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Machine Learning and Digital Twin Driven Diagnostics and Prognostics of Light-Emitting Diodes

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Light-emitting diodes (LEDs) are among the key innovations that have revolutionized the lighting industry, due to their versatility in applications, higher reliability, longer lifetime, and higher efficiency compared with other light sources. The demand for increased lifetime and higher reliability has attracted a significant number of research studies on the prognostics and lifetime estimation of LEDs, ranging from the traditional failure data analysis to the latest degradation modeling and machine learning based approaches over the past couple of years. However, there is a lack of reviews that systematically address the currently evolving machine learning algorithms and methods for fault detection, diagnostics, and lifetime prediction of LEDs. To address those deficiencies, a review on the diagnostic and prognostic methods and algorithms based on machine learning that helps to improve system performance, reliability, and lifetime assessment of LEDs is provided. The fundamental principles, pros and cons of methods including artificial neural networks, principal component analysis, hidden Markov models, support vector machines, and Bayesian networks are presented. Finally, discussion on the prospects of the machine learning implementation from LED packages, components to system level reliability analysis, potential challenges and opportunities, and the future digital twin technology for LEDs lifetime analysis is provided.

1. Introduction

Artificial light plays a critical role in our daily lives. From the earliest days of having light from burning firewood up to the present-day electric light, lighting has sustained life. After Edison's incandescent light was introduced in 1879, lighting technology has shown significant improvements in terms of brightness, size, and energy consumption. In 1962, Holonyak, Jr. and Bevacqua.[1] came up with a GaAsP semiconductor material based light-emitting diode (LEDs) that emitted red light followed by the LED based white light which has been the driving force for research and development in solid-state lighting (SSL). Three decades later, Nakamura introduced the first blue/green LEDs,[2] and brought white light into mainstream applications and receiving the Nobel prize in 2014 along with Akasaki and Amano for their great contribution to humanity.[3] Nowadays, LEDs are widely used in different applications including general indoor

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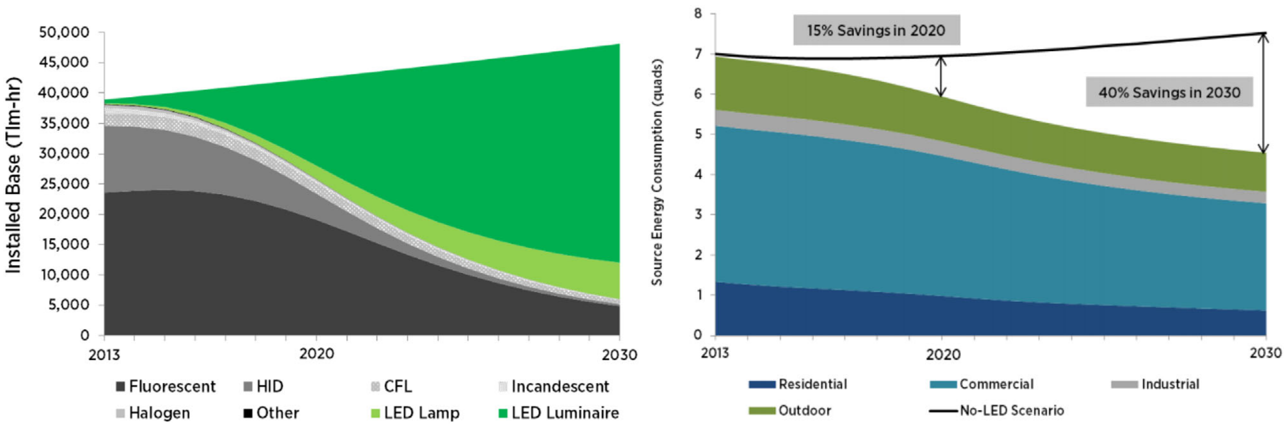


Figure 1. Lighting energy consumption (US) and market demand for different lamps.[10]

and outdoor lighting lamps, automotive lighting,[4] backlighting, robotics skin,[5] 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 counterparts (incandescent and fluorescent) lighting sources.[6–8]

Low energy consumption, which ultimately helps in energy saving programs, is one of the benefits of SSL-based LEDs. With the global energy crisis and environmental concerns, LED-based lighting is anticipated to reduce the electrical energy usage for lighting applications up to 50% and beyond. Currently, lighting consumes on average 19% of the total world energy production.[9] The replacement of traditional lighting sources with LEDs is anticipated to reduce the electrical energy usage for lighting applications by 15% by 2020, by 40% in 2030, and up to 75% in 2035 in the United States, according to latest forecast.[9,10]

It is evident that the superior performance of LEDs over their traditional counterparts in terms of longer service life, energy efficiency, resistance to extreme weather conditions, and eco-friendliness is manifested in their high market demand. As depicted in **Figure 1** (left), the demand prediction for LED lighting products in the United States has shown an exponential growth, while contributing in saving huge amount of energy for residential, outdoor, and industrial applications.

LEDs also have higher luminous efficiency (ratio of total luminous flux to total electrical power) compared with traditional light sources. According to U.S. Department of Energy (USDOE), the efficiency of a typical phosphor converted LED (pc-LED) has been forecasted to exceed 255 lm W^{-1} in 2025 from about 50 lm W^{-1} in 2005, as shown in **Figure 2**. However, research and development by some LED manufacturers, such as CREE, exceeded expectations by demonstrating lumen efficacy of 303 lm W^{-1} which surpassed its own previous 276 lm W^{-1} lumen efficiency at 350 mA and color temperature of 5150 K from high power white LEDs.[11] A summary of the evolution of different lighting technologies including LEDs, compact fluorescent lamps (CFL), halogen, and organic LEDs (OLEDs) along with its lumen efficacy is depicted in Figure 2.

It should be noted that the quality of the luminous flux produced by white LEDs depends on the color rendering index (CRI), the capability of the light to show the true color of an object. Dichromatic sources have higher luminous efficacy (as high as 425 lm W^{-1}) with lower CRI, whereas tetrachromatic sources have lower luminous efficacy with high CRI, and trichromatic sources being in the middle with good luminous efficacy (300 lm W^{-1}) and good CRI.[8,14] Depending on electric power usage, LEDs can be categorized into three types: low power LEDs (less than 1 W power and about 20 mA current), medium power LEDs (1 to 3 W power and 30 to 150 mA current), and high power LEDs (greater than 3 W of power and 350 mA to 1 A current).[15]

In the early days of LED luminaire introduction, the major challenge was related to the price of purchasing LED lamps. However, the cost of LED lamps has been dropping while the performance has improved in the past few years. This development was observed and studied by Haitz, as shown in **Figure 3**, and is formulated as Haitz's law,[16] which is considered as the equivalent of Moore's law for integrated circuits (IC).

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 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.[6,17,18] 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.[17,19–23] In early 2001, a discussion was initiated by Narendran et al.[24] 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

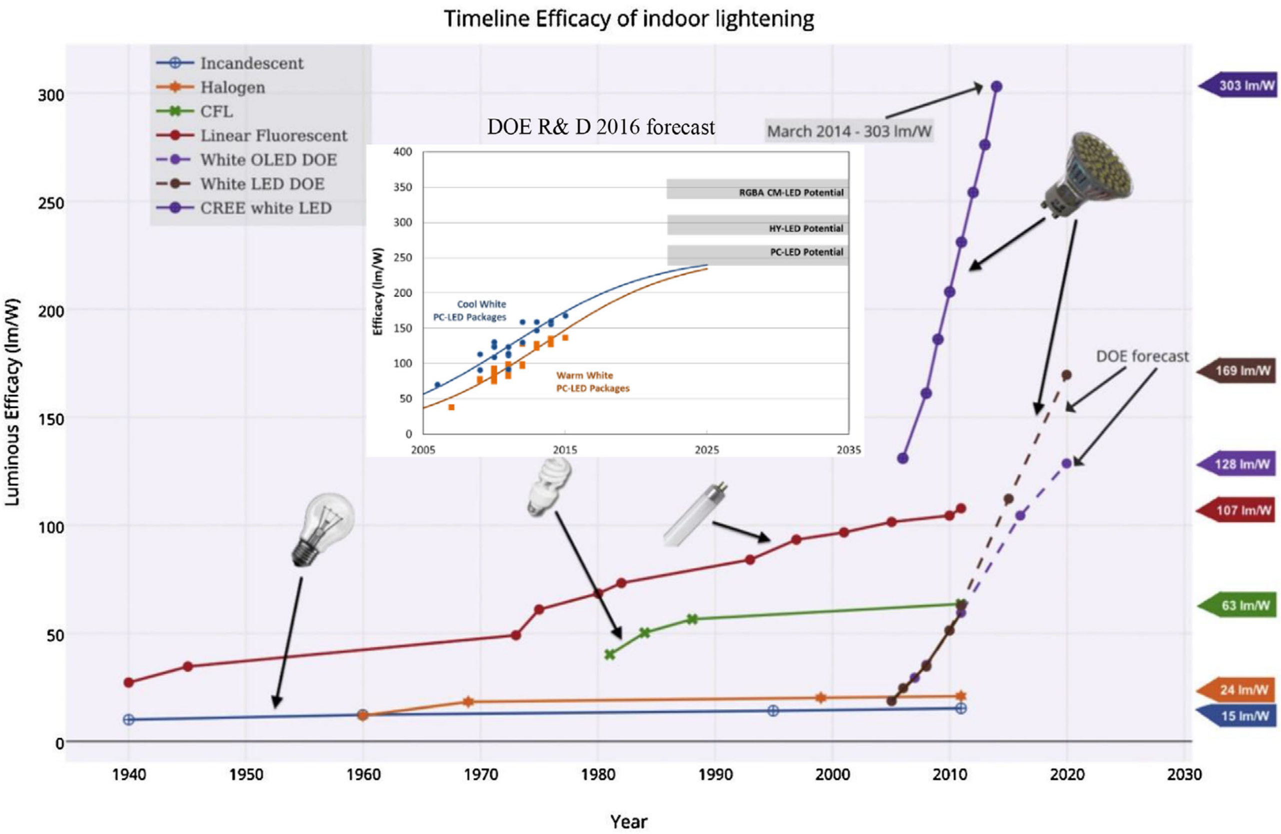


Figure 2. Development trends of lumen efficacy for different light technologies at normal working condition.[12,13]

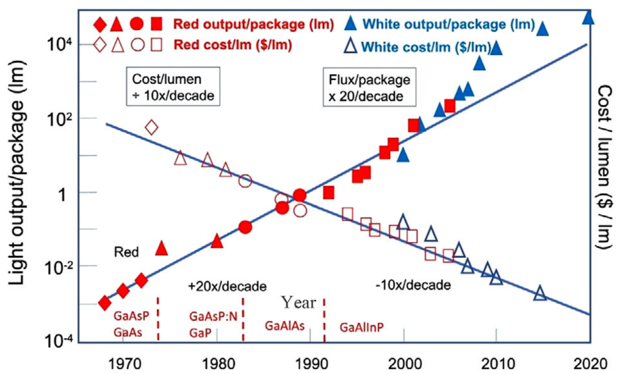


Figure 3. Haitz's Law demonstrating an increasing trend in luminous flux per package and decreasing trend in cost per lumen.[16]

manufacturers use TM-28-14,[25] released by Illuminating Engineering Society of North America (IESNA), to project lumen maintenance lifetime for LED lamps and luminaires where the required data are gathered according to industrial standard test report LM-84-14.[26] Previously, the TM-21-11 standard[27] has been used to predict the lifetime of LED light sources based on the light output degradation data from the standard LM-80-08 test report.[28] The approved TM-21-11 procedure uses the nonlinear least squares (NLS) regression 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.[6]

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.[29] 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.[6,30–34] An extensive review that mainly focused on failure causes, failure modes, and failure mechanisms of LEDs was presented by Chang et al.[6] while recently Sun et al.[34] 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

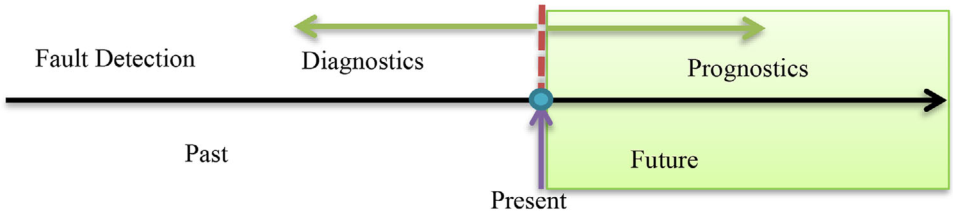


Figure 4. PHM problem architectures (fault detection, diagnostics, and prognostics).

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.

The remainder of this paper is organized as follows: An overview of the PHM of high-power white LED sources is presented in Section 2. In Section 3, the model-based or physics of failure (PoF) approaches including failure modes mechanisms and effects analysis (FMMEA), and the implementation for LED components and systems are discussed briefly. In Section 4, the concepts and framework of the machine learning and statistics-based data-driven (DD) methods applied in PHM for electronic products in general and LED light sources in particular are discussed. Section 5 focuses on the application of the fusion prognostic approach for LED reliability analysis. Section 6 investigates some of the system level reliability studies for LED products in the process of anomaly detection and lifetime prediction. Challenges and potential opportunities for LED prognostics are presented in Section 7. Section 8 discusses the prospect of the digital twins as a future reliability assessment and lifetime analysis. Finally, in Section 9 concluding remarks are presented.

2. PHM of Light-Emitting Diodes

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.[35,36] This phenomenon is no different in the case of lighting products, especially for the high-power white 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.[37] 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, decreasing life cycle, and operational costs of marketable products and systems in general, and customer electronic systems in particular.[38] Thus, the reliability assessment and prediction of RUL studies has 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.[39] 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 **Figure 4**.

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,[40] as illustrated in the PHM metro map shown in **Figure 5**. 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.[38] 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).[41] 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.[42]

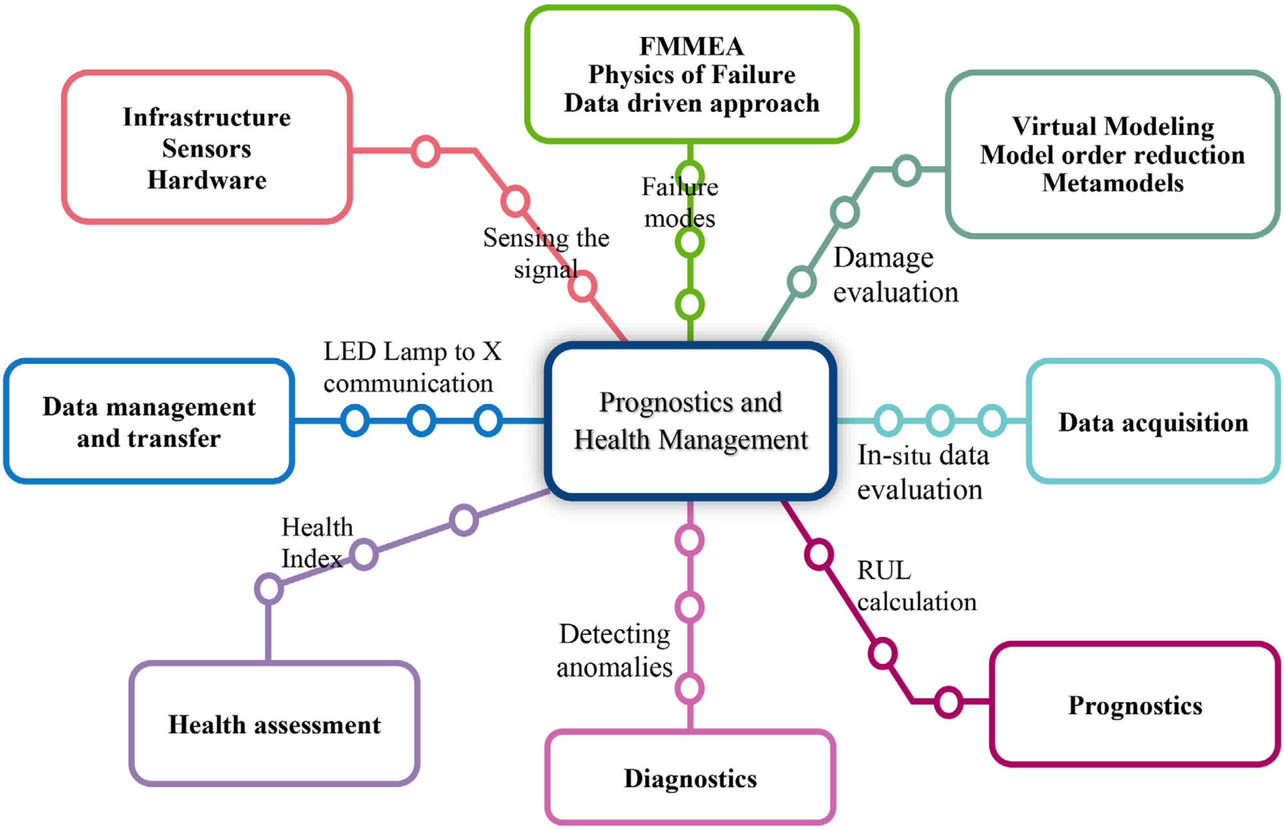


Figure 5. A generic PHM Metro Map for products/system such as LED lighting, automotive parts, etc.

Even though the expected lifetime for a 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.[43,44] 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. In addition, reliable approaches to monitor the health status and predict potential failures of LED products by considering operating conditions and application areas are needed, especially for safety critical and emergency systems/products including the medical, aviation, automotive, and nuclear sectors. So far, many diagnostics and prognostics activities have been implemented and executed based on a variety of approaches and algorithms. In general, the most commonly used approaches can be categorized as: i) model-based, also known as PoF methods, ii) data-driven methods, and iii) hybrid (fusion) prognostics methods.[45] A more refined and detailed taxonomy of PHM approaches is presented in **Figure 6**.

The 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.[46,47] 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.[48] 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 of Model-Based Approach

Model-based prognostics are also known as PoF methods and it makes use of information about a product's material characteristics, loading and stress conditions, shape/geometry, operational and working environmental conditions to assess reliability, identify failure modes, mechanisms, and estimate the RUL. PoF is also used in designing for reliability at the early stage of product design, as it makes use of product life cycle loading conditions (such as electrical, thermal, mechanical, chemical, electromechanical, etc.), product geometry, and material properties.[49,50] The PoF-based approach has the benefit of identifying the root

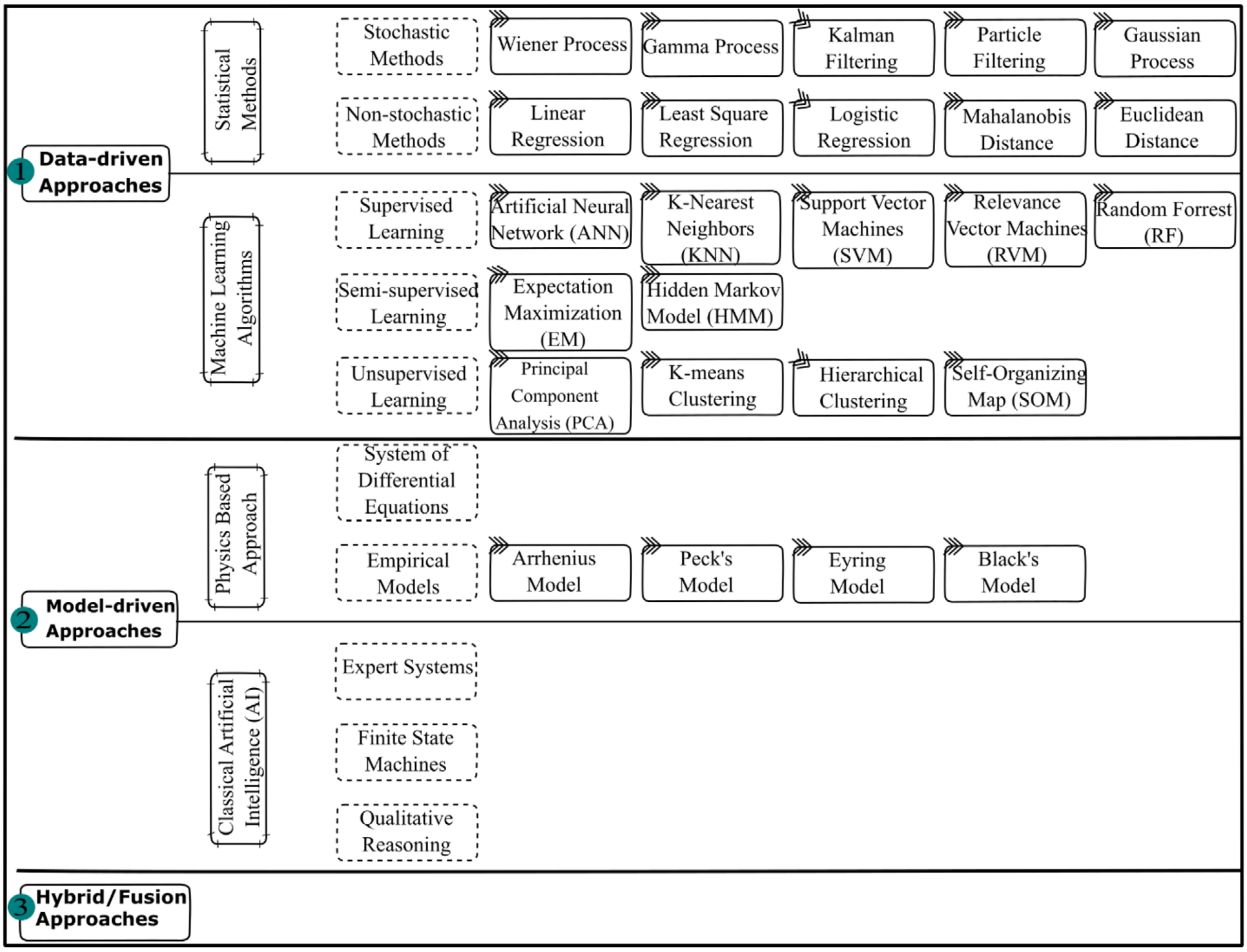


Figure 6. Taxonomy of prognostics and health management approaches.

causes of system failure.[34,41] 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 defined product/system at a particular lifecycle loading condition, PoF focuses mainly on identification of potential failure locations, failure modes as well as failure mechanisms. The stress at every failure location/site is obtained as a function of the lifecycle loading conditions, material properties, and product architecture/shape. Then faults caused and its propagation are determined by using damage models.[49] 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, operating and environmental conditions. These parameters are used to monitor the product during experiments, and can be categorized according to their domains. For the prognostics analysis of LED products, the different impact (stress) factors such as electrical, thermal, humidity, mechanical, thermomechanical, 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 1**. Pecht et al.[49] studied the PoF-based prognostics for electronic and information-rich components. In their study, they criticized the use of old reliability handbooks as it results in prediction errors and uncertainties (in design, material, and operating conditions). The growing trend of using PoF-based prognostics for electronic products in identifying critical component failure modes and mechanisms is also described.

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, 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 and environmental conditions 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.[21] Their study was focused on the investigation of failure sites, failure modes, and associated

Table 1. PoF models for LED products and systems.

Stress (impact) factors		PoF models	Performance indicators
Electrical (current)[52,53]		• Lumen depreciation gradient[52] • Inverse power law-Weibull[53]	• Luminous flux depreciation[52]
Thermal stress/shock[54–56,53,57]		• Coffin–Mansion equation[54] • System reliability analysis[55] • Hierarchical model (based on junction temperature)[55] • Arrhenius equation[56] • Arrhenius–Weibull[53] • Finite element simulation using ANSYS and numerical analysis simulation	• Lumen depreciation • Color shift over lifetime • Junction temperature gradient
Humidity/moisture[58,59]		• Luminous-efficiency gradient[58] • Finite element simulation using ANSYS[59]	• Lumen depreciation[58]
Multi-physics	• Thermal and humidity[51,60–62,59]	• Chromaticity shift equation[38] • Arrhenius equation[62] • Hallberg–Peck's model[60,62] • Subsystem isolation method[61] • Finite element simulation using ANSYS[59]	• Chromaticity shift[38,60] • Lumen depreciation[60,61]
	• Thermal and electrical (current)[63–66,53]	• Junction temperature distribution • Spectral power distribution (SPD) analysis[63] • Electrothermal simulation (junction temperature with Arrhenius equation) • Electrothermal simulation[66] • Generalized Eyring–Weibull[53]	• LED catastrophic failure for high thermoelectrical stress[64] • Spectral power distribution (SPD) and • Lumen depreciation[63,64,66]
	• Thermomechanical[67]	• Thermal and mechanical stress on solder alloy • Garafalo's hyperbolic creep model • Norris–Landzberg equation • Engelmaier equation for strain range	• Solder joint fatigue • Lumen depreciation
	• Thermomechanical[68] and hygromechanical stresses[68,69]	• Thermal and thermomechanical modeling • Moisture diffusion and hygromechanical modeling (Fick's law of diffusion) • Finite element analysis (simulation)	• Delamination in LED packages • Lumen depreciation
	• Hygro-thermal-mechanical coupling modeling[68]	• Heat conduction systems, Fick's law of diffusion, and FEA simulation	• Lumen depreciation • Color shift

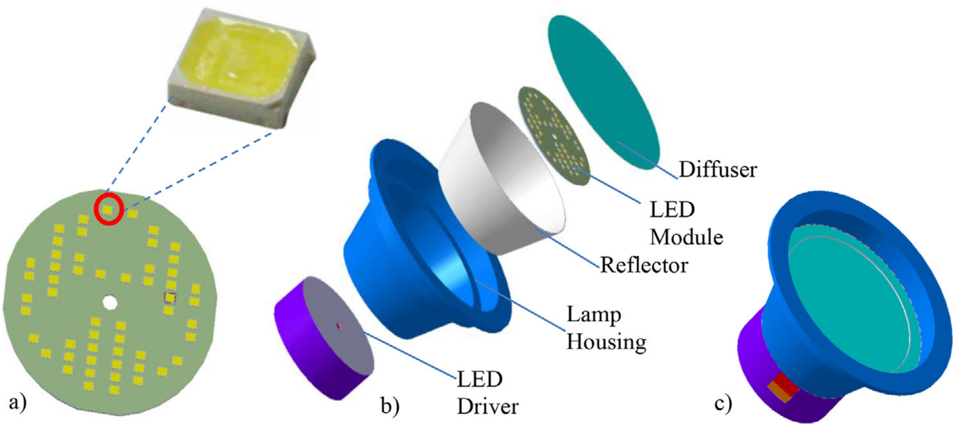


Figure 7. LED lamp and components: a) LED package and module, b) LED lamps exploded, and c) LED lamp and lighting lamps.

degradation mechanisms for HPWLEDs. The sample selected for demonstration was a typical commercial HPWLED lamp and analyzed according to "bottom-up" strategy at the chip, package, and system levels. Pictures in **Figure 7** are presented for the purpose of illustration.

Lu et al.[51] used the physics of failure-based approach to study down light color shift failure at the luminaire level conducted on the LED diffuser, reflector, and package parts of an LED lamp of 10 W, and correlated color temperature (CCT) of 4000k. The selected parts had undergone aging testing at room temperature,

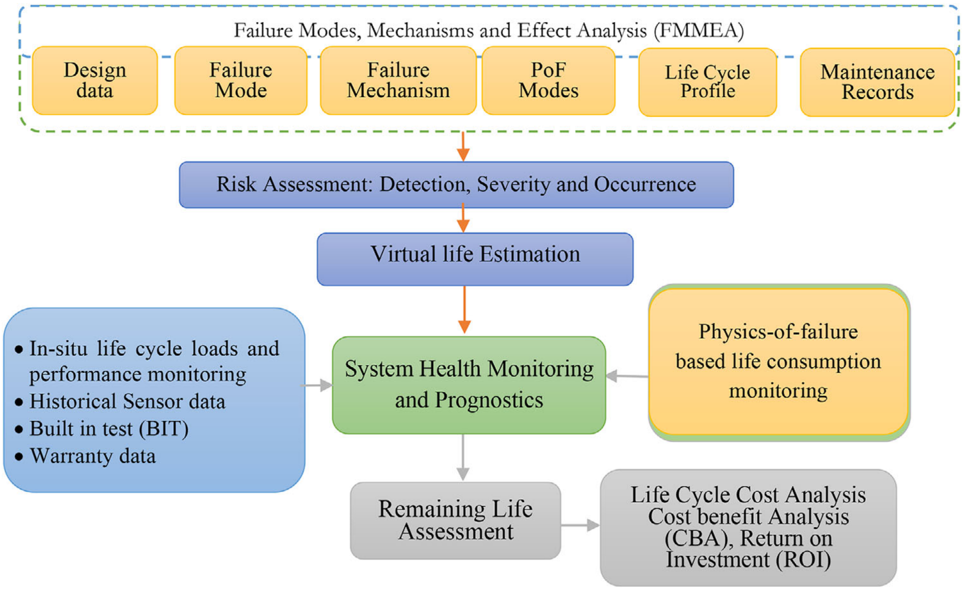


Figure 8. PoF-based PHM methodology.[39,71]

55 °C, 85 °C and irradiation testing at 85 °C, and humidity reliability test at 85 °C with 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 strongest impact.

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

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.[70] The PoF-based PHM process involves a series of techniques and activities to assess reliability of LEDs as shown in **Figure 8**. First, the FMMEA serves as input to the PoF-based prognostic approach. FMMEA includes design data, failure modes (lumen depreciation, color shift in LEDs), failure mechanisms, lifecycle profiles, and possible maintenance records. The second step involves risk assessment based on estimation of failure detection, severity, and occurrence. Then based on these two phases, virtual lifetime estimation can be undertaken. The historical sensor data, built-in-test data, and in situ monitoring data are used in identifying anomaly conditions and parameters. Third, the actual system health prognostics is conducted by making use of virtual reliability assessment results, existing sensor data warranty data, etc. Finally, the PoF models can be used in reliability assessment and lifetime estimation based on operational and environmental data. The information from system health prognostics can be used as input in decision making with cost–benefit analysis and return on investment.

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 luminous flux or open circuit, ii) chromaticity shift (i.e., color shift), and iii) lumen depreciation. 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.[49]

A comprehensive study was reported by Chang et al.[6] on the FMMEA at semiconductor, interconnect, and package levels for LED products. Subsequently, Fan et al.[22] conducted a study on the FMMEA of LED-based backlighting systems used for commercial displays and TVs. Since LED-based display systems are formed by LED strips and electric driver systems, the study aimed to identify failure sites, failure modes, and mechanisms at LED chip (die/semiconductor), driver, package, and strip levels of LED backlight system. As an LED-based device, the failure modes observed for backlight units are lumen depreciation, color shift, or catastrophic failures. In our review study, the FMMEA of LED products/systems is described by considering a more general architecture including chip (die/semiconductor) level, module (packages, drivers, LED arrays, interconnects), and system levels as presented in **Table 2**.

In general, the FMMEA of LEDs has been investigated at three levels: die/chip, interconnects, and packages levels.[6,21] 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 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 nonradiative 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

Table 2. FMMEA of LEDs at different levels.

LED failure site	Failure modes	Failure mechanisms
LED chip level (semiconductor/ die)[22,32,33,58,59,63,72,73]	• Lumen depreciation[58,59] • Luminous flux turned off, short-circuit[58] • Color shift	• Propagation of defect and dislocation • Diffusion of impurities (dopants) in the quantum well • Cracking of chip/die • Yellowing and cracking of the encapsulating lens[63]
LED module (LED package, driver, interconnects)—wire bond, bumps, attachments, encapsulate, lead frame, lens[33,58,60,63,68,74,75]	• Lumen degradation and color shift[33,60,74,75] • Delamination between chip and die, as well as lamp cup and outer shell[68] • Diffusion of moisture into the boundaries of packaging material[58]	• Propagation of defect and dislocation • Diffusion of impurities (dopants) • Cracking of chip/die • Yellowing and cracking of the encapsulating lens[63] • Package epoxy browning[75]
System level (LED chips, modules, diffuser, reflector, electrical driver),[51,55,56] Colaco et al.,[56,61,64,66,68,74] Colaco et al.[57,76]	• Lumen depreciation[68,74,56,57] • Luminous flux turned off, short/open circuit • Plastic housing crack, glass bulb crack • Optical coating discoloration • Color shift[51,64,76]	• Encapsulant yellowing • Solder joint fatigue • Silver reflector/mirror darkening • Thermal quenching of phosphor

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 to 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.[58,68]

4. Data-Driven Approaches

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.[77] It is assumed that the system statistical characteristics remain unchanged until an anomaly occurs in the LED product/system.[45] 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 help 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.[46] This approach has the capability of describing the uncertainties in performance degradation of LEDs by incorporating random and dynamic variances. On the other hand, 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.[29]

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.[42] In fact, statistical-based data-driven methods depend not only on the availability of data but also on the nature of the data collected.[46] 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 can be obtained by using DD methods, the prediction part can also be handled with PoF approaches.[40]

Assessing the reliability information of products (such as remaining useful lifetime, mean time to failure (MTTF)) 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.[78] In such conditions, the quality characteristics of products whose degradation path (degradation data over time) are 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,[21] 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.[27]

LEDs belong to highly reliable electronic devices with long lifetimes (more than 50 000 h), provided that proper thermal management techniques are applied.[43,44] 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 lifetime 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.[79] However, there are two considerations when using ALT in the LED case: first, relating the real operation life and rated life under accelerated conditions is not easy for the LED case. Second, 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 MTTF, RUL, confidence intervals) that helps in maintenance decision making before failures happen.[80–85] First introduced by Lu et al.,[82] the general degradation path method was used to model degradation data in relation to time. Fan et al.[18] implemented the degradation data-driven based PHM with statistical models into the high-power white LED to get additional reliability information (such as reliability function, confidence interval, MTTF) in addition to the luminous flux lifetime, the only information obtained from 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.[36,86] 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.[87] Recently, Si et al.[88] and Wang et al.[89] 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.[83,90] 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.[91] Therefore, distance measures were used to detect fault occurrence in a product's normal operation.[92–95] Based on this approach, Sutharssan et al.[96–98] applied distance measures (such as Euclidean (ED) and Mahalanobis distance (MD)) 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.[99] Sikorska et al.[100] 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 presented in **Figure 9**, enhanced from Sikorska et al.,[100] 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 LEDs 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 semisupervised), and so on. The data-driven approaches are widely used and the application spectrum is broader. A comprehensive summary on the machine learning algorithms is presented in Table A1 in Appendix A and similarly a brief summary of the advantages and disadvantages of the selected data-driven PHM algorithms is shown in Table A2 in Appendix A. Many of the data-driven techniques that are found effective from other fields of study could be adapted and customized for the LEDs lifetime estimation and reliability analysis with proper understanding are discussed in the following sections.

4.1. An Overview of Selected Statistical Data-Driven Methods

In this section, a brief overview of selected statistical data-driven methods are presented. Although there are many statistical data-driven methods in the prognostic application, few of the popular and widely used methods that are considered most appropriate for LEDs prognostics are selected and discussed.

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 as in Equation (1)

$$X(t) = x(0) + \lambda t + \sigma\beta(t) \tag{1}$$

where $X(t)$ is degradation of performance characteristics (PCs) (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.[101]

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,[102–104] and the probability density function (PDF) of T can be given as

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

where ω is a failure threshold, the mean and variance of T are $\theta = [\lambda, \sigma^2]$ and given as w/λ and $w\sigma^2/\lambda^3$, respectively.[105] A Wiener process is typically used to analyze degradation processes that vary bidirectionally over time with Gaussian noise: in other words, nonmonotonic degradation processes, and it is

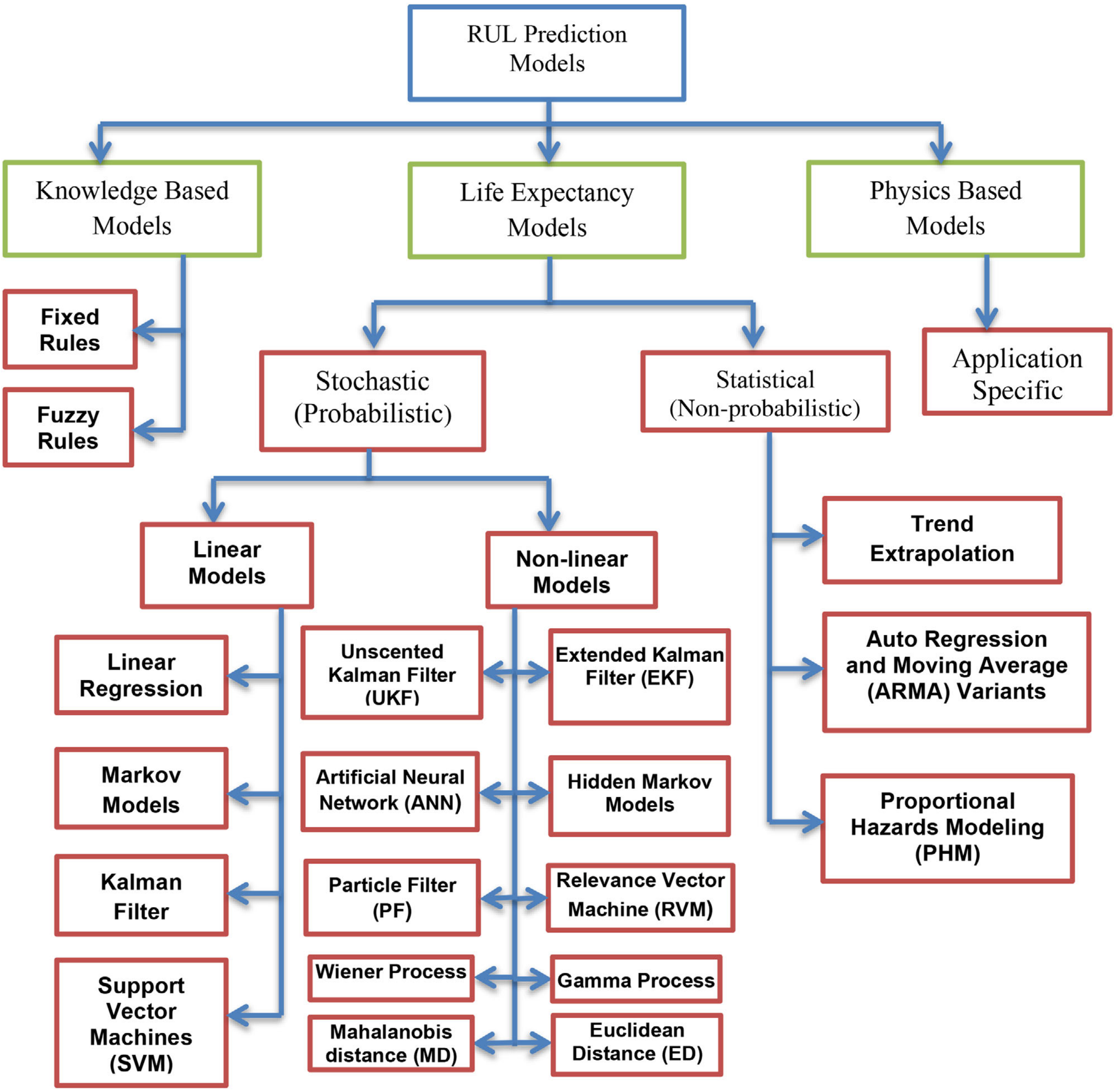


Figure 9. Prognostic modeling techniques for remaining useful life.

one of the widely used degradation modeling approaches. The Wiener process was applied to predict the RUL of variable-stress accelerated degradation tests (ADT) by pioneers Doksum and Hóyland.[106] 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.,[107] Peng and Tseng,[108] Tsai et al.,[78] and Guo et al.[109] On the other hand, Whitmore[110,111] proposed a Wiener diffusion process to address measurement errors and a time scale transformation method to address the time varying degradation drift. This method has been extensively applied in refs. [107, 108, 112–115] to describe the degradation modeling of LEDs, self-regulating heating cables,[111] bridge beams,[116] bearings,[117] and so on. Peng et al.[108] 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[115] 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.[118] investigated the lifetime estimation of high-power white LEDs based on lumen maintenance data using the Wiener process method. Jing et al.[119] 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.[60] that can handle dynamic and random variations of lumen degradation and color shift for mid-power white LEDs and predict their lifetime. The analysis of

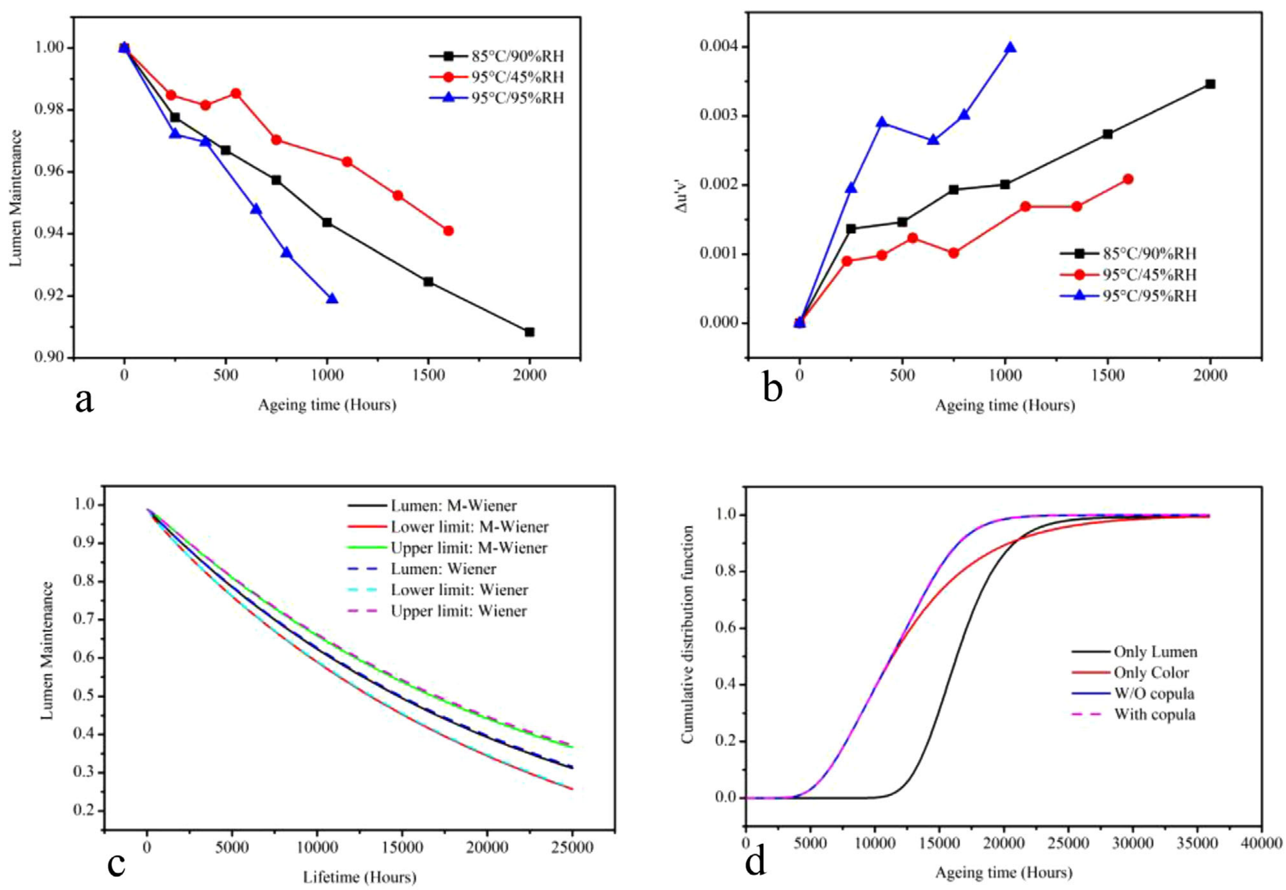


Figure 10. a) Luminous flux degradation, b) chromaticity shift, c) fitting lumen degradation data and lower and upper limits for Wiener process (WP) and modified WP, and d) cumulative distribution function for lumen and color with and without copula. Reproduced with permission.[60] Copyright 2015, The Optical Society.

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 **Figure 10**a–d.

Real-time reliability has been investigated by Xiaolin et al.[120] based on a generalized Wiener process-based degradation model and validated using a laser device and capacitor data. Recently, 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.[121] Generally, the Wiener process has many advantages in the degradation modeling, however, its weakness is that it only makes use of information in the current degradation data by ignoring the information given by the entire sequence of observations.

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.[122] The effectiveness of the gamma process for useful lifetime estimation and reliability assessment is due to relevant advantages. One of the main interesting feature 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.[87] The PDF for a degradation process $X(t)$, which can be described in terms of the gamma process, is given according to the following definition

$$f(x|\alpha,\beta) = \begin{cases} \dfrac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1}\exp(\beta x), & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{3}$$

where $X(t)$ is a performance degradation parameter (such as luminous flux, color shift, etc.), α is a shape parameter, β 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[123] as

$$\mathrm{MTTF}_G \cong \frac{w}{\alpha\beta} + \frac{1}{2\alpha} \tag{4}$$

Nevertheless, it is worth noting that the gamma process appears suitable for the monotonic degradation process, and this may

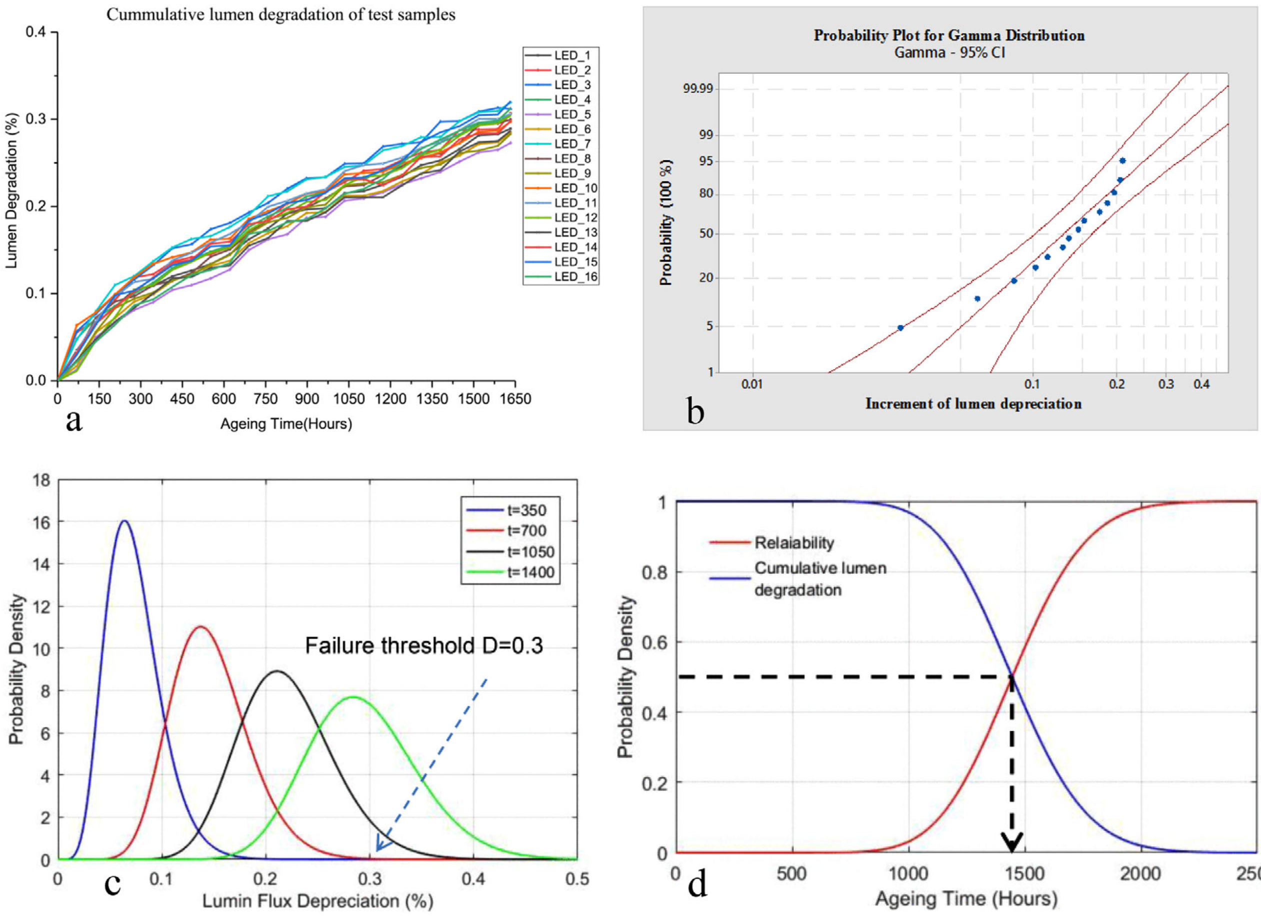


Figure 11. Gamma process: a) Average cumulative lumen degradation, b) probability distribution plots with gamma distribution, c) PDF at different times, and d) CDF and reliability plots. Reproduced with permission.[125] Copyright 2019, IEEE.

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.[124] Ibrahim et al.[125] 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 **Figure 11**.

4.1.3. Particle Filtering (PF) Approach

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.[126–128] On the contrary, the TM-21-11 standard for projecting lumen maintenance lifetime uses the NLS regression 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.

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.,[129] as follows: The first task is to choose a degradation model as suggested in the TM-21-11 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 NLS regression method used to estimate model parameters in TM-21-11 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;

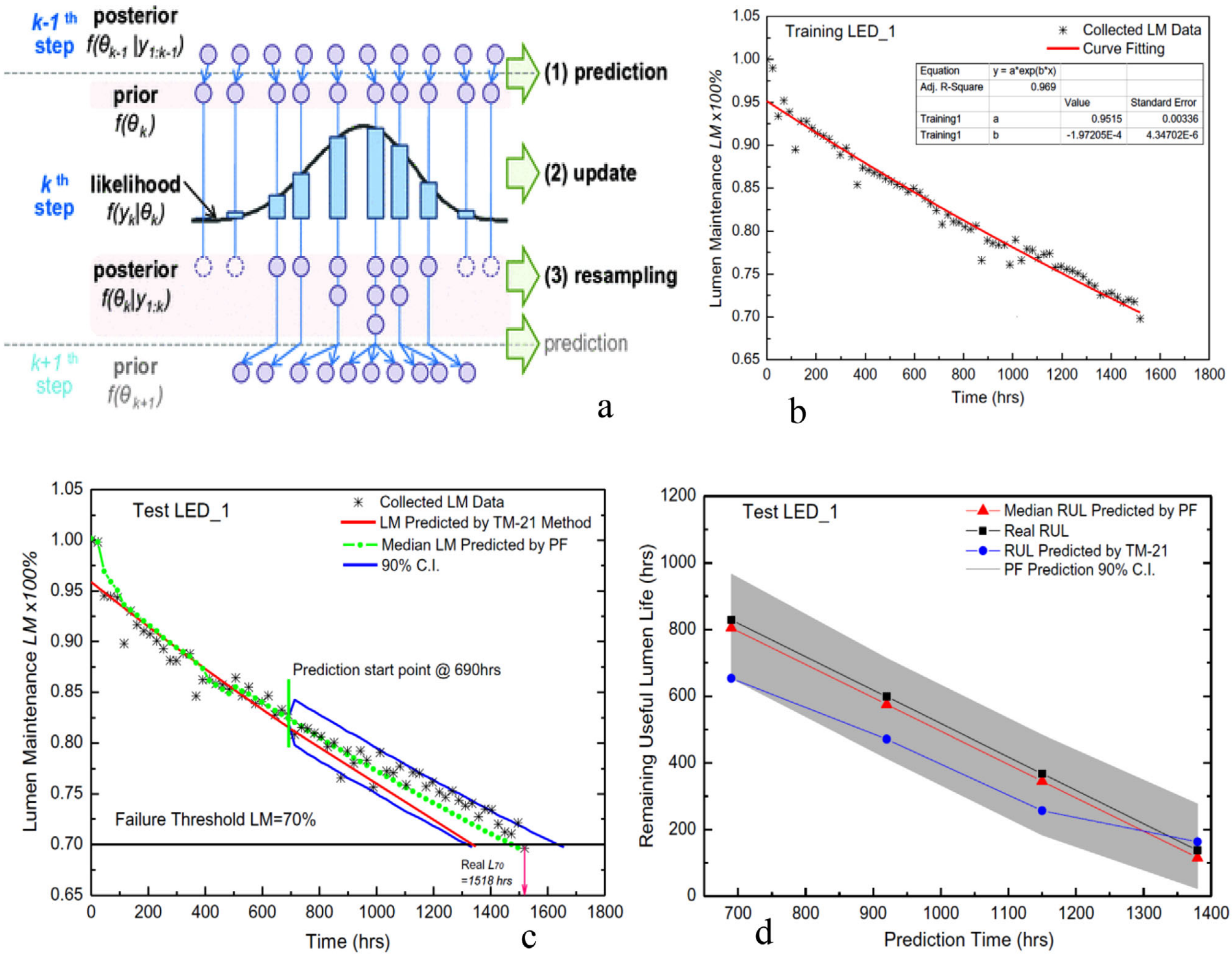


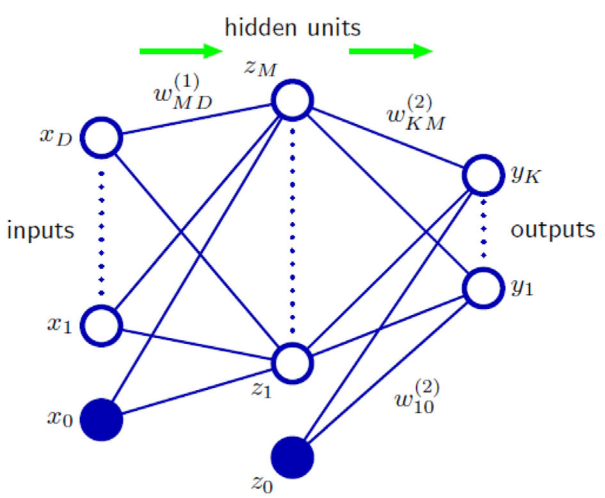
Figure 12. Illustration of particle filter process to predict the lifetime of high-power white LEDs based on luminous flux degradation data. a) Model parameter estimation process. Reproduced with permission.[130] Copyright 2017, Springer Nature. Implementation of Particle filtering algorithm: b) fitting all lumen degradation data to decay model as training samples, c) prediction of lumen maintenance life, and d) PF method and IES-TM-21 LSR approach estimating RUL based on lumen maintenance data. Reproduced with permission.[129] Copyright 2014, Elsevier.

iii) use the Bayesian inference algorithm to update values; iv) weight the particles and resample, as shown in **Figure 12**a. At the end, the experimental measurements will be terminated at time t_p and then the RUL, with confidence interval limits, will be estimated by manipulating the updated model with measurement noise. Fan et al.[129] employed this PF method to project the lumen maintenance lifetime for hight-power white LEDs. The feasibility of the PF method was validated and its prediction accuracy was evaluated and showed superiority over the current NLS regression-based TM-21-11 method. Illustration of the implementation of the PF approach to investigate the lumen maintenance lifetime for high-power LEDs is shown in Figure 12b–d.

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), unscented Kalman filtering (UKF), a brief review is given in Sun et al.[34] 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.[29] ML can be defined as the branch of artificial intelligence (AI) that deals with the development of algorithms and models that can automatically learn patterns from



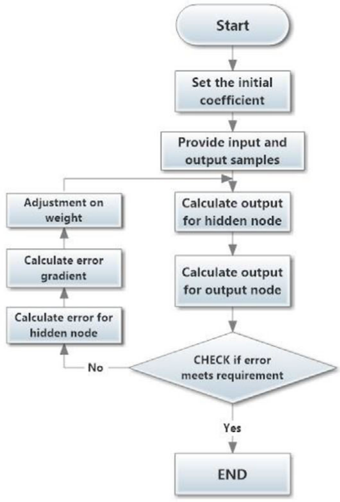


Figure 13. A representative network diagram for two-layer neural networks (left), flowchart for back propagation learning algorithm (right).

data and perform tasks without explicit instructions, according to Chen et al.[131] A more engineering-oriented definition of machine learning was presented by Mitchell[132] 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), semisupervised 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.[133] Some authors recognize linear regression[134,135] and logistic regression[136] 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 (SVM),[137] relevance vector machine (RVM),[138] decision trees,[139] artificial neural network (ANN),[29,100,140] and random forest. Some of the widely used machine learning methods are discussed as follows.

4.2.1.1. Artificial Neural Network: ANNs form a set of mathematical algorithms conceived and modeled after the human brain's neurons structure and designed to recognize patterns.[141] A typical neural network and back propagation learning[142,143] is shown in **Figure 13**.

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 ref. [142]. In an ANN, a network is modeled and it learns an effective way to produce a desirable output by reacting to give inputs,[46] as depicted in Figure 13. 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.[100] ANNs are known methods for modeling complex nonlinear systems effectively and efficiently and can generalize and adapt solutions from a limited data set.[140] Based on the mathematical operations and set of parameters required, ANN architecture can be of different types including feed forward neural network (FFNN), back propagation neural network (BPNN), radial basis function neural network (RBNN), recurrent neutral network (RNN), and self-organizing map (SOM). 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

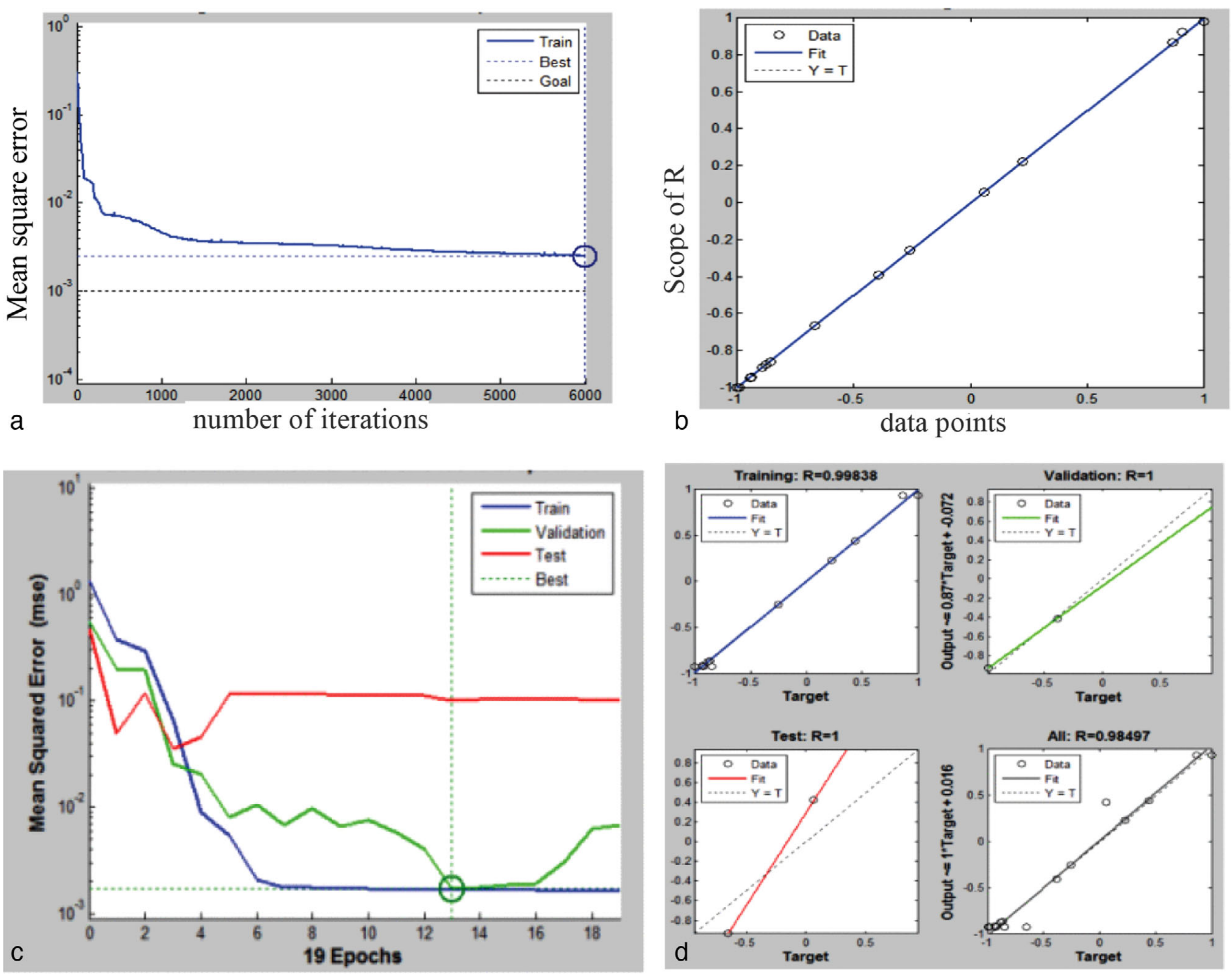


Figure 14. A typical neural network. a) BP neural network training convergence curve, b) effect of network training regression, c) Adaboost improved BPNN curves of iterations and training error, and d) state of prediction regression. Reproduced with permission.[150] Copyright 2017, IEEE.

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,[144] aircraft actuator components,[145] bearings,[146] nuclear turbo-generators,[147] electronic packages,[148] etc. However, application of ANN methods for high-power white LEDs lifetime estimation was not very common until Sutharssan[149] 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.[150] 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 back propagation 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 ageing temperature. The BPNN data training, iterations, training errors as well as predictions are shown in **Figure 14**. 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 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.[151] 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.[151] 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 **Figure 15**. Similarly, Wu et al.[152] deployed the LSTM approach in prognostics and demonstrated a good prediction accuracy using aircraft turbofan engines health performance data. While LSTM architecture RNN

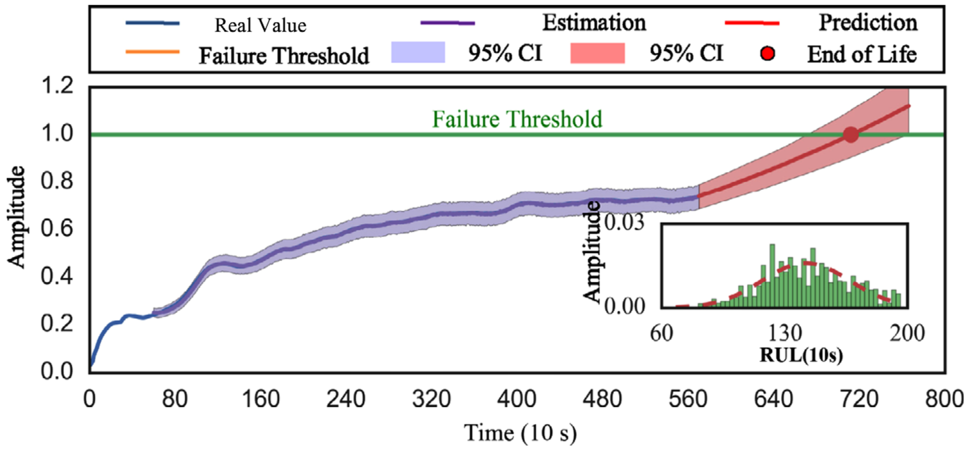


Figure 15. RUL prediction result for a bearing. Reproduced with permission.[151] Copyright 2017, Elsevier.

appears to be suitable for LEDs RUL estimation, application of this method has not been reported in the literature.

4.2.1.2. 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,[153] electromagnetic relays contact resistance,[154] and printed circuit boards (PCBs) ball grid array solder joints.[155] As an emerging trend in the prognostics approach, KNN has been used as a lifetime estimation tool for reciprocating compressor valves based on regression.[156] The prognostic performance, precision, and accuracy of KNN regression (KNNR) was compared with 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.[157] 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 data sets into clusters, and finally distance-based algorithm was 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 are illustrated in **Figure 16**.

4.2.1.3. Support Vector Machine and Relevance Vector Machine: The 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

$$y(x;\omega) = \sum_{n=1}^{N} \omega_n K(x, x_n) + \omega_0 \tag{5}$$

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 overfitting that leads to good generalization and results in a sparse model dependent only on a subset of kernel functions.[158] The SVM classifier algorithm has been demonstrated in the problem of health evaluation and novelty detection. In ref. [91], 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 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.[159] In ref. [159], 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.[158,160]

The 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 hyperparameters. 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.[138] 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 (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

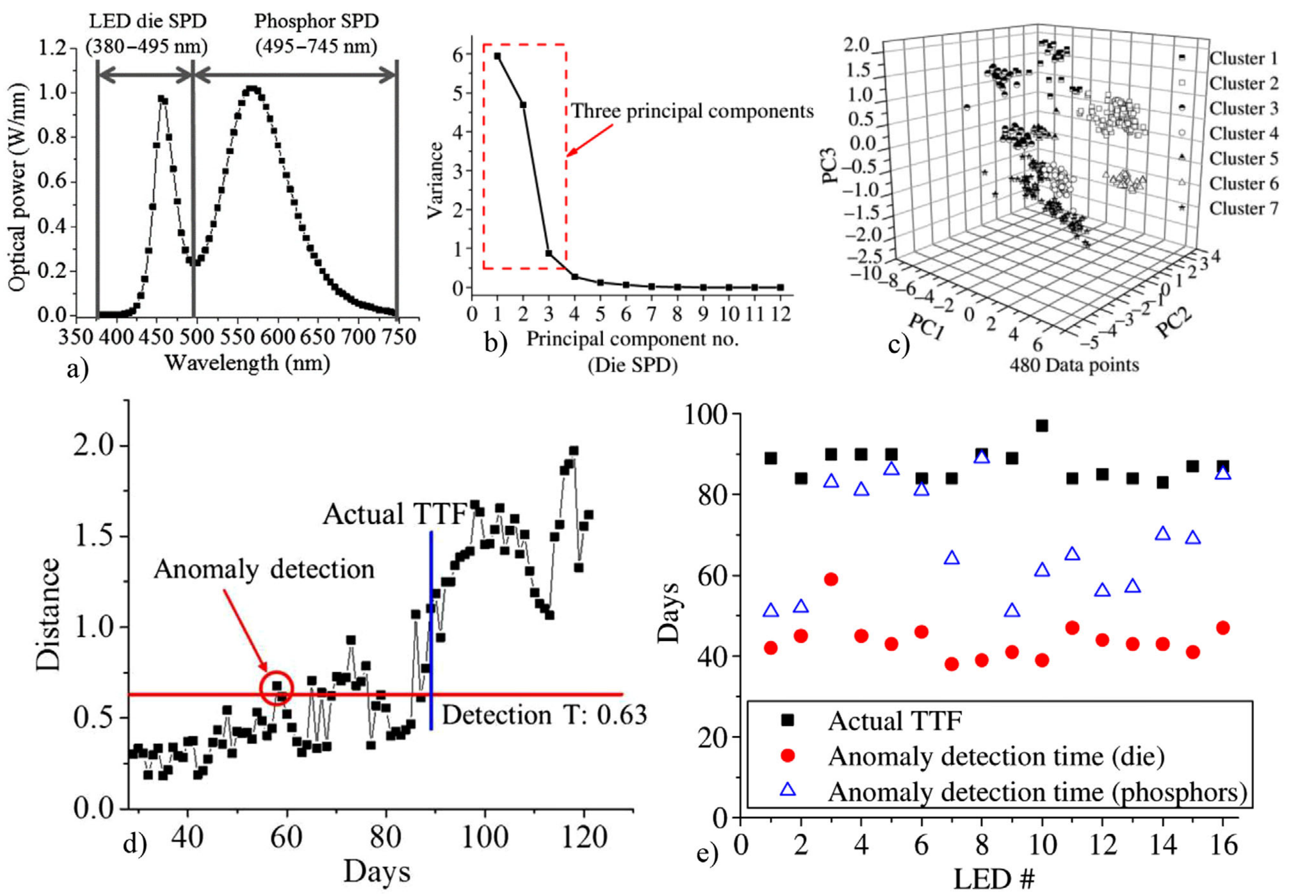


Figure 16. a) SPD feature extraction, b) principal components from extracted features, c) SPD training using KNN-kernel density-based clustering, d) distance measure from cluster centroid to detect anomaly, and e) anomaly detection using die SPD. Reproduced with permission.[157] Copyright 2014, IEEE.

has been reported to surpass the particle filtering approach.[161] The detailed results for the LED lifetime estimation based on RVM regression compared with the PF approach are depicted in **Figure 17**.

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 data set 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 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.[162] Some of the unsupervised algorithms are k-means clustering, PCA, and hierarchical clustering. The unlabeled instances are used to train a model for representing normal behavior[133] as shown in **Figure 18**. A few of these unsupervised learning approaches that have been investigated to conduct reliability assessment of LED products are described in this section.

4.2.2.1. 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.[163] 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[164] 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[165] 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.[166,167] demonstrated

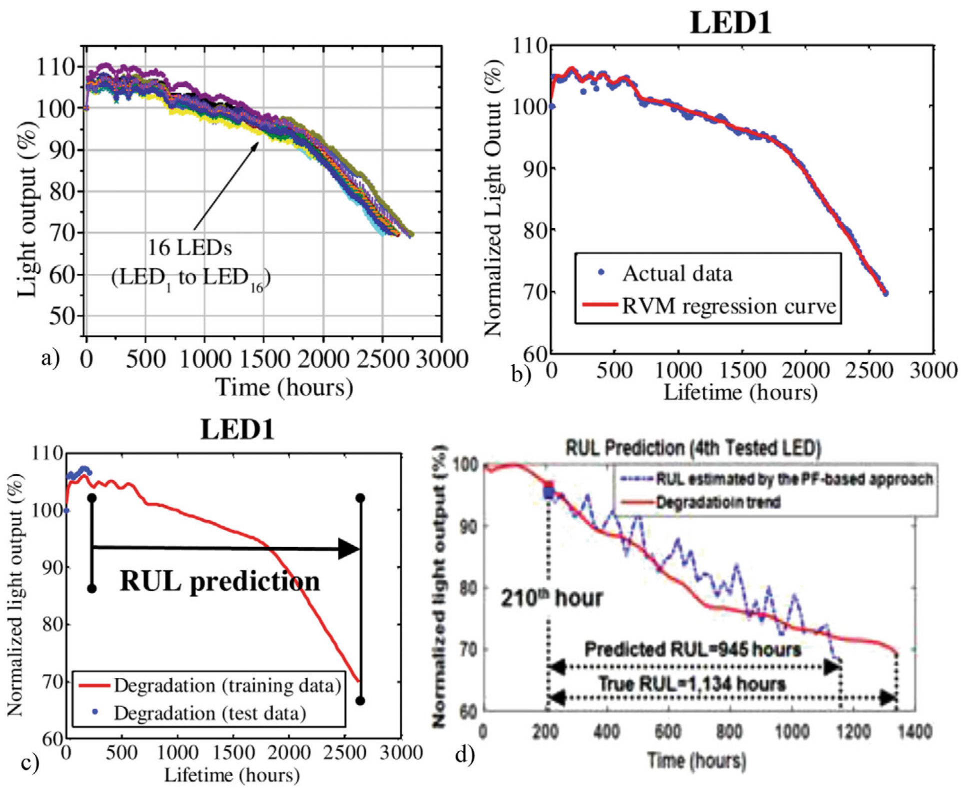


Figure 17. a) LED luminous flux degradation, b) parameter measurement for RUL, c) lumen degradation the RVM regression model, and d) PF-based lifetime prediction results. Reproduced with permission.[161] Copyright 2017, IEEE.

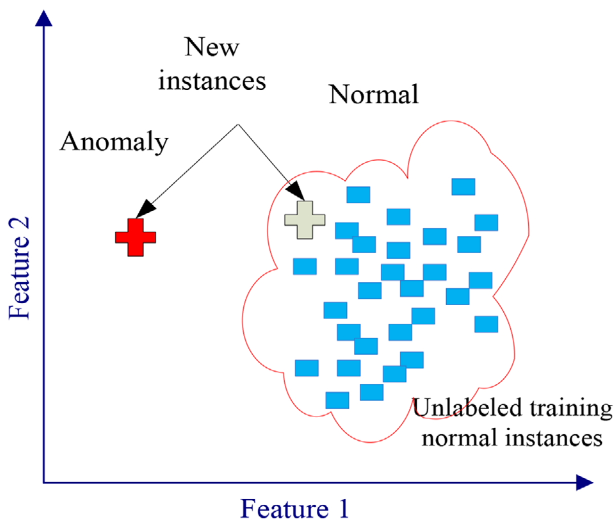


Figure 18. An unlabeled training data set for unsupervised learning.

PCA approaches for fault detection in reciprocating compressors by identifying five and seven most important 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[143] adopted PCA to process the various parameters and select the principal components (parameters) for further processing using neural networks. Chang et al.[157] 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 data sets and portioned into seven and eight clusters, respectively, and the results of feature extraction and principal component analysis are shown in Figure 16 along with SVM/RVM plots.

4.2.2.2. 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

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{6}$$

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

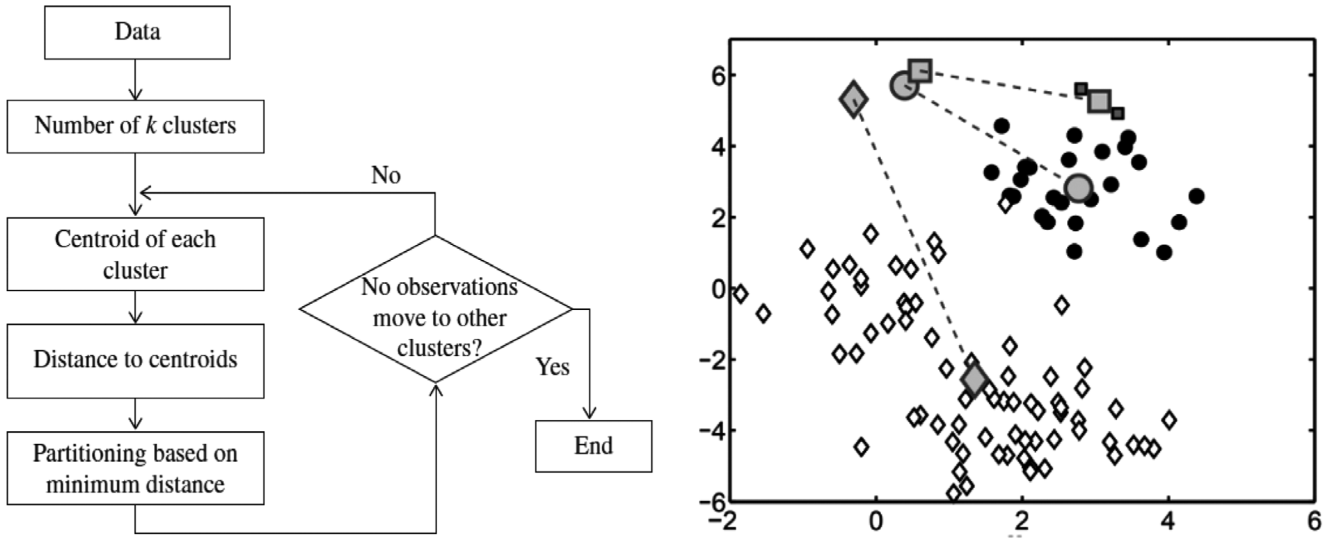


Figure 19. k-means clustering procedure (left), clustering illustrated (right). Reproduced with permission.[162] Copyright 2018, Wiley.

This method has been successfully applied for anomaly detection of mechanical components, such as rolling elements bearings,[168] as well as for wind turbines.[169] In ref. [169], data were 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 19** shows a typical implementation procedure for this approach (left) and how trained data can find their clusters based on the distance from the centroid (right).

4.2.2.3. Self-Organizing Map: First introduced by Kohonen,[170] the 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 2D 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.[171] Tian et al.[172] 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.[156] 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[156] suggests that, this method appears to be promising for the RUL estimation of LED products.[156] The RUL prediction performance of SOP along with KNNR, multiple linear regression, and Ensemble methods based on a historical failure data is depicted in **Figure 20**.

4.2.3. Semisupervised Learning Approaches

Semisupervised 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 semisupervised 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 semisupervised learning, suppose a data set $X = (x_i)_{i\in[n]}$ can be divided into two components: data points $X_j : (x_1, x_2, \dots, x_j)$ for which labels $Y_j : (y_1, y_2, \dots, y_j)$ are given and data points $X_k : (x_{j+1}, x_{j+2}, \dots, x_{j+k})$ for which the labels are unknown.[173] The semisupervised learning methods are widely applied for speech analysis, web content classification, protein sequence classification, and recently in prognostics. Some of the examples that can be considered as semisupervised learning algorithms include hidden Markov model (HMM), expectation maximization (EM) with generative mixture models, graph-based methods, and transductive SVM,[174] and two of these methods that have been successfully applied in prognostics are discussed here.

4.2.3.1. Expectation Maximization: EM is an iterative and general procedure employed to estimate model parameters in a parametric distribution. EM 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.[175] Although the EM algorithm is not widely seen in the PHM field, it is a very

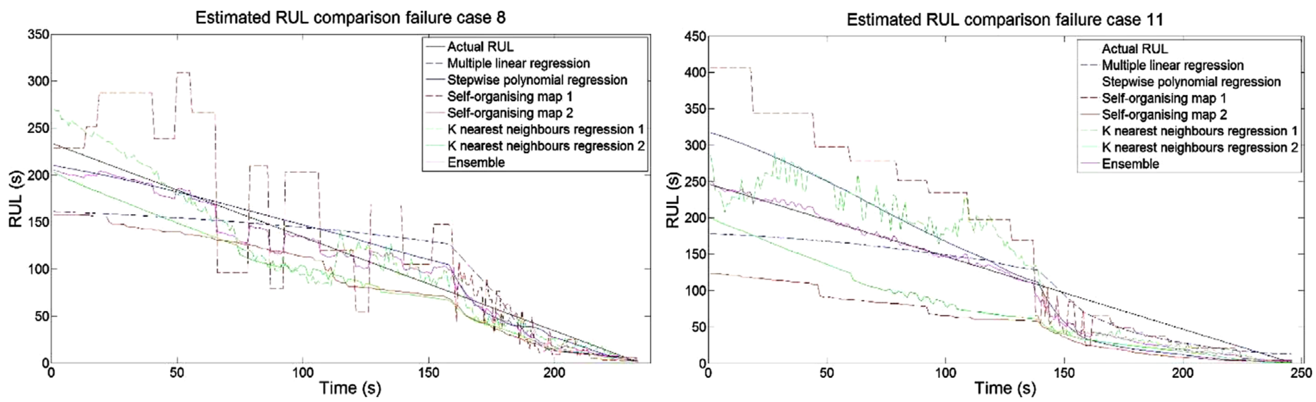


Figure 20. RUL estimation based on SOP, KNNR, multiple linear regression, and ensemble methods. Reproduced with permission.[156] Copyright 2018, Elsevier.

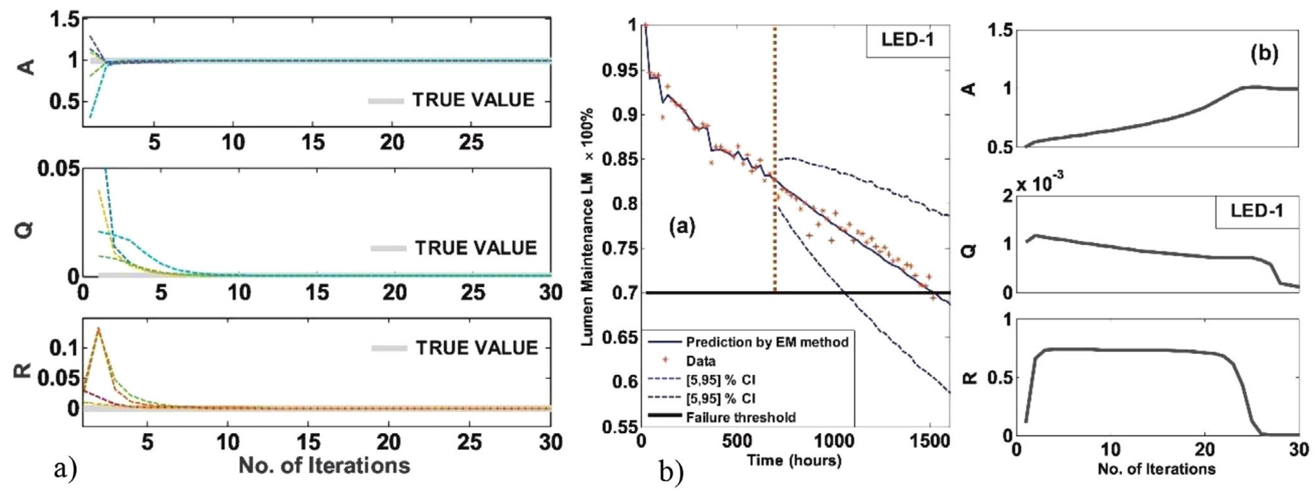


Figure 21. a) Parameter estimation using EM algorithm. b) RUL prediction based on EM estimated parameters and iterations trends values for parameters. Reproduced with permission.[177] Copyright 2018, Elsevier.

important algorithm and a typical application of EM for use in a RUL prediction is presented by Si et al.[176] 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 were obtained.[176] In solid-state lighting, a recent work showed that EM has been applied to estimate the model parameters of the exponential decay model and to calculate the remaining useful lifetime of HPWLEDs[177] as shown in **Figure 21**. 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-21-11 standard which is based on NLS regression method, and it showed a comparable accuracy to PF method (Figure 21).

4.2.3.2. 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.[178] 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 semisupervised 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,[179] 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,[180,181] helicopter gearboxes[182] as well for anomaly detection in an electronic component, insulated-gate bipolar transistor (IGBT).[183] A mixture of Gaussian hidden Markov models has also been employed to assess the current health status and estimate remaining useful lifetime of bearings.[184] 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

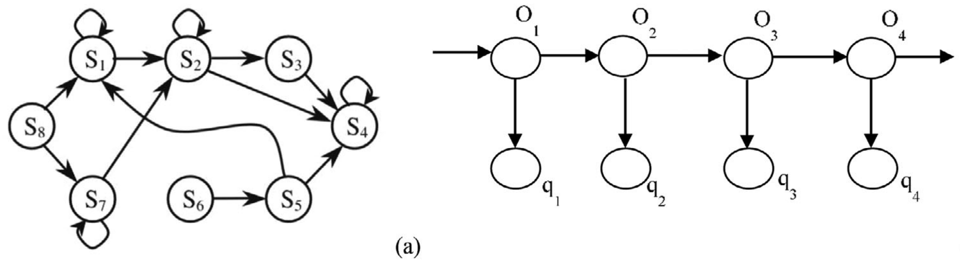


Figure 22. HMM graphical description: a) stochastic finite-state automation view of a HMM and b) a directed graphical model (DGM). Reproduced with permission.[179] Copyright 2007, Taylor & Francis.

products and systems so far. A comprehensive theoretical explanation and step by step tutorials on the general HMM is given in Rabiner,[185] while a review on the potential applications of HMM is demonstrated in ref. [186].

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

$$\lambda = \{A, B, \pi\} \tag{7}$$

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 is hidden state at time t. The HMM can be represented graphically in different ways[186] as shown in **Figure 22**. The first plot portrays a direct state transition graph while the second illustrates the allowable transitions.

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 LEDs

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).[48,187] However, the PoF methods[188–191,203,204] require comprehensive knowledge of products in advance (e.g., materials and geometries, thermal, electrical, mechanical, etc.), life-cycle conditions, and other processes that lead to failures always increases the time and cost in actual applications. On the other hand, the data-driven approaches[129,136,192–202] 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)[205–207] of LED product/systems.[48] Pecht and Jaai[45] 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 PCB case study. Cheng and Pecht[48] 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.[20] 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 categorized into three subparts as LED module/package (die, interconnect, 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 **Figure 23**.

6. System Level Reliability of Light-Emitting Diodes

As described in the previous sections, the diagnostics and prognostics of high-power white LEDs has been widely studied based on machine learning and statistical-based data-driven methods and algorithms, such as the Wiener process,[60,118] gamma process,[208,209] Kalman filter,[196,210] particle filtering,[37] neural networks,[150] expectation maximization,[177] RVM regression,[161] 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

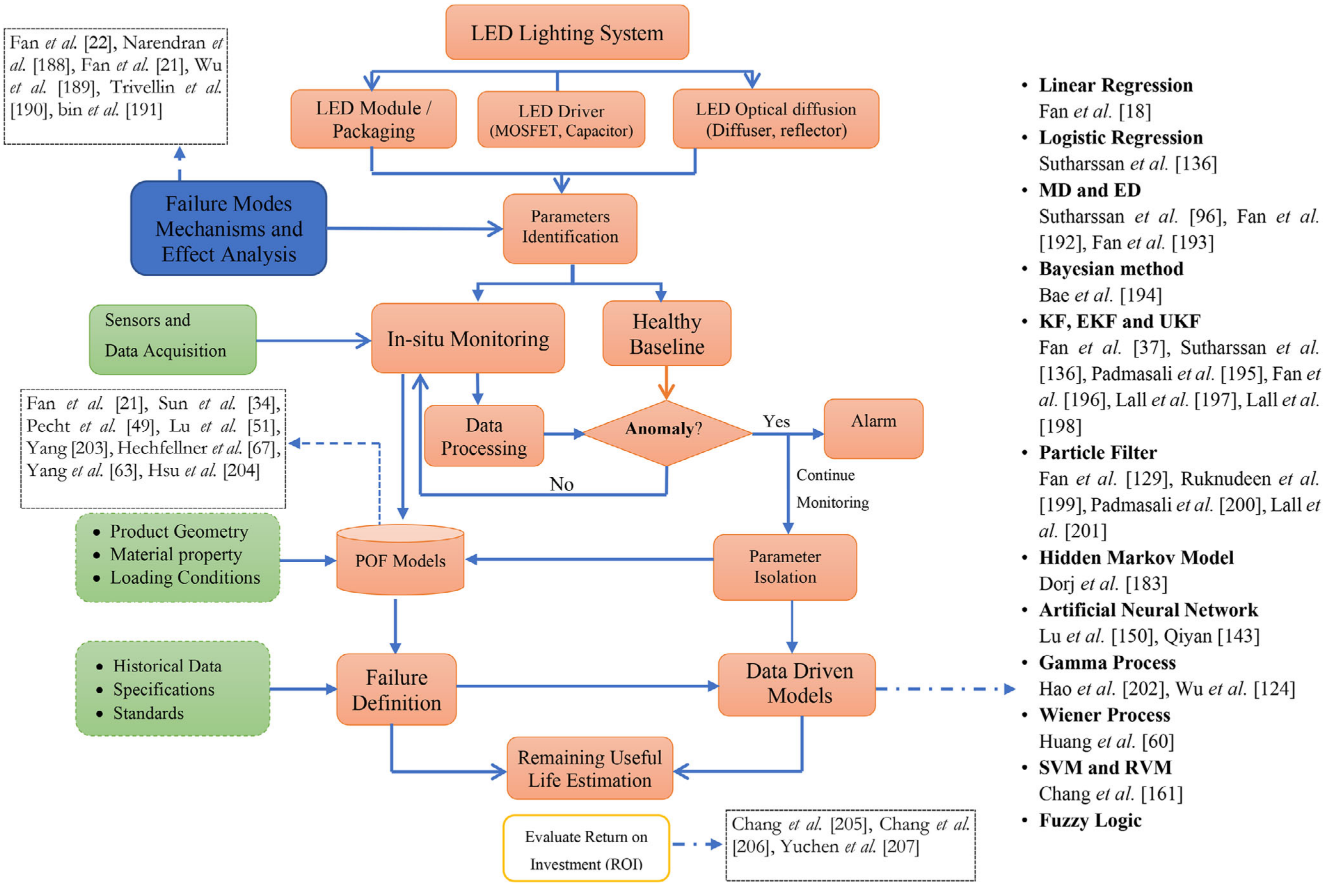


Figure 23. Fusion prognostics for LED lighting system. Adapted with permission.[20] Copyright 2014, IEEE.

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.[17] 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.[211] 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 USDOE[212] 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.[213] used the Monte Carlo approach to predict LED system level reliability by taking both the failure mode of the subcomponents 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.[74] 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 (USDOE[212] and Van Driel et al.[213]) previously mentioned. Song et al.[55] 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

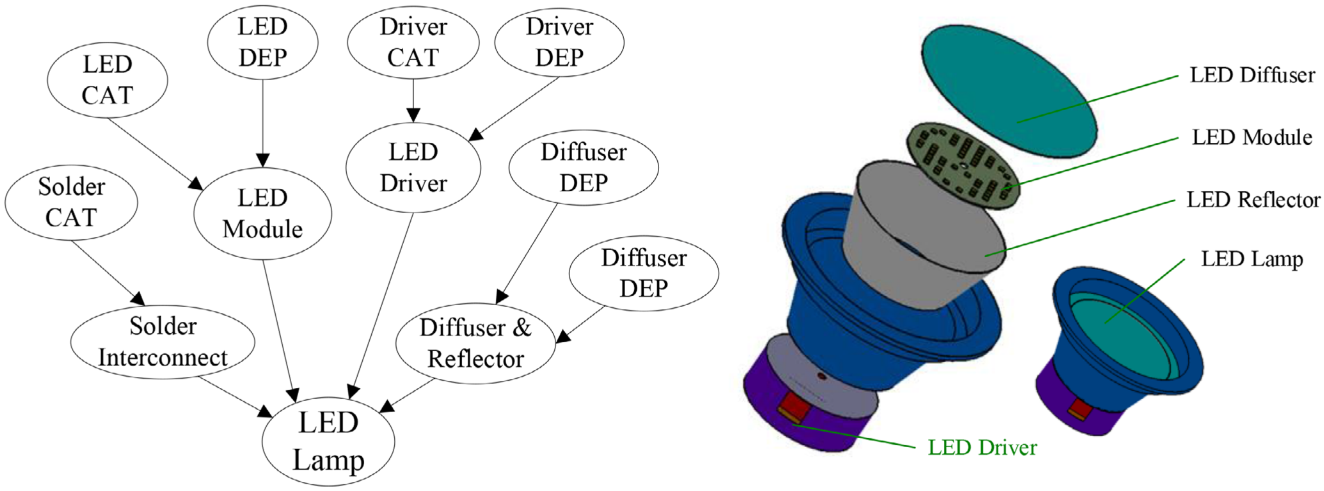


Figure 24. DAG for product level LED light sources (left), 3D model exploded and assembly view (right).

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 components/subsystems relationships in a system.[214] 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.[215] The BN model has also been applied in the field of reliability engineering including software reliability,[216] modeling maintenance,[217] and fault diagnosis in systems.[218,219] Recently, the BN model was found to be effective in estimating the system/product reliability of complex systems, such as high-speed trains,[219] solar-powered unmanned aerial vehicles,[220] and pitting degradation structural steel in marine systems.[221]

In this section, a BN method that considers the intricacies of the high-power 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 effect analysis (FMEA) are considered[6] in order to construct a DAG for a BN model. In the BN model constructed in **Figure 24** (left), the variables which have no parents, such as LED_CAT, LED_DEP, Driver_CAT, Driver_DEP, Solder_CAT, DifRef_DEP, and DifRef_CAT, are referred to 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 $R_{Xi}(t)$, $i = 1,\ldots,p$, the intermediate nodes as $R_{Mj}(t)$, $j = 1,\ldots,k$, 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 in Figure 24 (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

$$R_{pn} = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1n} \\ R_{21} & R_{22} & \cdots & R_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ R_{p1} & R_{p2} & \cdots & R_{pn} \end{bmatrix} \tag{8}$$

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

$$P(R_{Mj}(t)) = \sum_U P(R_{Mj}(t), R_{Xi}(t)) \tag{9}$$

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

$$\begin{aligned} P(R_L(t)) &= \sum P(R_{X1}(t), \ldots, R_{Xp}(t), R_{M1}(t), \ldots, R_{Mk}(t), R_L(t)) \\ &= \sum_{Pa(L)} P(R_L(t) | Pa(R_L(t)). \sum_{Pa(Mj)} P(R_{M1}(t) | Pa(R_{M1}(t)). \ldots \\ &\quad \sum_{Pa(Mk)} P(R_{Mk}(t) | Pa(R_{Mk}(t)). \ldots.\, P(R_{X1}(t)).P(R_{Xp}(t)) \end{aligned} \tag{10}$$

Here, $Pa(L)$, $Pa(M_j)$, and $Pa(M_k)$ are the parent nodes for leaf node L, 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 tradeoffs 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.[222,223] 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. • Less complex and more applicable than model-driven methods • Lower precision results compared with model-based approaches • Well-established theoretical basis and convenient to implement fast and accurate online pattern recognition • High dimensional noisy data can be transformed in to lower dimensions convenient for prognostics. • Relatively easy to calculate and predict future states • The more available information used, the better the accuracy • Requires large amount of data to be more accurate in general • 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	• For a well-controlled system, predicting the future propagation of the degradation without prior knowledge about the mathematical model is possible. • Has higher accuracy if the systems/products physics of models remains consistent • Requires fewer data compared to data-driven approaches • Usually complex and more stochastic to model system degradations • Might have difficulty to handle unit-unit variability in population and often provides overall estimate for entire sample • Might be difficult to get mathematical models for a particular kind of component or material • Computationally expensive • Requires simplifying assumptions

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.[224] A digital twin is a dynamic and comprehensive virtual prototype of a physical product/system. The concept of digital twins was initially conceived and introduced by Vickers (NASA) and Grieves (University of Michigan) in 2003.[225]

In the past few years, many companies started using digital twins to increase their system operation efficiency, testing new products before deployment and identifying problems.[224] According to prediction by Gartner, half of the large industrial corporations will be leveraging digital twins technology by 2021 to facilitate the assessment of system performance while gaining an improvement of 10% in system effectiveness.[226] The implementation and adoption of digital twins depends on the type of industry and products as there are no common standards, methods, or norms.[227] The National Aeronautics and Space Administration (NASA) built two identical spacecrafts for Apollo 13 mission with the idea of early "digital twins" 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 U.S. 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.[227] Singapore is also creating a virtual copy of the entire city in partnership with Dassault systems, to assess, improve, and monitor utilities.[228]

It can be recalled that PHM is very useful in the diagnostics and prognostics 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.[229] 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.[229] This gap could be filled with convergence of data from physical 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.[227] 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).[230]

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

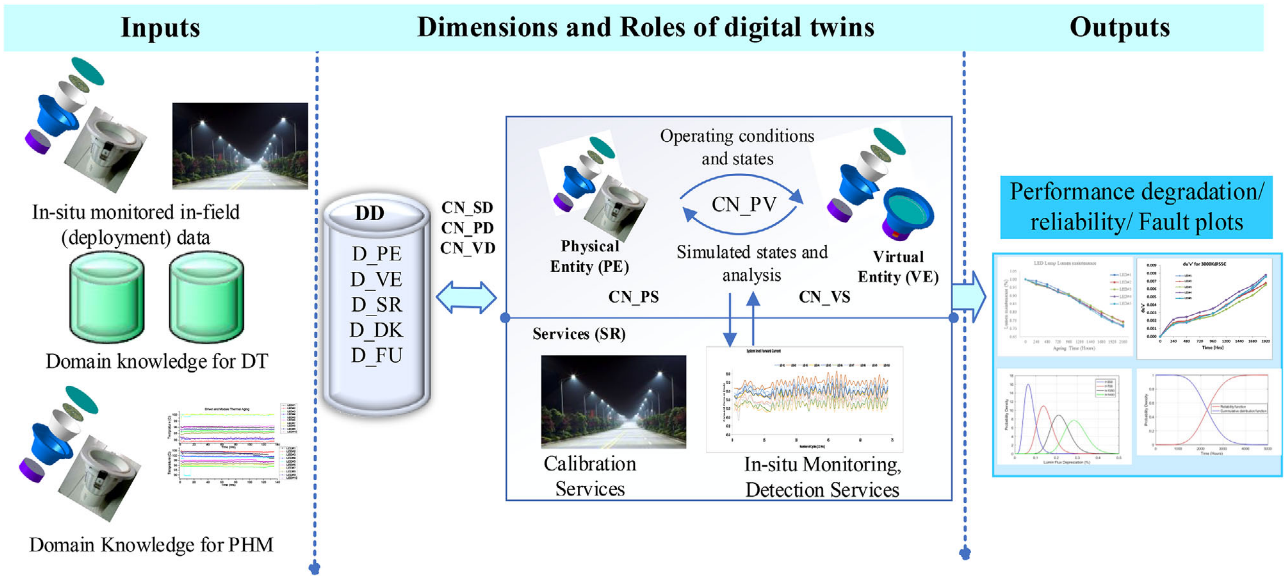


Figure 25. Digital twins implementation framework with the five dimensions (PE, VE, DD, CN, SR) for LED products. Adapted with permission.[229] Copyright 2018, Elsevier.

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).[225] Based on this, Tao et al.[229] 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 twins 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 **Figure 25**.

9. Conclusions

In this study, the prognostics and diagnostics methods used in LED lighting has 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 a 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 LSTM networks (a variety of recurrent neural networks), HMM, SOM, least-squares support vector machine, and fuzzy-logic. The emerging trend in the application of digital twins for PHM with the focus on LEDs has also been briefly investigated.

Appendix A

Table A1. 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[149,150,143] LSTM, recurrent neural network (RNN)[a)] [151,152]	• Forward current (I_F, electrical) and temperature[149] • One hidden layer and two neuron nodes in the hidden layer[149] • MATLAB neural network toolbox[150,143]	• Probability of health status of LEDs (healthy 0.99 and not healthy 0.01) • Predict the lifetime of power LEDs with <5% error[143]
	• Luminous flux, chromaticity coordinates u' and v', electric current, and temperature[150]	• Model can be used when the mean square error of data sets between estimated and expected life output narrow to the target • R value of 0.985 and 0.974 for two data set using Adboost BPNN
k-nearest neighbors (KNN) kernel density based algorithm[a)] [157,156]	• 24 features from die and phosphor SPD clustered[157]	• Anomaly detection conducted (two clusters for phosphor SPD and three clusters for die SPD)[157]
Relevance vector machine[a)] [161,138]	• LEDs light output (lumen maintenance and color shift)[161]	• RUL lifetime prediction with error less than 5%, claimed to be better than PF • Reduces qualification testing time (from 6000 to 210 h)[161]
	• Rotating component in aerospace setting (NASA) • Component feature damages (not specified)[a)] [138]	• Estimate the remaining useful life with acceptable accuracy[a)] [138] • Not employed to anomaly detection
Support vector machine[a)] [91,159]	• Data set with 22 parameters for mission critical system from Lockheed Martin[a)] [91]	• Identify system anomalies (with "healthy" and "unhealthy" class) • Helps to manage false alarms
	• Power gain degradation data of microwave[159]	• Point and interval estimates of RUL obtained[159] • Much more robust and stable as verified in comparison with RBF NN
Principal component analysis (PCA)[157,143]	• 12 features from SPD (die and phosphor) considered for dimensional reduction[157]	• PCA used to consider three features of SPD after reduction for further analysis (KNN)[157]
	• Eight parameters considered for selection[143]	• Four features with >85% contribution are reduced from eight to use as an input BPNN.[143]
Self-organizing map (SOM)[a)] [171,156]	• Temp of gearbox, oil, nacelle, and rotor speed of wind of wind turbine[171] • Failure data for an industrial reciprocating compressor[156]	• System level anomaly detection for WT[171] • RUL estimation is obtained with good accuracy.[156]
Hidden Markov model (HMM)[a)] [182,183] Bayesian networks (BN)[a)] [220]	• Experimental data for helicopter gearbox Vibration from 68 operating conditions[182] • Experimental data from IGBT from three operating conditions • Degradation data from unmanned aerial vehicles[220]	• Enabled defect level, defect-type, and torque level classification for CBM[182] • Anomalous behavior detection for IGBT based on Bayesian HMM classification[183]

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

Table A2. A brief summary of advantages and disadvantages for selected machine learning and statistical-based data-driven prognostics methods/algorithms.

PHM approach	Advantages	Disadvantages
Wiener process (PF)[60,121]	• Can handle nonlinear degradation processes • Favored over other stochastic process for nonmonotonic degradation data • Lifetime can be analytically formulated with inverse Gaussian distribution	• Makes use of current degradation data and ignores data from entire sequence of observations (Markov property)
Gamma process (GP)[87,125]	• Suitable for unidirectional degradation process • Mathematically, equations are easy to understand and underlying physical meaning is easy to comprehend.	• Unsuitable to handle nonmonotonic degradations
Particle filtering (PF)[129,140]	• Convenient for nonlinear and dynamic degradations • Higher accuracy compared to other filtering algorithms	• Requires failure threshold • Demands more computational time and experimental data • Requires to set equations dictating system dynamic and measurement model
Artificial neural network (ANN)[140]	• Suitable to model nonlinear, unstable, and multidimensional processes • Capable of modeling complex systems without prior knowledge • Capability to draw meaningful pattern from complex and imprecise data	• Requires data preprocessing to reduce complexity of model • Demands large amount of training data • Time consuming due to trial and errors in determining suitable model
k-nearest neighbors regression (KNNR)[156]	• Free from distribution, i.e., nonparametric regression family • Computationally cheap, easy to use, and fast	• Accuracy is highly affected by the availability of historical data.
Support vector machine (SVM)[140]	• More suitable for anomaly detection • Efficient for small or large data set and real-time analysis • Precise and robust result with nonlinear or high-dimension data	• Lack of standard method to choose kernel function • Unable to give RUL estimation directly • Difficult to form a univariate time series by the RUL and sampling time
Principal component analysis (PCA)[166,167]	• No need of training data to train the algorithm (unsupervised learning ability) • Mainly used for dimensional reduction tasks which makes it suitable for anomaly detection	• Could not be directly used for RUL estimation
K-means clustering[168]	• Used for anomaly detection • Does not require failure data or faulty system information	• Not convenient for RUL estimation purposes • Higher standard feature vectors are required compared to supervised classification.
Self-organizing map (SOM)[156]	• Missing data imputation capability • Enables the estimation of RUL directly	• Requires sufficient amount of historical data • System degradation information requires continuous monitoring.
Hidden Markov models (HMM)[140]	• Convenient for multifailure modes • Can model nonmonotonic degradations at different states of degradation • Quick management of incomplete data sets	• Accuracy of modeling depends on availability of large amount of data. • Computationally intensive for large number of hidden states

Appendix B

Lighting Terminology

Luminous flux (Φ): The total amount of visible light emitted by a light source, measured in units of lumen (lm).

Illuminance: The total amount of light (luminous flux) incident on a surface per unit area (lux = lm m^{-2}).

Luminous efficacy: The ratio of the luminous flux emitted by a lamp to the power the lamp consumes, which is measured in lm W^{-1}.

Luminous intensity: The power of light from the source in one or more directions measured in candela (cd).

Lumen depreciation: The decrease in the amount of luminous flux emitted from a light source over its operating time.

Luminous flux maintenance (often referred to as lumen maintenance): The remaining luminous flux output (usually expressed as a percentage of the initial luminous flux output) at any specific operating time. It is the converse of lumen depreciation.

Chromaticity shift (also referred to as color shift): The change in chromaticity of a light source with respect to the chromaticity at the beginning of the light source, represented as *Duv* (or $\Delta u'v'$).

Correlated color temperature (CCT): A measure of the color appearance light sources defined by the proximity of the light source's chromaticity coordinates to the blackbody locus. It is measured in degrees Kelvin (K).

Color rendering Index (CRI): The ability of a light source to render the true color of objects it illuminates, unit Ra.

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Conflict of Interest

The authors declare no conflict of interest.

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