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Prognostics of radiation power degradation lifetime for ultraviolet light-emitting diodes using stochastic data-driven models

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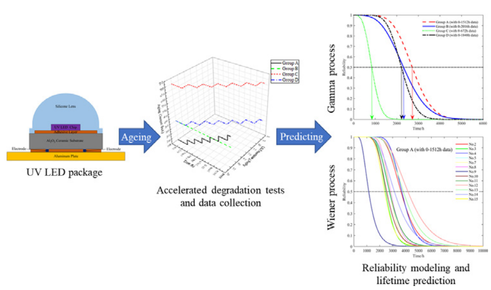
HIGHLIGHTS

- UV radiation is one of most effective virus disinfection method in public health.
- Traditional life tests are challenged in assessing the reliability of UV LEDs.
- Stochastic data-driven methods provide dynamic degradation process modelling of UV LEDs.
- High temperature and UV light exposure drive the degradation of lens in UV LEDs.
- Current overstress accelerates the delamination of ohmic contact in UV LEDs.

GRAPHICAL ABSTRACT



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ABSTRACT

With their advantages of high efficiency, long lifetime, compact size and being free of mercury, ultraviolet light-emitting diodes (UV LEDs) are widely applied in disinfection and purification, photolithography, curing and biomedical devices. However, it is challenging to assess the reliability of UV LEDs based on the traditional life test or even the accelerated life test. In this paper, radiation power degradation modeling is proposed to estimate the lifetime of UV LEDs under both constant stress and step stress degradation tests. Stochastic data-driven predictions with both Gamma process and Wiener process methods are implemented, and the degradation mechanisms occurring under different aging conditions are also analyzed. The results show that, compared to least squares regression in the IESNA TM-21 industry standard recommended by the Illuminating Engineering Society of North America (IESNA), the proposed stochastic data-driven methods can predict the lifetime with high accuracy and narrow confidence intervals, which confirms that they provide more reliable information than the IESNA TM-21 standard with greater robustness.

1. Introduction

Ultraviolet (UV) light, with a wavelength between 200–400 nm, has numerous useful and attractive applications, such as virucide, air and water purification, photolithography, optical stimulus in drug activation, polymer curing and phototherapy [1]. The UV radiation has been grasping public attention as one of most effective virus disinfection methods because of the outbreak and spread of the COVID -19 novel coronavirus. Due to its benefits of having a long life, compact size and unimodal spectrum as well as being environmentally friendly, the III-

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nitride based UV light-emitting diode (LED) is becoming a promising photoelectronic device to replace traditional UV light sources, such as mercury lamps [2, 3].

Radiation power is a critical physical quantity that reflects the optical radiation intensity of a photoelectronic device. Therefore, radiation power can be used as an index to reflect the optical performance degradation of UV LEDs. Several effects, i.e. UV LED chip degradation, yellowing of packaging materials, interconnect or interface cracking and delamination, contribute to the radiation power degradation of UV LEDs [4]. Although the theoretical lifetime of a UV LED is 5–10 times longer than that of a traditional mercury lamp, its lifetime prediction is challenged by the uncertainties of internal quantum efficiency, light extraction efficiency and thermal management [5]. These problems arise from the unclear failure physics and mechanisms of UV LEDs, which leads to inconsistencies in reliability and lifetime estimation methods [6]. Since it relies on failure data, the traditional reliability and lifetime estimation method requires a very long testing time to ensure highly reliable UV LEDs, which is unacceptable in the pursuit of efficient industry production [7, 8]. Usually, the accelerated life test (ALT), in which the accelerated failure time can be obtained by testing the product at higher stress levels (such as high temperature, voltage or pressure), is widely used to estimate the lifetime of LEDs [9, 10]. However, the ALT method for UV LEDs still requires a long time to collect failure data [11]. Therefore, to shorten the testing time, the degradation data, rather than failure data, are processed and modeled to predict the lifetime in the LED industry. However, there is currently few researches on accelerated testing of UV LEDs, and relatively more focus on white LEDs. Compared with other LED degradation tests that focus on luminous flux, this study selects the radiation power of UV LEDs which more representatively showing the energy of UV wavelengths that are not visible.

Currently, the non-linear regression methods are often recommended to analyze optical degradation data, such as the TM-21 and TM-28 standards recommended by IESNA [12, 13]. But their prediction accuracies are greatly challenged using a deterministic model without considering measurement dynamics and uncertainties [8]. In recent years, fusion approaches and machine learning methods, such as recurrent neural network (RNN) and particle filtering (PF), have been recognized as effective approaches that may be able to model degradation and predict remaining useful life (RUL) [14–16]. In addition, stochastic degradation modeling is an alternative method to evaluate the reliability and lifetime of products that require high reliability [17]. And different from the empirical model recommended by the IESNA standard, the dynamic stochastic degradation model describes the degradation process from the aspect of data-driven methodologies. In degradation modeling with failure rate function, the Wiener process, Gamma process and inverse Gaussian process are the three most commonly used stochastic modeling methods [18, 19]. In general, the Gamma process is more suitable for describing the monotonous and gradual increase/degradation paths of certain products, such as in the case of crack propagation [20, 21]. Model parameter estimation methods include the maximum likelihood method and the method of moments, as well as the Bayesian method with complete test and incomplete test [22, 23]. Compared to other stochastic processes, the critical advantage of Gamma process modeling is that its mathematical calculation is relatively simple. Wu et al. [24] successfully applied the Gamma process model to the correlated color temperature (CCT) shift lifetime prognostics of high-power white LEDs. Park et al. [25] found that the Gamma process was suitable to model the gradual and continuous performance degradation of LEDs, in which the sampling and time uncertainty were described as the statistical distribution of parameters with operating time. Zhai et al. [26] proposed a random effect Wiener process model based on the accelerated failure time principle and validated it with LED accelerated aging test data. Huang et al. [27] used the Wiener process to model the degradation of mid-power white LEDs. Liu et al. [28] applied the Bayesian model averaging method with the inverse Gaussian process model to fit GaAs laser degradation data. Although the lifetime estimation of UV LEDs is urgently important in some specialty lighting fields, such as virucide, biomedical devices and healthcare, methods for their accelerated degradation testing and lifetime prediction have not been clearly explored.

According to the uniqueness of UV LEDs mentioned above, accelerated degradation tests are designed in this paper for a UV LED package, and radiation power degradation data are selected to predict its lifetime. Two stochastic processing models, i.e., Gamma process and Wiener process, are compared with the IESNA TM-21 industry standard. The prediction errors and confidence intervals of mean time to failure (MTTF) under different accelerated degradation tests are used to verify the accuracy and robustness of the proposed methods. The degradation mechanisms occurring under different aging conditions are also analyzed. The rest of this article is organized as follows: Section 2 discusses the test samples, data collection procedure and lifetime data analysis. In Section 3, the degradation modeling theories and methodologies used in this study are explained. Section 4 compares and discusses the results calculated from different models. In Section 5, failure analysis is carried out to explain the degradation mechanisms of test samples aged under different conditions. Finally, the concluding remarks are given in Section 6.

2. Accelerated degradation test and lifetime data analysis

2.1. Test sample

Fig. 1(a and b) show two typical structures of UV LED chips. UV light is extracted through the UV-transparent AlGaN epitaxial layer and the sapphire substrate [29]. The UV LED chip is composed of a P-type semiconductor and an N-type semiconductor. When the forward current acts on the chip, a "P-N junction" is formed, the electrons will be pushed to the P area, where the electrons and holes recombine, and then emit energy in the form of photons.

A commercialized UV LED package with a size of 3.5 mm × 3.5 mm was selected as the test sample in this study. As shown in Fig. 1(c), it has a high-power UV LED chip mounted on an Al_2O_3 ceramic substrate to improve its thermal stability. Its emission peak wavelength is 372 nm, and the rated current is 350 mA. The specific parameters are list in Table 1.

2.2. Experimental design and setup

The initial step of this study was to design acceleration degradation testing experiments for the selected UV LED test samples [30]. The ambient temperature and driving current are loads that accelerate the degradation of LEDs. Both constant stress and step stress aging tests were considered in this study [31]. As the test plan in Fig. 2 shows, accelerated degradation tests were conducted for almost 3000 h, and optical measurements of all test samples were taken every 168 h. The aging tests were carried out in thermal chambers, and DC current was provided by a power supplier. The 60 selected UV LED test samples were randomly numbered as Nos. 1–60, and the sample grouping in the experimental design is shown in Table 2. Each group included 15 UV LED samples to be aged. After removing samples with catastrophic failure, there were 13–14 samples per group with effective degradation data.

2.3. Lifetime data analysis

Referring to the IESNA TM-21 industry standard [12], the radiation power degradation of a UV LED was assumed to satisfy the exponential degradation model as shown in Eq. (1):

$$P(t)=B_0 \cdot \exp(-at). \tag{1}$$

where t is the testing time in h, $P(t)$ is the normalized radiation power output at time t during the degradation process, B_0 is the projected initial constant of the radiation power and a is the decay rate constant.

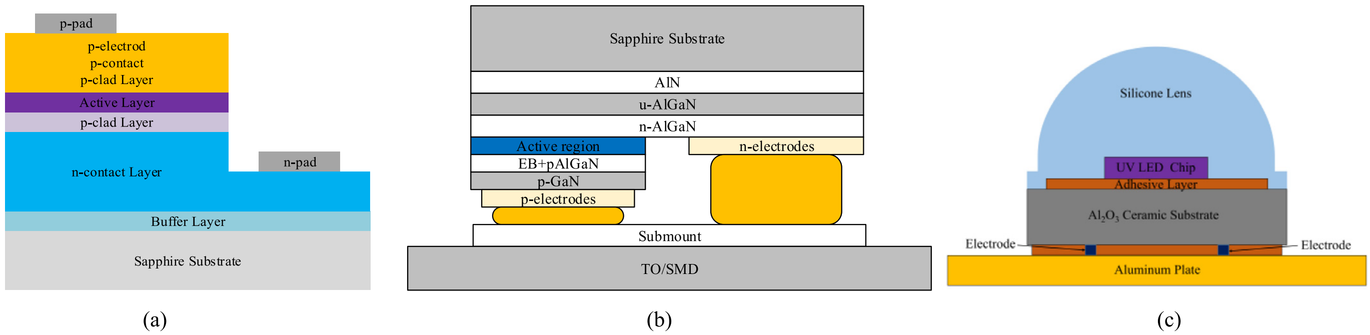

Fig. 1. (a and b) UV LED chip structure. (c) The packaging structure of the test sample used in this study.

Table 1
Information of selected UV LED test sample.

Package size	Peak wavelength	Power	Optical power	Thermal resistance	Beam angle
3535	372 nm	1.26 W @350 mA	0.35 W	6°C/W	120°

Table 2
Accelerated degradation test design.

Sample groups	Group A (Nos. 1–15)	Group B (Nos. 16–30)	Group C (Nos. 31–45)	Group D (Nos. 46–60)
Effective sample size	13	13	13	14
Driven current (mA)	150–450 (Step Stress)	350(Constant Stress)	700(Constant Stress)	350(Constant Stress)
Temperature (°C)	55(Constant Stress)	55(Constant Stress)	55–85(Step Stress)	55–85(Step Stress)
Test duration (h)	3360	3192	2856	3360
Data range for prediction (h)	(0–1512), (0–1680)	(0–2016), (0–2184)	(0–672), (0–840)	(0–1848), (0–2016)

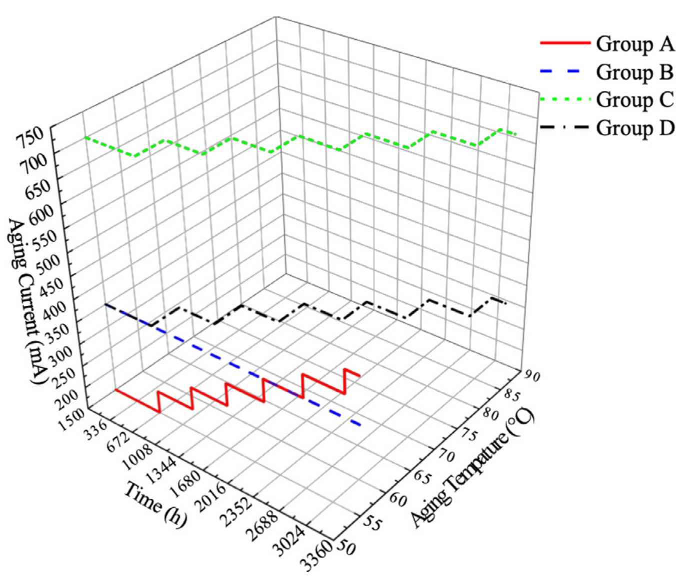

Fig. 2. Accelerated degradation test plan for UV LED test samples [30].

The cumulative radiation power degradation $X(t)$ of all UV LED test samples, which is equal to $1 - P(t)$, is plotted in Fig. 3. It can be seen that due to the high current and thermal stress conditions, the degradations of test samples in Group C were highly accelerated. In this study, the given failure threshold of the UV LEDs of Groups A, B and D was selected to be $\rho = 0.2$, and that of Group C was selected to be $\rho = 0.3$. This means the lifetimes of the test samples were defined as the time when the radiation power of the UV LED sample dropped to 80% of the initial value for Groups A, B and D and 70% of the initial value for Group C.

The degradation data processing and lifetime data analysis were planned as follows.

(i) For the constant stress test in Group B, the radiation power degradation data of each sample were fitted with Eq. (1) to extrapolate the exact lifetime for each sample. The obtained lifetime t, when the radiation power declined to the defined threshold, was considered as the pseudo-actual lifetime of each sample.
(ii) For the step stress tests in Groups A, C and D, the time interval with the same stress as the defined failure threshold was first determined, and the degradation data in the time intervals were then fitted and extrapolated with the degradation Eq. (1) as before.
(iii) Finally, all pseudo-actual lifetimes of test samples were obtained.

Next, the two-parameter Weibull distribution was used to model the lifetime distribution of UV LED samples [32]. The results are shown in Table 3, in which the MTTFs with 95% confidence intervals of samples from Groups A, B, C and D were estimated as 2891.91 h (2689.97 h, 3108.99 h), 2303.92 h (2070.17 h, 2564.06 h), 956.64 h (875.80 h, 1044.95 h) and 2313.90 h (2014.95 h, 2657.21 h), respectively.

3. Degradation modeling theory and lifetime prediction methods

3.1. IESNA TM-21 standard

As an industry-accepted method, the IESNA TM-21 standard proposed by IESNA is often used to predict long-term lumen maintenance of LED light sources [33]. This method uses data collected according to the IESNA LM-80-08 standard to estimate the rated lumen maintenance life of the LED [34]. As mentioned before, the radiation power is one of the most important performance parameters to evaluate the light output of UV LEDs. Therefore, it was used in this study to estimate the lifetime by replacing the lumen flux recommended for general light sources in the IESNA TM-21 standard. Different from fitting UV LED samples with Eq. (1) to obtain the pseudo-actual lifetimes as mentioned in Section 2.3, the radiation powers of group samples at every test time need to be averaged in the IESNA TM-21 standard. Then a nonlinear least squares regression method is applied to the averaged radiation power data to perform a curve-fitting [12]. The exponential radiation power degrada-

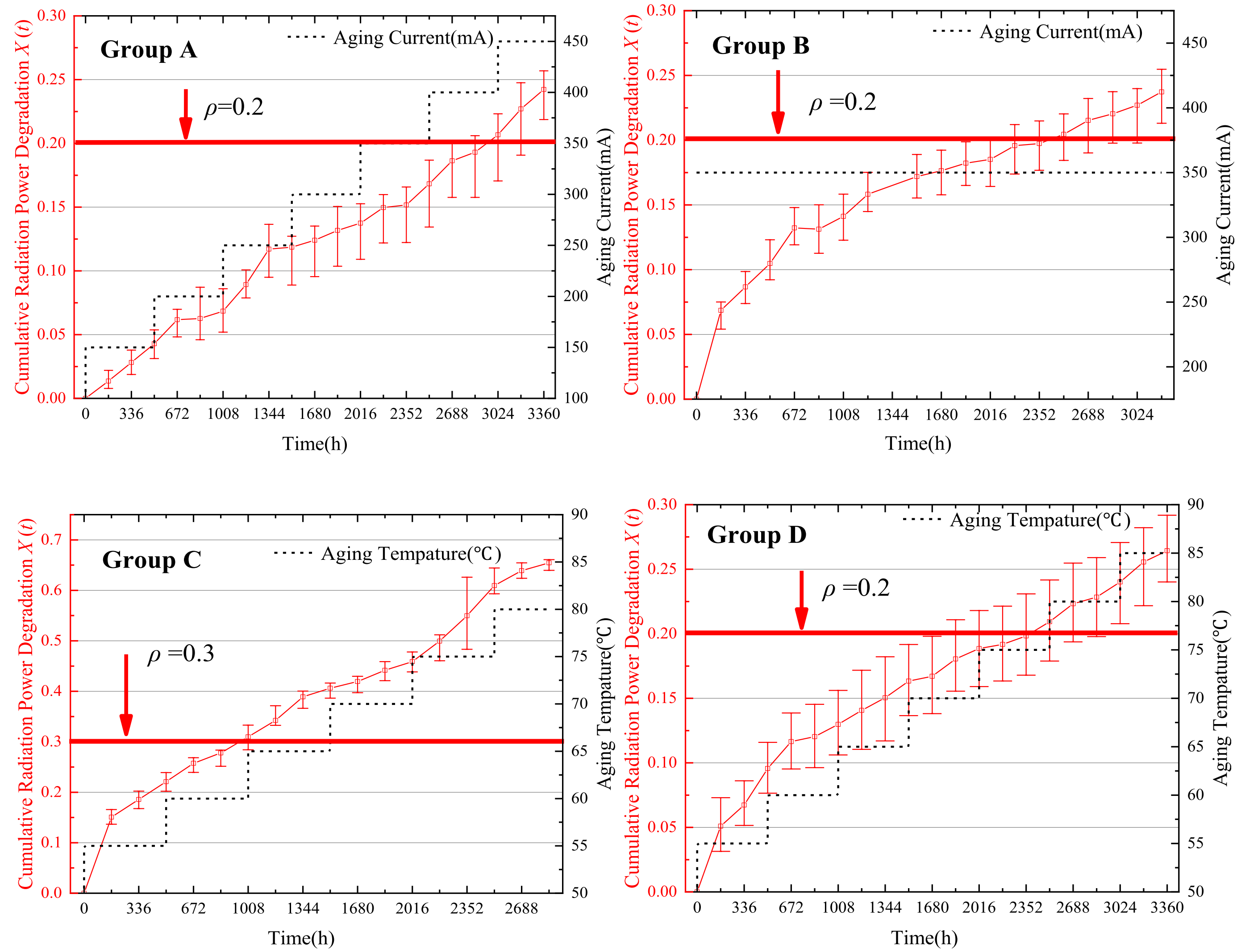

Fig. 3. The cumulative radiation power degradation data of all UV LED test samples.

Table 3
MTTF, confidence intervals and parameter information of two-parameter Weibull distribution plotting for each group.

	Group A	Group B	Group C	Group D
MTTF ($L_{80/70}$ Lifetime) (h)	2891.91	2303.92	956.64	2313.90
Confidence interval (h)	(2689.97, 3108.99)	(2070.17, 2564.06)	(875.80, 1044.95)	(2014.95, 2657.21)
Shape parameter of Weibull distribution	8.95	5.93	7.27	4.31
Scale parameter of Weibull distribution	3054.67	2485.13	1020.71	2542.09

tion model is expressed the same as Eq. (1), and the cumulative radiation power degradation $X(t)$ can be expressed as

$$X(t) = 1 - B_0 \cdot \exp(-at). \tag{2}$$

The rated radiation power degradation lifetime can be projected according to Eq. (3) as follows:

$$L_p = \frac{ln\left(100 \times \frac{B_0}{p}\right)}{a}, \tag{3}$$

where L_p is the rated radiation power degradation lifetime in hours, and p is the percentage of radiation power maintained compared with the initial radiation power output (80% or 70% assumed in Section 2.3).

3.2. Gamma process model and its lifetime prediction

The cumulative radiation power degradation of UV LEDs can be regarded as a time-dependent stochastic process $\{X(t), t \geq 0\}$. A stationary Gamma process model with the following properties [35] can be used to model this degradation process.

(a) $X(0) = 0$ with probability “1.”
(b) $X(t)$ has independent, non-negative random increments.
(c) $X(t + \Delta t) - X(t) \sim Ga(\alpha\Delta t, \beta)$ for all $t \geq 0, \Delta t$.

$Ga(\alpha, \beta)$ is a Gamma distribution with identical shape parameter $\alpha > 0$ and scale parameter $\beta > 0$. The probability distribution of $X(t)$ is given by Eq. (4):

$$f_{X(t)}(x) = Ga(x|\alpha, \beta). \tag{4}$$

The equation of the probability density function (PDF) [36, 37] is as follows:

$$f(x|\alpha,\beta)=\frac{1}{\Gamma(\alpha)\beta^{\alpha}}x^{\alpha-1}\exp(-x/\beta)I_{(0,\infty)}(x),\quad x>0, \tag{5}$$

where the Gamma function $\Gamma(\alpha)$ can be defined as

$$\Gamma(\alpha)=\int_0^{\infty}x^{\alpha-1}\mathrm{e}^{-x}\mathrm{d}x, \tag{6}$$

and $I_{(0,\infty)}(x)$ is expressed by

$$I_{(0,\infty)}(x)=\begin{cases}1, x\in(0,\infty)\\ 0, x\notin(0,\infty)\end{cases}. \tag{7}$$

It is generally assumed that α is related to stress, and it satisfies $X(t)\sim Ga(\alpha(t),\beta)$. Empirical studies show that the expected degradation at time t often satisfies a power law [38]:

$$\alpha(t)=\mathrm{ct}^{\mathrm{b}}. \tag{8}$$

In this paper, a linear relationship was used, namely $b=1$ and $\alpha(t)=$ c*t*. According to the statistical properties of the Gamma process, it is known that the expectation and the variance of $X(t)$ at time t can be expressed as follows:

$$E(\mathrm{X(t)})=\beta\cdot\alpha(\mathrm{t}),\quad Var(\mathrm{X(t)})=\beta^2\cdot\alpha(\mathrm{t}). \tag{9}$$

Assuming that the initial value of the Gamma degradation process $\{X(t), t\geq 0\}$ is 0, the threshold for degradation failure is ρ, which is a constant. The probability distribution function [39, 40] can be expressed as

$$\mathrm{F}_T(\mathrm{t})=\mathrm{P}(\mathrm{X(t)}\geq\rho)=\frac{\Gamma(\mathrm{ct},\rho/\beta)}{\Gamma(\mathrm{ct})}, \tag{10}$$

$$\mathrm{R}(t)=1-F_T(t)=1-\frac{\Gamma(\mathrm{ct},\rho/\beta)}{\Gamma(\mathrm{ct})}, \tag{11}$$

$$\begin{aligned}\mathrm{f}_T(\mathrm{t})&=\frac{d}{d\mathrm{t}}\frac{\Gamma(\mathrm{ct},\rho/\beta)}{\Gamma(\mathrm{ct})}\\ &=\frac{\mathrm{c}}{\Gamma(\mathrm{ct})}\int_0^{\rho/\beta}\left[\ln(\xi)-\frac{\Gamma'(\mathrm{ct})}{\Gamma(\mathrm{ct})}\right]\xi^{\mathrm{ct}-1}e^{-\xi}d\xi\end{aligned}. \tag{12}$$

An approximate formula to estimate the MTTF under model $X(t)\sim Ga(\alpha(t),\beta)$ was proposed by Park and Padgett [41] and is shown as follows:

$$MTTF=\frac{\rho}{\mathrm{c}\beta}+\frac{1}{2\mathrm{c}}. \tag{13}$$

In order to apply the Gamma process model to practical examples, statistical methods for the parameter estimation of Gamma processes are required. In this study, the parameters of c and β were estimated using the method of moments (MM) [38] as follows:

$$\mathrm{c}\cdot\beta=\frac{\sum_{i=1}^{n}(x_i-x_{i-1})}{\sum_{i=1}^{n}(t_i-t_{i-1})}=\frac{x_n}{t_n}=\delta, \tag{14}$$

$$\mathrm{x}_n\beta\left(1-\frac{\sum_{i=1}^{n}(t_i-t_{i-1})^2}{\left[\sum_{i=1}^{n}(t_i-t_{i-1})\right]^2}\right)=\sum_{i=1}^{n}\left[(x_i-x_{i-1})-\delta(t_i-t_{i-1})\right]^2. \tag{15}$$

3.3. Wiener process model and its lifetime prediction

In addition to the Gamma process, the Wiener process is also a stochastic model method that is widely used to describe degradation processes. Usually, the Wiener process with drift can be expressed in the following form [42]:

$$\mathrm{X}(t)=\mu\mathrm{t}+\sigma\mathrm{B}(t), \tag{16}$$

where μ is the drift parameter, σ is the diffusion parameter and $B(t)$ is the standard Wiener process or standard Brownian motion. Then the Wiener process with drift $\{X(t), t\geq 0\}$ satisfies the following property: the increment $\Delta\mathrm{X}(t)$ between times t to $\mathrm{t}+\Delta\mathrm{t}$ follows a normal distribution, which is $X(t+\Delta t)-X(t)\sim N(\mu\Delta t,\sigma^2\Delta t)$ for all $t\geq 0, \Delta t$[27].

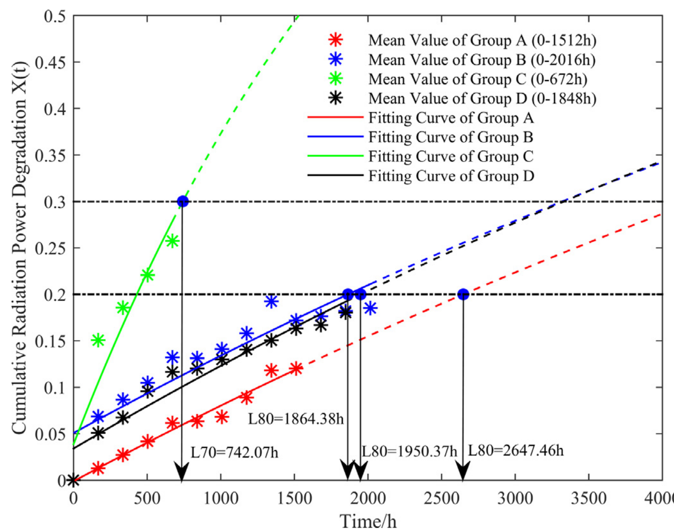

Fig. 4. Lifetime projecting results with the non-linear least squares regression method recommended in the IESNA TM-21 standard.

In this paper, assuming that the performance degradation process of UV LED obeys the above Wiener process, the corresponding failure threshold was denoted as ρ ($\rho>0$). The parameters μ and σ were estimated by fitting the normal distribution of the increments in the performance degradation process. The cumulative distribution function and PDF of the UV LED lifetime [26, 43] can be further obtained as follows:

$$\mathrm{F}_T(t)=\Phi\left(\frac{\mu\mathrm{t}-\rho}{\sigma\sqrt{\mathrm{t}}}\right)+\exp\left(\frac{2\mu\rho}{\sigma^2}\right)\Phi\left(\frac{-\rho-\mu\mathrm{t}}{\sigma\sqrt{\mathrm{t}}}\right), \tag{17}$$

$$\mathrm{f}_T(t)=\frac{\rho}{\sqrt{2\pi\sigma^2\mathrm{t}^3}}\exp\left[-\frac{(\rho-\mu\mathrm{t})^2}{2\sigma^2\mathrm{t}}\right]. \tag{18}$$

The lifetime distribution was assumed to follow an inverse Gaussian distribution [44]. If $\nu=\rho/\mu$ and $\lambda=\rho^2/\sigma^2$, then Eq. (18) can be denoted as $IG(\nu,\lambda)$ and rewritten as follows:

$$\mathrm{f}_T(t)=\sqrt{\frac{\lambda}{2\pi\mathrm{t}^3}}\exp\left[-\frac{\lambda(\mathrm{t}-\mathrm{v})}{2\mathrm{v}^2\mathrm{t}}\right]. \tag{19}$$

4. Results and discussion

In this section, the degradation modeling and lifetime prediction with the IESNA TM-21 standard, Gamma process and Wiener process methods, are implemented and compared. There are two selected time ranges in every group for degradation lifetime prediction in Table 2. The following analysis takes the prediction start points of {1512 h}, {2016 h}, {672 h} and {1848 h} of Groups A, B, C and D as examples. And the lifetimes of Groups A, B, C and D with the prediction start points of {1680 h}, {2184 h}, {840 h} and {2016 h} are also predicted. The prediction errors for each group are presented in Table 5.

4.1. Lifetime prediction with IESNA TM-21 standard

A plotting of the normalized average cumulative radiation power degradation data $X(t)$ with the first time ranges for four groups is shown in Fig. 4. The parameters for the non-linear least squares regression lifetime projection model (Eq. (2)) were calculated according to the IESNA TM-21 approach described in Section 3.1. The curve-fitting results are also plotted in Fig. 4.

The predicted lifetimes, marked as MTTF-T, of Groups A, B, C and D obtained by the IESNA TM-21 method are 2647.46 h (a = 8.471e-05, B_0 = 1.001), 1864.38 h (a = 9.174e-05, B_0 = 0.949), 742.07 h (a = 4.274e-04, B_0 = 0.961) and 1950.37 h (a = 9.663e-05, B_0 = 0.966),

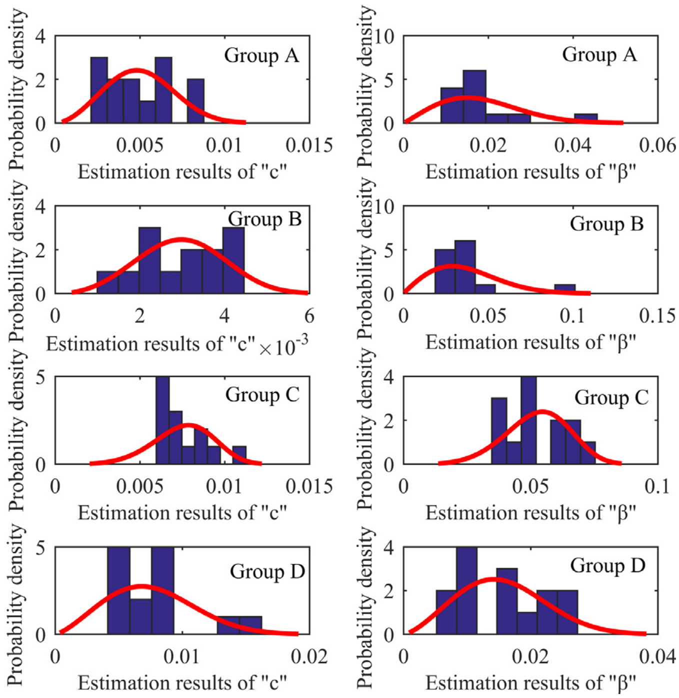

Fig. 5. The histograms of two parameters c and β and the Weibull fitting distribution of each group.

respectively. Compared to the pseudo-actual lifetimes calculated in Section 2.3, the prediction errors for each group data are presented in Table 5.

4.2. Lifetime prediction with Gamma process method

c and β were estimated by the MM method as expressed in Eqs. (14) and (15) according to the Gamma process method described in Section 3.2, and the corresponding lifetimes of all samples were calculated according to Eq. (13). Assuming the lifetimes of samples satisfied the two-parameter Weibull distribution, the mean time to failure (MTTF-G1) with 95% confidence intervals of the four groups was calculated as 2871.86 h (2499.41 h, 3299.80 h), 2416.00 h (2235.40 h, 2611.19 h), 860.85 h (817.74 h, 906.22 h) and 2173.29 h (1982.26 h, 2382.73 h) with the prediction start points of {1512 h}, {2016 h}, {672 h} and {1848 h}, respectively.

Furthermore, although the two-parameter Weibull statistical model can describe the effects of sampling uncertainty in MTTF estimation better than the averaging process of IESNA TM-21, it is still limited to a certain moment of sample failure. Moreover, since the parameters of the statistical distribution are fixed in time, it is very difficult to describe the changes caused by the temporal uncertainty. Therefore, when the Gamma process parameters c and β of each group are determined, the expected degradation $X(t)$ under any degradation time ranges can be obtained, and the lifetime of the whole group of UV LEDs also can be calculated with the determined failure threshold [45].

To determine the Gamma process parameters c and β for each group, a Weibull distribution and a normal distribution were used as the goodness fitting distributions for the estimated parameters. The Anderson–Darling (AD) method was used in the choice of distribution, in which the smallest AD calculation means the best fitting distribution. The results show that the Weibull distribution has the better fitting results of c and β. The histograms of the two parameters of each group and the Weibull distribution fittings are shown in Fig. 5. The average values of the Weibull distributions from each group are shown in Table 4. Combined with the failure threshold ρ, the estimated lifetimes (MTTF-G2) of Groups A, B, C and D were estimated by Eq. (13) as 2748.87 h, 2367.68 h, 864.21 h and 2235.93 h with the prediction start points of {1512 h}, {2016 h}, {672 h} and {1848 h}, respectively. The differences between MTTF-G2 and MTTF-G1 stayed at a relatively low level, which indicates that MTTF-G2 can estimate the lifetime of a whole group well. The difference between MTTF-G1 and MTTF-G2 is that MTTF-G1 obtains the group's lifetime from the Weibull distribution of the lifetimes of each sample, whereas MTTF-G2 obtains the mean of each sample's parameters by considering the Weibull distribution first and then calculating the group's lifetime from the average parameters.

Table 4
Unified parameters and estimated lifetime based on the Gamma process.

Test groups	Group A	Group B	Group C	Group D
c*E-03	5.021	2.981	7.550	7.581
β*E-03	15.03	30.50	49.79	12.16
MTTF-G2 (h)	2748.87	2367.68	864.21	2235.93

Based on the estimated parameters c and β in Table 4 and the failure threshold ρ of each group, the reliability function curves of each group are shown in Fig. 6(a). The average lifetimes of Groups A, B, C and D with the reliability probability equal to 50% were 2715.38 h, 2310.76 h, 841.70 h and 2213.79 h, respectively. The differences with MTTF-G2 were −1.22%, −2.40%, −2.60% and −0.99%, respectively. In addition, because the PDFs of $X(t)$ at any testing times can be plotted according to the degradation parameters, the effect of time variation on the cumulative radiation power degradation $X(t)$ of each group can be investigated. The PDFs of $X(t)$ at the MTTF-G2 of each group are shown in Fig. 6(b). The height ranking of the PDFs in descending order is D, A, B and C as shown in Fig. 6(b), which is consistent with the prediction accuracy of the reliability function (0.99% < 1.22% < 2.40% < 2.60%). The corresponding X (MTTF-G2) were 0.190, 0.180, 0.280 and 0.190, and the errors with a defined failure threshold of 0.2 or 0.3 were −5.0%, −10%, −6.7% and −5.0%, respectively.

4.3. Lifetime prediction with Wiener process method

The degradation increments $\Delta X(t)$ were tested for satisfying the normal distribution based on the Kolmogorov–Smirnov test in MATLAB, which means that the Wiener process method can be used for predicting lifetimes. As described in Section 3.3, the estimated normal distribution parameters μ and σ were estimated by fitting the normal distribution of$\Delta X(t)$. Combined with the corresponding failure threshold ρ, the estimated ν and λ values of the inverse Gaussian distribution that the lifetime obeys can be obtained. The reliability curves of each sample in Groups A, B, C and D with the prediction start points of {1512 h}, {2016 h}, {672 h} and {1848 h} are shown in Fig. 7. The average lifetimes with the reliability probability equal to 50% are the predicted lifetimes of each sample with the Wiener process method.

Therefore, with the two-parameter Weibull distribution curve fitting of the predicted lifetimes of each sample in every group, the estimated lifetimes, which were recorded as MTTF-W, and the 95% confidence intervals for Groups A, B, C and D with the prediction start points of {1512 h}, {2016 h}, {672 h} and {1848 h} were 2939.82 h (2564.98 h, 3369.45 h), 2221.82 h (2040.62 h, 2419.11 h), 913.09 h (855.50 h, 974.56 h) and 2212.63 h (2007.86 h, 2438.28 h), respectively.

4.4. Prediction result comparison and analysis

In this section, the estimated lifetimes of all groups of UV LEDs from the IESNA TM-21 standard, Gamma process method and Wiener process method are compared with the prediction error and the width of the confidence interval. The prediction errors, expressed in percentages between estimated lifetimes MTTF-E and pseudo-actual lifetimes MTTF,

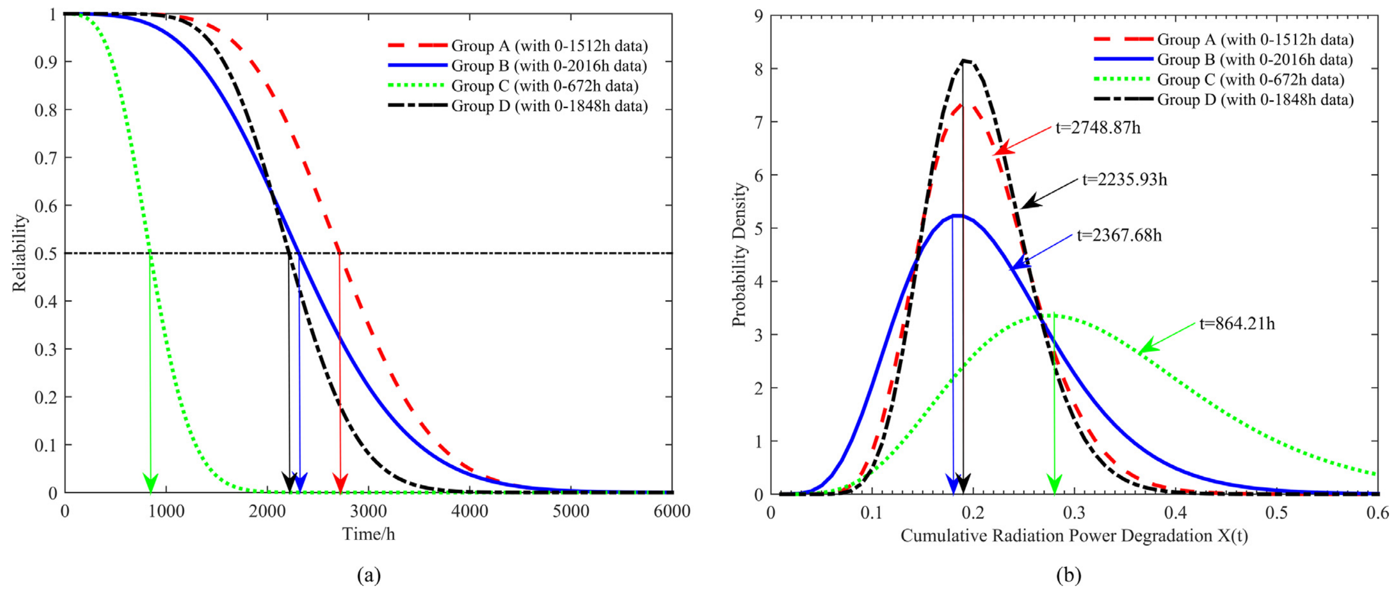

Fig. 6. (a) The reliability function curves of each group with Gamma process. (b) PDFs of the cumulative radiation power degradation $X(t)$ at MTTF-G2 testing times.

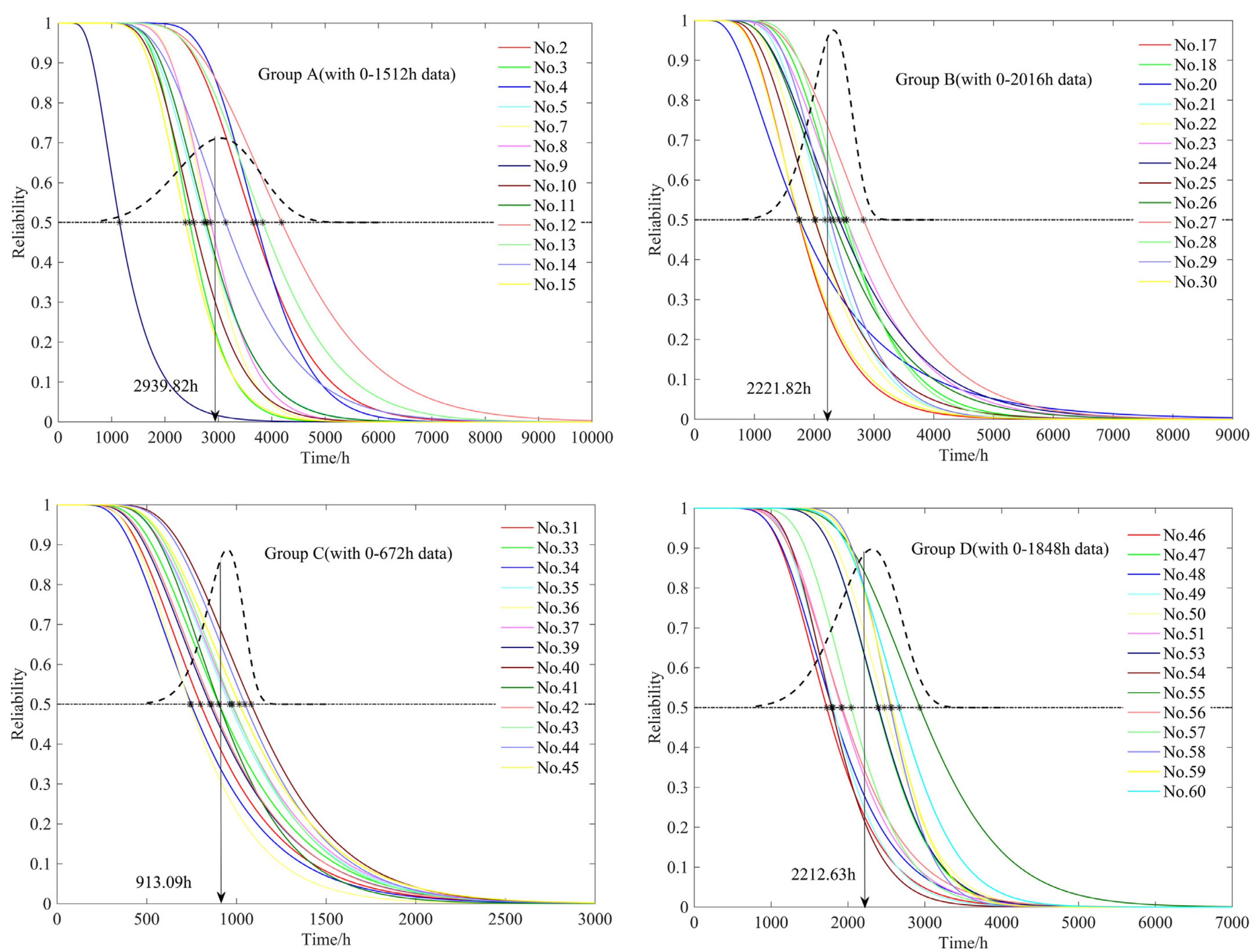

Fig. 7. Reliability function curves of each sample with the Wiener process.

Table 5
Comparison of lifetime prediction results with different methods.

Groups	MTTF (h)	Prediction Start Points	MTTF-T (h)	MTTF-T Prediction error%	MTTF-G1 (h)	MTTF-G1 Prediction error%	MTTF-G2 (h)	MTTF-G2 Prediction error%	MTTF-W (h)	MTTF-W Prediction error%
Group A	2891.91	1512 h	2647.46	8.45	2871.86	0.69	2748.87	4.95	2939.82	1.66
		1680 h	2696.87	6.74	3012.32	4.16	2909.25	0.60	3057.29	5.72
Group B	2303.92	2016 h	1864.38	19.08	2416.00	4.86	2367.68	2.77	2221.82	3.56
		2184 h	1941.20	15.74	2460.11	6.78	2425.65	5.28	2266.39	1.63
Group C	956.64	672 h	742.07	22.43	860.85	10.01	864.21	9.66	913.09	4.55
		840 h	821.00	14.18	1003.52	4.90	994.59	3.97	1020.03	6.63
Group D	2313.90	1848 h	1950.37	15.71	2173.29	6.08	2235.93	3.37	2212.63	4.38
		2016 h	2004.36	13.38	2270.39	1.88	2333.55	0.85	2298.72	0.66

Table 6
The goodness-of-fit comparison of different methods.

Models	IES-TM-21 Method (MTTF-T)	Gamma Method (MTTF-G1)	Gamma Method (MTTF-G2)	Wiener Method (MTTF-W)
MSE	89370.44	10612.06	7011.55	6774.47
RMSE	298.95	103.01	83.74	82.31

were obtained from Eq. (20):

$$Error\% = \left| \left(\frac{MTTF-E-MTTF}{MTTF} \right) \times 100\% \right|. \tag{20}$$

Additionally, the mean squared error (MSE) and the root mean squared error (RMSE) of each model for UV LED degradation data were calculated according to Eqs. (21) and (22):

$$MSE = \frac{1}{N} \sum_{m=1}^{N} \left(MTTF_m - MTTF - E_m \right)^2, \tag{21}$$

$$RMSE = \sqrt{MSE}, \tag{22}$$

where N is the number of MTTF-E or MTTF. The goodness-of-fit comparison of the mentioned models for the UV LED degradation data is shown in Table 6.

According to the comparisons shown in Tables 5 and 6, the following summary can be established: (i) The IESNA TM-21 standard depends on least squares regression to minimize the sum of the residuals between the actual measurements and the calculated values. It is a deterministic method that uses batch averaging data processing, ignoring the sample uncertainties and measurement dynamics. (ii) The stochastic data-driven methods, i.e., the Gamma process method and the Wiener process method, can provide accurate dynamic degradation process modeling of UV LEDs by considering uncertainties, and more reliable information, such as mean time to failure and confidence interval, can be obtained. (iii) The two proposed stochastic data-driven methods have the assumptions of non-negative or normal distribution of data increments, so each set of degradation data has a different processing effect. (iv) The prediction start points or the sizes of data ranges for prediction of the four groups are very different, which confirms that the proposed stochastic data-driven prediction methods have not only high accuracy but also high robustness.

5. Degradation mechanism analysis

To understand the degradation mechanisms under different aging conditions, four UV LED test samples after aging test, i.e., No. 2 (Group A), No. 25 (Group B), No. 41 (Group C) and No. 46 (Group D), were randomly selected from each group and were analyzed with the electrical test, electro-thermal coupling effect test and microstructure and material analysis. Meanwhile, a new UV LED sample was also chosen as the benchmark, which was denoted as No. 0 in Group N.

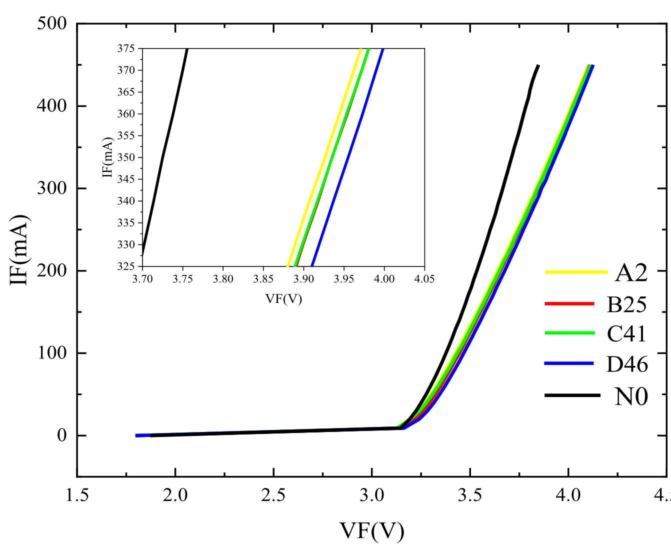

Fig. 8. The characteristic I-V curves of UV LED test samples.

5.1. Electrical test

The characteristic I-V curves of the five selected test samples were measured and are plotted in Fig. 8. It is shown that compared to the fresh sample, the curves of the aged samples were significantly shifted to a high range of forward voltage. The right shift of the I-V curve indicates an increase of contact resistance, which may be caused by the degradation of ohmic contact [46].

5.2. Electro-thermal coupling effect test

In addition, the electro-thermal coupling effects of five selected test samples were evaluated by measuring the radiation power and surface temperature under different case temperatures and driving current conditions. The driving currents were selected from 150 to 550 mA with 100 mA as with incremental interval, and the case temperatures were controlled from 30°C to 70°C with 10°C as the incremental interval. For the measurements, an integrating sphere and infrared camera were used to collect the photoelectric parameters and surface temperature, respectively.

The measurement results of test samples were obtained and are shown in Fig. 9, indicating that the fresh sample No. 0 had the highest

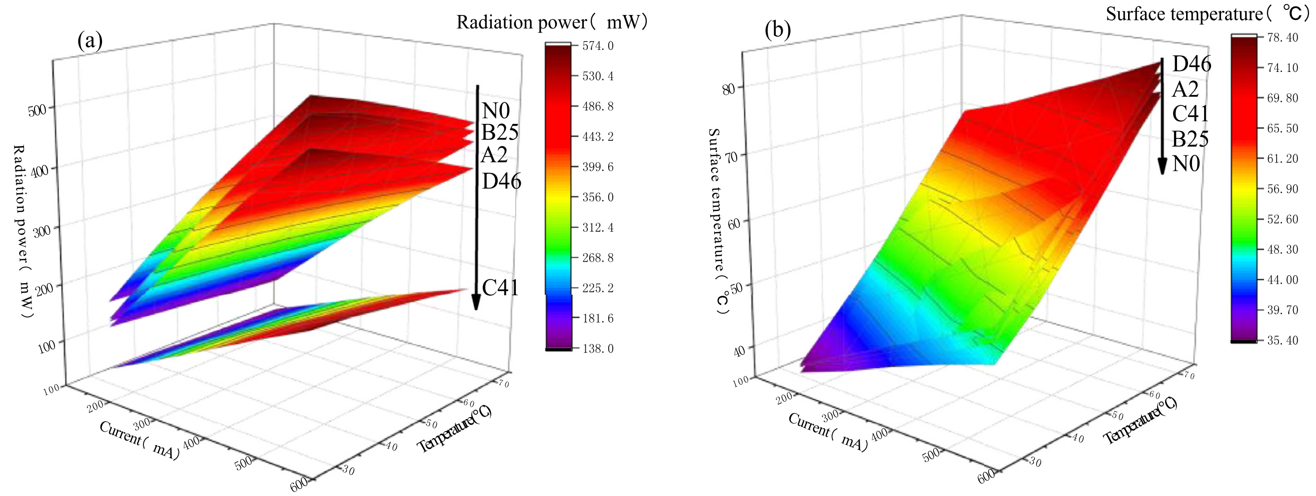

Fig. 9. (a) Radiation power and (b) surface temperature measurement results under different driving current and case temperature conditions.

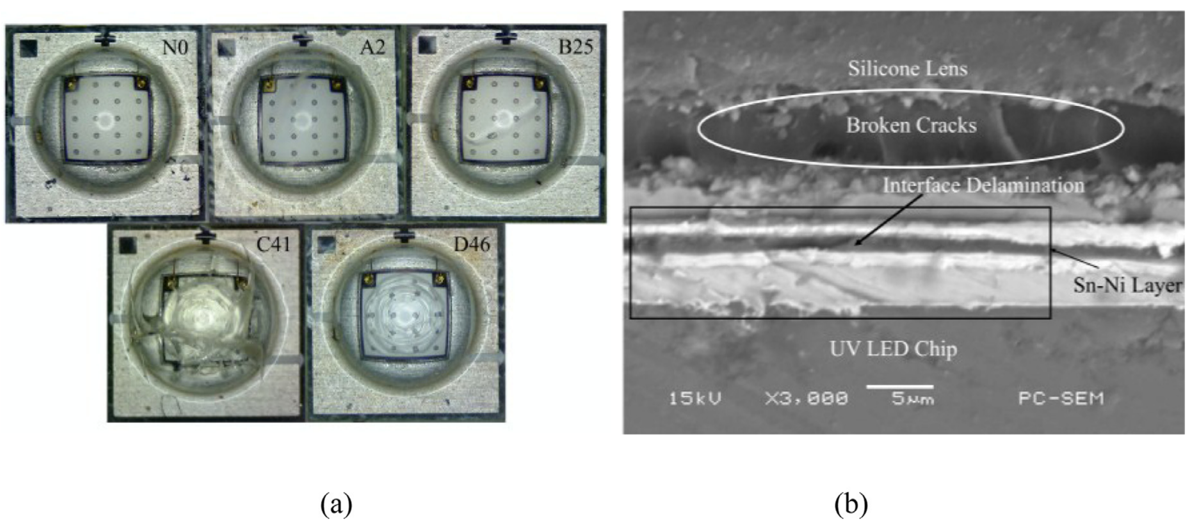

Fig. 10. (a) Overstress failure of silicone lens due to the high temperature and high UV light exposure. (b) SEM imaging shows the interface delamination on the Sn-Ni ohmic contact layer.

radiation power and lowest surface temperature. The other aged samples had significant degradation in luminous efficiency, and more heat was generated, which caused the rise of surface temperature. Furthermore, the increase of contact resistance at ohmic contact, as previously mentioned, can also introduce the Joule heating effect. In addition, it can be seen that the slope of the C41 sample is significantly different from others, indicating a different failure mode occurred in Group C's samples.

5.3. Microtopography analysis

Fig. 10(a) shows the appearances of all samples in each group, in which the silicone lenses of aged samples in each group were detected as anomalies compared to the new one. The most cracking and yellowing occurred in sample C41, which was attributed to the overstress aging of silicone under the high temperature and high UV light exposure from the high current. Moreover, the samples from Groups B, C and D suffered ohmic contact damage due to the current overstress aging.

As shown in Fig. 10(b), the scanning electron microscope (SEM) results indicate that interface delamination occurred on the Sn-Ni ohmic contact layer on the UV LED chip. Overall, the degradation of the silicone lens and ohmic contact were the main mechanisms causing the drop of radiation power in the selected UV LEDs. This is consistent with the above results of the electrical test and electro-thermal coupling effect test.

Generally, it is concluded as: (i) high temperature and UV light exposure drive the degradation of silicone lens in UV LEDs; (ii) current overstress accelerates the delamination of ohmic contact on the UV LED chip, which is mainly due to the effects of the internal defects, thermal diffusion of ions, and electromigration etc.; (iii) the lifetime of UV LED package highly depends on the used packaging materials and its failure mechanism will be changed when the accelerating stress exceeds the ultimate strength.

6. Conclusion

In this paper, long-term degradation tests under thermal and electrical stress were designed to evaluate the reliability of UV LEDs, and the radiation power degradation data of UV LEDs were modeled with stochastic data-driven methods, i.e., Gamma process and Wiener process methods, to predict UV LED lifetime. The results show that, compared to the IESNA TM-21 industry standard with the least squares regression method, the proposed stochastic data-driven methods can provide dynamic degradation process modeling of UV LEDs by considering measurement uncertainties, and more reliable information, i.e., mean time to failure and confidence interval, can be estimated. Moreover, both stochastic data-driven methods have much higher prediction accuracy compared to the IESNA TM-21 method at multiple prediction start points, which confirms that the proposed stochastic data-driven prediction methods have not only high accuracy but also high robustness. Finally, this paper also analyzes the degradation mechanisms of UV LED samples under different aging conditions, which reveals that high temperature and high UV light exposure drive the degradation of the silicone lens, and current overstress accelerates the delamination failure of ohmic contact on the UV LED chip.

Declaration of Competing Interest

All authors declare no conflict of interest.

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References

[1] Kneissl M. A Brief Review of III-Nitride UV Emitter Technologies and Their Applications; 2016.
[2] Song K, Mohseni M, Taghipour F. Application of ultraviolet light-emitting diodes (UV-LEDs) for water disinfection: a review. Water Res 2016;94:341–9.
[3] Kheyrandish A, Mohseni M, Taghipour F. Development of a method for the characterization and operation of UV-LED for water treatment. Water Res 2017;122:570–9.
[4] van Driel WD. Solid State Lighting Reliability Components to Systems (Solid State Lighting Technology and Application Series). New York, NY: Springer New York; 2013.
[5] Muramoto Y, Kimura M, Nouda S. Development and future of ultraviolet light-emitting diodes ~UV-LED will replace UV lamp~. In: Proceedings of the summer topicals meeting series; 2014.
[6] Liu M, Zhou S, Liu X, Gao Y, Ding X. Comparative experimental and simulation studies of high-power AlGaN-based 353 nm ultraviolet flip-chip and top-emitting LEDs. Jpn J Appl Phys 2018;57:031001 03/01.
[7] Arques-Orobon FJ, Nuñez N, Vazquez M, González-Posadas V. UV LEDs reliability tests for fluoro-sensing sensor application. Microelectron Reliab 2014;54(9-10):2154–8.
[8] Fan J, Yung W, Pecht M. Predicting long-term lumen maintenance life of LED light sources using a particle filter-based prognostic approach. Expert Syst Appl 2014;42 10/18.
[9] Meeker WQ, Escobar LA, Lu CJ. Accelerated degradation tests: modeling and analysis. Technometrics 1998;40(2):89–99.
[10] Qian C, Fan XJ, Fan JJ, Yuan CA, Zhang GQ. An accelerated test method of luminous flux depreciation for LED luminaires and lamps. Reliab Eng Syst Saf 2016;147:84–92.
[11] Tsai CC, Tseng ST, Balakrishnan N. Mis-specification analyses of gamma and Wiener degradation processes. J Stat Plan Inference 2011;141(12):3725–35.
[12] IESNA TM-21-11, Projecting Long Term Lumen Maintenance of LED Light Sources Illuminating Engineering Society New York (NY), 2011.
[13] IES- TM-28-14 Projecting long-term luminous flux maintenance of LED lamps and luminaries. Illuminating Engineering Society New York (NY); 2014.
[14] Jing Z, Liu J, Ibrahim MS, Fan J, Fan X, Zhang G. Lifetime prediction of ultraviolet light-emitting diodes using a long short-term memory recurrent neural network. IEEE Electron Device Lett 2020;41(12):1817–20.
[15] Cheng Y, Lu C, Li T, Tao L. Residual lifetime prediction for lithium-ion battery based on functional principal component analysis and Bayesian approach. Energy 2015;90:1983–93 2015/10/01/.
[16] Lyu C, Lai Q, Ge T, Yu H, Wang L, Ma N. A lead-acid battery's remaining useful life prediction by using electrochemical model in the Particle Filtering framework. Energy 2017;120:975–84 2017/02/01/.
[17] Ye Z-S, Xie M. Stochastic modelling and analysis of degradation for highly reliable products. Appl Stochastic Models Bus Ind 2015;31(1):16–32.
[18] Tsai C-C, Lin C-T, Balakrishnan N. A survey of modeling and application of non-destructive and destructive degradation tests. In: Chen D-G, Lio Y, Ng HKT, Tsai T-R, editors. Statistical modeling for degradation data. Singapore: Springer Singapore; 2017. p. 105–24.
[19] Ling MH, Tsui K-L, Balakrishnan N. Accelerated degradation analysis for the quality of a system based on the gamma process. IEEE Trans Reliab 2015;64:463–72 03/01.
[20] Park C, Padgett W. Accelerated degradation models for failure based on geometric Brownian motion and gamma processes. Lifetime Data Anal 2006;11:511–27 01/01.
[21] Park S-H, Kim J-H. Application of Gamma process model to estimate the lifetime of photovoltaic modules. Solar Energy 2017;147:390–8 2017/05/01/.
[22] Noortwijk JMV, Weide JAMVD, Kallen MJ, Pandey MD. Gamma processes and peaks-over-threshold distributions for time-dependent reliability. Reliab Eng Syst Saf 2007;92(12):1651–8.
[23] van Noortwijk JM. A survey of the application of gamma processes in maintenance. Reliab Eng Syst Saf 2009;94(1):2–21 2009/01/01/.
[24] Wu Z, et al. A Gamma process-based prognostics method for CCT shift of high-power white LEDs. IEEE Trans Electron Devices 2018;65(7):2909–16.
[25] Park SH, Kim JH. Lifetime estimation of LED lamp using gamma process model. Microelectronics Reliability, Article 2016;57:71–8.
[26] Zhai Q, Chen P, Hong L, Shen L. A random-effects Wiener degradation model based on accelerated failure time. Reliab Eng Syst Saf 2018;180 07/01.
[27] Jianlin H, et al. Degradation modeling of mid-power white-light LEDs by using Wiener process. Opt Express 2015;23(15):966–78.
[28] Liu D, Wang S-P, Zhang C, Tomovic M. Bayesian model averaging based reliability analysis method for monotonic degradation dataset based on inverse Gaussian process and Gamma process. Reliab Eng Syst Saf 2018;180 07/01.
[29] Peng Y, Liang R, Mou Y, Dai J, Mingxiang C, Luo X. Progress and perspective of near-ultraviolet and deep-ultraviolet light-emitting diode packaging technologies. J Electron Packaging 2019;141 08/01.
[30] Han W, Yu Z, Ma X. Mechanism equivalence in designing optimum step-stress accelerated degradation test plan under Wiener process. IEEE Access 2018(99):1 -1.
[31] Liang B, et al. Investigation of step-stress accelerated degradation test strategy for ultraviolet light emitting diodes. Materials 2019;12(19):3119.
[32] Almalki SJ, Nadarajah S. Modifications of the Weibull distribution: a review. Reliab Eng Syst Saf 2014;124(124):32–55.
[33] Fan J, Yung KC, Pecht M. Lifetime estimation of high-power white LED using degradation-data-driven method. IEEE Trans Device Mater Reliab 2012;12(2):470–7 6166442.
[34] IES-LM-80-08, Approved method for measuring lumen maintenance of LED Illuminating Engineering Society New York (NY), 2008.
[35] N. Singpurwalla, "Gamma processes and their generalizations: an overview," in Engineering probabilistic design and maintenance for flood protection, R. Cooke, M. Mendel, and H. Vrijling, Eds. Boston, MA: Springer US, 1997, pp. 67-75.
[36] Guida M, Penta F. A Gamma process model for the analysis of fatigue crack growth data. Eng Fract Mech 2015;142 05/22.
[37] M. D. Pandey, "Gamma process model for time-dependent structural reliability analysis," 01/01 2004.
[38] J. M. van Noortwijk and M. D. Pandey, "A stochastic deterioration process for time-dependent reliability analysis," 01/01 2004.
[39] Sun B, et al. Gamma degradation process and accelerated model combined reliability analysis method for rubber o-rings. IEEE Access 2018:1 vol. PP-101/30.
[40] Hao H, Su C, Li C. LED lighting system reliability modeling and inference via random effects gamma process and copula function. Int J Photoenergy 2015;2015:1–8 02/05.
[41] Tsai C-C, Tseng S-T, Balakrishnan N. Mis-specification analyses of Gamma and Wiener degradation processes. J Stat Plan Inference 2011;141:3725–35 12/01.
[42] Jing Z, Ibrahim MS, Fan J, Fan X, Zhang G. Lifetime prediction of ultraviolet light-emitting diodes with accelerated Wiener degradation process. In: Proceedings of the 20th international conference on thermal, mechanical and multi-physics simulation and experiments in microelectronics and microsystems (EuroSimE); 2019. p. 1–8.
[43] Pan Z, Balakrishnan N. Multiple-steps step-stress accelerated degradation modeling based on wiener and gamma processes. Commun Stat - Simul Comput 2010;39:1384–402 01/01.
[44] Chhikara RS. The inverse gaussian distribution: theory, methodology, and applications. Appl Stat 1988;39(2):259.
[45] Wang H, Tingxue X, Qiaoli M. Lifetime prediction based on Gamma processes from accelerated degradation data. Chin J Aeronaut 2014;52 12/26.
[46] Ma Z, et al. Failure mechanism of phosphors in GaN-Based White LEDs. Physica Status Solidi (a) 2019;216:1800335 02/18.