

Optimal Design of Life Testing for High-Brightness White LEDs Using the Six Sigma DMAIC Approach

Jiajie Fan, *Member, IEEE*, Cheng Qian, Kam-Chuen Yung, *Member, IEEE*, Xuejun Fan, *Senior Member, IEEE*, Guoqi Zhang, *Fellow, IEEE*, and Michael Pecht, *Fellow, IEEE*

Abstract—Life testing is an essential reliability assessment procedure to qualify a new product or technology before being released to the market. High-brightness white light-emitting diodes (HBWLEDs) with high efficiency, environmental benefits, and high reliability have attracted increasing interest in the field of lighting systems. However, owing to the long lifetime of LEDs, traditional life testing methods for LEDs, which record only failure time, are time consuming and expensive. Therefore, designing an optimal life testing process for HBWLEDs is desirable for accelerating LED technology innovation and development. This paper applies the Six Sigma define–measure–analyze–improve–control (DMAIC) approach to analyze the restrictions in the traditional life testing for HBWLEDs and optimize the life testing procedure. The goal is to shorten the testing time, reduce the testing operation cost, and maintain accurate reliability estimation. In this work, a general reliability estimation method with degradation data is developed by integrating a recursive unscented Kalman filter approach to estimate HBWLED reliability. The results show that, with the help of a recursive UKF, the accuracy of reliability estimation can be improved compared with the ordinary nonlinear least squares approach. Furthermore, the operation time and cost of LED life testing can be reduced by 57.75% and 71.51%, respectively, compared with traditional life testing.

Index Terms—High-brightness white light-emitting diodes (HBWLEDs), life testing design, Six Sigma define–measure–analyze–improve–control (DMAIC), recursive unscented Kalman filter (recursive UKF), reliability assessment.

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J. Fan is with the College of Mechanical and Electrical Engineering, Hohai University, Changzhou 213022, China, with the Beijing Research Centre, Delft University of Technology, 2628 Delft, The Netherlands, and also with the State Key Laboratory of Solid State Lighting, Changzhou 213161, China (e-mail: jay.fan@connect.polyu.hk).

C. Qian is with the State Key Laboratory of Solid State Lighting, Institute of Semiconductors, Chinese Academy of Sciences, Beijing 100083, China.

K.-C. Yung is with the Printed Circuit Board Technology Centre, Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong.

X. Fan is with the Department of Mechanical Engineering, Lamar University, Beaumont, TX 77710 USA.

G. Zhang is with the Faculty of Electrical Engineering, Mathematics and Computer Science, Delft University of Technology, 2628, Delft, The Netherlands.

M. Pecht is with the Center for Advanced Life Cycle Engineering, University of Maryland, College Park, MD 20742 USA.

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I. INTRODUCTION

SOLID state lighting has been considered as the second revolution in the history of lighting [1], [2]. High brightness white light-emitting diodes (HBWLEDs), known as one of the next generation solid state lighting sources, is a novel technology which uses semiconductor and phosphor materials to convert electricity into white light [3], [4]. HBWLEDs have been widely used as a light source for indoor lighting, street lamps, advertising displays, decorative lighting, and monitor backlights [5]. Compared to traditional lighting sources (such as incandescent lamps, halogen incandescent lamps, and cold cathode fluorescent lamps CCFLs), HBWLEDs have attracted increasing interest in the field of lighting systems owing to their high efficiency, environmental benefits, and long lifetime, with claims longer than 50,000 hrs [6], [7].

Life testing is an essential reliability assessment procedure to qualify a new product or technology before being released to the market. As concluded by previous studies [8], [9], the failure modes of HBLEDs in a life testing are usually divided into three types: (i) catastrophic failure; (ii) lumen degradation; and (iii) chromaticity shift. The failure sites in the package level are summarized as the InGaN chip, packaging materials (such as lens, silicon encapsulation, phosphors, chip attachments, thermal pads and molding house), and interconnections (such as wire bonds and anode and cathode leads). Because the lumen degradation is considered as a primary failure mode in LEDs [10], most of current life test methods are always designed by qualifying the luminous flux (or lumen maintenance) of LEDs [11], [12]. Owing to its long lumen maintenance lifetime, few or no lumen degradation failures will occur in HBWLEDs within short-term life testing. As a result, it is difficult to assess reliability with traditional approaches which record only failure time [13], [14]. Even though improved reliability testing and assessment methods, such as accelerated life testing and censoring technology [15], have been developed to estimate the rated lifetime distribution for highly reliable products, these approaches may not be feasible for products without failures during life testing with severe time and cost constraints [13]. Sometimes the duration of the reliability test and assessment procedure is longer than the time between product updates, which may delay technology innovation and development.

Therefore, designing an optimal life testing method for HBWLEDs with consideration of time and cost savings is desirable for accelerating LED technology innovation and development. Six Sigma has been recognized as a well-structured problem-solving methodology for improving and managing

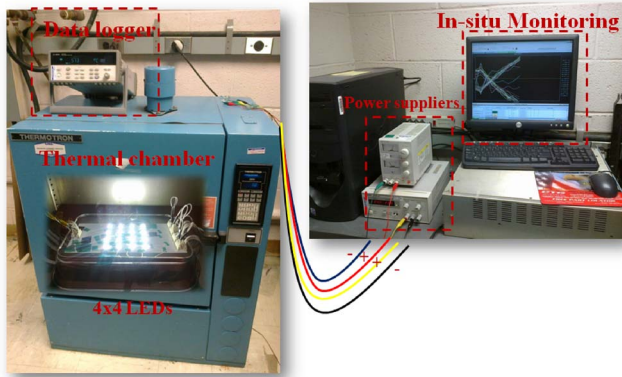


Fig. 1. LED life testing experiment setup.

product quality [16]–[18], reducing operation cycle time [19] and optimizing process management [20], [21] in many companies, such as Motorola, General Electric, and Raytheon [22]. The benefits of the Six Sigma approach can be achieved through the utilization of its systematic step-wise DMAIC approach, which enables participants to find problems in an old product and process and improve them with solutions from Design of Experiment (DOE) [23], [24]. In this study, we apply the step-by-step application of the Six Sigma DMAIC approach in an LED life testing case. Our purpose is to establish an optimal procedure for HBWLED life testing to shorten the testing time, reduce the testing operation cost, and maintain the accuracy of reliability estimation.

The remainder of this paper is organized into three sections. Section II introduces an LED life testing case and its experimental setup. Then, a step-by-step DMAIC approach is applied in this case from Section III. In the improve section, the degradation data-based reliability assessment methods are reviewed and improved to replace the traditional methods. Finally, we present a summary of research findings in Section IV.

II. CASE STUDY

In 2012, the Center for Advanced Life Cycle Engineering (CALCE) of the University of Maryland conducted life testing for one type of high brightness white LED provided by an LED manufacturer. The objectives of this testing were: 1) to know the LED's reliability information (such as the failure time distribution, the 100th percentiles of failure time distribution t_p , and mean time to failure MTTF); 2) to estimate its rated lifetime for the LEDs in the given accelerated aging condition.

Generally, according to the IES LM-80-08 standard requirement [12], the life testing condition for LED packages is recommended that: (i) the case temperatures are 55 °C, 85 °C and a third temperature selected by the manufacturer. (ii) the ambient temperature should be maintained to within -5 °C of the case temperature during testing. (iii) the input current selected at the same as during realistic operation. To predict the lifetime for LEDs aged under this condition, the minimum testing time is normally required by the IES TM-21-11 as 6000 hrs [11].

In this study, a cycle life testing experiment was conducted by CALCE's LED research group. The experiment setup is shown in Fig. 1. Sixteen HBWLEDs were soldered on an

MCPCB aging test board and were driven with the same constant direct current at 200mA provided by two DC power suppliers. The thermal chamber provides the constant aging temperature for this test (90 °C required by the customer). The traditional life testing and reliability assessment methods (including the censoring technology) require the testing units failed. After 1633 hrs of aging, only nine units failed and the remaining seven units were still alive. Its operation cost was estimated as larger than \$1000.

III. SIX SIGMA DMAIC APPROACH

A. Define Phase

The define phase of the DMAIC methodology aims to establish a cross-functional Six Sigma team to summarize the problems that happened in the above case, define the scope and goals of the improvement project in terms of customer requirements, and develop a process that delivers these requirements.

To begin with, a cross-functional team of people associated with the process was firstly established to solve the problems in the Six Sigma methodology. The team selected for this project included the center director, head of the LED research group, LED research assistants, the lab manager, and lab assistants. The center director was identified as the champion. The head of the LED research group acted as the team leader and was responsible for the overall success of the project and was also the process owner. The primary responsibility of the team members was to support the team leader in executing the project-related actions. This helped the team members to clearly understand the project objectives, project duration, resources available, roles and responsibilities of team members, project scope and boundaries, expected results from the project, etc [16].

After the cross-functional team was established, the project champion organized a meeting to discuss the problems within in the above LED life testing, which can be summarized as follows: Firstly, life testing operation time is too long. The customer is not satisfied with the operation time (1633 hrs aging time, more than 2 months operation) which is too long for the LED manufacturer to know the reliability of this device. Secondly, life testing cost is too high. The total operation cost of LED life testing is \$1142.60, which is largely out of the customer's expectation.

To solve the above problems, this project aims to achieve the following three goals: 1) reduce the life testing time by 50% from the existing life testing process and give the customer quick and reliable feedback; 2) reduce the life testing cost by 50%; 3) keep the errors of the estimated 10th percentiles of the failure time distribution t_{10} within 5%. As shown in Table I, our Six Sigma team used the critical-to-quality (CTQ) methodology to translate the voice of the customer to the engineering targets. The SIPOC (Supplier-Input-Process-Output-Customer) approach was implemented to help the team members understand the process.

As shown in the traditional LED life testing process and operation profile (Fig. 2), after receiving the test units from the customer, we first soldered them on an MCPCB aging test board. Then the traditional LED life testing was conducted

TABLE I
SUPPLIER-INPUT-PROCESS-OUTPUT-CUSTOMER (SIPOC) DIAGRAM

Supplier	Inputs	Process	Outputs	Customer
LED manufacturer	LED test units	LED life testing (See Fig. 1)	Standard LED life testing process and Reliability analysis report	LED manufacturer
Equipment suppliers	Aging chamber; Testing equipment; Data logger systems			
Planning and design team	DoE, statistical program design			
Facility department	Utility (power)			
CALCE reliability lab	Lab assistants			

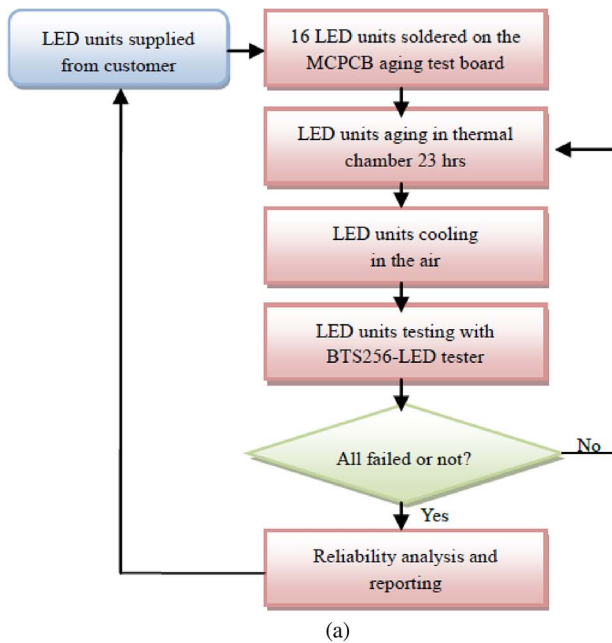


TABLE II
RESULTS OF GAUGE R&R STUDY

Source	StdDev (SD)	Study variance	Study variance (%)
Total Gauge R&R	0.15594	0.93567	15.42
Repeatability	0.15594	0.93567	15.42
Part-to-Part	0.99938	5.99626	98.80
Total Variation	1.01147	6.06882	100.00

the lighting performance data (such as light output, color coordinates, color temperature, color rendering index, and spectral power distribution) were measured manually through the BTS256-LED tester. After one hour of testing, the aging test board was returned to the thermal chamber to undergo the next aging cycle. When the test units failed, we terminated the life test and analyzed the LED's reliability with failure data or censored failure data based on traditional methods.

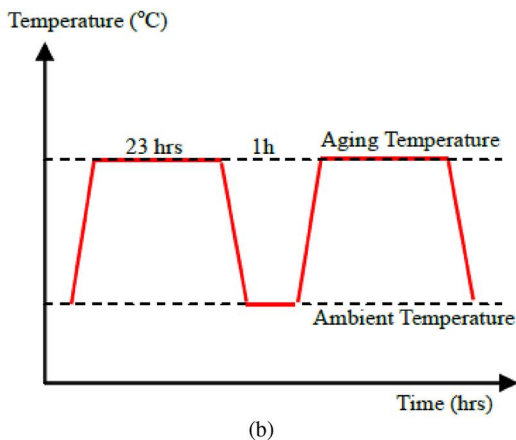


Fig. 2. (a) Traditional LED reliability testing process and (b) operation profile.

through the three sections: the aging section, the cooling section, and the testing section. For aging, sixteen high brightness white LEDs were thermally controlled by a chamber. After 23 hrs of aging, the aging test board was removed from the thermal chamber to be cooled to room temperature. For testing,

B. Measure Phase

In the measure phase, our objective was to select the appropriate product characteristics, map the respective process, study the accuracy of the measurement system, record the data, and establish the baseline performance of the process [25].

In this experiment, we used the BTS256-LED tester to collect the light output data of sixteen test units over a 23 hrs per day collecting cycle. The BTS256-LED tester is a hand-held measurement system which allows qualification of luminous flux, spectral flux distribution, and color data of single LEDs [26]. To validate the measurement system's accuracy and precision, a gauge repeatability and reproducibility (GR&R) study was conducted. Here, measurement on sixteen test units was repeatedly conducted five times by a lab assistant. After finishing collecting the data, GR&R analysis was performed with the help of Minitab statistical software. The result of the GR&R study is presented in Table II. According to the previous studies [27], [28], the measurement system may be acceptable when the measurement system variability is between 10% and 30%; at above 30% variability, a measurement system is not considered acceptable. Since the total GR&R variance value in this case was 15.42%, which was within the acceptable limit of 30%, it

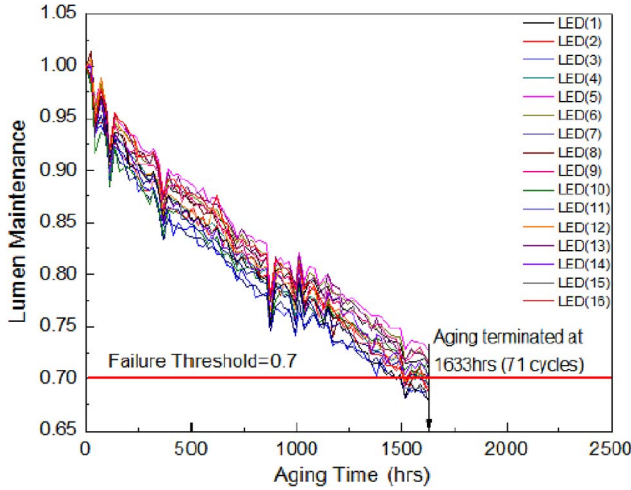


Fig. 3. Lumen degradation process of test units.

was concluded that the BTS256-LED measurement system was acceptable for further data collection.

In the LED industry, the light output data is usually used as one of the characteristics to determine the performance of LEDs. Normally, the LED’s lumen maintenance lifetime is calculated based on the lumen maintenance (LM), which can be defined as the maintained percentages of initial light output over time.

$$LM(t) = \frac{\Phi(t)}{\Phi(0)} \times 100\% \quad (1)$$

where $\Phi(0)$ is the initial light output, and $\Phi(t)$ is the lumen flux at time t .

Therefore, we transformed the light output data as the lumen maintenance data to determine LED failure. For LED general lighting, the lumen failure threshold is defined by the Alliance for Solid-State Illumination Systems and Technologies (ASSIST), as when the lumen maintenance decreases to 70% [29]. The transformed time series lumen maintenance data of sixteen test units are shown in Fig. 3. As shown in Fig. 3, in our case, after 71 aging cycles (approximately 1633 hrs of aging time), there were only nine units failed and the remaining seven units were still alive. In this condition, we applied the censoring approach to these time-truncated failure data to estimate LED reliability as the baseline performance of the traditional life testing process. Censoring is a reliability estimation technology commonly used to deal with cases when extract lifetimes are known for only a portion of the products. With the censoring technology, the reliability information of the traditional life testing (e.g. failure time distribution, the 100pth percentiles of the failure time distribution t_p , and the mean time to failure MTTF) can be obtained. In Fig. 4, we used the two-parameter Weibull distribution to fit the time-truncated data and estimated the shape and scale parameters of the Weibull distribution with the Maximum Likelihood (ML) method. The detailed results are shown in Table III.

C. Analyze Phase

The objective of the analyze phase is to identify the root cause that creates the problem for the process.

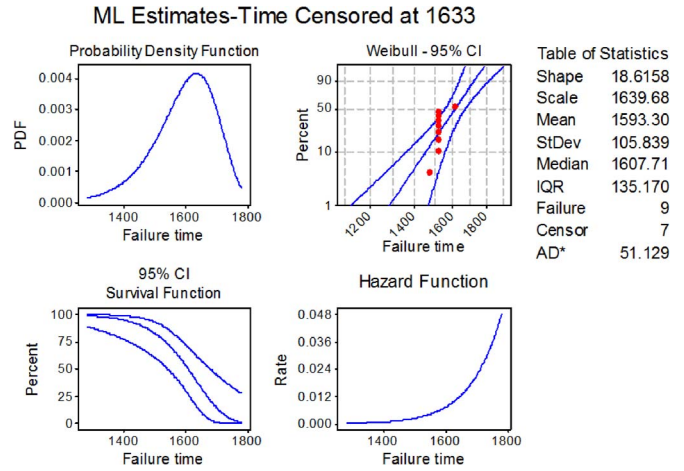


Fig. 4. Overview of failure time distribution of test units.

TABLE III
RELIABILITY ESTIMATION WITH TIME-TRUNCATED FAILURE DATA

No. of failures/Total No.	Weibull distribution parameters		MTTF	t_{10}
	shape	Scale		
9/16	18.6158	1639.68	1593.30	1452.98

1) *Cost Analysis:* Operation time and cost are two major metrics for evaluating the efficiency of the life testing process. We established a financial function to analyze the life testing operation cost. From the cost consideration in life testing, frequently asked questions from customers include “How many units do I need to test?”, “How long do I need to run this life testing?”, and “How many times do I need to inspect the units in this testing?” [30], [31]. As shown in the experimental procedure, the total cost of an experiment consists of the following three parts:

- Sample cost nC_s : this can be defined as the cost of the total test units, where C_s represents the cost of a single test unit and n is the sample size.
- Inspection cost $n\tau C_m$: this includes the cost of using inspection equipment and materials and the operator’s labor cost. C_m denotes the cost of one inspection on one test unit, and τ is the inspection frequency.
- Operation cost $t_d (\tau - 1)C_e$: this cost consists of the utility and depreciation of operation equipment (such as chambers, power suppliers, and data loggers). Let C_e be the operation cost in the time interval between two inspections, t_d .

Then the total operation cost, C_T , can be calculated as:

$$C_T = nC_s + n\tau C_m + t_d(\tau - 1)C_e. \quad (2)$$

Based on equation 2, the total operation cost of this LED life testing can be calculated as \$1142.60, which is out of the customer’s expectation. The relationship between total operation cost with inspection frequency and sample sizes was also numerically simulated based on two assumptions: 1) the experimental termination time is 1633 hrs; 2) the operation cost between time intervals can be set as $\$0.2 * n/16$, which means

TABLE IV
THE ESTIMATED COST OF TRADITIONAL LIFE TESTING

Items	Details
Sample size, n	16
Inspections frequency, τ	72 cycles
Time interval between two inspections, t_d	23 hrs per cycle
Termination time, T_d	71 cycles (1633 hrs)
Cost of a test unit, C_s	\$15
Cost of one inspection on one test unit, C_m	\$0.5
Operation cost in the time interval, C_e	\$0.2
Total cost, C_T	\$1142.6

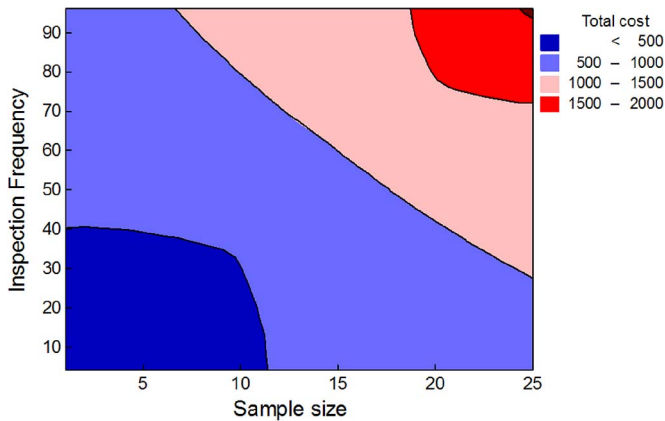


Fig. 5. Simulation contour plot of total operation cost vs. inspection numbers and sample size.

that the operation cost is mainly controlled by the sample sizes. A summary of the cost of traditional life testing is listed in Table IV. In Fig. 5, the simulation results show that with the increase of inspection frequency and sample sizes, the total operation cost of the life testing will be increased.

2) *Root Cause and Effect Analysis*: From the previous analysis, there are several causes that affect the LED life testing time, cost, and final reliability estimation results. The cause and effect diagram in Fig. 6 shows the main root causes contributing to the project outputs from six factors (Materials, Machines, Measurements, Mans, Methods and Environment). Three major factors resulting in project defects are summarized as: 1) too large of a sample size, which will increase the life testing cost; 2) inspection frequency is too high, which will also cost too much in terms of the depreciation of inspection equipment and materials and the operator's labor cost; 3) the traditional life test requires waiting for all test LEDs to fail (requires at least a portion of failures). Therefore, this process requires a long operation time for highly reliable products.

D. Improve Phase

During this phase of the Six Sigma methodology, solutions were identified and implemented for all root causes selected during the analyze phase. To solve the major root causes resulting in the problems identified before, we firstly improved the LED reliability estimation methods by dealing with degradation data. Here, a general reliability estimation method based on

degradation data was proposed and compared to the previous mixed-effect approach. Then, a DOE was planned for optimizing the LED life testing process parameters considering the reduction of both time and cost. Finally, an improved process flow for LED life testing was developed based on the DOE results.

1) *Reliability Estimation Methods Based on Degradation Data*:

a) *Nonlinear mixed-effect model*: For devices with long lifetimes, most of the traditional life testing techniques which require failure data are time-consuming and expensive. In this condition, using degradation data to do reliability assessment appears to be an attractive alternative to dealing with traditional failure time data, with benefits of identifying the degradation path and providing effective maintenance methods before failures occur [32]–[34]. The nonlinear mixed-effect model first proposed by Lu and Meeker [35] is widely used to estimate reliability by modeling the degradation data with the general degradation path model.

The degradation path can be registered as time-performance measurement pairs $(t_{i1}, y_{i1}), (t_{i2}, y_{i2}), \dots, (t_{imi}, y_{imi})$, for $i = 1, 2, \dots, n$; and m_i represents the test time points for each unit:

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

where a random sample size is n , and the measurement times are $t_1, t_2, t_3, \dots, t_s$. The performance measurement for the i th unit at the j th test time is referred to as y_{ij} . $D(t_{ij}; \alpha; \beta_i)$ is the actual degradation path of unit i at the measurement time t_{ij} ; α is the vector of fixed effects which remains constant for each unit; β_i is a vector of random effects which varies 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.

Previous work on LEDs indicated that the degradation trajectory of lumen performance followed an exponential curve [36], [37]. Therefore, we used the exponential degradation path model with mixed effect parameter vector $\theta(\alpha, \beta_i)$ to represent the lumen maintenance degradation:

$$y_{ij} = D(t_{ij}; \theta) = \alpha \cdot \exp(-\beta_{ij} \cdot t_{ij}) + \varepsilon_{ij}. \quad (4)$$

For the decreasing type of performance measurement (lumen degradation of LEDs), the failure definition for the general degradation path models is that the performance measurement, y_{ij} , is lower than the critical threshold, D_f , at time t . For LEDs, $D_f = 0.7$ is recommended by ASSIST [29]. The cumulative probability of the failure function, $F(t)$, is given as follows:

$$F(t) = P(t \leq T) = P[D(t_{ij}, \alpha, \beta_i) \leq D_f]. \quad (5)$$

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

Several statistical methods have been proposed by researchers to estimate reliability based on the degradation data [30], [31]. The estimation of the percentiles of the failure time distribution can be obtained with analytical methods by

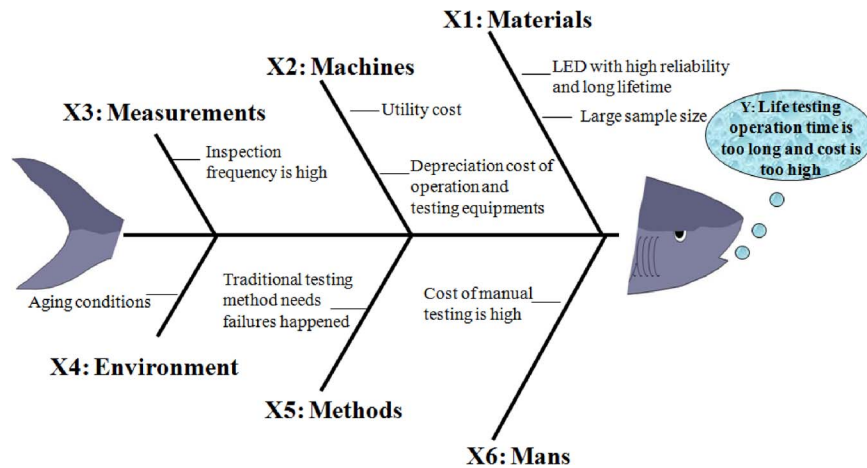


Fig. 6. Cause and effect diagram.

using the relation between the failure time distribution and the random effects parameter distribution. However, an assumption needs to be proposed first for the distribution of the random effects parameter, β_i . For example, Wu and Shao [38] assumed that the random effects parameter, β_i , followed a normal distribution. Wu and Chang [30] supposed it was an exponential distribution. Whereas Yu *et al.* [39] designed it as a reciprocal Weibull distribution. Then, the ordinary nonlinear least squares (ONLS) estimator was used to estimate the model parameter vector $\theta(\alpha, \beta_i)$ by minimizing the residuals between the observed data and the curve-fitted data from models. The accuracy of estimation depends on which distribution of random effects parameter is chosen. Therefore, this analytical method has some limitations in dealing with small sample size problems without detailed statistical distributions. Meanwhile, there are some limiting requirements for the degradation path model. This method will not solve the estimation problems in some complicated expressions of degradation path models.

$$\min_{\theta} \left\{ \frac{1}{s} \sum_j [y_{ij} - D(t_{ij}; \theta)] [y_{ij} - D(t_{ij}; \theta)]^T \right\}. \quad (6)$$

b) General reliability estimation method with nonlinear degradation data: In this paper, to establish a general reliability estimation method for LEDs with lumen maintenance degradation data, we propose the following three basic steps: (1) Estimating the pair parameter set for the degradation path models of each test unit $\Theta(\alpha_i, \beta_i)$; (2) extrapolating the degradation path model of each unit to critical failure threshold, D_f , to estimate the “pseudo” failure time for each unit; (3) Fitting the probability distribution for these “pseudo” lifetime data and calculating the 100pth percentile of the failure time distribution, t_p . The operation procedure can be specified as follows:

Step 1: The estimation of parameters for the degradation path models is the first and most important step in the whole reliability estimation process. Here, one parameter was not required to be assumed as a fixed value. Both parameters in the pair parameter set for the degradation path model are randomly distributed. We propose two estimation approaches to estimate

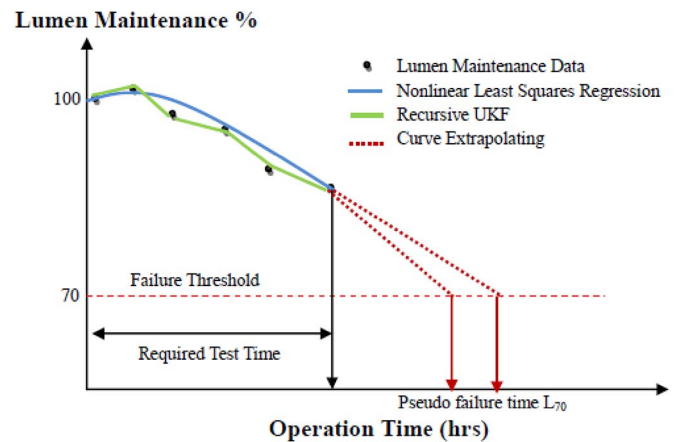


Fig. 7. General nonlinear estimation method with degradation data.

the pair parameter set $\Theta(\alpha_i, \beta_i)$: (1) nonlinear least squares (NLS); and (2) recursive unscented Kalman filter (Recursive UKF) (Fig. 7).

The NLS method is a similar approach to the above mentioned ONLS used in the analytical methods. It estimates parameters through minimizing the residuals between observed data and curve-fitted data from models. However, we did not assume any distribution for both parameters and we used the Matlab exponential curve-fitting tools with the trust region algorithm to estimate the pair parameter set $\Theta(\hat{\alpha}_i, \hat{\beta}_i)$ for each test unit.

Another approach proposed to estimate the pair parameter set of the degradation path model is the recursive UKF. The UKF approach was first proposed by Julier *et al.* and developed by E. A. Wan *et al.* [40]–[42] to estimate the state of nonlinear systems by using a deterministic sampling approach (sigma point sampling) to capture mean and covariance estimates with a minimal set of sample points. The UKF algorithm always involves estimation of the state of a discrete-time nonlinear dynamic system, which can be represented by both a state model and a measurement model [43]–[45]. Here, in order to estimate the pair parameter set $\Theta(\alpha_i, \beta_i)$, we used the lumen maintenance degradation model as the measurement model. The pair

parameter set of the degradation model of each test unit is seen as the state.

State Model:

$$x_{ij} = \Theta(\alpha_{ij}, \beta_{ij}) = [\alpha_{ij}; \beta_{ij}]$$

$$\alpha_{ij} = f(\alpha_{i,j-1}, v_{j-1}^\alpha) = \alpha_{i,j-1} + v_{j-1}^\alpha \quad v_{j-1}^\alpha \sim N(0, Q_v^\alpha)$$

$$\beta_{ij} = f(\beta_{i,j-1}, v_{j-1}^\beta) = \beta_{i,j-1} + v_{j-1}^\beta \quad v_{j-1}^\beta \sim N(0, Q_v^\beta). \quad (7)$$

Measurement Model:

$$y_{ij} = h(\alpha_{ij}, \beta_{ij}, \varepsilon_{ij}) = \alpha_{ij} \cdot \exp(-\beta_{ij} \cdot t_d \cdot j) + \varepsilon_{ij} \quad (8)$$

where v_{j-1} is the state noise and is assumed to be the mean zero white Gaussian noise.

Then we used the recursive UKF to estimate the pair parameter set $\Theta(\alpha_i, \beta_i)$ for the i th test unit. The main steps of the recursive UKF algorithm are summarized as follows:

- 1) $j = 0$ Initialize states with mean and covariance:

$$\bar{x}_0 = E[x_0]$$

$$P_0 = E[(x_0 - \bar{x}_0) \cdot (x_0 - \bar{x}_0)^T].$$

- 2) Express the initial state vector and covariance matrix as an augment vector:

$$\bar{x}_0^a = E[x_0^a] = [\bar{x}_0^T \quad 0 \quad 0]^T; \quad P_0^a = \begin{bmatrix} P_0 & 0 & 0 \\ 0 & Q_0 & 0 \\ 0 & 0 & R_0 \end{bmatrix}.$$

- 3) For $j \in [1, \infty)$
Calculate sigma points:

$$\chi_{j-1}^a = \left[\bar{x}_{j-1}^a \quad \bar{x}_{j-1}^a + \sqrt{n_a + \lambda} \right. \\ \left. \cdot \sqrt{p_{j-1}^a} \quad \bar{x}_{j-1}^a - \sqrt{n_a + \lambda} \cdot \sqrt{p_{j-1}^a} \right].$$

Time update:

$$\chi_{j/j-1}^x = f(\chi_{j-1}^x, \chi_{j-1}^v)$$

$$\bar{x}_{j/j-1} = \sum_{\pi=0}^{2n_a} W_\pi^{(m)} \chi_{\pi,j/j-1}^x$$

$$P_{j/j-1} = \sum_{\pi=0}^{2n_a} W_\pi^{(c)} \left[(\chi_{\pi,j/j-1}^x - \bar{x}_{j/j-1}) \cdot (\chi_{\pi,j/j-1}^x - \bar{x}_{j/j-1})^T \right]$$

$$y_{j/j-1} = h(\chi_{j/j-1}^x, \chi_{j-1}^\varepsilon)$$

$$\bar{y}_{j/j-1} = \sum_{\pi=0}^{2n_a} W_\pi^{(m)} y_{\pi,j/j-1}.$$

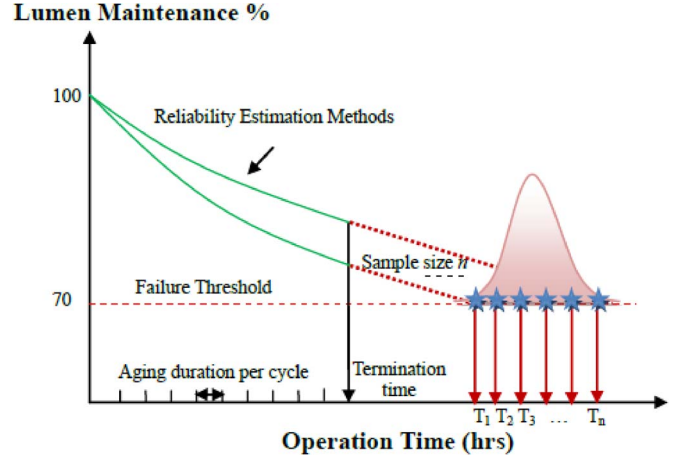


Fig. 8. The main parameters of LED reliability testing process.

TABLE V
THE FACTORS AND THEIR LEVELS OF DOE

Factors	Level 1	Level 2	Level 3
Reliability Estimation Methods	NLS	Recursive UKF	<i>N.A.</i>
Sample size of test units	12	10	8
Termination time (hrs)	1380	1035	690
Aging duration per cycle (hrs)	23	69	115

Measurement update:

$$P_{j/j-1}^{yy} = \sum_{\pi=0}^{2n_a} W_\pi^{(c)} [(y_{\pi,j/j-1} - \bar{y}_{j/j-1}) \cdot (y_{\pi,j/j-1} - \bar{y}_{j/j-1})^T]$$

$$P_{j/j-1}^{xy} = \sum_{\pi=0}^{2n_a} W_\pi^{(c)} \left[(\chi_{\pi,j/j-1}^x - \bar{x}_{j/j-1}) \cdot (y_{\pi,j/j-1} - \bar{y}_{j/j-1})^T \right]$$

$$K_j = P_{j/j-1}^{xy} (P_{j/j-1}^{yy})^{-1}$$

$$\bar{x}_j = \bar{x}_{j/j-1} + K_j (y_j - \bar{y}_{j/j-1})$$

$$P_j = P_{j/j-1} - K_j P_{j/j-1}^{yy} K_j^T.$$

- 4) If $j < T_d/t_d, j = j + 1$, repeat steps 2 to 3.

- 5) Otherwise, output the updated state x_j as the estimated pair parameter set $\Theta(\hat{\alpha}_i, \hat{\beta}_i)$ for the i th test unit.

where λ is the composite scaling parameter, $\lambda = \alpha^2(n_a + k) - n_a$; W_π is the weight factor, $W_\pi^{(m)} = \lambda / (\lambda + n_a)$; $W_\pi^{(c)} = \lambda / (\lambda + n_a) + (1 - \alpha^2 + \beta)$; $W_\pi^{(m)} = W_\pi^{(c)} = 1/2(\lambda + n_a)$, $\pi = 1, 2, \dots, 2n_a$. Here, we set $\alpha = 0.01$, $\kappa = 3 - n_a$, and $\beta = 0$. K_j is the Kalman gain. T_d and t_d are the design termination time and the time interval between two inspections, respectively.

With the inputs of the updated measurement data, the parameter vector $\Theta(\alpha_i, \beta_i)$ can be estimated and then updated as the initial state of next step recursively.

Step 2: After receiving the estimated pair parameter set $\Theta(\hat{\alpha}_i, \hat{\beta}_i)$ of each test unit, we extrapolated the degradation path

TABLE VI
TAGUCHI ORTHOGONAL ARRAY $L_{18}(3^3 * 1^2)$ DOE

DOE No.	Methods	Sample size	Termination time (hrs)	Aging duration per cycle (hrs)
1	NLS	12	1380	23
2	NLS	10	1380	69
3	NLS	8	1380	115
4	NLS	12	1035	23
5	NLS	10	1035	69
6	NLS	8	1035	115
7	NLS	12	690	69
8	NLS	10	690	115
9	NLS	8	690	23
10	Recursive UKF	12	1380	115
11	Recursive UKF	10	1380	23
12	Recursive UKF	8	1380	69
13	Recursive UKF	12	1035	69
14	Recursive UKF	10	1035	115
15	Recursive UKF	8	1035	23
16	Recursive UKF	12	690	115
17	Recursive UKF	10	690	23
18	Recursive UKF	8	690	69

model of each unit based on these parameters to the critical failure threshold to estimate the “pseudo” failure time as L_{D_f} :

$$L_{D_f} = \frac{\ln\left(\frac{\hat{\alpha}}{D_f}\right)}{\hat{\beta}} \quad (9)$$

where D_f is the lumen maintenance degradation critical failure threshold (i.e. $D_f = 0.7$ recommended by ASSIST).

Step 3: Fitting these “pseudo” lifetime data with the two-parameter Weibull probability distribution, Weibull(η, γ) [46], and calculating the 100 p th percentile of the failure time distribution, t_p .

$$\text{Weibull } p.d.f \ f(t; \eta, \gamma) = \frac{\gamma}{\eta} \left(\frac{t}{\eta}\right)^{\gamma-1} e^{-\left(\frac{t}{\eta}\right)^\gamma}, t > 0 \quad (10)$$

$$t_p = \eta \cdot [-(\ln(1 - p))]^{\frac{1}{\gamma}} \quad (11)$$

2) *Design of Experiment (DOE):* The degradation-data-driven reliability estimation method can also get reliability information (such as failure time distribution, the 100 p th percentiles of failure time distribution t_p , and mean time to failure MTTF) without waiting for failure to occur. Therefore, a new LED life testing process flow based on degradation data was planned by the Six Sigma team and a DOE was planned to optimize the LED life testing process parameters by considering the reduction of both time and cost. The team, along with the champion, conducted a series of brain storming sessions to identify the important parameters for experimentation. The parameters selected through these discussions are summarized as: 1) sample size of test units; 2) termination time (hrs); 3) aging duration per cycle (hrs); and 4) reliability estimation methods (Fig. 8). The factors and their levels for experimentation are presented in Table V.

In this study, we designed eighteen experiments with four effects and one interaction between the termination time and the reliability estimation methods for the LED life testing process with the help of Taguchi Orthogonal Array (OA), $L_{18}(3^3 * 1^2)$

(Table VI). According to the DOE plan, the designed eighteen experiments were conducted and the data (operation time, cost, the 10th percentile of the failure time distribution t_{10}) were calculated. Compared to the baseline data collected from the traditional life testing in the measure phase, the reduced operation time and cost and the estimated t_{10} absolute errors were calculated and are shown in Table VII.

To analyze the effects of the proposed factors on the accuracy of reliability estimation, we conducted three trials for each experiment and then used the Taguchi’s signal-to-noise (S/N) ratio method to treat the response (output) of the experiment. This experimental output can be evaluated as the absolute estimation errors of the 10th percentiles of failure time distribution, t_{10} . The S/N ratio for the *nominal is best* type characteristic was defined as:

$$S/N = 10 * \log\left(\frac{\bar{Y}^2}{s^2}\right) \quad (12)$$

where \bar{Y}^2 is the average of the response and s is the standard deviation.

The main effect and interaction plots for the S/N ratios were made with the help of Minitab statistical software (Figs. 9 and 10). After ranking from the response in Table VIII, it can be concluded that the termination time of life testing has the largest effect on the reliability estimation accuracy and the aging duration/cycle has the smallest effect. With the recursive UKF approach, the reliability estimation accuracy can be improved compared to the NLS approach. The reasons for this phenomenon can be concluded as [47], [48]: firstly, the UKF deals with dynamic stochastic systems, while least squares is used for deterministic systems; secondly, the UKF updates the system states recursively by absorbing new measurements while the least squares implementation uses batch processing.

After comparing the output results from the three project metrics mentioned in the project charter (time, cost, and accuracy) (Table VII), we chose the DOE16 with the associated

TABLE VII
SUMMARY OF LIFE TESTING PERFORMANCE FROM DOE

DOE No.	Project Y's metrics				
	Time reduced	Cost down	Accuracy <i>(estimated t_{10} absolute errors)</i>		
			Trial 1	Trial 2	Trial 3
1	15.49%	34.10%	3.79%	1.96%	3.46%
2	15.49%	62.59%	5.08%	5.24%	4.02%
3	15.49%	72.87%	4.11%	0.81%	1.84%
4	36.62%	46.50%	11.50%	8.77%	11.57%
5	36.62%	68.55%	12.87%	12.42%	12.10%
6	36.62%	76.94%	12.50%	8.46%	11.50%
7	57.75%	69.41%	22.23%	20.73%	23.25%
8	57.75%	76.26%	19.92%	20.29%	18.70%
9	57.75%	72.61%	17.34%	17.88%	18.49%
10	15.49%	59.30%	3.03%	4.04%	3.58%
11	15.49%	45.08%	2.29%	0.69%	4.09%
12	15.49%	70.07%	0.67%	1.43%	4.35%
13	36.62%	62.26%	8.08%	6.87%	8.93%
14	36.62%	71.17%	5.03%	3.26%	3.62%
15	36.62%	64.34%	7.29%	5.77%	8.45%
16	57.75%	71.51%	0.77%	0.38%	0.11%
17	57.75%	65.76%	8.63%	10.53%	8.46%
18	57.75%	79.61%	6.35%	10.06%	9.34%

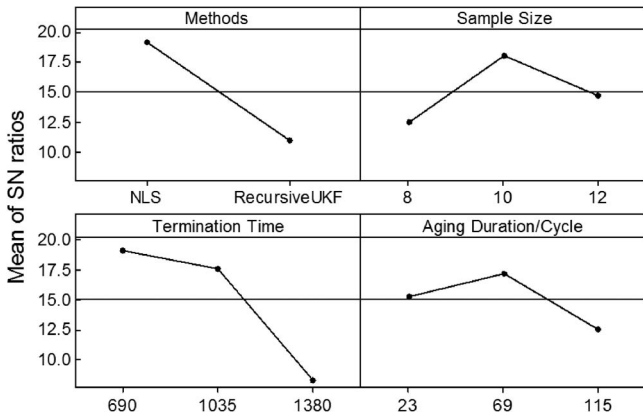


Fig. 9. Taguchi orthogonal array $L_{18}(3^3 * 1^2)$ DOE main effects plot for SN ratios.

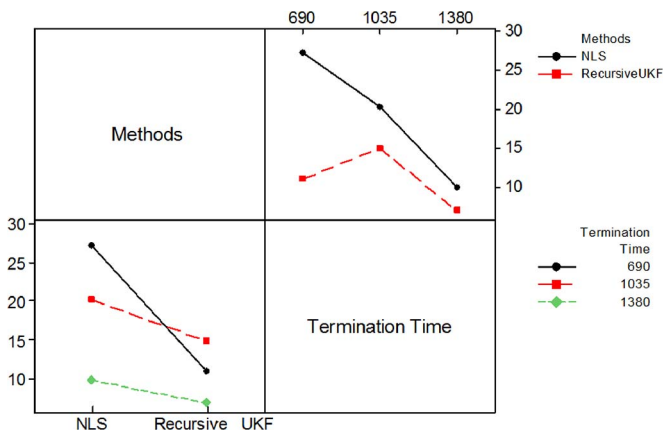


Fig. 10. Taguchi orthogonal array $L_{18}(3^3 * 1^2)$ DOE interaction plot for SN ratios.

factor levels as the optimal LED life testing process (Table IX). The improved process flow is shown in Fig. 11. Compared to

the traditional testing shown in Fig. 2, with the help of recursive UKF approach applied in the reliability estimation, the new LED life testing process can be terminated at 690 hrs with 115 hrs aging duration per cycle. The operation cost is reduced from \$1142.60 to \$325.50 and the required sample size can be reduced from 16 to 12. Therefore, the total operation time and cost can be reduced by 57.75% and 71.51%, respectively, and the absolute errors of the estimated t_{10} can be controlled under 5%.

E. Control Phase

Once the optimal results are achieved, the challenge for any process owner is to sustain the improvement in the achieved results. Standardizing of the improved methods and continuous monitoring of the results alone can ensure the sustainability of the results. As discussed in the improve phase, once we select the optimal LED life testing process flow with the associated process parameters (shown in Table IX), the experimental operation time and cost can be controlled to stable values (with 690 hrs of operation time and a cost of \$325.50). Besides the time and cost metrics, accuracy is another requirement for reliability estimation in this study. To show the stability of the improved LED life testing process flow in terms of the accuracy metric, a control chart showing the absolute errors of the estimated t_{10} is presented in Fig. 12. The results show that the improved life testing process is stable, having low estimation errors.

IV. CONCLUSION

Traditional life testing methods for high brightness white light-emitting diodes are always time-consuming and expensive. The Six Sigma DMAIC method is a project-driven management approach to discover and solve problems for a specified process. This study presents the step-by-step application of the Six Sigma DMAIC methodology in reducing the LED life testing operation time and cost and in maintaining highly accurate

TABLE VIII
RESPONSE FOR S/N RATIOS

Level	Main Effects for Accuracy of Reliability Estimation			
	Methods	Sample Size	Termination Time	Aging Duration/cycle
1	19.167	12.470	19.185	15.294
2	10.949	18.015	17.606	17.245
3	N.A.	14.688	8.382	12.634
Delta	8.217	5.545	10.803	4.611
Rank	2	3	1	4

TABLE IX
OPTIMUM FACTOR LEVEL COMBINATION

No.	Factors	Optimum level
1	Sample size of test units	12
2	Termination time (hrs)	690
3	Aging duration per cycle (hrs)	115
4	Reliability estimation method	Recursive UKF

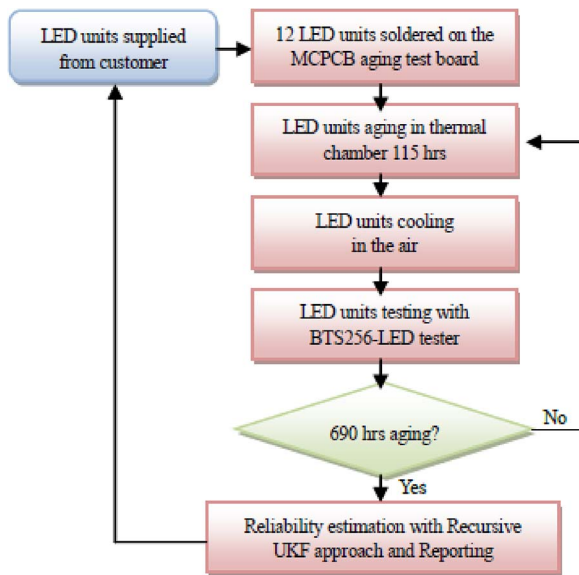


Fig. 11. The improved LED life testing process flow.

reliability estimations. The outcomes of this LED life testing Six Sigma project can be concluded as follows:

- 1) By implementing the proposed general reliability estimation method with both the NLS and recursive UKF approaches, the LED reliability (failure time distribution; percentiles of failure time distribution, t_p ; and MTTF) can be estimated with the lumen maintenance degradation data. There is no need to record failure data, such as the traditional life testing methods, with this proposed method.
- 2) Within dynamic stochastic systems, the recursive UKF approach can improve the accuracy of reliability estimation compared to the NLS approach.
- 3) With the optimum process parameter setting obtained from DOE, the operation time and cost of LED life testing can be reduced by 57.75% and 71.51%, respectively, compared to traditional testing. The reliability estimation errors from the improved process can also be controlled within customer's specification (within 5%);

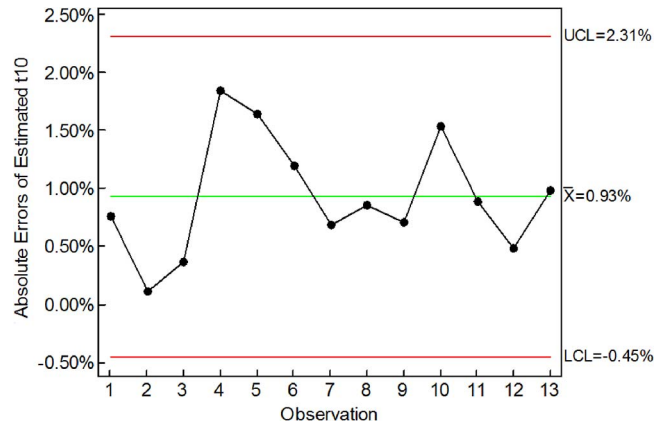


Fig. 12. Individual control chart for reliability estimation errors.

- 4) Finally, as revealed in the control chart, the new LED life testing process is stable with low estimation errors.

The future research direction of this research is that: as the proposed method in this paper was verified with the lumen degradation data of LED packages, its validation on the system level (like, LED luminaire) with considering the effect of LED driver will be studied to expand its application in the future.

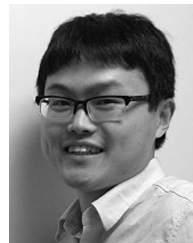
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Jiajie Fan (S'12–M'14) received the B.S. degree in inorganic materials science and engineering from Nanjing University of Technology, Nanjing, China, in 2006, the M.S. degree in material science and engineering from East China University of Science and Technology, Shanghai, China, in 2009, and the Ph.D. degree in industrial and systems engineering from The Hong Kong Polytechnic University, Kowloon, Hong Kong, in 2014.

He is currently a Lecturer with the College of Mechanical and Electrical Engineering, Hohai University, Changzhou, China. He is also currently a Postdoctoral Research Fellow with the Beijing Research Centre, Delft University of Technology, Delft, The Netherlands, and the State Key Laboratory of Solid State Lighting, Changzhou. He is registered as a certified Six Sigma Green Belt in the Hong Kong Society for Quality. His main research interests include lifetime estimation for LEDs, failure diagnosis and prognosis for electric devices and system, prognostics and health management for LED lightings, and advanced electronic packaging and assembly.



Cheng Qian received the B.S. and M.S. degrees in materials science and technology from Beijing Institute of Technology, Beijing, China, in 2003 and 2006, respectively, and the Ph.D. degree in aerospace engineering from Delft University of Technology, Delft, The Netherlands, in 2013.

After that, he joined Changzhou Institute of Technology Research for Solid State Lighting, Changzhou, China. Since 2014, he has been a Postdoctoral Fellow with the State Key Laboratory of Solid State Lighting, Institute of Semiconductors, Chinese Academy of Science, Beijing. His current work covers multiple subjects, including LED package/luminaire failure analysis and simulations, development of accelerating test techniques for LED luminaires, and lifetime predictions on photonic and chromatic parameters of the LED package/luminaire. His research interests are designing reliability of LED luminaires and systems using combined knowledge of multiphysics numerical simulations and statistical theories.



Kam-Chuen Yung (M'12) received the B.Eng. degree from The University of Sydney, New South Wales, Australia, the M.Sc.Eng. degree from The University of Hong Kong, Hong Kong, and the Ph.D. degree from Brunel University, Middlesex, U.K.

He is currently a Professor with the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University (PolyU), Hong Kong, where he is the Founder and Centre-in-Charge of the Printed Circuit Board Technology Centre. He has over 28 years of experience in both academia and industry with engineering and management responsibilities. His research areas include printed circuit board technology, integrated circuit manufacture, electronic assemblies and packaging, electronic materials, quality engineering, ISO9000 quality systems, TQM, and technology management.



Xuejun Fan (SM'06) received the bachelor's and master's degrees from Tianjin University, Tianjin, China, in 1984 and 1986, respectively, and the Ph.D. degree from Tsinghua University, Beijing, China, in 1989.

In 1991, he was promoted to Full Professor at Taiyuan University of Technology, where he was one of the youngest full professors in China at the time. He was a Technical Staff Member and the Group Leader with the Institute of Microelectronics, Singapore, from 1997 to 2000; a Senior Research Member with Philips Research Laboratory, Briarcliff Manor, NY, USA, from 2001 to 2004; and a Senior Staff Engineer with Intel Cooperation, Chandler, AZ, USA, from 2004 to 2007. He is currently a Professor with the Department of Mechanical Engineering, Lamar University, Beaumont, TX, USA. He has authored or coauthored over 150 technical papers and three books, namely, *Mechanics of Microelectronics*, *Moisture Sensitivity of Plastic Packages of IC Devices*, and *Solid State Lighting Reliability: Components to System* (Springer). He is the holder of five patents. His current research interests include design, modeling, material characterization, and reliability in micro- and nanoelectronic packaging and microsystems.

Dr. Fan is an IEEE CPMT Distinguished Lecturer. He was a nominee for the Ten Outstanding Youth of China Award in 1991. He was a recipient of the Best Paper Award of the IEEE TRANSACTIONS ON COMPONENTS AND PACKAGING TECHNOLOGIES in 2009 and the IEEE CPMT Exceptional Technical Achievement Award in 2011.



Guoqi Zhang (M'03–F'14) is currently the Director of the DIMES Centre for SSL Technologies and a Chairing Professor of Micro/Nano Electronics System Integration and Reliability with Delft University of Technology, Delft, The Netherlands. He has been responsible for the technology roadmap, strategy, and partnership of More-than-Moore. He has authored or coauthored over 100 scientific publications and has been invited as a keynote speaker by many international conferences and organizations. As an active player in the European's micro-/

nanoelectronics area, he has led and participated in several EC-funded research and development projects, networks, and initiatives.

Dr. Zhang is the Cochair of the Advisory Board of the International SSL Alliance. He has chaired and cochaired several international conferences (the IEEE International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems and the IEEE International Conference on Electronic Packaging Technology) and has participated in technical committees of several international conferences (the IEEE Electronic Components and Technology Conference, the IEEE Electronics Packaging Technology Conference, IEEE Nano Technology, and the European Symposium on Reliability of Electron Devices, Failure Physics and Analysis) and scientific societies. He is an Associate Editor of the IEEE TRANSACTIONS ON COMPONENTS AND PACKAGING TECHNOLOGIES.



Michael Pecht (F'92) received the M.S. degree in electrical engineering and the M.S. and Ph.D. degrees in engineering mechanics from the University of Wisconsin–Madison, Madison, WI, USA.

He is the Founder of the Center for Advanced Life Cycle Engineering, University of Maryland, College Park, MD, USA, where he is also a George Dieter Chair Professor in mechanical engineering and a Professor in applied mathematics. He has been leading a research team in the area of prognostics for the past ten years and has now formed a new Prognostics and Health Management Consortium at the University of Maryland. He has authored or coauthored over 20 books on electronic product development and use and supply chain management and over 400 technical articles. He has consulted for over 100 major international electronics companies, providing expertise in strategic planning, design, test, prognostics, IP, and risk assessment of electronic products and systems.

Dr. Pecht is a Fellow of ASME and IMAPS. He has served as the Chief Editor of the IEEE TRANSACTIONS ON RELIABILITY for eight years and on the advisory board of IEEE Spectrum. He is the Chief Editor of *Microelectronics Reliability* and an Associate Editor of the IEEE TRANSACTIONS ON COMPONENTS AND PACKAGING TECHNOLOGY. He was a recipient of the highest reliability honor, the IEEE Reliability Society's Lifetime Achievement Award, in 2008. He has been also a recipient of the European Micro and Nano-Reliability Award for outstanding contributions to reliability research, the 3M Research Award for electronics packaging, and the IMAPS William D. Ashman Memorial Achievement Award for his contributions in electronics reliability analysis. He is also a Professional Engineer.