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A Review of Prognostic Techniques for High-Power White LEDs

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***Abstract*—High-power white light-emitting diodes (LEDs) have attracted much attention due to their versatility in a variety of applications and growing demand in markets such as general lighting, automotive lamps, communications devices, and medical devices. In particular, the need for high reliability and long lifetime poses new challenges for the research and development, production, and application of LED lighting. Accurate and effective prediction of the lifetime or reliability of LED lighting has emerged as one of the key issues in the solid-state lighting field. Prognostics is an engineering technology that predicts the future reliability or determines the remaining useful lifetime (RUL) of a product by assessing the extent of deviation or degradation of a product from its expected normal operating conditions. Prognostics bring benefits to both LED developers and users, such as optimizing system design, shortening qualification test times, enabling condition-based maintenance for LED-based systems, and providing information for return-on-investment (ROI) analysis. This paper provides an overview of the prognostic methods and models that have been applied to both LED devices and LED systems, especially for use in long-term operational conditions. These methods include statistical regression, static Bayesian network, Kalman filtering, particle filtering, artificial neural network, and physics-based methods. The general concepts and main features of these methods, the advantages and disadvantages of applying these methods, as well as LED application case studies, are discussed. The fundamental issues of prognostics and photo-electro-thermal (PET) theory for LED systems are also discussed for clear understanding of the reliability and lifetime concepts for LEDs. Finally, the challenges and opportunities in developing effective prognostic techniques are addressed.**

***Index Terms*—Light-emitting diodes, prognostics, reliability, lumen degradation, color shift, physics of failure, data-driven.**

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I. Introduction

As a new type of solid-state lighting (SSL) source, light-emitting diodes (LEDs) have been applied in many fields, including general illumination, automotive lighting, automobile devices, display backlighting, communication devices/networks, and medical applications [1]-[6]. For example, a large number of LED lighting designs were adopted in the development of the latest generation of airplanes, such as the Boeing 787-8 Dreamliner and Airbus A380-800, including the instrument panel lights, interior cabin lights (attractive mood-lighting), exterior beacon lights, and navigation lights [7]. Another example, LED headlamps have been used for both high and low beam in some high-end cars, such as the Lexus LS600h, Audi V10 R8, Cadillac Escalade, and Toyota Prius [4]. In recent years, interest in the application of high-power LED lighting systems (which consume at least 1 W of power) has been increasing. Compared with traditional light sources, they have many advantages, such as high efficiency, low power consumption, high reliability, long lifetime, and environmental friendliness.

In recent years, researchers have carried out a number of studies on new materials, advanced manufacturing technology, improved packaging technology, thermal management, and reliability of LEDs and associated products [1][4]. Especially for high-power LEDs, with the characteristics of high-power operating conditions (over 1 W at least), high junction temperatures, and long operational life, the reliability issues have been of great concern. At present, the major worldwide LED manufacturers claim that the lifetime of LEDs is 50,000–100,000 hours. In general, the rated lumen maintenance lifetime (L_p) is the most appropriate characteristic used to qualify the performance, lifetime, and reliability of LED lighting [8]. The Alliance for Solid-State Illumination Systems and Technologies (ASSIST) recommends two kinds of lumen lifetimes under specific conditions. One is the L_{50} lifetime for decorative lighting, which is based on the time for 50% light output degradation, and the other is the L_{70} lifetime for general lighting, which is based on the time for 70% light output degradation [9][10]. L_{70} or L_{50} indicates the time at which the lumen output declines by 30% or 50% from the initial value (or time to 70% lumen maintenance). LED reliability and lifetime are related to many factors, including the operating temperature,

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driving forward current, packaging, materials, and manufacturing processes [1][4].

A wide range of literature has been published, underlining the reliability and failure behavior of LEDs. For example, Meneghini *et al*. [11] investigated the degradation mechanisms that limit the reliability of high-power LEDs for lighting applications. Chang *et al*. [1] presented a comprehensive review on LED reliability issues, focused on the failure mechanisms of LEDs. Several other reviews related to the reliability and failure mechanisms of LED have also been published [12]-[19]. The reliability information with respect to lifetime or remaining useful lifetime (RUL) of LEDs is of great significance to the manufacturers, as well as to the potential users and end-product manufacturers. For example, this information is used to maintain LED lighting systems (such as roadway lighting) after deployment. At present, however, the reliability and lifetime information provided by the LED manufacturers is neither sufficient nor accurate enough to be used for LED-based systems, especially for safety-critical systems such as aerospace, medical, energy, and nuclear.

Prognostics refers to the process of predicting the future reliability or determining the RUL of a product by assessing the extent of deviation or degradation of a product from its expected normal operating conditions [20]. As one of the most efficient engineering methodologies for prediction of lifetime/reliability, prognostic techniques have been successfully applied to various engineering systems and products over the last 10 years. The potential benefits, challenges, and opportunities associated with system prognostics have been discussed in the literature [21]. Several reviews related to prognostics for different systems/products have been published [22]-[29]. Heng *et al*. [22] and Kan *et al.* [29] summarized the prognostic techniques that can be applied to rotating machinery and associated systems. Sikorska *et al.* [23] discussed business issues that need to be considered when selecting an appropriate modelling approach for industrial applications. An *et al*. [24][27] reviewed prognostic methods in terms of their attributes, pros, and cons by using simple examples and provided practical options for prognostics. Baraldi *et al*. [25] proposed a strategy for selecting the prognostic methods using different available information. Yin *et al*. [26] surveyed data-driven methods used for process monitoring and fault diagnosis. Oh *et al*. [28] summarized past developments and recent advances in the area of prognostics for insulated gate bipolar transistor (IGBT) modules. However, there are no reviews that cover the increasing number of publications on LED prognostics.

Prognostics benefits both LED developers and users by improving the accuracy of reliability prediction and useful lifetime assessment, optimizing LED system design, shortening qualification test times, enabling condition-based maintenance for LED-based systems, and providing information for ROI analysis. To further promote and expand the application of LEDs, proper prognostic methods must be developed. This paper reviews the latest information regarding the prognostics of high-power white LEDs, with consideration of the efficiency and accuracy of each prognostic approach, and is intended to be helpful for improving the performance of prognostic methods for LEDs.

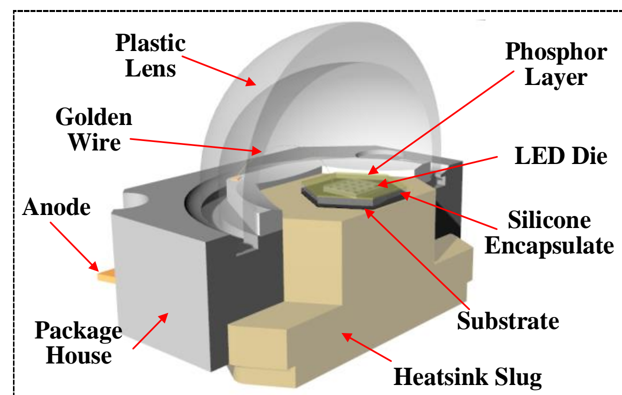
This paper is organized as follows: Section 2 discusses the fundamental issues for the prognostics of LED devices (packages) and drivers, including failure modes, mechanisms, indicators, PET relationships, and lifetime characterization. Section 3 presents various data-driven and physics-based methods and discusses prognostics on the LED system level. Section 4 analyzes challenges and opportunities in order to promote appropriate and effective methods. Section 5 presents concluding remarks.

II. Fundamental Issues of Prognostics for LEDs

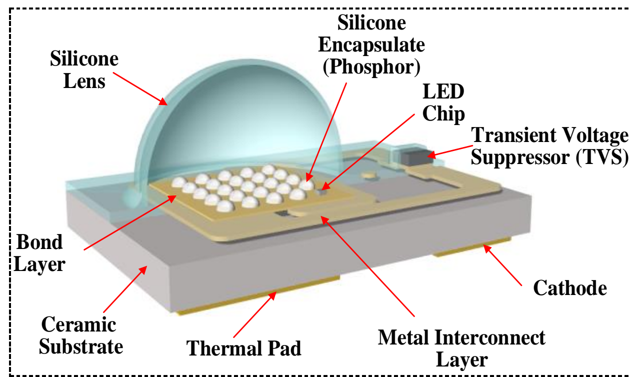
The fundamental issues of prognostics and photo-electro-thermal (PET) theory for LED systems are discussed for clear understanding of the reliability and lifetime concepts for LEDs. These issues include failure modes and mechanisms analysis of both LED devices (packages) and LED drivers, the PET theory for LED systems, and the lifetime characterization of LEDs.

A. Failure Modes, Mechanisms, and Indicators of LED Devices (Packages)

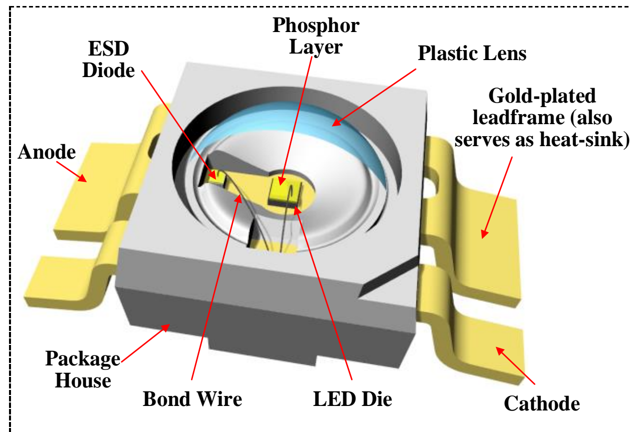
Generally, SSL begins with semiconductor-based LED technology and its packaging. There are six levels/processes in the whole SSL industrial chain, including LED chips, LED packages, multi-LED assemblies, LED modules, luminaires, and large SSL systems [2][3]. The multiple LED assembly is the basic assembly unit for the LED module and luminaire. While a high-power white LED has more comprehensive system reliability problems, this paper covers mainly white LED devices and LED systems. Nowadays, the phosphor-converted (pc) white LED has become one of the most widely used white light sources. There are several different and similar structures of the LED packaging between different LED manufacturers, such as Nichia (Japan), Cree (USA), Philips Lumileds (Netherlands), and Osram (Germany). For the convenience of further study, four typical structures of LEDs from the major vendors [30]-[34] are shown in Fig. 1. Typically, an LED package mounted on a printed circuit board (PCB) is composed of housing (such as polyphthalamide or liquid crystal polymer), plastic/silicone lens, resin encapsulant (such as epoxy or silicon), die/chip (such as InGaN/GaN), phosphor (such as cerium-doped yttrium aluminum garnet, YAG: Ce), bond wire, leadframe (anode and cathode), die attach (such as Ag paste and epoxy paste), and metal heat-sink slug.



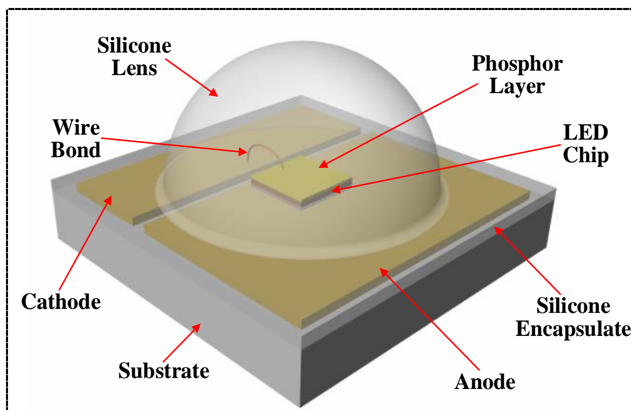
(a) Philips LUXEON K2



(b) Philips LUXEON Rebel



(c) Osram LUW



(d) Cree XLamp

Fig. 1. Some LED packages with different packaging types.

As shown in Fig. 1(a), this type of LED package utilizes standard FR4 PCB and surface mount technology (SMT) with a 4-lead gull-wing package outline. Fig. 1(b) shows that the leadless package outline with the thermal pad is electrically isolated from the anode and cathode contact pads. Similarly to Fig. 1(a), the LED package shown in Fig. 1(c) also utilizes SMT technology with 4-lead, and its gold-plated leadframe serves as a heat-sink. Fig. 1(d) shows another type of leadless package outline with the anode and cathode around the substrate.

The LED die is a compound semiconductor (with p-n junction), and its manufacturing process is similar to that of a microelectronics device. However, due to their unique functional requirements, electrical and optical properties, materials, and interfaces, LEDs have different failure modes and mechanisms. Various failure sites, causes, effects, modes, and mechanisms related to LEDs have been summarized by Chang *et al*. [1]. LED failures are classified by three levels: the semiconductors (die/chip), the interconnects, and the package [1][3]. The failures related to semiconductors include generation and movement of defects and dislocations, dopant diffusion, electrostatic discharge, and electromigration, which lead to lumen degradation, increase in reverse leakage current, and parasitic series resistance. The failures related to interconnects include bond wire fracture, wire ball bond fatigue, and electrical contact metallurgical interdiffusion, which result in lumen degradation and electrical open/short circuits. The failures related to the package include encapsulant carbonization, encapsulant yellowing, encapsulant delamination, lens cracking, phosphor thermal quenching, and solder joint fatigue, which result in lumen degradation, color change, forward voltage increase, and severe encapsulant discoloration.

Commonly, the high-power LED devices as microelectronics are created as wire-bond or flip-chip packages. For wire-bond and flip-chip interconnection technologies, the optical limitation of LEDs requires unique methods of transferring both heat and electrical signals through the bottom side of the package only, while leaving the top optical side exposed [35]. As discussed above, thermomechanical fatigue is a major issue of wire-bond and flip-chip packaged LEDs where the LED chip is mounted to the circuit board by a solder joint [2][3]. Recently, some of the new innovations for LED packaging are being adapted from advanced silicon and electronic packaging concepts such as chip-on-board (COB) [36], wafer-level packaging [37], and system-in-package concepts [2]-[4]. These efforts for changing the packaging of LEDs have been suggested to improve thermal performance and reliability. For example, in the case of the COB package, the critical factor for long-term reliability is degradation of the LED itself and not that of the board-level interconnects [4]. In future, the LED package will be designed to be capable of successfully providing general lighting with sufficient thermal management and reliability at a relatively low packaging and assembly cost.

This section focuses on the performance indicators (PIs), also called feature parameters, that are derived from the analysis results and information on the failure sites, modes, and mechanisms at the semiconductor, interconnect, and the package levels. These PIs can then be used to establish the foundations of prognostics, such as monitoring/measuring parameters, failure criteria, and prognostic method selection (see details in Section 3). From the relationship between the failure causes and associated mechanisms, the PIs can be preliminarily determined (recommended representative parameters) as illustrated in Table I (FMEA stands for failure modes and effects analysis).

TABLE I. FMEA-based information towards prognostics of LEDs (*DD stands for data-driven methods, PB stands for physics-based methods).

Failure Sites	Failure Modes	Failure Mechanisms	Performance Indicators (PIs)	Available Prognostic Methods
Die	Lumen degradation	Generation and movement of defect and dislocation; die cracking; dopant diffusion	⬩Lumen maintenance (luminous flux) ⬩Light output power (spectral power distribution) ⬩Geometries, material, environmental and operational conditions	DD*/PB*
	Increase in reverse leakage current	Generation and movement of defect and dislocation	⬩Reverse leakage current	DD
	Increase in parasitic series resistance	Generation and movement of defect and dislocation; dopant diffusion	⬩Parasitic series resistance	DD
	Increase in forward current	Dopant diffusion	⬩Forward current ⬩Forward voltage	DD
	No light/short circuit	Electromigration	⬩Geometries, material, environmental, and operational conditions	PB
Interconnect	No light/open circuit	Electrical overstress induced bond wire fracture; wire ball bond fatigue; electrostatic discharge	⬩Geometries, material, environmental, and operational conditions	PB
	Lumen degradation	Electrical contact metallurgical interdiffusion	⬩Lumen maintenance (luminous flux) ⬩Light output power (spectral power distribution)	DD
	Increase in parasitic series resistance	Electrical contact metallurgical interdiffusion	⬩Parasitic series resistance	DD
	Short circuit	Electrical contact metallurgical interdiffusion	⬩Parasitic series resistance	DD
Package	Lumen degradation	Encapsulant carbonization; encapsulant delamination; encapsulant yellowing; lens cracking; phosphor thermal quenching; solder joint fatigue	⬩Lumen maintenance (luminous flux) ⬩Light output power (spectral power distribution) ⬩Color coordinates (x, y) (chromaticity coordinates (u', v')) ⬩Geometries, material, environmental, and operational conditions	DD/PB
	Color change/discoloration of the encapsulant	Encapsulant yellowing	⬩Color coordinates (x, y) (chromaticity coordinates (u', v')) ⬩Color rendering index ⬩Spectral radiant flux distribution	DD
	Broadening of spectrum (color change)	Phosphor thermal quenching	⬩Color coordinates (x, y) (chromaticity coordinates (u', v')) ⬩Color rendering index ⬩Spectral radiant flux distribution	DD
	Forward voltage increase	Solder joint fatigue	⬩Forward current/forward voltage ⬩Geometries, material, environmental, and operational conditions	PB/DD

B. Failure Modes and Mechanisms of LED Drivers

LED drivers are integral to SSL systems; they provide constant current, stabilize the voltage, and adjust the brightness of the LED. However, because the LED driver is a kind of power electronic subsystem, it presents unique reliability problems for both power electronics and lighting sources [38][39]. The LED driver is found to be a weak point in an LED system, as reported by the U.S. Department of Energy [40]. It contributes up to 52% of the total system failure [18]. Hence, the reliability of LED drivers that match the life span of LED devices is one of the key barriers to further applications of LEDs.

Many different LED driving solutions address a number of lighting design challenges, and many will still be developed at an increasing speed. From different aspects, the LED drivers can be classified into: constant current and constant/stable voltage (drive mode), passive and switched mode (circuit topology), or linear mode and switch mode (function element). The circuit topologies for LED drivers can be categorized into passive LED drivers and switched-mode LED drivers based on whether a high-frequency switching operation is performed [41]. Passive drivers do not control the output current tightly and provide a DC current with AC current ripple. They are composed of only passive components (such as resistor and capacitor), magnetic components (such as inductor and transformer), and diodes, and are operated at line or double-line frequency. They are thus reliable and applicable for outdoor applications and are cost-effective for some low-power applications. Switched-mode LED drivers operate at high frequency and can realize precise output current regulation. They are usually less reliable than passive LED drivers and are sensitive to extreme weather conditions such as wide variations in temperature and lighting. However, the properties of high-frequency operation, active control, and easily integrated novel functions make switched-mode drivers very attractive for a wide range of indoor applications. The reliability of LED systems depends on the type of switched converter used, their efforts on electronic devices, operation temperature, and heat-sink. Various driver architectures are applied for different

applications, such as buck, boost, flyback, and transformer-isolated converters. Among these types of converters, the flyback converter topology was chosen to provide galvanic isolation between the input AC voltage of 120 V rms at 60 Hz and the output voltages. Flyback converters are well understood and have been widely used in traditional lighting applications [3].

From a functional point of view, an LED driver can be divided into two types: switched-mode driver and linear-mode driver [45]. The linear-mode driver uses an error amplifier to control the output current linearly, while the switch-mode driver controls the output current by using a voltage-controlled switch with a feedback circuit. In the switch-mode driver's configuration, the electrolytic capacitors (E-cap) serve as the energy storage part and play a more significant role in device failure [46]. Whereas in the linear-mode driver, the output current of the driver is maintained by adjusting the gate voltage of the output transistor through the feedback circuit. Thus, switching noise is absent in this type of driver, and an output electrolytic capacitor is not necessary [45]. Research on components and subsystems of LED drivers is attracting increasing attention since the U.S. DoE released its Multi-Year Planning Program for Solid State Lighting [6]. Recently, some emerging switched-mode drivers have been proposed that do not use the electrolytic capacitor. According to the power processing stages, these circuit topologies are classified as single stage, two stages, and three stages [41]. Research on eliminating the use of E-cap in lighting products has increased. For example, Chang *et al*. [42] presented AC driver and protection circuits of LEDs. An AC power source can be applied to drive an LED without a further conversion stage, and circuits provide failure indication and protection. Chen *et al.* [43] studied an AC-DC LED driver without E-cap. Compared with other methods to eliminate E-cap, this driver has the advantages of unity input power factor and constant output current for LEDs. Lin *et al*. [44] proposed a novel pulse current driving technique for LED drivers. Compared with a constant current driver, this new driver supply's maximum peak current is 200 mA and operating frequency is between 500 kHz and 1 MHz. The structure is simple without output capacitance compensation for stability and with low power consumption. It is implemented in integrated circuits with relatively longer lifetimes.

Most of these studies focus on the reliability of external components (e.g., the electrolytic capacitor) and the internal circuitry of the driver IC. Lan *et al*. [38] presented a pseudo black-box testing method to study the reliability of the IC used in LED drivers. Sun *et al*. [39] proposed isolated component accelerated lifetime testing to investigate the effects of high-temperature degradation of electrolytic capacitors on the entire driver. Lan *et al*. [45][47] studied the degradation of a linear mode high-power LED driver and found that the hot carrier injection (HCI) was the main degradation mechanism. Lin *et al*. [48] established a thermal simulation model based on a tapped-inductor quasi-resonant buck LED driver to analyze the effect of temperature on performance and reliability.

For analyzing the complex failure modes and mechanisms of LED drivers, Popovic *et al*. [49] introduced an approach to break down a power electronic converter to its construction parts according to the functions they perform. In different types of LED drivers, the functional elements (function level) are associated with different failure modes and mechanisms, as illustrated in Table II (column 2). In addition to the fundamental functions described above, other functional elements (package level) are necessary to provide the integrity of the driver to maintain the functionality, including interconnection, insulation, mechanical support, protection, and heat dissipation. Numerous studies on the failure mechanisms and reliability of these package elements have been reported in the literature [50][51].

TABLE II. FMEA of LED drivers towards prognostics.

Driver Types	Functional Elements	Failure Modes	Failure Mechanisms
Linear mode	Amplifier	Open circuit	Overcurrent damage; bond wire crack; electrostatic discharge
		Short circuit	Dielectric breakdown; hot carrier effects; electromigration (EM)
		Electric leakage	Corrosion in metallization
		Parameter drift	PN junction defects
	Output transistor	Dielectric breakdown	Hot carrier injection (HCI)
		Electric parameter drift	Electromigration; dopant diffusion
	Resistor	Resistance drift exceeds the allowable range	Corrosion in metallization; silver migration
		Open circuit	Lead fracture; solder leads fatigue
		Contact damage	Impurity contamination
	Transformer	Reduction/loss of efficiency	DC magnetization or displacement of the core steel
		Short circuit	Winding transient overvoltage; hot spot; movement of transformer
		Insulation breakdown	Aging; overload; corrosion; careless handling
		Coil short circuit	Insulation breakdown
		Coil open circuit	Overvoltage damage
Switch mode	Electrolytic capacitor	Capacitance decrease and equivalent series resistance (ESR) increase	Electrolyte evaporation; aging in the dielectric material; degradation of oxide film; degradation loss of capacitance of anode/cathode foil
		Open circuit	Lead fracture; fatigue in solder leads
		Short circuit	Insulating materials breakdown
	Metal oxide semiconductor	Contact damage	Contact spring break; impurity contamination

Driver Types	Functional Elements	Failure Modes	Failure Mechanisms
	field effect transistor (MOSFET)	Breakdown	Overcurrent damage
	Inductor	Electromagnetic transmission degradation	Wire corrosion; silver migration; dielectric breakdown
	Diode	Forward current decrease	Dielectric breakdown; die cracking
		Reverse leakage current increase	Die attach fatigue; dopant diffusion
		Short circuit	EM in metallization
	Sampling/feedback resistor	Resistance drift exceeds the allowable range	Corrosion in metallization; silver migration
		Open circuit	Lead fracture; solder leads fatigue
		Contact damage	Impurity contamination

C. Photo-Electro-Thermal Theory for LED Systems

The LED product is a new kind of microelectronic device with complex multiple failure modes. The multi-dimensional performance requirements must be met, which include photometric parameters such as luminous flux and luminous efficacy; electrical parameters such as electric power; driven current and voltage; thermal parameters such as junction temperature; and thermal resistance of the heat-sink and junction to the case. Life characteristics and reliability issues are involved in the coupling of multiple physical fields, and the photometric, electrical, color, and thermal characteristics of LEDs are highly dependent on one another. Especially for high-power LED applications, increasing the electric power of LEDs can lead to an increase of the LED junction temperature, which will greatly affect the performance of the LED, including reduced output luminous flux and shortened lifetime [4]. For example, Christensen *et al.* [52] concluded that the LED lifetime decreases exponentially with the increase of the junction temperature. Meanwhile, Narendran *et al.* [53] found that the junction temperature increase from 40 ℃ to 50 ℃ will shorten the LED lifetime from 42,000 hours to 18,000 hours. Uddin *et al.* [54] found that the mechanism of the increased non-radiative recombination centers is related to the generation of defects in the active region due to the high current flow through the quantum well structure and the increase of LED chip temperature. Trevisanello *et al.* [55] reported that the luminous efficacy (lm/W) degradation with junction temperature can be up to 1% per ℃ after accelerated aging tests. Loo *et al.* [56] and Fu *et al.* [57] reported that research into theoretical modeling and parameter extraction is essential for understanding the interactions of heat, color, light, and power in LED systems under different driver methods, including direct current (DC), pulse width modulation (PWM), and bilevel drives. However, these studies focused only on the LED device and not the LED system, which includes the thermal design of the heat-sink and the electric power control. Hui *et al.* [58]-[60] presented a general and extended PET theory for LED systems as shown in Fig. 2.

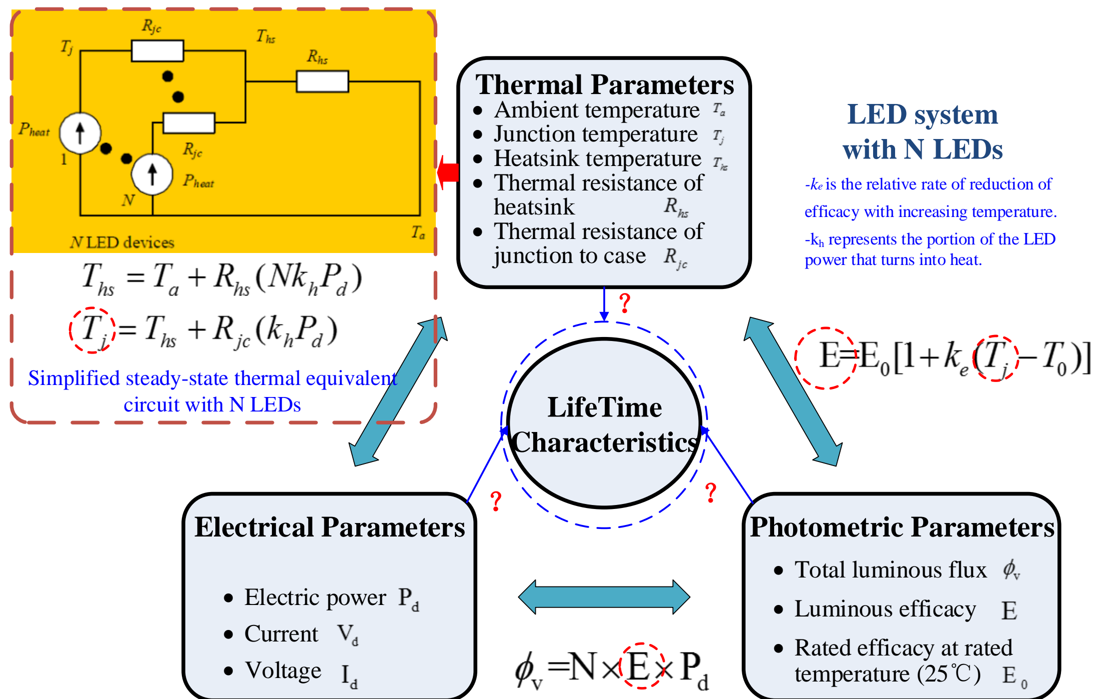


Fig. 2. Schematic diagram illustrating PET theory.

Fig. 2 shows that photometric parameters such as luminous flux and luminous efficacy; electrical parameters such as electric power, current, and voltage of an LED; and thermal parameters such as junction and heat-sink temperature and thermal resistance are closely linked. Through the relationship of each two types of parameters, a universal equation can be established that integrates the PET features of the LED system. On the basis of general PET theory, Tao *et al*. [61] developed a dynamic PET theory for LED systems by incorporating the time domain into the generalized equations. Hence, the fact that the luminous flux of an LED system will decrease with the time from the initial state to the steady state due to the rising temperature of the heat-sink and the LED devices can be quantitatively explained. Further, Almeida *et al*. [62] presented a static and dynamic PET model by considering the impact of low-frequency current ripple on LED performance.

The PET theory has been verified as useful in the optimal design and thermal management of both LED devices (e.g., optimal operating point of electric power, reduced junction thermal resistance) and LED systems (e.g., optimal thermal design of the heat-sink). For example, the peak wavelength of GaN-based white LED shifts in opposite directions under the influence of the drive current, and the junction temperature changes on the correlated color temperature (CCT) of white LEDs [56]. The optimal thermal management approach can be adopted for improving the color stability in all pc-white LED-based lighting systems under DC, PWM, and bilevel drives.

Generally, the IRC of the LED and the LED driver is affected by PET of LED, such as increased resistance with increased temperature, decreased current and electric power, and decreased luminous flux. However, these problems have not been fully considered in the existing PET theory. Besides, for compact systems with multiple LED devices closely placed together, the improper geometrical arrangement of the devices on the heat-sink and its uneven heat distribution can degrade both the devices' and system's performance. The thermal, optical, and electrical properties of the LED can be affected by LED's geometrical placements on the heat-sink [63]. The PET theory can be used to help understand the impact of LED array density, LED power density, and active versus passive cooling methods on device operation. Further, this PET theory can also provide a way of predicting the luminous flux output accurately for a given LED system design. Therefore, the PET theory is expected to be extended to the PET-lifetime theory in future studies. Thus, the prognostics can be implemented more easily by considering physical explanations.

D. Lifetime Characterization of LEDs and Drivers

In the process of the literature search, many similar words/concepts appear to describe the life/reliability characteristics of LEDs, including useful life/lifetime, operation lifetime, RUL, residual life, lumen maintenance life, long-term lumen maintenance (life), long-term performance, lumen lifetime, L_{70} life, luminaire lifetime, and luminous flux lifetime. Accordingly, the terms prediction, estimation, assessment, projection, and prognostics are used for characterization. Since a number of concepts are mentioned throughout the manuscript, the scope and intention of each concept must be discussed. Among these concepts, the rated lifetime, the useful/operation lifetime, and reliability characteristic parameters are essential for characterization of LEDs. Other characterizations can be classified in terms of these essential parameters.

The reliability of electronic products is usually characterized by MTTF (mean time to failure)/MTBF (mean time between failure)/failure rate, whereas rated lifetime is commonly used for LEDs. For electronic devices and equipment, the military or industrial standard, such as MIL-HDBK-217F Note2 [64], IEEE-STD-1413 [65], IEC-62380 [66], RiAC-HDBK-217Plus [67], and Telcordia SR-332 [68], are usually used for failure rate and MTBF prediction. However, these standards have a lot of limitations when they are applied to new electronic products. For example, most of the above-mentioned handbooks on reliability prediction are less able to keep pace with new technologies, account for complex usage profiles, address soft and intermittent faults, and so on. Until now, there has been no standard method to predict the reliability of LEDs due to their longer lifetime, high reliability, and different mechanisms compared to traditional light sources. There are often large gaps between the warranted life of an LED product and its real application life.

The rated lifetime specified by a manufacturer is a statistical estimate of the expected operational time that a product can perform its intended functions under specific/typical operational and environmental conditions. Typically, a single number is given as an estimate of more complex failure distributions, such as L_{70}/L_{50} life of LEDs. In other words, the average lifetime of LEDs is specified by the manufacturer. Unavoidable uncertainty exists in the LEDs' design, materials, component selection, manufacturing process, and operation environment, among other factors. Reliability is a different statistical measure of product performance that describes the ability of a product to perform its intended functions under specific operational and environmental conditions for a specific period of time. Reliability metrics (such as MTBF) are useful for approximating the average maintenance interval of repairable systems. However, MTBF only describes an average failure rate, and the accuracy of such estimation is reduced for products that do not have a constant failure rate during their useful life. Narendran *et al*. [69]-[71] initiated discussion within the lighting community regarding standardized measurement procedures and definitions for useful life in LED technology. From this point of view, prognostic techniques can be used to improve the ability to estimate the in situ/actual lifetime and reliability characteristics of LEDs.

Some methodologies for classical/traditional estimation of reliability/life compounds using life testing methods or accelerated life testing (ALT) methods (with life data) are beyond the scope of this paper. These classical reliability approaches basically use historical time-to-failure (life) data to estimate the population characteristics (such as MTTF and probability of reliable operation). Elsayed [72], Nelson [73], and Turner [74] summarized the general procedures and models of reliability tests and accelerated testing. For LEDs, the ALT-based research has been conducted from different aspects. For example, Yanagisawa *et al*. [75] performed reliability tests under accelerated current conditions and estimated mean half-life of white LEDs. Trevisanello *et al*. [55] and Vazquez *et al*. [76] reported the ALT submitted to two

types of stress conditions: high temperature and high drive current. In addition to different stress types, ALT has also been carried out from the perspective of interconnect [77][78] and package [79] failure. Lifetime predictions based on ALT have also been conducted on white organic LED (OLED) and LED lamps [80]-[82].

In practical terms, however, because it is difficult to obtain the lifetime data of LEDs due to their characteristics of high reliability and long lifetime, accelerated degradation testing (ADT) and RUL estimation methods have been utilized. This section discusses these concepts and points out the differences between them, as illustrated in Fig. 3. The different perspectives in this figure illustrate the relationships among the terms/concepts: lifetime, reliability, and RUL. For the convenience of further study, the general process of failure diagnostics and prognostics related to LEDs is also illustrated.

The implementation of a prognostic process generally includes several key steps and models/methods, such as data acquisition/monitoring, data processing, diagnostics, prognostics, and decision reasoning [20][21]. In every step, several models and methods are used to handle data/information and obtain reliability characterization in different forms. For instance, at the current prognosis time ($t_{present}$) as shown in Fig. 3, the LED's failure indicator (such as lumen flux/maintenance, chromaticity coordinates, forward voltage, spectral power distribution, Euclidean/Mahalanobis distance) should be compared with the failure threshold (such as 30% reduction in the light output, decrease of 20% or 4.7 mW for optical power [157], and 0.007 color shift on the CIE 1976 chromaticity diagram [105]-[107]); this comparison is the process of anomaly detection or failure diagnostics. As shown in the central part of Fig. 3, the indicator degradation path from the starting point of operation or testing to the present can be modeled with linear, nonlinear, and other mathematical models (such as regression models, Kalman filters, and particle filters). Further, considering the uncertainty and statistical properties of these model parameters, reliability-related characteristics can be derived (normal, lognormal, and Weibull models are usually used for distribution fitting) by using a generalized stress-strength (comparing indicator with failure criterion) interference model, as shown in the upper-right part of Fig. 3. As mentioned above, for long-lifetime components like LEDs, accelerated (degradation) test conditions are often used to replace the normal operating conditions to shorten the test and analysis time. The Arrhenius model is generally used to calculate an acceleration factor (AF). Then, the lifetime under operational conditions can be predicted by using the AF multiplied by the lifetime of the accelerated conditions, as shown in the upper-left part of Fig. 3. Further, the future status of the reliability can be extrapolated and the RUL of LEDs can be determined by using various prognostic methods and models (details are given in Section III). In summary, the understanding of the above fundamental issues is essential to develop an effective prognostic method that can provide better lifetime prediction for LEDs and drivers.

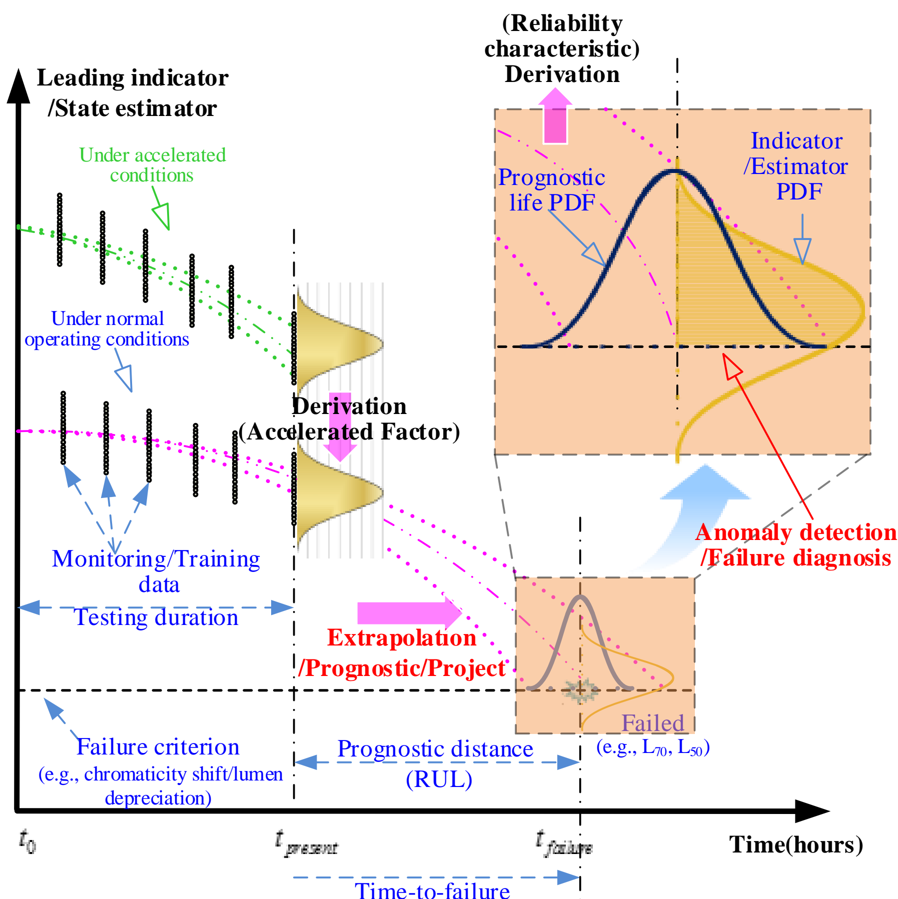


Fig. 3. Schematic diagram illustrating lifetime and reliability concepts.

III. Discussion of Prognostic Methods for LEDs

This section provides an overview of the available prognostic methods and models that have been applied to both LED devices and LED systems. These methods include statistical regression, static Bayesian network, Kalman filtering, particle filtering, artificial neural network, and physics-based methods. The general concepts and main features of these methods, the pros and cons of applying these methods, as well as LED application case studies, are discussed.

A. *Overview of Available Prognostic Methods*

Prognostic methods can be grouped into data-driven methods, physics-based methods, and hybrid/fusion methods [20][21][24]-[29]. Data-driven (DD) methods use prior experience, information, and observed/monitoring data as training data to identify the current system reliability state, further forecast the trends, and predict the future system reliability state without using any particular physical model [21][24][25]. DD methods are mainly based on artificial intelligence (AI) or statistics originating from machine learning (ML) or pattern recognition techniques. For physics-based methods, information about system failure mechanisms and models and operational and environmental conditions in the system life cycle are used to assess the RUL and reliability of a system [21][24][25]. A physical model that represents the system failure behavior is available for physics-based methods. Then, the measured/monitoring data is combined with the physical model to identify model parameters and predict the future failure behavior of a system. Fusion/hybrid methods combine the above-mentioned methods to improve the prediction performance [20].

Various prognostic methods have been widely adopted for products/systems with different characteristics and failure modes. Selecting an accurate and effective method is the key to the successful application of prognostic techniques. Researchers have also carried out lots of studies and tried to apply various optional methods for the prognostics of high-power LEDs, as summarized in Fig. 4. A comprehensive summary of these methods or models and literature cited is presented in the Appendix, Table A1, which lists the input data, failure criterion, and output data of these methods applied to LEDs.

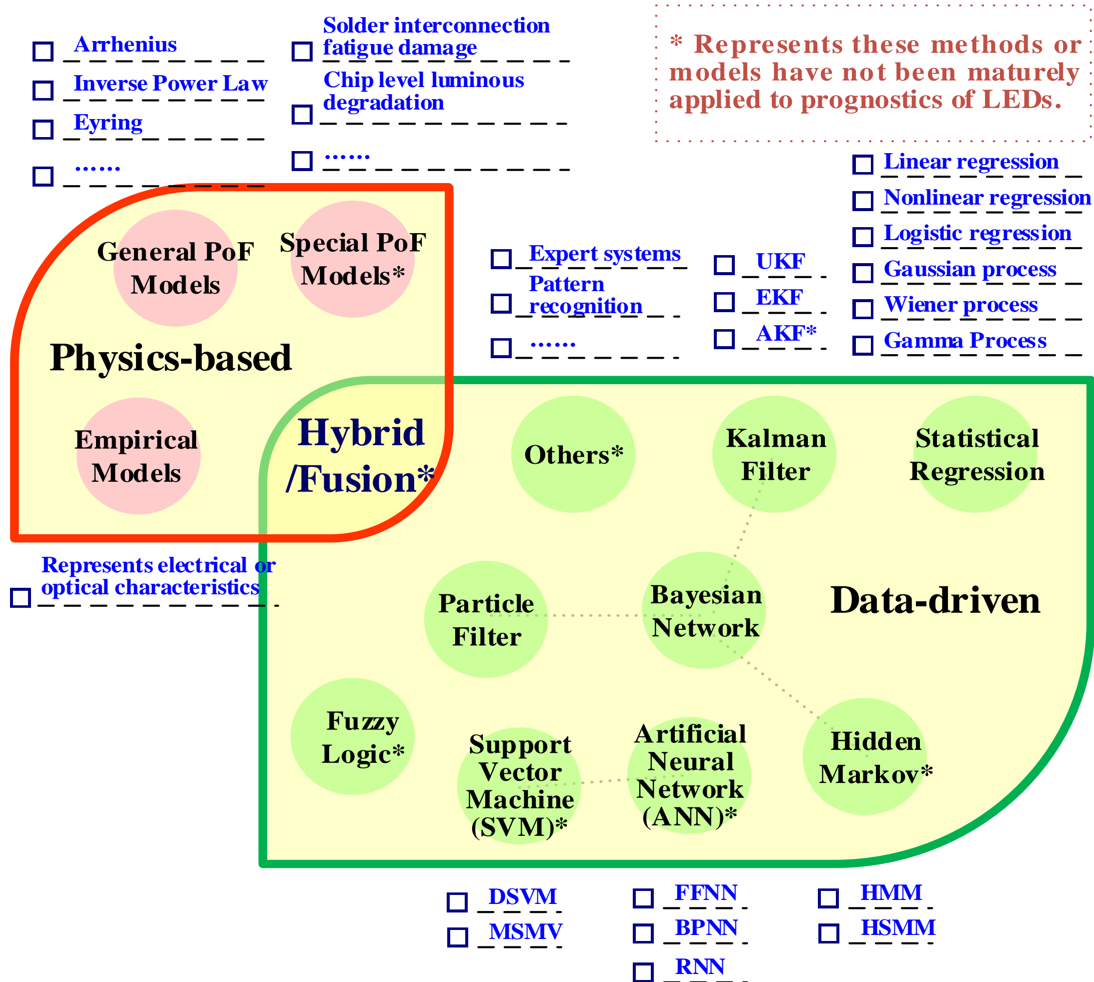


Fig. 4. Available prognostic methods/models for LEDs and categorization.

B. Data-Driven Methods

At present, five types of data-driven methods have been applied to LED prognostics. All of these methods are discussed in detail in the following sections.

1) Statistical Regression

A simple and direct idea for prognostics is based on trend analysis/extrapolation (or model-fitting/curve-fitting) of characteristic parameters correlated with lifetime. The characteristic parameter may be a single variable or a set of variables. Multiple variables can sometimes be further aggregated into a single variable that is plotted as a function of time. Different types of statistical regression models are then implemented to evaluate the RUL of a component or system [84]-[87]. There are many application cases for the prognostics of LEDs in the refereed literature.

Due to their simplicity, statistical regression methods are usually used for lifetime estimation in engineering practice. These methods project the health/degradation of systems by key performance indicators (PIs) that are then monitored and trended. The RUL is eventually predicted by comparing the PIs against a predetermined threshold. As a typical example, the IES-TM-21 standard [8] recommends a statistical regression method to predict the long-term lumen maintenance of an LED light source. Approved by the Illuminating Engineering Society of North America (IESNA), IES-TM-21 is the most commonly used standard in the LED industry. The collected lumen maintenance data is based on 6,000 hours (or more) of testing following the IES-LM-80 standard [10]. The IES-TM-28 standard [88] was recently promulgated by IESNA to project the long-term luminous flux maintenance under different operational temperature conditions. Similarly, the required data can be obtained using approved methods according to relevant measurement standards [89]-[93]. The exponential regression model and least-squares regression (LSR) approach are employed in IES-TM-21 and IES-TM-28. However, in practical applications, both IES-TM-21 and IES-TM-28 will generate large errors caused by different types of uncertainties, such as discontinuous measurement, operating environment, and future load. The above-mentioned standards have been carried out without consideration of the statistical characteristics and do not provide detailed reliability information [101][117][126]. In fact, the reliability information with respect to lifetime or RUL of LEDs is of great significance to manufacturers, as well as to potential users. Therefore, accurate lifetime prediction for such highly reliable electronic products is still a key issue in popularizing this novel device in the LED lighting market.

Along the line of IES-TM-21, many variants and extensions have been developed, including linear regression [80][94]-[101] and nonlinear regression [83][94][102][103], where the least-squares method (LSM) and maximum likelihood estimation (MLE) are two popular methods used for fitting function and estimating function parameters. For example, a data-driven approach for the RUL prediction of LED packaging based on two kinds of distance measure techniques—Mahalanobis distance (MD) and Euclidean distance (ED)—was developed by Sutharssan *et al.* [95][96]. MD and ED were used to measure the deviation or degradation of an LED's light output, and a linear extrapolation model was then used to predict the RUL of LEDs. For nonlinear regression, the commonly used function forms include exponential function [94], inverse power law model [102], Arrhenius model [83], and Weibull function [103].

Researchers have also developed many variants by considering time-varying performance indicators and monitoring/measuring data or prior knowledge by using a two-stage method [86][104]-[108], logistic regression [84][98][109][110], approximation methods [104]-[108][111][112], analytical methods [104]-[108][112], the Wiener process (Brownian motion with drift) [113]-[117], the Gaussian process [118], and the gamma process [119][121]. For example, Fan *et al.* [104] used the general degradation path model to analyze the lumen maintenance data of LEDs with three approaches (approximation approach, analytical approach, and two-stage method) and three statistical models (Weibull, lognormal, and normal) to predict the lumen lifetime of LEDs. The final predicted results showed that much more reliability information (e.g., mean time to failure, confidence interval, reliability function) and more accurate prediction results could be obtained by the above methods compared to the IES-TM-21 lumen lifetime estimation method. Logistic regression is another method widely used to deal with the nonlinear regression problem by introducing a sigmoid function based on the linear regression model. Sutharssan *et al.* [110] further compared the performance of data-driven methods and model-driven methods. This study used the logistic regression method and identified the key parameters in the logistic function of LEDs as temperature and forward current. These two approaches were both found suitable for prognostics of LEDs. As discussed by Burmen *et al.* [94] and Song *et al.* [122], the spectral power distribution (SPD) change, which has been caused by the degradation into the contributions of individual degradation mechanisms, such as chip degradation, phosphor layer degradation, and packaging material degradation, can significantly affect the reliability of LEDs. Further, Qian *et al.* [123] developed an SPD-based method to analyze and predict reliability of LED lamps. In this study, an exponential degradation model was used to fit the decomposed SPD model parameters extracted from the test data of an LED lamp during the aging process.

The basic Wiener process has had wide applications in degradation analysis. A Wiener process $\{Y(t), t \geq 0\}$ can be represented as $Y(t) = \lambda t + \sigma B(t)$, where λ is a defined drift parameter, $\sigma > 0$ is a diffusion coefficient, and $B(t)$ is the standard Brownian motion. For the case of a degradation process varying bi-directionally over time with Gaussian noise, Wiener processes for degradation modeling are appropriate. One of the advantages of degradation modeling with Wiener processes is that the distribution of the first passage time (FPT) can be analytically formulated and is known as the inverse Gaussian distribution. As an example, Ye [114] took the LED as an illustrative example to define the lifetime as the time when the lumen output of the LED lighting first crosses the threshold line of 70% of its initial lumen output level. Huang [117] employed a modified Wiener process for modeling the degradation of LED devices. The MTTF was obtained and showed a comparable result with the IES-TM-21 predictions, indicating the feasibility of the proposed method. The Wiener process with drift is a Gaussian process given by $X(t) = x_0 + \mu t +$

$\sigma W(t)$, where $W(t)$ denotes a standard Brownian motion, x_0 is some initial degradation level, and μ and σ are the drift and the variance coefficient, respectively. For example, Goebel [118] compared the relevance vector machine (RVM), Gaussian process regression (GPR), and neural network-based approaches and employed them on relatively sparse training sets with very high noise content. The results showed that all of the methods can provide RUL estimates, although with different damage estimates of the data. However, such an application in prognostics for LEDs has not been found.

Sometimes, degradation processes vary one-directionally and are monotonic, for example, light output degradation processes of LEDs. The gamma process is a natural model for the degradation processes in which the deterioration is supposed to take place gradually over time in a sequence of tiny positive increments. Since the gamma distribution is used in gamma processes, the mathematical advantage is that the sum of the gamma-distributed increments remains a variable obeying the gamma distribution. Gamma process-based methods have been proven effective for the prediction of LED lifetime, where the light intensity assumed the performance characteristic was governed by a random-effects gamma process [119][121]. Another advantage of modeling degradation processes with a gamma process is that the contained physical meaning is easy to understand and the required mathematical calculations are relatively straightforward. In summary, the above statistical methods are more suitable for engineering applications because it is easier to program them and estimate the model parameters.

2) Static Bayesian Network

A Bayesian network (BN) is a probabilistic graphical model that represents a set of random variables and their conditional or probabilistic dependencies by using a directed acyclic graph (DAG). BN is often also referred to as a Bayesian belief network (BBN), belief network, or causal probabilistic network [124][125]. BN is a probabilistic approach that is used to model and predict the behavior of a system based on observed stochastic events. It consists of a set of nodes and directional arcs. Each node represents a random variable that denotes an attribute, feature, or hypothesis for the system under study. Each directional arc represents the relationship between nodes. This relationship is usually a direct causal relationship, and its strengths can be quantified by conditional probabilities. Compared with the traditional statistical models mentioned above, BN does not distinguish between independent and dependent variables. Alternatively, it approximates the entire joint probability distribution of the system under study. As a result, BN can be used for omnidirectional inference. For example, forward application (i.e., from cause to effect) will provide prognostic abilities, while reverse application (i.e., from effect to cause) will provide diagnostic abilities.

Developing a BN model consists of: (1) network design; (2) network training; (3) instantiation of new evidence; (4) evidence propagation; (5) belief updating; and (6) belief propagation. A few studies have been conducted on LED prognostics by using the static BN method. Lall *et al.* [126]-[129] introduced Bayesian probabilistic models into life prediction and failure mode classification in Philips LED lamps. Bayesian probabilistic generative models have been used to classify and separate damaged solid-state luminaire assemblies from healthy assemblies. Further, the Bayesian regression method was used to determine the RUL for every test lamp. Lumen maintenance degradation has been used as the main indicator of system decay, by fitting the lumen maintenance degradation curve. The response variables of the luminous flux output and correlated color temperature (CCT) are the target variables for the Bayesian regression models. In addition, a degradation path-dependent approach for RUL estimation was presented through the combination of Bayesian updating and the expectation maximization (EM) algorithm [130]. The model parameters and RUL distribution are updated when newly observed data are obtained by using both Bayesian updating and the EM algorithm.

There are many advantages to the BN-based prognostic method, such as (but not limited to): (1) incomplete or multivariate data can be derived; (2) models are simple to construct and easy to modify; (3) computer modeling software is available; and (4) confidence limits are intrinsically provided. However, the historical and empirical information must be considered when using BN methods to predict the failure time of LEDs. Therefore, a comprehensive understanding of the failure modes, causes, and effects of LEDs; conditional probabilities; and prior distribution is a prerequisite for effective and validated prediction results. Ultimately, static BN cannot deal with time-dependent situations because the directional arcs used are time-independent. Hence, dynamic Bayesian networks have been introduced in which the directional arcs flow forward time-dependently. The most commonly used dynamic Bayesian networks include Kalman filters and particle filters (as discussed in the next two sections). Dynamic Bayesian networks are useful for modeling time series data, such as LED lumen degradation or color shift data.

3) Kalman Filtering

Kalman filtering (KF) is frequently used as an optimized prognostic technique [131]-[133]. It is one kind of recursive method used to predict the system state by combining the prior information with the measured/monitoring data. KF is based on the assumption that the posterior density at every time step is Gaussian and hence is parameterized by the mean and covariance. Sutharssan *et al.* [98] introduced Kalman filters to filter the noisy output data from the logistic regression model. Their results showed that this method filters the output data from the logistic regression model very effectively and provides a better approximate curve for the diagnostics and prognostics of LEDs.

For linear systems with Gaussian noise, the Kalman filter has been proven to be effective for state estimation. However, the degradation process is nonlinear and/or the related noise is non-Gaussian, so the application of the Kalman filter is limited and restricted. To overcome these problems, many variants, from different aspects, have been developed based on the basic Kalman filter, such as the extended Kalman filter (EKF), the Gaussian-sum filter, the unscented Kalman filter (UKF), or the grid-based filter.

The EKF is the nonlinear version of the basic Kalman filter without any assumptions of linearity. Neither the underlying degradation process nor the relationship between the process and the measurements need to assume linearity. Through a Jacobian matrix and first-order Taylor series expansions, a nonlinear model can be converted to a linear model, then the

nonlinear problem can be solved by approximate solutions. Sakalaukus [134] used KF and EKF methods to predict the RUL of aluminum electrolytic capacitors (AECs) inside an electrical driver (ED) as a potential indication of failure for LED systems. This analysis demonstrated that the EKF is best suited to predict the RUL of AECs in terms of both leading indications of failure, relative capacitance (CAP), and relative equivalent series resistance (ESR). In Lall [135][136] and Padmasali [137], EKF was employed to predict the lumen degradation, color temperature degradation, and chromaticity shift over the life of an LED luminaire. The estimated state-space parameters based on lumen degradation and chromaticity were used to extrapolate the feature vector into the future and predict the time-to-failure at which the feature vector will cross the failure threshold of 70% lumen output. RUL was calculated based on the evolution of the state-space feature vector. Failure distributions of the L_{70} life have been constructed based on normal, lognormal, and Weibull distributions. The proposed algorithm EKF eliminates the shortcomings of the regression method employed in IES-TM-21 L_{70} life estimation. This prediction method is not complex and can be implemented practically as an alternative to the linear regression method for better accuracy.

When the system state transition and observation are highly nonlinear, the EKF will introduce large errors and perform poorly. As an improved filtering method, the UKF addresses this problem by using a deterministic sampling approach. Several sampling points (sigma points) are generated through unscented transformation and second- or higher-order Taylor series expansions. Since UKF develops sigma point sampling, it increases the accuracy and reduces the computational cost drastically. To improve the prediction accuracy and overcome the limitations of the IES-TM-21 recommended projecting method, a UKF method based on short-term measured data (collected from the IES-LM-80 test) was presented for prediction of LED lumen maintenance [105][138]-[141]. Compared to PF and EKF, UKF shows many advantages including making the estimation procedure easier, increasing the estimation accuracy, and reducing the computational cost. In the literature [139][141], the lumen flux degradation was taken into consideration, and in [138][140], the chromaticity state shift was considered.

4) Particle Filtering

On the basis of the sequential Monte Carlo simulation, particle filtering (PF) uses a set of "particles" to approximate the posteriori distribution (probability densities) [134]. PF is based on the concept of sequential important sampling (SIS) and Bayesian theory. Theoretically, PF is suitable for highly nonlinear or non-Gaussian processes or in the observation of noise. PF has demonstrated its robustness in nonlinear projection in forecasting and online (real-time) estimation of the RUL of a system [142]-[146]. Similar to EKF and UKF without assumptions of linearity or Gaussian noise, PF can also be used to estimate the posterior distribution by using BN models. In particular, when the posterior distribution is multivariate or non-standard, the PF method is more useful than EKF and UKF. In the case of sufficient samples, the results provided by the PF method are more accurate than EKF or UKF. PF has been employed to assess the RUL of the LEDs [141][147]-[150].

Recently, a PF-based algorithm was proposed to overcome the shortcomings of the linear regression method for L_{70} prediction approved by IES-TM-21 [112]. The prediction results are further compared with the L_{70} results obtained from the IES-TM-21 regression method and the EKF method. PF is the most accurate of these methods, followed by UKF and then EKF. Meanwhile, PF has been employed to assess the RUL of a bare LED [147]-[149]. The shift of the forward-voltage/forward-current curve and lumen degradation was recorded to help build the failure model and predict the RUL. The experiments were done on single LEDs subjected to combined temperature-humidity environments of 85 ℃, 85% relative humidity. The results showed that prediction of RUL of LEDs by PF works with acceptable error-bounds. The presented method can be employed to predict the failure of LEDs caused by thermal and humid stresses.

A PF-based prognostic approach has also been developed for improving the prediction accuracy and shortening the qualification testing time of the long-term lumen maintenance life for LEDs [150]. The presented approach was intended to replace the IES-TM-21 recommended LSR method. By taking into account the measurement noise, this PF-based approach can estimate the prognostic model parameters and adjust these parameters as new measurement data becomes available. Compared with the IES-TM-21 method, the PF-based method obtained a higher accuracy (error less than 5%) in its prediction of LED lifetime. Lan *et al.* [173] applied PF for lifetime determination of LED drivers. For improving the accuracy of lifetime estimation, PF was implemented and combined with nonlinear least squares (NLS) for a single test unit, and with nonlinear mixed-effect estimation (NLME) for grouped test units.

However, the initialization of PF-based prognostic model parameters and the existence of unavoidable uncertainties have a greater impact on the prediction accuracy. Especially for new LED product qualification, this limits use of the PF-based approach. In order to overcome this limitation, it is necessary to make full use of historical data for used products and to carry out calibration testing for new products, which leads to a reasonable initialization process of the model parameters.

5) Artificial Neural Network

The artificial neural network (ANN) is a data-driven method widely used in prognostics [23][29][85]. ANN directly or indirectly computes an estimated output for the RUL of a product/system from a mathematical representation of the product/system derived from observation data rather than a physical understanding of the failure processes. The major advantage of ANN is that it can usually be used without any assumptions regarding the functional form of the underlying system behavior model. ANN can effectively and efficiently model complex, multi-dimensional, unstable, and nonlinear systems. The ANN-based prognostic method has been applied to numerous applications for different types of components/systems [151]-[155].

A typical ANN consists of a layer of input nodes, one or more layers of hidden nodes, one layer of output nodes, and connecting weights. The network learns the unknown function by adjusting its weights with repetitive observations of inputs and outputs. This process is usually called training of an ANN. The inputs of the ANN can include various types of data, such

as process variables, condition monitoring parameters, performance indicators, and key characteristics. The outputs of ANN depend on the purpose and intention of the modeling application, such as RUL or other lifetime/reliability characterizations. The main determinants of a particular ANN include network architecture (i.e., arrangement of nodes), synaptic weights, and nodal activation function parameters.

Neural network models applied in system prognostics include the feed-forward neural network (FFNN), back-propagation neural network (BPNN), radial basis function neural network (RBFNN), recurrent neural network (RNN), and self-organizing map (SOM) [29]. ANN is commonly used as an alternative to the statically regression method in cases where there is less understanding of the system behavior. Goebel *et al*. [118] provided a comparison study of three data-driven methods—relevance vector machine (RVM), Gaussian process regression (GPR), and NN-based method. The results showed that all the methods can provide RUL estimation, although different damage estimates of the data (diagnostic output) change the outcome considerably. Similarly, Riad *et al*. [156] used the multilayer perceptron neural network (MLP NN) to overcome the complexity of using dynamic models, and showed that MLP NN, as a static network, is extensively superior to the linear regression model and does not involve the complexity of dynamic models.

Although the ANN methods are suitable for prognostic modeling, few application cases relating to LEDs have been found in the literature. Sutharssan *et al*. [98] developed a simple NN with one hidden layer and two hidden neurons for the prognostics of LEDs. In this case, the NN approach is only a preliminary application without comprehensive consideration of the relevant factors that affect and reflect the reliability of LEDs. This study seems to be the first application of ANN for LED prognostics. The use of NNs offers significant potential for applications since the failure behavior of LEDs is too complex to establish an analytical deterministic prognostic model. However, the ANN method cannot provide the failure mechanism details, which will limit the effective design feedback and cannot fundamentally improve the reliability of the LED product. High computational efficiency is one of the advantages of ANN. Parallel processing can be realized by the ANN multiple nodes when computing the activation function. In addition, many software packages (i.e., MATLAB®, Mathematica®, R statistical programming language) are available for developing ANN, making the modeling and computing process more simple and operational.

C. Physics-Based Methods

Physics-based methods assume that a physical model describing the behavior of degradation or damage is available and combines the physical model with measured data (life cycle loading and operating conditions) to identify model parameters and to predict the future behavior of degradation or damage. The model parameters are usually obtained from laboratory tests under normal or accelerated conditions, or estimated using real-time measurement data. Finally, the RUL can be estimated when the degradation state or accumulated damage reaches a predefined failure threshold. Compared to data-driven methods, the specific algorithms for physics-based methods are not so different from each other.

Three kinds of physical models can be used for LED prognostics, as illustrated in the upper left part of Fig. 4. They are: special physics-of-failure (PoF) models (special failure mechanism models for different components or sites, such as chip-level degradation and solder interconnection fatigue), general PoF models (general models that can describe different failure mechanisms, such as Arrhenius, Eyring, and inverse power law), and empirical models (that represent electrical and optical characteristics). For example, Deshayes *et al*. [157] reported the results for commercial InGaAs/GaAs 935-nm packaged LEDs using electrical and optical measurements versus aging time. Cumulative failure distributions were calculated using degradation laws and process distribution data of optical power. Sutharssan *et al*. [98] presented an empirical model by considering the voltage-current characteristics of LEDs. The model parameters were estimated with data obtained under accelerated life conditions. Philips Corp. [158] carried out a cross study of the evolution of electrical and optical characteristics. Models of the typical lumen depreciation and leakage resistance depreciation were made using electrical and optical measurements during the aging tests. The LED lifetime was then defined as the minimum value between optical lifetime L_{70} and electrical lifetime t_2. These empirical models mainly depend on the electrical and optical characteristics of performance without detailed consideration of failure mechanisms for LEDs.

Further, Fan *et al*. [105][159] established PoF-based damage models for high-power white LED lighting. Failure modes, mechanisms, and effects analysis (FMMEA) was used to identify and rank the potential failures emerging from the design process at different levels (i.e., chips, packages, and systems). In this study, thermal-induced luminous degradation and thermal cycle-induced solder interconnect fatigue were the two potential failure mechanisms with the highest degree of risk. However, this study only dealt with simple and single situations without consideration of the complex mechanism interactions and uncertainty that exist in real-life predictions. Meanwhile, Shailesh *et al*. [160] obtained the Arrhenius-Weibull, generalized Eyring-Weibull, and inverse power-Weibull models from the IES-LM-80 test data. The models proposed in this work can be used to model and predict long-term lumen maintenance (reliability) of LED arrays by using IES-LM-80 test data of single LEDs. Edirisinghe *et al*. [161] used an Arrhenius accelerated life test model with the modeling parameter as the junction temperature in the determination of the useful lifetime of 1-W HBLEDs (high-bright light-emitting diodes). However, the proposed PoF models are too general, and they do not provide details about the various failure/degradation mechanisms for LEDs. For LED drivers, Zhou *et al*. [172] proposed a PoF-based approach for the prognostics of RUL by considering the failure mechanisms and degradation models of three critical components, including aluminum electrolytic capacitors, diodes, and MOSFETs.

The physics-based method provides details about the various degradation mechanisms and thereby improves understanding of the associated root causes of the failure. Hence, this method can help in designing better LED luminaires and effectively assessing their long-term reliability with identification of failure locations and failure mechanisms. Despite the

advantages of the physics-based method, one of its limitations is that the establishment of models requires a sufficient understanding of the physical processes leading to system failure. Especially for complex systems, it is more difficult to establish a unified dynamic model denoting the underlying multiple PoF processes [21]. It is important to note that the physics-based method has higher requirements for data sources, such as design parameters, material parameters, process parameters, operational conditions, and environmental conditions. These data are necessary but may not always be available or may be difficult to obtain. Thus, the physics-based methods are much more suitable than DD methods for LED devices or components and power electronics in LED drivers. While for LED systems, the data-driven prognostic methods may be more applicable.

D. LED System-Level Prognostics

As discussed above, the LED-based lighting product itself is a complex system. To ensure long lifetime, the reliability of each part in an entire LED system must be assessed. For example, Ishizaki *et al*. [83] applied the ALT method and the Arrhenius model to estimate the lifetime of early developed LED modules. Such a module contains five LED chips in a package, and they are connected in series to obtain a high light flux. Further, a hierarchical model to assess the lifetime of an actively cooled LED-based luminaire was proposed [162]. The model was articulated on four levels: LED, optical components in the fixture, heat-sink, and active cooling device. Each submodel of the proposed hierarchical model is a PoF model that describes the degradation mechanisms of different components. However, a mature PoF model should be developed for each degradation mechanism. An example of another component is the plastic lens, in which an exponential luminous decay model and the Arrhenius equation were used to predict the lumen depreciation over different times and temperatures [163].

After reviewing the system structure and failure modes of LED lamps, Philips [164] proposed a methodology for the reliability of LED lamps. In this study, the LED lamp included four subsystems: LED light source, electronic driver, mechanical housing (used for thermal dissipation, electronic isolation, and final installation), and optical lens. The reliability of the whole LED lamp was described with a simple series model. Narendran *et al*. [165] further discussed the LED system's lifetime versus LED package lifetime. Meanwhile, luminaire manufacturers have also carried out parallel studies on the failure behavior and lifetime estimation of the many other components that constitute the whole LED system, including drivers, optics, mechanical fixings, and housings. Each component is a factor in the determination of the lifetime of a luminaire [166].

Compared to the LED device, the claimed lifetime of an LED driver is generally 10,000–30,000 hours, which is a major obstacle to further and wider application of LEDs in the general and public lighting industry. LED drivers with long (>15 years) lifetime are expected by LED manufacturers and potential end-users. Recently, Li *et al*. [41] reviewed the current status, design challenges, and selection guidelines of LED drivers, and the lifetime and reliability were mentioned as one of the primary challenges. To select the appropriate circuit topologies for a given application, an application-based LED driver design flowchart was suggested, which can help the designers make appropriate choices. Literature that focuses on the reliability and useful life of an LED driver has also been published. For example, Han *et al*. [167] predicted the useful life of an LED driver by using the ALT method, in which the electrolytic capacitor was considered as the weakest link. Bo *et al*. [46] considered the failure of aluminum electrolytic capacitors as one of the major failure modes of the LED drivers and proposed a degradation model by considering the impacts of operation time and temperature. Lall *et al*. [168]-[170] conducted an accelerated aging test in order to assess the reliability of the LED drivers, in which the electrical drivers were exposed to a standard wet hot-temperature operating life of 85% RH and 85 ℃. Lan *et al*. [38] presented a pseudo black-box testing method to evaluate the reliability of the integrated circuit used in LED drivers. Similarly, the critical component(s) were isolated and tested to estimate the reliability or lifetime of the LED drivers, such as electrolytic capacitors [39] and voltage regulators [171]. Recently, Sun *et al*. [253] developed a PoF-based reliability prediction method to estimate the failure rate distribution of electrolytic capacitors used in LED drivers with considering the temperature effect of electrolytic capacitors under operation conditions. Furthermore, Sun *et al*. [254] also applied the reliability assessment method on the electrolytic capacitor-free LED drivers to investigate the failure rate of MOSFETs in the drivers. Comparatively little research has been conducted on the prognostics of LED drivers [172][173]. However, as a typical application of a constant-current switch mode power supply (CC-SMPS), the relevant prognostic methods suitable for CC-SMPS can be directly applied to LED drivers. Currently, these methods are relatively rich and mature in terms of data-driven, physical-based, and/or fusion prognostics [174]-[179]. In the future, the suitable prognostic methods for LED drivers will be further developed with respect to the emerging types of drivers, such as drivers without capacitor converters, or converters that provide a pulsed current to the LED. In addition, to increase the accuracy of lifetime prediction for an integrated LED lamp, the interaction between the degradations of the LED light source and the driver should be considered in establishing the PoF-based model.

IV. CHALLENGES AND OPPORTUNITIES

Although numerous studies on prognostics have been conducted for LEDs using data-driven or physics-based methods in recent years, prognostic technologies are still not mature enough for practical engineering applications. Undoubtedly, all prognostic techniques that are reviewed in this paper need further development and improvement in their ability to accommodate proprietary features of LEDs and be used in practical situations. The implementation of prognostic technologies for LEDs includes several aspects, such as selecting and developing effective methods and models, addressing the uncertainty existing in the prognostic process, assessing the prognostic performance, validating prognostic

models, and analyzing cost–benefit of different applications (see Fig. 5). The following subsections discuss the challenges and opportunities facing the implementation of prognostics for LEDs.

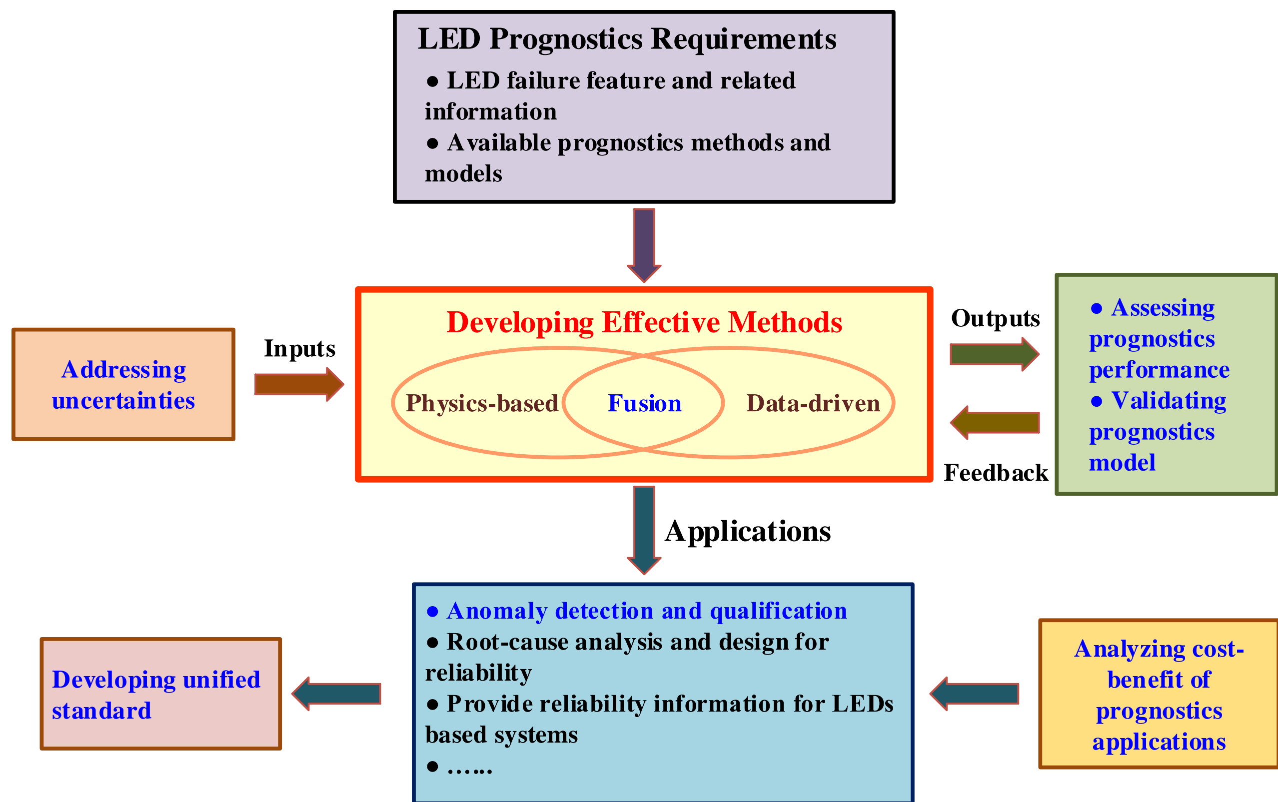


Fig. 5. Major challenges in the implementation of LED prognostics.

A. *Developing Effective Methods for Accurate Prediction*

Up to the present, a number of prognostic methods have already been applied to LEDs by researchers. There are still other available methods as indicated in Fig. 3 that have been proven effective for various products or systems. Some typical examples include hidden Markov models (HMMs) [29][180]-[182], the support vector machine (SVM) [29][184]-[186], the relevance vector machine (RVM) [118][187][188], fuzzy logic [29][189], and other pattern recognition approaches. In order to achieve successful and effective applications for LEDs, selecting an appropriate prognostic model is crucial. Future research should also focus on overcoming the shortcomings/limitations of the various methods.

Essentially, the advantages and disadvantages of different prognostic methods must be explored, and the requirements and restrictions from the application objectives for proper model selection must be considered. There have been excellent review papers on the comparison of related modeling techniques and prognostics; see, for example, Sikorska *et al.* [23], which shows the generic advantages and disadvantages that can be attributed to a type of model and summarizes the necessary considerations for using or avoiding a particular type of model. Baraldi *et al.* [25] proposed a prognostic methods/models selection strategy based on the information available for the model development. The information setting included the availability of physics-based degradation models, similar degradation observations, and degradation observations. The accuracy of the RUL prediction and the ability of confidence measurement were evaluated. Kan [29] described the advantages and disadvantages of different prognostic methods in applications in rotating systems. These general conclusions are also applicable for LEDs.

In theory, the physics-based prognostic methods are more accurate than the data-driven methods. However, the overall degradation in LED lumen maintenance and chromaticity may result from several combined long-term decay functions triggered by multiple failure modes and mechanisms, such as chip degradation, encapsulant degradation, and phosphor degradation. Thus, the true degradation profile may be fairly complicated. For all these different degradations, it is difficult to determine the single activation energy used for PoF models. Although the weight method can be used to give each failure mechanism a different weight, a large amount of population statistics is required. Even in the case that the physical model is known, the accurate estimation of RUL is also difficult due to particular limitations, such as a not directly observable degradation state, noise, and disturbances influencing measurements.

Because the data-driven methods do not require special failure models or failure-specific knowledge, they are considered a black-box method. Monitored and historical data are used to identify the characteristics of the currently measured

degradation state and to perform the prognostics. From this point of view, data-driven methods are more suitable for complex systems in which failure behavior cannot be derived and assessed from basic physical principles. One major advantage of data-driven methods is the simplicity of their implementation and computation, which can be carried out on a programmable calculator. For example, the underlying IES-TM-21 standard provides an Excel-based calculator. However, these methods rely on past patterns of degradation to project future degradation. It is not easy to apply due to the lack of efficient procedures to obtain the training data and specific knowledge, which are required to train the models. So far, most of the applications in the literature only used experimental data for model training. Because the performance-related parameters and other key parameters that can indicate the state of the underlying system are used, data-driven methods depend substantially on the measurement data. Therefore, unavoidable measurement error and noise can significantly affect prediction accuracy. In some cases, information about failure mechanisms has been a concern for LED developers and users. The active failure mechanisms (such as degradation of chip, encapsulant, phosphor, and reflector) cannot be distinguished, which is another major disadvantage for data-driven methods.

A fusion/hybrid prognostic approach that combines physics-based and data-driven methods to estimate the RUL in actual life cycle conditions has been presented [190]-[197]. This method integrates the advantages and overcomes the limitations of the data-driven and the physics-based methods to provide better and advanced predictions. Fusion prognostic approaches have been found effective for electronic products [190][191], mechatronic systems [194], lithium-ion batteries [196], and micro-electro-mechanical systems (MEMS) [197]. However, a review of the recent literature has failed to extract studies conducted for specific LED applications. There are only a few conceptual descriptions and no substantive studies. For example, Sutharssan [98][110] conducted preliminary research and proposed a fusion approach based on the Kalman filter to estimate the best RUL from the estimated RULs from the model-driven and data-driven approaches. The model-driven and data-driven approach estimates were assumed to have errors and respectively follow a Gaussian distribution with mean μ_1, standard deviation σ_1 and mean μ_2, standard deviation σ_2. Different weights were given for RUL estimation from these kinds of approaches according to accuracy. In fact, Sutharssan claimed that he attempted to demonstrate the fusion approach using the Kalman filter. The fusion approach that incorporates the model-driven and data-driven approaches can be developed further to obtain better performance.

B. Addressing Uncertainties and Assessing Prognostic Performance

One of the most significant characteristics of prognostics is the ability to deal with objective uncertainty. A proper prognostic method not only provides accurate and precise prediction of RUL but also specifies the confidence level associated with such predictions. Without such statistical information about uncertainty, any prognostic estimate is of limited use and cannot be incorporated in decision-making activities and mission-critical applications. Common sources of uncertainty affecting prognostic accuracy include modeling uncertainties (e.g., model simplification, model parameters estimation, and model errors), measurement uncertainties (e.g., sensor noise, data preprocessing, approximations, and simplifications), operating environment uncertainties and future load uncertainties (e.g., unforeseen future and variability in usage history data), and input data uncertainties (e.g., estimate of initial state of the system, variability in material properties, and manufacturing variability). These uncertainties can lead to significant deviation of the prognostic results from the actual situation.

Existing methods need further improvement to be able to address uncertainty. The importance of considering uncertainty in prognostics has been noted by researchers [198]-[201]. For LED applications, the situation is also quite complex, due to multiple operating factors (e.g., forward current, usage patterns), environmental factors (e.g., temperature, humidity) in real life, and multiple failure modes with different indicators (e.g., luminance degradation, color shift). The ability to consider the complexities is crucial in selecting an appropriate prognostic method for real-life applications. In general, the data-driven methods for RUL prediction can provide confidence limits for their predictions. As shown in Table A1, only a few studies and prognostic results for RUL or MTTF are within the confidence intervals/limits/boundaries [108][117][126]-[129][147]-[150]. As for physics-based methods, the confidence limits cannot be naturally provided for their predictions. The Monte Carlo simulation method should be used for considering the uncertainties existing in prognostic processes to obtain relevant information on the confidence limits.

Apart from addressing different sources of uncertainty in prognostics, there is a lack of standard and uniform criteria for evaluating the performance of prognostic methods applied to LEDs. Prognostic methods have their own advantages and disadvantages, and they behave differently depending on the situation. However, there are no widely accepted appropriate metrics that can be effectively employed to assess the technical performance of prognostics. These metrics include prediction accuracy, computation time, sample size requirement, prediction horizons, reliance on historical data, the ability to deal with high-dimensional and multi-source data, difficulty in implementation, real-time analytical capability, and the requirement of specifying the failure threshold. In the past few years, the prognostic performance and evaluation method has attracted the attention of some researchers [202]-[210]. For example, Leão et al. [205][206] described a set of metrics developed to evaluate the performance of prognostic algorithms, including prognostic hit score (PHS), false alarm rate (FAR), missed estimation rate (MER), correct rejection rate (CRR), and prognostic affectivity. The usefulness of this set of metrics for prognostic algorithm design, verification, and cost-benefit analysis was further illustrated with a sample application. Saxena *et al*. [207][208] also suggested a series of metrics to evaluate key aspects of RUL predictions, such as prognostic horizon (PH), prediction spread, relative accuracy (RA), convergence, and horizon/precision ratio. Further, Tang *et al*. [209] proposed several new metrics and methodologies stemming from weather forecast verification. Although the proposed metrics have tried to cover most prognostic performance requirements, further refinements in concepts and

definitions are still expected as prognostics matures, especially for LED applications.

C. Validating the Prognostic Model

Verification and validation (V&V) remains a challenge for prognostic techniques and systems development [211]-[214]. V&V has been identified as a critical phase in the practical engineering application of prognostic technologies. V&V consists of correlated entities with distinct definitions depending on the application objective and scope. Different industries use different definitions and approaches [212]. For prognostic application, "verification" denotes the process of determining that a prognostic model accurately represents the developer's conceptual description as a function of the design specifications, whereas "validation" denotes the process of determining the degree to which the prognostic model achieves the performance specifications within the system constraints and provides accurate results in the operational environment.

Further to the prognostics of LEDs, three types of systems are specifically related: the conceptual system (failure/degradation behavior of LEDs), the realized system (prognostic model), and the real system (practical failure of LEDs). This means that verification deals with the relationship between the conceptual system and the realized system and that validation deals with the relationship between the experimental measurements and reality. Normally, the off-line available data (e.g., historical and empirical data) are used for verification, and the on-line available data (e.g., monitoring and measurement data) are used for validation.

The difficulties lie in the fact that usually insufficient statistical data are used for V&V. As mentioned above, for long-lifetime and high-reliability components like LEDs, monitoring and sampling the degradation data under normal operational conditions is expensive and time-consuming. In order to make these data available, ALT is usually used [129][160][215]. Especially for data-driven models, historical data play an essential role in performing prognoses. The need for historical data is a challenge for implementation of prognostic systems in real industrial applications because historical data are not always available or are well stored/catalogued/collected. Taking into account the basic characteristics of data-driven methods, available historical and empirical data have a great influence on the confidence level of predictions. For example, these data are required for training the prognostic model and for defining the respective failure threshold values. Another disadvantage of data-driven methods is that they cannot distinguish different failure modes and mechanisms in the system. This will limit root-cause analysis (RCA) and increase uncertainty in V&V.

To validate different prognostic methods, the prediction errors of LED lifetime are always used to rate these validation results. Prognostic accuracy assessment technologies are necessary for building and quantifying the confidence level of a prognostic method. Methods to impartially evaluate the effectiveness and accuracy of prognostics are required [21]. There is no general agreement on an appropriate and acceptable set of metrics that can be employed effectively to assess the technical performance of prognostic methods. Some researchers presented a series of metrics for evaluating the performance of prognostic techniques from different perspectives. For example, Saxena *et al*. [216] suggested a list of metrics to assess critical aspects of RUL predictions, such as prognostic horizon, prediction spread, relative accuracy, convergence, and horizon/precision ratio. Tang *et al*. [217] and Leão *et al*. [218] also proposed several metrics and methodologies stemming from weather forecast verification, nonlinear exact filtering, nonlinear uncertainty propagation, and the Monte Carlo method. Although efforts have been made to cover most PHM requirements, further refinements in concepts and definitions are expected as prognostic matures.

In summary, many reliability problems and characteristics of LEDs are related to temperature [1][4][219][220]. In particular, the junction temperature directly affects the accuracy of results. Therefore, the junction temperature of LEDs plays an important role in the V&V process [221]. Cai *et al*. [99] proposed a hybrid method for estimating the junction temperature of high-power LEDs at the system level by combining thermal modeling with temperature measurement. A hybrid numerical approach [120] was also presented to provide a way to predict the lifetime based on the maximum junction temperature of LED products, instead of running lumen maintenance tests at the system level to extrapolate the lifetime. Complete verification and successful real-life implementation of prognostic techniques are still big challenges. More effort should be made to improve the simplicity of technique implementation, as well as establish effective methods to validate the technique. Ultimately, the implementation of prognostic systems in real-life industries can be improved.

D. Developing a Unified Standard for Anomaly Detection and Qualification

Similar to traditional lighting systems, an LED system should comply with associated luminaire standards and international regulations. These standards and regulations set basic requirements for LED systems. They could affect the designer's selection of a proper circuit topology and control method. The LED industry is growing rapidly, and this naturally brings up the need for reliable measurements of LED and SSL products. These measurements often form the foundation for a fair comparison between SSL products from different vendors. Consequently, there is an industry-wide push for standards and regulations with respect to accurate and repeatable measurements of optical, electrical, and thermal properties, and safety and warranty aspects for LED and SSL products. These standards have been developed or approved by ANSI [222][223], JEDEC [224], NEMA [225][226], IEC [227][228], and leading LED manufacturers [229]-[233]. Despite the current use of IES-TM-21 by many LED manufacturers, there are still no widely accepted standards and procedures for assessing LED useful/operation lifetime for lighting applications. There is a big gap between the lifetime prediction results according to IES-TM-21 and the actual failure results. Besides, IES-TM-21 requires a long testing time (usually more than 6,000 h) and costly testing processes [1]. Particularly, it is not acceptable for manufacturers to wait for 6,000 h of testing data for lifetime prediction before a product launch. Further, as a newly released standard, IES-TM-28 recommends the use of the Arrhenius equation to determine SSL device-specific reaction rates from thermally driven failure mechanisms used to characterize a single failure mode (the relative change in the

luminous flux output or "light power" of the SSL luminaire). One problem with IES-TM-28 is the lack of additional stresses or parameters needed to characterize non-temperature-dependent failure mechanisms. Another problem is that IES-TM-28 has no process for the determination of acceleration factors or lifetime estimations. Therefore, effective qualification testing needs to be developed to assist designers in preliminary verification in order to eliminate failures and make improvements before product release.

Some researchers have tried to solve these problems encountered by the LED industry. Lin *et al*. [234] proposed an automated detection method for surface blemishes that fall across two different background textures in an LED chip. Jeong *et al*. [235] suggested a method that enables screening the potential field failure LEDs in mass production, in which the failure can occur by an external noise factor, by adding a "turn on current level screen" on an "operating current level screen". Dong *et al*. [236] proposed an estimation approach to diagnosing individual LED failures using a photosensor system. Fan *et al*. [237] used a data-driven method based on a multivariate distance measure, the Mahalanobis distance (MD), to detect the chromaticity shift anomaly of high-power white LEDs after aging tests. Philips [238] demonstrated the trend of lumen maintenance in the wet high-temperature operation test (WHTOT), indicating that a prediction method for LED lumen maintenance could be initiated with a rather short testing time. Yang *et al*. [239] proposed an accelerated aging test for high-power LEDs under different high-temperature stresses without input current. The results of this accelerated aging test show that a sufficiently high-temperature stress effectively shortens the unstable period of the LED chip. Chang *et al*. [240] developed a prognostics-based anomaly detection technique, called the similarity-based metric test, to identify anomalies without using historical libraries of healthy and unhealthy data. Zhang [241] also studied the fast qualification of solder reliability in SSL systems. Qian *et al*. [215] developed an accelerated test method based on the lumen maintenance boundary curve for luminous flux depreciation to solve some problems in IES-TM-28 and reduce the test time to less than 2,000 h at an elevated temperature.

Most traditional methods and standards for anomaly detection, lifetime prognostics, and reliability assessment depend on off-line measurements, which involve high costs and long testing times. Off-line methods lead to other problems, such as ignoring the random degradation status of tested LED samples with non-continuous measurement, and result in evaluation error in an uncontrollable testing environment. Recently, anomaly detection methods for LEDs related to online/in situ measurement have been published [242]-[245]. The partial luminous flux on the receiving surface of a fiber cable was captured, and it was proportional to the total luminous flux of the LED light source. The lumen depreciation of LEDs can be monitored in continuous forms. As a result, on-line methods can help improve the accuracy of measurement and prognostics, enhance the discrimination of LED degradation details, and highlight the analysis of failure mechanisms of LED devices.

The LED light source community must develop a preliminary unified methodology for assessing lamp life and a definition for useful life for LEDs. When life values are reported by manufacturers, the lighting community can compare LEDs to other sources and develop this unified methodology for practical lighting applications. Currently, sufficient information regarding the lifetime and reliability of these LEDs is not available for developing good definitions of useful life and assessment technique. The lack of uniform standards allows LED manufacturers to publish reliability and lifetime data however they choose. The published reliability data and claimed lifetimes for LEDs are often limited or mistakenly used in practice. Uniform standards for LED qualification still need to be derived as a means to compare luminaires and reliability data that have been tested and claimed at different facilities, research labs, or companies.

E. Analyzing the Cost–Benefit of LED Prognostics Applications

Although prognostics can provide many benefits, its implementation is costly and these costs vary across different engineering practices [21][246]. Especially in large-scale applications such as street lighting and traffic lights, and safety-related applications such as automotive headlights, the return-on-investment (ROI) for LED lighting systems is a concern for designers. To reduce life cycle cost (LLC), prognostics-based maintenance with health monitoring/management (HM) is considered as a cost-effective approach that can provide advanced failure warning, minimize unscheduled maintenance, and increase maintenance effectiveness. Currently, few researchers are working on ROI evaluation of LED lighting systems with prognostics-based maintenance by comparing them with LED lighting systems with unscheduled maintenance [247].

ROI is the monetary benefit derived from having spent money on developing, changing, or managing a product or system. ROI is a common economic measure used to evaluate the efficiency of an investment or to compare the efficiency of a number of different investments. As the ratio of gain to investment, ROI is often calculated by the equation: ROI = (return – investment)/investment. An ROI equal to zero means a break-even situation, an ROI less than zero means a loss situation, and an ROI greater than zero means a gain situation [248].

A cost–benefit analysis (CBA) of alternative LED lighting systems was conducted by comparing with traditional lighting systems [248]. ROI research on LED lighting systems has assumed that LED lighting systems are successfully maintained over long lifetimes (e.g., 100,000 operating hours) [249]-[251]. Compared with traditional light sources, the LED light sources have obvious financial benefits owing to their longevity. However, little research has been conducted on how ROI is determined and thus how prognostics-based maintenance using HM can be cost-effective and applicable to the LED lighting industry. As a case study, the ROI for implementing prognostics in LED lighting systems was evaluated in the view of the LLC [247][248]. This study assumed exponential TTF distributions with three different failure rates and normal TTF distributions with three different MTTFs to investigate how ROI is impacted. The annual rate of total LLCs for an LED lighting system with prognostics-based maintenance is compared with that of an LED lighting system with

unscheduled maintenance. According to the calculated results, the annualized costs decreased due to advanced warning replacement of failed LEDs—the time for replacement decreased from 157.3 h to 1.5 h, replacement maintenance costs decreased from $245 to $170, and downtime costs decreased from $3.59 to $1.55 per hour out of service for single LEDs.

Another challenge for determining ROI in prognostics for LED systems is that cost savings must be estimated by using prognostics-based methods in related LED development processes, such as design and analysis and testing and qualification. Specifically, the efficiency and cost of qualification testing have a great impact on the final market price for an LED. A financial function can be established to evaluate the operation cost of a qualification test by taking two metrics, time and cost, into account. The total cost can be calculated using the following formula [105]:

$$C_T = nC_S + n\tau C_m + t_d(\tau - 1)C_e \quad (1)$$

where C_s is the cost of a single test sample; n is the sample size; C_m is the cost of one inspection on one test sample; τ is the inspection frequency; and C_e is the operation cost in the time interval t_d between two inspections.

As far as the whole life cycle is concerned, LEDs can be even more environmentally friendly if they are recycled correctly and effectively. With a large number of LED applications, the issue of recycling is becoming more and more critical. The U.S. Department of Energy (DOE) noted this issue in its 2012 report "Part 2: LED Manufacturing and Performance" [252], in which the life-cycle environmental and resource costs for the manufacturing, transport, use, and disposal of LED lighting products were assessed in relation to comparable traditional lighting technologies. In this study, a life-cycle assessment (LCA) method was used to quantify the environmental and sustainability impacts across a range of categories for an LED product over its entire life cycle. ROI research on LED lighting systems can provide a useful data source and information base for both life-cycle inventory (LCI) analysis and life-cycle impact assessment. The assessment results will further provide evidence that LEDs are a sensible and appropriate alternative to traditional light sources.

An LED lighting system with prognostics capability can meet the requirements of energy savings, emission reduction, and a green environment. A large number of qualification tests have to be conducted per year before new LED products can be released to the market. However, if the traditional qualification testing plans continue to be used, the total cost will be a huge expense for LED manufacturers. An optimal qualification testing plan that uses prognostic methods will shorten testing time and testing operational costs. All these cost savings will further reduce the price of LEDs and promote the replacement of traditional light sources.

V. Concluding Remarks

Prognostics is a necessary engineering activity in industry for predicting the RUL/reliability and further optimizing the design, testing, manufacture, and usage of LEDs. This review paper has attempted to summarize recent research and development in prognostic technologies for high-power white LEDs. As for common prognostic methods, statistical regression, static Bayesian network, Kalman filtering, particle filtering, artificial neural network, and physics-based methods have been reviewed to illustrate their basic concepts, pros and cons, applicable conditions, and LED application case studies. For professionals involved in LED prognostics, this review will be helpful in choosing the most appropriate method for their application. The fundamental issues of prognostics have been discussed for a clear understanding of the reliability and lifetime concepts for LEDs. The challenges and opportunities for new developments have been addressed. The research directions will be useful for researchers who are interested in implementing prognostics for high-power white LEDs. The following benefits of prognostics for LEDs can be derived for the development and application of a new generation of SSL products.

1) Prognostics can improve the accuracy and effectiveness of reliability prediction and useful lifetime assessment of LED lighting systems, thereby improving customer satisfaction, increasing market share, and reducing warranty costs.

2) The PET interaction in LEDs should be considered in optimized prognostic methods. A prediction error caused by neglecting this multi-physical field coupling can be avoided.

3) The reliability and prediction of LED drivers is important for real applications of LEDs, and prognostics can provide useful information and guidelines for selecting an appropriate LED driver for a specific application. The relevant prognostic methods suitable and appropriate for CC-SMPS can be directly applied to LED drivers from the point of view of power electronics.

4) The optimal prognostic methods involve the ability to identify failure mechanisms and failure sites, further enabling root-cause analysis (RCA) and providing feedback for the design and manufacture of LEDs with improved inherent reliability.

5) The standardization of prognostic methods is necessary for wider application of these methods in the LED industry. A universally accepted standard needs to be established, including the selection of appropriate methods, monitoring and/or measurement of performance indicators/parameters, prognostics procedures, and support software tools.

6) Anomaly detection and RUL prediction of LEDs in a shorter timeframe (e.g., ⩽1,000 h) than the currently adopted qualification method according to IES-TM-21 or IES-TM-28 (e.g., >6,000 h) is possible by using prognostic models and the observed/monitoring electrical, optical, and thermal characteristics data under test. Shorter test/qualification times will result in lower energy consumption, low-cost LED lighting products, shorter time-to-market, and reduced carbon emissions.

7) Prognostics capability is necessary for LED-based systems with the requirement of prognostics and health management (PHM) for condition-based maintenance (CBM), especially for safety-critical systems and emergency applications. The accurate reliability assessment of LED lighting systems is a requirement for these applications. Prognostic techniques make more accurate reliability information available for use with respect to the maintainability of the LED lighting systems, which can remove the barriers to the further expansion of the LED application scope.

8) Prognostics can become a key enabling technology for the

research and development of high-reliability and low-cost LEDs, which can potentially meet the requirements for greener technology and environmental protection.

APPENDIX

TABLE A1. Inputs and Outputs of Prognostic Approaches/Models for LEDs.

Classification	Approaches/Models	Input Data (Performance Indicators/ Key Parameters)	Failure Mode/ Failure Threshold	Output Data (Lifetime or Reliability Characteristics)
Statistical Regression Methods	⬩Linear regression (including least-squares, maximum likelihood) [8] [80][88][89][94]-[101] ⬩Nonlinear regression (including exponential function, inverse power law, Arrhenius model, Weibull function) [83][94][102][103] ⬩Logistic regression [98][109] [110] ⬩Two-stage method [104]-[108] ⬩Approximation method [104]-[108][111][112] ⬩Analytical method [104]-[108] [112] ⬩Wiener process [114][117] ⬩Gamma process [119][121] ⬩Gaussian process [118]	⬩Lumen maintenance (collected from IES-LM-80) [8][88][89][99]-[101] [104]-[108][112][117] ⬩Light output power spectrum [83][102] ⬩Thermal resistance (R_0) (calculated for junction temperature) [83] ⬩Light intensity [96][109][114][119][121] ⬩Spectra S(λ, t, i) [94] ⬩Color coordinates (x, y) [94] ⬩Luminosity [111] ⬩Forward current (current through p-n junction) [95]-[98][110] ⬩Junction temperature [95]-[99][110] ⬩Output in volts [95]-[98] ⬩Euclidean distance (ED) and Mahalanobis distance (MD) [95]-[98] ⬩Average luminance at each current stress [103] ⬩Color shift [117]	⬩Maintained percentage of the initial lumen output [8] [88][89][99]-[101][104]-[108][112][117] ⬩50% reduction in luminous flux [83][102][103] ⬩Degradation critical level [109][114][119][121] ⬩Spectral degradation (initial intensity decreases to d%) [94] ⬩Decrease in luminosity [111] ⬩30% of initial lumen depreciation [95]-[98] ⬩Probability for the LED health status (healthy = 0.99, not healthy = 0.01)/healthy margin [98][110]	⬩Lumen maintenance life L_p (L_{50}/L_{70}) [8][88][89] [99]-[101][104]-[108][112] ⬩Lifetime [83][102] ⬩Failure probability and reliability [109][114][119][121] ⬩Lifetime T_d(i) [94] ⬩Lifetime distribution [111] ⬩RUL [95]-[98][110][119] ⬩Time-to-failure (TTF) [95]-[98] ⬩Reliability (Weibull, lognormal and normal) [104]-[108][112] ⬩MTTF with confidence interval [108][117] ⬩Average life [103]
Static Bayesian network	⬩Bayesian probabilistic and regression models [126]-[129]	⬩Luminous flux and correlated color temperature (CCT) [126]-[129]	⬩70% light output maintenance [126]-[129]	⬩RUL with confidence interval [126]-[129]
Kalman filtering (KF)	⬩Kalman filter [98][110] ⬩Extended Kalman filter (EKF) [134]-[137] ⬩Unscented Kalman filter (UKF) [105][138]-[141]	⬩Forward current, forward voltage, board temperature, light output [98] ⬩Lumen flux (lumen maintenance) [105][137]-[139][141] ⬩Chromaticity coordinates (u', v') [105] [135]-[137][139][140] ⬩Forward voltage [105][139] ⬩Euclidean distance [105][140] ⬩Color shift distance (D_{uv}) [135]-[138] ⬩Correlated color temperature (CCT) [135]-[137]	⬩Probability for the LED health status (healthy = 0.99, not healthy = 0.01) [98] ⬩Maintained percentage of the initial lumen output [105][137]-[139][141] ⬩Chromaticity state shift ($\triangle u'$, v') [105][135]-[138][140]	⬩RUL without confidence limits [98][138] ⬩Lumen maintenance life L_p (L_{50}/L_{70}) [105] [135]-[137][139][141] ⬩Depend on different application (2-step, 4-step, 5-step, or 7-step SDCM) [105][137][138][140]
Particle filtering (PF)	⬩Particle filter model [141] [147]-[150]	⬩Peak forward voltage and forward current [147][148][149] ⬩Luminous flux [141][147]-[150]	⬩Shift of forward-voltage/forward-current curve [147]-[149] ⬩Lumen degradation (luminous flux drops to 70%) [141][147]-[150]	⬩L_{70} life time [141] ⬩RUL with confidence boundary [147]-[150]
Artificial neural network (ANN)	⬩Three layers NN (forward- and back-propagation algorithms) [98]	⬩Forward current, board temperature [98]	⬩Probability for the LED health status (healthy = 0.99, not healthy = 0.01) [98]	⬩RUL without confidence limits [98]
Physics-based methods	⬩Empirical model based on V-I characteristics [98] ⬩Electrical and optical models (Fick's law), analytical degradation law [157] ⬩Lumen depreciation and leakage resistance depreciation [158] ⬩Relevant PoF models for potential high-risk failure mechanism, exponential degradation model (two parameters estimated by least-squares method) [105][159] ⬩Arrhenius-Weibull, generalized Eyring-Weibull,	⬩Forward current, forward voltage [98] ⬩Electrical (I_{hj}, I_r, I_s, n_{id}, V_{th}, I_{th}, R_s) and optical (γ, α, E_g, $\triangle E$, E_c) parameters, temperature [157] ⬩Optical characterizations (optical power, luminous flux, forward voltage) and electrical characterizations (current-voltage) [158] ⬩Geometries, material construction, environmental and operational conditions [105][159] ⬩Case temperature, drive current [160] ⬩Junction temperature, forward current (I_D), forward voltage (V_D) [161]	⬩Residual (difference between predicted and actual current) [98] ⬩Increase in recombination current, decrease of 20% or 4.7 mW for optical power (optical power drift) [157] ⬩Lost 30% of its initial flux, increase of the leakage resistance and non-radiative current (I_L) up to a critical value [158] ⬩Chip-level luminous degradation and solder inter-connection fatigue damage [105][159] ⬩50% light output reduction	⬩RUL without confidence limits [98] ⬩F(t), MTTF, failure rates, minimal and maximal lifetime [157] ⬩Optical lifetime (L_{70}) and electrical lifetime t_2 [158] ⬩TTF (ex. L_{70} age) [105][157] [159] ⬩L_{70} values and 60% reliability values [160] ⬩70% luminary lifetime (L_{70}) [161]

Classification	Approaches/Models	Input Data (Performance Indicators/ Key Parameters)	Failure Mode/ Failure Threshold	Output Data (Lifetime or Reliability Characteristics)
	and inverse power-Weibull [160] ♦Arrhenius accelerated life test model [161]		[160] ♦70% light output maintenance [161]	

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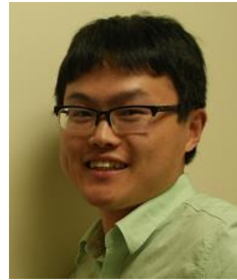

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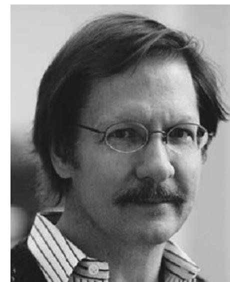

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