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Bayesian based Lifetime Prediction for High-Power White LEDs

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Abstract

The introduction of high-power white LEDs has revolutionized the lighting industry in the past few decades due to the multiple benefits in terms of high reliability, environmental friendliness and versatile applications. However, challenges have arisen in assessing the reliability and lifetime prediction because it is difficult to record the failure data in a short period of time. Currently, the nonlinear least squares (NLS) regression-based method is used in industry for projecting the lumen maintenance lifetime from degradation data. The model parameters estimated using the NLS regression approach are deterministic and introduce high prediction errors. In this paper, a Bayesian method is proposed to estimate the remaining useful lifetimes (RULs) of both high-power white LED packages and lamps. The accelerated degradation tests conducted for gathering lumen degradation data are used to validate the proposed method. The exponential decay model is used as the degradation model and the parameters are estimated based on Markov Chain Monte Carlo (MCMC) sampling and using the Metropolis-Hasting (MH) algorithm. The lifetime prediction results showed that the Bayesian method has better prediction accuracy compared to the NLS method. Thus, the proposed Bayesian method is shown to be a promising approach to address the lifetime prediction issue for high-power white LEDs with improved prediction accuracy.

Keywords—Light-emitting diodes (LED), Bayesian methods (BM), Monte Carlo Markov Chain (MCMC), Metropolis Hasting (MH), Lifetime prediction

1. Introduction

Nowadays, many innovative products that have huge influence on our daily lives are being released to the market at an unprecedented pace. These products range from lighting devices, medical and communication equipment and industrial machines, to consumer electronic devices (such as smartphones, notebooks, tablets and TVs, etc.). This is due to the technological advancements in design and manufacturing, especially in the semiconductor, electronics and information communication sectors (Chang, 2012). The lighting industry is a good example of one of these developments that has shown dramatic changes from the traditional (incandescent and fluorescent lamps) to the current solid-state lighting (SSL) based light-emitting diodes (LEDs) in the past few decades. High-power white LEDs provide light via electroluminescence, a process in which light is created when electrical energy passes through a semiconductor material. In addition to indoor, outdoor and street lighting applications, LEDs are being widely used for automotive lighting, medical and communication devices, advertising display backlighting and aviation lighting and so on. This is due to many advantages that include low power consumption, compactness in size and multicolor options (Nair & Dhoble, 2015).

The high-power white LEDs are known for their higher reliability and longer lifetime compared to traditional light sources under normal operating conditions. However, this has brought another challenge for manufacturers in obtaining sufficient failure data to assess the reliability and estimate the remaining useful lifetimes (RUL) in relatively short lifetime testing periods (Tseng & Peng, 2007). On the other hand, advancements in design and manufacturing technology has shorten the product development time and new products are released to the market before the reliability of preceding versions are analyzed, which makes it difficult to fulfill the guarantee requirement of customers. Traditionally, accelerated lifetime tests (ALT) have been used to estimate the lifetime of highly reliable, products including high-power white LEDs. However, it has been challenging to evaluate the reliability of such products based on the classical approaches including censoring and/or accelerated lifetime-based methods that record time-to-failure (Chen et al., 2017). This is because, ALT are found to be expensive for estimating the lifetime of such products in a short time as it needs a longer time to collect sufficient time-to-failure data (Tseng & Peng, 2007). In addition to the long lifetime of such products that contributes to the recording of few or no failures during the reliability testing but also the fact that little information can be extracted from such lifetime data (Meeker & Escobar, 2014; Nelson, 2009). Nowadays, accelerated degradation tests (ADT) have become a promising alternative in capturing the degradation paths for the performance characteristics of products (Liao & Elsayed, 2006). Thus, ADT based on high-stress conditions enables the gathering of appropriate lumen degradation, color shift, and catastrophic failure results efficiently and in a relatively short time for LEDs (Meneghini et al., 2014).

Data-driven (DD) as well as physics-of-failure (PoF) methods have been studied as the two main types of prognostics approaches to assess the reliability and model performance degradations of high-power LEDs (Ibrahim et al., 2020). These approaches have different properties that contribute to the preferred choice of each algorithm. The DD methods are mainly dependent on large amounts of training data and/or degradation data collected through sensors in order to derive degeneration models for products and systems. The data collected in real-time can be used to adjust and modify the model parameters. On the other hand, the PoF (also known as model-based) method requires prior mathematical models to describe the product's degeneration process based on physical laws. The DD methods are helpful for complex systems where component interaction is indeterminate and when large amounts of training data are available, while the PoF method demands knowledge of the physical laws governing the product degeneration expressed in mathematical models (An et al., 2015; Yin et al., 2014). Fusion/hybrid approaches that combine the benefits and eliminate the drawbacks of both DD and physics-based methods, can also be implemented in prognostics studies (Cheng & Pecht, 2009).

A pristine LED light source is considered as failed when the luminous flux degrades to a failure threshold of 70% (L_{70}) from its initial rated light output or when the color shift reaches a threshold of du'v' 0.007 (ASSIST, 2005). The Illuminating Engineering Society of North America (IESNA) implemented the TM-21 standard for LED packages (IES-TM-21, 2011) and the TM-28 standard for LED lamps (IES-TM-28, 2014), which are based on nonlinear least squares (NLS) regression to predict the L_{70} lifetime. The NLS method is based on the principle of average error minimization between the actual degradation data and the model prediction. However, due to product degradation uncertainties and measurement dynamics, the NLS approach is known to introduce large prediction errors and uncertainties (Fan et al., 2014a; Fan et al., 2015). This leads the use of ADT as an effective approach for gathering performance degradation data (such as lumen maintenance, color shift, correlated color temperature (CCT) and Color Rendering Index (CRI) for LEDs) at relatively higher-stress levels and used to analyze important extrapolated reliability information using either DD, PoF or fusion prognostics approaches. Using degradation data, many research studies have been conducted to address lifetime estimation and reliability assessment issues of LED light sources as well as overcome the shortcomings of the NLS regression approach. Fan et al. (2012) introduced a degradation data driven method to predict the lumen maintenance lifetime of high-power white LEDs using degradation data. Similarly, other nonlinear state estimation methods proposed for LED light sources include the Kalman filter (Padmasali & Kini, 2017), Extended Kalman filter (Padmasali & Kini, 2017), Unscented Kalman filter (Fan et al., 2014a), (Fan et al., 2014b) and Recurrent Neural Network (Jing et al., 2020). Stochastic data driven methods such as the Wiener process, Lévy process and Gamma process have also been implemented in LED prognostics (J. Huang et al., 2015; Ibrahim et al., 2019; Ibrahim et al., 2018; Yung et al., 2017) and degradation modeling of carbon film resistors, batteries, crack growth, metal wear and ball bearing degradation (Z. Huang et al., 2017; J. Li et al., 2017). As a natural degradation modeling approach, the Gamma process has been applied to model degradations including corrosion, fatigue, erosion, consumption, swell, creep, degrading health index, etc. (van Noortwijk, 2009). The Gamma process method has also been used to predict the lumen maintenance lifetime of high-power white LEDs (Ibrahim et al., 2019) along with maximum likelihood estimation and the method of moments for parameter estimation. However, the Gamma process approach is also limited to non-increasing monotonic and gradual degradation data. On the other hand, Ibrahim et al. (2018) used the Wiener Process to predict the lumen maintenance lifetime of LEDs and Bayesian Inference based on Gibbs sampling applied for unknown parameter estimation. J. Huang et al. (2015) also applied a modified Wiener process method to model the lumen maintenance and color shift of mid-power white LEDs. Even though the Wiener process is helpful to handle nonlinear systems, it has a drawback because it utilizes only the current state degradation to predict the future by ignoring previous sequences of degradation data.

In addition to the previously mentioned DD methods, model-based prognostics have also been used for reliability assessment and lifetime prediction of systems. The main task in model-based prognostics is model parameters estimation and it has a huge effect on system reliability assessment and lifetime prediction. The increased computational capabilities and developments in the application of Monte Carlo Markov Chain (MCMC) methods have contributed to the frequent application of Bayesian methods in reliability assessment studies. The Bayesian statistical methods are known to combine degradation data with prior information (such as historical data/expert experience) to obtain posterior distributions for inference (M. Li & Meeker, 2014). Lall et al. (2015) used Bayesian classifiers to formulate the decision boundary between damaged and pristine lamps and Bayesian regression to estimate the lifetime of LED lamps. An et al. (2012) applied Bayesian model-based prognostics approaches: Particle filter, Bayesian method and recursive Bayesian method, comparing parameter estimation and demonstrating crack growth data as well as battery performance degradation (An et al., 2012). In addition, Fan et al. (2015) predicted the lumen maintenance lifetime of LEDs using the particle filter algorithm. In Particle Filtering, single particles (samples) are used to represent both the prior and posterior PDF of unknown parameters. Thus, when a new measurement value is obtained, the previous posterior distribution is used as a prior distribution for the current step and the multiplication of the prior and likelihood from the new measurement is used to update the values of parameters. On the contrary, all measurement data available are used to determine a single posterior distribution in Bayesian methods, which makes it a better and more efficient prognostics approach (Dong et al., 2019). Previous studies (Fan et al., 2015; Lall & Zhang, 2015) based on the model-based approach implemented the PF algorithm in the process of model parameter estimation. However, PF suffers from a particle leanness problem that may lead to misestimation of future states or parameters. To fill this gap, a Bayesian method is implemented in this study to estimate the remaining useful lifetimes (RULs) for high power white LED packages and lamps. The degradation model parameters are estimated based on Markov Chain Monte Carlo (MCMC) using the Metropolis-Hasting (MH) algorithm.

The remaining part of this paper is organized as follows: Section 2 describes the experimental setup and data collection procedure for obtaining performance degradation data. Description of the NLS regression method as well as BM based prognostics approach, parameter estimation with MCMC sampling and MH algorithm and lifetime prediction are presented in Section 3. In Section 4, the analysis results, and evaluation of the proposed prognostics approach are described. Finally, concluding remarks are presented in section 5.

2. Experimental Setup and Data Collection

In this study, two types of test samples were considered in order to gather the required lumen degradation data set and use the data to validate the proposed methodology.

2.1 12W high-power white light LED spot lamp

The first set of test samples consisted of 12W high-power white light LED spot lamps with a correlated color temperature (CCT) of 3000K. The LED package used in this lamp was composed of an InGaN-based blue LED chip coated with yellow phosphor in which the LED package generates white light when the phosphor gets excited by the blue-LED chips once supplied with appropriate forward current. The structure of the LED package, the LED module and the test sample spot lamp is shown Figure 1 in an exploded and assembled view.

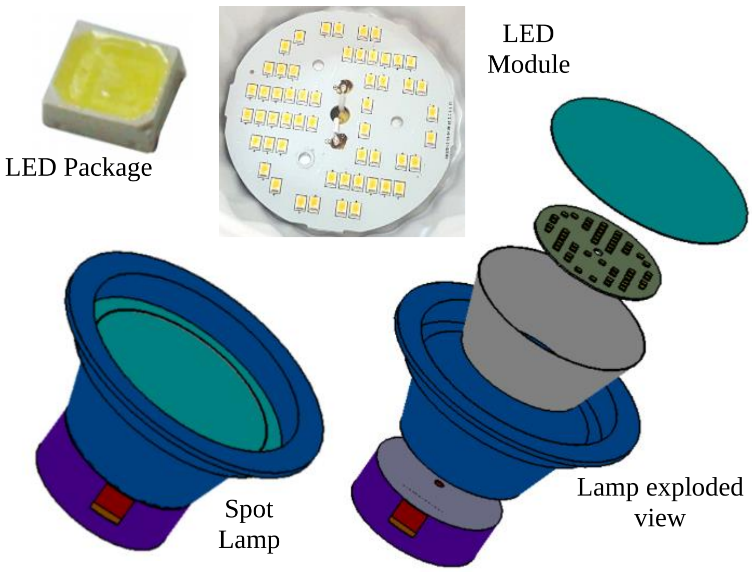


Figure 1. 12W high-power white light LED spot lamp components and exploded view

The experimental setup and ageing test procedure for the LED spot lamps is depicted in Figure 2. According to the TM-28 (IESNA, 2014), a sample size of at least three lamps or luminaires should be tested to collect performance indicator (i.e., luminous flux, colour shift, colour temperature,…) data.

A total of five test samples were aged under an elevated temperature of 55 ºC while placed in a thermal chamber. The LED lamps were supplied with AC power and aged for a total of 2160 hours, with each cycle of ageing set for 240 hours. After each cycle of thermal ageing, the test samples were taken out of chamber to cool down and optical measurement undertaken using an integrating sphere (EVERFiNE SPEKTRON Coating, Model YF1000) to collect lumen maintenance data.

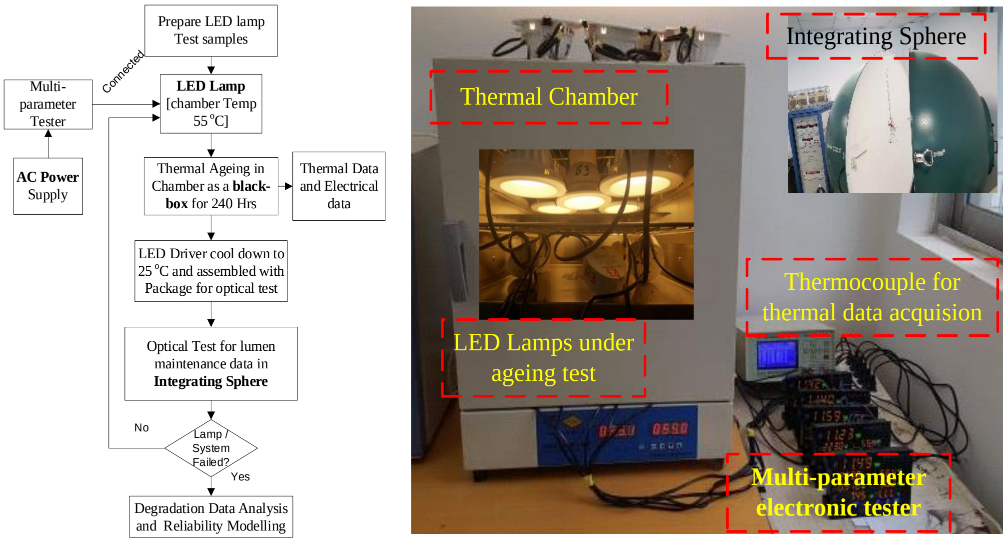


Figure 2. Experimental setup for LED lamps data collection

2.2 *3W high power white LED package*

The second set of test samples consists of InGaN based phosphor converted white LEDs as shown in Figure 3. The LED test samples had a 3W power supply with a CCT of about 4000K and the white light is generated when the coated yellow phosphor is excited and combines with the blue light emitted from the InGaN chip.

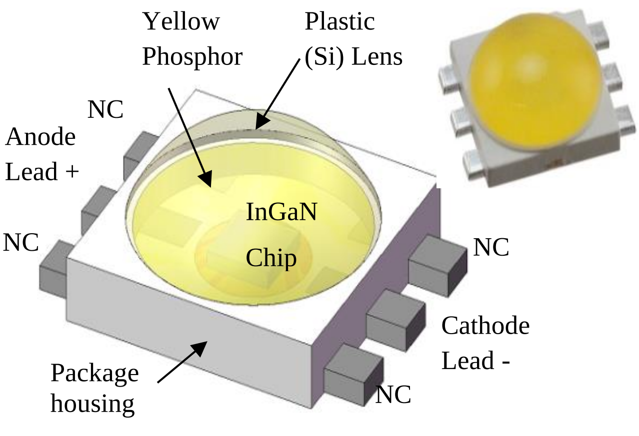


Figure 3. LED package architecture schematic view (left) and pictorial view (right)

The experimental setup for the ADT of the 3W high power white LED packages test sample is shown in Figure 4. A total of sixteen test samples were prepared for accelerated degradation testing based on thermal stress. The selected test samples were connected in series and supplied with a DC current (I_c=200mA using Agilent E3611A) after being soldered on a metal printed circuit board. The test samples were aged for a total of 1633 hours inside the thermal chamber set at an elevated temperature of 90ºC. The test samples were taken out of the thermal chamber every 23 hours and cooled down in order to conduct optical testing and to collect lumen maintenance data.

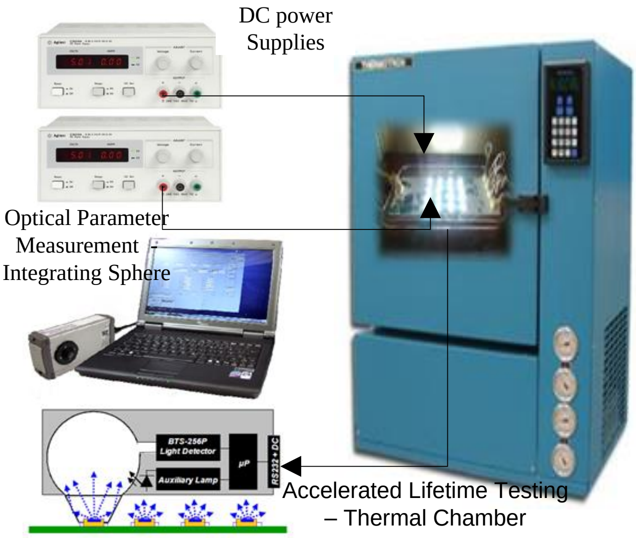


Figure 4. Accelerated Testing Experimental Setup for data collection

3. Theory and Methodology

In this section, the methods and algorithms used for parameter estimation and lifetime estimation are introduced. The NLS regression-based TM-21 and TM-28 standards approved by IESNA, Markov Chain Monte Carlo (MCMC) sampling and the Metropolis-Hasting (HS) algorithm are described.

3.1 Nonlinear Least Squares (NLS) Regression Method

The NLS based regression methods, the TM-21 and TM-28 standards, are approved by IESNA and used to project the lumen maintenance lifetime for high power LED packages, lamps and luminaires. The method is based on the principle of minimizing the difference between the predicted values with measured data. The lifetime of LED lamps is determined as the operating time that which the luminous flux depreciation reaches 70% of the initial light output (L_{70}) as recommended by the Alliance for Solid-State Illumination Systems and Technologies (ASSIST). Nowadays, LED manufacturers and various stakeholders use the exponential decay equation, assumed by the TM-28 standard method, given as:

$$\Phi\ (\mathrm{t}) = \beta.\exp\,(-\alpha.t) \tag{1}$$

where $\Phi\ (\mathrm{t})$ is the normalized luminous flux at time t hours, β is the projected initial constant of the normalized light output of the test samples, α is the lumen decay rate and *t* is the operation time in the ageing process. Here, the estimation of parameters α and β is based on the regression method from experimental data.

The implementation of this approach is as follows: (i) gather lumen degradation data and normalize to 1.0 to calculate the lumen maintenance life from the initial luminous flux output as $LM(t) = [\Phi(\mathrm{t})/\Phi(0)]\mathrm{x}100\%$; (ii) apply curve fitting using the exponential least squares for the normalized lumen maintenance data according to equation (1) (iii) perform lumen maintenance lifetime projection to estimate the L_{70} lifetime of LEDs using $L_{70} = \ln\,(\beta/0.7)\,/\alpha$.

3.2 *Bayesian Method (BM) based prognostics*

Bayesian methods (BM) are well-known as a model-based prognostics approach that enables estimation of model parameters in the form of probability density functions (PDF) based measurement data (Choi et al., 2010). It incorporates prior knowledge or expert opinion and data collected to obtain a posterior (or updated) distribution, which can be an input for inference of the model parameters. MCMC sampling is used to draw samples from a proposed distribution. This process of updating the posterior distribution of defined model parameters by incorporating measured degradation data is known as Bayesian inference, and is clearly described in Figure 5.

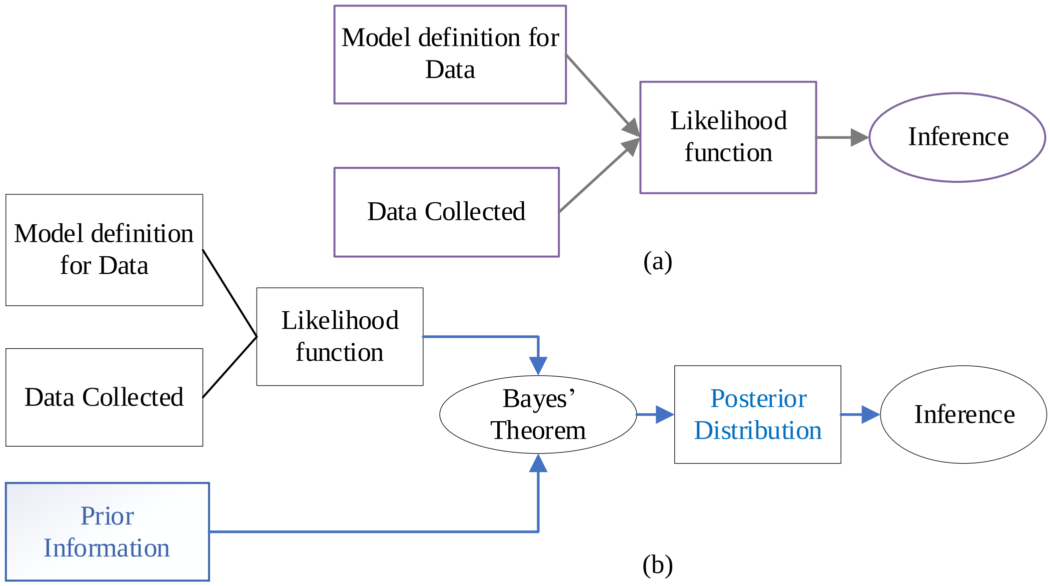


Figure 5. A Comparison of (a) non-Bayesian and (b) Bayesian Methods (M. Li & Meeker, 2014)

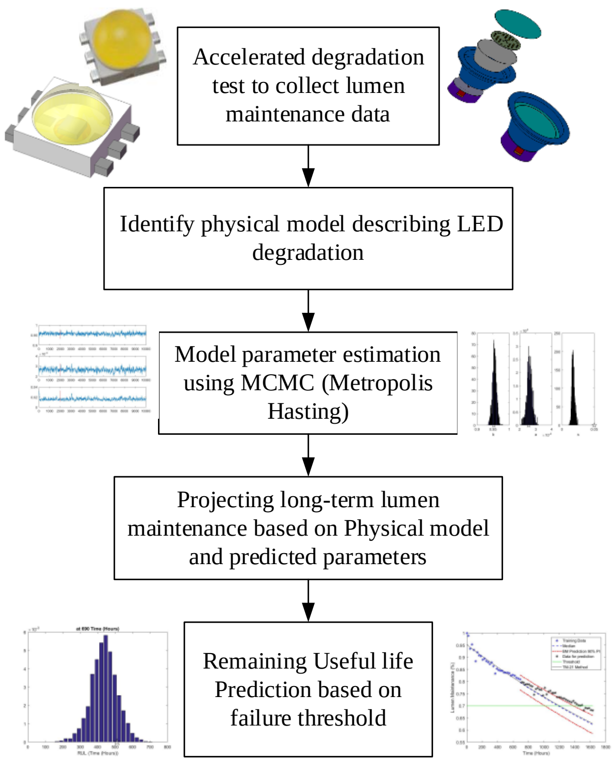


Figure 6. Bayesian Method Implementation Procedure

The Bayesian method is suitable when there is a physical model that describes the degradation of performance indicators. In the case of high-power white LEDs, lumen maintenance lifetime is modeled using an exponential decay model, according to IESNA (IES-TM-21, 2011). Thus, the BM-based prognostics approach can be implemented according to the procedures: (i) conduct an ADT to gather lumen degradation data for LEDs (ii) identify the physical model that describes the degradation (iii) estimate the model parameters based on MCMC sampling using the MH algorithm and (iv) propagate the lifetime based on the model to estimate remaining useful lifetime (RUL). The overall flowchart of the methodology is shown in Figure 6.

The BM implementation procedure mentioned above and depicted in Figure 6 is briefly explained step by step as follows:

A. Define degradation model

It is known that the degradation of high-power LED lamps is too complicated to described by a simple empirical mode, due to many random factors. However, for typical LED degradation, LED manufacturers and stakeholders use an exponential decay model, the NLS regression-based model shown in equation (1), i.e. $\Phi(t)= \beta.\exp(-\alpha t)$, to project the lumen maintenance lifetime. In our study, the simple empirical decay model is used as a physical model for BM based prognostics. The lumen maintenance data $\Phi(t)$ is gathered at discrete sets of ageing time *t*. In practice, the measured data may not be accurate due to uncontrolled environmental factors; thus, noise will be included in the degradation data with a Gaussian distribution.

B. Estimation of parameters

After the completion of the degradation test and experimental data collection, the next step is to determine the model parameters based on the Bayesian inference method. Bayesian inference enables an estimation of the degree of belief in a hypothesis when measured data is available as evidence.

Suppose the unknown model parameters from the degradation model are represented as Θ, measured data or lumen degradation is denoted as Y for *m* number of test samples and *n* is the number of degradation readouts.

In order to estimate the model parameters using measurement data from experimentation, the Bayes theorem $P(\Theta \cap Y) = P(\Theta|Y).P(Y) = \mathrm{P}(\mathrm{Y}|\Theta).\mathrm{P}(\Theta)$ can be applied in terms of probability density function (PDF) (An et al., 2011) and is formulated as follows:

$$f(\theta, y) = f(y|\Theta = \theta).f(\theta) = f(\theta|Y = y).f(y) \tag{2}$$

where $f(\theta)$is the prior PDF/ joint PDF of model parameter/s Θ, $f(\theta|Y = y)$is the posterior PDF of parameters Θ, $f(y)$ is the marginal PDF of the degradation feature Y and $f(y|\Theta = \theta)$ is the likelihood function or the probability of obtaining Y, given parameter Θ.

Now all the components of the Bayes' theorem are discussed as follows: First, the posterior PDF $f(\theta|Y = y)$, is the conditional probability of model parameters Θ, given measured data Y and is rearranged as follows:

$$f(\theta|y) = \frac{f(y|\theta).f(\theta)}{f(y)} \tag{3}$$

The prior distribution $f(\theta)$ with the likelihood function $f(y|\Theta = \theta)$ updates the posterior distribution $f(\theta|y)$. This process of updating the model parameter θ in the posterior distribution based on prior information and measured data is referred as Bayesian inference. Here the denominator $f(y)$ is considered as a normalizing constant, and from the property of PDF, the integral of the posterior distribution can have a maximum value of 1.

When a number of measurement data sets are available, the posterior distribution can be updated according to the Bayesian inference in two different ways. The Bayesian method make use of all the degradation data available to update a single posterior distribution and this approach is employed in this paper. On the other hand, single measurements are used to update the posterior distribution and the previous posterior PDF is used as a prior for the next measurement in PF method and has been previously studied (Fan et al., 2015). Suppose there are *n* number of test samples, $y = \{ y_1, y_2, \ldots, \ y_m\}$ is the vector for *m* number of degradation readouts, then the posterior distribution can be written in terms of Bayes theorem as follows:

$$f(\theta|Y = y) = \frac{1}{K_i} \prod_{i=1}^{m} [f(y_i|\Theta = \theta)] f(\theta) \tag{4}$$

In this equation K is acts as a normalizing constant and is the product of all marginal probabilities, as the integration of the posterior distribution gives a value of one. And i represents the beginning of the iteration for *m* number of lumen degradation readouts.

Secondly, the prior distributions of the model parameters are illustrated. As noted earlier, there are two assumptions that users are supposed to make in implementing the Bayesian methods, i.e., distribution types for degradation data noise and the prior distribution of model parameters. In this study, a Gaussian distribution is assumed for the degradation data noise, $\varepsilon \sim N(0, \sigma^2)$ where 0 is the mean and σ is the standard deviation and also for the prior PDF of model parameters α and β . Therefore, all the model parameters to be estimated will include the measurement noise and can be written as $\Theta = \{\beta, \alpha, \sigma\}$. Based on the independence assumption of all the model parameters to be estimated, the joint prior distributions can be formulated as:

$$\mathrm{f}(\theta) = f(\beta).f(\alpha).f(\ \sigma) \tag{5}$$

Thirdly, it is required to build the likelihood function based on the degradation data. The likelihood function is the probability of obtaining degradation data y_k given the model parameters $\Theta = \{\beta, \alpha, \sigma\}$. As the degradation data readouts are measured at *m* number of discrete times, the evaluation of the degradation model will be at the corresponding discrete times and it is denoted respectively as follows:

$$\begin{gathered} y_m(\sigma) = \ y_m(t_m; \sigma), for\ i = 1,2, \ldots, m \\ \hat{y}_m(\alpha, \beta) = \ y_m(t_m; \alpha, \beta), for\ i = 1,2, \ldots, m \end{gathered} \tag{6}$$

It should be noted that the measured degradation data is a function of the measurement noise σ while the model prediction is governed by the model parameters α and β.

Then the likelihood function of the degradation data at m^{th} readout can be defined as:

$$f(y_m|\theta) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{1}{2\sigma^2}(y_m - \hat{y}_m)^2\right], for\ i = 1,2, \ldots, m \tag{7}$$

From this, the posterior joint distribution shown in equation (04) can be rewritten as the product of the likelihood functions of the multiple data and the prior PDF as:

$$f(\theta|y) = \frac{1}{K\sigma^2} exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{m}(y_m - \hat{y}_m)^2\right] f(\theta) \tag{8}$$

C. Markov Chain Monte Carlo (MCMC) Sampling

The posterior distribution shown in equation (8) can be obtained after a proper assignment of probability distribution for the prior and likelihood functions. However, due to the complexity of the posterior distribution, it is intractable to solve through analytical approaches. To solve this problem, MCMC sampling is employed as one of the modern computational approaches for effective sampling in drawing samples of parameters with complex distributions in order to estimate the model parameters. The MCMC sampling can be applied with one of the two forms of standard techniques: Metropolis-Hastings (MH) algorithm, and Gibbs sampling (Steyvers, 2011). In this paper, the MH algorithm is selected as it is widely applied for reliability engineering applications, and a summary of procedures in the MH-simulation process is given as:

(i) Initialize sample $\theta^{(0)}$ and posterior PDF $f\left(\theta^{(0)}\middle|y\right)$

(ii) For i=1 to Ns (number of sampling, can be set 5,000 to 10,000)

Sample from proposal distribution. $\theta^{*} \sim g(\ \theta^{*}|\ \theta^{i-1})$ and posterior $f(\theta^{*}|y)$

Acceptance ratio: $Q\left(\theta^{(i-1)}, \theta^{*}\right) = min\left\{1, \frac{f(\theta^{*}|y)\ g(\theta^{(i-1)}|\theta^{*})}{f(\theta^{(i-1)}|y)\ g(\theta^{(i-1)}|\theta^{*})}\right\}$

Acceptance probability: u ~ U(0,1)

If u < $Q\left(\theta^{(i-1)}, \theta^{*}\right)$, Accept the newly generated candidate sample $\theta^{(i)} = \theta^{*}$

Otherwise, Reject the candidate and continue with previous: $\theta^{(i)} = \theta^{(i-1)}$ end

In this algorithm, $\theta^{(0)}$ is initial value of the unknown parameters, Ns is the total number of sampling, $f(\theta^{*}|y)$is the posterior distribution (i.e., the target distribution after Bayesian updates), $g(\theta^{*}|\theta^{i-1})$is proposal distribution that is used when a new sample $\theta^{*}$is drawn based on previous sample θ^{i-1}. The acceptance rate $Q\left(\theta^{(i-1)}, \theta^{*}\right)$ is used to compare the posterior probability of the new sample against that of the old sample. If the new sample has a higher probability than the current sample, i.e., $Q\left(\theta^{(i-1)}, \theta^{*}\right)$>1, then it will be accepted as new sample (Dong et al., 2019). This algorithm can be easily programmed and executed in the MTALAB environment.

Finally, lifetime prediction results will be obtained based on the degradation model. The performance of a prognostics approach can be evaluated based on accuracy-based metrics or root mean squares error (RMSE) (Saxena et al., 2008). The prediction accuracy based on accuracy-based metrics is often described quantitatively using relative error, given as:

$$Relative\ Prediction\ Error = \frac{y_i - \hat{y}_i}{y_i} * 100\% \tag{9}$$

where y_i are measured values, $\hat{y}_i$ is predicted value for i = 1 to n number of test samples.

4. Results and Discussion

In this section, the ADT experimental results for high-power LED packages and lamps, implementation of the NLS regression-based TM-21 and TM-28 as well as the parameter estimation and lifetime prediction based on BM are described.

4.1 Luminous Degradation Results

In this study, the lumen maintenance data is selected to demonstrated the proposed method as it is considered the dominant performance parameter for LEDs. Lumen maintenance is defined as the remaining luminous flux output (usually expressed as a percentage of the initial luminous flux output) at any specific operating time. It is the converse of lumen depreciation (Ibrahim et al., 2020). The luminous flux degradation data for the high-power white LED lamps (i.e., test data set 1), measured at intervals of 240 hours for a total of 2160 hours, is shown in Figure 7. It can be noted from the degradation that all the test samples are very close to the failure threshold of L_{70}, however none of the test samples failed when the experiment terminated.

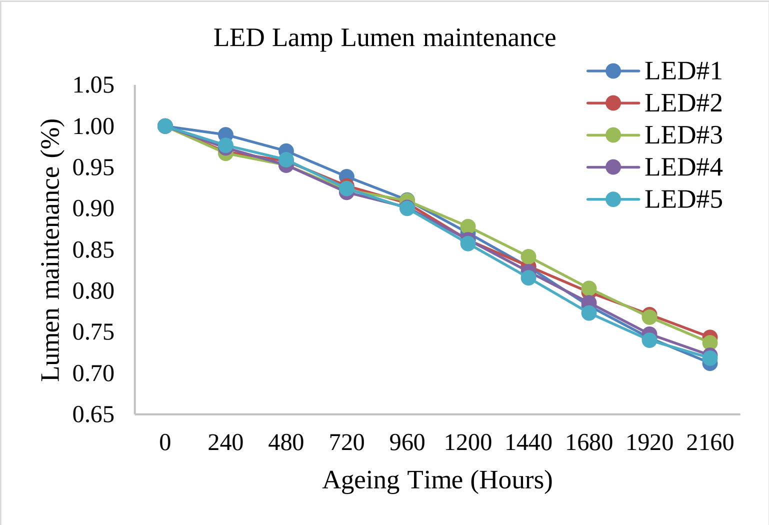


Figure 7: Luminous flux degradation of high-power white LED lamps (test data set 1)

Similarly, the lumen maintenance results for the second group of test samples (i.e., LED packages, test data set 2) are depicted in Figure 8. This plot showed a total of sixteen test samples, where the degradation measurement was taken every 23 hours for a total of 1633 hours (i.e., 71 cycles). In this experiment, six of the test samples failed (lumen maintenance depreciated below the threshold L_{70}=0.7) while nine samples had not failed when the experiment terminated.

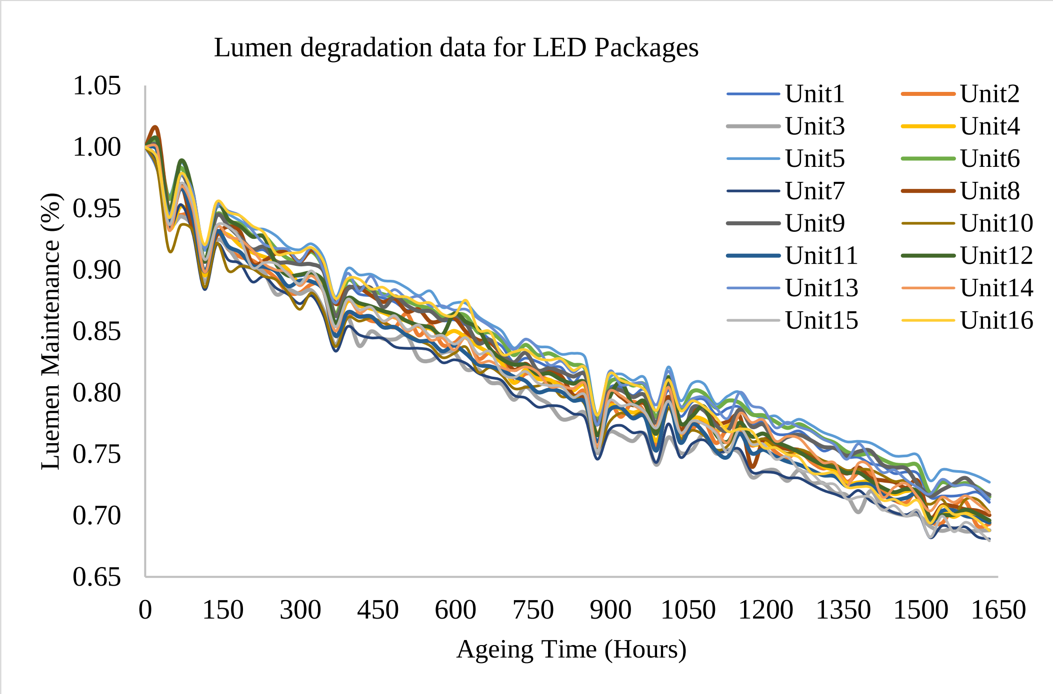


Figure 8. Luminous flux degradation of high-power white LED packages (test data set 2)

4.2 *Case Study 1: LED Lamp Level Analysis*

A. *NLS regression-based lifetime prediction*

The prediction of the lifetime for the test samples depends on the estimated value of the model parameters. The estimation of model parameters for the test samples is obtained according to NLS regression-based approach recommended by IESNA.

The model parameters are estimated using 45% of the total ageing time i.e., 0 to 960 hours out of the total 2160 hours based on the NLS regression curve fitting technique. The estimated model parameters and lifetime prediction results based on TM-28 method are presented in Table 1.

Table 1. Model parameters for LED Lamps (test data set 1)

Test Samples	Parameters		L70's	TM-28 Method	Prediction Error
	α	β			
Lamp 1	1.66E-04	1.038942	L71 = 2160	3499.71	62.02%
Lamp 2	1.40E-04	1.015198	L74 = 2160	2958.63	36.97%
Lamp 3	1.39E-04	1.015901	L73= 2160	3047.24	41.08%
Lamp 4	1.55E-04	1.020984	L72 = 2160	2960.39	37.05%
Lamp 5	1.62E-04	1.025857	L71 = 2160	3026.30	44.8%

Once the model parameters are estimated, the future degradation state and RUL can be predicted by inserting the values of the model parameters into the degradation model. In addition, the values of the estimated model parameters based on the NLS regression are also used as initialization values for the posterior distribution in BM approach, which is presented in the next section.

B. BM-based lifetime prediction results

As described in the methodology section, the model parameters are estimated using the MCMC sampling method with the MH algorithm. The process of sample tracing to estimate the model parameters β and α based on the MH algorithm is shown in Figure 9. This plot demonstrates a sample MCMC sample trace output for parameter estimation based on the Bayesian inference for LED Lamp #1, and similar procedure has been implemented for all the other LED lamp test samples.

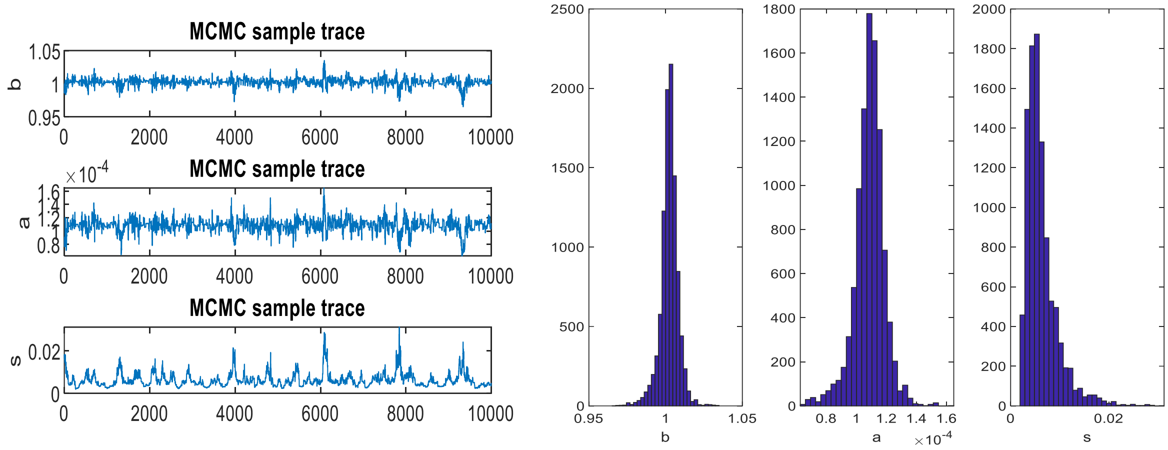
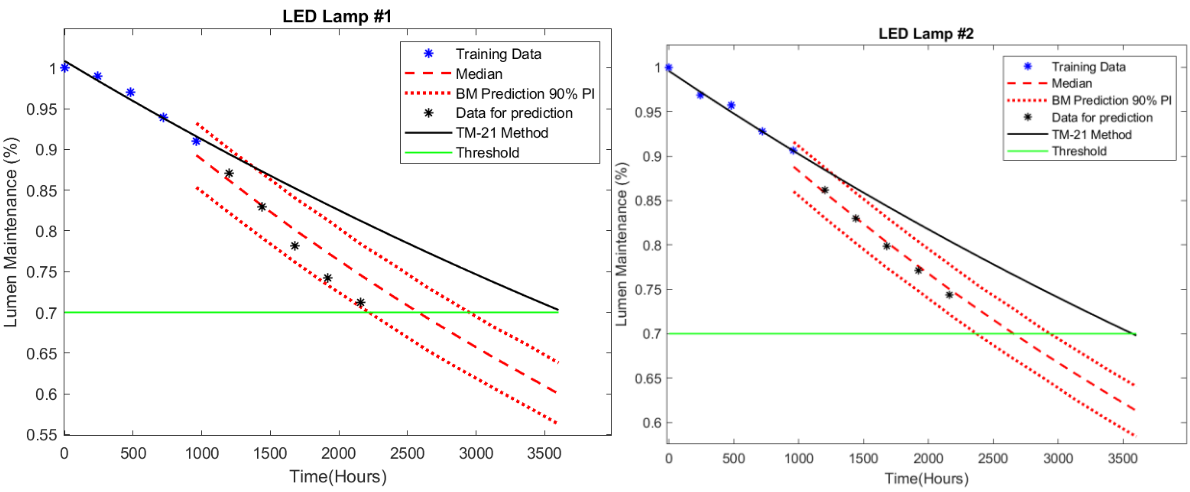


Figure 9. Estimated model parameters (a) MCMC Sampling trace (b) distribution plot

The prediction of the lumen maintenance lifetime based on the 45% of lumen degradation data (i.e., 960 hours of total degradation time of 2160 hours) is presented in Figure 10 as follows.



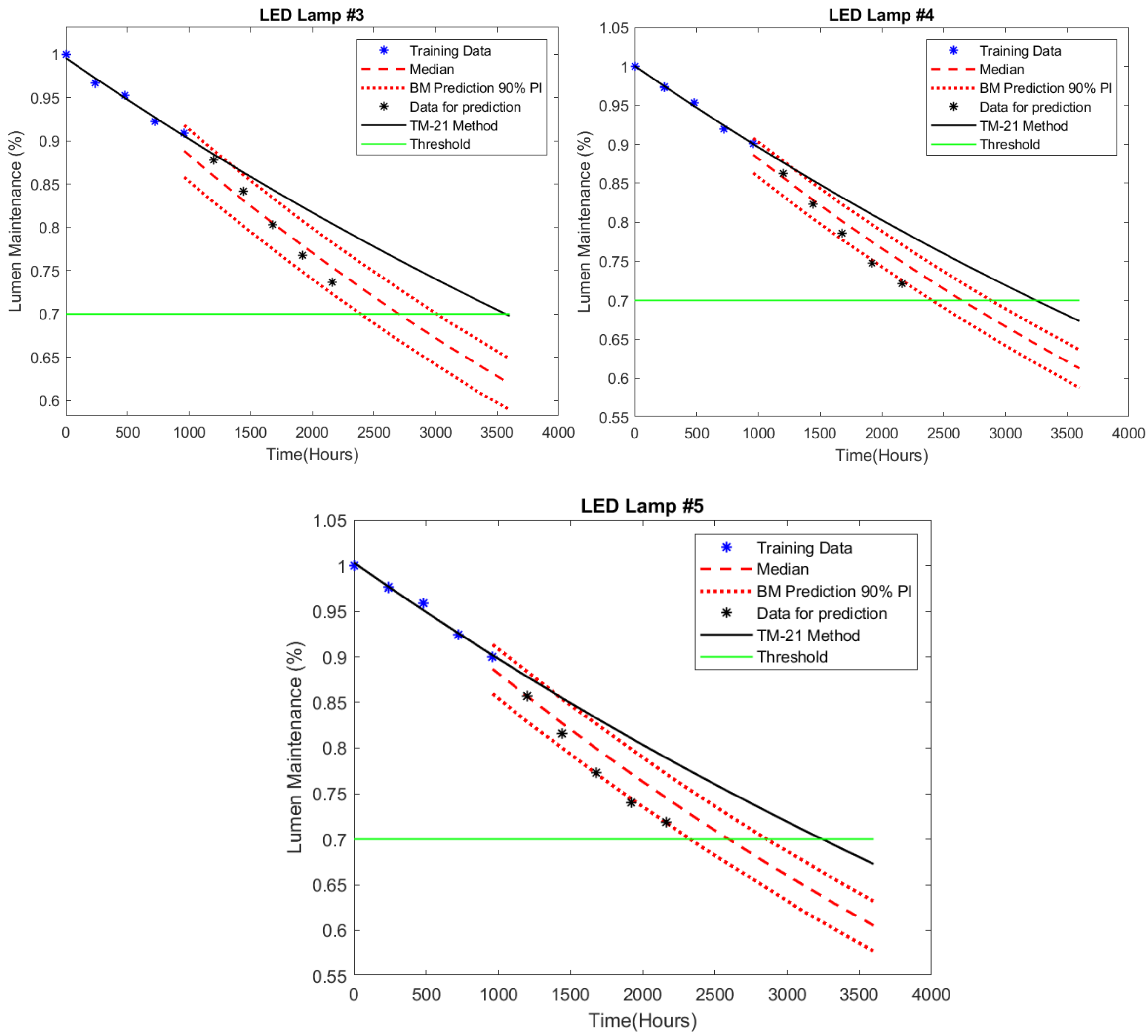


Figure 10. lumen maintenance lifetime prediction at 960 hours for LED Lamps

The summary of the BM-based lifetime prediction results is shown in Table 2. Furthermore, the RUL prediction for the LED Lamp test samples based on the experimental data (lumen maintenance) from 0 to 960 hours is depicted in Figure 11. It can be noted that, the RUL prediction is well fitted as a normal distribution with a 90% confidence interval. In the RUL prediction plots, it is clear that the y-axis denotes the density and often left as unlabeled. The RUL prediction accuracy of the BM compared with the actual hidden experimental results shows the prediction accuracy in Table 2.

Table 2. LED Lamp Lifetime prediction based on BM

Test Samples	α	β	s (i.e., σ)	L70 Prediction	Actual L70's Lifetime 2160	BM (90% Confidence Interval width)	
						BM-based prediction	BM- Prediction Error
Lamp #1	1.4918E-4	1.003706	0.0168	3120	L71=2160	3120	44.44% (225.5 hrs)
Lamp #2	1.2874E-4	1.019083	0.0105	2880	L74=2160	2880	33.33% (215.03 hrs)
Lamp #3	1.4155E-4	0.964918	0.0158	2880	L73=2160	2880	33.33% (231.44 hrs)
Lamp #4	1.3936E-4	1.047713	0.0087	2880	L72=2160	2880	33.33% (233.0 hrs)
Lamp #5	1.4379E-4	1.022348	0.0118	3120	L71=2160	3120	33.33% (188.76 hrs)

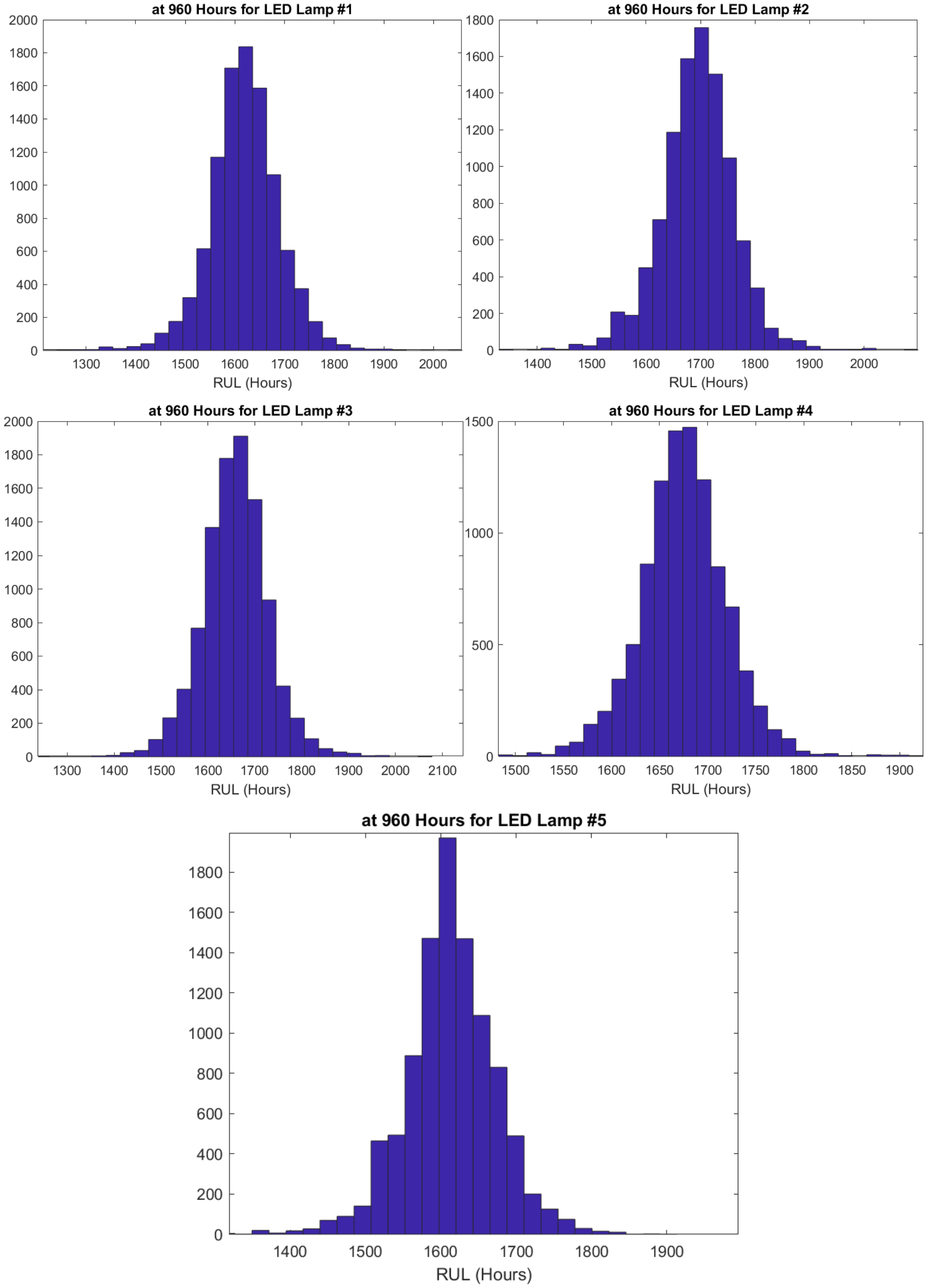


Figure 11. BM based RUL prediction result at 960 hours for LED Lamps

In this section, an estimation of the remaining useful lifetime for LED lamps is demonstrated based on TM-28 and BM, and is shown in Table 1 and Table 2. The summary and comparison of lifetime prediction results between the two proposed methods, BM and TM-28, for the LED lamps are shown in Figure 12.

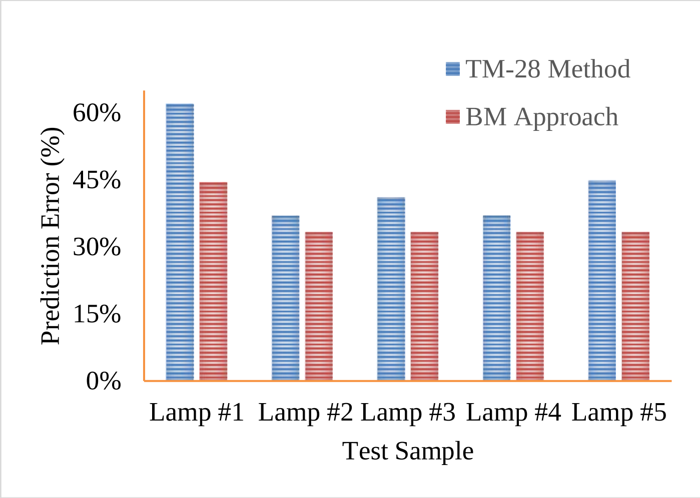


Figure 12. Prediction results for BM and TM-28

4.3 *Case Study 2: LED Package Level Analysis*

A. NLS Regression-based prediction results

There were a total of sixteen LED package test samples. However, in order to reduce the routine of NLS regression and BM analysis, a representative number of randomly selected test samples were used to demonstrate the proposed methodology. Therefore, the model parameters for the second data set are estimated based the NLS regression approach by using 45% of the lumen degradation (0 to 690 hours), and the results are shown in Table 3.

Table 3. NLS regression model parameters

Sample No	α	β	Actual L70's lifetimes (hours)	TM-21 Method (hours)	Prediction Error (%)
Unit 3	2.59E-04	0.95539	L70=1518	1199.15	21.00
Unit 7	2.56E-04	0.95219	L70=1518	1203.32	20.73
Unit 10	2.28E-04	0.94680	L70=1633	1323.55	18.95
Unit 11	2.53E-04	0.96311	L70=1518	1261.65	16.89
Unit 12	2.43E-04	0.97498	L70=1518	1364.71	10.10
Unit 14	2.46E-04	0.96552	L70=1633	1307.8	19.91

B. BM-based lifetime prediction results

As described in the methodology section, the model parameters were estimated using MCMC sampling method with the MH algorithm. The process of sample tracing to estimate the model parameters β and α and standard deviation (s or σ) for experimental data noise, based on the MH algorithm, is shown in Figure 13.

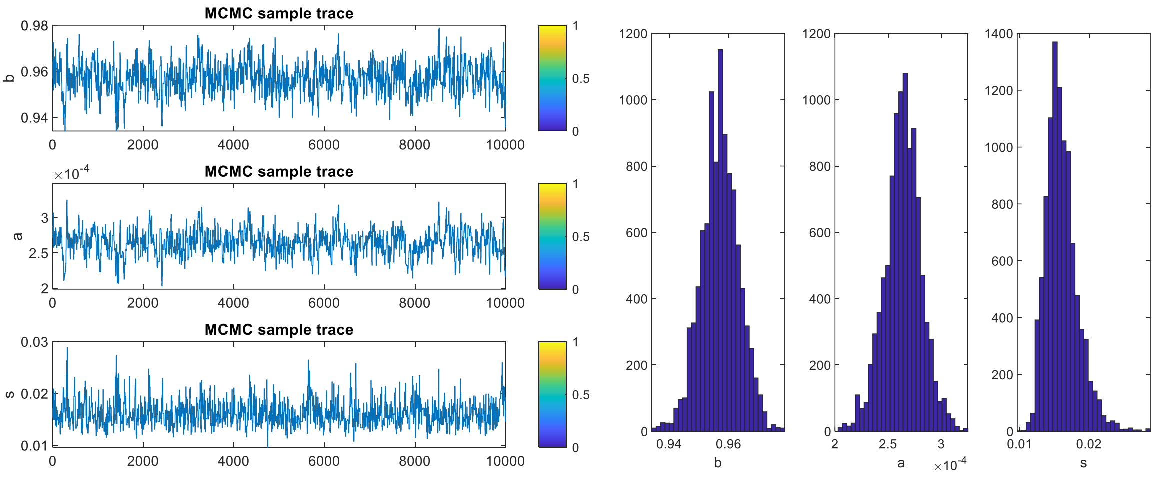
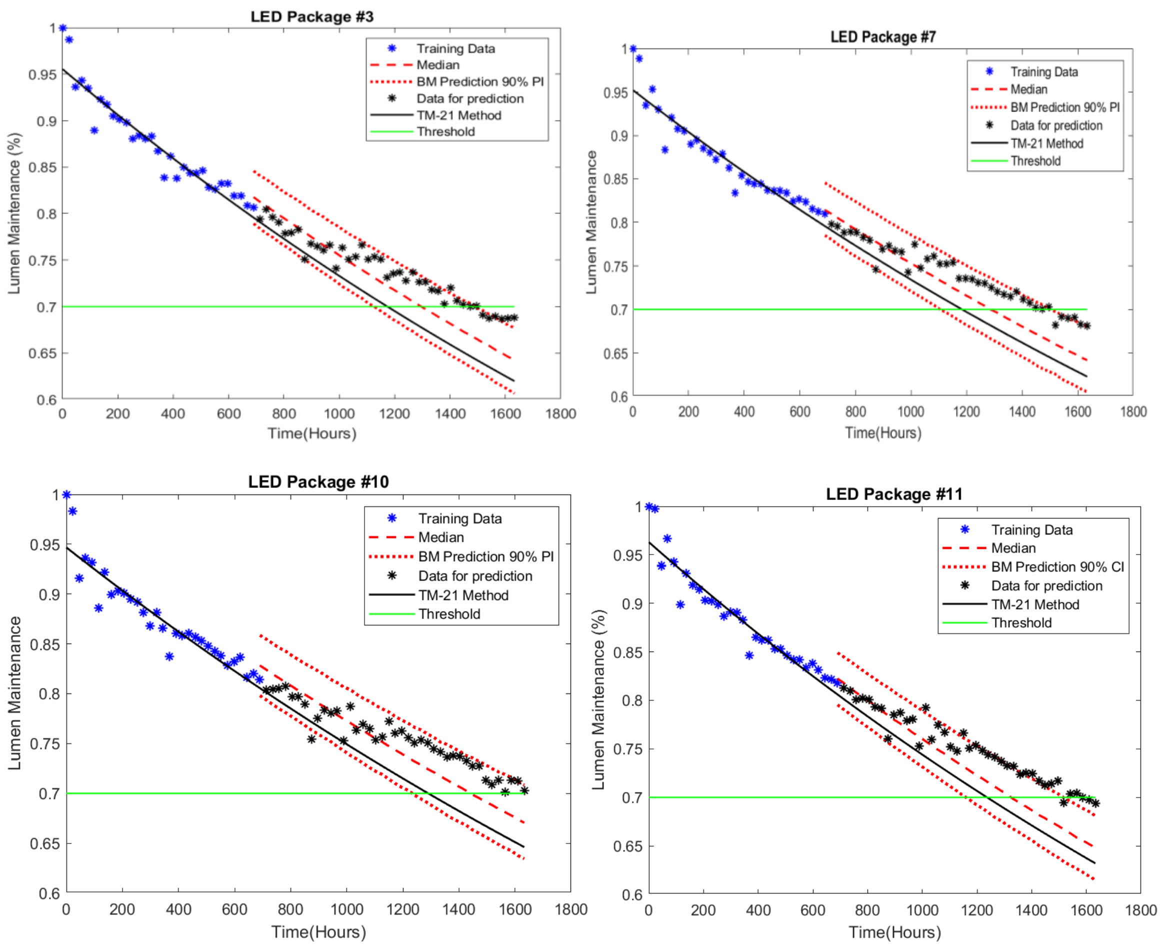


Figure 13. Estimated model parameters (a) MCMC Sampling trace (b) distribution plot

The plot shown in Figure 13 is depicted to illustrate the sample output of the Bayesian inference for LED Package #3, and a similar procedure has been implemented for all the test samples. Based on parameters estimated using MCMC sampling and the MH algorithm, the prediction of the lumen maintenance lifetime is conducted using 45% of the experimental data (i.e., 690 hours of the total 1633 hours of degradation data) and is presented in Figure 14.



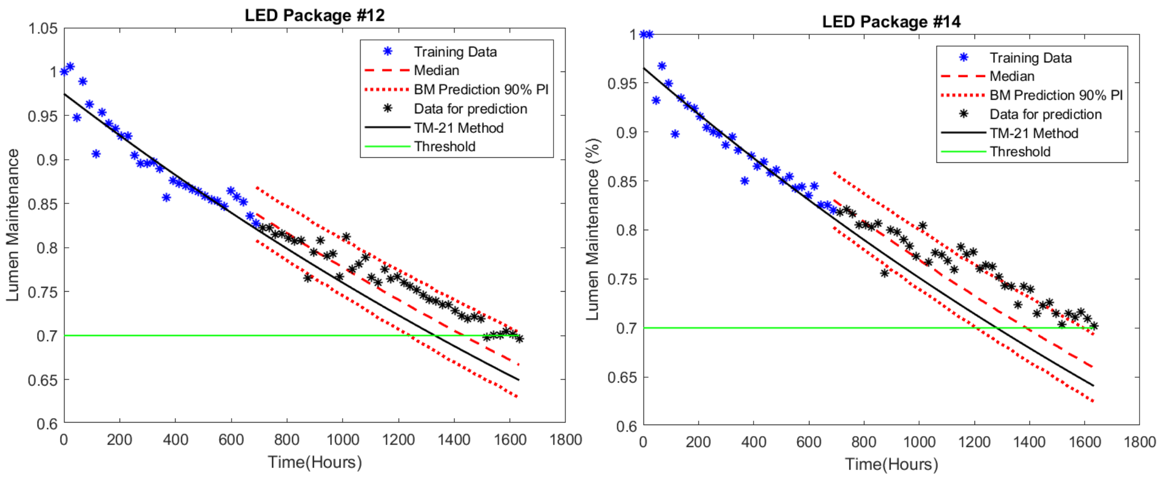
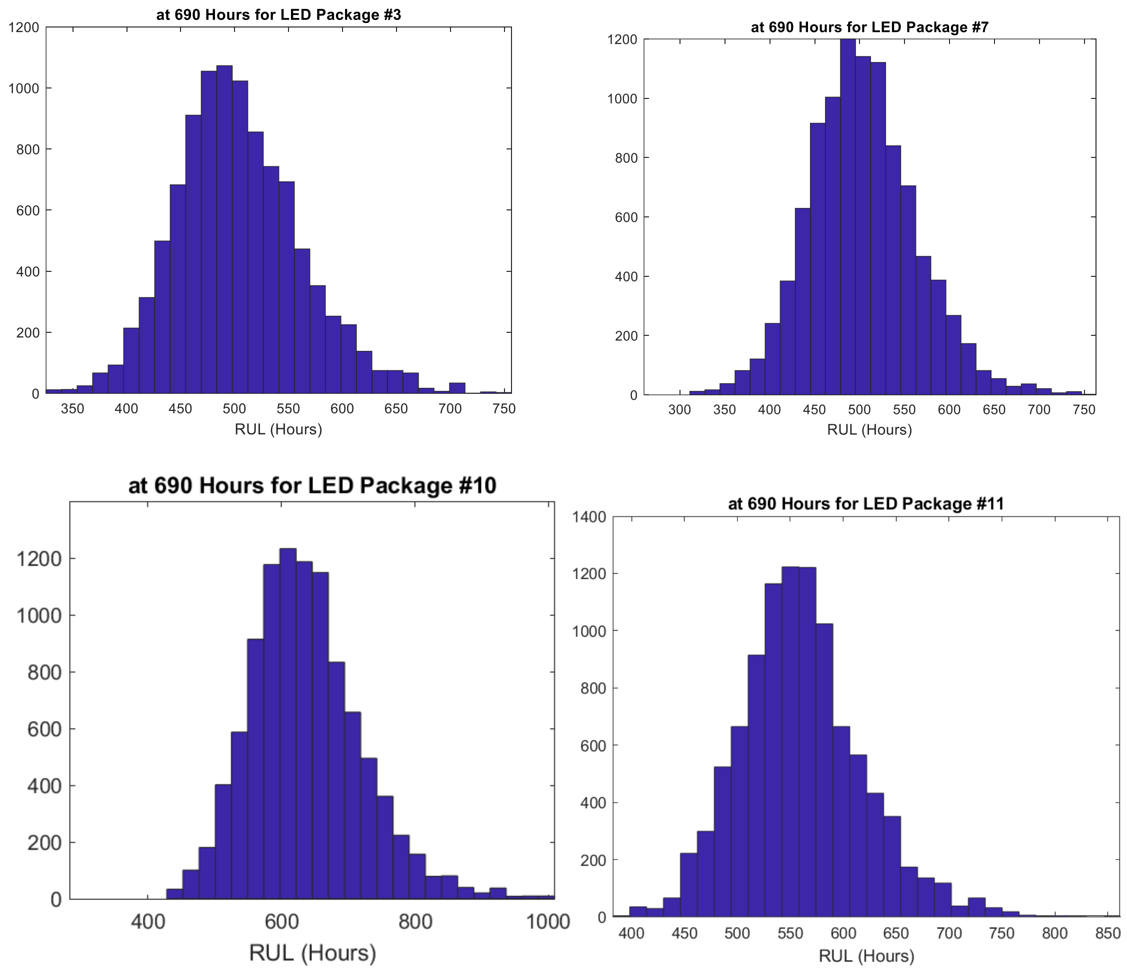


Figure 14. Prediction of lumen maintenance degradation at 690 hours for LED Packages

The distribution of the RUL prediction from the current time (690 hours) until the failure threshold (i.e., L70=0.7 of the lumen maintenance data) is shown in Figure 15.



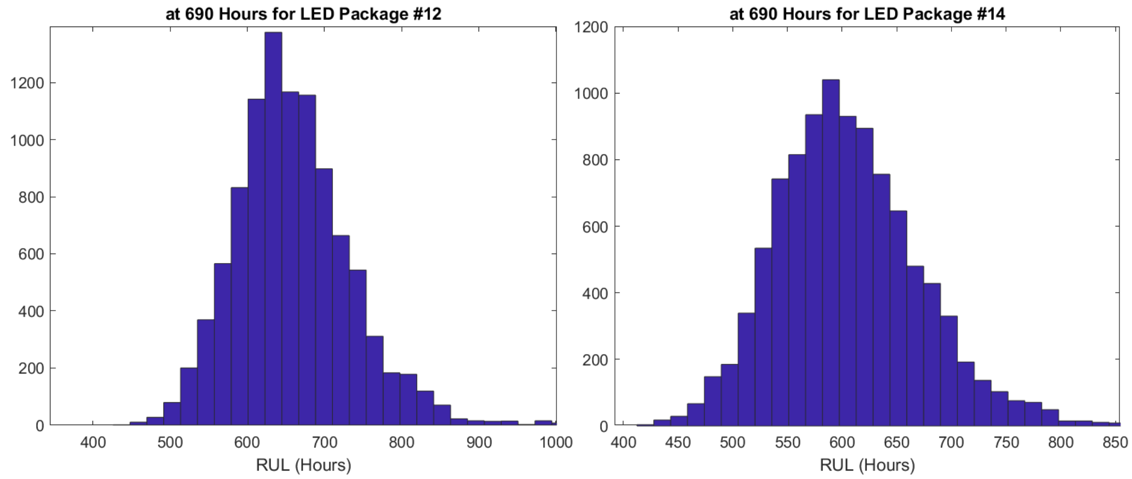


Figure 15. BM based RUL prediction result at 690 hours for LED Packages

Based on the BM-based approach, the lifetime prediction and prediction error results are presented in Table 4. The prediction results based on BM shows its superior performance compared with the traditional NLS regressions approach used by LED manufacturers.

Table 4. LED package Lifetime prediction based on BM

Test Samples	Actual L70's lifetimes	α	β	s (i.e., σ)	BM-based analysis	
					BM lifetime prediction	BM (90% C.I prediction width)
LED #3	1518	2.593E-4	0.9691	0.0143	1380	9.09% (198.56 hrs)
LED #7	1518	2.5257E-4	0.9523	0.0165	1403	7.58% (197.53 hrs)
LED #10	1633	2.357E-4	0.9511	0.0179	1587	2.82% (272.66 hrs)
LED #11	1518	2.1829E-4	0.9635	0.0204	1449	4.55% (193.29 hrs)
LED #12	1518	2.4819E-4	0.9810	0.0232	1587	-4.55% (251.38 hrs)
LED #14	1633	2.3918E-4	0.9687	0.0168	1495	8.45% (214.25 hrs)

In the previous sections, the lifetime prediction based on the TM-21 and BM are presented. Here the comparison of lifetime prediction results, as well as prediction errors between the proposed BM and TM-21, for the LED lamps are shown in Figure 16.

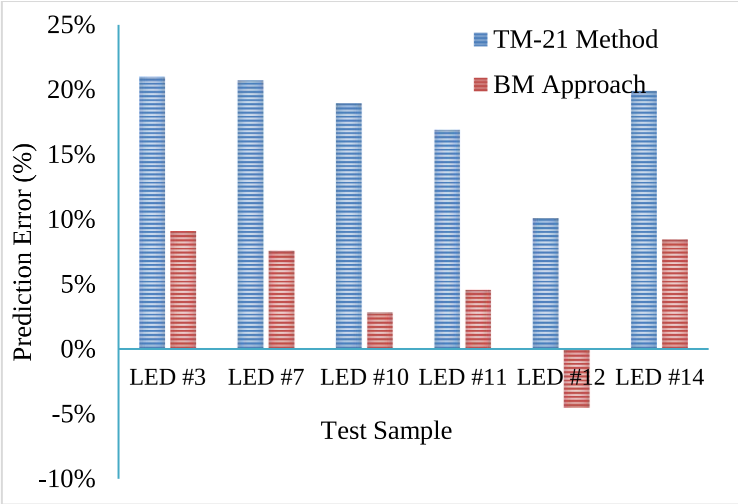


Figure 16. Comparison of BM and TM-21 prediction results for LED Packages

Similarly, the lumen maintenance lifetime prediction results using the BM-based approach is compared with one of the previously mentioned state-of-the-art Particle filter approach for different test samples and the comparative results are shown in Table 5 and Figure 17. It can be noted that the prediction results of BM is close to that of the PF approach while it has advantage of estimating parameters without parameter initialization process.

Table 5. Comparing prediction results of PF and BM Methods

Test Sample	Prediction time	Prediction Error (PF)-Fan et al 2015	Test Sample	Prediction time	Prediction Error (BM) -Proposed BM
Test LED_1	920 h	1.52(299 h)	Test LED_3	960 h	9.09% (198.56 hrs)
Test LED_2	920 h	6.06(414 h)	Test LED_7	960 h	7.58% (197.53 hrs)
Test LED_3	920 h	4.55(391 h)	Test LED_10	960 h	2.82% (272.66 hrs)
Test LED_4	920 h	1.56(345 h)	Test LED_11	960 h	4.55% (193.29 hrs)

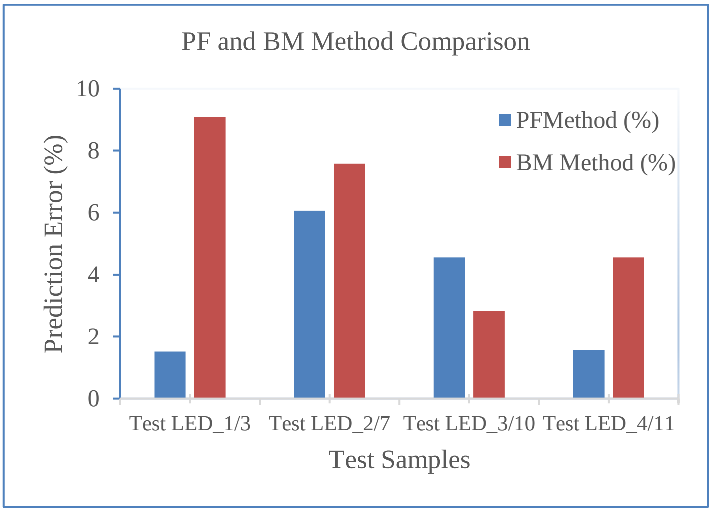


Figure 17. BM and PM method prediction result comparison for Selected LED Packages

The efficiency of MCMC sampling depends on a proper selection of the proposed prior distribution and sample initial values. In cases of inaccurate initial samples, the initial portion of the samples is discarded to prevent potential estimation error. The lumen maintenance lifetime prediction error is depicted in Figure 12 and Figure 16. Compared to the NLS regression-based TM-21 and TM-28 methods, the BM showed a better prediction accuracy with a certain level of confidence interval (90% CI in this case), as demonstrated on a representative number of LED package level and LED lamp test samples. It can be noted from the lifetime prediction results that the prediction accuracy for LED packages is better than for the LED Lamps. This can be attributed to the amount of training data (i.e., experimental data), where about 31 cycles of data for LED packages (690 hours of degradation data with 23 hours/cycle) was considered while only 5 cycles of data (i.e., 960 hours of degradation data with 240 hours/cycle) were used for LED lamp test samples. This shows that as the number of training test samples increases, the accuracy of the parameter estimation increases, which eventually leads to an improved lumen maintenance lifetime prediction for high power white LEDs.

5. Conclusions

In this study, the model-based Bayesian method is demonstrated to predict the lifetime of high-power white LEDs. The exponential decay model was used as the physical model to describe the degradation of luminous flux for high power LEDs. An accelerated degradation test was conducted to gather lumen maintenance data in a shorter operating time at an elevated thermal stress. The estimation of model parameters is an important task in model-based approaches, once the degradation data is collected. The Monte Carlo Markov Chain (MCMC) sampling and Metropolis-Hasting (MH) algorithm was employed to estimate the model parameters as probability distributions, and to handle the measurement noise. The results showed that the lifetime prediction results based on the BM have a better prediction accuracy compared to the IES-TM-21 and TM-28 methods, which are based on the NLS regression approach. The average prediction error for the randomly selected LED packages LED #3, LED#7, LED#10, LED #11, LED#12 and LED#14, as well as LED lamps #1 to #5, based on BM, is about 5% and 35% with a 90% confidence interval while it is about 18% and 44 % respectively based on the NLS approach. Thus, the model-based BM is an efficient lifetime prediction approach especially when a physical model and relatively small amounts of data are available. Thus, this approach can be employed by LED manufacturers and stakeholders to provide accurate lifetime time labels to customers and end-users.

6. Acknowledgments

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