Expert Systems with Applications 42 (2015) 2411–2420

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Predicting long-term lumen maintenance life of LED light sources using a particle filter-based prognostic approach

Jiajie Fan [a,b,*], Kam-Chuen Yung [b], Michael Pecht [c]

[a] Department of Mechanical Engineering, College of Mechanical and Electrical Engineering, Hohai University, Changzhou, Jiangsu 213022, China
[b] PCB Technology Center, Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong
[c] Center for Advanced Life Cycle Engineering, University of Maryland, College Park, MD 20742, USA

ARTICLE INFO

Article history:
Available online 18 October 2014

Keywords:
LED light sources
Lumen maintenance
Remaining useful life
Prognostics
TM-21 standard
Particle filter

ABSTRACT

Lumen degradation is a common failure mode in LED light sources. Lumen maintenance life, defined as the time when the maintained percentages of the initial light output fall below a failure threshold, is a key characteristic for assessing the reliability of LED light sources. Owing to the long lifetime and high reliability of LED lights sources, it is challenging to estimate the lumen maintenance life for LED light sources using traditional life testing that records failure data. This paper describes a particle filter-based (PF-based) prognostic approach based on both Sequential Monte Carlo (SMC) and Bayesian techniques to predict the lumen maintenance life of LED light sources. The lumen maintenance degradation data collected from an accelerated degradation test was used to demonstrate the prediction algorithm and methodology of the proposed PF approach. Its feasibility and prediction accuracy were then validated and compared with the TM-21 standard method that was created by the Illuminating Engineering Society of North America (IESNA). Finally, a robustness study was also conducted to analyze the initialization of parameters impacting the prediction accuracy and the uncertainties of the proposed PF method. The results show that, compared to the TM-21 method, the PF approach achieves better prediction performance, with an error of less than 5% in predicting the long-term lumen maintenance life of LED light sources.

1. Introduction

Light-emitting diodes (LEDs) are widely used as a next generation light source including indoor lighting, street lamps, advertising displays, decorative lighting, and monitor backlights (Schubert & Kim, 2005). Compared to traditional light sources (such as incandescent lamps, halogen incandescent lamps, and cold cathode fluorescent lamps), LED light sources have attracted interest due to their high efficiency, environmental benefits, high reliability, and long lifetime, with claims of 50,000 h or longer (Haitz & Tsao, 2011; Lafont, van Zeijl, & van der Zwaag, 2012; Tarashioon et al., 2012). However, owing to the long lifetime and high reliability, few or any failures should occur in LED light sources during a short-term life test, even in an accelerated life test (Challa, Rundle, & Pecht, 2013; Chang, Das, Varde, & Pecht, 2012). Thus, it is time-consuming and expensive for LED developers to estimate the life for LEDs using traditional destructive life testing, which records failure data. Therefore, the capability to explore an expert system by conducting short-term and cost-effective qualification tests to predict long-term remaining useful life (RUL) is a critical economic and business requirement to new LED adoption, and it is the motivation of this research topic.

Apart from the traditional destructive life test, predicting RUL with a degradation test appears to be an attractive alternative for qualifying highly reliable products, bringing benefits by shortening the testing time, identifying the degradation path, and providing effective maintenance methods before failures occur (Hua et al., 2012; Lu & Meeker, 1993; Si, Wang, Hu, & Zhou, 2011). When applied to LEDs, many previous RUL prediction methods based on degradation data rely on the least-squares regression (LSR) approach. For instance, the IESNA released the TM-21 standard (IES-TM-21-11, 2011) in 2011 to predict the lumen maintenance life for LED light sources based on the collected lumen maintenance data from the IES LM-80-08 test report (IES-LM-80-08, 2008). In the TM-21 standard, the LSR method is used to estimate the parameters involved in the lumen degradation model, and the degradation

* Corresponding author at: Department of Mechanical Engineering, College of Mechanical and Electrical Engineering, Hohai University, Changzhou, Jiangsu 213022, China.

E-mail addresses: jay.fan@connect.polyu.hk (J. Fan), wincokc.yung@polyu.edu.hk (K.-C. Yung), pecht@calce.umd.edu (M. Pecht).

http://dx.doi.org/10.1016/j.eswa.2014.10.021
0957-4174/

curve is then projected to the failure threshold to get the lumen maintenance life. Currently, many LED manufacturers have accepted the TM-21 standard to predict the lifetime for their LED products (such as Philips Lumileds (LUXEON, 2011) and CREE (CREE, 2012)). Additionally, our previous work (Fan, Yung, & Pecht, 2012) proposed a degradation data-driven method to estimate the lumen lifetime of high power white LEDs wherein the parameters of the lumen degradation model were estimated by using an ordinary LSR fitting method. Zhang et al. applied statistical distribution functions (such as a lognormal function (Zhang et al., 2012) and the Weibull function (Zhang et al., 2014)) to describe the relationship between OLED's lumen degradation and time, and the parameters of both statistical functions were calculated with the least-squares method. Wang and Lu (Wang & Lu, 2014) presented a bi-exponential model to fit the lumen degradation data for LEDs, and the model parameters were also estimated by the nonlinear LSR. However, previous studies (Fan, Yung, & Pecht, 2014a; Fan, Yung, & Pecht, 2014b; Fan et al., 2012) have shown that using the LSR method to estimate parameters for the lumen degradation curve has many weaknesses in terms of guaranteeing prediction accuracy, because it does not consider the measurement dynamics and uncertainties. This can result in a large gap between the product lifetime estimated by LED manufacturers and the actual application life.

To improve the accuracy of lifetime prediction, this paper proposes a dynamic recursive particle filter-based (PF-based) approach to model the lumen degradation data of LED light sources by taking measurement dynamics and uncertainties into consideration. As a nonlinear filtering approach, the PF prognostic approach has been widely used in state estimation and prediction for nonlinear/non-Gaussian systems (Arulampalam, Maskell, Gordon, & Clapp, 2002; Miao, Xie, Cui, Liang, & Pecht, 2013; Xing, Ma, Tsui, & Pecht, 2013). Normally, PF uses a set of weighted particles simulated by the Sequential Monte Carlo (SMC) method (Caesarendra, Niu, & Yang, 2010) to approximate the state as a posterior probability density distribution and then dynamically update it and predict the future state with measurement data within a Bayesian framework (Chen et al., 2012; Orchard & Vachtsevanos, 2009; Zhao & Li, 2010).

This paper focuses on modeling the dynamic nonlinear lumen degradation process of LED light sources in an accelerated degradation test with considering the measurement uncertainties. Firstly, we selected the exponential degradation model recommended in the TM-21 standard to describe the lumen degradation process of LED light sources. The PF method, which replaces the LSR method used in the TM-21 standard, was then used to track the lumen degradation process by estimating and adjusting the model parameters from updated measurements. Finally, when the measurements terminated, the RULs with prediction confidence intervals were predicted by extrapolating the updated model with measurement noise to the failure threshold. The main contributions of this paper are as follows: (i) a recursive solution of PF, replacing the batch processing of LSR, is first proposed to deal with lumen degradation data of LED light sources and estimate the parameters of the lumen degradation model dynamically; (ii) with consideration of measurement uncertainties, an SMC method is employed in the PF to predict RUL as a life distribution with a confidence interval; (iii) a robustness study is conducted to analyze the initialization of parameters impacting the prediction accuracy and the uncertainties of the proposed PF method.

The remainder of this paper is organized as follows: Section 2 presents the methodologies and algorithms for lumen maintenance life prediction, including the TM-21 projecting method and our proposed PF prognostic approach. Section 3 introduces the device used in our test and the design of the accelerated degradation test programme. Section 4 implements the proposed PF method in RUL estimation based on the collected lumen maintenance degradation data and provides results and discussion on the prediction accuracy, uncertainty, and robustness. Finally, concluding remarks and possible directions for future work are presented in Section 5.

2. Methodologies and algorithms

In this section, the methodologies and algorithms of both the TM-21 standard method and the proposed PF prognostic approach are introduced to predict the lumen maintenance life of LED light sources.

2.1. TM-21 projecting method

Lumen degradation, which refers to the decrease in light output during the aging process, is recognized as a critical failure mode in LED light sources (Narendran & Gu, 2005). In the lumen degradation process, the lumen maintenance (LM) of LED light sources is defined as the maintained percentage of the initial light output. According to different applications, the Alliance for Solid-State Illumination Systems and Technologies (ASSIST) uses lumen maintenance to define the lumen maintenance lifetimes of LED light sources. For example, L_{50} for decorative lighting means the time at 50% lumen maintenance, and L_{70} for general lighting means the time at 70% lumen maintenance (Assist recommendation, 2005).

The TM-21 method is a lumen maintenance life prediction standard published by the IESNA in 2011 (IES-TM-21-11, 2011). It is used to determine the operating lifetime of LED light sources based on the lumen maintenance data collected from the IES LM-80-08 test report. The main procedure of the TM-21 method is implemented as follows:

(i) Normalize the collected luminous flux data as lumen maintenance data. Luminous flux data is used to represent the optical performance of LED light sources. Luminous flux data is normalized as lumen maintenance data to determine when the failure occurs. Lumen maintenance can be defined as the maintained percentage of the initial luminous flux over time:

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

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

(ii) Curve-fit the lumen maintenance data with the LSR method. The exponential expression, as shown in Eq. (2), is well proven and is a widely used model to describe the lumen degradation path of LED light sources. Therefore, exponential curve-fitting is applied to the collected lumen maintenance degradation data, and the model parameters are estimated by the LSR (Eq. (3)):

$$LM(t) = B \cdot \exp(-\alpha \cdot t) \tag{2}$$

$$\min_{B,\alpha} \left\{ \frac{1}{m} \sum_{i}^{m} [y_i - LM(t_i; B, \alpha)][y_i - LM(t_i; B, \alpha)]^T \right\} \tag{3}$$

where B is the initial constant and α is the degradation rate constant, both of which are derived by the least-squares curve-fitting; and m is the number of collected lumen maintenance degradation data points for each test sample.

(iii) Project the lumen maintenance life, L_p. As introduced in Section 1, the LED lumen maintenance life is defined as the time when the lumen maintenance data decreases below the failure threshold ($LM_{threshold}$ = 70% is defined for LED light sources used as general lighting). Thus, L_p can be predicted by projecting the degradation model with the estimated model parameters to the defined failure threshold:

$$L_p = \ln\left(\frac{100 \times B}{p}\right) \bigg/ \alpha \tag{4}$$

where p is the maintained percentage of the initial luminous flux (p = 70 is used in this paper).

2.2. PF prognostic approach

PF is widely known as a state estimation and prognostic approach for nonlinear/non-Gaussian systems. It integrates Sequential Monte Carlo computation with Bayesian estimation (Orchard & Vachtsevanos, 2009; Zio & Peloni, 2011). Usually, most dynamic processes of systems can be described by a state-space model, with both state and measurement (or observation) models (Eqs. (5) and (6)). Differing from other nonlinear filtering approaches (Fan et al., 2014b), PF simulates a set of particles with the Sequential Monte Carlo technique to approximate the system state at the kth cycle as a probability density function (PDF), $x_k \sim p(x_k|z_{1:k})$:

$$\text{State model}: x_k = f(x_{k-1}, \upsilon_{k-1}) \tag{5}$$

$$\text{Measurement model}: z_k = h(x_k, \omega_k) \tag{6}$$

where $f(\cdot)$ and $h(\cdot)$ are the nonlinear state and measurement functions; x_k and z_k are the state and measurement; and υ_k and ω_k donate the white noise of the state and measurement, respectively.

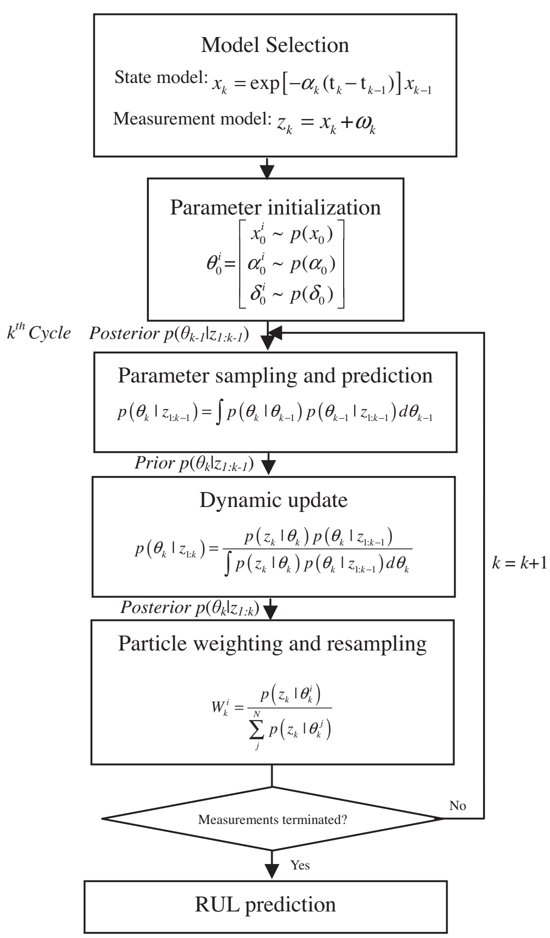

Fig. 1. Flowchart of implementation of PF prognostic approach.

The procedure for predicting the lumen maintenance life with the proposed PF prognostic approach can be separated into six steps (see Fig. 1): (i) model definition; (ii) parameter initialization; (iii) parameter sampling and prediction; (iv) dynamic update with the Bayesian algorithm; (v) particle weighting and resampling; and (vi) RUL prediction.

2.2.1. Model definition

The state model used in this section is derived from the lumen degradation exponential model used in the TM-21 standard (Eq. (2)). For simplicity, the initial constant B is assumed to be 1. The state noise υ_k can be integrated into the uncertainty of the degradation model parameters (An, Choi, & Kim, 2013). The measurement model helps in mapping the actual states with the measured lumen maintenance data and measurement noise.

$$\text{State model}: x_k = \exp[-\alpha_k(t_k - t_{k-1})]x_{k-1} \tag{7}$$

$$\text{Measurement model}: z_k = x_k + \omega_k \quad \omega_k \sim N(0, \delta^2) \tag{8}$$

2.2.2. Parameter initialization

As shown in Eqs. (7) and (8), the parameter vectors for both the state and measurement models can be expressed as θ, and each parameter will be initialized by assuming a distribution drawn by the Monte Carlo simulation, with N particles.

$$\theta_0^i = \begin{bmatrix} x_0^i \sim p(x_0) \\ \alpha_0^i \sim p(\alpha_0) \\ \delta_0^i \sim p(\delta_0) \end{bmatrix} \quad \text{where} \quad i = 1, 2, \ldots, N \tag{9}$$

2.2.3. Parameter sampling and prediction

Before receiving knowledge of the measurement z_k, given a posterior probability density function at the $k-1$th cycle as $p(\theta_{k-1}|z_{1:k-1})$, the prior probability density function of the parameter vector at the kth cycle, $p(\theta_k|z_{1:k-1})$, can be calculated based on the state model with the Chapman–Kolmogorov equation:

$$p(\theta_k|z_{1:k-1}) = \int p(\theta_k|\theta_{k-1})p(\theta_{k-1}|z_{1:k-1})d\theta_{k-1} \tag{10}$$

where $p(\theta_{k-1}|\theta_k)$ is the transition probability distribution defined by the state model (Eq. (7)).

2.2.4. Dynamic update with the Bayesian algorithm

As shown in Eq. (11), with the new input measurement, z_k, the posterior probability density function at the kth cycle, $p(\theta_k|z_{1:k})$, can be updated by using the Bayesian algorithm and the Markov assumption:

$$\begin{aligned} p(\theta_k|z_{1:k}) &= \frac{p(z_k|\theta_k, z_{1:k-1})p(\theta_k|z_{1:k-1})}{p(z_k|z_{1:k-1})} \\ &= \frac{p(z_k|\theta_k)p(\theta_k|z_{1:k-1})}{\int p(z_k|\theta_k)p(\theta_k|z_{1:k-1})d\theta_k} \end{aligned} \tag{11}$$

where $p(z_k|\theta_k)$ is the likelihood function of the measurement model. Since the measurement noise, ω_k, follows a Gaussian distribution, the likelihood function of the ith particle at cycle k, $p(z_k|\theta_k^i)$, can be formulated as follows:

$$p\left(z_k|\theta(x, b, \delta)_k^i\right) = \frac{1}{\sqrt{2\pi}\delta_k^i} \exp\left[-\frac{1}{2}\left(\frac{z_k - x_k^i(b_k^i)}{\delta_k^i}\right)^2\right] \tag{12}$$

2.2.5. Particle weighting and resampling

Based on the likelihood function of the measurement z_k at the kth cycle, the ith particle can be weighted as shown in Eq. (13)

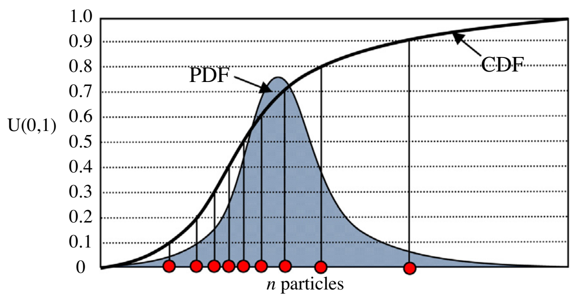

Fig. 2. Resampling with inverse CDF method (An et al., 2013).

(Zio & Peloni, 2011). The particle weight is proportional to the PDF value of the likelihood function.

$$W_k^i = \frac{p\left(z_k|\theta_k^i\right)}{\sum_j^N p\left(z_k|\theta_k^j\right)} \tag{13}$$

To avoid the degeneracy problem in the iteration process (Li, Sun, Sattar, & Corchado, 2014; Orchard & Vachtsevanos, 2009), resampling is always used to eliminate low-weight particles and condense high-weight particles. In this paper, the inverse cumulative density function (CDF) method, based on the likelihood function, is used to resample particles (An et al., 2013; Zio & Peloni, 2011).

As illustrated in Fig. 2. Firstly, the CDF of the likelihood function is established based on Eq. (12). Next the uniform distributed random values are assumed as the CDF values, for instance, U(0, 1). Then a particle with the CDF value can be found for the parameter distribution. Finally, by repeating n times, the resampled n particles, with the calculated CDF values, are selected as the posterior probability density function at the kth cycle, $p(\theta_k|z_{1:k})$.

Next, if $k \leqslant p$ (where t_p is the prediction time when the measurement is terminated), let $k = k + 1$, set the posterior $p(\theta_k|z_{1:k})$ at the kth cycle as the prior distribution at the $k + 1$th cycle, and repeat steps (iii) to (v) until the measurement is terminated (see Fig. 3).

2.2.6. RUL prediction

As shown in Fig. 3, when the measurement is terminated at the pth cycle, the parameter vector finishes the updating as θ_p, and the future lumen maintenance can be predicted by extrapolating the state model based on the estimated degradation parameter and measurement noise (α_p and δ_p). The time when the predicted lumen maintenance reaches the failure thresholds defined by ASSIST ($LM_{threshold}$ = 70%) is the time to failure, t_f. The RULs can then be obtained by calculating the distance between the time to failure and the time at the pth cycle.

3. Device under test and experimental design

The device under test (DUT) selected in this study is a type of high brightness phosphor-converted white LED light source with an InGaN chip from Avago (Type: 3 W Mini Power White LED (ASMT-JN31-NTV01)) (ASMT-Jx3x, 2012). The packaging structure of the test vehicle is shown in Fig. 4(a), and indicates that the mechanism for generating white light from the test vehicle is a combination of blue light emitted by an InGaN chip (Fig. 4(b)) and excited yellow light emission from a phosphor layer. The basic optical characteristics of DUT at the recommended test conditions

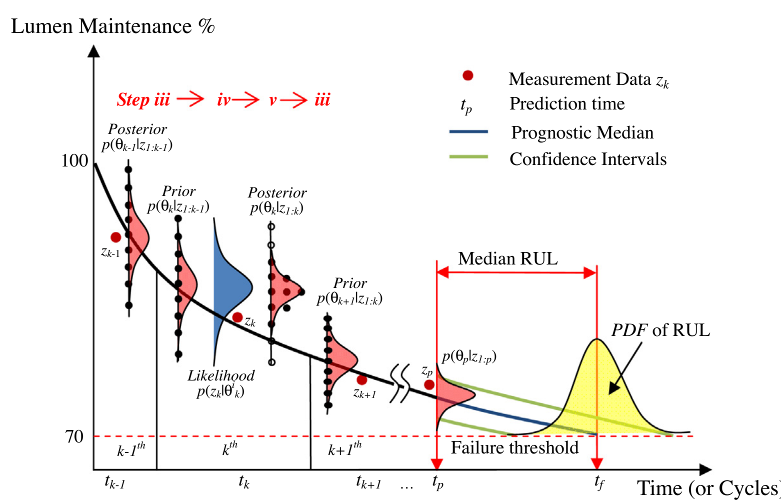

Fig. 3. PF prognostic approach.

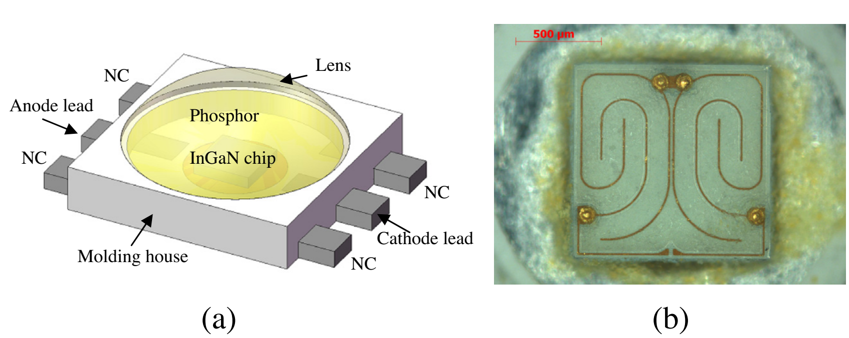

Fig. 4. Device under test: (a) schematic of LED packaging structure; (b) InGaN chip.

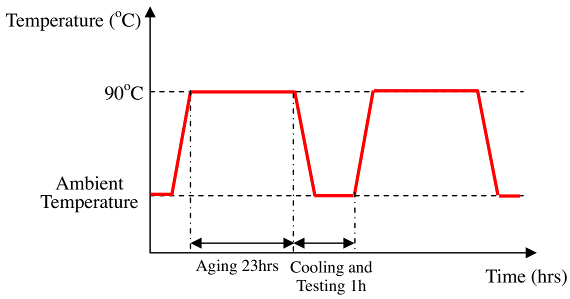

Fig. 5. Operation profile of accelerated degradation test for LED light sources.

(drive current, I_c = 350 mA; forward voltage, V_F = 3.2 volts; and junction temperature, T_J = 25 °C) are listed as follows: (i) luminous flux is around 85 lm; (ii) correlated color temperature, CCT, is 3500–4500 K with neutral white color; and (iii) luminous efficiency is 76 lm/W.

An accelerated degradation test under a high temperature condition was designed in this study for the selected LED light sources. The DUTs soldered on a metal core printed circuit board (MCPCB) test board were electrically driven by the same DC current (I_c = 200 mA) provided by a DC power supply (Agilent E3611A). The thermal chamber provided a constant aging temperature (T_a = 90 °C). The experimental procedure of this accelerated degradation test included three steps: (i) aging; (ii) cooling; and (iii) testing. As shown in the operation profile (Fig. 5), after 23 h of high temperature thermal aging, the DUTs were removed from the thermal chamber to be cooled to ambient temperature for testing. In the testing step, the luminous flux of DUTs was measured by a Gigahertz-Optik BTS256-LED tester. When the lumen flux data were collected and transformed to the lumen maintenance, the test board was returned to the thermal chamber to undergo the next round of aging. After 1518 h of aging (66 cycles of operation), nine DUTs failed, with the lumen maintenance dropping below the threshold of 70%.

4. Implementation results and discussion

The lumen maintenance degradation data of selected LED light sources were collected from the accelerated degradation test, and they were used to demonstrate the prediction algorithm and methodology of the proposed PF prognostic method and to validate its feasibility, accuracy, and robustness. Following the methodology implementation steps introduced in Section 2.2, the validation process of the PF prognostic method can be separated into three major steps: (i) method training; (ii) method testing; and (iii) robustness study.

4.1. Method-training

Normally, method training is a step to initialize the parameter vector of the selected state-space model with the historical database. However, for new products without historical records, either a calibration test (Fan et al., 2014a, 2014b) or an assumption (Xing, Ma, Tsui, & Pecht, 2012) is always required for initializing the parameters. In this study, we selected five out of nine DUTs as training samples to collect initialization information for testing. As shown in Fig. 6, the lumen maintenance degradation data of these five training samples were exponentially curve-fitted with the lumen degradation model, and the model parameters were estimated by means of the nonlinear least-squares regression approach. According to the curve-fitting results of the training samples listed in Table 1, the standard deviation (SD) of the measurement noise was represented by the standard deviation of the curve-fitting residuals, and the estimated parameters from the training samples were averaged to initialize the parameter vector. The initial distributions of the parameters defined in Eq. (9) were assumed to be uniform distributions, which were represented as follows:

$$\theta_0^i = \begin{bmatrix} x_0^i \sim U(0.9, 1.1) \\ \alpha_0^i \sim U\left(1.8 * 10^{-4}, 2.2 * 10^{-4}\right) \\ \delta_0^i \sim U(0.01, 0.02) \end{bmatrix}$$

4.2. Method testing

In method testing, the remaining four DUTs were chosen as test samples to validate the feasibility and accuracy of the proposed PF prognostic approach. The lumen maintenance life prediction results of the four test samples based on both the PF prognostic approach and TM-21 standard method are shown in Fig. 7. The prediction time was chosen to be 690 h (30 cycles, approximately 45% of the full lifetime profile of DUTs). The results in Fig. 7 show that the median lumen maintenance lives of the four test samples predicted by the PF approach were close to the actual lifetimes, with a prediction error of less than 5%, while the prediction errors using the TM-21 method were larger than 10%.

As introduced in the PF methodology and algorithm, the initial distributions of the parameters of both the state and measurement models were first simulated by Monte Carlo simulation with N particles. Based on the Bayesian estimation, the periodical measurement data from 0 to 690 h were used to recursively update and adjust the parameter vector via the likelihood function. After 690 h, the lumen maintenance values of the test samples were estimated by extrapolating the updated degradation model with the measurement noise. When the estimated lumen maintenance reached the failure threshold ($LM_{threshold}$ = 70%), the lumen maintenance life could be predicted. Table 2 compares the theoretical differences between the proposed PF approach and the TM-21 standard in LED life prediction. The PF approach estimates and updates the parameter vector dynamically by absorbing new measurements with considering the measurement noise. Thus, the PF approach can take measurement dynamics and uncertainties into consideration. While, as shown in Eq. (3), the LSR used in the TM-21 method only depends on the minimization of the sum of the residuals between the actual measurements and the calculated values by using batch processing.

Fig. 8 shows the RUL prediction results at different prediction times for both the PF approach and the TM-21 method. In addition to 690 h, some other prediction times, such as 960 h (40 cycles, approximately 63% of the full lifetime profile), 1150 h (50 cycles, approximately 76% of the full lifetime profile), and 1380 h (60 cycles, approximately 91% of the full lifetime profile) were also designed in this study. Compared to the TM-21 method, the predicted median RULs from different prediction times predicted by the PF approach were closer to the actual RULs, especially at lower prediction times (such as 690 h with the long-term prediction distance). This indicates that the accuracy of the PF approach is better than the TM-21 method in predicting long-term lumen maintenance life for LED light sources.

With increasing prediction times, the accuracy of the RUL prediction by the TM-21 method improved, because the LSR method can track the real lumen maintenance degradation trajectory of LED light sources by dealing with sufficient measurement data. However, the TM-21 method requires a longer test time to predict the lifetime than the PF approach. A comparison of the prediction performances of the PF approach and the TM-21 method is given in Table 3. Among all test samples, the prediction errors of the PF

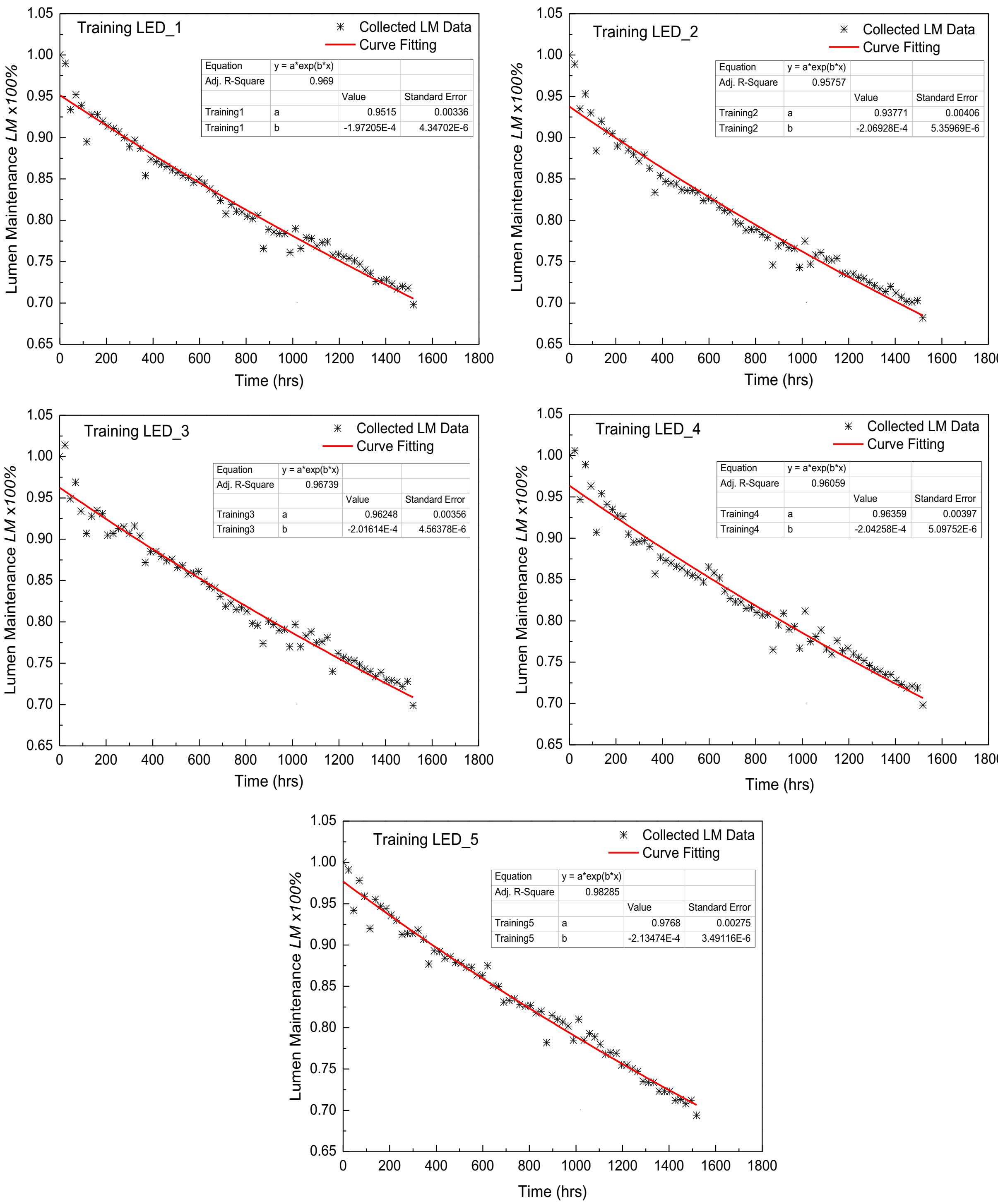

Fig. 6. Curve-fitting for full lifetime data of training samples.

Table 1
Parameter initialization with training samples.

Training samples	B	$\alpha * 10^{-4}$	Adjust R^2	SD of curve-fitting residuals
Training LED_1	0.95150	1.97	0.96900	0.012848
Training LED_2	0.93771	2.07	0.95757	0.015493
Training LED_3	0.96248	2.02	0.96739	0.013598
Training LED_4	0.96359	2.04	0.96059	0.015175
Training LED_5	0.97680	2.13	0.98285	0.010460
Averaged values	0.95842	2.05	0.96748	0.013515

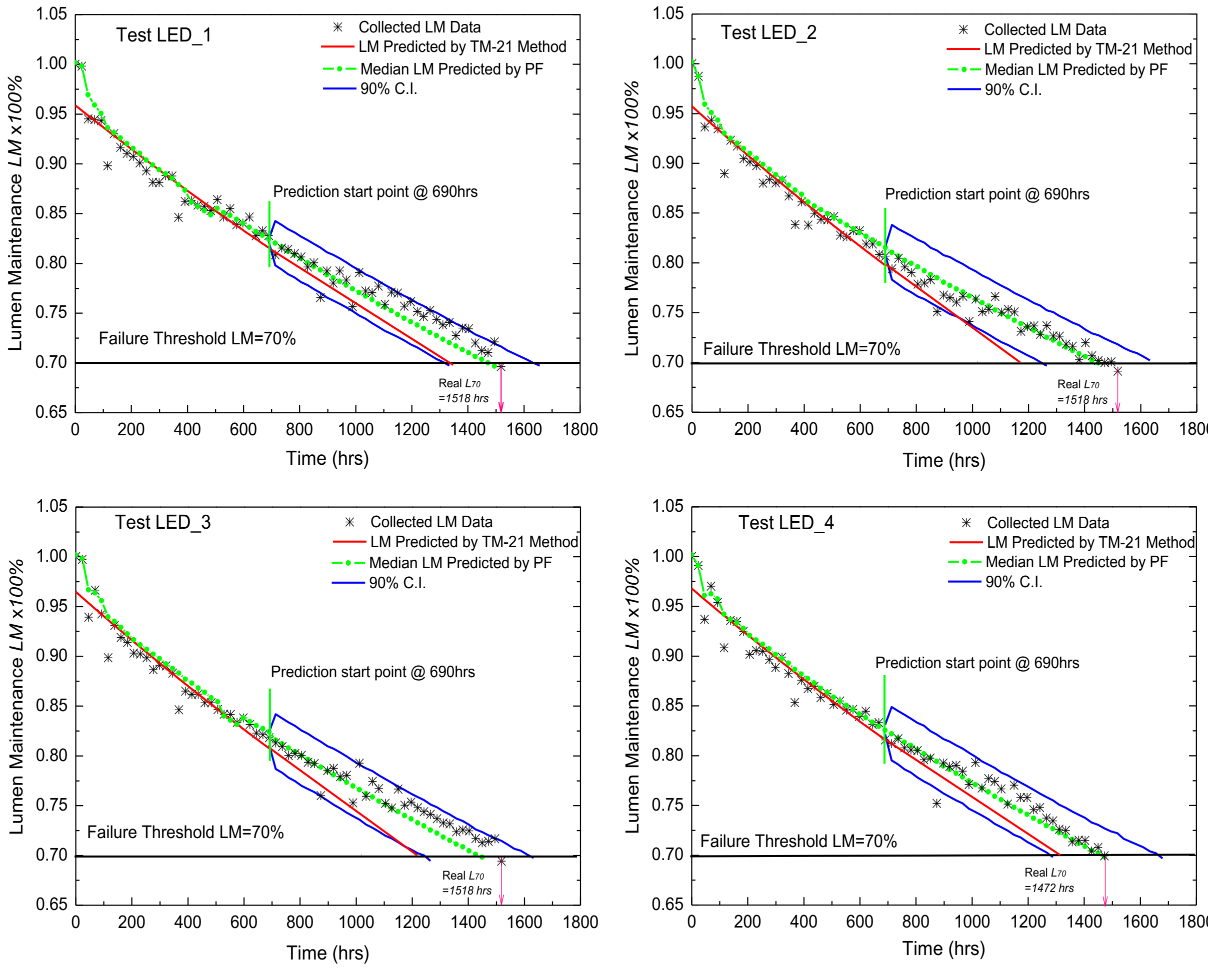

Fig. 7. Lumen maintenance life prediction: PF prognostic approach vs. TM-21 method.

Table 2
Theoretical comparison of LED life prediction methods (the proposed PF approach vs. TM-21 standard).

TM-21 standard with least-squares regression	Proposed PF prognostic approach with sequential Monte Carlo simulation
1. Batch least-squares on finite data span	1. Recursive solution on unlimited data span
2. Periodic execution	2. Real-time processing suitable for online prediction
3. Deterministic model	3. Stochastic model with consideration of measurement dynamics and uncertainties
4. Solution for both linear and nonlinear processes	4. Solution for nonlinear/non-Gaussian problems
5. No requirement of prior information	5. Requires prior estimation (or initial assumptions)

approach can be controlled within 7% for all prediction times (under 5% when applied to long-term prediction). The widths of the prediction confidence intervals (90% C.I.) become narrower with increasing measurement time, which means the prediction uncertainties are reduced.

4.3. Robustness study

Referring to previous studies (Fan et al., 2014a, 2014b; Xing et al., 2012), the prognostic performances of filtering techniques are always related to the selection of the initial parameters. Thus, the effect of parameter initialization was studied to validate the robustness of the proposed PF prognostic approach in actual applications. As introduced in Section 2.2, the degradation rate of the lumen maintenance degradation model α and the standard deviation of the measurement noise δ are two critical parameters to determine the lumen degradation trajectory and the state updating process in the implementation of the PF approach. Except for the full lifetime training test (1518 h) used in Section 4.1, the assumptions of the initial distribution for the degradation rate were based on the curve-fitting results from some other calibration tests for training samples, which included a 91% of full lifetime test (1380 h); a 76% of full lifetime test (1150 h); a 63% of full lifetime test (920 h); and a 45% of full lifetime test (690 h). The initial distributions of the two parameters were also assumed to be uniform distributions, as listed in Table 4.

Based on the assumed initial parameter vectors listed in Table 4, the prediction results for lumen maintenance life obtained by the PF prognostic approach are shown in Fig. 9. Among all four test samples, the prediction errors of the PF approach from a shorter term calibration test are larger than those from tests with a longer calibration time. The widths of the prediction confidence intervals mainly depend on the assumptions for the measurement noise. As shown in the time listed beside the prediction error in Fig. 9, with increases in the standard deviation of measurement noise, the widths of the prediction confidence intervals in the lumen maintenance life prediction by the PF approach increased, indicating that the prediction uncertainties were raised.

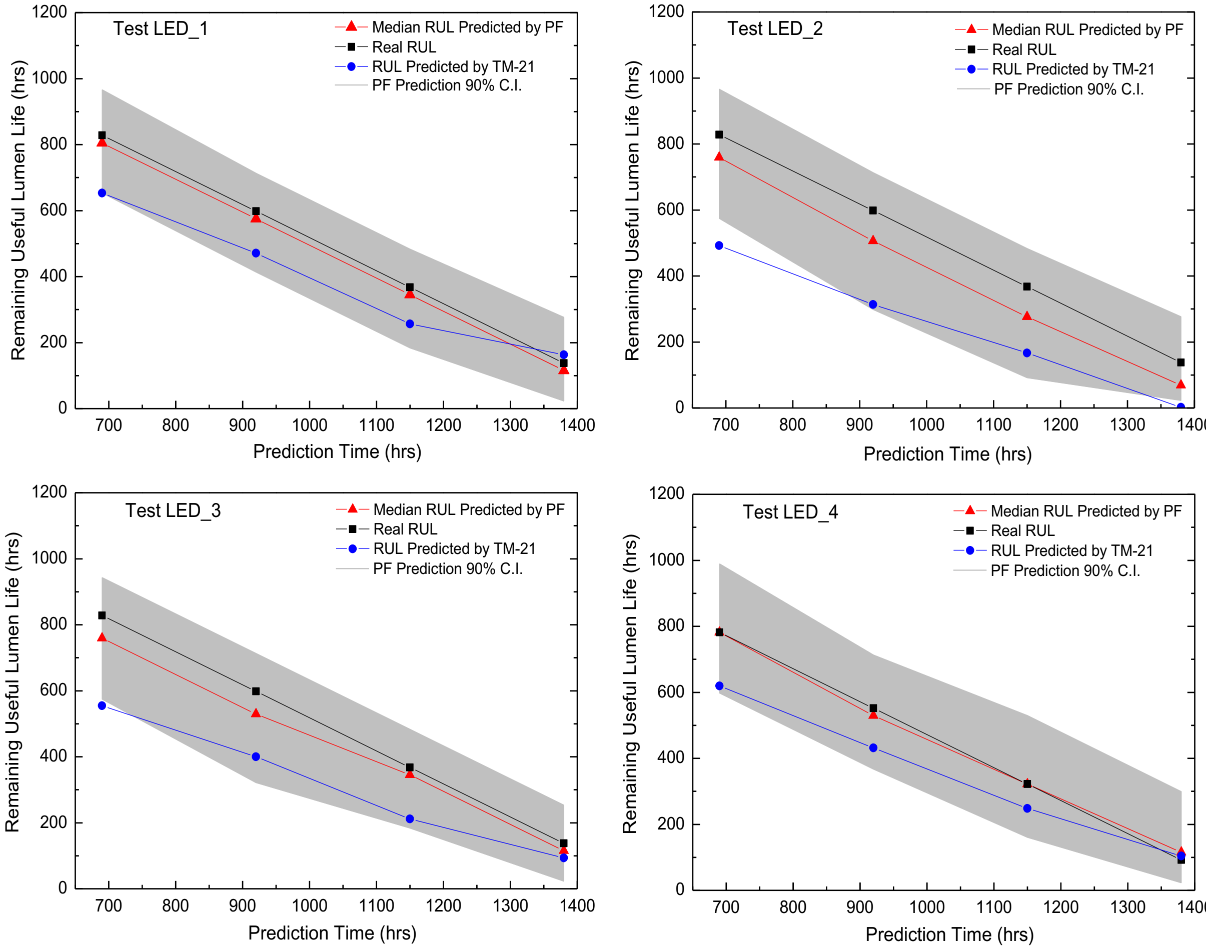

Fig. 8. Remaining useful life prediction: PF prognostic approach vs. TM-21 method.

Table 3
Comparison of prediction results: PF prognostic approach vs. TM-21 method.

Test samples	Prediction time (h)	Prediction error of LM life %	
		TM-21	PF (the widths of 90% C.I.)
Test LED_1	690	11.52	1.52(312 h)
	920	8.38	1.52(299 h)
	1150	7.32	1.52(299 h)
	1380	−1.66	1.52(253 h)
Test LED_2	690	22.12	4.55(391 h)
	920	18.73	6.06(414 h)
	1150	13.29	6.06(391 h)
	1380	8.94	4.55(253 h)
Test LED_3	690	18.03	4.55(368 h)
	920	13.06	4.55(391 h)
	1150	10.32	1.52(299 h)
	1380	2.95	1.52(230 h)
Test LED_4	690	11.03	0.00(391 h)
	920	8.19	1.56(345 h)
	1150	5.01	0.00(368 h)
	1380	−0.80	−1.56(276 h)

5. Conclusions

Lumen maintenance life is a key characteristic for assessing the reliability of LED light sources. Owing to the long lifetime and high reliability of LED light sources, estimating the lumen maintenance life by using traditional destructive life testing methods is time-consuming and expensive. Even the IESNA TM-21 standard, which is widely accepted by many LED manufacturers, has weaknesses in terms of guaranteeing life prediction accuracy, because it relies on the LSR method without considering measurement dynamics and uncertainties. In order to improve the accuracy of long-term lumen maintenance life prediction for LED light sources

Table 4
The assumption of parameter initialization for robustness study.

No.	Initial distribution assumption for degradation rate, $\alpha * 10^{-4}$	No.	Initial distribution assumption for SD of measurement noise, δ
1	$U(1.8,2.2)_{\text{assumed from full lifetime training data}}$	1	U(0,0.01)
2	$U(1.9,2.3)_{\text{assumed from 1380 h training data}}$	2	U(0.01,0.02)
3	$U(2.0,2.4)_{\text{assumed from 1150 h training data}}$	3	U(0.02,0.03)
4	$U(2.1,2.5)_{\text{assumed from 920 h training data}}$		
5	$U(2.2,2.6)_{\text{assumed from 690 h training data}}$		

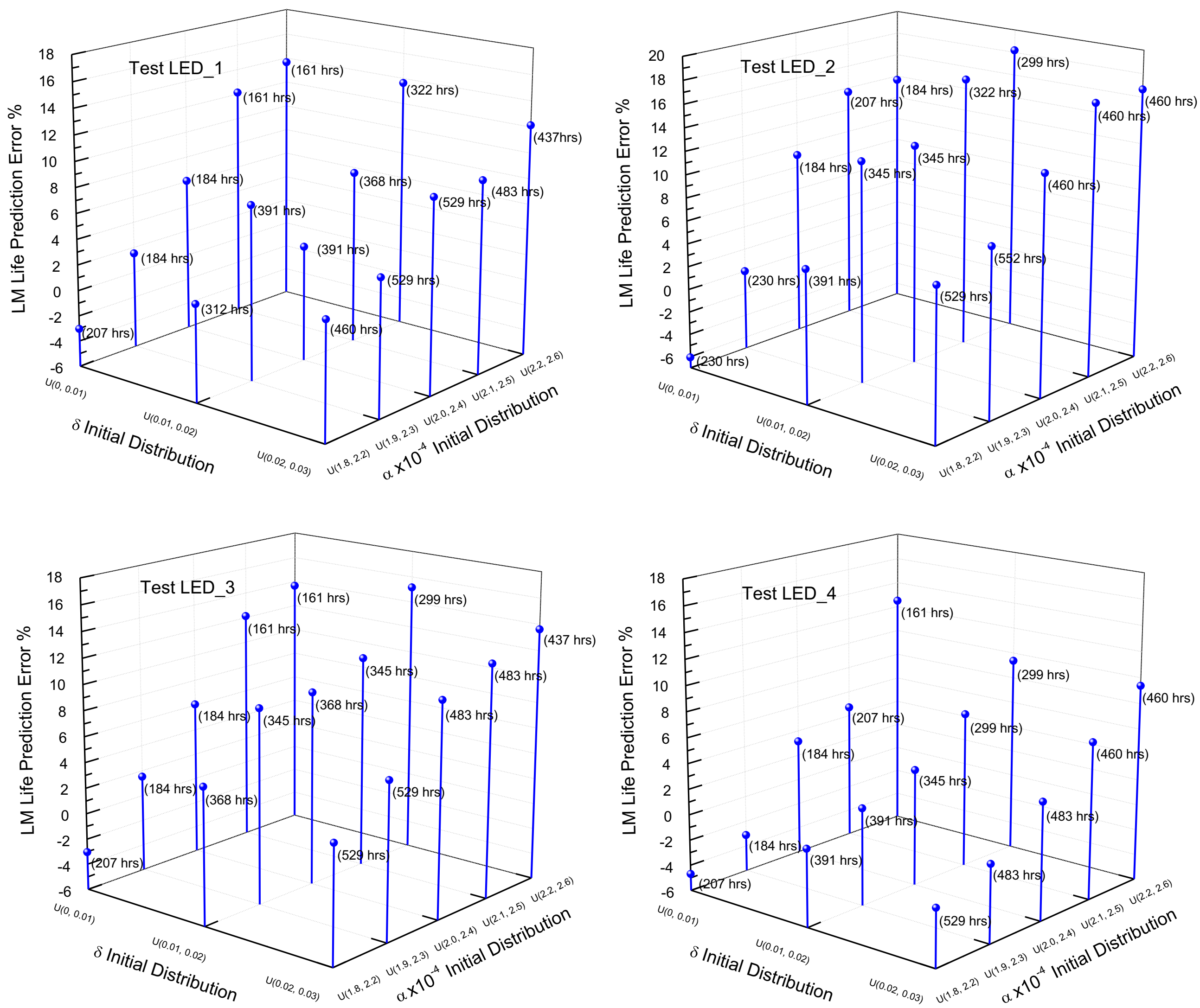

Fig. 9. Robustness study of PF prognostic approach (LM life prediction error with the width of 90% C.I. in brackets).

and shorten the qualification test time, we developed a PF-based prognostic approach to replace the LSR method applied in TM-21 standard. Our PF-based prognostic approach dynamically estimates and adjusts the lumen degradation model parameters by absorbing new measurements with consideration of the measurement noise. Theoretically, there are at least two advantages of the PF approach in RUL prediction. Firstly, the PF approach delivers a recursive and stochastic parameter estimation by dynamically updating measurements, while the LSR used in the TM-21 standard conducts batch-processing estimation by minimizing the sum of the residuals between the actual measurements and the calculated values. Secondly, the SMC simulation in PF can predict a RUL distribution with a confidence interval by taking measurement uncertainties into consideration, whereas the TM-21 standard can only extrapolate the estimated curve to a deterministic lifetime.

Our results show that the PF approach possesses higher prediction accuracy (with an error of less than 5%) than the TM-21 method when applied for long-term lumen maintenance life prediction for LED light sources. In addition, the prediction uncertainties of the PF approach can be lowered by increasing the measurement time. The robustness study on the proposed PF method indicates that the prediction accuracy and uncertainties are related to the initialization of the parameters. This is a limitation of proposed PF approach when it is applied to qualify new products. To guarantee the advantages of the PF method, a reasonable initialization process for the parameters based on historical databases (for used products) or calibration testing (for new products) is needed.

The future research directions of this research can be summarized as follows. Firstly, the design of an effective calibration test for the proposed PF approach with the aim of getting accurate parameter initialization and minimizing the test time will be studied for new LED light sources without historical information on the degradation rate and measurement noise. Secondly, a method for online RUL prediction by integrating the proposed recursive PF approach with in-situ monitoring will be developed to qualify LED light sources, with the goal of reducing the measurement errors from the off-line data collection process and increasing prediction accuracy. Thirdly, a system-level prognostics and health management expert system based on the sequential data-processing function of PF approach will be designed for LED lighting systems (e.g., street lighting, indoor lighting) to achieve real-time anomaly detection, RUL prediction, and reliability assessment.

Acknowledgements

The work presented in this paper was partially supported by the grants from the Research Committee of The Hong Kong Polytechnic University (G-45-37-YN57 and H-45-37-ZG1H). We would like to thank the Center for Advanced Life Cycle Engineering (CALCE) of the University of Maryland for providing the experimental setup and materials.

References

An, D., Choi, J. H., & Kim, N. H. (2013). Prognostics 101: A tutorial for particle filter-based prognostics algorithm using Matlab. *Reliability Engineering & System Safety, 115*, 161–169.

Arulampalam, M. S., Maskell, S., Gordon, N., & Clapp, T. (2002). A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *IEEE Transactions on Signal Processing, 50*, 174–188.

ASMT-Jx3x (2012). Data sheet: 3W mini power LED light sources. USA: Avago Technologies.

Assist recommendation (2005). LED life for general lighting, Lighting Research Center: Troy, NY, USA.

Caesarendra, W., Niu, G., & Yang, B. S. (2010). Machine condition prognosis based on sequential Monte Carlo method. *Expert Systems with Applications, 37*, 2412–2420.

Challa, V., Rundle, P., & Pecht, M. (2013). Challenges in the qualification of electronic components and systems. *IEEE Transactions on Device and Materials Reliability, 13*, 26–35.

Chang, M. H., Das, D., Varde, P. V., & Pecht, M. (2012). Light emitting diodes reliability review. *Microelectronics Reliability, 52*, 762–782.

Chen, C. C., Brown, D., Sconyers, C., Zhang, B., Vachtsevanos, G., & Orchard, M. E. (2012). An integrated architecture for fault diagnosis and failure prognosis of complex engineering systems. *Expert Systems with Applications, 39*, 9031–9040.

CREE (2012). LED Components IES LM-80-2008 testing results (Revision: 12), CREE, USA.

Fan, J. J., Yung, K. C., & Pecht, M. (2012). Lifetime estimation of high-power white led using degradation-data-driven method. *IEEE Transactions on Device and Materials Reliability, 12*, 470–477.

Fan, J. J., Yung, K. C., & Pecht, M. (2014a). Prognostics of chromaticity state for phosphor-converted white light emitting diodes using an unscented kalman filter approach. *IEEE Transactions on Device and Materials Reliability, 14*, 564–573.

Fan, J. J., Yung, K. C., & Pecht, M. (2014b). Prognostics of lumen maintenance for high power white light emitting diodes using a nonlinear filter-based approach. *Reliability Engineering & System Safety, 123*, 63–72.

Haitz, R., & Tsao, J. Y. (2011). Solid-state lighting: 'The case' 10 years after and future prospects. *Physica Status Solidi A-Applications and Materials Science, 208*, 17–29.

Hua, C., Xu, G. H., Zhang, Q., Zhang, Y. Z., Xie, J., & Li, S. Z. (2012). Long-term potential performance degradation analysis method based on dynamical probability model. *Expert Systems with Applications, 39*, 4410–4417.

IES-LM-80-08 (2008). Approved method for lumen maintenance testing of LED light source. USA: Illuminating Engineering Society.

IES-TM-21-11 (2011). Projecting long term lumen maintenance of LED light sources. USA: Illuminating Engineering Society.

Lafont, U., van Zeijl, H., & van der Zwaag, S. (2012). Increasing the reliability of solid state lighting systems via self-healing approaches: A review. *Microelectronics Reliability, 52*, 71–89.

Li, T. C., Sun, S. D., Sattar, T. P., & Corchado, J. M. (2014). Fight sample degeneracy and impoverishment in particle filters: A review of intelligent approaches. *Expert Systems with Applications, 41*, 3944–3954.

Lu, C. J., & Meeker, W. Q. (1993). Using degradation measures to estimate a time-to-failure distribution. *Technometrics, 35*, 161–174.

LUXEON (2011). LM-80 Test Report (DR04), PHILIPS, Netherlands.

Miao, Q., Xie, L., Cui, H. J., Liang, W., & Pecht, M. (2013). Remaining useful life prediction of lithium-ion battery with unscented particle filter technique. *Microelectronics Reliability, 53*, 805–810.

Narendran, N., & Gu, Y. M. (2005). Life of LED-based white light sources. *Journal of Display Technology, 1*, 167–171.

Orchard, M. E., & Vachtsevanos, G. J. (2009). A particle-filtering approach for on-line fault diagnosis and failure prognosis. *Transactions of the Institute of Measurement and Control, 31*, 221–246.

Schubert, E. F., & Kim, J. K. (2005). Solid-state light sources getting smart. *Science, 308*, 1274–1278.

Si, X. S., Wang, W. B., Hu, C. H., & Zhou, D. H. (2011). Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal of Operational Research, 213*, 1–14.

Tarashioon, S., Baiano, A., van Zeijl, H., Guo, C., Koh, S. W., van Driel, W. D., et al. (2012). An approach to "Design for Reliability" in solid state lighting systems at high temperatures. *Microelectronics Reliability, 52*, 783–793.

Wang, F. K., & Lu, Y. C. (2014). Useful lifetime analysis for high-power white LEDs. *Microelectronics Reliability, 54*, 1307–1315.

Xing, Y. J., Ma, E. W. M., Tsui, K. L., & Pecht, M. (2012). Influence of parameter initialization on battery life prediction for online applications. In *2012 13th international conference on electronic packaging technology & high density packaging (Icept-Hdp 2012)* (pp. 1043–1047).

Xing, Y. J., Ma, E. W. M., Tsui, K. L., & Pecht, M. (2013). An ensemble model for predicting the remaining useful performance of lithium-ion batteries. *Microelectronics Reliability, 53*, 811–820.

Zhang, J. P., Li, W. B., Cheng, G. L., Chen, X., Wu, H., & Shen, M. H. H. (2014). Life prediction of OLED for constant-stress accelerated degradation tests using luminance decaying model. *Journal of Luminescence, 154*, 491–495.

Zhang, J. P., Liu, F., Liu, Y., Wu, H. L., Zhu, W. Q., Wu, W. L., et al. (2012). Life prediction for white OLED based on LSM under lognormal distribution. *Solid-State Electronics, 75*, 102–106.

Zhao, J., & Li, Z. Y. (2010). Particle filter based on particle swarm optimization resampling for vision tracking. *Expert Systems with Applications, 37*, 8910–8914.

Zio, E., & Peloni, G. (2011). Particle filtering prognostic estimation of the remaining useful life of nonlinear components. *Reliability Engineering & System Safety, 96*, 403–409.