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# Chapter 6
# Health Monitoring, Machine Learning, and Digital Twin for LED Degradation Analysis

**Mesfin Seid Ibrahim, Zhou Jing, and Jiajie Fan**

## 1 Introduction

Nowadays, light-emitting diode (LEDs) are widely used in different applications including general indoor and outdoor lighting lamps, automotive lighting [1], backlighting, robotics skin [2], medical and communication equipment, and so on. This is due to the many advantages, including longer lifetime (50,000–100,000 h), higher reliability, environmental friendliness, compactness in size, and quicker switching time when compared with traditional counter parts (incandescent and fluorescent) lighting sources [3–5].

Regardless of the many benefits and promising future applications that LED lighting sources provide, there are challenges facing LED manufacturers on the lack of a unified standard method to monitor in situ LED degradation and to gather reliability assessment information, thermal management, potential glare due to small size lamp, and color stability. In addition to this, there is also lack of accurate

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remaining useful lifetime estimation and evaluation methods. This is due to the long lifetime and high reliability at normal operating conditions, various failure mechanisms, rapid technology advancement, and multicomponent features of LEDs compared to the traditional light sources [3, 6, 7]. However, this has brought another challenge for manufacturers in terms of obtaining sufficient failure data, determining reliability and estimating remaining useful lifetimes (RUL) in relatively short lifetime testing before the products are released to the market and with better prediction accuracy.

To address the challenges and shortcomings related to reliability assessment and lifetime prediction of LEDs, a number of research studies have been undertaken on the prognostics and lifetime estimation in academia and industry [6, 8–12]. In early 2001, a discussion was initiated by Narendran et al. [13] among the lighting industry experts concerning the standardization of definitions, procedures, and approaches in the process of useful lifetime estimation for LED products. Currently, LED manufacturers use IES-TM-28 [14], released by IESNA, to project lumen maintenance lifetime for LED lamps and luminaires where the required data is gathered according to industrial standard test report IES-LM-84 [15]. Previously, the IES-TM-21 standard [16] has been used to predict the lifetime of LED light sources based on the light output degradation data from the standard IES-LM-80 test report [17]. The approved IES-TM-21 procedure uses the nonlinear least-squares regression (LSR) approach to project lumen maintenance data to predict the lifetime (L50 or L70) of LED lighting sources. This lifetime testing method can be a good approach for comparing lifetime information of LEDs, but it does not provide detailed information regarding failure modes, mechanisms, and failure locations [3].

Recently, machine learning (ML) has emerged and is breaking new frontiers in reliability assessment and lifetime prediction studies due to systematic generation of large amount of data, newly introduced state-of-the-art algorithms, and an exponential increase in computing power. ML algorithms are a set of methods and procedures that can be used to capture, detect, and learn relevant information patterns from large amounts of data and then use the unhidden patterns for further decision-making in prognostics or predicting lifetime [18]. Thus, the ability of ML to learn from training data, generalize from historical data, and perform tasks without being explicitly programmed makes it tantalizing panacea for challenges in reliability analysis, anomaly detection, diagnostics, and prognostics.

There have been some reviews that studied the degradation mechanisms influencing the reliability of GaN-based white LEDs for different lighting purposes [3, 19–23]. An extensive review that mainly focused on failure causes, failure modes, and failure mechanisms of LEDs was presented by Chang et al. [3], while recently Sun et al. [23] have presented a literature review on recent trends in the prognostics of high-power white LEDs (HPWLEDs), including the failure modes, mechanisms, and some lifetime estimation approaches. Most of these reviews mainly focused on statistical-based data-driven approaches, failure modes, and mechanisms as well as physical degradation mechanisms of LEDs. While these topics are very important for the prognostics and health management (PHM) study of LEDs, it is not the focus of this study, which mainly focuses on the machine learning-based PHM approaches applicable for LEDs anomaly detection, diagnostics, and lifetime prediction. Thus, the main aim of this study is to review machine learning algorithms, methods and approaches and their pros and cons in the reliability assessment, failure or anomaly detection, and the remaining useful life prediction in general and focusing on LED light source products in particular.

## 2 PHM of LEDs

Nowadays, there is an increasing competition in the global market and the need to enhance customer satisfaction. In addition, huge advancements in technology, materials, and manufacturing processes are observed which facilitate the design and manufacturing of many consumer products that are highly reliable and have a longer lifetime before they fail. All of these factors lead to a shorter product development time, and that becomes challenging for manufacturers to evaluate the lifetime of high reliability items in a shorter period before being released to the market [24, 25]. This phenomenon is no different in the case of lighting products, especially for the high-power white light-emitting diodes (LEDs) that belong to highly reliable and long lifetime products that require a longer time to collect adequate degradation and/or failure data. That is why long-term lifetime estimation and reliability assessment of LEDs in a moderately shorter period of time before products are released to market have become challenging for LED manufacturers [26]. For this reason, PHM has evolved as an important method to solve the challenges in terms of increasing system reliability, availability, and maintainability, enhancing safety and decreasing life-cycle and operational costs of marketable products and systems in general and customer electronic systems in particular [27]. Thus, the reliability assessment and prediction of remaining useful life (RUL) studies have become an important aspect of PHM of many consumer electronic products, including high-power white LEDs.

Basically, PHM is an engineering discipline that helps to prevent the failure of products, components, and subsystems which can lead to inadequate performance and safety concerns. It helps to anticipate problems in products and systems through signal and sensor data under actual application conditions [28]. PHM uses inputs such as information known about products/system, data collected from sensor measurements, and applies an algorithm or a set of algorithms to analyze and provide relevant outputs at various levels of prognostics, such as fault detection, diagnostics, and lifetime estimation, as depicted in Fig. 6.1.

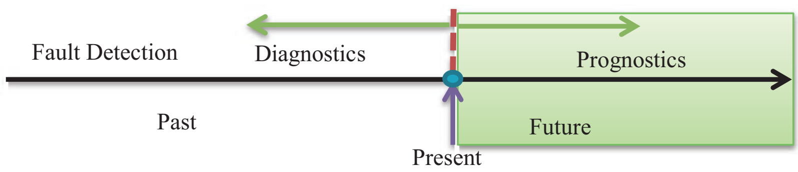



**Fig. 6.1** PHM problem architectures (fault detection, diagnostics, and prognostics)

A well-organized prognostic health management framework should include data collection using sensors, data processing, security and integration, feature extraction, fault detection and recognition, damage models, physics of failure, reliability testing, physical models, prognostics, and so on [29], as illustrated in the PHM metro map shown in Fig. 6.2.

The main purpose of anomaly detection is to detect unusual or strange anomalous responses of systems and products through identification of deviations from normal healthy behavior, so that precautionary measures can be taken in advance to avoid potential failures. It is worth noting that anomalies may not necessarily indicate failure as changes in working or environmental conditions enable sensors to detect anomalous behavior. Diagnostics enable us to extract and gather failure magnitudes, failure modes, failure mechanisms, and other related data from anomalous behavior of a product/system through sensors. The term prognostics deals with the process of estimating the lifetime or predicting the future reliability of a product based on historic and current degradation data and assessing the degree of deviation from its normal operating conditions [27]. Prognostics can provide help in all product and/or system life cycles including design and development, production and ramp-up, product testing, operations and maintenance, as well as end-of-life phase (i.e., phase out and disposal) [30]. In this regard, the PHM of mechanical systems has been well studied, and as a result there is a considerable body of knowledge in the area. However, prognostics have only been applied to consumer electronic products/systems quite recently, and this is due to the fact that degradation is difficult to detect in electronic systems when compared with mechanical systems [31].

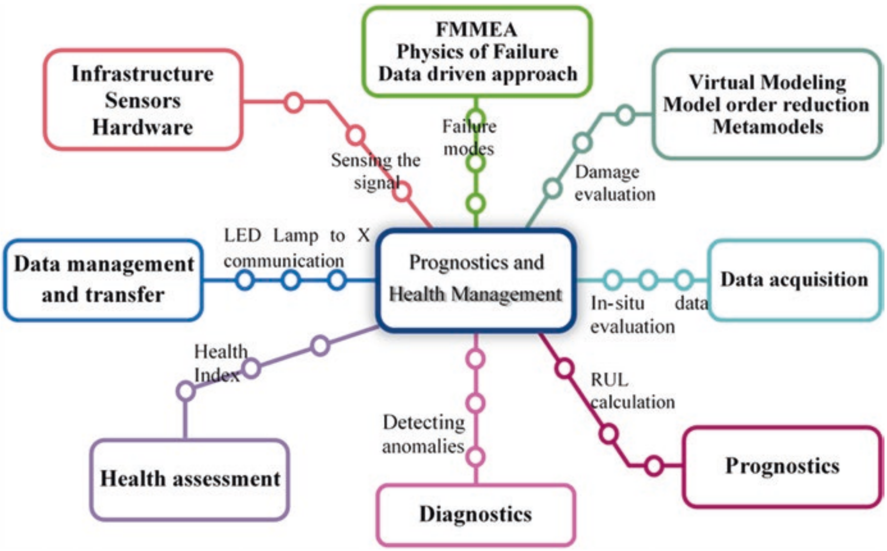



**Fig. 6.2** A generic PHM metro map for products/system such as LED lighting, automotive parts, etc.

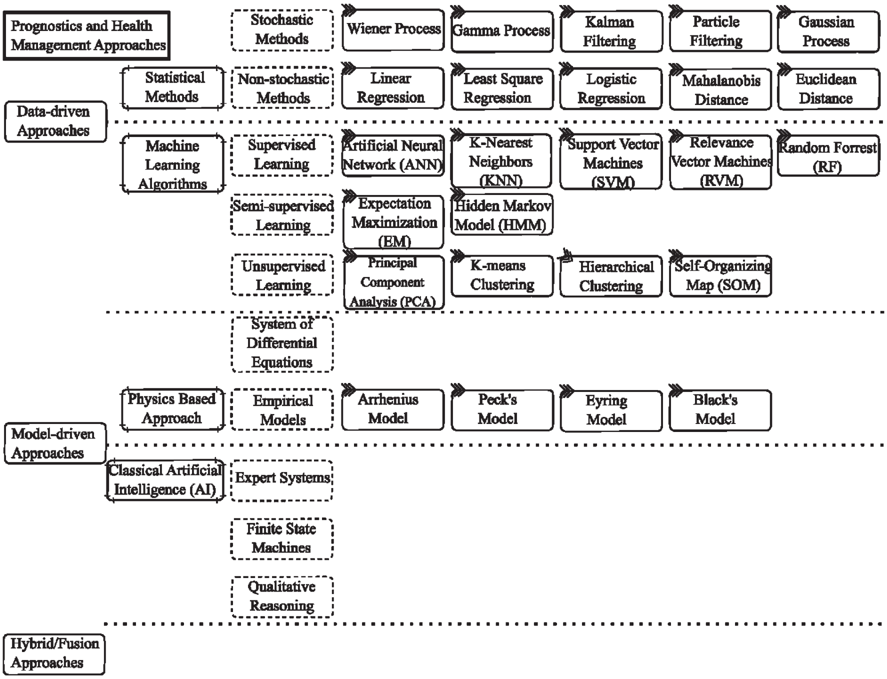



**Fig. 6.3** Taxonomy of prognostics and health management approaches

Even though the expected lifetime for typical high-power LEDs can be rated up to 50,000 h, practical statistics indicate that about half the LED products failed to reach the rated lifetime [32, 33]. This has raised demands from experts in the LED sector, end-product manufacturers, and potential customers for dependable reliability information and remaining useful lifetime estimation approaches. Thus, through the application of PHM, the inadequate lifetime and reliability information provided by LED manufacturers should be addressed, and reliable approaches to monitor the status of LEDs and predict potential failures, especially for safety critical and emergency systems and products including the medical, aviation, automotive, and nuclear sectors, are needed. So far, many diagnostic and prognostic activities have been implemented and executed based on a variety of approaches and techniques. In general, the most commonly used approaches can be categorized as (i) model-based, also known as physics of failure (PoF) methods, (ii) data-driven methods, and (iii) hybrid (fusion) prognostic methods [34]. A more refined and detailed taxonomy of PHM approaches is presented in Fig. 6.3.

The data-driven (DD) methods are mainly dependent on large amounts of training data and/or degradation data collected through sensors in order to derive degeneration models for products and systems. The data collected in real time can be used to adjust and modify the model parameters. On the other hand, the model-based method requires prior mathematical models to describe the product's degeneration process based on physical laws. The DD methods are helpful for complex systems where component interaction is indeterminate and when large amounts of training data are available, while the model-based method demands knowledge of the physical laws governing the product degeneration expressed in mathematical models. Statistical-based and ML models and algorithms are used in DD approaches while physical models and classical AI methods implemented in model-based approach [35, 36]. Fusion/hybrid approaches that combine the benefits and eliminate the drawbacks of both DD and physics-based methods have also been implemented in prognostics studies [37]. The preferred choice of each algorithm depends on the different properties manifested for use in the intended analysis.

# 3 Model-Based Approaches

## *3.1 An Overview to Model-Based Approach*

Model-based prognostics, also known as physics of failure (PoF) methods, makes use of information about a product's material characteristics, loading and stress settings, shape/geometry, and operational and working environmental conditions to assess reliability, identify failure modes and mechanisms, and so as to estimate the RUL. By using product life-cycle loading conditions (such as electrical, thermal, mechanical, chemical, electromechanical, etc.), the product geometry, and material properties, PoF is also used to design for reliability at the early stage of product design [38, 39]. The PoF-based approach has the benefit of identifying the root causes of system failure [23, 30]. However, sufficient knowledge about the product geometry, materials, properties, and operating conditions are required, and it may be difficult to obtain such information, especially for complex systems. For a certain product/system at a particular life-cycle loading condition, PoF focuses mainly on identification of potential failure locations, failure modes, as well as failure mechanisms. The stress at every failure location is obtained as a function of the life-cycle loading conditions, material properties, and product architecture/shape. Then fault generation and propagation are determined by damage models [28, 40]. Model-based approaches are also used to develop mathematical models in order to process and evaluate collected degradation data based on the prior knowledge of the product/system.

In the study of prognostics, PoF models implement the use and monitoring of performance parameters, physical characteristics, and operating and environmental conditions. These parameters are used to monitor the product during experiments and can be categorized according to their domains. For the prognostic analysis of LED products, the different impact (stress) factors such as electrical, thermal, humidity, mechanical, thermomechanical, and creep stress applied on the test sample can be monitored by sensors, and the PoF models with mathematical equations can be used for further analysis depending on the experimental plan. A brief summary of PoF models employed for LED products and systems is shown in Table 6.1. Pecht and Jie [38] studied the PoF-based prognostics for electronic and information-rich components. In their study, they criticized the use of old reliability handbooks due to prediction errors and uncertainties (in design, material, and operating conditions) caused and showed the growing trend of using PoF-based prognostics for electronic products so as to identify critical component failure modes and mechanisms.

The implementation approach framework for PoF-based PHM has been demonstrated in such a way that the first step is to undertake virtual life assessment. Virtual life assessment can be conducted using inputs from design data; failure mode, mechanisms, and effects analysis (FMMEA); expected lifetime conditions; and PoF models. During the product life cycle, high-priority failure mechanisms might be triggered by different severe and frequently occurring operational, environmental and loading conditions. The virtual life assessment which is the first phase in the physics of failure-based prognostics has been further investigated by Fan et al. [10]. Their study was focused on the investigation of failure sites, failure modes, and associated degradation mechanisms for high-power white LEDs (HPWLEDs). The sample selected for demonstration was a typical commercial HPWLED lamp according to "bottom-up" strategy at the chip, package, and system levels as shown in Fig. 6.4. Pictures in this figure are presented for the purpose of illustration.

Lu et al. [41] used the physics of failure-based approach to study down light color shift failure at the luminaire level conducted on the diffuser (PMMA), reflector and package parts of an LED lamp of 10 W, and CCT of 4000 k. The selected parts had undergone aging testing at room temp, 55 °C and 85 °C, irradiation testing at 85 °C, and humidity reliability test at 85 °C and 85% RH. The experimental results showed that LED packages have a greater contribution to color shift. Humidity and temperature also accelerate the color shift, where humidity has the stronger impact (Table 6.1).

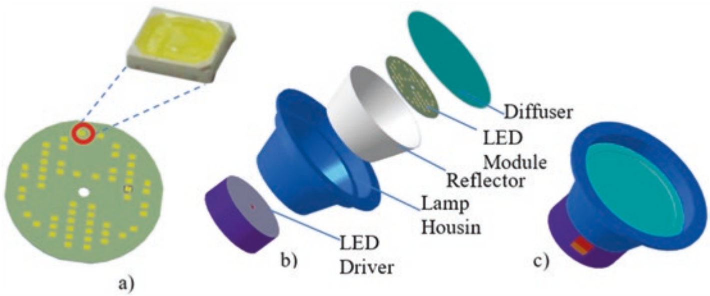



**Fig. 6.4** LED lamp and components: (**a**) LED package and module, (**b**) LED lamps exploded, (c) LED lamp and lighting lamps

**Table 6.1** PoF models for LED products and systems

| Stress (impact) factors | | PoF models | Performance indicators |
|---|---|---|---|
| Electrical (current) [42, 43] | | Lumen degradation gradient [42] | Lumen flux depreciation [42], |
| | | Inverse power law-Weibull [43] | |
| Thermal stress/shock [44, 45, 46, 43, 47] | | Coffin-Mansion Eq. [44] | Lumen depreciation |
| | | System reliability analysis [45] | Color shift over lifetime |
| | | Hierarchical model (based on junction temperature) [45] | Junction temperature gradient |
| | | Arrhenius Eq. [46] | |
| | | Arrhenius-Weibull [43] | |
| | | Finite element simulation using ANSYS and numerical analysis simulation | |
| Humidity/moisture [48, 49] | | Luminous-efficiency gradient [48] | Lumen flux depreciation [48] |
| | | Finite element simulation using ANSYS [49] | |
| Multi-physics | Thermal and humidity [41, 50, 51, 52, 49] | Chromaticity shift eq. [38] | Chromaticity shift, [38, 50] Lumen flux degradation [50, 51] |
| | | Arrhenius Eq. [52] | |
| | | Hallberg-Peck's model [5052] | |
| | | Subsystem isolation method [51] | |
| | | Finite element simulation using ANSYS [49] | |
| | Thermal and electrical (current) [53, 54, 55, 56, 43] | Junction temperature distribution | LED catastrophic failure for high thermo-electrical stress [54] Spectral power distribution (SPD) and Luminous intensity depreciation [53, 54, 56] |
| | | Spectral power distribution (SPD) analysis [53] | |
| | | Electrothermal simulation (junction temperature with Arrhenius equation) | |
| | | Electrothermal simulation [56] | |
| | | Generalized Eyring-Weibull [43] | |
| | Thermomechanical [57], | Thermal and mechanical stress on solder alloy | Solder joint fatigue |
| | | Garafalo's hyperbolic creep model | Lumen depreciation |
| | | Norris-Landzberg equation | |
| | | Engelmaier equation for strain range | |
| | Thermomechanical [58] and hygro-mechanical stresses [58, 59] | Thermal and thermomechanical modeling (transient heat conduction equation) | Lumen flux depreciation |
| | | Moisture diffusion and hygro-mechanical modeling (Fick's law of diffusion) | |
| | | Finite element analysis (simulation) | |
| | Hygro-thermal-mechanical coupling modeling [58] | Heat conduction systems, Fick's law of diffusion and FEA simulation | Lumen flux depreciation |

## 3.2 Failure Modes, Mechanisms, and Effects Analysis for LEDs

The failure modes, mechanisms, and effects analysis (FMMEA) could be considered as input to the PoF-based prognostic approach, as depicted in Fig. 6.5. The exposure of LED lighting products/systems to different loading and operational stresses such as electrical, thermal, mechanical, or chemical causes performance degradation and/or failure [60].

In LED systems, a failure mode is a recognizable way in which a failure of a package/lamp is noticed, and it can be classified as (i) loss of light output or open circuit, (ii) chromaticity shift (i.e., color shift), and (iii) degradation of luminous flux (decreasing in light output). Each failure mode could also be due to one or a combination of failure mechanisms which could be caused by thermal, mechanical, humidity, chemical, etc. Failure mechanisms can be described as thermal, mechanical, physical, chemical, or other processes that cause a failure. Failure mechanisms can be broadly classified as wear-out (gradual) and overstress (catastrophic) failures. The wear-out failures are caused by cumulative stresses (loads) for a prolonged period of time. On the other hand, overstress (catastrophic) failures occur as a result of a one type of stress /load condition that surpasses the optimal threshold of the product characteristic [38].

A comprehensive study was reported by Chang et al. [3] on the FMMEA at semiconductor, interconnect, and package levels for LED products. Subsequently, Fan et al. [11] conducted a study on the FMMEA of LED-based backlighting systems used for commercial displays and TVs. Since LED-based display systems are

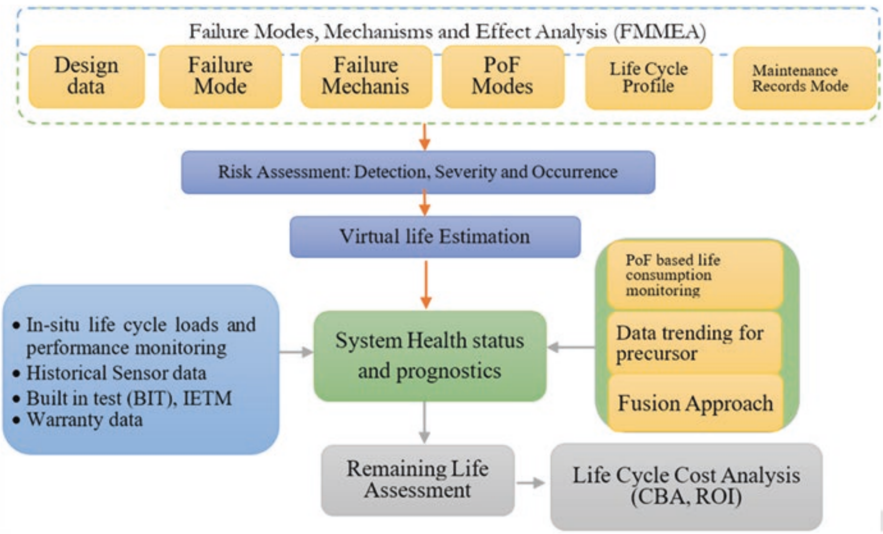



**Fig. 6.5** PoF-based PHM Methodology [28, 61], with permission

formed by LED strips and electric driver systems, the study aimed to identify failure sites, failure modes and mechanisms at the chip (die/semiconductor), driver, package, and strip levels of LED backlight system. As an LED-based device, the failure modes for backlight units are lumen flux degradation, color change, and loss of light failure modes. In our review study, the FMMEA of LED products/systems are described by considering a more general architecture including chip (die/semiconductor) level, package (module along with interconnects), and system levels as presented in Table 6.2.

In general, the FMMEA of LEDs has been investigated at three levels: die/chip, interconnects, and LED package levels [3, 10]. At the chip level, an increased nonradiative recombination can cause a degradation of the active layer of LEDs which impacts in decreasing the luminous flux and power efficiency. Subsequently, the

**Table 6.2** FMMEA of LEDs at different levels

| LED failure site | Failure modes | Failure mechanisms |
|---|---|---|
| LED chip level (semiconductor/die) [11, 21, 22, 48, 49, 53, 62, 63] | Lumen flux depreciation [48, 49] | Propagation of defect and dislocation |
| | Light output off, short circuit [48] | Diffusion of impurities (dopants) in the quantum well |
| | Color shift | Cracking of chip/die |
| | | Yellowing and cracking of the encapsulating lens [53] |
| LED module (package level including interconnects) – wire bond, bumps, attachments, encapsulate, lead frame, lens [22, 48, 50, 53, 58, 64, 65] | Lumen degradation and color shift [22, 50, 64, 65] | Propagation of defect and dislocation |
| | Delamination between chip and die, as well as lamp cup and outer shell [58] | Diffusion of impurities (dopants) |
| | Diffusion of moisture into the boundaries of packaging material [48] | Cracking of chip/die |
| | | Yellowing and cracking of the encapsulating lens [53] |
| | | Package epoxy browning [65] |
| System level (diffuser, reflector, electrical driver) [41, 54, 58, 64, 45, 51, 46, 66, 56, 47] | Lumen flux depreciation [58, 64, 46, 47] | Encapsulant yellowing |
| | Light output off, short circuit | Solder joint fatigue |
| | Plastic housing crack, glass bulb crack | |
| | Optical coating discoloration | |
| | Color shift [41, 54, 66] | |

diffusion of dopants (impurities) in to the quantum well, defect propagation (due to defect/dark spot, propagation, and dislocation), and electromigration due to crystalline defects are the factors that play major roles to the non-radiative recombination.

At the package level, the commonly known failure mechanisms are delamination of the interface, encapsulant carbonization, encapsulant yellowing, thermal quenching of phosphor, solder joint fatigue, and lens cracking. These failures will eventually cause lumen flux depreciation and change the chromatic properties of the LEDs. The failure mechanisms at the interconnections can be fracture of the bond wire as well as fatigue on the wire ball bond due to thermal and electrical overstress, electrical contact degradation due metallurgical interdiffusion, and electrostatic discharge (resulting in rapid failure due to the open circuit). The failure mechanisms at different levels of LED devices will cause at least one of these failure modes to occur [48] [58].

## 4 Data-Driven Approaches

Data-driven (DD) approaches rely on the use of historical and observation data to learn intelligently without prior knowledge of the system, to obtain statistical and probabilistic lifetime estimates, and to provide help in making valuable decisions on system/product health and reliability. The DD approaches help to detect anomalies and predict RUL for a system based on the investigation of historical monitoring data collected from sensors [67]. It is assumed that the system statistical characteristics remain unchanged until an anomaly occurs in the LED product/system [34]. The DD approaches are usually considered as the black box approaches to PHM as they do not require prior knowledge on the system models. There are many ways to classify DD approaches; however, for simplicity, DD approaches can be categorized into two, statistical-based and machine learning-based DD, methods depending on the data analysis methods.

In the first case, statistical-based approaches rely on the use of empirical or analytical equations to build statistical models that helps to predict the degradation trend of LED performance parameters. These approaches are convenient to implement as they make use of primarily historical data and do not need to rely on expert knowledge. In fact, statistical-based data-driven methods depend not only on the availability of data but also on the nature of the data collected [35]. This approach has the capability of describing the uncertainties in performance degradation of LEDs by incorporating random and dynamic variances. On the other hand, machine learning (ML) algorithms refer to a set of methods and procedures that can be used to capture, detect, and learn relevant information patterns from large amount of data and use the unhidden patterns for further decision-making in prognostics or predicting the future lifetime [18].

The main advantage of the DD approach is that the methods and algorithms provide quick results and are computationally efficient. In addition, DD methods can also handle complex systems having multicomponent interaction, such as in the case of LED lighting systems, which are difficult to deal with using the physics-based method. On the other hand, one of the drawbacks of the DD approach is its dependency and demand for training (or historical) data to create correlations, understand patterns, and evaluate data trends and deliver accurate results [31]. In fact, statistical-based data-driven methods depend not only on the availability of data but also on the nature of the data collected [35]. In some cases where the products have a long lifetime, nonoperating, and standby systems, there will be insufficient training or operational data. In such conditions, data-driven approaches have to incorporate model-based approaches to bring a better prognostic solution. Commonly, data-driven methods are used in fault detection, diagnostics, and lifetime prediction. Even though the first two parts are mostly handled by using DD methods, the prediction part can also be handled with PoF approaches [29].

Assessing the reliability information of products (such as remaining useful lifetime, mean time to failure) plays a central role in the process of continuous quality and reliability improvement. This is especially true for highly reliable products such as LEDs, where it is time-consuming and expensive to assess their lifetime using traditional lifetime tests [68]. In such conditions, the quality characteristics of products whose degradation path (degradation data over time) is related to the reliability of the product can be collected and analyzed to infer important reliability information about the lifetime of the product. Lumen depreciation is the most common failure mode in LEDs [10]; thus the luminous flux maintenance lifetime, defined as the amount of time left until the initial light output falls below a failure threshold of 70%, is widely recognized as one of the critical characteristics for representing the LED's life and assessing its reliability (Fig 6.6).

LEDs belong to highly reliable electronic devices with long lifetimes (more than 50,000 h), provided that proper thermal management techniques are applied [32, 33]. Therefore, traditional reliability assessment methods based on failure data are not suitable for LEDs which have few failures even under accelerated conditions. Previously, the accelerated life test (ALT) was used to qualify the LED's reliability and was designed to cause the failure of LED packages/lamps at a faster pace compared to the usage under normal conditions [69]. However, there are two considerations when using ALT in the LED case; firstly, relating the real operation life and rated life under accelerated conditions is not easy for the LED case. Secondly, keeping the same failure modes and mechanisms under both normal operations and accelerated conditions is also difficult. In such situations, the use of degradation data to handle reliability assessment has been found to be a superior alternative compared with traditional censored failure data. It provides the benefits of identifying the degradation path as well as more reliability information (such as mean time to failure (MTTF), confidence intervals) that helps in maintenance decision-making before failures happen [70–75]. First introduced by Lu and Meeker [72], the general degradation path method was used to model degradation data in relation to time. Fan et al. [7] implemented the degradation data-driven-based PHM with statistical models into the high-power white LED to get additional reliability information

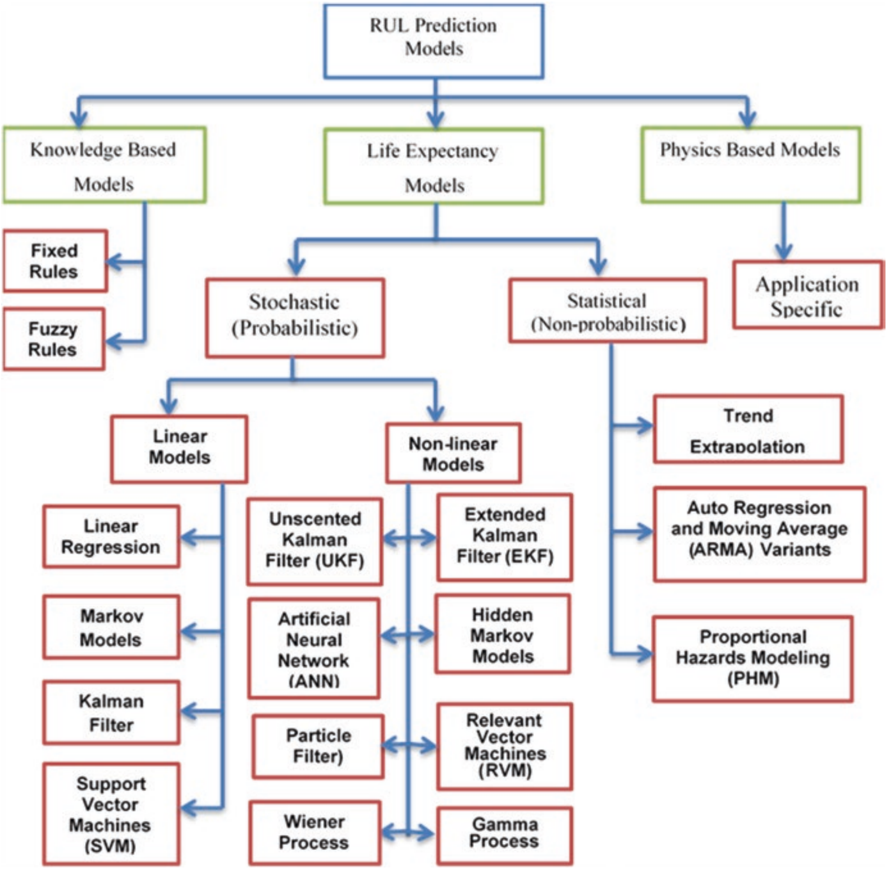



**Fig. 6.6** Prognostic modeling techniques for remaining useful life

(such as reliability function, confidence interval, and MTTF) in addition to the luminous flux lifetime, the only information obtained from IES-TM-21-11.

Besides the deterministic statistical methods, stochastic modeling was also used to predict the lifetime of LEDs based on degradation data, where the degradation path was modeled as a stochastic diffusion process [25, 76]. Such stochastic degradation of products (e.g., lumen depreciation) is often modeled based on a failure rate function or a stochastic process such as random deterioration rate, Markov process, Brownian motion with drift (wiener process), or the gamma process [77]. Recently, Si et al. [78] and Wang et al. [79] proposed an improved remaining useful life estimation method in the diffusion degradation process, which can also be used to describe the LED's degradation path. Meanwhile, the Bayesian approach was also found to be an effective method to predict the residual life distributions from degradation data [73, 80]. In addition to dealing with degradation data, another data-driven-based PHM used in LED lighting is anomaly detection that uses distance measures to monitor the operating characteristics in LED (such as junction temperature, driving current). In this case, the health of an LED product/system can be described as the degree of depreciation or deviation from its anticipated typical performance. In order to evaluate the reliability of the product and predict the lifetime, the degree of deviation from the normal performance has to be evaluated precisely [81]. Therefore, distance measures were used to detect fault occurrence in a product's normal operation [82–85]. Based on this approach, Sutharssan et al. [86–88] applied distance measures (such as Euclidean and Mahalanobis distance) to do real-time health monitoring and determine remaining useful lifetime estimation for high-power LED.

In general, DD methods are based on statistical techniques, pattern recognition, deep learning and machine learning algorithms, and artificial intelligence approaches. These methods can be employed at the component, subsystem, or system levels [89]. Sikorska et al. [90] presented a comprehensive review on available prognostic modeling methods, strengths, and weaknesses that help to estimate remaining useful life and reliability of engineering assets. Some of these methods or approaches have been widely applied by researchers in the past few years. The appropriate application of these methods requires not only mathematical knowledge but also appropriate system understanding. The summary in Fig. 6.6, enhanced from Sikorska et al. [90] shows a general classification of most of the RUL prediction data-driven approaches that can be used for LED lighting system reliability assessment, failure analysis, and remaining useful life prediction. In the study of LED's reliability and lifetime prediction, many data-driven approaches can be found in the literature. The DD approaches can be categorized into different types depending on the nature of the degradation data (deterministic or stochastic), data training requirement (supervised, unsupervised, or semi-supervised), and so on. The data-driven approaches are widely used and the application spectrum is broader. A comprehensive summary of the machine learning algorithms is presented in Table 6.3, in the Appendix section. Many of the data-driven techniques that are found effective from other fields of study could be adapted and customized for the LED's lifetime estimation and reliability analysis with proper understanding as discussed in this section.

## *4.1 An Overview of Selected Statistical Data-Driven Methods*

### 4.1.1 Wiener Process-Based Approach

A Wiener process is generally described as a drift component plus a diffusion component based on Brownian motion. A simple Wiener process with constant drift can be represented by Eq. (6.1):

$$\mathrm{X}(\mathrm{t}) = \mathrm{x}(0) + \lambda t + \sigma\beta(\mathrm{t}) \tag{6.1}$$

where $X(t)$ is degradation of performance characteristics (such as lumen maintenance, color shift, etc.), $x(0)$ is initial deterioration, $\lambda > 0$ is a drift parameter, $\sigma > 0$

is a diffusion coefficient, and $\{\beta(t), t > 0\}$ is a standard Brownian motion that represents the stochastic dynamics of the degradation process [91].

Degradation modeling with the Wiener process is mathematically important because the distribution of the first hitting time (FHT) at which the degradation process exceeds a threshold, i.e., lifetime (T) can be formulated analytically based on the inverse Gaussian distribution. That is why the Wiener process has been widely studied for lifetime prediction and reliability assessment [92–94], and the pdf of T can be given as:

$$f_T\left(t;\theta\right) = \frac{w}{\sqrt{2\pi\sigma^2 t^3}} \exp\left[-\frac{\left(w-\lambda t\right)^2}{2\sigma^2 t}\right] \tag{6.2}$$

where $\omega$ is a failure threshold and the mean and variance of T are $\theta = [\lambda, \sigma^2]$ and given as $w/\lambda$ and $w\sigma^2/\lambda^3$, respectively [95].

A Wiener process is typically used to analyze degradation processes that vary bidirectionally over time with Gaussian noise, in other words, non-monotonic degradation processes, and it is one of the widely used degradation modeling approaches. The Wiener process was applied to predict the RUL of variable stress-accelerated degradation tests by pioneers Doksum and Hbyland [96]. Whitmore [97, 98] proposed a Wiener diffusion process to address measurement errors and a timescale transformation method to address the time-varying degradation drift. This method has been extensively applied in [99–104] to describe the degradation modeling of light-emitting diodes (LEDs), self-regulating heating cables [98], bridge beams [105], bearings [106], and so on. Peng and Tseng [99] employed the Wiener process to analyze the degradation path of LEDs and to estimate the equations for median life as well as MTTF. Liao and Elsayed [104] applied the Wiener process to model the degradation of electronic devices such as LEDs sources exposed to variable stresses under field conditions. Ibrahim et al. [107] investigated the lifetime estimation of high-power white LEDs based on lumen maintenance data using the Wiener process method. Jing et al. [108] used the constant drift Wiener process to model the radiation power degradation for ultraviolet LEDs. Recently, a modified Wiener process was proposed by Huang et al. [50] to handle dynamic and random variations of lumen degradation and color shift for mid-power white LEDs and predict their lifetime. The analysis of lumen maintenance and chromaticity shift of mid-power white LEDs with the modified Wiener process along with the cumulative distribution function (CDF) is shown in Fig. 6.7a–d.

Apparently, the Wiener process has been observed to entertain some variations as limiting cases. A common variation is a Wiener process with a linear drift which has been studied by Tseng et al. [100], Peng and Tseng [99], Tsai et al. [68], and Guo et al. [109]. On the other hand, a timescale-transformed Wiener process has been explored by Whitmore [97], Whitmore and Schenkelberg [98], and Wang [105]. Real-time reliability has been investigated by Xiaolin et al. [110] based on a

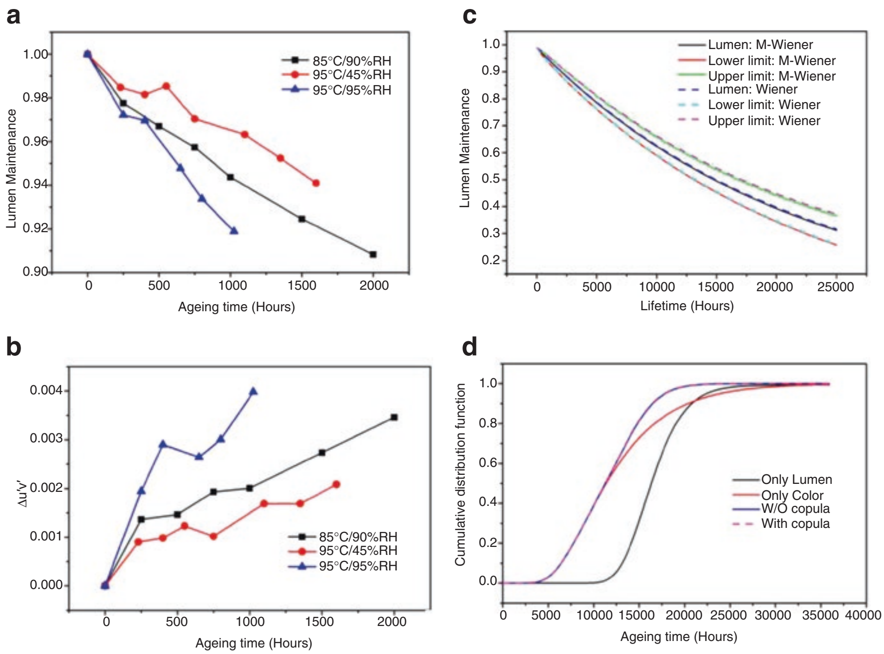



**Fig. 6.7** (**a**) Luminous flux degradation, (**b**) chromaticity shift, (**c**) fitting lumen degradation data and lower and upper limits for Wiener process (WP) and modified WP, (**d**) cumulative distribution function for lumen and color with and without copula. [50] Copyright 2015 Optical Society of America

generalized Wiener process-based degradation model and validated based on a laser device and capacitor data. A comprehensive review on the Wiener process based methods and its implementation for degradation data analysis and lifetime estimation is given in Zhang et al. [111].

### 4.1.2 Gamma Process-Based Approach

The gamma process is one of the popular stochastic process models used for modeling nonnegative degradation increments taking place in a sequence of small step time increments. The gamma process is thus a suitable model for unidirectional degradation processes including crack growth, erosion, creep, fatigue, wear process, corrosion, swell, and related degrading health index or performance degradations [112]. The effectiveness of the gamma process for useful lifetime estimation and reliability assessment is due to relevant advantages. One of the main interesting features of gamma process in terms of lifetime prediction is that the mathematical calculations needed are fairly understandable and the underlying physical meaning is easy to comprehend [77]. The PDF for a degradation process *X*(*t*), which can be described in terms of the gamma process, is given according to the definition as:

$$f\left(x|\alpha,\beta\right)=\begin{cases}\dfrac{\beta^{\alpha}}{\Gamma\left(\alpha\right)}x^{\alpha-1}\exp\left(\beta x\right),\mathrm{x}\geq 0\\ 0,x<0\end{cases} \tag{6.3}$$

where X(t) is a performance degradation parameter (such as luminous flux, color shift, etc.), $\alpha$ is a shape parameter, $\beta$ is a scale parameter, and $\Gamma(\alpha)$ is the gamma distribution function.

The system/product's MTTF under this model $M_G$ and failure threshold w has been approximated by Park and Padgett [113] as:

$$MTTF_G \cong \frac{w}{\alpha\beta}+\frac{1}{2\alpha} \tag{6.4}$$

Nevertheless, it is worth noting that the gamma process appears suitable for the monotonic degradation process, and this may restrict the application of the gamma process to some other dynamic degradation patterns. For this reason, incorporating the modified gamma process that uses the method of moments to estimate the model parameters can enhance degradation modeling and lifetime estimation process. Recently, the gamma process has been employed to model the lifetime of high-power white LEDs based on CCT shift [115]. Ibrahim et al. [114] also used gamma process to model reliability of phosphor-converted white LEDs by estimating the long-term lumen maintenance lifetime and validate by comparing with the NLS regression method. The results showed that the prediction accuracy of the gamma process was superior compared with the NLS regression-based approach. The plots demonstrating the luminous flux degradation, probability distribution with gamma, PDF at different time points, CDF, and reliability estimation are shown in Fig. 6.8.

### 4.1.3 Particle Filtering (PF) Approach

Particle filtering (PF) is a Monte Carlo simulation-based method which provides a convenient framework to handle Bayesian-framed prognostics. PF is a commonly used method to model and manipulate non-Gaussian processes and/or nonlinear performance degradations and measurement noise. PF uses a number of particles and set of weights associated with them to compute the prior distributions (probability densities) of the model parameters [116–118]. On the contrary, the IES TM-21 standard for projecting lumen maintenance lifetime uses the LSR to compute model parameters which depends on the minimization of the sum of errors or offsets between the estimated values by using proposed analytical equation and experimental or real measurements.

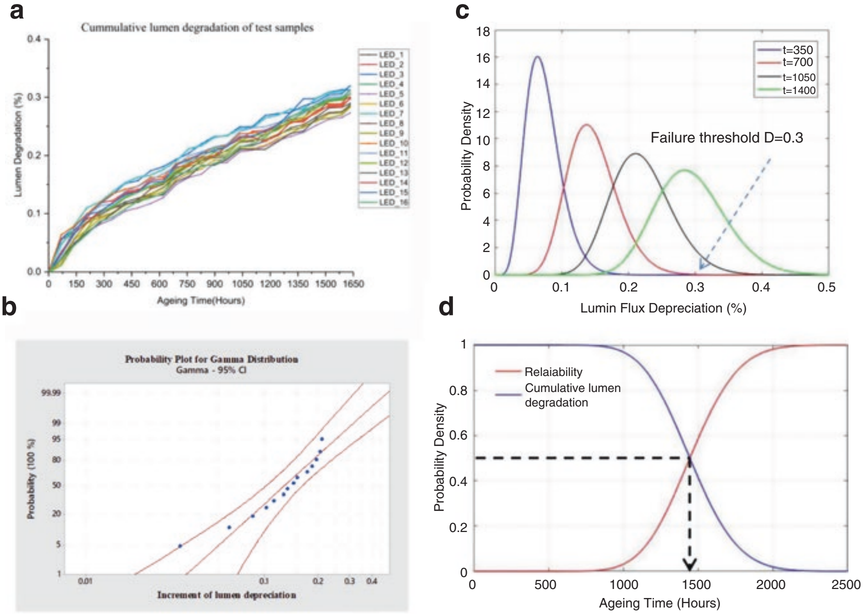



**Fig. 6.8** Gamma process (**a**) average cumulative lumen degradation, (**b**) probability distribution plots with gamma distribution, (**c**) PDF at different times, (**d**) CDF and reliability plots [114]. Copyright, the authors

Due to its features, PF is found to be effective to model the lifetime of LED sources that are known to manifest dynamic and nonlinear performance deterioration, such as luminous flux and chromaticity shift. A typical procedure to apply PF method can be described according to Fan et al. [119], as follows: the first task is to choose a degradation model as suggested in the IES TM-21 standard (i.e., exponential-based decay model) to represent the performance degradation in the LED light source. Then the second step is to replace the LSR method used to estimate model parameters in TM-21 with Bayesian inference in PF approach. The Bayesian inference makes use of observations or experimental values to estimate the value of unknown model parameters and update their values in the form of distribution function. Within a proposed PF method, the procedure of the recursive state estimation and optimization with updated measurements can be performed in four steps: (i) initialize the model parameters, (ii) sample the model parameters and prediction, (iii) use the Bayesian inference algorithm to update values, and (iv) weight the particles and resample, as shown in Fig. 6.9a. At the end, the experimental measurements will be terminated at time $t_p$, and then the remaining useful life (RUL), with confidence interval limits, will be estimated by manipulating the updated model with measurement noise. Fan et al. [119] employed this PF method to project the lumen maintenance lifetime for high-power white LEDs. The feasibility of the PF method was validated, and its prediction accuracy was evaluated and

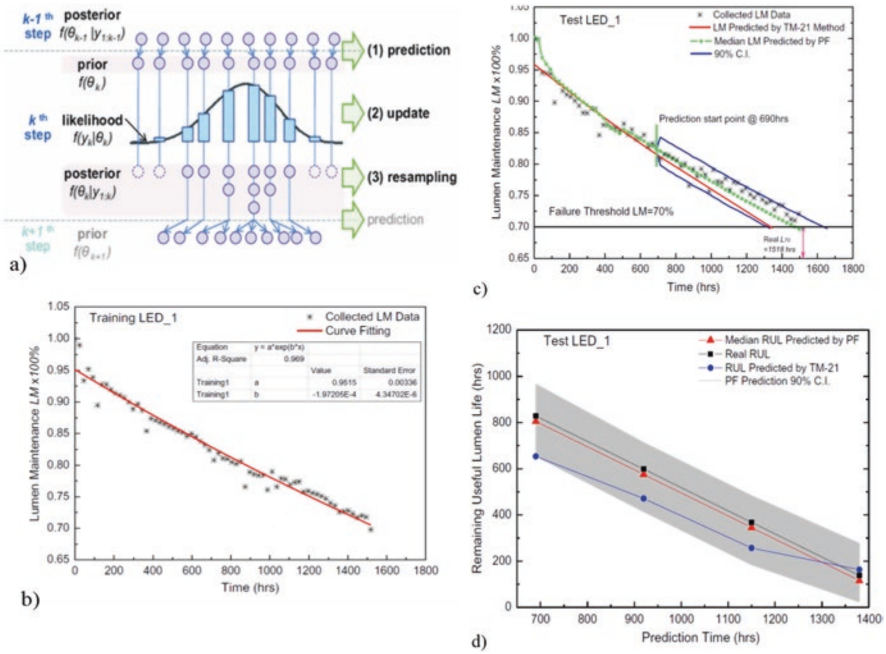



**Fig. 6.9** Illustration of particle filter process to predict the lifetime of high-power white LEDs based on luminous flux degradation data (**a**) model parameter estimation process. [120] Copyright 2017 Springer International Publishing. Implementation of particle filtering algorithm (**b**) fitting all lumen degradation data to decay model as training samples, (**c**) prediction of lumen maintenance life, (**d**) PF method and IES-TM-21 LSR approach estimating RUL based on lumen maintenance data. [119] Copyright 2015, the authors

showed superiority over the current NLS regression-based TM-21 method. Illustration of the implementation of the PF approach to investigate the lumen maintenance lifetime for high-power LEDs is shown in Fig. 6.9.

As the main focus of this review is on the machine learning-based data-driven approaches, the review on statistical approaches is limited to the updated and well-revised Wiener process, gamma process, and PF approaches. For other statistical-based data-driven approaches such as Mahalanobis distance, Euclidean distance, Kalman filter (KF), and unscented Kalman filtering (UKF), a brief review is given in Sun et al. [23]. The different types of ML algorithms employed to handle lifetime estimations of LED sources are presented in the next section.

## 4.2 An Overview of Selected Machine Learning Methods for PHM

Recently, an exponential increase in computing power, introduction of new state-of-the-art algorithms, and systematic generation of large data have been observed. Due to this, ML has emerged by breaking new frontiers in reliability assessment and lifetime prediction field of studies. ML algorithms are a set of procedures and methods that can be used to capture, detect, and learn relevant information patterns from large amounts of data and use the unhidden patterns for the process of decision-making in anomaly detection, diagnostics, and prognostics or predicting remaining useful lifetime [18]. ML can be defined as "the branch of artificial intelligence that deals with the development of algorithms and models that can automatically learn patterns from data and perform tasks without explicit instructions," according to Chen et al. [121]. A more engineering-oriented definition of machine learning was presented by Mitchell [122] as "a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E." In short, machine learning enables computers to learn through experience and improve performance without requiring explicit programming. For instance, if the task T is to identify the failure of LED systems, the training data such as lumen degradation and chromaticity shift can be considered as the experience E, and the failure prediction or estimation accuracy is the performance measure P. Depending on the amount and the type of human supervision required, it can be broadly categorized into supervised learning (predictive modeling), semi-supervised learning, and unsupervised learning (descriptive modeling).

### 4.2.1 Supervised Learning Approaches

In supervised learning, an output value or desired pattern can be estimated/predicted based on a classified or labeled set of input data. Depending on the output or response variable, the problem can be described as either classification (such as normal or abnormal) or regression (such as lumen degradation level, chromaticity shift, CCT degradation). As a result, the choice of the learning method is an important factor in achieving desired outputs or in discovering the group of input data. A typical supervised ML task is classification, and a diagnostic problem is a typical classification task. Due to this, the majority of supervised ML methods are used to address diagnostic problems (i.e., failure mode identification, normal, anomaly, etc.). However, supervised ML methods are also applicable in the estimation of remaining useful lifetime (RUL) which is a regression task [123]. Some authors recognize linear regression [124] [125] and logistic regression [126] as supervised machine learning methods. However, the well-known supervised machine learning approaches applied for the prognostics of systems include k-nearest neighbors (KNN), support vector machine (SVMs) [127], relevance vector machine (RVM)

[128], decision trees [129], artificial neural network (ANN), [18] [90] [130], and random forest. Some of the widely used machine learning methods are discussed as follows.

### Artificial Neural Network

Artificial neural networks (ANN) form a set of mathematical algorithms conceived and modeled after the human brain's neurons structure and designed to recognize patterns [131]. A typical neural network and back-propagation learning [132, 133] is shown in Fig. 6.10. The working principle of the ANN algorithm mimics the human brain which connects many nodes in a complex structure. The nodes represent input, output, and hidden variables, while the links represent the weight parameters. The bias parameters are denoted by links coming from additional inputs and hidden variables $x_0$ and $z_0$, and more details about ANN are given in [132]. In an ANN, a network is modeled, and it learns an effective way to produce a desirable output by reacting to give inputs [35], as depicted in Fig. 6.10. In a back-propagation ANN, the learning process consists of forward propagation of the signals and backward propagation of the errors.

ANN is a popular ML approach used to perform many tasks such as prognostics (prediction/regression problems) and diagnostics (classification problems). ANN helps to compute a predicted output for the lifetime of a product explicitly or implicitly, from a mathematical representation of the product derived from measurement/experimental data rather than a physical understanding of the failure processes [90]. ANNs are known methods for modeling complex nonlinear systems effectively and

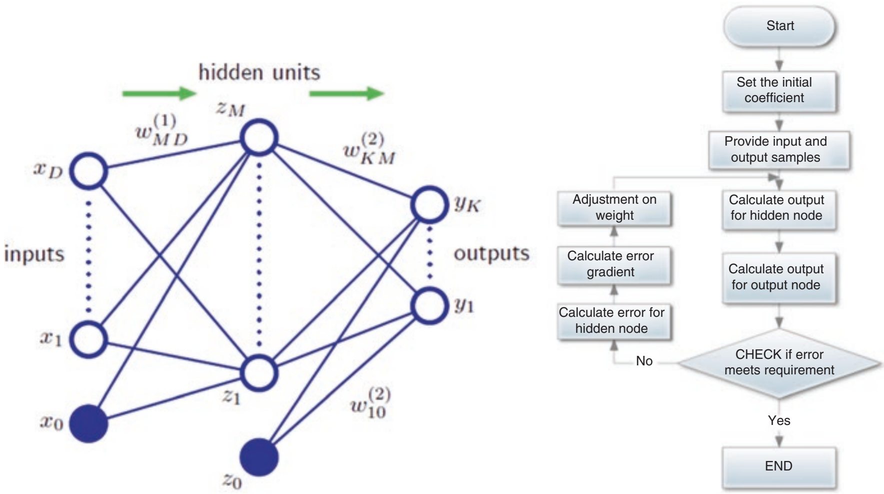



**Fig. 6.10** A representative network diagrams for two-layer neural networks (left), flowchart for back-propagation learning algorithm

efficiently and can generalize and adapt solutions from a limited dataset [130]. Based on the mathematical operations and set of parameters required, ANN architecture can be of different types including feedforward neural network, backpropagation neural network, radial basis function neural network, recurrent neutral network (RNN), and self-organizing map. Although ANN has been widely applied in prognostics, it has two main limitations. The first is a lack of transparency or lack of documentation on how decisions are made in a trained network. The second one is related to optimization of results as there are no established methods to determine the optimal network structure.

As one of the popular approach in prognostics, ANN has been implemented to study transformers [135], aircraft actuator components [136], bearings [137], nuclear turbogenerators [138], electronic packages [139], etc. However, application of ANN methods for high-power white LEDs lifetime estimation was not very common until Sutharssan [140] demonstrated a basic neural network for lifetime prediction of LEDs. The model used consists of one hidden layer and two neuron nodes in the hidden layer. Recently Lu et al. [134] proposed and tested a model for lifetime prediction of high power as well as mid-power LED light sources. In their investigation, both the radial basis function network and backpropagation neural network were demonstrated. The AdaBoost algorithm is adopted to enhance backward propagation NN in training the weight points connecting input neurons with hidden layer neurons and predict the lifetime with a multidimensional input parameter such as lumen depreciation, color coordinates, driving current, and aging temperature. The BPNN data training, iterations, training errors, as well as predictions are shown in Fig. 6.11. In general, the performance of ANNs has good performance for lifetime estimation of systems due to the capability of learning complex relationships by training multilayer networks. However, it has few undeniable limitations, such as low transparency and the demand for high-quality data, which could be difficult for new products in industrial applications.

The recurrent neural network (RNN) is a type of ANN designed to recognized sequential data such as speech recognition, precise timing, and so on, due to its added feature of time dimension to NN model. However, RNN still suffers from gradient exploding or vanishing during the learning process [141]. With the capability of learning long-term dependencies, a special type of RNN called the long short-term memory (LSTM) architecture was found to be suitable to overcome the shortcomings of the traditional RNN architecture. Guo et al. [141] used LSTM architecture to predict the RUL of bearings, and, compared to SOM, the prediction performance of LSTM was found to be superior, as shown in Fig. 6.12. Similarly, Wu et al. [142] deployed the LSTM approach in prognostics and demonstrated a good prediction accuracy using aircraft turbofan engine's health performance data. While LSTM architecture RNN appears to be suitable for LED RUL estimation, application of this method has not been reported in the literature.

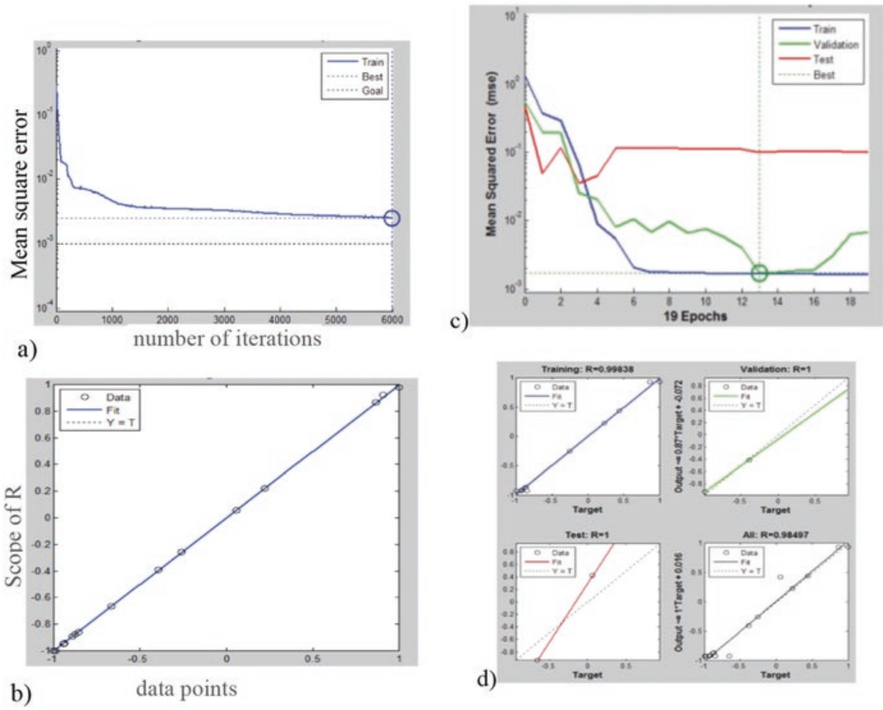



**Fig. 6.11** A typical neural network (**a**) BP neural network training convergence curve, (**b**) effect of network training regression, (**c**) AdaBoost-improved BPNN curves of iterations and training error, (**d**) state of prediction regression [134]. Copyright 2018, the authors

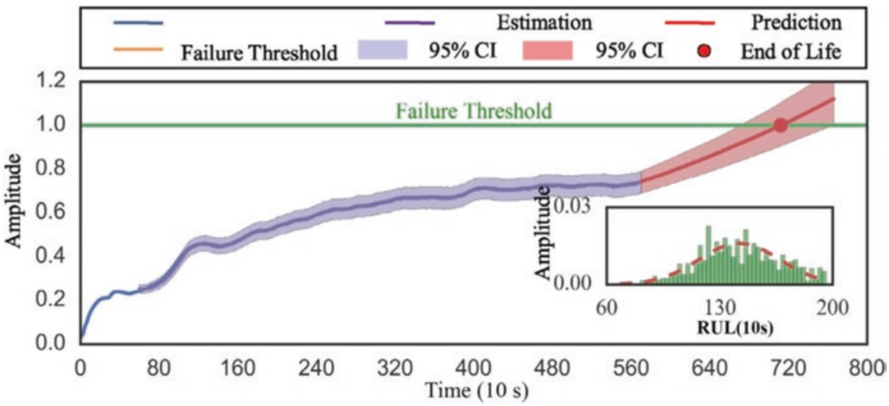



**Fig. 6.12** RUL prediction result for a bearing [141]. Reproduced with permission from publisher/ Elsevier

### K-Nearest Neighbors

K-nearest neighbors (KNN) is a supervised learning algorithm with a non-probabilistic property that belongs to similarity-based prognostics, and it has been employed in PHM for crack propagation [143], electromagnetic relay contact resistance [144], and printed circuit boards ball grid array solder joints [145]. As an emerging trend in the prognostics approach, KNN has been used as a lifetime estimation tool for reciprocating compressor valves based on regression [146]. The prognostic performance, precision, and accuracy of KNN regression (KNNR) was compared with self-organizing map (SOM) and multiple regressions using actual operating data of a valve from an industrial compressor. The result for all the approaches showed that the performance was relatively good and comparable to each other. A typical application for LED anomaly detection has been conducted based on the KNN-kernel density-based clustering algorithm [147]. In this study, peak analysis was used to extract features from spectral power distribution (SPD), the principal component analysis (PCA) was used for the reduction of dimensionality of feature, the KNN-kernel density-based clustering technique was used to partition the principal components datasets into clusters, and finally distance-based algorithm were used to detect anomalies. In this case study, the KNN algorithm was used to list *kth* nearest neighbor distances to each of the N single clusters formed by PCA. This typical application of KNN algorithm and related techniques to investigate the qualification of LEDs along with some results is illustrated in Fig. 6.13.

### Support Vector Machine and Relevance Vector Machine

The support vector machine (SVM) is a modern and advanced technique used for classification problems (anomaly detection, diagnostics such as normal/anomaly) and regression (prediction) types of problems. It is a very successful approach in supervised learning using the flexible (i.e., multiparameter) linear kernel approach. Predictions are made in SVM based on a function of the form given as:

$$\mathrm{y}(\mathrm{x};\omega) = \sum_{n=1}^{N} \omega_n K(x,x_n) + \omega_0 \tag{6.5}$$

where $w_n$ are the model weights and $K(x, x_n)$ is a kernel function. The target function of SVM has a key feature that attempts to reduce the number of errors on the training set while maximizing the margin between two classes in a classification study.

Due to this, it has the advantage of preventing over fitting that leads to good generalization and results in a sparse model dependent only on a subset of kernel functions [148]. The SVM classifier algorithm has been demonstrated in the problem of health evaluation and novelty detection. In [81], the Bayesian SVM was trained to model the posterior class probability in the absence of failure data (i.e., anomaly or negative class data), as in the case for a safety and mission critical

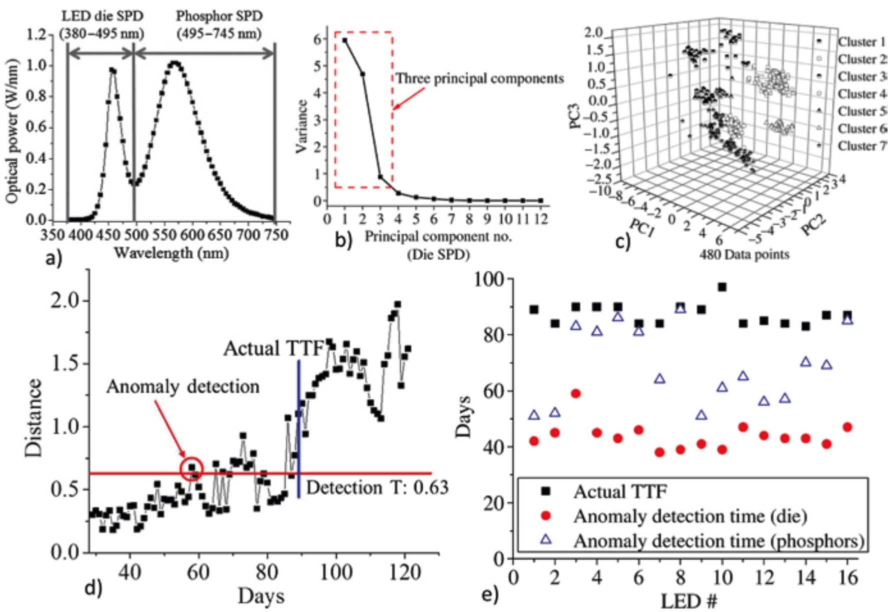



**Fig. 6.13** (**a**) SPD feature extraction, (**b**) principal components from extracted features, (**c**) SPD training using KNN-kernel density-based clustering, (**d**) distance measure from cluster centroid to detect anomaly, (**e**) anomaly detection using die SPD [147]. Reproduced with permission from publisher/IEEE. Copyright 2014, the authors

system in Lockheed Martin equipment. In addition to this, a least-squares SVM combined with Bayesian inference was developed and used to investigate lifetime prediction of a microwave component [149]. In [149], the radial basis function NN (RBFNN) algorithm was also employed for RUL estimation and validation purposes, and the point and interval estimate of RUL based on least-squares SVM has been found to be more robust and stable compared with the RBFNN algorithm. Despite its success, SVM suffers from a disadvantage in terms of lack of probabilistic prediction outputs (for regression and classification problems) which is an important aspect in prognostics applications [148, 150].

The relevance vector machine (RVM) is an identical functional form to the SVM which has a probabilistic sparse kernel model as an additional feature. The RVM achieves this through the Bayesian approach and introduces a prior over the weights that are governed by a set of hyper-parameters. In addition to its generalization performance capability that is similar to SVM, the other feature of RVM is that it makes use of considerably fewer kernel functions compared to the SVM approach. In the PHM area, the RVM has been successfully explored to estimate the RUL of rotating equipment in an aerospace setting [128]. The RVM regression (i.e., a Bayesian machine learning technique) has also been implemented effectively to predict the RUL of LEDs, and the qualification result showed that the testing time for LEDs can be reduced from the IES standard (i.e., 6000 h) to hundreds of hours

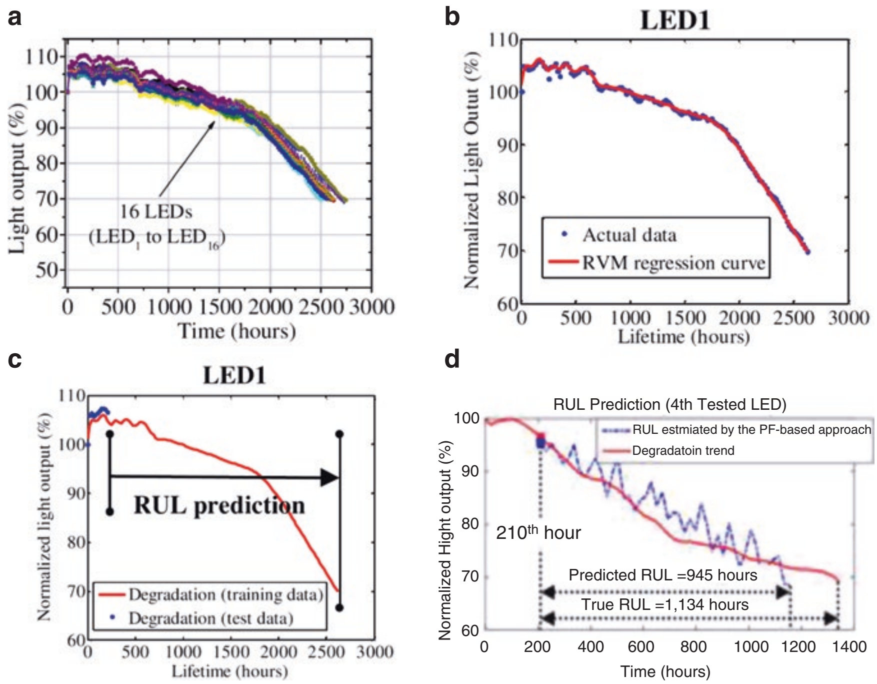



**Fig. 6.14** (**a**) LED luminous flux degradation, (**b**) parameter measurement for RUL, (**c**) lumen degradation the RVM regression model, (**d**) PF-based lifetime prediction results [151]. Reproduced with permission from publisher / IEEE. Copyright 2017, the authors

(210 h). This approach was also reported to handle unit-to-unit variation and also has the capability of handling transient degradation dynamics. Due to this feature, the RUL prediction accuracy of the RVM approach has been reported to surpass the particle filtering approach [151]. The detailed results for the LED lifetime estimation based on RVM regression compared with the PF approach are depicted in Fig. 6.14.

In general, the SVM and RVM demonstrated superior performance compared to the ANN approaches for experiments with small sample sizes. Due to this, SVM and RVM may be suitable for lifetime prediction where limited measurements are available. On the other hand, challenges such as parameter estimation may slow down its wider application.

### 4.2.2 Unsupervised Learning Approaches

Unsupervised learning is a machine learning procedure where the input dataset is unlabeled, and also there is no classified or labeled target response value $Y_i$ or response variable. In other words, there is no labeled output value to supervise the learning process of a learner, or there is no need of data to train algorithm. In

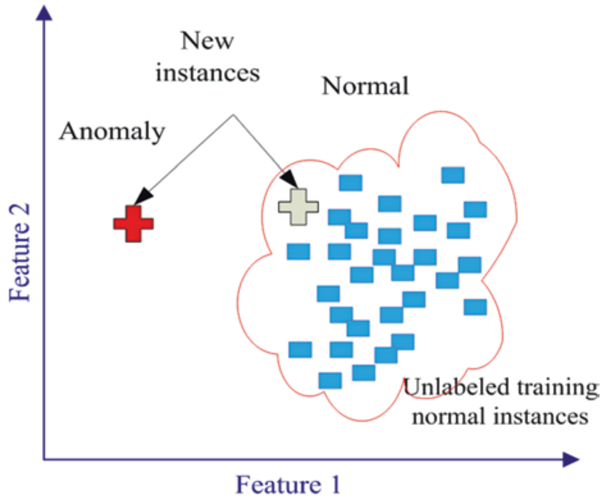



**Fig. 6.15** An unlabeled training dataset for unsupervised learning

unsupervised learning methods, an unlabeled or unclassified set of data is used to find interesting patterns or outputs in the data. Due to this, the main tasks of unsupervised learning are clustering and dimensionality reduction, and the nature of these ML approaches enables the addressing of anomaly detection [152]. Some of the unsupervised algorithms are k-means clustering, principal component analysis (PCA), and hierarchical clustering. The unlabeled instances are used to train a model for representing normal behavior [123] as shown in Fig. 6.15. A few of these unsupervised learning approaches that have been investigated to conduct reliability assessment of LED products are described in this section.

#### Principal Component Analysis

Principal component analysis (PCA) is an exploratory data analysis technique used in dimensionality reduction to simplify the complexity of data while retaining patterns and trends. It performs this by transforming the original data into fewer comprehensive dimensions (indexes), which act as summaries of features [153]. Similar to clustering, PCA is an unsupervised learning method, and it finds patterns without reference to prior knowledge of the data. This approach was first introduced in 1933 by Hotelling [154] to transform the statistical dependency of groups of correlated variables in multivariate data to uncorrelated variables and to achieve optimal conditions.

The PCA method has been widely implemented in condition monitoring for mechanical systems. Wang and Zhang [155] used PCA to transform a set of variables for aircraft engine experimental observations to a new set of uncorrelated variables. The new set of data are known as principal components and then used in the aircraft engine lifetime recursive filtering-based prediction model. On the other hand, Ahmed et al. [156, 157] demonstrated PCA approaches for fault detection in reciprocating compressors by identifying 5 and 7 most important performance characteristics (PCs), respectively, from 9 and 14 original features.

The life of high-power LED is influenced by numerous parameters including series resistance, optical output saturation, junction temperature, and so on. Qiyan [133] adopted PCA to process the various parameters and select the principal components (parameters) for further processing using neural networks. Chang et al. [147] used PCA for dimensional reduction among 24 extracted features from LEDs die SPD (12 features) and phosphor SPD (12 features) to study anomaly detection of LEDs. The six principal components from 24 extracted features were further analyzed using a KNN-kernel density-based clustering technique. This study analyzed 480 and 640 training datasets and portioned into 7 and 8 clusters, respectively, and the results of feature extraction and principal component analysis are shown in Fig. 6.13 along with SVM/RVM plots.

### K-Means Clustering

K-means clustering is an unsupervised learning fault detection approach which is widely used in industry because it can be applied without the need to be trained on data obtained from a faulty machine or system. In k-means a number of centroids are selected that define the number of clusters, and each data point is assigned to its closest centroid based on Euclidean distance. The k-means clustering helps to partition n number of objects into k clusters where each object will have the nearest mean distance from the cluster. The main objective of this method is to minimize the total distance between clusters or the square error function. This objective function can be formulated as follows:

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n} x_i^{(j)} - c_j^{\,2} \tag{6.6}$$

where $J$ is the objective function, $n$ is number of objects, $k$ is number of clusters, and $x_i^{(j)} - c_j^{\,2}$ is the chosen distance function among the data point $x_i^{(j)}$ and the cluster centroid $c_j$.

This method has been successfully applied for anomaly detection of mechanical components, such as rolling elements bearings [158], as well as for wind turbines [159]. In [159], data was collected from a normally operating turbine supervisory control and data acquisition system (SCADA) and fitted using the k-means clustering algorithm. This approach shows the suitability for employment in anomaly detection in LED systems as it does not require failure data or faulty system information. However, application of this approach for diagnostics and prognostics of LEDs was not found in the literature. Figure 6.16 shows a typical implementation

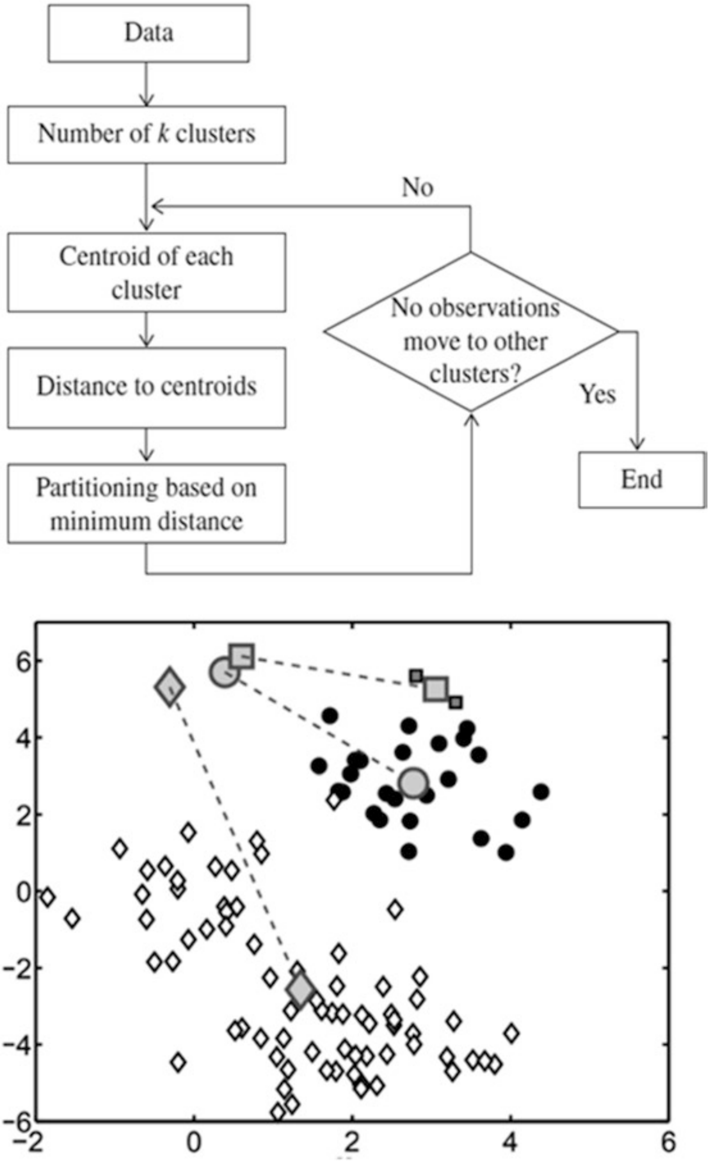



**Fig. 6.16** K-means clustering procedure (top), clustering illustrated (bottom). [152]. Reproduced with permission from publisher/Wiley

procedure for this approach (left) and how trained data can find their clusters based on the distance from the centroid (right).

Self-Organizing Map (SOM)

First introduced by Kohonen [160], the self-organizing map (SOM) is one variety of ANN method mainly applied for unsupervised learning. The SOM has been employed to project high-dimensional data obtained from supervisory control and data acquisition system of a wind turbine into a two-dimensional space to capture the pattern of input training data. A Euclidean distance method was used to represent difference between new input data and target value as the indicator for system-level anomaly detection [161]. Tian et al. [162] demonstrated a SOM-based method for the purpose of anomaly detection with the k-nearest neighbor algorithm for the purpose of reducing sensitivity to noise in mechanical and electronic systems (cooling fan with ball bearing) data.

Recently, this approach has been applied as a lifetime estimation approach for compressor valve failure data, and the result was found to be relatively competitive with other approaches applied for purpose of comparison, such as KNNR and multiple regression [146]. The study claimed that the SOM was used for the first time as a standalone program for remaining useful lifetime estimation. Even though an implementation of this method was not found in the PHM of LEDs, the similarity of the nature of degradation data in the mechanical component observed in the study [146] suggests that this method appears to be promising for the RUL estimation of LED products [146]. The RUL prediction performance of SOP along with KNNR, multiple linear regression, and ensemble methods based on a historical failure data is depicted in Fig. 6.17.

### 4.2.3 Semi-supervised Learning Approaches

Semi-supervised learning paradigm is a ML approach that falls within supervised and unsupervised learning methods by introducing both labeled and unlabeled data for training. This approach has evolved recently and has been increasingly applied to automatically manipulate and exploit large amounts of unlabeled data and small amounts of labeled data for training without requiring human experts. The aim of semi-supervised learning is to classify a set of unlabeled data using the information set from the labeled data, and it is mainly applied for anomaly detection problems. For a typical semi-supervised learning, suppose a dataset $X = (x_i)_{i \in [n]}$ can be divided into two components: data points $X_j : (x_1, x_2, \ldots, x_j)$ for which labels $Y_j : (y_1, y_2, \ldots, y_j)$ are given and data points $X_k : (x_{j+1}, x_{j+2}, \ldots, x_{j+k})$, for which the labels are unknown [163]. The Semi-supervised learning methods are widely applied for speech analysis, web

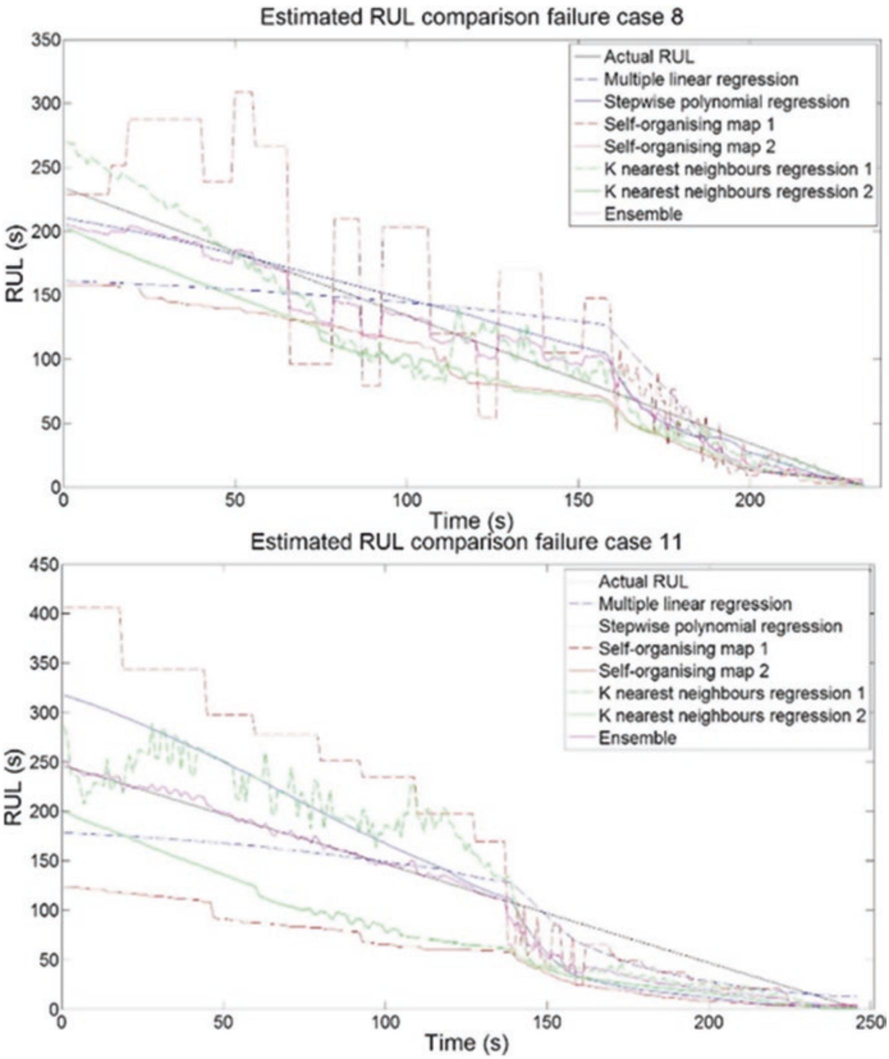



**Fig. 6.17** RUL estimation based on SOP, KNNR, multiple linear regression, and ensemble methods [146]. Reproduced with permission from publisher/Elsevier

content classification, protein sequence classification, and recently in prognostics. Some of the examples that can be considered as semi-supervised learning algorithms include Hidden Markov Model, expectation maximization (EM) with generative mixture models, graph-based methods, and transductive SVM [164], and two of these methods that have been successfully applied in prognostics are discussed here.

### Expectation Maximization

Expectation maximization (EM) is an iterative and general procedure employed to estimate model parameters in a parametric distribution. ML is often considered as a special case of maximum likelihood estimation where missing or incomplete data is examined and computed by alternating between (i) estimation of expectation (E-steps) and (ii) maximization during model re-estimation (M-steps) until it converges [165]. Although the EM algorithm is not widely seen in the PHM field, it is a very important algorithm, and a typical application of EM for use in a RUL prediction is presented by Si et al. [166]. In this study, linear and exponential-based closed-form degradation models were considered to demonstrate a degradation path approach for RUL prediction. The expectation maximization algorithm along with Bayesian updating was used to update the RUL distribution and model parameters when new degradation data was obtained [166]. In solid-state lighting, a recent work showed that expectation maximization (EM) has been applied to estimate the model parameters of the exponential decay model and to calculate the remaining useful lifetime of HPWLEDs [167] as shown in Fig. 6.18. In this study, the EM was applied to estimate the degradation model parameters for the state space model from unlabeled luminous flux degradation data. The RUL estimation results were claimed to be superior to TM-21 standard which is based on NLS regression method, and it showed a comparable accuracy to PF method (Fig. 6.18).

### Hidden Markov Models

Hidden Markov Models (HMMs) are standard approaches for encoding, analyzing, and predicting patterns in multivariate and univariate observation data. Even though the HMM technique was developed in the late 1960s, it is still going through development and gaining popularity [168]. The HMMs are based on a stochastic model and Markovian hypothesis, where the current hidden (not observable) state of the model is influenced by its previous state. In HMM, each of the current model states (hidden) displays an outcome which is observable state. For instance, in case of LEDs, when estimating the lumen degradation or color shift state at time point $t$, the HMM considers not only the feature values $X(t)$ at time $t$ but also the preceding value $X_{t-1}$.

The HMM is a semi-supervised approach, typically used for anomaly detection. However, HMMs can also address detection problems, decoding problems, as well as learning problems. This method was successfully applied for the first time in PHM study by Baruah and Chinnam [169], where the sensor signals from a machine were modeled using the HMM method to identify the health status as well as facilitate the remaining useful life estimation of cutting tools. The HMM has also been applied in PHM for mechanical parts, including hydraulic pumps [170, 171], helicopter gearboxes [172], as well for anomaly detection in an electronic component, insulated gate bipolar transistor (IGBT) [173]. A mixture of Gaussian Hidden Markov Models has also been employed to assess the current health status and

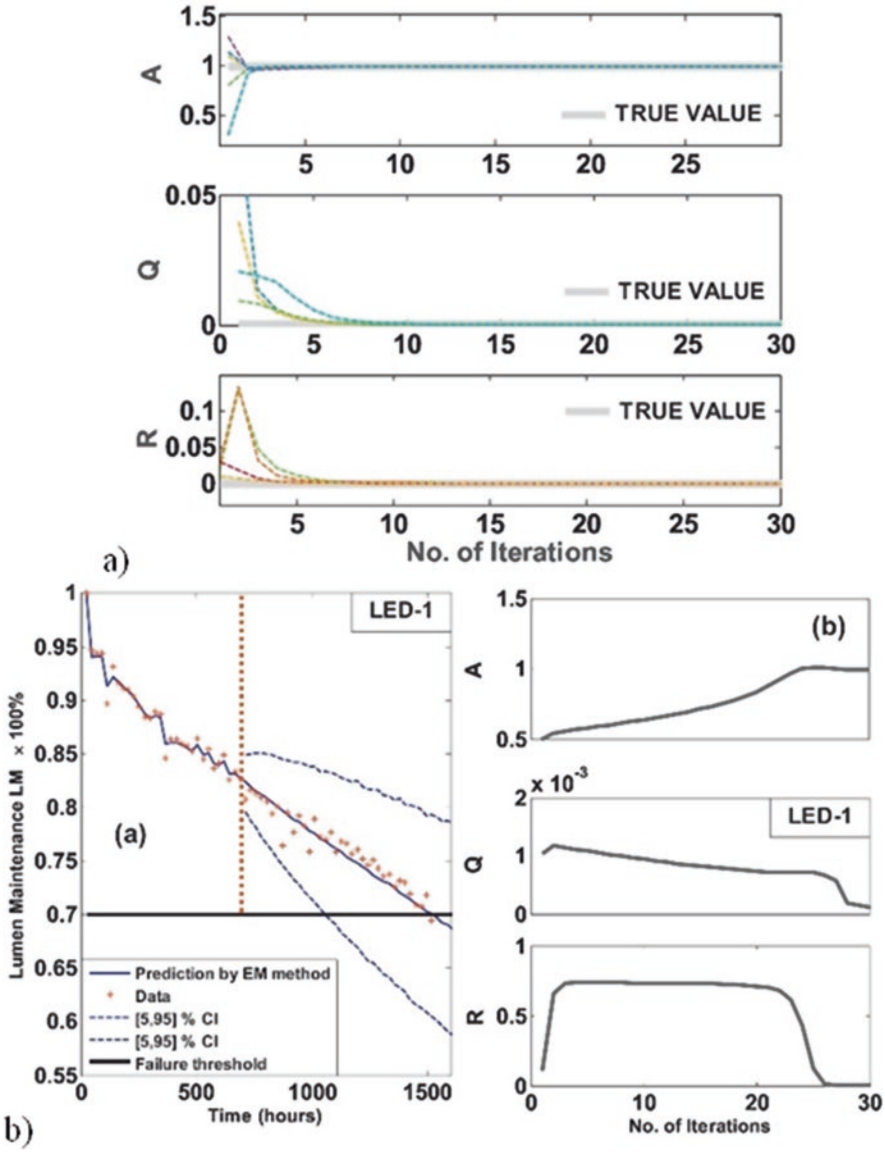



**Fig. 6.18** (**a**) Parameter estimation using EM algorithm, (**b**) RUL prediction based on EM-estimated parameters and iteration trends values for parameters [167]. Reproduced with permission from publisher/Elsevier

estimate remaining useful lifetime of bearings [174]. Even though it has been applied for diagnostics and prognostics for mechanical parts and electronic components, its application has not been found in PHM for LED products and systems so far. A comprehensive theoretical explanation and step-by-step tutorials on the general HMM are given in Rabiner [175], while a review on the potential applications of HMM is demonstrated in [176].

The observation sequence $O = O_1\ O_2 \ldots O_T$ can be generated by HMM when appropriate values for $N$, $M$, $A$, $B$, and $\pi$ are given. The compact notation for the discrete HMM model $\lambda$, when model parameters ($N$ *and* $M$) and probability measures ($A$, $B$ *and* $\pi$) specified are as:

$$\lambda = \{A, B, \pi\} \tag{6.7}$$

where $N$, $M$, $A$, and B are, respectively, number of hidden states in the model, number of distinct observations per state, state transition probability matrix, and the observation probability distribution of each state. The observed states are represented as $O$ and $Q$ which is hidden state at time $t$. The HMM can be represented graphically in different ways [176] as shown in Fig. 6.19. The first plot portrays a direct state transition graph, while the second illustrates the allowable transitions.

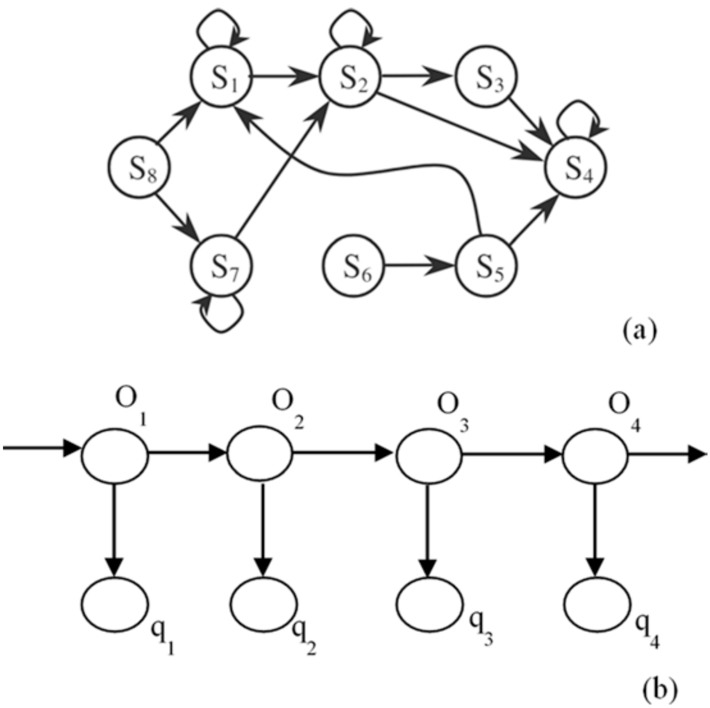



**Fig. 6.19** HMM graphical description (**a**) stochastic finite-state automation view of a HMM, (**b**) a directed graphical model (DGM) [169]. Reproduced with permission from publisher/Taylor & Francis

In recent years, an increasing number of research studies can be found on prognostics using HMM. However, HMM still suffers from heavy computational workload problems, and consequently future research should focus on addressing the limitations and improve its applicability for complex and practical industrial systems and products including LEDs.

## 5 Fusion Prognostics Approach for Light-Emitting Diodes

Both the PoF- and DD-based PHM methods have been employed successfully in the prediction of failures in many devices and systems (e.g., machinery systems, LED lighting devices and systems, hybrid systems) [37, 177]. However, the PoF methods [178–183] require comprehensive knowledge of products in advance (e.g., materials and geometries, thermal, electrical, mechanical, life-cycle conditions, and other processes that lead to failures) that always increases the time and cost in actual applications. On the other hand, the data-driven approaches [119, 126, 184–194] need sufficient measurement or experimental data to estimate the health conditions and to predict trend thresholds from failure prognostics, but it is not easy to obtain these data in advance, especially for newly introduced LED lighting products. Thus, the fusion-based PHM is believed to solve these concerns by combining the advanced qualities and features of both the PoF and DD approaches. Fusion prognostics could apply PoF modeling, in situ monitoring procedures, and deployment of both statistics-based and ML-based DD methods to detect the performance deviation or degradation, predict the RUL, and assess the reliability for LED lighting products and systems. Because it uses in situ monitoring with the use of sensor technologies, fusion-based PHM can realize real-time failure diagnostics and RUL prediction in field applications.

The fusion (hybrid) prognostics approach combines the strengths of both PoF-based and data-driven methods, while eliminating their disadvantage to assess reliability, detect anomalies, and predict the lifetime of LED products and systems. The Fusion prognostics approach enables effective use of information from both methods for dynamic PHM and RUL prediction as well as to evaluate return on investment (ROI) [195–197] of LED product/systems [37]. Pecht and Jaai [34] assessed the state of applications in the PHM of electronic and information-rich products and presented a framework on the implementation of PHM for these products and systems by further illustrating a printed circuit board (PCB) case study. Cheng and Pecht [37] presented a fusion prognostic method to elaborate the useful lifetime of multilayer ceramic capacitors (MLCCs). They demonstrated this method with a special case study on the multivariate state estimation technique (MSET). Yao et al. [9] presented an implementation roadmap of PHM approaches for LED lighting systems. In their study, the LED lighting system was categorized into LED strings (including die, interconnect, and package) and the LED driving system (MOSFET, capacitor, etc.). However, for ease of understanding and the convenience of implementing prognostics approaches, the LED lighting product/system can be

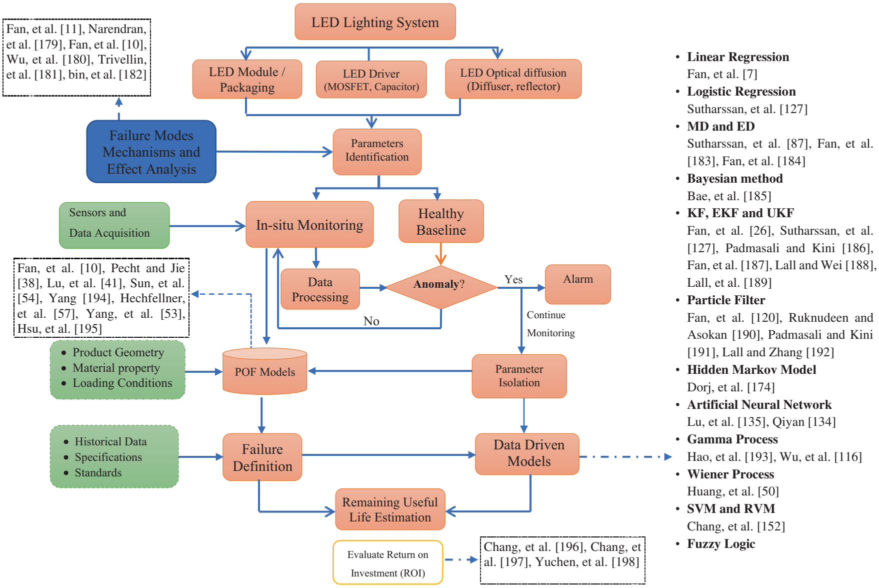



**Fig. 6.20** Fusion prognostics for LED lighting system (adapted from Yao et al. [9], with permission)

categorized into three sub-parts as LED module/package (die, inter connect, encapsulates), LED driver (electrical part), and optical diffusion (diffuser and reflector parts). In general, the fusion prognostic approach based on PHM is an increasingly demanding method as it has not been well designed and developed for LED lighting. The detailed procedure for fusion prognostic approach implementation is shown in Fig. 6.20.

## 6 System-Level Reliability of Light-Emitting Diodes

As described in the previous sections, the diagnostics and prognostics of high-power white LEDs have been widely studied based on machine learning and statistical-based data-driven methods and algorithms, such as the Wiener process [50, 107], gamma process [114, 198], Kalman filter [186, 199], particle filtering [26], neural networks [134], expectation maximization [167], RVM regression [151], and so on. The reliability assessment and lifetime prediction of most of these studies are at the component level (such as package/module, LED driver, diffusers, and reflectors) using direct performance characteristics (i.e., lumen maintenance, color shift) and indirect characteristics (i.e., junction temperature and driving current) to examine the luminaire/system-level (such as LED luminaire, LED street lighting, LCD backlights, etc.) reliability. However, high-power white LEDs are complex products/systems composed of several subsystems/components, and it appears to be difficult to deduce the reliability of LED systems based on single component analysis as the product lifetime is affected by the health status of its components and their interaction. Due to this, LED manufacturers are facing challenges regarding system-level reliability assessment and remaining useful lifetime prediction of LED products/systems.

An LED system consists of several subsystems, including LED chip, electrical driver for power supply and control, thermal management module, optical part, and so on. One of the major challenges for a generic system-level approach for LED systems reliability is the large variety of products and applications [6]. In a high-power LED lamp system, the LED driver serves as the constant current source and optimizes the power to drive high-power LEDs [200]. Usually, the LED drivers are considered as the weakest part among all components in LED lighting products. Based on a family of outdoor luminaires failures, the US Department of Energy (DOE-US) [201] reported that the LED driver (power supply) is the weakest link in the LED lighting system, constituting 52% failure, LED package (10%), housing (31%), and control circuit driver (7%). On the other hand, Van Driel et al. [202] used the Monte Carlo approach to predict LED system-level reliability by taking both the failure mode of the sub-components and the operation conditions into account. The result showed that the LED emitters, solder interconnect, and driver accounted for 30%, 44%, and 26% failure rates, respectively, after 20,000 h of operation, showing that the solder interconnects are weakest parts in LED systems. Recently Ke et al. [64] introduced a subsystem isolation method to estimate the lumen degradation LED lamps, and the result showed lumen degradation of 70.5% due to the LED emitter, 21.5% the optical part, and 6.5% the driver, which contradicts the two studies (US DOE [201] and Van Driel et al. [202]) previously mentioned. Song et al. [45] also proposed a hierarchical life prediction model, which consists of component-level sub-physics-of-failure models, for the actively cooled LED luminaire system. In general, the results among studies based on subsystems and components for system-level lifetime analysis showed inconsistency.

In order to address the long-term reliability assessment concerns of complex and highly reliable products such as high-power LEDs and fulfill the guarantee of high prediction accuracy in less time and in a cost-effective manner, developing a system-level reliability assessment and lifetime prediction methods is necessary. Traditionally, graph model-based reliability block diagrams (RBD) and failure tree analysis (FTA) have been used to assess the system-level reliability of products and systems. However, these methods are based on deterministic relationships between components/subsystems. To address these concerns, the Bayesian network (BN) method, a probabilistic graphical machine learning method, appears to be a promising approach. The BN uses a directed acyclic graph (DAG) to represent the conditional and probabilistic relationship between component/subsystem relationships in a system [203]. As one of the popular modeling and reasoning tools, the BN model has been employed in the fields of machine learning, artificial intelligence, and uncertainty management [204]. The BN model has also been applied in the field of reliability engineering including software reliability [205], modeling maintenance [206], and fault diagnosis in systems [207, 208]. Recently, the BN model was found to be effective in estimating the system/product reliability of complex systems, such as high-speed trains [208], solar-powered unmanned aerial vehicles [209], and pitting degradation structural steel in marine systems [210].

In this section, a BN method that considers the intricacies of the high-power light-emitting diode (LED) lamp system and the functional interaction among components for reliability assessment and lifetime prediction is briefly introduced. This approach considers the parametric (degradation based) and catastrophic failure modes of each component in order to assess the system-level reliability, and it also requires the design of experiments to gather the required data. The functional and structural relationship analysis between components and the failure mode and effects analysis (FMEA) are considered [3] in order to construct a DAG for a BN model. In the BN model constructed in Fig. 6.21 (left), the variables which have no parents, such as LED_CAT, LED_DEP, Driver_CAT, Driver_DEP, Solder_CAT,

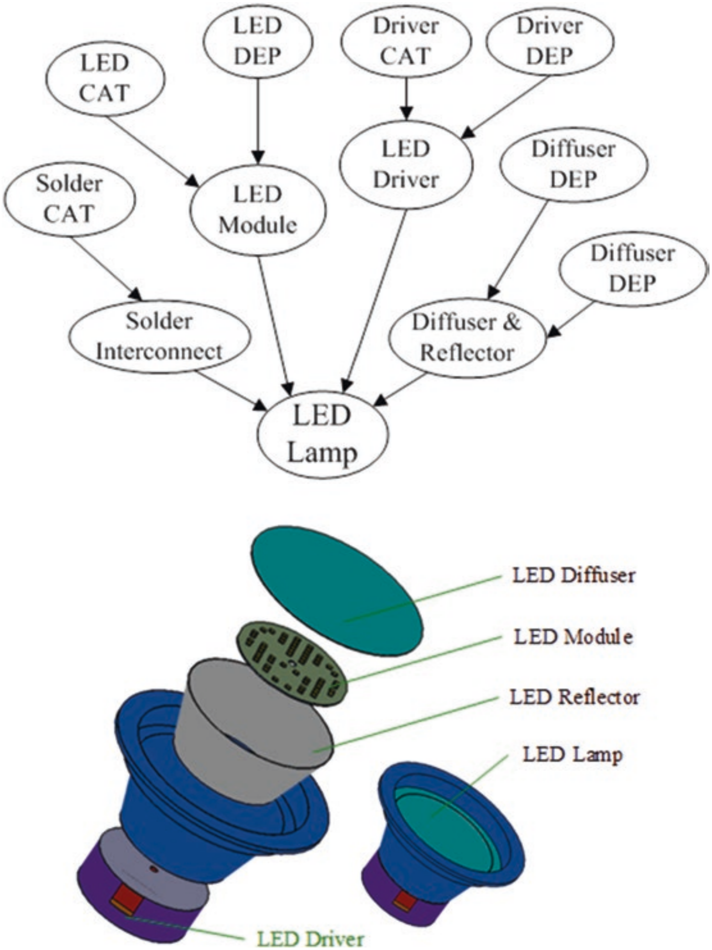



**Fig. 6.21** DAG for product level LED light sources (top), 3D model exploded and assembly view (bottom)

DifRef_DEP, and DifRef_CAT, are referred as root nodes. On the other hand, the variables with no children are the leaf nodes (LED_Lamp), while the remaining variables are the intermediate nodes (LED_Module, LED_Diffuser, and LED_DifRef). The root nodes have unconditional probabilities, represented here as reliability state functions of the node $X_i$ at time $t$ $R_{Xi}(t)$, i = 1,…,p; the intermediate nodes as $R_{Mj}(t)$, j = 1,…,k; and the leaf node as $R_L(t)$. The BN model DAG analysis is based on the construction of a test sample, shown as a 3D model, with an exploded and assembled view Fig. 6.21 (right).

The reliability status of each root node or component is assessed based on the corresponding prediction model at a future time $t_n$, and the reliability state prediction matrix can be represented as follows:

$$R_{pn} = \begin{bmatrix} R_{11} & R_{12} & \dots & R_{1n} \\ R_{21} & R_{22} & \dots & R_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ R_{p1} & R_{p2} & \dots & R_{pn} \end{bmatrix} \tag{6.8}$$

The reliability state of the intermediate nodes can also be predicted based on the prediction models of the root nodes $U = \{R_1, R_2, \dots, R_p\}$ and the assumption of conditional independence:

$$P\left(R_{Mj}\left(t\right)\right) = \sum_U P\left(R_{Mj}\left(t\right), R_{Xi}\left(t\right)\right) \tag{6.9}$$

Similarly, the reliability state of the leaf node can be predicted based on the probability of the intermediate and root nodes as follows, and the junction tree algorithm synchronizes the DAG of the BN model for product level lifetime prediction:

$$\begin{aligned} P\left(R_L\left(t\right)\right) &= \sum P\left(R_{X1}\left(t\right),\dots,R_{Xp}\left(t\right),R_{M1}\left(t\right),\dots,R_{Mk}\left(t\right),R_L\left(t\right)\right) \\ &= \sum_{Pa(L)} P(R_L\left(t\right) \mid Pa\left(R_L\left(t\right)\right). \sum_{Pa(Mj)} P(R_{M1}\left(t\right) \mid Pa\left(R_{M1}\left(t\right)\right).\dots \\ &\sum_{Pa(Mk)} P(R_{Mk}\left(t\right) \mid Pa\left(R_{Mk}\left(t\right)\right).\dots.P\left(R_{X1}\left(t\right)\right).P\left(R_{Xp}\left(t\right)\right) \end{aligned} \tag{6.10}$$

Here $Pa(L)$, $Pa(M_j)$, *and* $Pa(M_k)$ are the parent nodes for leaf node L and intermediate nodes $M_j$ and $M_k$ respectively.

## 7 Challenges and Opportunities of Diagnostics and Prognostics Approaches

Recalling that PHM is a multifaceted engineering discipline that facilitates the safety, reliability, and maintenance aspect of components and systems, it helps to avoid unexpected product problems that can lead to products' performance deficiencies. Even though this approach has been widely accepted for product and system reliability assessment, lifetime prediction, and maintenance decision-making, it is still facing some challenges, especially for electronic systems, including LED lighting systems. The data-driven methods are based on the extraction of historical data collected from sensors, to exploit and learn the degradation behavior of the system through relevant feature identification using machine learning, AI, and statistical tools. On the other hand, model-based approaches implement a set of mathematical and analytical equations obtained from classical physics laws to represent the degradation behavior and predict the future behavior of physical components and systems.

The different approaches for the PHM in general need further improvement to be able to reduce the computational time, effort, and availability of historical data to accommodate the increasing demand in the reliability assessment and remaining useful life prediction in the LED light industry. There are always trade-offs in terms of accuracy, applicability, cost, and complexity while implementing DD approaches. While some approaches can handle complexity, it may be deficient in regard to computational time and accuracy and vice versa [211, 212]. Some algorithms, such as Hidden Markov Model and Gaussian process regression, consume longer computational time, while others such as artificial neural network, particle filtering, neuro-fuzzy systems, and Hidden Markov Model demand large amounts of historical data to perform prognostics. Accordingly, the advantages and disadvantages of the two main prognostics approaches are briefly summarized as follows:

| Data-driven (statistical and machine learning methods) | Model-based (POF-based) approach |
|---|---|
| Assumptions or empirical estimations of physical parameters are not required | For a well-controlled system, predicting the future propagation of the degradation without prior knowledge about the mathematical model is possible |
| Less complex and more applicable than model-driven methods | Has higher accuracy if the systems'/products' physics of models remains consistent |
| Lower precision results compared with model-based approaches | Requires fewer data compared to data-driven approaches |
| Well-established theoretical basis and convenient to implement fast and accurate online pattern recognition | Usually complex and more stochastic to model system degradations |
| High-dimensional noisy data can be transformed in to lower dimensions convenient for prognostics | Might have difficulty to handle unit-unit variability in population and often provides overall estimate for entire sample |
| Relatively easy to calculate and predict future states | Might be difficult to get mathematical models for a particular kind of component or material |
| The more available information used, the better the accuracy | Computationally expensive |

| Data-driven (statistical and machine learning methods) | Model-based (POF-based) approach |
|---|---|
| Requires large amount of data to be more accurate in general | Requires simplifying assumptions |
| May lead to inaccurate time of change of predictions as it relies mainly on historical degradation | |
| Poor performance with high-dimensional data and longer learning time | |

## 8 Digital Twin as Emerging LED Lifetime Analysis

In the past few years, dramatic advancement in information technology such as Internet of things, artificial intelligence, and big data has evolved which has led to an increasing interaction trend between virtual spaces and physical entities. This has led to the introduction of digital twins – a pragmatic method of cyber-physical fusion [213]. A digital twin is a dynamic and comprehensive virtual prototype of a physical product/system. The concept of digital twin was initially conceived and introduced by Vickers (NASA) and Grieves (University of Michigan) in 2003 [214].

In the past few years, many companies started using digital twin to increase their system operation efficiency, testing new products before deployment, and identifying problems [213]. According to prediction by Gartner, half of the large industrial corporations will be leveraging digital twin technology by 2021 to facilitate the assessment of system performance while gaining an improvement of 10% in system effectiveness [215]. The implementation and adoption of digital twin depend on the type of industry and products as there are no common standards, methods, or norms [216]. The National Aeronautics and Space Administration (NASA) built two identical spacecrafts for Apollo 13 mission with the idea of early "digital twin" where one was launched to space, while the other was kept on Earth to simulate and monitor the launched spacecraft. Later, with few technical improvements, NASA and the US Air Force introduced digital twins to the aerospace industry. Companies such as Chevron and General Electric also use digital twins to track operation of wind turbines [216]. Singapore is also creating a virtual copy of the entire city in partnership with Dassault Systemes, to assess, improve, and monitor utilities [217].

It can be recalled that PHM is very useful in the diagnostics and prognostic analysis of a product/system of a physical object. On the other hand, digital twins appear to have the capability to fill the gap in PHM by creating a link between the physical system and the virtual model. Recently, Tao et al. [218] introduced the application of digital twins in the PHM sector and demonstrated a case study on wind turbines. The implementation of PHM for products and systems in terms of fault detection, diagnostics, and prognostics is mainly based on the performance degradation and failure in the physical space which has a limited connection to the virtual model [218]. This gap could be filled with convergence of data from physical

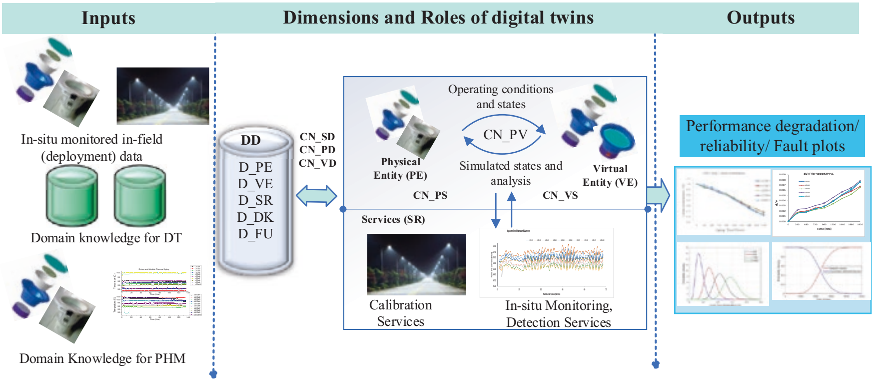



**Fig. 6.22** Digital twin implementation framework with the five dimensions (PE, VE, DD, CN, SR) for LED products (adapted from Tao et al. [218]

and virtual space through digital twins to improve the PHM of systems/products seamlessly. Due to its comprehensive virtual representation of a physical object, digital twins can simulate the behavior and conditions of products and systems through mathematical models and data. Oftentimes, machine learning algorithms and artificial intelligence are employed to analyze system operation models and identify correlations among data generated in in situ and in-field (deployment) operation [216]. The machine learning algorithms used in digital twins include supervised learning (such as artificial neural network), unsupervised learning (such as clustering methods for virtual and real-world environment), and reinforcement learning approaches (during uncertain or partially observable operating environments) [219].

Leveraging the digital twin technology has the potential to enable real-time system performance assessment and improve PHMs of light-emitting diodes as well as other safety critical complex products and systems. Due to its potential to generate accurate data from physical and virtual space for lifetime assessment and real-time data and condition monitoring, digital twins represent the future technology for lifetime assessment of LED products/systems. Initially, Grieves proposed three dimensions of digital twins: physical entity (PE), virtual entity (VE), and the connection between physical and virtual systems (CN) [214]. Based on this, Tao et al. [218] extended the digital twins to a five-dimensional model of digital twins with the addition of services for the physical and virtual entity (SR) and digital twin data (DD). The extended five-dimensional (PE, VE, DD, CN, SR) digital twin concept along with a framework of implementation in PHM for light-emitting diode products and systems is highlighted in Fig. 6.22.

## 9 UV LED Degradation Modeling and Analysis

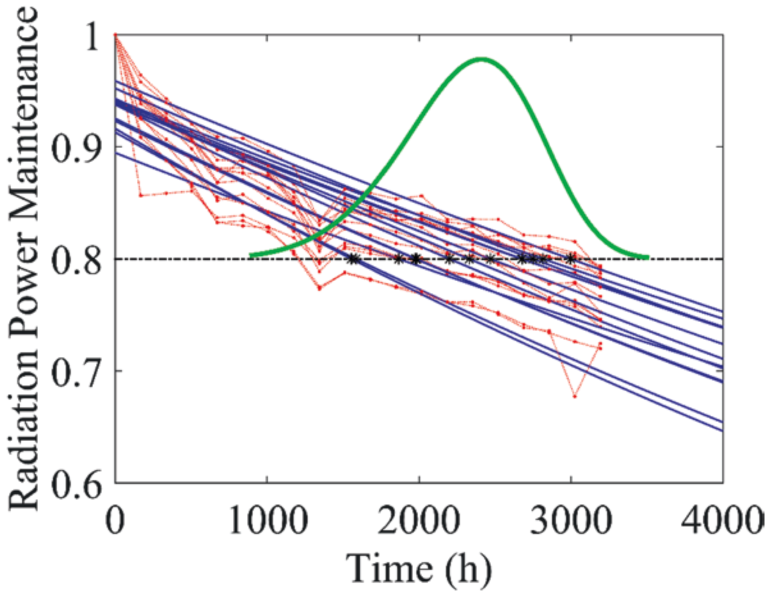
Ultraviolet (UV) light, with a wavelength between 250 and 350 nm, has numerous useful and attractive applications, such as virucide, air and water purification, photolithography, optical stimulus in drug activation, polymer curing, and laser surgery [220]. Due to its benefits of having a long life, compact size, and unimodal spectrum as well as being environmentally friendly, the III-nitride-based UV light-emitting diode (LED) is becoming a promising photoelectronic device to replace traditional UV light sources, such as mercury lamps [221, 222]. UV LEDs are important variations in the LED field. Especially after the global pandemic of coronavirus disease 2019 (COVID-19), ultraviolet rays from UV LEDs are being used for noncontact disinfection in an environment that is not high-temperature and cannot be wiped with alcohol [223]. Therefore, UV LEDs will continue to play a greater role in the future in phototherapy, sterilization, and related applications.

Radiation power is a critical physical index that reflects the optical radiation intensity of a photoelectronic device. The radiation power degradation of UV LEDs can cause by the UV LED chip degradation, the yellowing of packaging materials, and the cracking or delamination of interface [4]. The lifetime of UV LEDs is still challenged by the uncertainty of internal quantum efficiency, light extraction efficiency, and thermal management [224]. And due to the unclear failure physics and mechanisms of UV LEDs, the reliability and lifetime estimation methods are inconsistent [225]. This section focuses on modeling the dynamic nonlinear radiation power degradation process of UV LED packages in an accelerated degradation test. Firstly, we selected the exponential degradation model recommended in the TM-21 standard to describe the lumen radiation power degradation process of UV LEDs. Next, a LSTM neural network algorithm and two stochastic processing models, i.e., gamma process and Wiener process, are compared with the nonlinear least-squares (NLS) regression method recommended by the IESNA TM-21 standard. Finally, the prediction accuracy and robustness characteristics of the proposed methods are analyzed.

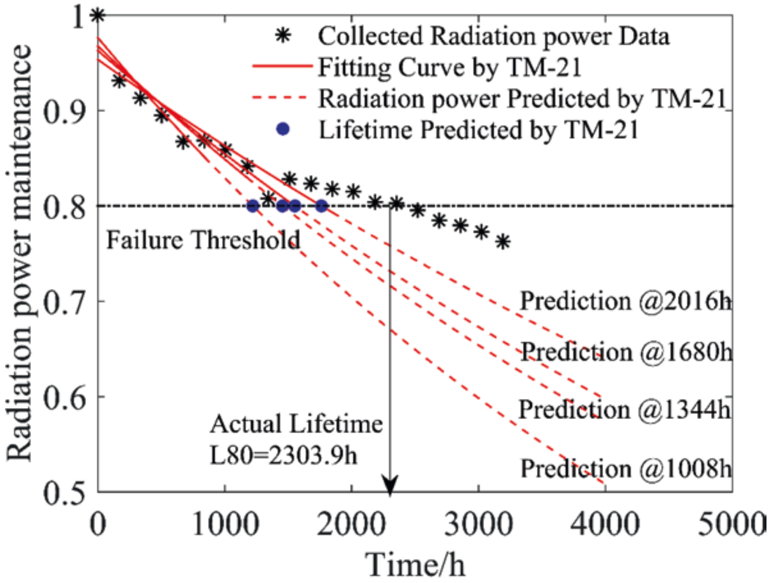
The TM-21 standard proposed by IESNA is a commonly used method in the industry to deal with the lumen maintenance of LED light sources and project long-term lifetimes [7, 16]. In this section, the radiation power of UV LEDs was adopted to evaluate the light output and predict long-term lifetime [108] (Fig. 6.23). And $L_P$ is the lifetime when the UV LEDs mean radiation power maintenance decays to $P\%$ of the initial value ($P = 80$ is considered as an example).

The cumulative radiation power degradation of UV LEDs can be regarded as a time-dependent stochastic gamma process which can be used to model this degradation process. Assuming the $L_{80}$ lifetimes of samples satisfied the two-parameter Weibull distribution, the mean of the distribution (MTTF-G1) can be predicted. Meanwhile, with the gamma process parameters of the whole group, the estimated $L_{80}$ lifetimes (MTTF-G2) can be estimated by eq. (6.4).

In addition to the gamma process, the Wiener process is also a stochastic model method that is widely used to describe degradation processes. With the




(a)




(b)

**Fig. 6.23** (**a**) Lifetime calculation of 13 UV LEDs based on Weibull distribution; (**b**) NLS regression fitting based on IES-TM-21 standard two-parameter Weibull distribution curve fitting of the predicted lifetimes of each sample, the estimated lifetimes, which were recorded as MTTF-W, can be estimated.

Also, ML approaches can be used to perform prediction. Neural network prediction does not need to determine the specific functional relationship between input and output. RNN can effectively and flexibly model the nonlinear relationship of dependent long time series data, that is, the current input is related to the previous input [226]. Hochreiter and Schmidhuber [227] proposed LSTM for solving the vanishing gradient problem in RNN.

$h_t$ is a short-term state, which is equal to the output $Y_t$ at time $t$. $c_t$ stands for long-term memory, running horizontally above the cells in the hidden layer, with less interaction and better information maintenance. $c_t$ determines what information is read, kept, and discarded in the long-term state of network learning. The output process can be expressed by the following eqs. [228]:

$$\begin{bmatrix} i_t \\ f_t \\ o_t \\ g_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{bmatrix} \bullet W \bullet \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} \tag{6.11}$$

$$c_t = f_t \bigotimes c_{t-1} + i_t \bigotimes g_t \tag{6.12}$$

$$h_t = o_t \bigotimes \; tanh\,(c_t) \tag{6.13}$$

where $\sigma$ and *tanh* are the sigmod and *tanh* nonlinear activation functions in the neural network, respectively; $W$ is the weight coefficient matrix.

Figure 6.24, shows a flowchart of the lifetime prediction of UV LEDs with the LSTM neural network. In this chapter, we have 9 input layers and 3 output layers, and the number of hidden layers is set to 18 after repeated trial calculations, as described in the Fig. 6.25, after multiple adjustments, the optimal weight matrix was obtained, and the lifetimes were predicted.

The comparison of prediction errors of each method is shown in Fig. 6.26. It can be seen that both the stochastic process method and the LSTM RNN method significantly improve the prediction accuracy compared to the TM-21 method. In general, the stochastic process method can achieve good prediction results as the prediction time increases. The LSTM neural network algorithm requires a small amount of test data to achieve better prediction accuracy compared with the other methods. It effectively reduces the collection and test time of UV LEDs and also has good robustness characteristics. It is found to be a very reliable and robust lifetime prediction algorithm for UV LEDs.

In a brief summary, by designing the experimental aging scheme and obtaining the actual lifetimes according to the two-parameter Weibull distribution, the NLS regression method, the stochastic process method, and the LSTM neural network algorithm were adopted to project the radiation power maintenance data to predict

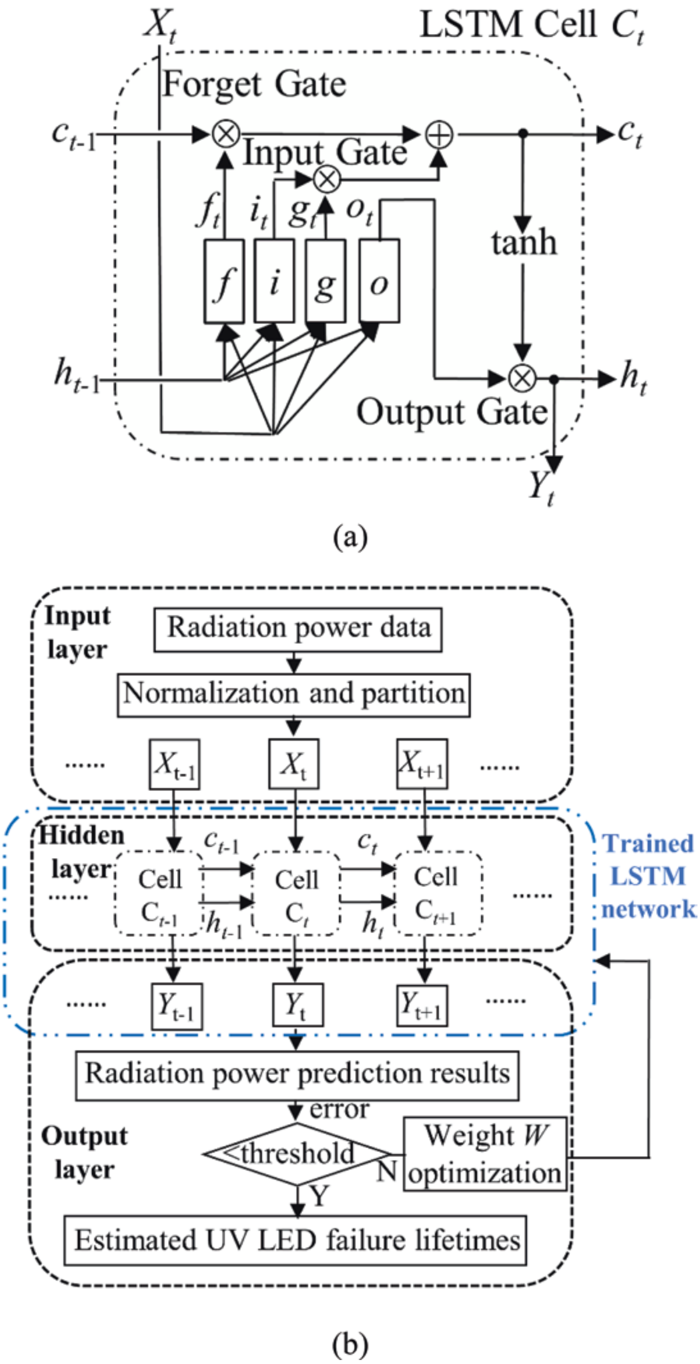



**Fig. 6.24** (**a**) The basic structure of LSTM cell $C_t$ in hidden layer; (**b**) the flowchart of the lifetime prediction of UV LEDs with the LSTM neural network

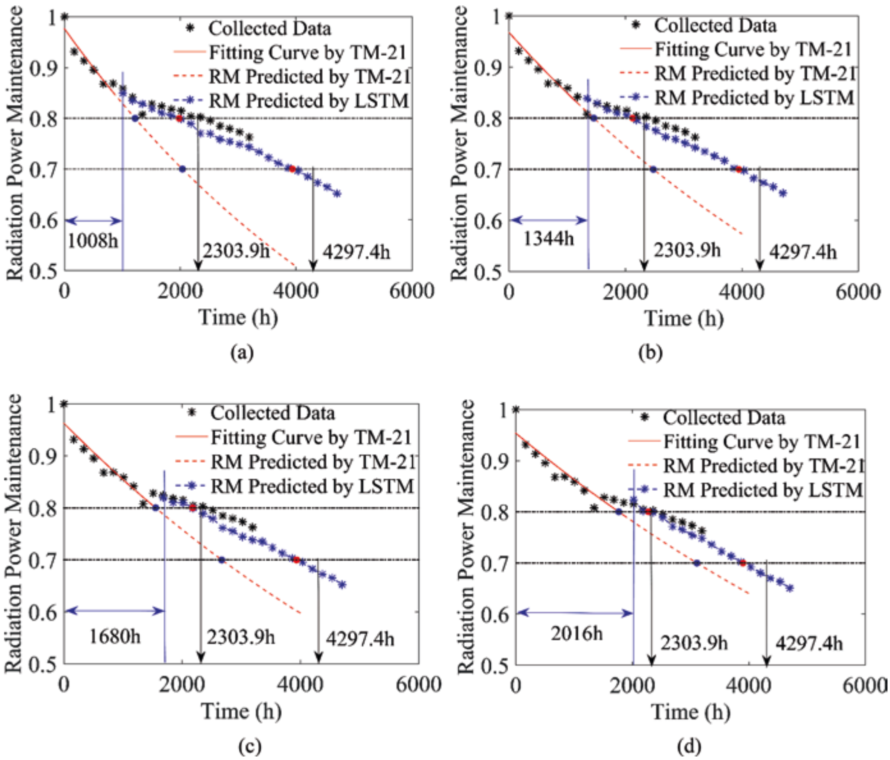



**Fig. 6.25** The NLS regression method vs. the LSTM neural network method, lifetime prediction at different starting points: (**a**) 1008 h, (**b**) 1344 h, (**c**) 1680 h, (**d**) 2016 h

the lifetimes of UV LEDs. The results show that the prediction accuracy of the LSTM neural network is higher; the results also show that the stochastic process method and the LSTM neural network method have better robustness by varying the prediction starting points. Therefore, the LSTM neural network method can effectively project the UV LEDs' radiation power maintenance data with time series for lifetime prediction, which provides the feasibility for the rapid lifetime prediction of UV LEDs to accelerate the development of the UV LED industry and reduce the R&D costs.

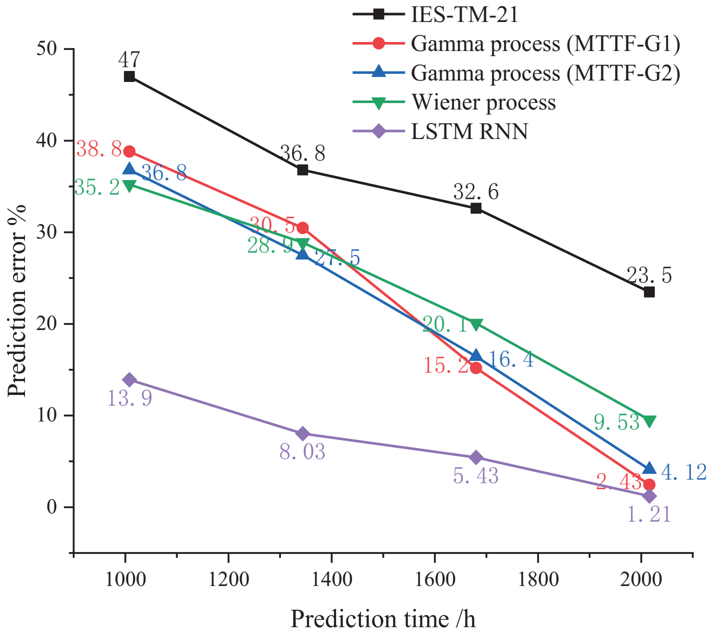



**Fig. 6.26** Comparison of $L_{80}$ lifetime prediction results: the TM-21 NLS regression method, the gamma process method, the Wiener process method, and the LSTM RNN method

## 10 Conclusions

In this study, the prognostic and diagnostic methods used in LED lighting have been reviewed, with due attention to machine learning-based data-driven approaches. Currently, there is an increasing number of studies on the reliability assessment and lifetime prediction of high-power white LEDs. However, the majority of conventional methods and approaches investigated have limitations in addressing the prognostics demand of the dynamic and unpredictable degradation behavior of LED systems. In addition to this, situations with sensor monitoring and data acquisition systems have shown an increasing trend in recent years. This has created opportunities as well as huge challenges to address the issues of diagnostics, RUL prediction, and extraction of useful information quickly from the abundantly generating operational and experimental big data. In the reliability study and lifetime prediction of LEDs, there are many machine learning algorithms that can help to provide lifetime prediction with improved accuracy. Some of the ML algorithms that have been employed in the study of mechanical components and systems can also be leveraged for LED lighting sources in future potential applications, including long short-term memory (LSTM) networks (a variety of recurrent neural networks), Hidden Markov Model (HMM), self-organizing maps (SOM), least-squares support vector machine, and fuzzy logic. An illustrative example is demonstrated on UV LED radiation degradation data based on NLS regression, Wiener, gamma, and LSTM neural network methods. The emerging trend in the application of digital twins for PHM with the focus on LEDs has also been briefly investigated.

# Appendix

**Table 6.3** A Brief Summary of machine learning algorithms for prognostics of LED products

| Machine learning algorithm/method | Input data analysis and parameter estimations | Main study analysis results and findings |
|---|---|---|
| Artificial neural network [140, 134, 133] LSTM, recurrent neural network (RNN)[a] [141, 142] | Forward current ($I_F$, electrical) and temperature [140] | Probability of health status of LEDs (healthy 0.99 and not healthy 0.01) |
| | One hidden layer and two neuron nodes in the hidden layer [140] | Predict the lifetime of power LEDs with <5% error [133] |
| | MATLAB neural network toolbox, [134, 133] | |
| | Luminous flux, chromaticity coordinates u’ and v’, electric current and temperature [134] | Model can be used when the mean square error of datasets between estimated and expected life output narrow to the target |
| | | R value of 0.985 and 0.974 for two dataset using AdaBoost BPNN. |
| K-nearest neighbors (KNN) kernel density-based algorithm [147, 146][a] | 24 features from die and phosphor SPD clustered [147] | Anomaly detection conducted (two clusters for phosphor SPD and three clusters for die SPD) [147] |
| Relevance vector machine [151, 128][a] | LED light output (lumen maintenance and color shift) [151] | RUL lifetime prediction with error less than 5%, claimed to be better than PF |
| | | Reduces qualification testing time (from 6000 h to 210 h) [151] |
| | Rotating component in aerospace setting (NASA) | Estimate the remaining useful life with acceptable accuracy [128] [a] |
| | Component feature damages (not specified) [128][a] | Not employed to anomaly detection |
| Support vector machine[a] [81][a], [149][a] | Dataset with 22 parameters for mission critical system from Lockheed Martin [81][a] | Identify system anomalies (with “healthy” and “unhealthy” class) |
| | | Helps to manage false alarms |
| | Power gain degradation data of microwave [149] | Point and interval estimates of RUL obtained [149] |
| | | Much more robust and stable as verified in comparison with RBF NN |
| Principal component analysis (PCA) [147, 133] | 12 features from SPD (die and phosphor) considered for dimensional reduction [147] | PCA used to consider three features of SPD after reduction for further analysis (KNN) [147] |
| | Eight parameters considered for selection [133] | Four features with >85% contribution are reduced from 8 to use as an input BPNN [133] |

(continued)

**Table 6.3** (continued)

| Machine learning algorithm/method | Input data analysis and parameter estimations | Main study analysis results and findings |
|---|---|---|
| Self-organizing map (SOM)[a] [161][a], [146][a] | Temp of gearbox, oil, nacelle, and rotor speed of wind of wind turbine [161]<br>Failure data for an industrial reciprocating compressor [146] | System-level anomaly detection for WT [161],<br>RUL estimation is obtained with good accuracy [146] |
| Hidden Markov Model (HMM)[a] [172][a], [173][a]<br>Bayesian networks (BN)[a] [209] | Experimental data for helicopter gearbox vibration from 68 operating conditions [172]<br>Experimental data from IGBT from three operating conditions<br>Degradation data from unmanned aerial vehicles [209] | Enabled defect level, defect type, and torque level classification for CBM [172]<br>Anomalous behavior detection for IGBT based on Bayesian HMM classification [173] |

[a] Shows that the machine learning algorithm has not been adopted yet for LEDs products

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