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Life Prediction Method for White LED Based on Covariance Matrix

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Abstract. With the rapid development of electronic products, it is crucial for designers and manufacturers to understand the lifespan information of new products before launching them on the market in order to provide high-quality products on a global scale. Therefore, life prediction has become a necessary procedure for manufacturers to evaluate the quality of their products. For high-power white LED, an efficient lifespan prediction method can not only shorten the reliability evaluation time of LED products, timely launch new products, and help manufacturers gain greater market share, but also provide users with clear understanding of product quality based on the reliability information provided by manufacturers, providing guidance for selecting appropriate products. Therefore, this article proposes a white LED lifespan prediction method based on covariance matrix. By studying its performance of lumen degradation and chromaticity shift, a mathematical model is established to help more accurately evaluate the lifespan of LED products.

Keywords. White LED, covariance matrix, life prediction.

1. Introduction

LED is known as the fourth generation light source. With the driving force of market demand and the innovation of production technology, solid-state lighting sources have shown more and more advantages compared to traditional light sources, such as safety and environmental protection, high energy efficiency, low power consumption, high reliability, and long service life. The use and promotion of high-power white LED in our country are still in the initial stage, and an important reason that hinders the further promotion of white LED products is the lack of reliability information, and an important aspect of reliability information is related to lifespan. Life prediction is an important part of product reliability assessment. Based on the prediction results, it provides decision-making for product maintenance and replacement, timely implementation of maintenance measures, and reduction of losses and hazards caused by product failure. Although LED has high reliability, its failure may still cause significant harm in some special application fields (such as aerospace, medical, energy, etc.). Therefore, it is extremely important to conduct reliability assessment and lifespan prediction of LED and predict its failure time in a timely manner.

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2. Research on Life Prediction Methods for White LEDs

A prediction method based on failure physics. Constructing a failure physical model can describe the dynamic response of a product to external stress and the complex damage evolution process. Specifically, for LED products, it is necessary to construct a failure physical model based on its own failure mode and mechanism information, system structure information, material characteristics, and load condition information, and then use this model to achieve life prediction. In reference [1], two failure physics (PoF) models were described. After a comprehensive failure physics analysis of LEDs, two failure physics models were designed based on the two key failure mechanisms obtained from the analysis (thermal induced lumen degradation and thermal cycling induced solder interconnect fatigue).

A data-driven prediction method. The data-driven approach is to use product condition monitoring data to analyze the current state and predict future health status, without the need to construct specific failure physical models based on comprehensive product failure analysis results. In reference [2], the author takes high-power white LED as the research object and proposes three data-driven methods based on lumen maintenance rate (including approximate methods, analytical methods, and two-stage methods).

A prediction method based on particle filtering. In recent years, scholars have applied particle filtering algorithms to the reliability evaluation and lifespan prediction of LEDs. Reference [3] studied the application of particle filtering algorithm in predicting the long-term lumen maintenance life of LED. In references [4][5], the particle filter algorithm was also applied to process the lumen maintenance rate data of LEDs and predict their lifespan.

A prediction method based on stochastic process degradation model. From the above main prediction methods, it can be found that the current modeling types for the degradation process of high-power white LED are relatively single, mainly exponential degradation models and double exponential degradation models. The randomness of the degradation process cannot be reflected in the model due to the determinacy of exponential or double exponential functions. The randomness of the degradation process reflects the close relationship between the performance and lifespan of LED devices. Therefore, considering the randomness of LED optical performance degradation process in research can better understand the distribution of LED optical performance degradation and obtain more accurate lifespan prediction results.

Currently, the research on LED reliability in China is in its early stages, and there is still relatively little research on the reliability evaluation and lifespan prediction of white LEDs.

In his doctoral thesis [6], Shen Haiping studied the reliability prediction mechanism of high-power white LED and proposed a lifespan prediction method based on neural networks. This method models the measured characteristic parameters with lifespan and color degradation through artificial neural networks. Reference [7] proposed an LED lifespan prediction model based on the theory of optical electrical thermal lifespan. The output luminous flux, input electrical power, junction temperature, and lifespan of the LED are connected to form a relationship, and lifespan prediction is achieved based on this relationship. In his doctoral thesis [8], Zhang Qin studied the temperature and humidity accelerated life test of high-power LED modules. Through a series of experiments on LEDs with different packaging characteristics under different conditions, he studied the effects of temperature, humidity, and rapid temperature changes on LED reliability. Using a combination of finite element simulation and failure analysis, he revealed the failure mechanism of LEDs and established a working life model of LEDs under high temperature and high humidity conditions.

At present, most research on the reliability of white LEDs is based on individual performance or independent states between performance. The TM-21-11 method [9] is the first life prediction method released by IES, which combines LM-80 test data to achieve more effective life assessment. This method has been accepted and used by multiple LED manufacturers, and has great application value. However, this method only predicts the lumen degradation data in test reports, so it has significant uncertainty. However, in reality, there is a very special situation where product performance is independent of each other, which rarely exists in practice. The more common aspect of performance is interdependence and mutual determination. The quality of one performance will more or less affect the reliability of other performance and components, such as poor contact, electrolyte oxidation or aging, retesting, mechanical damage, etc., which can simultaneously induce the failure of resistors, capacitors, integrated blocks, and contact parts. Therefore, the degradation performance parameters corresponding to various fault modes are usually linked in response. If the degradation of each performance parameter is separated and the mutual interference between them is ignored, and reliability analysis is conducted separately, the comprehensive reliability evaluation of the components is often inaccurate or even incorrect.

Therefore, this article introduces a covariance based method for predicting the lifespan of high-power white LED. Based on the analysis of the basic principle and operating process of this method, combined with the test data of a certain type of high-power white LED, a case study is conducted to provide the final lifespan prediction results.

3. Life Prediction Based on Covariance Matrix Method

3.1. The Basic Principle of Covariance Matrix Method

For white LEDs, the main focus is on studying their lumen degradation and chromaticity shift properties. Before conducting LED reliability analysis, it is necessary to evaluate the correlation between these two degradation properties. The interdependence is complex, and the covariance matrix represents the correlation between performance. The joint distribution function of degradation amount is estimated through the covariance matrix, which is dynamic and changes over time. The relationship between its distribution parameters and time needs to be estimated, and the degradation amount distribution method [10] is used to evaluate the reliability of white LEDs. Then, based on the obtained mathematical model and the selected failure threshold, the corresponding LED lifespan is obtained through inverse analysis.

3.2. The Life Prediction Process of Covariance Matrix Method

3.2.1. Correlation Analysis between Lumen Degradation and Chromaticity Shift

Reliability $R(t)$ is the probability of a component completing a specific function within a specified time t_d and under specified conditions. If used to represent the lifespan of a component under specified conditions, then completing the specified function within the specified time t_d is considered the probability of the component's lifespan being greater than t_d, and reliability can be considered as the probability of event $\Omega=\{T>t_d\}$.

For these two degraded performance data, they are the same as in the independent case. Use the covariance matrix of the data to determine whether there is correlation between the two and the strength of their correlation. To evaluate the reliability of white LED at time t_d, we evaluated the correlation between performance at time t_d by examining the degradation performance correlation at time $t_1,t_2,....,t_c$.

Table 1. Degradation data under two key performance degradation modes

time / Degradation / sample	t_1	t_2	…	t_c
1	y_{111},y_{121}	y_{112},y_{122}	…	y_{11c},y_{12c}
2	y_{211},y_{221}	y_{212},y_{222}	…	y_{21c},y_{22c}
…	…	…	…	…
n	y_{n11},y_{n21}	y_{n12},y_{n22}	…	y_{nmc},y_{n2c}

The mean and covariance matrix of the data in the table 1 at time $t_1,t_2,....,t_c$:

Time t_1 :

$$\mu_{t_1}=(\mu_{1t_1},\mu_{2t_1}) \tag{1}$$

$$\Sigma_{2t_1}=\begin{pmatrix} Cov(y_1(t_1),y_1(t_1)) & Cov(y_1(t_1),y_2(t_1)) \\ Cov(y_2(t_1),y_1(t_1)) & Cov(y_2(t_1),y_2(t_1)) \end{pmatrix} \tag{2}$$

Time t_2 :

$$\mu_{t_2}=(\mu_{1t_2},\mu_{2t_2}) \tag{3}$$

$$\Sigma_{2t_2}=\begin{pmatrix} Cov(y_1(t_2),y_1(t_2)) & Cov(y_1(t_2),y_2(t_2)) \\ Cov(y_2(t_2),y_1(t_2)) & Cov(y_2(t_2),y_2(t_2)) \end{pmatrix}. \tag{4}$$

Time t_c :

$$\mu_{t_c}=(\mu_{1t_c},\mu_{2t_c}) \tag{5}$$

$$\Sigma_{2tc}=\begin{pmatrix} Cov(y_1(t_c),y_1(t_c)) & Cov(y_1(t_c),y_2(t_c)) \\ Cov(y_2(t_c),y_1(t_c)) & Cov(y_2(t_c),y_2(t_c)) \end{pmatrix}. \tag{6}$$

When $Cov(y_i(t),y_j(t))=E(y_i(t)-E(y_i(t)))(y_i(t)-E(y_j(t)))$ approaches 0, it is considered that the correlation between the two degradation performances is weak, otherwise it is considered that they are correlated.

Fit the corresponding positions μ_{ij} and Cov_{ij} within the matrix with time t to obtain:

Classic fitting function as:

$$\begin{cases} \mu_{ij}(t) = a_{ij}t + b_{ij}. \\ \ln \mu_{ij}(t) = a_{ij}t + b_{ij}. \\ \mu_{ij}(t) = a_{ij}e^{t}. \end{cases} \quad (7)$$

$$\begin{cases} Cov_{ij}(t) = a_{ij}t + b_{ij}. \\ \ln Cov_{ij}(t) = a_{ij}t + b_{ij}. \\ Cov_{ij}(t) = a_{ij}e^{t}. \end{cases} \quad (8)$$

We can obtain the expected mean vector at the moment as:

$$\mu_{t_d} = (\mu_1, \mu_2) \quad (9)$$

Similarly, the expected covariance matrix at time td as:

$$\Sigma_{2t_d} = \begin{pmatrix} Cov_{11}(t_d) & Cov_{12}(t_d) \\ Cov_{21}(t_d) & Cov_{22}(t_d) \end{pmatrix}. \quad (10)$$

3.2.2. Reliability Analysis of White LED Based on Degraded Distribution

If these two degradation performances are related, similar to a single performance based on the degradation quantity distribution method, the degradation quantity distribution is a joint distribution function of the two degradation performances in a dependent case. Assuming time t_j, the joint distribution function between lumen degradation (performance 1) and color shift (performance 2) is $G_{Yt_j}(y_{j1}, y_{j2}; \hat{\theta}_{t_j})$, $\hat{\theta}_{t_j}$ is the parameter estimation of the joint distribution function of the two, and it is a function of time t.

Let the degradation thresholds for lumen degradation and color shift be D_{f1}, D_{f2}, respectively, and the reliability of white LED be the probability of event $\Omega = \{Y_{t_d1} < D_{f1}, Y_{t_d2} < D_{f2}\}$. The calculation of reliability is as follows:

$$R(t_d) = P(Y_{t_d1} < D_{f1}, Y_{t_d2} < D_{f2}) = G_{Y_{t_d}}(D_{f1}, D_{f2}; \hat{\theta}_{t_d2}). \quad (11)$$

For example, assuming that lumen degradation and color shift follow a binary normal distribution, the probability density function of the binary normal distribution is:

$$f(y_{t_d}) = (2\pi)^{-1} \left|\Sigma_{t_d}\right|^{-\frac{1}{2}} \exp[-\frac{1}{2}(y_{t_d} - \mu_{t_d})^T \Sigma_{t_d}{}^{-1}(y_{t_d} - \mu_{t_d})]. \quad (12)$$

Where $y_{t_d} = (y_{t_d1}, y_{t_d2})^T$ and $\mu_{t_d} = (\mu_{t_d1}, \mu_{t_d2})$ are mean vectors, Σ_{t_d} is the covariance matrix at time t_d, and $\left|\Sigma_{t_d}\right|$ is the modulus of the covariance matrix.

Based on performance degradation data, obtain the characteristic parameters of the binary normal distribution at time $t_1, t_2, \ldots, t_c$, and estimate the normal distribution parameters of degradation performance k at time t_j as:

$$\hat{\mu}_{kj} = \frac{1}{n}\sum_{i=1}^{n} y_{ijk}.\ k = 1,2 \tag{13}$$

$$\hat{\sigma}_{kj} = \frac{1}{n}\sum_{i=1}^{n}(y_{ijk} - \overline{y}_{jk})^2.\ k = 1,2 \tag{14}$$

Where $\overline{y}_{jk} = \frac{1}{n}\sum_{i=1}^{n} y_{ijk}$ is the average degradation amount of degradation performance k at time t_j.

By estimating the mean at time $t_1, t_2, ..., t_c$ and fitting it, we can obtain:

$$\mu_{t_d 1} = u_1(t). \tag{15}$$

$$\mu_{t_d 2} = u_2(t). \tag{16}$$

Fit the corresponding positions of the covariance matrix at time $t_1, t_2, ... t_c$ to obtain:

$$Cov_{ij}(t) = c_{ij}(t). \tag{17}$$

The covariance matrix between performance 1 and 2 at time t_d is:

$$\sum\nolimits_{2t_d} = \begin{pmatrix} c_{11}(t_d) & c_{12}(t_d) \\ c_{21}(t_d) & c_{22}(t_d) \end{pmatrix} \tag{18}$$

The probability density function of the normal distribution at time t_d is:

$$f\left(y_{t_d 1}, y_{t_d 2}\right) = (2\pi)^{-1} \left| \begin{pmatrix} c_{11}(t_d) & c_{12}(t_d) \\ c_{21}(t_d) & c_{22}(t_d) \end{pmatrix} \right|^{-\frac{1}{2}} \bullet \exp\left[-\frac{1}{2}\left(\begin{pmatrix} y_{t_d 1} \\ y_{t_d 2} \end{pmatrix} - \begin{pmatrix} u_1(t) \\ u_2(t) \end{pmatrix} \right)^T \begin{pmatrix} c_{11}(t_d) & c_{12}(t_d) \\ c_{21}(t_d) & c_{22}(t_d) \end{pmatrix}^{-1} \left(\begin{pmatrix} y_{t_d 1} \\ y_{t_d 2} \end{pmatrix} - \begin{pmatrix} u_1(t) \\ u_2(t) \end{pmatrix} \right) \right]. \tag{19}$$

Therefore, based on the degradation performance of binary normal distribution, the reliability of white LED is:

$$\begin{aligned} R(t_d) &= P(Y_{t_d 1} > D_{f1}, Y_{t_d 2} < D_{f2}) = \int_{D_{f1}}^{100}\int_{0}^{D_{f2}} f\begin{pmatrix} y_{t_d 1} \\ y_{t_d 2} \end{pmatrix} dy_{t_d 1} dy_{t_d 2} \\ &= \int_{D_{f1}}^{100}\int_{0}^{D_{f2}} \left\{ (2\pi)^{-1} \left| \begin{pmatrix} c_{11}(t_d) & c_{12}(t_d) \\ c_{21}(t_d) & c_{22}(t_d) \end{pmatrix} \right|^{-\frac{1}{2}} \bullet \exp\left[-\frac{1}{2}\left(\begin{pmatrix} y_{t_d 1} \\ y_{t_d 2} \end{pmatrix} - \begin{pmatrix} u_1(t_d) \\ u_2(t_d) \end{pmatrix} \right)^T \begin{pmatrix} c_{11}(t_d) & c_{12}(t_d) \\ c_{21}(t_d) & c_{22}(t_d) \end{pmatrix}^{-1} \left(\begin{pmatrix} y_{t_d 1} \\ y_{t_d 2} \end{pmatrix} - \begin{pmatrix} u_1(t_d) \\ u_2(t_d) \end{pmatrix} \right) \right] \right. dy_{t_d 1} dy_{t_d 2}. \end{aligned} \tag{20}$$

Regardless of the distribution of degradation performance, before conducting reliability calculations, it is necessary to conduct correlation tests on multiple performance degradation data, and use the results of the covariance matrix to assist in estimating the distribution of degradation and calculating reliability. This method of reliability evaluation for dependent single components based on covariance matrix is more suitable for situations where the degradation amount distribution is normal.

3.2.3. Life Prediction

After obtaining a reliability calculation model, given the reliability, the lifespan of white LED can be inversely solved. For example, if the two degradation quantities follow a binary normal distribution, as discussed in section 3.2.2, the reliability model of white LED is a function of time t. Therefore, we specify a reliability of 50% and introduce $R(t_d)=50\%$ into the reliability calculation model. The inverse solution can obtain the lifespan of white LED.

4. Case Analysis and Discussion

In order to verify the effectiveness of the covariance method and analyze its practical value, this chapter selects a high-power white LED product as the test sample, and conducts performance degradation testing of batch LED products according to the test standards.

Taking the samples under low working stress (as shown in table 2 for specific testing information) as an example, after removing 1000 hours of maturity data, the corresponding lumen maintenance degradation data and chromaticity offset data are obtained as shown in table 3 and table 4.

Table 2. Test Information

Sample quantity	Test duration (hours)	Drive current (mA)	Sample temperature (℃)	ambient temperature (℃)
25	6029	100	55	>50

Table 3. LED lumen maintenance rate data (55 ℃ 100mA) (%)

NO.	0h	1008h	1722h	2389h	3128h	3815h	4505h	5218h	6029h
1	100.0	99.9	99.9	99.3	99.2	99.4	99.2	99.0	99.1
2	100.0	99.7	99.7	99.0	99.1	99.3	99.9	98.7	98.7
3	100.0	99.8	99.7	99.1	99.3	99.4	99.0	98.8	98.6
4	100.0	99.0	98.8	98.2	98.3	98.2	97.8	97.7	97.4
5	100.0	99.9	99.7	99.1	99.1	99.0	98.6	98.5	98.3
6	100.0	99.0	98.7	98.0	98.0	97.8	97.6	97.3	97.2
7	100.0	99.2	99.0	98.2	98.0	97.8	97.6	97.3	97.2
8	100.0	98.9	98.8	97.9	97.7	97.6	97.6	97.2	97.3
9	100.0	98.9	98.6	97.6	97.3	97.4	97.3	96.9	97.0
10	100.0	99.2	99.2	98.5	98.4	98.6	98.5	98.1	98.3
11	100.0	99.3	99.2	98.5	98.4	98.7	98.4	98.1	98.1
12	100.0	99.1	99.0	98.3	98.3	98.5	98.2	98.0	97.9
13	100.0	99.4	99.2	98.5	98.6	98.4	98.1	97.9	97.7
14	100.0	99.3	99.0	98.2	98.3	98.0	97.7	97.6	97.4
15	100.0	99.2	98.9	98.3	98.4	98.2	98.0	97.8	97.7
16	100.0	99.4	99.3	98.7	98.7	98.6	98.5	98.4	98.4
17	100.0	99.1	98.9	98.2	98.0	97.8	97.7	97.5	97.4
18	100.0	99.2	99.0	98.2	97.9	98.1	98.0	97.7	97.7
19	100.0	99.1	99.0	98.2	98.0	98.4	98.3	98.0	98.0
20	100.0	99.2	99.1	98.4	98.2	98.5	98.3	98.0	98.1

21	100.0	99.1	98.9	98.3	98.3	98.4	98.2	97.9	97.8
22	100.0	99.5	99.3	98.6	98.7	98.8	98.5	98.2	98.0
23	100.0	99.4	99.1	98.3	98.4	98.3	98.0	97.7	97.6
24	100.0	99.5	99.2	98.4	98.6	98.3	98.0	97.8	97.3
25	100.0	99.2	98.9	98.2	98.1	97.9	97.7	97.4	97.3

Table 4. Chromaticity offset (55 ℃ 100mA)

NO.	0h	1008h	1722h	2389h	3128h	3815h	4505h	5218h	6029h
1	0.0000	0.0013	0.0016	0.0019	0.0020	0.0018	0.0020	0.0020	0.0022
2	0.0000	0.0011	0.0014	0.0016	0.0017	0.0016	0.0018	0.0018	0.0019
3	0.0000	0.0013	0.0015	0.0019	0.0020	0.0018	0.0019	0.0021	0.0022
4	0.0000	0.0013	0.0016	0.0019	0.0019	0.0017	0.0019	0.0019	0.0021
5	0.0000	0.0013	0.0015	0.0017	0.0018	0.0016	0.0018	0.0019	0.0020
6	0.0000	0.0011	0.0014	0.0017	0.0020	0.0017	0.0019	0.0021	0.0023
7	0.0000	0.0012	0.0015	0.0018	0.0018	0.0017	0.0019	0.0020	0.0022
8	0.0000	0.0012	0.0014	0.0017	0.0018	0.0016	0.0017	0.0018	0.0020
9	0.0000	0.0014	0.0017	0.0021	0.0023	0.0021	0.0024	0.0024	0.0025
10	0.0000	0.0012	0.0014	0.0018	0.0019	0.0018	0.0019	0.0020	0.0021
11	0.0000	0.0014	0.0016	0.0019	0.0020	0.0018	0.0020	0.0021	0.0022
12	0.0000	0.0016	0.0018	0.0022	0.0023	0.0021	0.0023	0.0024	0.0025
13	0.0000	0.0014	0.0017	0.0021	0.0021	0.0020	0.0022	0.0023	0.0025
14	0.0000	0.0013	0.0015	0.0019	0.0020	0.0018	0.0019	0.0020	0.0021
15	0.0000	0.0015	0.0017	0.0021	0.0021	0.0019	0.0022	0.0022	0.0023
16	0.0000	0.0013	0.0016	0.0019	0.0020	0.0018	0.0019	0.0021	0.0021
17	0.0000	0.0014	0.0017	0.0020	0.0021	0.0019	0.0021	0.0022	0.0023
18	0.0000	0.0014	0.0016	0.0020	0.0022	0.0020	0.0022	0.0022	0.0023
19	0.0000	0.0014	0.0018	0.0022	0.0022	0.0020	0.0022	0.0020	0.0024
20	0.0000	0.0013	0.0016	0.0019	0.0020	0.0018	0.0020	0.0017	0.0022
21	0.0000	0.0013	0.0015	0.0017	0.0018	0.0016	0.0017	0.0018	0.0020
22	0.0000	0.0014	0.0016	0.0019	0.0020	0.0017	0.0018	0.0020	0.0021
23	0.0000	0.0013	0.0015	0.0018	0.0019	0.0017	0.0019	0.0019	0.0020
24	0.0000	0.0014	0.0017	0.0020	0.0022	0.0020	0.0021	0.0022	0.0022
25	0.0000	0.0014	0.0016	0.0020	0.0021	0.0018	0.0020	0.0022	0.0023

Based on the data of lumen maintenance rate and chromaticity shift degree of two sets of samples, combine the two sets of data into pairs and use MATLAB to obtain the mean vector and covariance matrix of the two performance values at each time step, as shown in table 5.

Table 5. Mean vectors and covariance matrices of two performance metrics at different time points

Time	Mean value	Covariance
0h	$\mu_{0h} = (100, 0)$	$\sum_{0h} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$
1008h	$\mu_{1008h} = (99.3000, 13.2800)$	$\sum_{1008h} = \begin{pmatrix} 0.0817 & -0.0375 \\ -0.0375 & 1.2933 \end{pmatrix}$
1722h	$\mu_{1722h} = (99.1240, 15.8000)$	$\sum_{1722h} = \begin{pmatrix} 0.1094 & -0.0742 \\ -0.0742 & 1.4167 \end{pmatrix}$
2389h	$\mu_{2389h} = (98.4080\ , 19.0800)$	$\sum_{2389h} = \begin{pmatrix} 0.1533 & -0.1715 \\ -0.1715 & 2.5767 \end{pmatrix}$
3128h	$\mu_{3128h} = (98.3720, 20.0800)$	$\sum_{3128h} = \begin{pmatrix} 0.2263 & -0.2685 \\ -0.2685 & 2.5767 \end{pmatrix}$
3815h	$\mu_{3128h} = (98.3760, 18.1200)$	$\sum_{3815h} = \begin{pmatrix} 0.2844 & -0.1887 \\ -0.1887 & 2.3600 \end{pmatrix}$

4505h	$\mu_{4505h} = (98.1880, 19.8800)$	$\sum_{4505h} = \begin{pmatrix} 0.3328 & -0.3015 \\ -0.3015 & 3.3600 \end{pmatrix}$
5218h	$\mu_{5218h} = (97.9000, 20.5200)$	$\sum_{5218h} = \begin{pmatrix} 0.2633 & -0.2458 \\ -0.2458 & 3.4267 \end{pmatrix}$
6029h	$\mu_{6029h} = (97.8200, 22.0000)$	$\sum_{6029h} = \begin{pmatrix} 0.2883 & -0.2708 \\ -0.2708 & 2.7500 \end{pmatrix}$

Combining the classic fitting function mentioned in Section 3.2, data fitting was performed to obtain the expressions of the mean vector and covariance matrix over time, as shown in table 6.

Table 6. Expression of mean vector and covariance matrix over time

	Fitting results	P value
值	$\mu_1(t) = -0.00034131 \times t + 99.66457201$	0.000093354635233
	$\mu_2(t) = 0.00274413 \times t + 8.04832100$	0.007583024635715
	$Cov_{11}(t_d) = 0.000052137380764 \times t_d + 0.032150099047754$	0.000335645117068
	$Cov_{12}(t_d) = -0.000049844385881 \times t_d - 0.019125361234950$	0.001069336393232
方差	$Cov_{12}(t_d) = -0.000049844385881 \times t_d - 0.019125361234950$	0.001069336393232
	$Cov_{22}(t_d) = 0.000485013450266 \times t_d + 0.696659543812480$	0.001828805895463

By inputting the results of table 6 into equation (20), the corresponding reliability attenuation curve was obtained by selecting the LED lumen flux to decrease to 70% of the initial value and the chromaticity shift tolerance of 0.007 as its failure threshold, as shown in figure 1.

When the LED is reliable, the lifespan of the white LED is 23155 hours.

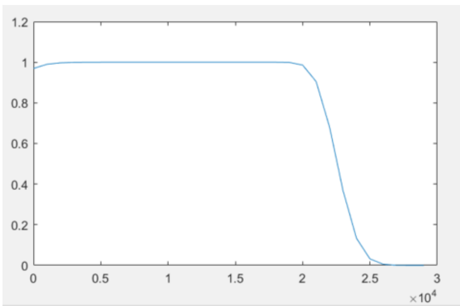

Figure 1. Reliability attenuation curve

5. Conclusion

Based on the sorting and research of covariance matrix knowledge, it was found that its model is simple and computationally efficient, which can better describe the correlation between the two degradation performances of LED, providing a convenient calculation method for dependent multi key performance failure components. After constructing the covariance model, the model was validated with a case study, and the results showed that this method can obtain a large amount of reliability information for LED products, including life probability density function and reliability function. This information can help evaluate the reliability of LED products more accurately.

References

[1] Fan, J J. Model-based failure diagnostics and reliability prognostics for high power white light-emitting diodes lighting: [D]. Hong Kong: The Hong Kong Polytechnic University, 2014.
[2] An D, Kim N H, Choi J H. Practical options for selecting data-driven or physics-based prognostics algorithms with reviews[J]. Reliability Engineering & System Safety, 2015, 133:223–236.
[3] Lan S, Tan C M. Application of Particle Filter Technique for Lifetime Determination of a LED Driver[J]. IEEE Transactions on Device & Materials Reliability, 2015, 15:163-173.
[4] Lall P, Zhang H, Davis L. Assessment of Lumen Degradation and Remaining Life of LEDs Using Particle Filter[J]. American Society of Mechanical Engineers, 2013: V001T04A024.
[5] AN Padmasali BTech, SG Kini Prognostic algorithms for L70 life prediction of solid state lighting. Lighting Res. Technol. 2015; 0: 1–16
[6] Shen H P. Research on Reliability Prediction Mechanism of High Power LED[D]. Zhejiang University, 2008.
[7] Qian M H, Lin Y D, Sun Y J. LED lifespan prediction model based on the theory of light electricity thermal lifespan[J]. Journal of Optics, 2012, 08(8):177-182.
[8] Zhang Q. Research on Temperature and Humidity Accelerated Life Test of High Power LED Modules[D]. Huazhong University of Science and Technology, 2011.
[9] Projecting Long-term Lumen Maintenance of LED Light Sources, Illuminating Engineering Society, IES TM-21-11, USA, 2011.
[10] Zhong Q H, Zhang Z H, Liang S J. A reliability analysis method based on multivariate degradation data[J].System Engineering Theory and Practice, 2011, (03):544-551.