Anomaly Detection of Light-Emitting Diodes Using the Similarity-Based Metric Test

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Abstract—Today’s decreasing product development cycle time requires rapid and cost-effective reliability analysis and testing. Qualification is the process of demonstrating that a product is capable of meeting or exceeding specified requirements. Light-emitting diode (LED) qualification tests are often as long as 6000 h, but this length of time does not guarantee the typically required lifetime of 10 years or more. This paper presents a prognostics-based technique that reduces the LED qualification time. An anomaly detection technique called the similarity-based metric test is developed to identify anomalies without utilizing historical libraries of healthy and unhealthy data. The similarity-based metric test extracts features from the spectral power distributions (SPDs) using peak analysis, reduces the dimensionality of the features using principal component analysis, and partitions the data set of principal components into groups using a k-nearest neighbor (KNN)-kernel density-based clustering technique. A detection algorithm then evaluates the distances from the centroid of each cluster to each test point and detects anomalies when the distance is greater than the threshold. From this, the dominant degradation processes associated with the LED die and phosphors in the LED package can be identified. In our case study, anomalies were detected at less than 1200 h using the similarity-based metric test. Thus, our method could decrease the amount of LED qualification testing time by providing users with an earlier time to begin remaining useful life prediction without waiting 6000 h as required by industrial standards.

Index Terms—Anomaly detection, clustering, light-emitting diode (LED), prognostics and health management (PHM), prognostics-based qualification, similarity-based metric test.

I. INTRODUCTION

LIGHT-EMITTING diodes (LEDs) have been implemented in a wide range of applications, such as medical devices, automobiles, and general lighting, because they enable design flexibility, have low power consumption, and are eco-friendly (e.g., no mercury) [1]–[3]. The U.S. Energy Independence and Security Act of 2007 encourages the use of energy-efficient alternatives, such as LEDs, over incandescent bulbs [4]. However, customers want LED manufacturers to guarantee the lifetimes of their LED products. This has created a competitive edge for LED manufacturers who can guarantee the reliability of their products for the widest array of applications, while getting their products to market more quickly than their competitors.

Qualification tests are conducted to meet the reliability expectations of commercial end users [5], [6]. The performance of LEDs is evaluated during qualification tests, where the performance of the product consists of quality (which includes function) and reliability, and the requirements are set during product design. Qualification test times vary depending on the manufacturer [7]–[9]. Some qualification tests require testing the products to failure in order to provide reliability information about the product [10]. As a result, it can take several years to observe failures under the operating life test conditions. Accelerated testing is used to reduce the qualification test time and predict the lifetime of LEDs by multiplying the estimated lifetime based on the projection of light output degradation (up to 70% of the original light output) by an acceleration factor, often based on the Arrhenius model [11], [12]. In addition to light output degradation, LED manufacturers track color shift during qualification tests. LED lifetime is defined by the general lighting industry as the time to reach 70% light output [13] and 0.007 color shift [14] on the Commission Internationale De L’Eclairage (CIE) 1976 chromaticity diagram. The Illuminating Engineering Society (IES) recommends that LED manufacturers collect color data from LEDs over 6000 h of operation while collecting light output data [13]. The U.S. Department of Energy (DOE) also published the “Energy Star Program Requirements: Product Specification for Luminaires” with the Environmental Protection Agency (EPA) to address LED color failure [15]. It describes color shift using the seven-step standard deviation of color matching (SDCM) in product qualification tests, where the change in chromaticity over the first 6000 h of LEDs should be within 0.007 on the CIE 1976 chromaticity diagram. Color degradation is a critical issue for some application areas of LEDs, such as museum lighting or decorative lighting, as one of the benefits of LEDs is that they can produce a wide range of colors from 2500 K to 12 000 K [1]. If an LED product cannot maintain its initial color properties, the product will lose its advantage over traditional lighting sources, such as fluorescent lamps or incandescent bulbs. The qualification
testing method for color failure utilizes the 0.007 color shift without identifying whether it was die degradation or phosphor degradation. However, if qualification testing could identify the parts in an LED that degrade, such as the die, phosphors, or encapsulant, then the product design, including the geometric dimensions and material properties, can be optimized to meet the specified targets for products.

Light and color output are evaluated from the LED spectral power distribution (SPD). An example SPD for a phosphor-converted white LED is shown in Fig. 1. The phosphors convert some portion of the short wavelength light from the LED (i.e., leaked blue light) into long wavelength light (phosphor-converted light), and the LED light combined with the down-converted light produces the desired white light. Depending on the product design, application, cost, and material properties, the number of SPD components can be two or more. LED phosphors are embedded inside a resin that surrounds the LED die. The two SPDs in the LED SPD show the effects of die degradation, phosphor degradation, and package degradation.

A life prediction method based on the color failure of LEDs has not yet been developed. It is difficult to extrapolate color change because of the differences in the design, materials, manufacturing processes, and optics applied to LEDs and in their use conditions. LED color change has been studied under different current loads [16]–[18], but there is no model that provides detailed information on color degradation. Therefore, an anomaly detection technique is needed for qualification testing to obtain an earlier time to predict the remaining useful life of the products so that accurate prognostics-based qualification can be achieved that does not require 6000 h or increase the prediction error.

Figure 1 shows an approach that uses the entire SPDs for anomaly detection. Figure 2 shows an approach that utilizes each specific SPD, including the die SPD and phosphor SPD. Individual anomaly detection with each SPD (i.e., die and phosphor) in the entire SPD was conducted to identify the die and the phosphor degradation or to determine whether the die or phosphors degrade faster depending on the failure mechanisms of the LEDs. The die SPD and phosphor SPD were separated based on the wavelength range (in this case study, 380–495 nm for the die SPD and 495–745 nm for the phosphor SPD) in the entire SPD. Song and Han [25], [26] also stated that an SPD is required to analyze the performance of LEDs, since the die and phosphor SPDs are changed by different degradation mechanisms.

The detection method is described in Section II as follows. Twelve features [e.g., peak area, full width at half maximum (FWHM), and peak centroid] were extracted from each die and phosphor SPD (see Section II-A). Then, the features from all
the component SPDs (i.e., using the entire SPD) in Fig. 2 and the features from each separate SPD in Fig. 3 were reduced to three principal components to reduce the dimensionality (see Section II-B). Each data set (the entire SPD, die SPD, and phosphor SPD) was partitioned into clusters using a k-nearest neighbors (KNN)-kernel density-based clustering technique (see Section II-C). The similarity-based metric test was developed to evaluate the distance from each centroid in each individual cluster to the test data points to conduct anomaly detection (see Section II-D). If the distance was greater than the predetermined threshold, an anomaly was detected. Otherwise, the algorithm continued to measure the distance between the centroids and the test data points in three-dimensional PC space.

A. Feature Extraction

Data from an aging test were used to develop and validate the anomaly detection process. The test samples in this study were 3 W InGaN white LEDs. Sixteen LEDs samples were mounted on an aluminum metal core-printed circuit board (MCPCB), as shown in Fig. 4. LEDs were in contact with the surface of the top copper (Cu) trace layer of the aluminum MCPCB by SnPb solder. The MCPCB dimensions were 223 mm × 105 mm × 1.6 mm, and the pitch between each LED was 25 mm in each direction.

The test setup is shown in Fig. 5. The test condition was a 350-mA constant current (i.e., the typical current recommended by its manufacturer) and a chamber temperature of 40 °C (as the third temperature by the IES-LM-80-08 standard). The junction temperature was expected to stay below the absolute maximum rating junction temperature of 135 °C [27]. The SPDs of all 16 LEDs were measured after every 22.5 h of exposure to this condition. The relative humidity conditions in both the aging and test environments were controlled in the same conditions and chamber.

The failure criterion was a seven-step SDCM for color shift. The times to color failure data are plotted with a three-parameter Weibull in Fig. 6. The shape parameter was 1.2, the scale parameter was 91.3, and the location parameter was 1859.6. The time-to-failure (TTF) range for color failure was 1891–2206 h. The mean time to color failure was 1945.5 h (referred to as the unadjusted plot) in Fig. 6.

Features were extracted from both the LED die SPD and phosphor SPD, as shown in Fig. 7. The LED die SPD was the wavelength range between 380 and 495 nm, and the phosphor SPD was the wavelength range between 495 and 745 nm. Twelve features were extracted from each SPD: peak area (denoted as $v_1$), average of the peak ($v_2$), peak centroid ($v_3$), peak height ($v_4$), root-mean-square (RMS) ($v_5$), crest factor ($v_6$), standard deviation ($v_7$), skewness ($v_8$), kurtosis ($v_9$), FWHM ($v_{10}$), peak wavelength ($v_{11}$), and left half width ($v_{12}$). The entire SPD was defined by a function $f(x)$ in the range of wavelength $x$ of $a$ and $b$ (i.e., $a < x < b$), as
shown in Fig. 8. All features are described in (1)–(12) in mathematical terms

\[ v_1 = \int_a^b f(x)dx \]  
(1)

\[ v_2 = \frac{1}{b-a} \int_a^b f(x)dx \]  
(2)

\[ v_3 = \frac{\int_a^b x f(x)dx}{\int_a^b f(x)dx} \]  
(3)

\[ v_4 = h \]  
(4)

\[ v_5 = \text{RMS}_x = \sqrt{\frac{1}{b-a} \int_a^b f(x)^2dx} \]  
(5)

\[ v_6 = \frac{h}{\text{RMS}_x} \]  
(6)

\[ v_7 = \sqrt{\left[ \frac{\int_a^b f(x)^2dx}{b-a} \right]^2 - \left[ \frac{1}{b-a} \int_a^b f(x)dx \right]^2} \]  
(7)

where \( x_1, x_2, v_4, v_{10}, \) and \( v_{11} \) are shown in Fig. 8, and \( N \) is the number of data points in the SPD by optical measurements.

B. Dimensionality Reduction Using Principal Component Analysis

Principal component analysis, an exploratory data analysis technique, was used to transform the 24 extracted features (12 from the die SPD and 12 from the phosphor SPD) into principal components. A number of training data points (i.e., the initial test data points) can be applied to detect anomalies. Having a larger number of training data points reduces the error in anomaly detection because more training data points include more information on the degradation trend of LEDs. To analyze the detection accuracy into the number of training data points, anomaly detection using the entire SPD, with die and phosphor SPDs together, was conducted with four different training data sets: 10 data points, 20 data points, 30 data points, and 40 data points from each LED.

For each LED, 123 data points were collected. The data points that were not used in the data set were used for testing (i.e., anomaly detection). In addition to detection with the entire SPD, anomaly detection was conducted for each SPD from each LED with 10 data points, 20 data points, 30 data points, and 40 data points. Each training data set was used to evaluate the loading matrix and variances for the principal component analysis. The principal component scores for the test data points were obtained by multiplying the loading matrix and the feature vectors.

The 12 features for the die SPD and the phosphor SPD were reduced to three principal components using the Scree test results for dimensionality reduction, as shown in Figs. 9 and 10, respectively. The Scree test plots the principal components in the x-axis and their corresponding eigenvalues (i.e., variances of principal components) in the y-axis. All of the points along the level part of the line, including the transition point, are dropped, and three points are counted along the precipitously dropping part of the line.

C. KNN-Kernel Density-Based Clustering

Clustering is the process of partitioning a set of data (or objects) into sets of meaningful subclasses called clusters. A cluster is a collection of data (or objects) that are similar (based on proximity measures) to one another, and thus can
be treated collectively as a group [28], [29]. It is difficult to define clusters and to determine the number of clusters in data when clusters have different sizes, densities, and shapes [30], [31]. Also, it is challenging to find clusters in data when the data contain a large amount of noise and outliers, particularly with higher dimensional data.

Density-based clustering algorithms define clusters based on the density of data points in a region. In other words, density-based algorithms define a cluster as a region in the data space that exceeds a given density threshold. One advantage of density-based clustering is that it can identify clusters of arbitrary shapes. For anomaly detection in this paper, clusters were partitioned with a KNN-kernel density-based clustering technique. The KNN-kernel density-based clustering method is based on a combination of nonparametric KNN and kernel density estimation methods [32]. The KNN-kernel density estimation technique makes it possible to model clusters of arbitrary shapes. For anomaly detection in this paper, clusters were partitioned with a KNN-kernel density-based clustering method.

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The KNN-kernel density-based clustering satisfies the classification rule (i.e., a method to assign objects, or data, to clusters) based on KNN-kernel density estimates [33], [34]. The KNN-kernel density-based clustering algorithm adjusts and selects all parameters and conditions except for the user-defined parameter k, which is the number of neighborhood points. The number of clusters decreases with a larger k. In this study, the optimal number for k was selected by trying multiple values of k and picking the one that captured the features of the data set with three-dimensional (3-D) graphical exploratory data analysis. The optimal numbers for k for 160, 320, 480, and 640 training data points with the entire SPD were 12, 19, 22, and 28, respectively. The number of partitioned clusters from the four training data sets was 9 for a data set with 160 training data points, 10 for a data set with 320 training data points, 8 for a data set with 480 training data points, and 14 for a data set with 640 training data points. The results show that having more training data results in better cluster formation.
To identify the degradation components in the LED package, the optimal numbers for $k$ were 60 (for 480 training data points) and 68 (for 640 training data points) using the triangular kernel function for both the die SPD and the phosphor SPD. In addition to the 3-D graphical exploratory data analysis, a plot similar to the Scree test was used to determine the correct number of clusters in the data set. The “protrusion of the curve” in the plot (along the sharply declining part of the line) was considered based on within-cluster sum of squares (WCSS) to choose the number of clusters. The WCSS was defined for given a set of observations $(x_1, x_2, \ldots, x_n)$, where each observation is a $d$-dimensional real vector. The KNN-kernel density-based clustering partitions the $n$ observations into $k$ sets ($k \leq n$) of clusters $C = \{C_1, C_2, \ldots, C_k\}$ with the centroid $v_j$ in cluster $C_j$ [35], [36]

$$\text{WCSS} = \sum_{i=1}^{k} \sum_{x_j \in C_j} \|x_j - v_j\|^2. \quad (18)$$

Two training data sets (one for die SPD and the other for phosphor SPD) were partitioned with seven clusters by the algorithm for a data set with 480 training data points, as shown in Figs. 12 and 13. Elbows (i.e., protrusion of the curve) were observed in the third and seventh clusters shown in Fig. 12 and in the second and seventh clusters shown in Fig. 13. Due to multiple bins (i.e., classification) of LEDs based on optical properties (such as light output and color) in the specification sheet, the degradation paths and patterns of LEDs were grouped in seven clusters rather than in two or three clusters.

Anomaly detections were made with three clusters for die SPD training data and two clusters for phosphor SPD training data with 480 data points. The detection results missed the anomalies. Seven clusters were utilized for both die SPD, as shown in Fig. 14, and phosphor SPD training data, as shown in Fig. 15. With the same algorithm, two training data sets with 640 training data points were partitioned with eight clusters.

D. Similarity-Based Metric Test for Anomaly Detection of LEDs

After partitioning the training data into clusters using the KNN-kernel density-based clustering technique, the similarity-based metric test (depicted in Fig. 16) was conducted to detect anomalies in the color change. When the training data were partitioned with $m$ clusters, each centroid $(V_j)$ from each cluster was evaluated. Then, the distance $(D_j)$ between one data point and each cluster was evaluated with the Euclidian distance from the data point to the centroid. The distance from each cluster was evaluated and compared to a predetermined threshold. The detection threshold $(T_j)$ for anomaly detection was the threshold of the cluster with the shortest distance $(D_j)$ from the threshold (i.e., the maximum $T_j - D_j$ distance). This procedure was repeated for the next test data point if the distance $(D_j)$ was smaller than the detection threshold $(T_j)$. If the distance $(D_j)$ was greater than the detection threshold $(T_j)$, then the algorithm detected an anomaly.
The mean radius \( R(C_j) \) is the average distance from member points in the cluster to the centroid of each cluster. In other words, the mean radius \( R(C_j) \) is a measure of the tightness of the cluster around the centroid. Given \( m \)-dimensional data vectors \( v_i \) in a cluster \( C_j = \{v_i | j = 1, 2, \ldots, m\} \), the centroid \( v_j \) and mean radius \( R(C_j) \) are evaluated as \([37], [38]\):

\[
v_j = \frac{\sum_{i=1}^{m} v_i}{m}
\]

(19)

\[
R(C_j) = \sqrt{\frac{\sum_{i=1}^{m} (v_i - v_j)^2}{m}}.
\]

(20)

If the data form a spherical shape, the detection threshold \( T_j \) is ideally the mean radius \( R(C_j) \) of the closest cluster. The data shown in Figs. 14 and 15 are not spherical, but elliptical. The elliptical shape has regions of clusters wider than the mean radius \( R(C_j) \) and regions of clusters narrower than the mean radius \( R(C_j) \). So, the accuracy of the detection is determined by the detection threshold. If the cluster shapes are not spherical, then the threshold is in a range between the minimum distance from the centroid (i.e., the distance between the closest member point and the centroid) and the maximum distance from the centroid (i.e., the distance between the farthest member point and the centroid) in the cluster.

The threshold changes the sensitivity of the anomaly detection. In other words, the fault detection rate increases if the detection threshold \( T_j \) is close to the minimum distance from the centroid in the cluster, whereas the missed alarm rate increases if the detection threshold \( T_j \) is close to the maximum distance from the centroid in the cluster. To improve the accuracy of anomaly detection, the distributions of points in a cluster are considered to define a new threshold for each cluster. In this study, a detection threshold metric was developed as

Detection threshold \( T \) = mean radius \( r \) + standard deviation \( \sigma \) dimensional factor \( d \)

(21)

where the standard deviation \( \sigma \) is the standard deviation of all distances of member points from the centroid in the cluster and the dimensional factor \( d \) is the number of dimensions of the data space. In this study, the dimensional factor \( d \) was 3, because data analysis was conducted in 3-D principal component space, as shown in Figs. 2 and 3. This metric minimizes the error from the cluster shape and the data distribution of the cluster.

The anomaly detection threshold is determined with data characteristics in terms of the similarity-based metric (i.e., unit) based on feature extraction from SPD, dimensionality reduction in principal components, and grouping with the KNN-kernel density-based clustering technique. The data characteristics are based on the degradation of LEDs in each test condition and on the device under test (DUT). Anomalies are detected with the early signature of degradation characteristics in terms of the new similarity-based metric. For this reason, the detection threshold does not change in terms of \( n \)-step SDCM (e.g., even if the conventional color failure threshold does change from 0.007 threshold to 0.004). In the case of 0.004 color shift, 94% (i.e., 15 of 16) of anomalies was successfully detected using the same detection thresholds as in the case of 0.007 color shift. This means that the developed threshold defining method is more consistent than the conventional \( n \)-step SDCM method.

1) Anomaly Detection Using the Entire SPD: For the entire SPD, including both the die SPD and the phosphor SPD, 160 training data points were used to detect anomalies, with the thresholds of both the mean radius in (20) and the developed detection threshold in (21). The centroids of the clusters were evaluated using (19) for the ten clusters. Data were collected for 123 days in total, with 113 days for anomaly detection after the initial data points and 10 days to create the clusters. When a new data point was collected during the accelerated test, the closest cluster was found by evaluating the distance \( D_j \) of the data point from the each centroid \( (C_j) \). Anomalies were detected when \( D_j \) was greater than \( T_j \), as shown in Fig. 16.

Data points from LED 15 are used to illustrate this detection scheme. Detailed distance plots were constructed for the entire data collection period from clusters 1 to 8 for LED 15 utilizing the developed detection thresholds. Clusters 1 and 2 gave false alarms, as shown in Figs. 17 and 18, respectively, with an alarm at 11 days immediately after starting the detection algorithm.

An anomaly was detected at day 72 from cluster 8, as seen in Fig. 19. The anomaly was detected in cluster 8 because the maximum \( T_j - D_j \) distance came from cluster 8. The actual TTF for LED 15 was day 88. The distance plots of clusters 3, 4, and 5 are similar to cluster 1, as shown in Fig. 17, while the distance plots of clusters 6, 7, and 9 are similar to cluster 2, as shown in Fig. 18.

Application of the developed detection threshold improved the anomaly detection rate from 25% (4 of the 16 LEDs) with the mean radius metric to 50% (8 of the 16 LEDs) for the case with 160 training data points, as shown in Table I. A false alarm was defined as when anomalies were detected immediately after beginning the algorithm (within 5% of the ratio of the detection time divided by the actual TTF).
Detection results with 320, 480, and 640 training data points were also improved using the detection threshold in (21).

Table I summarizes the anomaly detection results for LEDs based on the similarity-based metric test. As the number of training data points increases, the anomaly detection rate increases. Anomalies were successfully detected in 81.25% of LEDs using 14 clusters with 640 training data points, as shown in Fig. 20. The algorithm missed an alarm for LED 14, where the anomaly was detected at day 88, but the actual TTF was day 84 (Fig. 20). The detection rate increases with the number of training data points. The initial data points have variation caused by the short-term aging effect of the color degradation parameters. When the number of training data points increases, the short-term aging effect is decreased and the detection accuracy increases. The detection results showed that the similarity-based metric test can provide advance warning of failures.

2) Anomaly Detection Using Die SPD and Phosphor SPD: An advanced technique that does not necessarily wait until the signature of the anomalies is close to the TTF, as shown in Fig. 20, is required for the fast qualification of LEDs. The die SPD and the phosphor SPD were independently utilized for anomaly detection to identify the die and phosphor degradation and to determine whether the die or phosphors degrade faster. As a case study, the training data set with 480 data points (i.e., 30 data points from each of the 16 LEDs) was partitioned into seven clusters, as shown in Fig. 14 for the die SPD and Fig. 15 for the phosphor SPD, and 93 data points from each LED were used for anomaly detection. LED 3 is used to illustrate the detection scheme. First, the centroids of the clusters were evaluated using (19) for seven clusters. Then the developed threshold \( (T_j) \) of each cluster from the die SPD and phosphor SPD were calculated.

The distances from the centroids of the clusters to the new data points of LED 3 were evaluated for the entire data collection period. The \( T_j - D_j \) distances over time were greatest at cluster 4 for the die SPD and cluster 2 for the phosphor SPD. An anomaly was detected at day 59 from cluster 4 for the die SPD, as shown in Fig. 21. An anomaly was detected at day 83 from cluster 2 for the phosphor SPD, as shown in Fig. 22. The actual TTF for LED 3 was day 91.
Fig. 21. Distance measure of cluster 4 from LED 3 for the die SPD.

Fig. 22. Distance measure of cluster 2 from LED 3 for the phosphor SPD.

Fig. 23. Anomaly detection using 480 data points (i.e., 30 data points from each LED).

Fig. 24. SPD changes at different detection times for LED 3.

Fig. 25. Anomaly detection using 640 data points (i.e., 40 data points from each LED).

Fig. 23 shows the anomaly detection results for all LEDs based on the similarity-based metric test using 480 data points. The results showed that die degradation is an earlier sign of color failure of LEDs than phosphor degradation. Therefore, die degradation initiates color failure of LEDs. As a result, future package designs must consider how to strengthen LED die performance.

The die and phosphor degradation can be explained by SPD changes over time during the aging test. The SPDs for LED 3 at day 0, the anomaly detection times for die and phosphor SPDs, and the actual TTF are shown in Fig. 24. The phosphor SPD degraded together with the die SPD due to die degradation. All LEDs degraded in a manner similar to the result in Fig. 24. In Fig. 23, most of the anomalies from the die SPDs were detected in less than 1000 h. This shows that this test can reduce the time needed for predicting the remaining useful life of LEDs during qualification tests. The starting point for early anomaly detection is the earliest time at which users can begin to predict the remaining useful life of LEDs.

For all LEDs, the die SPD increased from day 0 until detection (i.e., days 59 and 83), and then decreased to the initial day 0 value at the actual TTF. On the other hand, the phosphor SPDs decreased from day 0 until the actual TTF. The amount of die degradation was less (i.e., 0.066) than the amount of phosphor degradation (i.e., 0.143), but the die degradation detected the anomalies earlier than the phosphor degradation. As seen in Fig. 25, using the same algorithm with 640 data points, the anomalies were first detected from the die degradation and later from the phosphor degradation. The anomalies were detected at about 1200 h in the die SPD data. The detection time for both the die and phosphor SPDs increased due to the larger amount of training data (640 data points vs. 480 data points), and therefore provided more information about the degradation trends.

III. DISCUSSION

This is the first study to use SPD for anomaly detection in qualification tests. SPD, which denotes the radiant power at each wavelength per wavelength interval in the visible spectrum, can be used to obtain degradation information for LEDs. The similarity-based metric test utilizes features from
the SPDs as leading indicators. The entire SPD of the tested LEDs includes two parts: 1) SPD from the LED die; and 2) SPD from the phosphors. LED phosphors are embedded inside a resin that surrounds the LED die. The blue light emitted from the die excites the phosphors, which then emit yellow light; the blue light and yellow light combine to emit white light.

Previous research driven by industrial standards has utilized $u'v'$ color shift in the CIE 1976 chromaticity diagram to explain color change in LEDs. Color shift can be used to identify color change; however, it cannot explain the internal phenomena of how each optical element in the entire SPD degraded.

The aging time varies depending on the range of the color temperatures (usually having different spectral shapes), the test condition with applied current, the ambient temperature, and the humidity. In the test conditions recommended by the IES standards, the measurement has to be continued for at least 6000 h. When the test conditions are over stress test conditions (i.e., more severe than the IES test conditions), the number of training data points can be modified based on the level of stress and possible type of failure mechanisms for quick anomaly detection.

The similarity-based metric test was developed to diagnose degradation in the die and phosphors inside LEDs using the KNN-kernel density-based technique to cluster the data with independent optical components in the SPDs and measure the distance from the centroid. The underlying assumption is that die degradation reduces the phosphor SPD as well as the LED die SPD. As the amount of photons extracted from the LED die is reduced, the amount of phosphor light converted from the short wavelength (i.e., the LED die SPD) is also reduced. When phosphors are only degraded by phosphor thermal quenching, the phosphor SPD decreases and the LED die SPD will not change shape, since the LED die emits light as a normal condition independent of phosphor degradation.

The similarity-based metric test does not require historical data. It integrates the advantages of anomaly detection under wearout performance degradation and is suitable for the qualification of new products. LED manufacturers can use the similarity-based metric test to increase the quality of their LED products by detecting anomalies early on and fixing potential problems. Combined with a remaining useful life (RUL) prediction method, this process will make product development, design improvement, and qualification better and will reduce qualification testing time. This will enhance the competitiveness of LED manufacturers that employ the qualification method by enabling them to quickly identify bad batches or designs during tests. As LED lighting is a growing field in the world, the similarity-based metric test will enable new technologies to be assessed and improved more rapidly.

IV. CONCLUSION

The similarity-based metric test for LED anomaly detection presented in this paper extracted features from the SPD, reduced the dimensionality of the features by using principal component analysis, and grouped the data set into clusters using the KNN-kernel density-based clustering technique. Then, the distances from the centroid of each cluster to each test point were measured. The algorithm detected anomalies when the distance was larger than the predetermined threshold. This technique can be applied to any type of phosphor-converted white LED composed of two or more optical elements in terms of different types of dies and phosphors in the entire SPD with various correlated color temperatures such as warm white, neutral white, and cool white LEDs.

The similarity-based metric test can significantly decrease the amount of time needed for LED qualification by using prognostic techniques. This anomaly detection method will provide users with an earlier time to begin remaining useful life prediction than LED qualification tests, such as those based on the IES LM-80-08 standard and the U.S. DOE’s “Energy Star Program Requirements: Product Specification for Luminaires,” which require at least 6000 h of test time. The similarity-based metric test presented in this paper can potentially decrease the amount of time needed for qualification testing to about 1000 h.

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REFERENCES
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