Lifetime Estimation of High-Power White LED Using Degradation-Data-Driven Method

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Abstract—**High-power white light-emitting diodes (HPWLEDs) have attracted much attention in the lighting market. However, as one of the highly reliable electronic products which may be not likely to fail under the traditional life test or even accelerated life test, HPWLED's lifetime is difficult to estimate by using traditional reliability assessment techniques. In this paper, the degradation-data-driven method (DDDM), which is based on the general degradation path model, was used to predict the reliability of HPWLED through analyzing the lumen maintenance data collected from the IES LM-80-08 lumen maintenance test standard. The final predicted results showed that much more reliability information (e.g., mean time to failure, confidence interval, reliability function, and so on) and more accurate prediction results could be obtained by DDDM including the approximation method, the analytical method, and the two-stage method compared to the IES TM-21-11 lumen lifetime estimation method. Among all these three methods, the two-stage method produced the highest prediction accuracy.**

Index Terms—**Degradation-data-driven method (DDDM), high-power white light-emitting diode (HPWLED), lifetime estimation, reliability.**

I. INTRODUCTION

HIGH-POWER WHITE LIGHT-EMITTING DIODES (HPWLEDs) have attracted increasing interest in the field of lighting systems owing to their high efficiency, environmental benefits and long lifetime ($> 50\,000$ hrs, if thermal management techniques are well performed) in applications [1]. Due to its longer lifetime, higher reliability, and its different failure mechanisms compared to traditional light sources (like incandescent or fluorescent), there has been no standard method to evaluate and predict the reliability of HPWLED until now. Therefore, how to predict the lifetime accurately for such highly reliable electronic product is becoming a key issue in popularizing this novel device in the LED lighting market.

Traditional reliability assessment techniques, like Failure Mode Mechanism and Effect Analysis (FMMEA), Fault Tree Analysis (FTA), Lifetime Test, and Accelerated Lifetime Test (ALT), are always time and cost consuming during operation [2], [3]. In addition, with highly reliable products, there may be few failures happened during reliability tests. Another drawback of ALT is that the failure mechanisms are different when devices are under different accelerating stress levels, which may not properly imitate the actual failure process. In this situation, using degradation data to do reliability assessment appears to be an attractive alternative to deal with traditional failure time data, like that with more reliability information and benefits of identifying the degradation path and providing effective maintenance methods before failures happen [4].

Using degradation data to perform reliability assessment was proposed by statisticians some years ago. Nelson [5] reviewed two methods for modeling the degradation data. One was called a "general degradation path model" which was developed by Lu and Meeker [6] who modeled the degradation as a function of time and multidimensional random variables. M.A. Freitas *et al.* [14] applied this model to the train wheel linear degradation data and assessed its reliability. Another approach was the stochastic method which assumed that degradation was a random process in time (for instance, the Wiener process model [7] and the Gamma process [8]). But few research has been applied these methods to assess the reliability of HPWLED which usually follows a nonlinear degradation path

In this paper, a degradation-data-driven method (DDDM) based on the general degradation path model was used to analyze the lumen maintenance data of HPWLEDs. And the stochastic approach will be used in future work. In detail, DDDM deals with the degradation data with three different approaches (the approximation method, analytical method and the two-stage method) to estimate the failure time distribution and evaluate the product's reliability (e.g., mean time to failure (MTTF), confidence interval (CI), and reliability function). Meanwhile, another method named the IES TM-21-11 method provided by the Illuminating Engineering Society (IES) [13] was also used to estimate the lifetime of the same product with the same degradation data. The estimation results from both methods were discussed and compared.

II. RESEARCH DEVICE DESCRIPTION

LUXEON Rebel is one type of HPWLED with high luminous flux (>100 lumens in cool white at 350 mA) and advanced packaging techniques (Chip-on-Board technique without wire bonding) [9]. From the cross-section of this device, the packaging structure is shown in Fig. 1. An LED InGaN chip is

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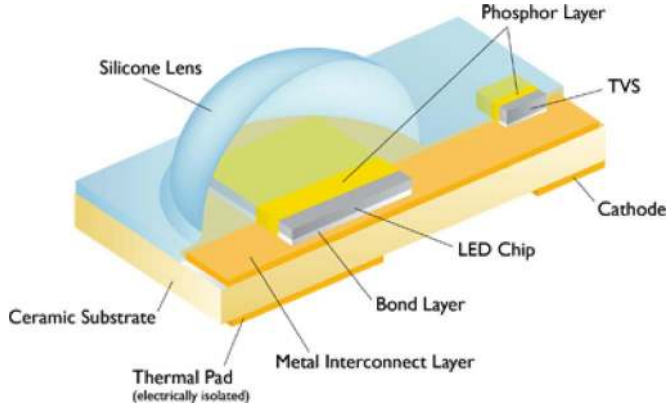
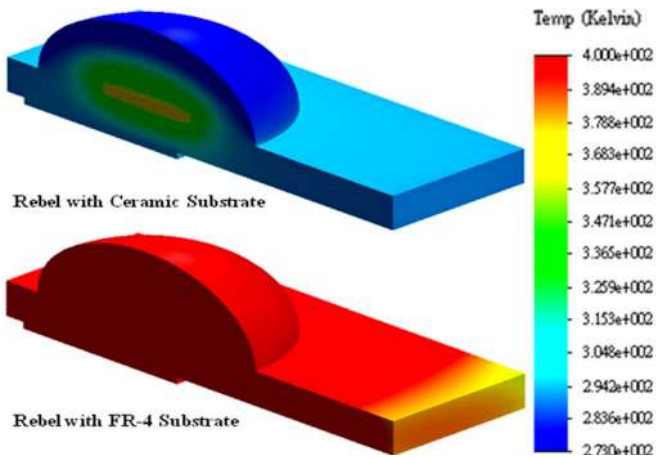Fig. 1. White LUXEON Rebel and its structure [9].

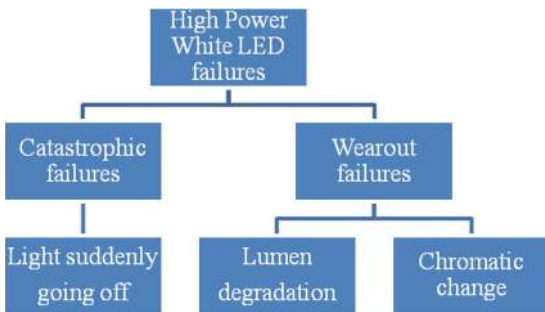

Fig. 2. Thermal management of White LUXEON Rebel.

Fig. 3. Failure modes of HPWLED.

attached to the surface of the metal interconnect layer (copper) by the bond layer (silver adhesives) and in order to improve the thermal dispersion capacity of the whole package, ceramic with higher thermal conductivity (>20 W/m.K) compared to the traditional glass fiber reinforced epoxy material (FR-4) (0.35 W/m.K) is introduced as the substrate. At the same time, a copper thermal pad is set at the bottom of the ceramic substrate in order to conduct the heat produced by a LED InGaN chip to the air effectively (Fig. 2). The top surface of the LED InGaN chip is covered with phosphor to convert the blue light to a white color.

From the FMMEA results [10], it can be seen that the common failures modes of HPWLED as shown in Fig. 3 include catastrophic failure, lumen degradation failure and chromatic

TABLE I
IES LM-80-08 TEST CONDITIONS

LM-80-08 Test Temperature	Input Current	Ambient Temperature	Case Temperature	Relative Humidity
55 °C	350 mA	64 °C	60 °C	18%

change failure. However, for LUXEON Rebel, InGaN types of LED without wire bonding interconnects, the probability of catastrophic failure (like the light suddenly going off due to an open circuit) under standard aging test conditions recommend by IES LM-80-08(shown in Table I) [12] is low, especially at the beginning of the test period (before 6000 h) [11]. The lumen degradation and chromatic change are the two dominating failures in LUXEON Rebel LED. This paper is focused on predicting the lumen degradation failure which is one of the most disturbing technical problems for both LED manufacturers and LED reliability engineers and the chromatic change failure will be analyzed in the future.

III. THEORY AND METHODOLOGY

A. IES TM-21-11 Method

[IES TM-21-11, Projecting Long Term Lumen Maintenance of LED Light Sources]is a lumen lifetime estimation standard proposed by the IES, which provides a method to determine the LED luminaire operating life (lumen output decreases to some percents, 50% or 70%, of the initial one over a certain length of operation time) based on the lumen maintenance data collected from IES LM-80-08. And the main implementation procedure of the IES TM-21-11 method provided by TM-21 working group [13] is as follows:

a) Selecting the sample size. Minimum sample size is recommended as 20 and the lumen maintenance data are collected based on the IES LM-80-08 test standard.

b) Preprocessing the lumen maintenance data. Firstly, for each unit, remove the initial data ($0 \sim 1000$ h) to reduce the noise from the nonchip decay failure mechanisms (like encapsulant decay); and then normalize all data to 1 at time zero test point. The next step is to average the data from all 20 samples at each test point (normally, Additional measurements after the initial 1000 h at intervals smaller than 1000 h (including every 1000 h points)) as the fitting data (not considering the influence of variance between the samples).

c) Fitting model. Previous work on the HPWLEDs indicated that its degradation of lumen performance followed the exponential curve [18], [19]. Therefore, in this paper, applying the LED exponential lumen degradation path model (1) to fit the averaged degradation data using the nonlinear least squares (NLS) method.

$$D(t) = \alpha \cdot \exp(-\beta \cdot t) \qquad (1)$$

where $D(t)$ is the averaged normalized luminous flux at time t, α is initial constant, and β is the degradation rate which varies from unit to unit.
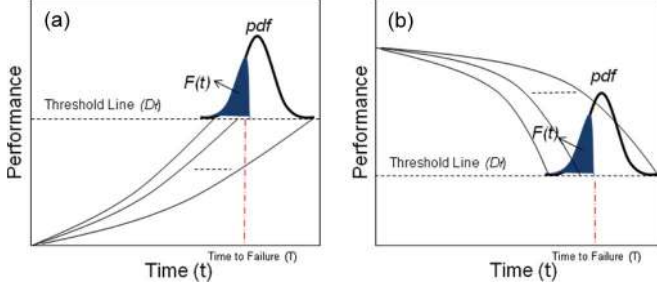
Fig. 4. General degradation path model. (a) Increasing type. (b) Decreasing type.

d) Projecting the lumen maintenance life L_p

$$L_p = \ln\left(\frac{100 \times \alpha}{p}\right) / \beta \qquad (2)$$

where p is the maintained percentage of the initial lumen output (i.e., 50, 70).

e) Adjusting the result with the "6-times rule". "6-times rules" means that if the lumen maintenance data before 6000 hrs are used to fit the model, the projected lumen maintenance life L_p must be smaller than 36 000 hrs (from 6000 × 6). If the lumen maintenance data during 6000–10 000 h is collected, the maximum projected lumen maintenance life L_p is 60 000 hrs (from 10 000 × 6 hrs).

B. DDDM

DDDM used in this paper is based on the general degradation path model presented by Lu and Meeker [6]. For the general degradation path model, a random sample size is supposed as n, and the measurement times are $t_1, t_2, t_3, \ldots \ldots t_s$. The performance measurement for the ith unit at the jth test time is referred to as y_{ij}. So the degradation path can be registered as the time-performance measurement pairs (t_{i1}, y_{i1}), $(t_{i2}, y_{i2}), \ldots \ldots, (t_{imi}, y_{imi})$, for $i = 1, 2, \ldots \ldots, n$. and m_i represents the test time points for each unit

$$y_{ij} = D(t_{ij}; \alpha; \beta_i) + \varepsilon_{ij} \qquad (3)$$

where $D(t_{ij}; \alpha; \beta_i)$ is the actual degradation path of unit i at the measurement time t_{ij}. α is the vector of fixed effects which remain constant for each unit. β_i is a vector of random effects which vary according to the diverse material properties of the different units and their production processes or handing conditions. ε_{ij} represents the measurement errors for the unit i at the time t_{ij} which is supposed to be a normal distribution with zero mean and constant variance, $\varepsilon_{ij} \sim \boldsymbol{Normal}(0, \delta_\varepsilon^2)$.

Failure definition for the general degradation path models is that the performance measurement y_{ij} exceeds (or is lower than) the critical threshold D_f at time t. And pdf is the probability density failure distribution of sample. The cumulative probability of failure function $F(t)$ is given as follows (Fig. 4): The increasing type of performance measurement

$$F(t) = P(t \leq T) = P\left[D(t_{ij}, \alpha, \beta_i) \geq D_f\right]$$

Time to Failure $\quad T = \inf\left(t \geq 0; D(t_{ij}, \alpha, \beta_i) \geq D_f\right). \quad (4)$

The decreasing type of performance measurement

$$F(t) = P(t \leq T) = P\left[D(t_{ij}, \alpha, \beta_i) \leq D_f\right]$$

Time to Failure $T = \inf\left(t \geq 0; D(t_{ij}, \alpha, \beta_i) \leq D_f\right). \quad (5)$

To estimate the time to failure distribution, $F(t)$, based on the degradation data, several statistical methods have been proposed by researchers, including the approximation method, the analytical method, the two-stage method and others [14]. After reviewing these methods, it can be concluded that two basic steps are involved: (1) estimating the parameters for degradation path model (2) evaluating the time to failure distributions, $F(t)$.

1) Approximation Method [14]: The approximation method predicts each unit's time to failure based on the general degradation model and projects to the "pseudo" failure time when the degradation path reaches the critical failure threshold, D_f. Normally, the steps of the analysis are as follows:

a) Use the NLS method to estimate the parameters (fixed effect parameter α and random effect parameter β_i) of degradation path model, based on the measured path data $(t_{i1}, y_{i1}), (t_{i2}, y_{i2}), \ldots \ldots, (t_{imi}, y_{imi})$ for each unit, and the estimated results are $\boldsymbol{\alpha}$ and $\boldsymbol{\beta_i}$, respectively.

b) Extrapolate the degradation path model of each unit to critical failure threshold, D_f. When $D(t_{ij}; \boldsymbol{\alpha}; \boldsymbol{\beta_i}) = D_f$, the "pseudo" failure (not real failures) time for each unit $(\boldsymbol{t_1}, \boldsymbol{t_2}, \boldsymbol{t_3}, \ldots \ldots \boldsymbol{t_s})$ can be predicted.

c) Fit the probability distribution for these "pseudo" lifetime data and estimate the associated parameters for each distribution.

d) Assess the sample's reliability, based on analysis reliability function, $R(t)$, hazard function, $h(t)$, MTTF, and CI.

The approximation method is simple to implement not only for statisticians but also for manufacturers. However, there are also some requirements for this method if believable prediction results are required. First, the degradation path model, $D(t_{ij}; \alpha; \beta_i)$, needs to be relatively simple. Secondly, sufficient degradation data is the essential requirement to get accurate parameter estimation results for $\boldsymbol{\alpha}$ and $\boldsymbol{\beta_i}$. Last but not least is that both magnitudes of error ε_{ij} and extrapolation width which means the time period from cut time of data collection to projected failure time need to be small [15].

2) Analytical Method: Regarding simple degradation path models, researchers found that there were some relationships between the random effect parameters of degradation path models and cumulative probability of failure distribution $F(t)$ [15]. Therefore, the reliability information of the sample could be obtained by analyzing the statistical properties of random effects parameters β_i. The LED empirical lumen degradation path model (1) is used to show the details of the inference procedure of this method.

a) The first step of the analytical method is also to estimate the parameters (fixed effect parameter, α, and random effect parameter, β_i) using the NLS method for each unit, like the first step of the approximate method.

b) It is assumed that the random effect parameter β_i, which varies from unit to unit, follows the widely used two-parameter Weibull distribution with shape parameter δ_β and scale parameter λ_β, $\beta \sim \boldsymbol{Weibull}(\delta_\beta, \lambda_\beta)$. Next, estimate the two parameters in $\boldsymbol{\delta_\beta}$, $\boldsymbol{\lambda_\beta}$ using the maximum likelihood estimation (MLE) method.

c) Infer the cumulative probability of failure distribution, $F(t)$, from $\boldsymbol{Weibull}(\boldsymbol{\delta_\beta}, \boldsymbol{\lambda_\beta})$.

$$F(t) = P(t \leq T) = P\left[t \leq \frac{\ln\left(\frac{D_f}{\alpha}\right)}{-\beta}\right] = P\left[\beta \leq \frac{\ln\left(\frac{D_f}{\alpha}\right)}{-t}\right]$$

$$= 1 - \exp\left[-\left(\frac{\ln\left(\frac{D_f}{\alpha}\right)}{-t\lambda_\beta}\right)^{\delta_\beta}\right]. \tag{6}$$

In this situation, the reciprocal of time to failure, T, is also Weibull distribution with shape parameter $\delta_{1/T} = \delta_\beta$, scale parameter $\lambda_{1/T} = \lambda_\beta/ln(\alpha/D_f)$, $1/T \sim \boldsymbol{Weibull}(\delta_{1/T}, \lambda_{1/T}) = \boldsymbol{Weibull}(\delta_\beta, \lambda_\beta/ln(\alpha/D_f))$. So finally the time to failure distribution can be inferred from the probability distribution of the random effect parameter, ignoring the step of extrapolating the degradation path model; however, the analytical method does not consider the measurement errors ε_{ij}.

3) Two-Stage Method: To solve the problems in the above two methods, W.Q. Meeker *et al.* [15] proposed a two-stage method to implement the parameter estimation.

a) In the first stage, for each unit, the degradation path model is also fitted with the nonlinear least squares method to estimate the parameters (fixed effect parameter, α_i, and random effect parameter, β_i), however, the difference between this method and the two methods mentioned above is that the measurement errors, ε_{ij}, is taken into consideration and the error variance, σ_ε^2, for the ith unit is estimated by

$$\sigma_{\varepsilon_i}^2 = \left[\sum_{i=1}^{m_i} \frac{\{y_{ij} - D(t_{ij}; \alpha_i; \beta_i)\}^2}{(m_i - q)}\right] \tag{7}$$

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

And then by some appropriate reparameterization, transfer the distribution of the random effect parameter, β_i, into a multivariate normal distribution with asymptotic mean, μ_φ, and variance covariance matrix, Σ_φ, $\boldsymbol{\varphi} = H(\boldsymbol{\beta_i}) = \boldsymbol{Normal}(\mu_\varphi, \Sigma_\varphi)$ [10].

b) In the second stage, estimate the parameters including $\boldsymbol{\alpha}$, $\boldsymbol{\mu_\varphi}$, and $\boldsymbol{\Sigma_\varphi}$, for the degradation path model

$$\alpha = \sum_{i=1}^{n} \frac{\alpha_i}{n} \tag{8}$$

$$\mu_\varphi = \sum_{i=1}^{n} \frac{\varphi_i}{n} \tag{9}$$

$$\sum_\varphi = \left(\sum_{i=1}^{n}(\varphi_i - \mu_\varphi)\frac{(\varphi_i - \mu_\varphi)^i}{(n-1)}\right) - \left(\sum_{i=1}^{n} \text{var}_\varepsilon(\varphi_i)/n\right). \tag{10}$$

c) Randomly generate N (normally is $100\,000$) simulated realizations $\boldsymbol{\varphi}^*$ of $\boldsymbol{\varphi}$ from $\boldsymbol{Normal}(\mu_\varphi, \Sigma_\varphi)$ and then the corresponding N simulated realizations $\boldsymbol{\beta}^*$ of $\boldsymbol{\beta}$ from $H^{-1}(\boldsymbol{\varphi})$.

d) Calculate the simulated failure time t^* by inserting the $\boldsymbol{\beta}^*$ into the $D_f = D(t; \boldsymbol{\alpha}; \boldsymbol{\beta})$.

e) With Monte Carlo simulation, time to failure distribution $F(t)$ can be expressed by:

$$F(t) = \frac{(\text{Number of simulated first crossing times} \leq t)}{N} \tag{11}$$

and the CI can be calculated by the bootstrap method.

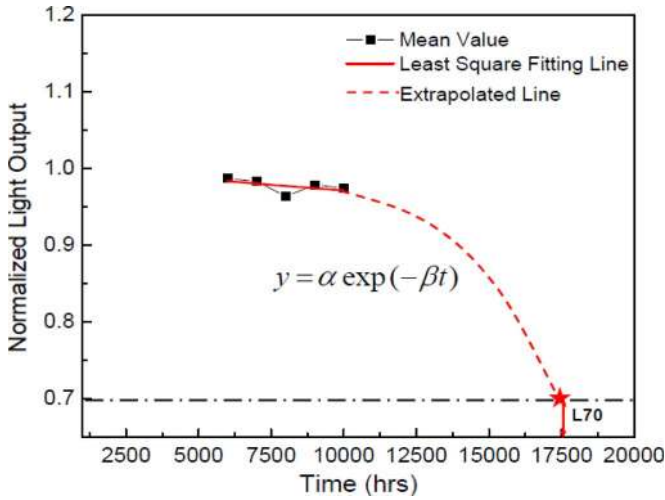## IV. RESULTS AND DISCUSSION

A. Lumen Maintenance Data

Lumen maintenance data of LUXEON Rebel LED device were collected by LUMILEDS, PHILIPS and published in the document [DR03: LM-80 Test Report] [16]. The data analyzed in this paper were collected under one test condition as shown in Table I.

According to the IES LM-80-08 standard, lumen degradation failure is defined as that the lumen output decreases to the 70% of the initial one over a certain length of operation time, which is also the lumen lifetime L_{70}. Therefore, in this paper, L_{70} is the critical failure threshold of the lumen degradation model, D_f. The sample size is chosen as 20. For each unit, lumen maintenance data was collected every 1000–10 000 h (totally 10 test time points) and normalized to 1 at the time zero test point.

B. Lumen Lifetime Estimation With the IES TM-21-11 Method

Following the IES TM-21-11 operation procedure shown in Section III, the mean value of the lumen maintenance data from 20 units at each test time was used to fit the degradation path model ((1)) using the nonlinear least squares method. Figs. 5 and 6 are the projected lumen lifetime L_{70} based on two different test time intervals (1000–6000 and 6000–10 000, respectively). And the parameter estimation of the degradation path model and the lumen lifetime L_{70} projection results are shown in Table II.

By applying the "6 times rule" required in IES TM-21-11, both projecting results exceed the 6 times limitation (like L70(6 k) > 36 000 hrs). Therefore, more test time and more lumen maintenance data are required to estimate lumen lifetime under these test conditions for the LUXEON Rebel 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 MTTF, CI, and reliability function and so on, could be obtained. This may be not effective
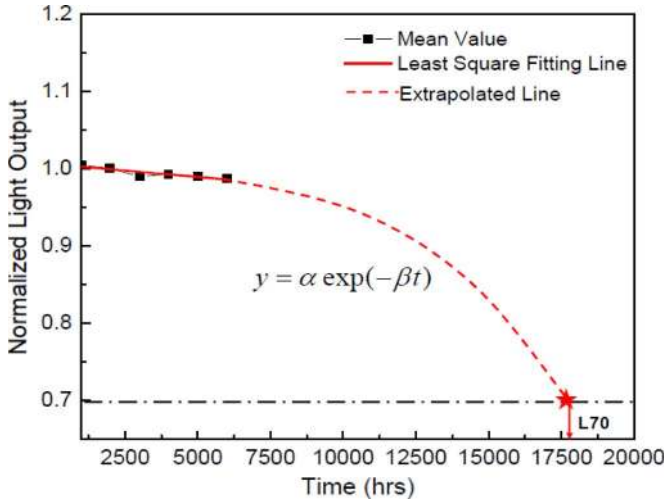
Fig. 5.   Projecting L_{70} with lumen maintenance data from 1000 to 6000 h.

Fig. 7.   Extrapolating degradation path model with 1000–10 000-h data.

Fig. 6.   Projecting L_{70} with lumen maintenance data from 6000 to 10 000 h.

TABLE II
RECOMMENDED IES TM-21-11 ESTIMATION REPORT

Tested Device	LUXEON Rebel, LUMILEDS, PHILIPS	
Sample Size	20	
Driven Current (mA)	350	
Test Case Temperature (°C)	60	
Test Duration (hrs)	10,000	
Test Duration used for Projection (hrs)	1,000~6,000	6,000~10,000
α	1.00633	1.00216
β	3.35252*e^{-6}	3.11021*e^{-6}
Lumen Lifetime L_{70} (hrs)	108,272.3	115,372.5
6 times limitation	36,000	60,000

for maintenance decision making by either LED manufacturers or designers.

C. Lumen Lifetime Estimation With the Approximation Method

To overcome the problems encountered in the IES TM-21-11 method, the approximation method was used to estimate the lumen lifetime using the same data as shown in the previous section. Using the nonlinear least squares estimator, parameters
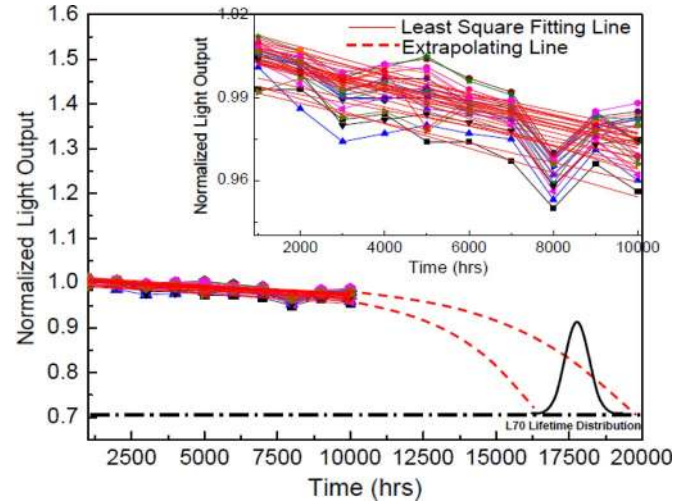
TABLE III
LIST OF ESTIMATED PARAMETERS FOR DEGRADATION
PATH MODEL AND PSEUDO FAILURE TIME

Sample No.	α	β	Pseudo failure time (hrs)
1	0.99858	4.57E-06	77816.5
2	1.01269	5.06E-06	72988.9
3	0.99518	3.66E-06	96138.6
4	1.00629	3.88E-06	93511.0
5	1.00624	4.28E-06	84788.7
6	0.99682	2.88E-06	122853.4
7	1.00572	3.22E-06	112472.9
8	1.01317	3.67E-06	100867.2
9	1.01559	4.42E-06	84287.7
10	1.0167	4.17E-06	89440.3
11	1.00823	3.34E-06	109122.0
12	1.00993	3.30E-06	111008.9
13	1.00618	2.90E-06	125152.1
14	1.00721	3.77E-06	96535.9
15	1.00053	3.52E-06	101485.3
16	1.00859	3.54E-06	103196.0
17	1.00537	3.29E-06	110133.4
18	1.0056	3.01E-06	120175.9
19	1.01107	3.23E-06	113760.5
20	1.00772	3.62E-06	100602.0

of general degradation path model (α_i, β_i) were estimated for each unit (Fig. 7). This is different from the IES TM-21-11 method which just considered the average data. And next, by extrapolating the model of each unit to the critical failure threshold (30% light decrease), "pseudo failure times" can be predicted (Table III).

The next step of the approximation method is to fit the probability distribution for the "pseudo failure times" obtained from the extrapolating method. In this paper, three types of statistical models (Weibull, Lognormal and Normal) were selected to fit the "pseudo failure times" (Fig. 8) and the fitting results were
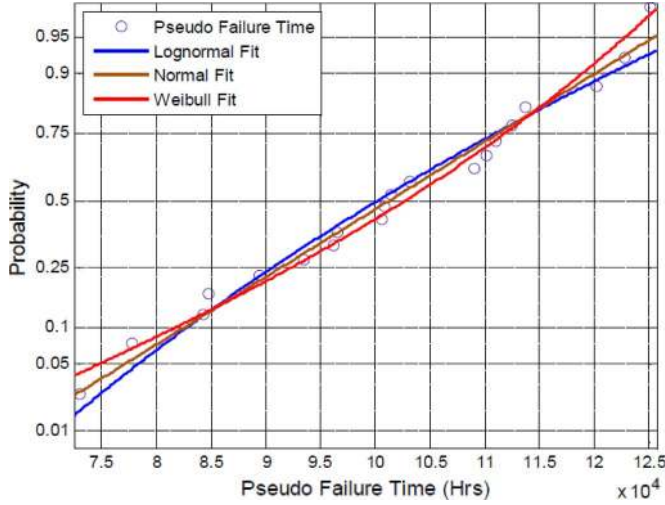
Fig. 8.   Statistical models fitting for "pseudo failure time."

TABLE IV
ESTIMATED PARAMETERS OF EACH STATISTICAL
MODELS BY APPROXIMATE METHOD

Parameters	Weibull	Lognormal	Normal
k^*	2	2	2
Log (L)	-219.554	-220.171	-219.712
AIC	443.108	444.342	443.4242

justified by the Akaike Information Criterion (AIC) which is one method proposed by H. Akaike [20] to verify the goodness of fit of a proposed statistical model. The AIC is quantitatively defined as follows:

$$AIC = -2\log(L) + 2 \cdot k \quad (12)$$

where L is the maximum likelihood estimation (MLE) of the fitting model and k is the number of independently adjusted parameters within the model. The judgment standard of this theory is to compare the AIC value of proposed fitting models and the lowest AIC value means the best model-fitting. According to the AIC value shown in Table IV, Weibull model with lowest AIC value presents the best fitting performance among them.

As shown in Fig. 9, the "pseudo failure times" followed the Weibull distribution with shape parameter δ and scale parameter λ, $T \sim \boldsymbol{Weibull}(\delta, \lambda)$. The reliability function is shown as follows:

$$R(t) = \exp\left[-\left(\frac{t}{\lambda}\right)^{\delta}\right] = \exp\left[-\left(\frac{t}{107{,}500}\right)^{8.223}\right]. \quad (13)$$

Fig. 10 reveals the reliability and the 95% confidence limit prediction results for our research device. The parameters of the reliability function, which were estimated by the maximum likelihood estimator (MLE), are listed in Table V.

By comparing from the prediction results, because of considering the sample's variance, approximation method provides more reliability information (i.e., reliability function, MTTF, and CI) than IES TM-21-11 method, which benefits not only for manufactures to make decisions but also for customers to
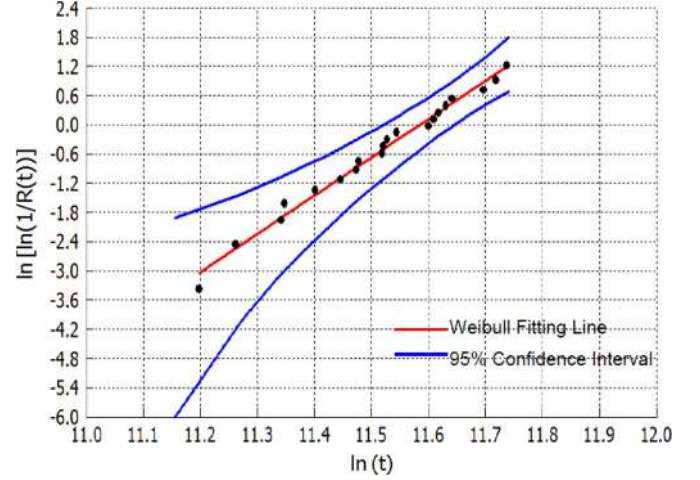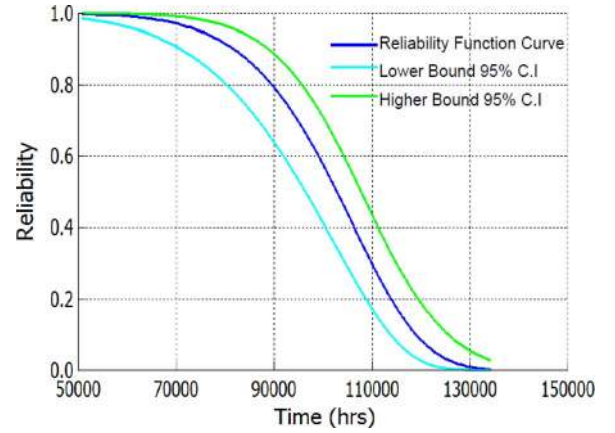

Fig. 9.   Weibull plotting for "pseudo failure times."

Fig. 10.   Reliability prediction for LUXEON Rebel.

TABLE V
PARAMETER ESTIMATION AND RELIABILITY PREDICTION USING
THE APPROXIMATION METHOD

Parameters	Estimation Results
α	8.223
β	107,500
MTTF (hrs)	101,300 (95,870, 107,000)
$t_{0.1}$ (hrs)	119,000 (113,500, 124,700)
$t_{0.5}$ (hrs)	102.800 (97,530, 108,400)

understand products clearly. But due to assuming fitting model $D(t_{ij}; \alpha; \beta_i)$ as degradation path and ignoring the measurement errors ε_{ij}, the approximation method also has some limitations.

D. Lumen Lifetime Estimation Using the Analytical Method

The analytical method is similar to the approximation method, just replacing the extrapolating step as the probability analysis for random effect parameters, β_i. And the parameter, α_i, was supposed as fixed effect and equals to 1 as all lumen degradation data of each unit were normalized to 1 at the original test point. So after parameter estimation for the degradation path model (shown in Table III), the Weibull probability curve
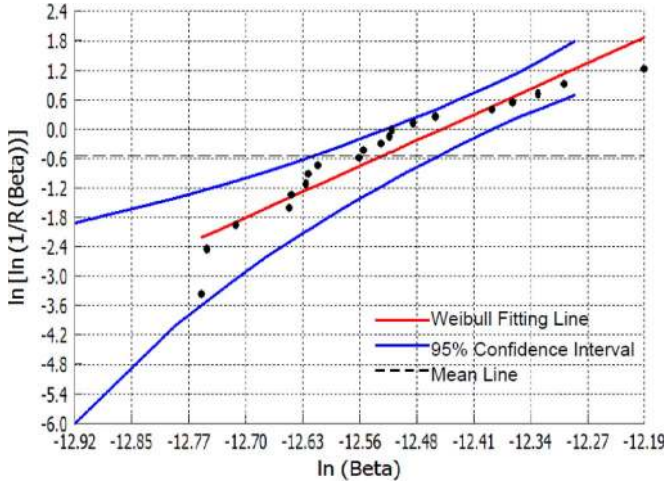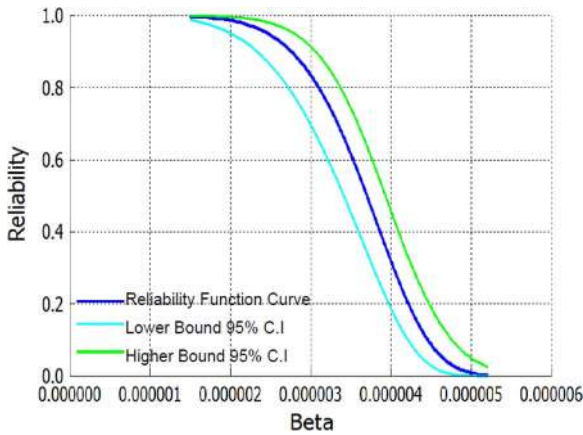
Fig. 11. Weibull plotting for random effect parameters β_i.

TABLE VI
PARAMETER ESTIMATION AND RELIABILITY PREDICTION
IN THE ANALYTICAL METHOD

Random Effect parameter β Estimation		Reciprocal Time to Failure $1/T$ Estimation	
δ_β	6.433	$\delta_{1/T}$	6.433
λ_β	$3.918{*}e^{-6}$	$\lambda_{1/T}$	$1.098{*}e^{-5}$
Mean	$3.649{*}e^{-6}$ ($3.404{*}\,e^{-6}$, $3.912{*}\,e^{-6}$)	MTTF (hrs)	97,745.9 (91,174.6, 104,781.1)
$\beta_{0.1}$	$4.46{*}\,e^{-6}$ ($4.206{*}\,e^{-6}$, $4.731{*}\,e^{-6}$)	$t_{0.1}$ (hrs)	79,972.0 (75,391.0, 84,801.5)
$\beta_{0.5}$	$3.701{*}\,e^{-6}$ ($3.46{*}\,e^{-6}$, $3.959{*}\,e^{-6}$)	$t_{0.5}$ (hrs)	96,372.6 (90,092.2,103,085.2)
$R(1.5{*}\,e^{-6})$	0.998 (0.987, 0.999)	$R(1/80,000)$	0.100 (0.035, 0.207)

Fig. 12. Reliability prediction for random effect parameters β_i.

was used to fit the random effect parameters, β_i, shown in Fig. 11. And then the two parameters for Weibull distribution were estimated $\boldsymbol{\delta_\beta}$, $\boldsymbol{\lambda_\beta}$ with maximum likelihood estimation (MLE) method (Table VI). The reliability function with its 95% confidence limits was predicted (Fig. 12).

As discussed in Section III, if random effect parameters, β_i, follow a two-parameter Weibull distribution, $\beta \sim \boldsymbol{Weibull}(\delta_\beta, \lambda_\beta)$, the reciprocal of time to failure is also a Weibull distribution, $1/T \sim \boldsymbol{Weibull}(\delta_{1/T}, \lambda_{1/T}) =$

TABLE VII
PARAMETER ESTIMATION AND RELIABILITY PREDICTION
IN THE TWO-STAGE METHOD

Parameters	Estimation Results
MTTF (hrs)	101,763 (101,618, 101,908)
$t_{0.1}$ (hrs)	79,977.8
$t_{0.5}$ (hrs)	96,375 (96,265, 96,510)
$R(80,000)$	0.900

TABLE VIII
95% CI WIDTHS OF MTTF

Methods	MTTF (hrs)	Widths (hrs)
IES TM-21-11	108,272.3[i] 115,372.5[ii]	N.A.
Approximation method	101,300	11,130
Analytical method	97,745.9	13,606
Two-stage method	101,763	290

Note: i is estimated based on the data from 1,000 to 6,000 hrs,
ii is estimated based on the data from 6,000 to 10,000 hrs,

$\boldsymbol{Weibull}(\delta_\beta, \lambda_\beta / ln(\alpha / D_f))$. Based on the inference from (6), both reliability functions are calculated as follows:

$$R(\beta) = \exp\left[-\left(\frac{\beta}{\lambda_\beta}\right)^{\delta_\beta}\right]$$
$$= \exp\left[-\left(\frac{\beta}{3.918{*}e^{-6}}\right)^{6.433}\right] \tag{14}$$

$$R\left(\frac{1}{t}\right) = \exp\left[-\left(\frac{\frac{1}{t}}{\lambda_{\frac{1}{T}}}\right)^{\delta_{\frac{1}{T}}}\right]$$
$$= \exp\left[-\left(\frac{\frac{1}{t}}{1.098{*}e^{-5}}\right)^{6.433}\right]. \tag{15}$$

E. Lumen Lifetime Estimation With Two-Stage Method

As mentioned above, random effect parameters, β_i, follow a Weibull distribution with scale parameter, λ_β, and shape parameter, δ_β, $\beta \sim \boldsymbol{Weibull}(\delta_\beta, \lambda_\beta)$. So it was possible to move to the third step of this method directly, randomly generating $N(= 100\,000)$ realizations $\boldsymbol{\beta^*}$ of $\boldsymbol{\beta}$ from two-parameter $\boldsymbol{Weibull}(6.433, 3.918^{*}e^{-6})$ with S-PLUS (one software for statistical computing from Bell Laboratories) random number generation function [17]. And the corresponding N simulated failure time $\boldsymbol{t^*}$ was calculated by substituting each $\boldsymbol{\beta^*}$ into $D_f = D(t; \boldsymbol{\alpha}; \boldsymbol{\beta})$. Time to failure distribution, $F(t)$, was estimated by (11) with a Monte Carlo simulation. The lifetime estimation results are shown in Table VII.

Through comparing the prediction results of the two-stage method with others, the estimated results of MTTF by the two-stage method and the approximation method are very closely, but the widths of the 95% CIs obtained by using the two-stage method are smaller than others (Table VIII), which means the last method has the highest prediction accuracy.

V. CONCLUSION AND PROPOSALS

In this paper, the lumen lifetime of one type of HPWLED (LUXEON Rebel, LUMILEDS, PHILPS) was estimated by the DDDM including the approximation method, the analytical method and the two-stage method and the estimation results were compared to those obtained when using the IES TM-21-11 method.

From the IES TM-21-11 method, only lumen lifetime, L_{70}, could be estimated by projecting the empirical degradation model without other reliability information. Moreover, the prediction results based on two sets of periodical degradation data revealed different prediction results, both of which exceeded the maximum requirements of the "6 times rules". This suggests that the prediction results were not acceptable without extending the data collecting time. However, with the general degradation path model, more reliability messages, in addition to the lumen lifetime (e.g., MTTF, CI, and reliability function), could also be predicted. And among these three methods, the two-stage method with smallest widths of the 95% CIs produced the highest degree of prediction accuracy.

But due to its long lifetime, up to now there has still been no actual measurement of the complete lifetime of LUXEON Rebel against which to evaluate the prediction results obtained from these DDDMs. Therefore, for these highly reliable electronic products, some other prediction methods with more advantages (such as an Accelerated Degradation Test or stochastic approaches) should be introduced.

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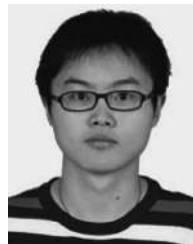
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