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Article

Prognostics and Health Monitoring of High Power LED

Thamo Sutharssan *, Stoyan Stoyanov, Chris Bailey and Yasmine Rosunally

Computational Mechanics and Reliability Group, University of Greenwich, Old Royal Naval College, Park Row, London SE10 9LS, UK; E-Mails: S.Stoyanov@gre.ac.uk (S.S.); C.Bailey@gre.ac.uk (C.B.); Y.Z.Rosunally@gre.ac.uk (Y.R.)

* Author to whom correspondence should be addressed; E-Mail: T.Sutharssan@gre.ac.uk; Tel.: +44-20-8331-8669; Fax: +44-20-8331-8665.

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Abstract: Prognostics is seen as a key component of health usage monitoring systems, where prognostics algorithms can both detect anomalies in the behavior/performance of a micro-device/system, and predict its remaining useful life when subjected to monitored operational and environmental conditions. Light Emitting Diodes (LEDs) are optoelectronic micro-devices that are now replacing traditional incandescent and fluorescent lighting, as they have many advantages including higher reliability, greater energy efficiency, long life time and faster switching speed. For some LED applications there is a requirement to monitor the health of LED lighting systems and predict when failure is likely to occur. This is very important in the case of safety critical and emergency applications. This paper provides both experimental and theoretical results that demonstrate the use of prognostics and health monitoring techniques for high power LEDs subjected to harsh operating conditions.

Keywords: real-time health monitoring; data driven prognostics; high power LED

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1. Introduction

Prognostics and health monitoring is a technology used to monitor degradation in engineering systems, understand when failure may occur, and provide a cost effective strategy for scheduled maintenance. Health monitoring and prognostics of engineering systems or products has become very important as failures may cause severe damage to the system, environment and users, and may result in

significant costly repairs. Adopting health monitoring and prognostics techniques requires continuous monitoring of key performance parameters and detecting any anomalies in these parameters.

Even though typical life time of a high power light emitting diode (LED) is very high, typically specified in the order of 50,000 h [1], statistics show that half of the light emitting diodes fail before this limit is reached. The reason for this is that this specification is not based on individually measured characteristics of LEDs. Therefore, manufacturers and lighting system designers still need to monitor the health of assembled LEDs and predict their failures, especially for safety emergency critical applications in sectors such as aerospace, medical, energy and others.

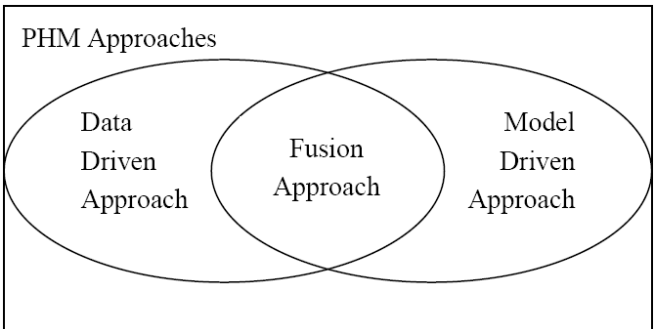
Numerous papers have been published that characterise the reliability and thermal behaviour of LEDs [1–9]. Recent publications have detailed the importance of temperature on the reliability of LEDs and the need for suitable packaging to ensure that appropriate heat is extracted [4]. Physics of Failure Models for high power LEDs have also been developed where thermomechanical models have been used to characterise a number of failure modes [10]. At present there is no reported work on real-time monitoring of LED degradation or the use of data driven models to predict degradation and remaining useful life for LEDs. This paper investigates two data driven methods which can easily be programmed onto a microcontroller for real time monitoring of LEDs.

This paper demonstrates a data driven prognostics approach to monitor and identify LED failures, based on the requirement for the light output power. In the case of general lighting it is established that the light power should not be less than 70% of the initial power of the lights (referred to as typical expectation of the light power) [5]. It is also reported that the LED actually will not fail physically, but rather its light output power will decrease with time [5]. Therefore, the approach adopted in this work is to assess the life of an LED lighting system after their deployment based on the power of the light output emitted. This paper discusses two distance measure techniques, (i) Euclidean Distance and (ii) Mahalanobis Distance that have been used to analyse the degradation of light output and assess remaining life-time of LEDs. These data driven techniques are based on monitoring selected operational and performance indicators using sensors. The main advantage of these two distance measure techniques is that they can be implemented in a microcontroller used to control the LED drive circuit, and hence monitor the LED degradation in real time.

2. Prognostics Approaches

Figure 1 illustrates the three approaches to prognostics, which are (i) Data driven, (ii) Model driven and (iii) Fusion based modeling which combines both (i) and (ii) methodologies.

Figure 1. Prognostics and health management approaches.



2.1. Data Driven Approach

Data driven approach is considered as a black box approach to PHM as they do not require system models or systems specific knowledge to start the prognostics [11]. Monitored and historical data are used to learn the systems behaviours and used to perform the prognostics. Hence the data driven approach is suitable for the systems which are complex and which behaviours cannot be assessed and derived from first principles. The implementation of data driven techniques for the purpose of health monitoring and prognostics generally based on the assumption that the statistical characteristics of system's performance will not change until fault occurs [11]. Therefore, the main advantage of data driven approach is that the underlying algorithms are quicker to implement and computationally more efficient to run compared to other techniques. However, it is necessary to have historical data and knowledge of typical operational performance data, the associated critical threshold values and their margins. Data driven techniques rely completely on the analysis of data obtained from sensors and exploit operational or performance related signals that can indicate the health of the monitored system. Data driven strategies for diagnostics and prognostics have been applied in a number of different Prognostics and Health Management (PHM) applications [12–19].

The principal disadvantage of the data driven approach is that the confidence level in the predictions depends on the available historical and empirical data. Historical and empirical data are required in the data driven approach to define the respective threshold values. In some instances it is difficult to obtain or have historical data available, for example in the case of a new system or device that may require long time and/or expensive tests to failure to generate this data. However, there are techniques and procedures available that can be used to achieve this [20,21]. Two of the strategies used to address this challenge are based on the use of:

1. Hardware-in-the-Loop simulations (HiL).

   Hardware-in-the-Loop is a computer simulation which is used to test a real product or system by connecting it hardware that applies simulated loads as in real application. It is very fast and cheap to implement. In addition, several failure parameters (*i.e.*, operational and environmental) can be controlled independently. HiL can also be used for algorithm development, testing and validation, benchmarking and development of metrics for prognostics [20].

2. Accelerated Life Test (ALT)

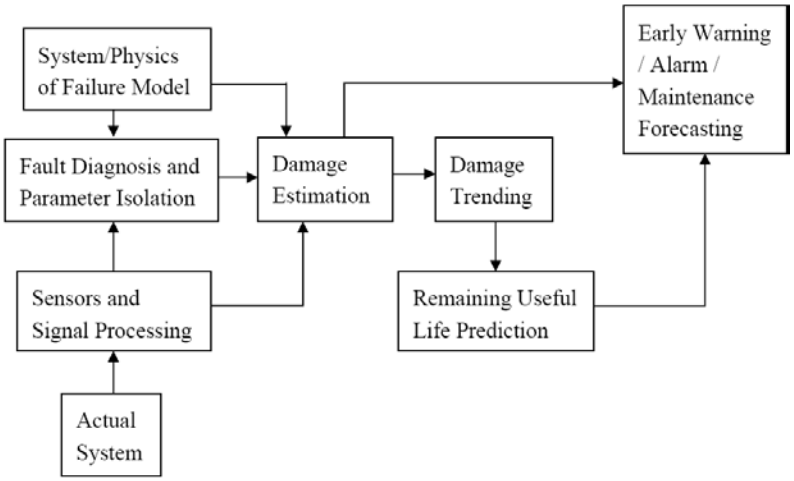
   Accelerated load test is designed to cause the product to fail more quickly than under normal conditions by applying accelerated (elevated) stress conditions resulting in the same failure mechanisms. ALT becomes an important methodology in the development of the PHM for electronics. Several environmental and loading conditions can be applied independently to accelerate the failure [21].

2.2. Model Driven Approach

The model driven approach uses mathematical equations that predict the physics governing failures and therefore is sometimes referred to as the Physics of Failure (PoF) approach. It requires knowledge of the failure mechanisms, geometry of the system, material properties and the external loads being

applied to the system. An accurate mathematical model can benefit the prognostics process, where the difference between the output from a mathematical model and the real output of the system can be used to find the anomalies, malfunctions, disturbance *etc*. [22]. Using the difference between model and data values for a performance parameter, the early warnings for failures and remaining useful life can be predicted. There are many PHM work have been reported based on model-driven approach [16–19,22–26]. A block diagram of a typical model based approach shown below in the Figure 2.

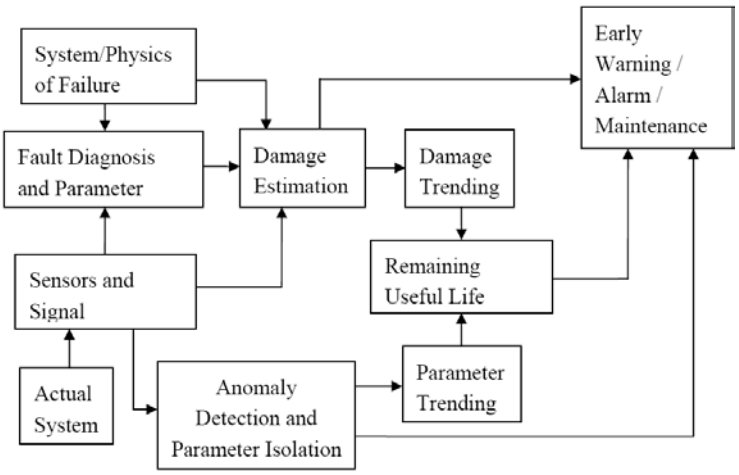
Figure 2. Block diagram of a model driven approach.



2.3. Fusion Approach

The fusion approach is based on the advance features of both data driven and model based approach. This approach will require an accurate mathematical model of the system for physics based failure approach and enough historical data and knowledge of typical operational performance data for data driven approach. The aim of the fusion approach is to overcome the limitations of both the model and data driven approach to estimate the remaining useful life (RUL) [19]. Therefore the accuracy of the fusion approach should be high [19], although for real-time analysis it may not be suitable due to the computational resource required. There are many applications reported based on fusion approach [27–29]. A block diagram of a typical model based approach shown below in the Figure 3.

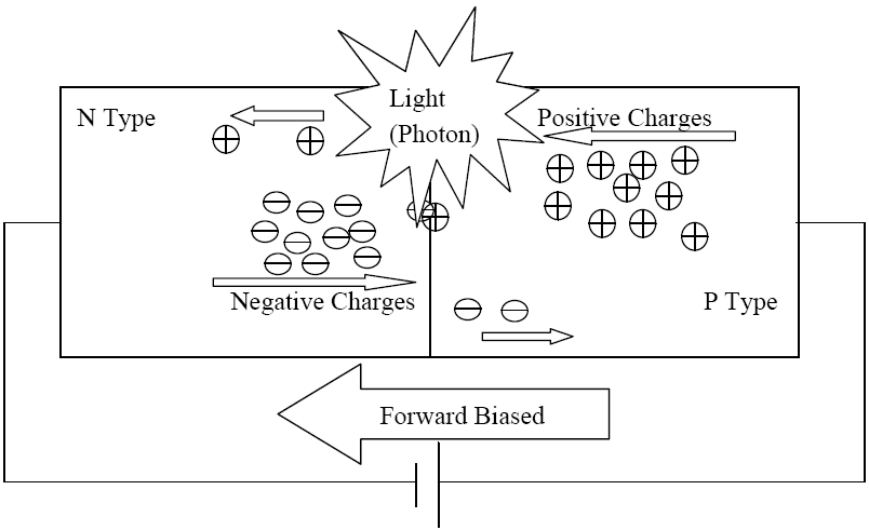
Figure 3. Block diagram of a fusion approach.



3. High Power Light Emitting Diodes (LEDs)

A high power LED is an optoelectronic device which consists of a p-type region, n-type region and a p-n junction. A high power LED is defined as an LED with power equal or greater than 1 Watt. When the LED is forward biased and current passes through the p-n junction, electron in the n-region get sufficient energy to move across the p-n junction into the p-region and holes are injected into the n-region from the p-region through p-n junction [30]. Some of the electrons and holes recombine in the active region (p-n junction) where electrons move one energy band to another. This process is known as the radiative recombination process. When the radiative recombination takes place, energy is released in the form of photons with the wavelength related to the change in the energy band. This process is illustrated in the Figure 4. Applications of High Power LEDs are continuously increasing as they are energy efficient (typically 85%), green (e.g., no mercury), have demonstrated longer life than traditional lighting sources, and emits low UV radiation [30]. Single colour LEDs have demonstrated over ten time efficient than the incandescent lamps and white LEDs are more than two times efficient than the incandescent lamps [30]. For example, typical LEDs can operate for >50,000 h (approximately 11.5 years for a 50% calendar time usage) provided the drive current and p-n junction temperature remain within the limits specified by the manufacturer [4]. For example, for the Philips Luxeon Star when operated in warm white mode, the maximum values recommended for the DC forward current and junction temperature are 350 mA and 135°C respectively [31]. A schematic cross-section of a LED assembly with typical construction is shown in Figure 5.

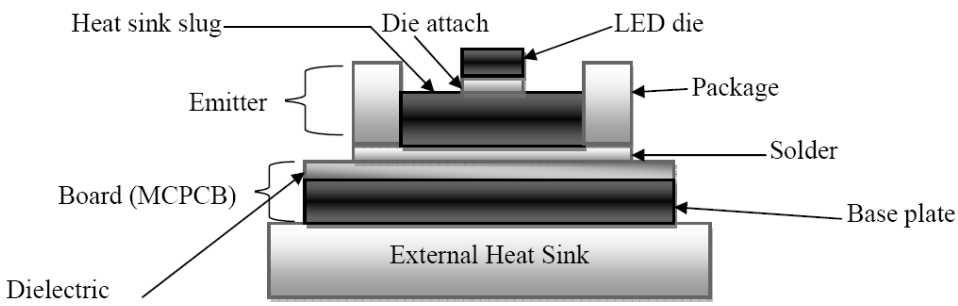
Figure 4. Radiative recombination process in the p-n junction (LED die) where the photon emitted in the form of light.



Previous research in performance of LEDs has shown that gradual reduction of the luminance up to 30% is expected for non-safety critical applications [5]. Therefore, the useful life of a LED for general lighting is given by the time in which it takes for the luminance to reduce by 30% from its initial value. But some for safety critical and emergency application, the amount of luminance reduction allowed may be less than 30%. It should also be noted that the life time specified by the manufacturer is the

average life time of LEDs, and some LEDs would fail before this specified life time due to variations in individual characteristics, manufacturing quality and environmental conditions.

Figure 5. Cross section of LED assembly.



In addition to light output power depreciation, another mode of failure is due to discolouration of the LEDs or LED die encapsulate. Before the light output of an LED depreciates to a certain level, the colour of the light changes with time. This is because of the surrounding environmental conditions such as moisture, temperature, *etc*. Hence the LED lighting systems require maintenance which requires labour and measuring instruments. PHM approach can be used to change the unschedule maintenance activity into an evidence based scheduled maintenance activity which will reduce the maintenance cost by a considerable amount.

Monitoring the light output power and the wavelength of the light in real-time might be difficult as they require light and colour sensors respectively. Although the light sensors are available in the market, placing the sensors into the luminaries is difficult. This work is carried out based on current and temperature measurements to perform the prognostics and health monitoring, and considered only the failure mode related to light output power reduction. We use the 30% reduction of light output as the failure criteria, and any LED in operation that has lumens below this limit is defined as a failed LED.

There is no life time model developed and reported in the literature so far for LEDs [32–34]. The main cause of the failure in the LEDs is the heat generated at the p-n junction [4]. Under the forward bias condition the p-n junction carries a current which is almost an exponential function of the applied voltage which means if there is an increase in the applied voltage, the current through the p-n junction increases exponentially. This characteristic is explained by the Shockley's Equation [35]. An increase in the current will cause the temperature to increase dramatically which means the heat generated in the p-n junction increases.

In the experiments detailed below, the current through the p-n junction and the p-n junction temperature can be defined as the performance indicators of the LED. Therefore, any accelerated test can use the current or the temperature as the stress parameter of the LED. LEDs are controlled by controlling constant current through the sense voltage (analogue diming) or pulse width modulated switching (digital diming) [30]. In this experiment the constant current required to operate the LED is controlled by controlling the forward voltage across the LED and the experiment is designed to test a single LED at a time. This experiment also designed to accelerate the failures based on current and the temperature. Therefore, the forward/applied voltage is used as an accelerating damage condition in the experiments. The acceleration of the applied voltage results in the elevation of both stress parameters (e.g., the current and the temperature).

4. Prognostics for LED's using the Data Driven Approach

The health of a product or system is defined as the extent of deviation or degradation from its expected typical operating performance [36]. This extent of deviation or degradation from the expected typical operating performance has to be determined accurately to assess the reliability of a product and predict its remaining useful life.

In the case of High power LEDs which are semiconductor devices, overall reliability (*i.e.*, an individual LED) depends on several factors such as properties of p-n junction, band gap energy, internal quantum efficiency (*i.e.*, product of current injection efficiency and radiative efficiency), light extraction efficiency, cavities or defects in the active region, *etc*. Modeling these individual LED characteristics for the purpose of prognostics and health monitoring is difficult. Data-driven approach for PHM has been identified as a best candidate as they do not require system specific knowledge but require historical and failure data. Data-driven approach is also easy to implement in particular in a real-time environment. Focus of this paper is to apply data driven approach for the prognostics and health monitoring of the high power LEDs based on light output power degradation failure mode.

Light output power degradation is caused by high temperature at the p-n junction due to the heat generated at the p-n junction. Heat generated depends on the current through the p-n junction. Injection current (current through the p-n junction) and the p-n junction temperature can be used as the performance indicators of the LEDs. Monitoring the current and temperature at the p-n junction and relating them to the drop in output lumens (*i.e.*, power) will provide the ability to monitor the degradation of the LED in real time. To achieve this, two distance measure techniques have been assessed (1) Euclidean Distance and (2) Mahalanobis Distance.

4.1. Euclidean Distance

Euclidean distance (ED) is the physical distance between two data points and it is the most commonly used distance measure in many different fields. It is defined as the distance that examines the root of square differences between any data sets *i.e.*, it can be in any dimension. For a data matrix X which contains n objects measured by p variables (*i.e.*, n × p matrix), ED can be calculated in the vector space as follow [37]:

$$ED_i = \sqrt{(X_i - \overline{X})(X_i - \overline{X})^T} \tag{1}$$

Here $\overline{\boldsymbol{X}}$ is the mean vector. In the case of prognostics and health monitoring of high power LEDs, $\overline{\boldsymbol{C}}$ and $\overline{\boldsymbol{T}}$ are the mean values of current through the p-n junction and p-n junction temperature under typical operating conditions. C_i and T_i are the new observation data. ED_i will be computed for the new observation data as follows (*i.e.*, two dimensional data) [37]:

$$ED_i = \sqrt{(C_i - \overline{C})^2 + (T_i - \overline{T})^2} \tag{2}$$

The ED value will give an estimate of LED's deviation or the degradation from the typical healthy LED. Higher values for the ED will indicate anomalies in the performance and by monitoring the ED values prognostics of LED can be achieved.

4.2. Mahalanobis Distance

Mahanobis distance (MD) is another physical distance measure [37,38]. Although similar to the Euclidean distance, the Mahalanobis distance takes into account the actual correlations of the data sets. Since the health of the system is defined as the deviation from expected typical operating performance, Mahalanobis distance is useful in determining the similarity/distance between the typical operating performance and monitored operating performance. This strategy has been applied successfully in different data-driven PHM approach [38–43]. For a data matrix X which contain n objects measured by p variables as above MD can be estimated in the vector space as follows [37,38]:

$$MD_i = \sqrt{(X_i - \overline{X})Cov_X^{-1}(X_i - \overline{X})^T} \tag{3}$$

Here $\overline{\boldsymbol{X}}$ is the mean vector and Cov_x is the variance-covariance matrix of data matrix X. In the case of prognostics and health monitoring of LEDs, $\overline{\boldsymbol{C}}$ and $\overline{\boldsymbol{T}}$ are the mean values of current through the p-n junction and p-n junction temperature, and Cov_{CT} is the variance-covariance matrix of current and temperature under the typical operating conditions. $\boldsymbol{C_i}$ and $\boldsymbol{T_i}$ are the new observation data. Whenever new data becomes available MD can be calculated as follows for two dimensional data [37].

$$MD_i = \sqrt{(C_i - \overline{C})Cov_{CT}^{-1}(T_i - \overline{T})^T} \tag{4}$$

R De Maesschalck *et al.*, formulated MD formula for two dimensional data using the variance-covariance matrix given below [37]:

$$Cov_{CT} = \begin{bmatrix} \sigma_C^2 & \rho_{CT}\sigma_C\sigma_T \\ \rho_{CT}\sigma_C\sigma_T & \sigma_T^2 \end{bmatrix} \tag{5}$$

In this case σ_C^2 and σ_T^2 are the variance of current and temperature and $\rho_{CT}\sigma_C\sigma_T$ is the covariance of current and temperature under the typical operating conditions. Using these variables MD can be derived as follows [37]:

$$MD_i = \sqrt{\left(\frac{C_i - \overline{C}}{\sigma_C}\right)^2 + \left[\left\{\left(\frac{T_i - \overline{T}}{\sigma_T}\right) - \rho_{CT}\left(\frac{C_i - \overline{C}}{\sigma_T}\right)\right\}\frac{1}{\sqrt{1-\rho_{CT}^2}}\right]^2} \tag{6}$$

The MD value will give an estimate of LED's deviation or the degradation from the typical healthy LED. Higher values for the MD will indicate anomalies in the performance and by monitoring the MD values prognostics of LED can be achieved.

The advantage of the above techniques is that they transform multi-dimensional sensor readings into a single performance parameter. In addition, fault parameters can also be isolated in the event of faults or anomalies in the ED or MD estimates by monitoring the individual sensors data. This can be used to analyse the fault and find the root cause of the anomalies or fault. Using MD or ED techniques for the purpose of health monitoring and prognostics of LEDs require historical data to establish the threshold values representing when the LED is performing outside its safe limits. To generate this data we have used an accelerated voltage to stress the components to failure. As a result of this, the current and the temperature also increase.

5. LED Health Monitoring

Measuring the light output of an LED in real-time (*i.e.*, in the field) is difficult. Instead, performance indicators of the LEDs such as current through the p-n junction, and the p-n junction temperature, can be used to measure any deviations in performance and to realise any prognostics assessment. Current through the p-n junction is measured using power resistors (*i.e.*, current sensor) as the ordinary resistors cannot handle the typical expected current through the LEDs which is 350 mA. It is impossible to measure the p-n junction temperature directly as it is impossible to reach the p-n junction. However, it is possible to estimate this value by measuring the temperature at a nearest point to the p-n junction, and then use the following one-dimensional heat conduction equation to estimate the junction temperature [2,3].

$$T_j = T_b + R\theta_{jb} \times V \times I \tag{7}$$

where T_j is the p-n junction temperature, T_b is the board temperature, $R\theta_{jb}$ is the p-n junction to board thermal resistance coefficient, V is the input voltage and I is the input current. Thermal resistance coefficient depends on the power dissipation at the junction, ambient temperature, amount of heat sink and the orientation of the heath sink [2,3].

For the purpose of real-time health monitoring and prognostics, we assume the average power dissipation of the LED remains constant and ambient temperature, amount of heat sink and orientation of the heat sink remain same. If the power dissipation, ambient temperature and heat sink remain same, board temperature and junction temperature will vary linearly [3]. In addition a large heat sink is used in the experiment and hence the junction temperature can be estimated with the board temperature [3]. For the Philips Luxeon Star the thermal resistance co-efficient is 20C/W [31] which can be assumed as a constant. This allows us to monitor the board temperature and use this temperature to train the data driven approach instead of the p-n junction temperature.

The real-time health monitoring and prognostics approach adopted in this study is based on the output from both thermocouple data and current sensor data. This data is then fed into the data driven techniques to predict the anomalies in LED performance. Appropriate extrapolation techniques are used to predict the remaining useful life and discussed in the Section 9. The test data was obtained using a National Instruments' (NI) PXI real-time platform which gathered data for a High Power Luxeon Star LED under accelerated voltage conditions.

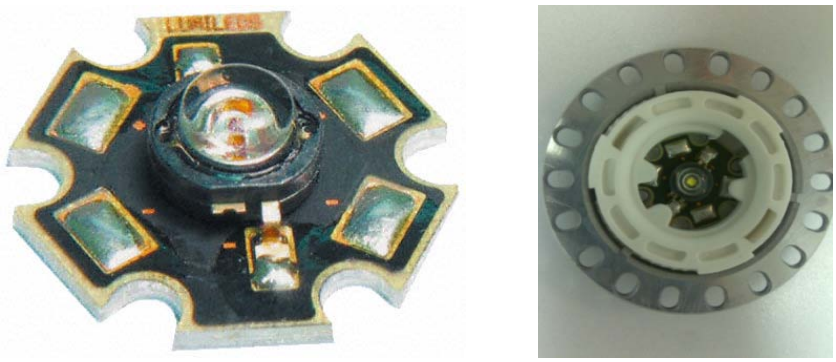
6. Experiment Setup

There are standard developed by the Illuminating Engineering Society of North America (IESNA) to test the LED lighting systems for the purpose of qualifications. IESNA LM-79-08 was developed as a standard to measure electrical and photometric characteristics solid state lighting products such as LED luminaries and integrated LED lamps. IESNA LM-80-08 was developed as a standard to test the solid state light source such as LED packages, arrays and modules (not luminaries) for lumen maintenance. Purpose of these standards is to allow all the manufacturers to follow a common measuring procedure so that the users can compare the performance of the different product in the market. This is also a requirement of the Energy Star which is international standard for energy efficient products [33,34].

The Alliance for Solid State Illumination Systems and Technology (ASSIT) has also developed standard for life test of the LED based on 50% light output degradation (L-50) and 30% light output degradation (L-70) [5,6]. Manufactures are performing tests and producing the result based on these standard and tests. These standard and testing procedures will provide the data for comparing the life expectancy of the different solid state lighting product but does not provide detailed information on the failure modes and mechanisms hence it will not help to estimate the life time of an LED in the field [30]. When the LEDs are deployed in the field, there are many known and unknown factors which affect the performance of the LED lighting systems and increase the possibility of the catastrophic failures. The experiment below is designed to capture such failures caused by voltage and current fluctuations, driver break down, temperature increases, *etc*.

Figure 6(a) shows a Luxeon star LED from Philips Lumileds lighting and Figure 6(b) shows a fitted LED on a holder that represents the LED test set up.

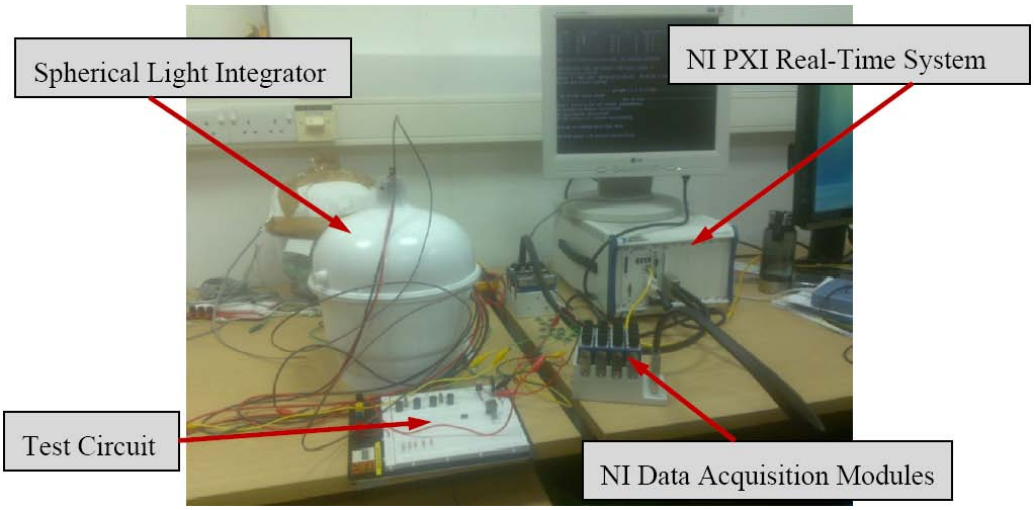
Figure 6. (**a**) Luxeon star LED from Philips; (**b**) Luxeon star LED with holder.



(**a**) (**b**)

Figure 7 details the experimental test setup, which consists of a data acquisition system (National Instruments PXI), a voltage regulator and sensors, and a single High Power Philips Luxeon Star LED. For purpose of light measurement the LED is placed within a semi spherical enclosure which also contains a photodiode light sensor.

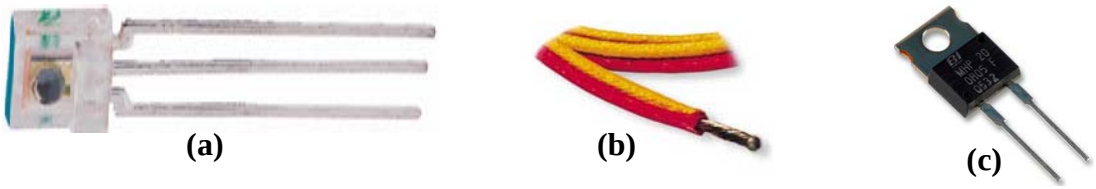
Figure 7. Test bench–Experiment setup with National Instruments' PXI Systems.



The National Instruments PXI platform can be connected to both analog and digital input modules providing the ability to measure voltage levels for different types of signals. For this experiment we use a 24-bit universal analog input module (NI 9219) to measure the applied voltage, and the voltage across the three sensors (current, temperature, and light).

The applied voltage is measured by connecting the anode and cathode terminals of the LED. This together with the three sensors (current, light, temperature) are all connected to the data acquisition platform. Voltage is measured for all three sensors, for example to measure light output we use a photodiode which converts light into voltage and is calibrated to convert the light into voltage in a proportional manner. To measure temperature we use a thermocouple which generates very small voltage (mV) related to the temperature on the board. For current we measure the voltage across the power resistor and this is converted into current. Figure 8 shows all three sensors used in this experiment.

Figure 8. (**a**) Photodiode TSL250R-LF; (**b**) NI readymade J type thermocouple; (**c**) Current sensor (Power resistor, MHP 100-0.25 Ω).



7. Data Acquisition for Training the Algorithms

Data is obtained under both normal conditions and accelerated stress condition. The sensor data obtained under normal conditions is used to predict the mean values of voltage for the three sensors (current, temperature and light). The data obtained from the accelerated stress test is used to identify the threshold values for the ED and MD algorithms, above which the LED will start to degrade.

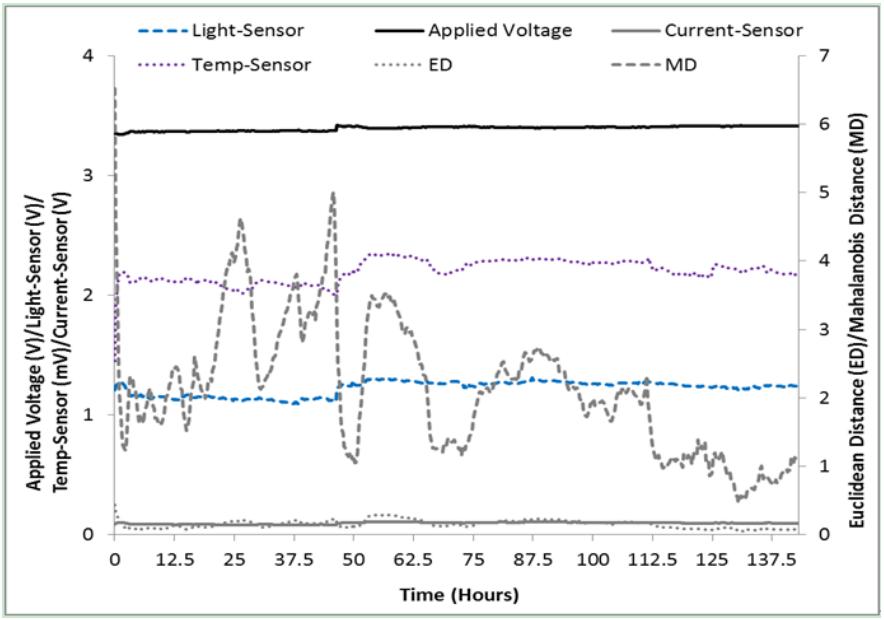
7.1. Data Acquisition–Normal Operating Conditions

Sensor data is obtained when the LED is operating under normal conditions. This data is then analysed to identify the mean values for the sensors when the LED is operating normally. In addition to this the MD and ED values are also calculated under these conditions. Table 1 details the mean values of the data collected for all three sensors, when the applied voltage is 3.42 V. Figure 9 shows the collected data and the calculated values for both of the data driven techniques (MD and ED).

Table 1. Mean Sensor readings when LED is operating normally.

Parameters	Sensor Values	Real Values
Applied Voltage	3.42 V	3.42 V
Light Output	1.18 V	Not Available
Board Temperature	2.2 mV	42.7 °C
Current	0.09 V	0.35 A

Figure 9. Sensor data for normal operating conditions.



What is interesting in the above is the sensitivity of the MD method to small changes in the sensor readings. Table 2 below shows the ED and MD values (mean, maximum and minimum) for normal operating conditions. Under these conditions an LED typical life time will be on average 50,000 h. High values for ED and MD are observed at the initial stage as the temperature is increasing with time until it reaches a stabe value (*i.e.*, in this case actual temperature is increasing from the room temperature to 42° C which is normal operating board temperature) while the current quickly reached its stable value. In this case maximum value for MD is observed at the initial stage of the experiment.

Table 2. Mean, maximum and minimum values for ED and MD under typical operating conditions.

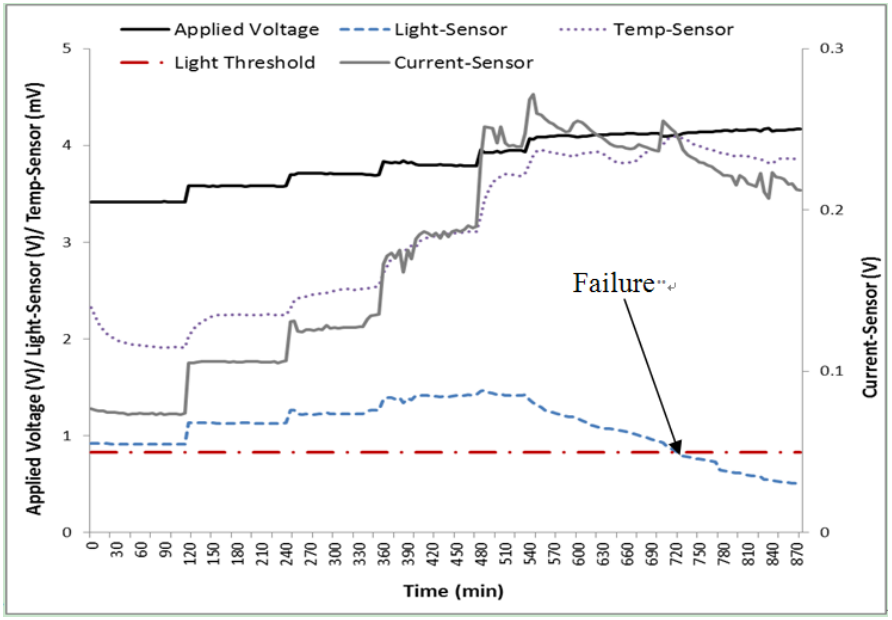
Distance Measure	Minimum	Maximum	Mean Value
Euclidean Distance (ED)	0.046	0.44	0.16
Mahalanobis Distance (MD)	0.47	3.80	2.16

7.2. Data Acquisition–Accelerated Life Test

A run-to-fail accelerated voltage test is designed to provide data to identify the threshold values for both MD and ED algorithms. In this test the applied voltage is increased in steps from the initial of 3.29 V to a maximum of 3.99 V. This maximum is also the typical maximum forward voltage of the LED. Note that the normal operational voltage that is required for the LED is 3.42 V. Data from the sensors are then analysed to identify the threshold values for ED and MD.

Figure 10 shows the voltage applied to a single LED and the readings from the current, light and temperature sensors. In addition to this the graph shows the value of light threshold which represents a 30% drop in the light output from what its value would be when operating normally (e.g., with an applied voltage of 3.42 V). Hence if the light reading goes below this value then we have a reduction in light output over 30% and hence a failure.

Figure 10. Sensor data from accelerated life test.



We can calculate the ED values using the data above from the temperature and current sensors. The light readings are only used to observe the reduction of light from the LED and hence when it fails due to a drop of 30% or more. Figure 11 shows the predicted ED values, the applied voltage and the data from the light sensor and its threshold value. We would expect the light output to increase as the voltage increases. Hence, to calculate the threshold value for the ED parameter we identify the point at which the light output starts to decrease continuously. This threshold value represents the point in time at which the LED starts to degrade. For the data set shown in Figure 10 the threshold value for ED is 2.5. So, any value for ED which goes above this threshold value identifies that degradation in light output is taking place. Hence by monitoring the ED parameter we can diagnose when light output is degrading based on the monitored data from both a temperature and current sensor.

Figure 11. Euclidean Distance analysis for sensor data.

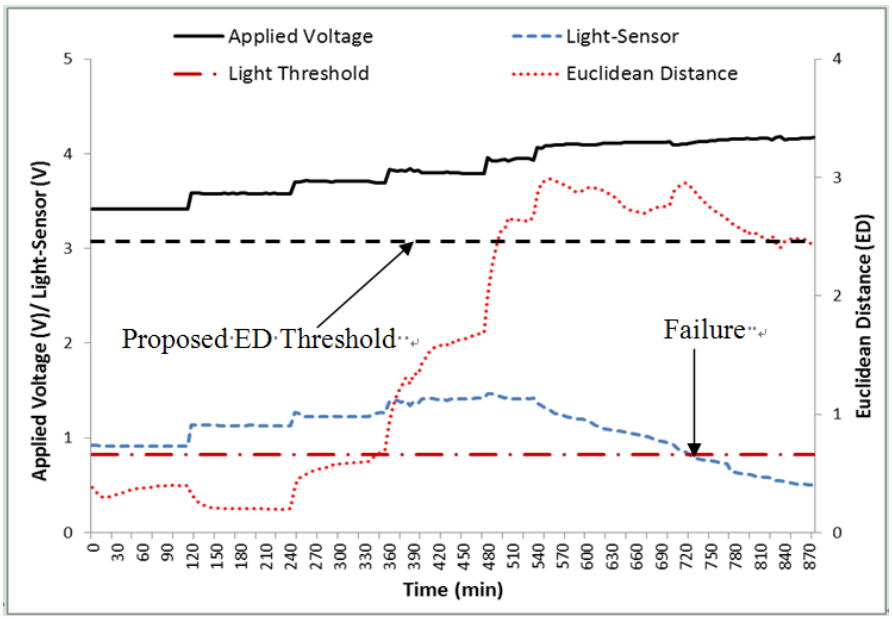
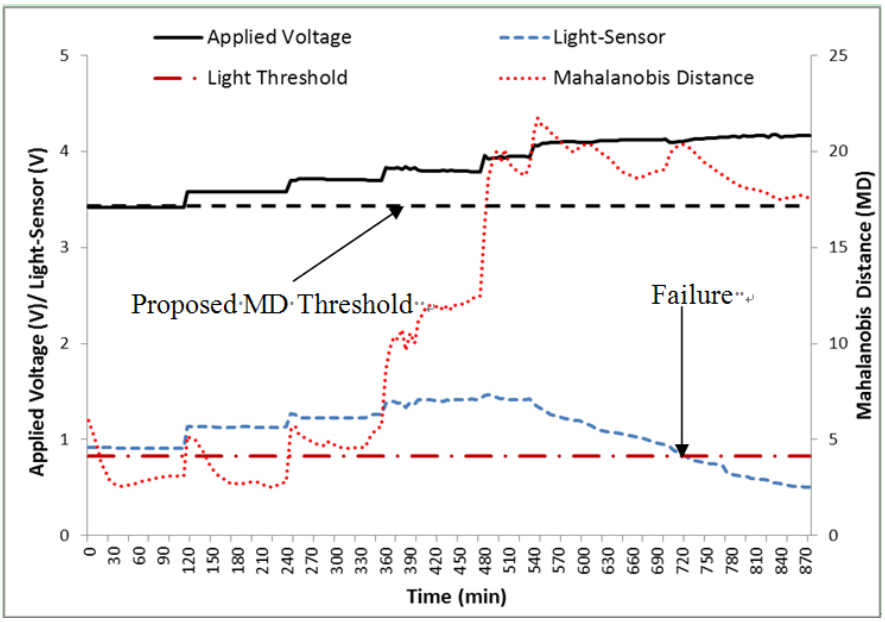


Figure 12 shows a similar analysis for the Mahalanobis Distance (MD) algorithm, again using same data set as shown in Figure 10. For the MD method the light output is observed to decrease continuously from the MD value of 17, onwards. Hence the threshold value for MD is 17, above which the light output is degrading. So, as with the MD method, by monitoring changes in current and temperature, we can use the MD calculation and its threshold value to diagnose when light output degradation starts.

Figure 12. Mahalanobis Distance analysis for sensor data.



The above was undertaken on seven different LED's where the threshold values were calculated separately for each. For ED and MD the calculated threshold values were similar. For the following validation cases we have used the minimum predicted threshold values which are ED = 2.5 and MD = 17.

8. Validation of Diagnostics Capability

Data shown in the Figure 13 is used to demonstrate both data driven techniques in terms of their diagnostics capability. This data is again collected from an accelerated stress test, where the applied voltage is increased over time beyond its normal operating value. The LED used for this test was again a Philipis Luxeon Star, but a different one from the batch of ten used to derive the threshold values. In this accelerated test the applied voltage is increased every 30 min by 0.2 V. This is a different voltage profile to that used for the generating data for the predicting the threshold values. Clearly we can see when the light output has degraded by 30% which is after 485 min. We can also observe when the light begins to degrade which is after approximately 145 min.

Figure 14 demonstrates the ED technique for the data shown in Figure 13. It shows that using the defined treshold value of 2.5 an early warning for having a LED operating at conditions that lead to failure is given. ED is gradually increasing after it's maximum healthy value of 0.44 (Table 2) as the applied voltage is increased gradually. In this case ED equals 2.5 predicts start of the degradation in the light output at time approximately 145 mins and it takes another 340 min to degrade completely to reach the light failure threshold value of 0.83 V (*i.e.*, 70% light degradation from typical value).

Figure 13. Sensor data from accelerated life test.

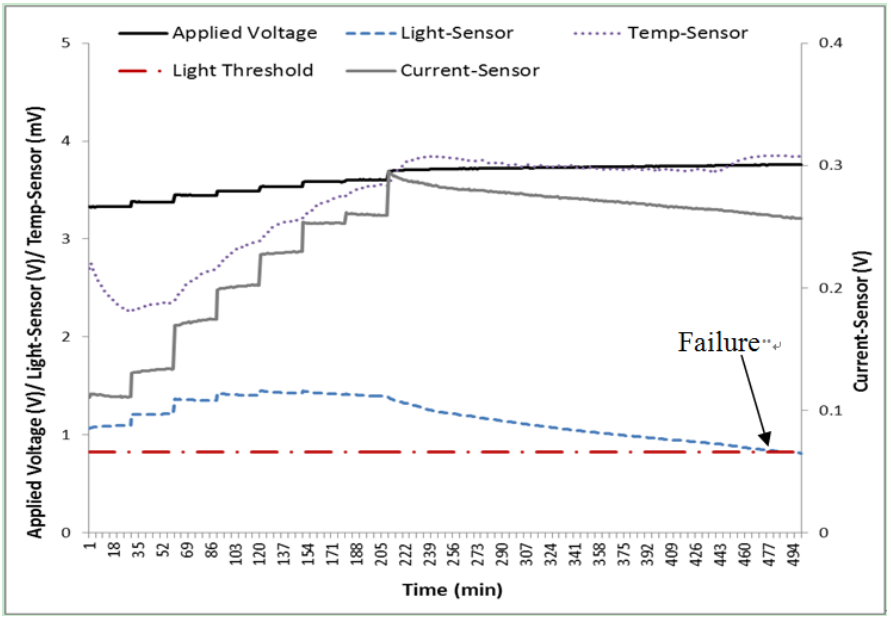


Figure 14. Demonstration of Euclidean Distance.

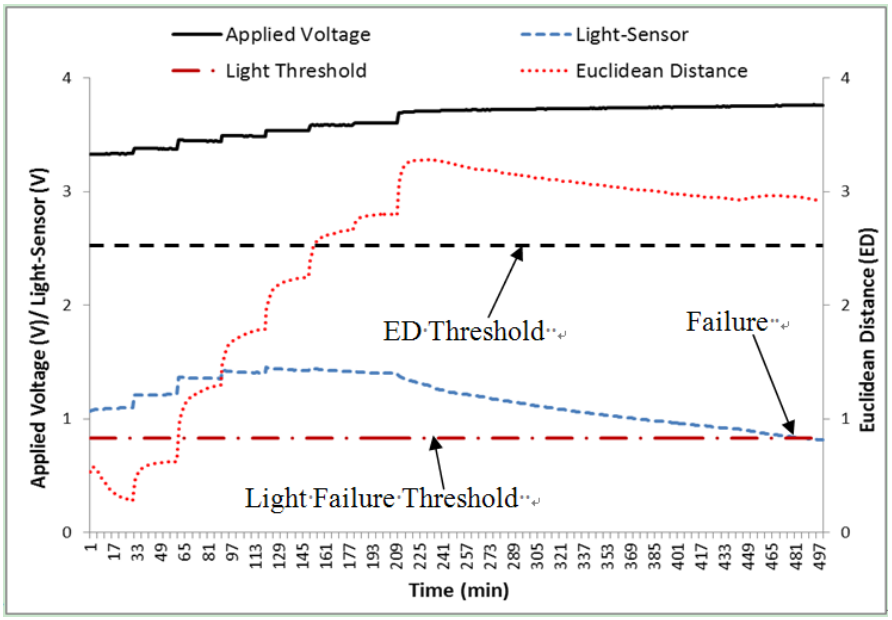


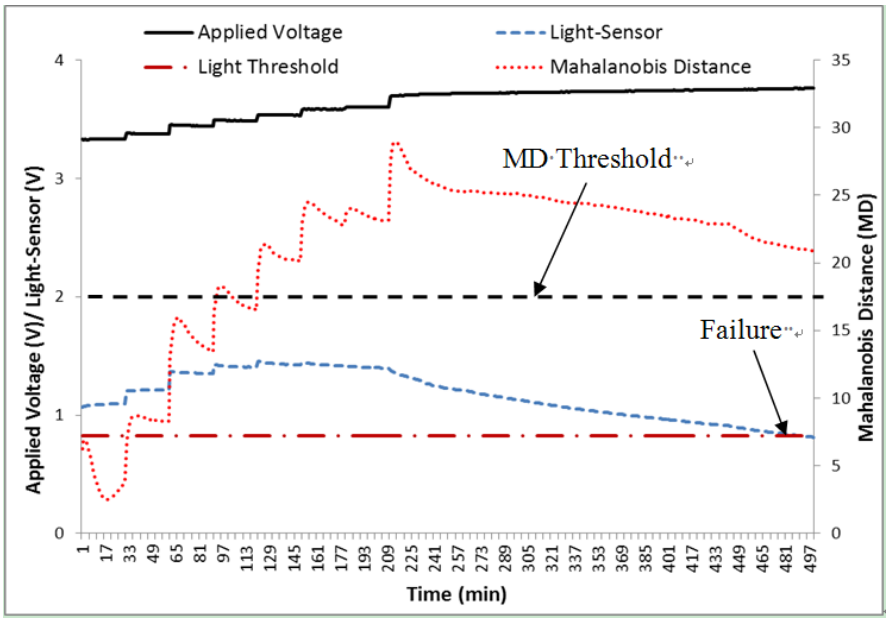
Figure 15 demonstrates MD analysis of the test data set shown in the Figure 13. It shows that the early degradation in the light output can be predicted using MD. When MD reaches its threshold values of 17, light output starts to degrade. This is the point of giving an early warning.

Although both ED and MD detect the degradation in the light output, ED curve demonstrates a more accurate result compared with the MD curve. At time 443 min there is an increase in ED which corresponds to the temperature increases even though the current continuously decreases. But the MD curve illustrates opposite behavior because of the correlation between current and temperature.

Parameters which cause the degradation can be identified by monitoring the individual sensor reading (*i.e.*, current or temperature) and their variation from the typical values. This can be done soon after anomalies detected in the ED and MD values. This information can be used further to analyse and

identify the corresponding failure mechanism and root cause of the degradation. Such study is not undertaken as part of this work as the main focus is on the data driven techniques and their diagnosis/prognostics capability.

Figure 15. Demonstration of Mahalanobis Distance.



9. Validation of Prognostics Capability

The values for ED and MD can be used also to make predictions for the remaining useful life of LEDs. During light degradation both current and temperature values that are monitored decrease with time when the applied voltage to the LED does not change. This observation is made during the experiment. This will correspond to ED and MD parameters also decreasing over time (*i.e.*, reach a peak value and start to decrease). The observed maximum values (peak) for ED and MD vary for different LED and they indicate the different individual characteristics of the LEDs. In the case of the LED lighting systems, the extent of deviation or degradation (*i.e.*, ED or MD) will not continuously increase until LED completely fails (*i.e.*, output drops to 70%). As light output degrades to 70%, current will also decrease and this implies that the ED or MD should decrease to certain level. Continuous constant rate of degradation in the light output can be observed in the rate of reduction in the ED and MD.

The gradient of the ED and MD curves can be used to forecast the Time-to-Failure (TTF). ED and MD values that correspond to the failure of LEDs, *i.e.*, when light output drops below 70% from the typical value, are defined using experimental data and referred as ED failure limit and MD failure limit respectively. Almost linear reduction in the ED and MD is observed during the tests when the LED undergoes degradation process. Linear extrapolation of the ED and MD decreasing trend when light degrades, above the respective threshold limit, can be applied and used with the ED and MD failure limits to calculate the remaining useful life (RUL). This prediction for the RUL can be undertaken at any particular time point if the ED and MD curves are above the threshold value (indicating

degradation takes place) and the trend is decreasing. As new data becomes available over time, and ED and MD are re-calculated, their trends are adjusted and RUL predictions re-calculated.

9.1. Estimation of ED and MD Failure Limits

Test data obtained using seven LED devices are used to observe the respective values of ED and MD at the time when the power light output drops below 70% from the initial value (*i.e.*, LED failure). Each LED was tested under slightly different accelerated voltage test where the peak value of the applied voltage was set to be in the range 3.6 to 3.99 V. The aim is to obtain data for the relationship between the extreme ED and MD values (denoted ED_{Max} and MD_{Max} respectively) computed at the applied voltage peaks and the respective ED and MD failure limits (denoted FL_{ED} and FL_{MD} respectively). It is observed that the values of ED and MD at LED failure, *i.e.*, FL_{ED} and FL_{MD}, are dependent on the elevated applied voltage level, respectively on the associated peak value of ED and MD at that voltage level (*i.e.*, ED_{Max} and MD_{Max}). To capture the existing relationships between the peak values of ED and MD, and the related ED and MD failure limits, power law approximations from the available datasets are derived as follows:

$$FL_{\mathrm{ED}} = 1.0912 \times (\mathrm{ED}_{\mathrm{Max}})^{0.8086} \tag{8}$$

$$FL_{\mathrm{MD}} = 2.3105 \times (\mathrm{MD}_{\mathrm{Max}})^{0.6746} \tag{9}$$

9.2. Real-Time Sequential Estimation of RUL

Since the data is collected periodically, RUL is estimated sequentially by estimating the mean trend of the ED and MD curves over time period when they exhibit decreasing trend and are over the respective early warning threshold. If ED_t and MD_t denote the ED and MD values obtained at the discrete time step t, then mean trend m_t of ED is calculated sequentially using the following equation:

$$m_t = \frac{t-1}{t} m_{t-1} + \frac{1}{t}(\mathrm{ED}_{\mathrm{t}} - \mathrm{ED}_{\mathrm{t\text{-}1}}) \tag{10}$$

where m_t is the mean trend at a given time step t and the time step $t = 0, 1, 2\ldots n$, starting with $t = 0$ at the time when ED_{Max} and MD_{Max} are detected. In this study, the time steps are defined over intervals of one minute, *i.e.*, the mean trend for ED and MD is calculated every minute following the observation of a decreasing trend of the ED and MD curves when ED and MD are above their respective threshold values.

Similarly, mean trend in the case of MD distance measure is defined as follows:

$$m_t = \frac{t-1}{t} m_{t-1} + \frac{1}{t}(\mathrm{MD}_{\mathrm{t}} - \mathrm{MD}_{\mathrm{t\text{-}1}}) \tag{11}$$

Once the mean trends above are available, they can be used to predict the future time point when the trends of the ED and MD intercept the respective failure limits. This extrapolation of the trend provides a prediction for the remaining useful life. Using the approximations for computing the failure limits (Equations (6) and (7)), and Equations (8) and (9), the RUL can be estimated from Equations (10) and (11) using ED and MD values respectively:

$$RUL = \frac{\mathrm{ED}_t - 1.0912 \times \mathrm{ED}_{\mathrm{Max}}^{\ 0.8086}}{m_t} \tag{12}$$

$$RUL = \frac{\mathrm{MD}_t - 2.3105 \times \mathrm{MD}_{\mathrm{Max}}^{\ 0.6746}}{m_t} \tag{13}$$

9.3. Failure Prediction Example

To demonstrate the predictions for RUL, and for the Time-to-Failure of an LED respectively, the LED test data used in Section 8 (see Figure 13) is used again. Figures 16 and 17 illustrate the change with time of ED and MD parameters for the studied LED and also show the failure limits. In this case the $\mathrm{ED}_{\mathrm{Max}}$ and $\mathrm{MD}_{\mathrm{Max}}$ values used in the prognostics calculations are 3.28 and 28.81 respectively. The respective failure limits are: (i) $\mathrm{FL}_{\mathrm{ED}}$ = 2.85 and (ii) $\mathrm{FL}_{\mathrm{MD}}$ = 21.7. The failure limits are obtained from the approximations shown in Equations (6) and (7).

Figure 16. ED history and the ED failure limit for LED test data in the Figure 13.

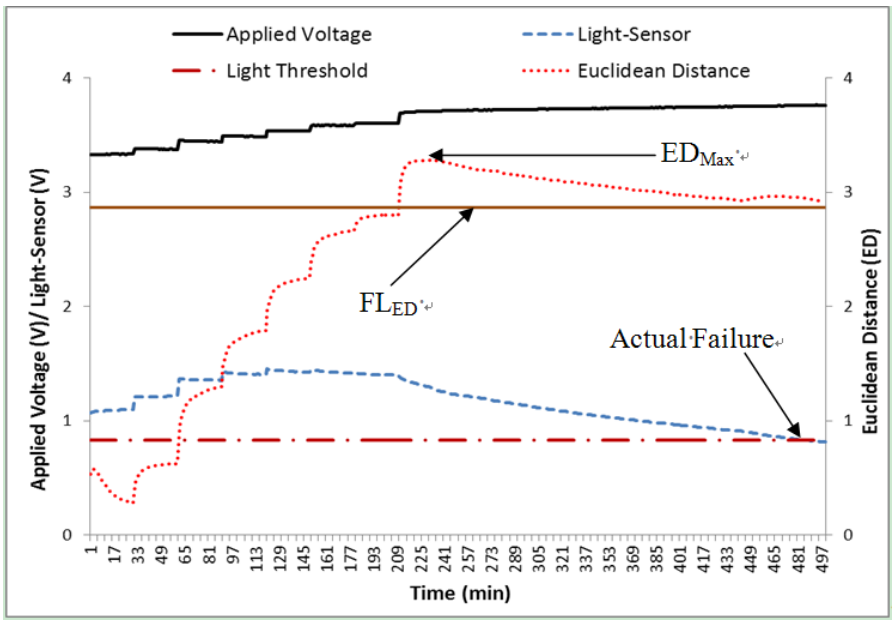


Table 3 shows a summary of prediction results for failure time at five different time points based on both ED and MD curves and using Equations (10) and (11). For exampe, the predictions for failure time of the LED made at time 400 min estimate failure times 473 min (RUL = 73 min) and 457 min (RUL = 57) from ED and MD data respectivly. The actual failure time for this LED is 481 min. It is evident from Table 3 that with time the predictions become more accurate as more data is used in the caluclation of the mean trends of ED and MD. In this case the results using ED data curve provide better predictions with time. On the other hand, the predictions based on the MD produce some fluctuation because the MD is very sensitive to the correlation between the current and temeprature data used to calculate the MD.

Figure 17. MD history and the MD failure limit for LED test data in the Figure 13.

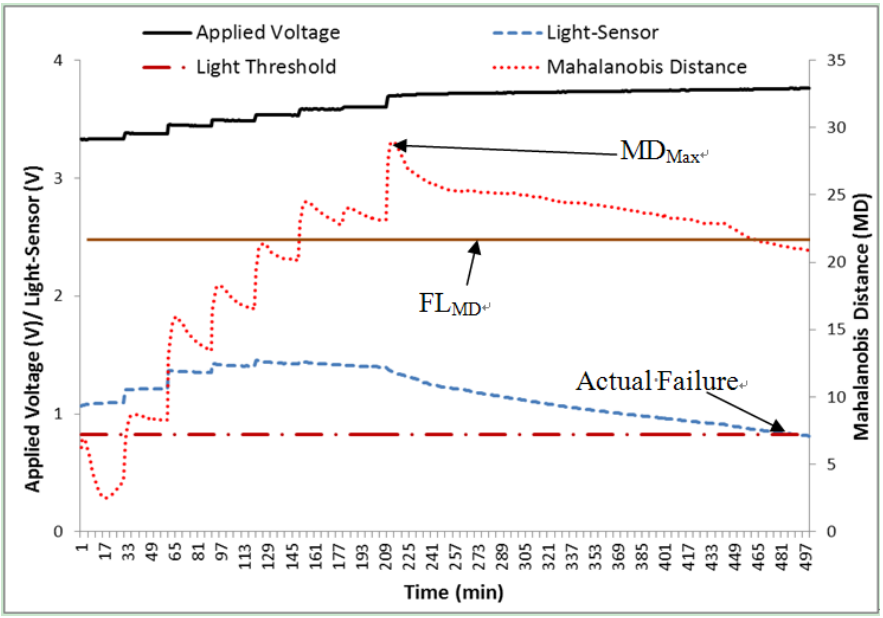


Table 3. Time-to-Failure (TTF) estimation from ED and MD parameters.

Time at which TTF prediction is made (min)	Failure Time from ED (min)	Failure Time from MD (min)	True Failure Time (min)
300	434	373	481
350	458	425	481
400	473	457	481
450	484	475	481

Data collected from 7 LEDs are used to find the threshold value and establish the relationship between ED_{Max} and FL_{ED}, and MD_{Max} and FL_{MD}. ED_{Max} and MD_{Max} are calculated for specific LED based on current and temperature sensor readings. FL_{ED} and FL_{MD} are calculated from the established relationships between ED_{Max} and FL_{ED}, and MD_{Max} and FL_{MD}, and calculated ED_{Max} and MD_{Max}. Obtained different values for ED_{Max}, MD_{Max}, FL_{ED} and FL_{MD} indicate how differently same type of LED perform under the same accelerated conditions. This is because of the individual characteristics of the LEDs. ED_{Max} and MD_{Max} are used to detect the start of degradation in the light output. FL_{ED} and FL_{MD} are used to detect the 30% reduction in the light output power. Reliability of this approach can be improved by undertaking more tests, incorporating the data collected from tests to establish better relationship between the maximum values (ED_{Max} and MD_{Max}) and failure limits (FL_{ED} and FL_{MD}) and establishing more reliable value for threshold value.

10. Conclusions

This paper has discussed data driven PHM approach for real-time health monitoring and prognostics of high power LEDs using temperature and current data from sensors. The results from the undertaken experiments show that data driven techniques for PHM can be used to detect accurately when unusual changes in the expected performance of an LED start to take place, and can successfully provide an early warning if light output degrades and approaches the failure limit. In addition to the diagnostics

capabilities of the data driven approach, this paper also demonstrated how remaining useful life of an LED can be predicted. The accuracy of the prognostics calculations improve with time as more data to perform the sequential estimation of the ED and MD trends becomes available. In addition, embedding the temperature sensors very close to the junction will improve the temperature measurement in all situations hence the approach will become more accurate. The ED technique is found to be more suitable for this application as it involves less mathematical operations and require less computational time compared to the MD technique. The undertaken tests have indicated that the ED curves are generally less sensitive to noise in the monitored parameters and when test conditions (*i.e.*, applied voltage) change.

Further study is required to generalize this result for harsh operating conditions which are not considered in this work such as high and low room temperatures which will affect the board temperature *etc*. This will require controlling the current and temperature independently. Further experiments are also necessary to integrate other parameters which affect the LED life, into a generalized approach of LED health monitoring under harsh operating conditions.

Studied data driven prognostics algorithms can be implemented in any LED lighting systems along with the LED driver to monitor the reliability and report the risk of failure in advance. Future research in this real-time data driven prognostics systems will focus on the development and deployment of an intelligent LED driver to monitor and improve the remaining useful life of LEDs. Embedding temperature and current sensors into an LED package will make this implementation possible and will also make the temperature measurement more accurate.

Future work will focus also on improving the accuracy of studied data driven approach, for example by including appropriate physics-of-failure (PoF) models. Future research in these real-time PHM systems will aim at the development of hybrid or fusion approach for real-time health monitoring and prognostics of LEDs. This can be accomplished by integrating the modeling of temperature and current profiles using p-n junction characteristic models with sensor data on LED parameters. The main challenge here will be to develop fast PoF models that can run in real time and in parallel with the data driven computations. A specific topic that requires further studies is the failure related to discolouration of the LED die or LED encapsulate.

The data driven PHM presented in this paper can be applied to other semiconductor devices such as microprocessors to monitor the real-time health and do the prognostics by embedding suitable sensors (*i.e.*, temperature, accelerometer, vibration, humidity *etc*.) into those semiconductor devices. This will allow the semiconductor devices to have embedded health and usage monitoring capabilities and execute these in real-time.

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