fig. 3. The useful lifetime curves with junction temperature.
Anderson–Darling test statistic indicates a good fit of the distribution to the parameters. The results are shown in Tables 4 and 5.

In approximation method, after obtain a good fit distribution of useful lifetime, we can then compute the lifetime of the LUXEON Rebel White LED devices with a 95% confidence interval at each stress level based on the best fit distribution. The result is shown in Table 6. It appears that the failure times of the HPWLEDs for two models are different for all stress levels.

In analytical method, the mean of the fixed effect parameter and the probability distribution of the random effect parameters were used to infer the MTTF and CI. The result is shown in Table 7. It appears that the failure times of the HPWLEDs for two models are different for all stress levels.

However, the approximation and analytical methods still ignore the measurement error $\epsilon(t_i)$. The steps (1–3) of the two-stage method are the same as the approximation and analytical methods. Then the least squares estimation method is used to obtain the fixed effect and random effect parameters of each degradation model. In order to use the two-stage method one would have to transfer the distribution of the random effect parameters into a multivariate normal distribution with asymptotic mean $\mu_0$ and variance covariance matrix $\Sigma_0$.

However, as mentioned above, the probability distribution of the random effect parameter could be used to fit those values. So, it was possible to move onto step (4) of this method directly. $N = 100,000$ simulated realizations $\beta^*$ of $\beta$ were randomly generated from the probability distribution of the random effect parameter. The corresponding $N$ simulated failure times were calculated by substituting each $\beta^*$ into $D(t) = D(t; \beta)$. The useful lifetime estimation results are shown in Table 8. It appears that the failure times of the HPWLEDs for two models are different for all stress levels.

Through comparing the results of MTTF based on different methods, it appears that in most situations, the estimated failure time is larger than the other methods by using the two-stage method at each stress level. The widths of the 95% bootstrap CIs, obtained by using the two-stage method, are smaller than the others at each stress level, meaning that the two-stage method has the highest ability to explain variation.

Depending on the junction temperature, a response model based on an inverse power (exponential) law for the useful lifetime was used to predict the useful lifetime under operating conditions (see Fig. 3). From Fig. 3, the $R$-squares values of this response model based on exponential and bi-exponential degradation models using three methods, including approximate method, analytical method, and Two-stage method, are obtained as 0.9968, 0.9352, 0.9806, 0.9604, 0.9761, and 0.9258, respectively. These models are fitted well. The junction temperature under operating conditions is assumed as 38 °C (350 mA, 25 °C). Utilizing the response models, the useful lifetimes based on exponential and bi-exponential degradation models using three methods, including approximate method, analytical method, and Two-stage method, are obtained as $206,256$ h, $210,025$ h, $191,239$ h, $206,026$ h, $206,565$ h, and $206,026$ h, respectively.

5. Conclusions

The lifetime analysis used an ADT to measure LUXEON Rebel White LED devices. However, the LED light outputs are strongly affected by the junction temperature, which is based on the combination of current and ambient temperature. We presented a general procedure to analyze the ADT data. The degradation model based on a bi-exponential function can provide better fit for the lumen depreciation of light sources than the exponential model in term of SSE. Therefore, we used the bi-exponential function to increase the fit accuracy for the lifetime of the HPWLEDs. In this study, we used the DDDM, which includes the approximation method, the analytical method, and the two-staged method to measure the useful lifetime of HPWLEDs. It appears that in most situations, the estimated useful time is larger than the other methods by using the two-stage method at each stress level. Among these three methods, the two-stage method has the smallest interval width at a 95% confidence level. The two-stage method provides the highest ability to explain variation. A response model based on the inverse power law for the useful lifetimes under different stress levels was used to predict the useful lifetime under operating conditions.

Further research could investigate the relationship between the field return data and the accelerated degradation data for LED devices. Applying evolutionary algorithms, such as genetic algorithms and particle swarm optimization, to accelerated degradation data could also be valuable research topics.

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