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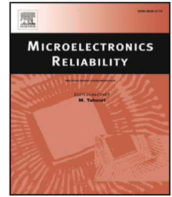

Review paper

A survey on LED Prognostics and Health Management and uncertainty reduction

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ABSTRACT

Hybrid Prognostics and Health Management (PHM) frameworks for light-emitting diodes (LEDs) seek accurate remaining useful life (RUL) predictions by merging information from physics-of-failure laws with data-driven models and tools for online monitoring and data collection. Uncertainty quantification (UQ) and uncertainty reduction are essential to achieve accurate predictions and assess the effect of heterogeneous operational-environmental conditions, lack of data, and noises on LED durability. Aleatory uncertainty is considered in hybrid frameworks, and probabilistic models and predictions are applied to account for inherent variability and randomness in the LED lifetime. On the other hand, hybrid frameworks often neglect epistemic uncertainty, lacking formal characterization and reduction methods. In this survey, we propose an overview of accelerated data collection methods and modeling options for LEDs. In contrast to other works, this review focuses on uncertainty quantification and the fusion of hybrid PHM models with optimal design of experiment methods for epistemic uncertainty reduction. In particular, optimizing the data collection with a combination of statistical optimality criteria and accelerated degradation test schemes can substantially reduce the epistemic uncertainty and enhance the performance of hybrid prognostic models.

1. Introduction

Light-emitting diodes revolutionized the lighting industry due to their high efficiency, reliability, and durability. LED systems can perform consistently for a long time and display very low degradation even under accelerated aging conditions. Ensuring the reliability and estimating the RUL of LEDs require careful quantification of both aleatory and epistemic uncertainties. Aleatory uncertainty stems from fluctuations in operational profiles, measurement noises, and manufacturing variability. Given the exceptional durability of LEDs, degradation experiments can extend over several months or years, resulting in a scarcity of data that inevitably affects reliability qualification and RUL analysis. To address these challenges, and enhance data quality and prediction accuracy, accelerated degradation tests such as the IES LM-80/84 or the JESD22 are commonly employed during the reliability qualification phase, [1–3]. Probabilistic models and reliability theory are utilized to quantify the natural variability (aleatory uncertainty) affecting the durability and lifetime of LED groups. However, formal treatments of epistemic uncertainty, model imprecision, and data scarcity are less common. Advanced PHM frameworks for LEDs must carefully quantify both aleatory and epistemic uncertainty and, whenever possible, reduce the latter. Hybrid PHM frameworks offer a promising approach to addressing epistemic uncertainty issues by integrating physics-of-failure (PoF) laws, statistical degradation models, and data from online monitoring or accelerated experiments within a unified framework. Advanced PHM frameworks have been introduced to tackle the LED reliability problem, e.g., [4,5], and accelerated degradation methods have been considered to improve the quality of reliability data, including generally applicable statistical methods [6,7], or focusing on specific applications like for solder joints [8,9], power modules [10], and LEDs [11].

Data collection and uncertainty quantification [12,13] are fundamental steps for achieving successful PHM of LEDs. However, while many authors have addressed the characterization of aleatory uncertainty and randomness in degradation and lifetime distributions, methods to quantify and reduce epistemic uncertainty from data collection, data scarcity, and model imprecision are not widely discussed.

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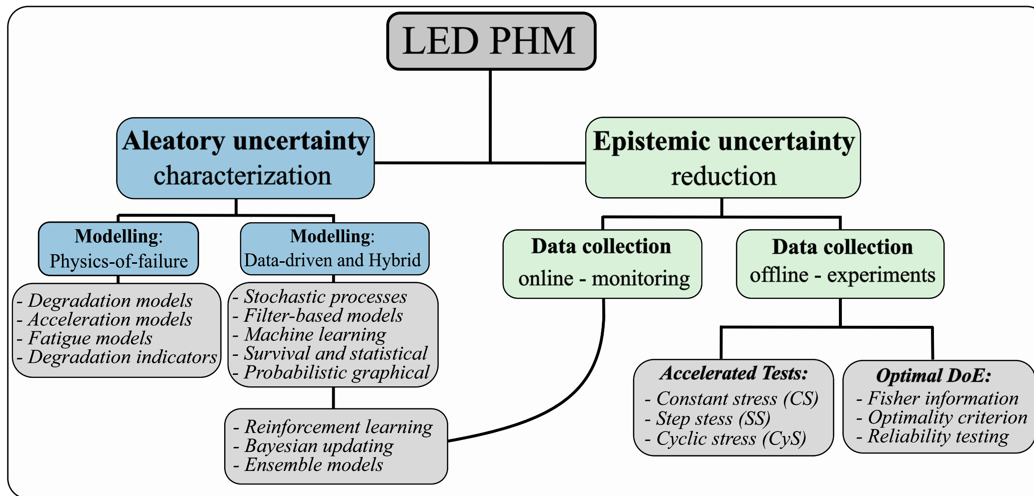

Fig. 1. A summary of the PHM models and epistemic uncertainty reduction techniques reviewed in this paper.

Advanced data collection methods for epistemic uncertainty reduction must be embedded within hybrid PHM frameworks and a better link between specific modeling choices and data collection strategies provided. In particular, moving from unstructured and model-agnostic data collection strategies to optimized model-based data collection methods could be beneficial. In this paper, we aim to bridge this gap by providing a complete review of PHM models and epistemic uncertainty reduction techniques which are based on accelerated degradation tests and optimal design of experiments. In particular, we wish to emphasize the importance of uncertainty quantification on both the definition of suitable prognostic models and also on data collection. Hence, a review of accelerated data collection methods for LEDs, including constant-stress, step-stress, and cyclic-stress experiments is proposed. Prevalent indicators for durability and reliability analysis are discussed together with the limitations of existing approaches. Additionally, we explore the potential of optimal design-of-experiment to further reduce the epistemic uncertainty affecting PHM models, which can lead to improved accuracy by efficiently allocating resources such as budget and samples and reducing the number of stressors levels, sampling frequency and test duration. Finally, we conclude with recommendations for future research directions. Fig. 1 illustrates the PHM models for LEDs and epistemic uncertainty reduction techniques reviewed in this paper.

The rest of the paper is organized as follows: Section 2 presents the mathematical background, Section 3 proposes an overview of PHM models for LEDs reliability analysis, Section 4 reviews accelerated tests for LED, whilst Section 5 discusses Optimal Design of Experiment (ODoE) methods. This survey is closed by Section 6 with a discussion and recommendations for future research.

2. Background: Reliability and uncertainty quantification

The reliability of an asset defines its ability to function without a substantial loss in functionality or failures [14]. LED failures can be categorized into two main groups [15,16], namely, *Degradation-induced Failures* and *Catastrophic Failures*. The former are the most common failure modes and result from wear-out events, gradual functionality loss, and degradation processes. On the other hand, catastrophic failures occur suddenly, resulting in a total loss of LED functionality, e.g., zero light output due to die cracking or bond wire fractures from electrical over-stress.

Uncertainty Quantification for reliability systematically addresses imprecision and variability that affect the performance of an asset, to improve decision-making for the system's design, maintenance, and control [17]. Uncertainty is generally divided into aleatory and epistemic components. Aleatory uncertainty is considered irreducible and associated with stochastic/random behaviors and intrinsic variability in events, e.g., natural fluctuations in performance and random occurrence of failures. In contrast, epistemic uncertainty (reducible) arises because of incomplete or inaccurate models, small data sets and censored information as well as conflicting evidence, vagueness and tolerance errors [18,19]. Aleatory uncertainty is typically considered in PHM frameworks for LED, and stochastic models embedded within prognostic and diagnostic tools to characterize natural variability in, e.g., LED parameters, external stressors, and LED reliability performance scores. Such variability may arise from manufacturing imperfections affecting LED parameters, hence leading to a population of non-identical LEDs and non-deterministic activation energy. Similarly, aleatory uncertainty affects standarized lifetime parameters like lumen depreciation [1] or color shift [2]. Numerous studies acknowledge the significance of aleatory uncertainty in LED reliability analysis, see Section 3.2 for modeling examples. In fact, reliability theory is frequently used in this context, with stochastic processes and other established probabilistic models effectively capturing this variability. An aleatory characterization implicitly assumes that factors modeled using probability theory are inherently stochastic and the uncertainty cannot be further reduced by collecting more data. On the other hand, there is no agreement on how to deal with epistemic uncertainty, and many approaches have been proposed, such as Bayesian statistics, set theory, or generalizations of probability theory, see e.g. [20–23] for additional discussions.

In the next sections, we will give a general overview of uncertainty quantification methods for the reliability and durability assessment of LED, briefly overawing modeling approaches used to quantify and reduce the epistemic uncertainty in the lifetime predictions.

2.1. Remaining useful life

The lifetime L_p corresponding to a minimum acceptable performance level p is defined as follows:

$$L_p = \min_t \{ t : \phi(t) \leq p\phi(0) \} . \tag{1}$$

where $\phi(t)$ is a performance indicators related to degradation, for instance, the luminous flux at time t. The fraction $\frac{\phi(t)}{\phi(0)}$ is a normalized degradation score and $\phi(0)$ is the nominal performance level for the new system. In principle, samples of L_p can be obtained from Eq. (1) by observing sufficiently long degradation trajectories for ϕ. However, large depreciation events are seldom observed in practice and parametric models are necessary to extrapolate and characterize the uncertainty in the LED lifetime. Note that a threshold level $p \in [0, 100]$ defines the failure boundary as a percentage of retained performance. A higher

value of p indicates a stricter lifetime requirement and its selection is application-dependent, e.g., up to 30% for indoor applications and only 10% depreciation for street lighting. Besides flux depreciation, several other degradation indicators can be considered [14,24–26].

The residual life, also known as remaining useful life, is the remaining operating time before failure and it is defined as follows, $RUL(t) = L_p(t) - t$, where t is operating time and $L_p(t)$ is the service life at time t. Both $RUL(t)$ and $L_p(t)$ change over time and are inherently uncertain, i.e., their true value is known only a-posteriori after a failure occurs. Sources of epistemic uncertainty and randomness affect the RUL and lifetime, e.g., because of system-specific mission profiles, censoring, natural variability in material properties and non-identical LEDs. Aleatory and epistemic uncertainties must both be carefully quantified.

2.2. Mean time-to-failure and mean RUL

Because natural variability affected L_p and RUL, probabilistic tools are generally employed to model this aleatory uncertainty. Random variables, probability density functions (PDF), and cumulative distribution functions (CDF) are typical examples of traditional probabilistic models. Let us define the failure time as $T = L_p$, such that its probability density is $f_T(t)$ and corresponding CDF given by $F_T(t) = \int_0^t f(\tau)\,d\tau = \mathbb{P}[T \leq t]$, where $F_T(t)$ is the unreliability function at time t. The unreliability function represents the probability of a failure (an unacceptable performance) occurring before time t and its complement defines the reliability function $R_T(t) = \mathbb{P}[T > t] = 1 - F_T(t)$. Both $F_T(t)$ and $R_T(t)$ describe the variability of an LED population. The hazard function $\lambda(t) = \frac{f_T(t)}{R_T(t)} = -\frac{d}{dt}log(R_T(t))$ defines the rate of occurrence of the failure at time t and, based on its definition, the survival function can be conveniently rewritten as the exponent of the negative cumulative hazard (or risk) as:

$$R_T(t) = \exp\left(-\int_0^t \lambda(u)du\right). \tag{2}$$

The mortality rate is the alpha-level quantile of L_p, obtained by inverting the failure time CDF $B_\alpha = F_T^{-1}(\alpha)$, with probability level $\alpha \in [0,1]$ defining the percentage of failed LED. The Mean time-to-failure (MTTF) gives the mean service for a group of new assets, whilst the Mean Residual Life (MRL) is the expected value of RUL averaged over a group of assets that operated for some time without failure. Both MTTF and MRL provide summary statistics on the expected durability and reliability of a group of LEDs, where the MTTF is specifically defined as follows:

$$\mu_{L_p} = \mathbb{E}[T] = \int_0^\infty R_T(\tau)\,d\tau = \int_0^\infty \tau f_T(\tau)\,d\tau \tag{3}$$

whilst the mean RUL, $m(t)$, is a conditional expectation computed as follows:

$$m(t) = \mathbb{E}(T - t \mid T \geq t) = \frac{\int_t^\infty R(\tau)\,d\tau}{R(t)}. \tag{4}$$

where T is a non-negative random variable. Fig. 2 illustrates the effect of natural variability in $RUL(t)$, the service life distribution f_{L_p}, and the resulting mortality rate B_α. The service life strongly depends on the selected p, and failures are often right-truncated, requiring careful extrapolation while accounting for aleatory and epistemic.

2.3. Epistemic uncertainty quantification

Recent efforts have focused on explicit treatments of imprecise knowledge and non-consistent information, addressing both the aleatory and epistemic uncertainty quantification problem. Classical reliability and probability theory are well-suited for modeling aleatory uncertainty. However, the use of probabilities to characterize severe lack of data and epistemic uncertainty is debatable. To overcome these issues, advanced theories and tools have been developed. Some of the widely applied concepts are Evidence theory [27], Fuzzy-set theory [28], Info-gap theory [29], hierarchical Bayesian frameworks [30], Imprecise probability theory [31–34], and statistical method based on Kolmogorov's and Fisher's statistics [35–37]. Another classification of uncertainties considers their originating source, encompassing model-form uncertainties, from input, parameters, or limitations in model complexity and structural form [38]. Over the last decade, significant efforts have been directed toward reducing model-form uncertainties, facilitated by advanced artificial intelligence methods and the amalgamation of big data with universal function-approximating models like deep networks and deep learning models. Despite advancements, uncertainty challenges also affect these models. For an insightful review of Uncertainty Quantification in the context of deep learning models, refer to [39]. The authors of [23] proposed an epistemic uncertainty quantification and interval prediction framework for LED. For additional discussion on the role of epistemic and aleatory uncertainty in the reliability analysis of LEDs refer to [21,22].

3. Prognostics models

PHM frameworks can be divided into three main groups: Physics-of-failure (PoF), Data-driven (DD), and Hybrid. The former use knowledge of the failure dynamics and physical laws to achieve successful RUL estimation and often rely on prior engineering knowledge of failure mechanisms. In contrast, data-driven methods use large databases of degradation and monitoring data to learn statistically relevant failure patterns affecting the system's reliability. In DD approaches, expert opinion and prior engineering and physical knowledge of the degradation and failure mechanisms are not required (at least in principle). In contrast, hybrid approaches combine health monitoring data, expert knowledge, and physical insights in a common framework, hence combining the strengths of DD and PoF approaches. For an overview of PHM applied in long-term operations of high-power white LEDs (both for devices and systems) the interested reader is reminded of [40].

3.1. Physics-of-failure approaches

PoF has several advantages, as they provide a detailed explanation of failure mechanisms and do not require large volumes of data [4], and this facilitates the identification of failure root causes and the definition of prevention strategies. The main drawback is that physical models for complex failure processes are typically unavailable or uncertain. A detailed review of flux depreciation models (degradation models), accelerated models, fatigue models and other PoF approaches is presented next.

3.1.1. Flux models

Flux degradation models capture degradation as the percentage loss in the retained nominal flux $\frac{\phi(t)}{\phi(0)}$. This ratio is a direct indicator of the health state of an LED as it is explicitly linked to a definition of failure, i.e., an LED fails if the flux loss exceeds a predefined threshold. An exponential flux model is often used to capture flux loss as follows:

$$\phi(t;\theta) = Be^{-(\alpha\times t)^\beta} \tag{5}$$

where $\phi(t;\theta)$ is the flux at time t, and $\theta = (\alpha, B, \beta)$ are the model parameters, with α representing the decay rate, B representing the pre-decay factor, and β representing the power factor.

3.1.2. Acceleration models

The decay rate α is considered to be a function of the accelerating factors which were applied to efficiently collect usable reliability data. The Arrhenius equation is often used to quantify the effect of thermal stressors of the degradation process and given by [25,26]:

$$\alpha(T) = C_T e^{-E_a/(K_b\cdot T)}, \tag{6}$$

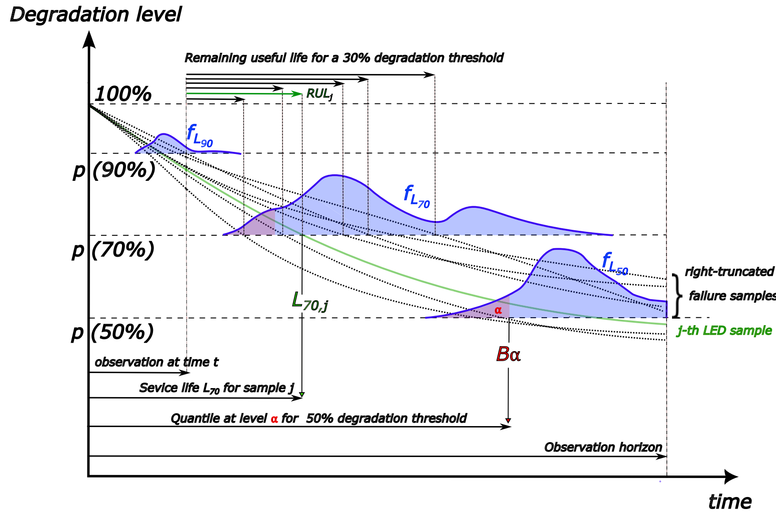

Fig. 2. An graphical summary of degradation trajectories, lifetime L_p, alpha-quantile B_α, and remaining useful life for different degradation thresholds, p.

where T is the temperature (K), $K_b = 8.617 \times 10^{-5}$ is the Boltzmann constant (eV/K), E_a is the activation energy (eV), and C_T is the pre-exponential factor. For LED light sources it is not uncommon to observe E_a between 0.11–0.26 eV [41] whilst is usually around 0.20 eV for LED luminaire and often ranges from 0.18 eV to 0.23 eV [42]. The effect of high forward currents on the acceleration rate α is often captured via a power-law model, $\alpha(I) = C_I \times I^{\beta_I}$, where β_I is a current parameter. Similarly, the individual effect of relative humidity, RH, on the flux decay rate is modeled as follows, $\alpha(RH) = C_H \times RH^{\beta_{RH}}$. The Eyring and Black models are used in the semiconductor industry to quantify the combined effect of multiple accelerating factors on LED degradation speed. Black's model is given by [43,44]:

$$\alpha(T, I) = C_{T,I}\, I^{\beta_I} e^{-E_a/(K_b T)}. \tag{7}$$

The combined Hygro-thermal-electrical effect on the lifetime can be modeled analogously, see for instance Hallberg–Peck's model [45]. Note that lifetime models can be reformulated in terms of acceleration factor AF, defining a relative speed of degradation as the ratio between degradation rate under accelerated and normal stress, as follows [45,46]:

$$AF(S_a, S_u; \theta) = \left[\frac{I_a}{I_u}\right]^{\beta_I} \left[\frac{RH_a}{RH_u}\right]^{\beta_{RH}} e^{\left[\left(\frac{E_a}{k}\right)\left(\frac{1}{T_u} - \frac{1}{T_a}\right)\right]} \tag{8}$$

where S_a are the stressors at testing conditions and S_u are the stressors at the normal usage condition.

3.1.3. Fatigue models

Fatigue-related degradation occurs due to repeated stress cycles, such as thermal and power gradients. Fatigue models are generally classified based on the type of stress, strain and energy. For example see the Palmgren–Miner, Coffin–Manson, and the Akay and Darveaux models respectively [47,48]. The Coffin–Manson model is probably one of the most well-established fatigue models and it defines a relationship between the number of cycles to failure as follows:

$$N_f(\theta) = \frac{1}{2}\left(\frac{\Delta\gamma}{2\epsilon_f}\right)^c \tag{9}$$

where $\theta = (\epsilon_f, c)$ are model parameters and $\Delta\gamma$ accounts for elastic and plastic strains. Refer to [49] for a complete overview of fatigue models and related modeling issues in this context.

3.1.4. Approaches based on indirect degradation indicators

Advanced prognostic frameworks for LEDs have been recently developed and exploit indirect indicators of the system and device health state. Indirect indicators are performance factors that correlate with a loss of functionality, i.e., factors for which an exact definition of failure is unavailable. For instance, a limit state function for the junction temperature (T_j) is not explicitly defined [50]. Nonetheless, T_j can be a very useful indicator of LED health state, as it is affected by changes in case temperature and thermal dissipation, possibly triggered by cracks in the insulation. Other examples of indirect degradation indicators recently adopted include: the LED current–voltage characteristics ($I - V$) [51–54], optical power and current profile ($L - I$), [55], data from Electroluminescence measurements, T_j and Joule Power curves, forward voltage and junction temperature profiles ($V - T_j$) [56], normalized reverse leakage current [53], and forward-voltage-based thermal resistance, [41,46,57]. Other factors that indirectly contribute to LED degradation may include air pollutants [58], external sources of vibration [59] or humidity (rain/fog) combined with lack of insulation [60], and thermal gradients [61].

3.2. Data-driven and hybrid PHM

An overview of data-driven and hybrid PHM approaches is presented in the next sections.

3.2.1. Stochastic processes

Stochastic processes, such as the Wiener, Gamma, and Poisson processes, are often used to model the degradation of LED over time. For instance, a Wiener process can be defined as follows

$$\phi(t; \theta) = \phi_0 e^{-\alpha t + \sigma W_t}, \tag{10}$$

where α is the degradation rate and σ defines the variability of the diffusion process [62,63]. Various studies, including [64], and [65], leverage modified Brownian motion, Gamma processes, and Frank copula for LED degradation modeling. Additionally, Gaussian process models are applied, as seen in [66,67], showcasing advantages over traditional regression-based methods. In [63], the authors criticize exponential flux depreciation models and propose a modified Gamma process to account for non-monotonic color shifts while assessing the LED lifetime. [64] highlighted challenges of using stationary and independent incremental assumptions in stochastic processes and proposes a modified Brownian motion for modeling nonlinear degradation trajectories from step-stress tests. In [68], Gamma processes and regression models for LED lifetime estimation are compared on data from accelerated degradation tests. The Gamma model outperforms the classical lifetime estimation approach according to IES TM-21 [1], while the regression model achieves better performance in predicting the progression of color shift. This suggests that different models may have varying

strengths and weaknesses in predicting different aspects of LED lifetime behavior. A model combining Gamma processes with Frank copula is investigated in [69] seeking a characterization of dependencies between different performance characteristics (like lumen and color). The outcomes demonstrate that ignoring the dependence between different performance characteristics can affect the reliability of results. In [70], the study Gamma distributed degradation modes for high-power white LED are estimated via maximum likelihood and method of moments. A comparison to the IES TM-21 standard demonstrates that Gamma degradation processes can achieve more accurate results. For additional discussions on the limitations of the IES TM-21 standard and for an approach based on Lévy stochastic processes refer to [67]. Wiener process models are also widely adopted to model LED degradation, e.g., [62, 71]. Specifically, [71] introduced a hybrid PHM that combines permutation entropy based on thermodynamics and a data-driven Wiener process to characterize the LED degradation and successfully provide early failure warning. Gaussian process models have also been explored [65,66], particularly focusing on multi-output characterization and missing data issues. [72] recently compared stochastic data-driven models (Gamma, Wiener) for effective prognostics of UV-LED radiation power degradation lifetime, showing higher accuracy and robustness compared to traditional methods like the TM-21. Stochastic process models are crucial for understanding LED degradation, offering insights into nonlinear trajectories and estimating long-term lumen depreciation. These tools play a crucial role in studying LED degradation and capturing nonlinear dynamics.

3.2.2. Filter-based approaches

Filtering methods estimate the joint PDF of uncertain variables over time given noisy (generally nonlinear and non-Gaussian) degradation processes see, e.g., [73]. While filter-based methods are prevalently used to analyze dynamical systems and for signal processing, a few authors have applied them to LED lifetime prediction. In [74], a Bayesian calibration and filtering approach are introduced and compared with the traditional TM-21 models for lifetime prediction. Markov Chain Monte Carlo sampling and Metropolis–Hasting algorithms calibrated the parameters of the flux degradation model over time. [75] proposes a Bayesian method for identifying the onset of degradation and classifying different failure mechanisms in solid-state luminaires. [5] employed a nonlinear Unscented Kalman filter approach for predicting the lumen service life of high-power white LEDs, and [76] combines a Particle filtering approach with a sequential Monte Carlo method to predict the remaining useful life of LEDs. [77] used the Kalman smoothing method for LED lumen maintenance life prognosis, demonstrating superior prediction performance compared to standard methods. Similarly, [78] applies an extended Kalman filter approach to predict the L_{70} of solid-state LEDs.

3.2.3. Survival models other statistical methods

[79] proposed a popular statistical method named "general degradation path model", where degradation indicators were used to estimate the time-to-failure distribution for a broad range of degradation models. [80] applied a nonlinear random-coefficients model to model degradation trajectories (flux depreciation) and this allows the individual variability of specific LED devices into the degradation model. A bi-variate model to account for multiple performance indicators to predict LEDs maintenance life was proposed by [81]. An early application of the Cox proportional hazard model for LED can be found in [82]. General purpose statistical models for degradation analysis have been proposed and reviewed by Meeker and co-workers and include, e.g., [83–85]. In full generality, a Cox proportional hazard model can be defined as follows:

$$\lambda_i(t|\mathbf{x}_i;\theta) = \lambda_0(t)\exp(\mathbf{x}_i^\top \boldsymbol{\theta}), \tag{11}$$

where λ is the hazard function, λ_0 is the baseline hazard, $\mathbf{x}_i$ is a vector of explanatory variables. A mathematical expression for a nonlinear random-coefficients model describing the flux depreciation is given by:

$$\phi_i(t;\theta) = f(t,\mathbf{x}_i^\top;\boldsymbol{\theta}_i) + \epsilon_i(t) \tag{12}$$

where ϕ_i is the dependent variable for observation i, f is a nonlinear function of $\mathbf{x}_i$ and random coefficients $\boldsymbol{\theta}_i$ and ϵ_i are the residual terms for observation i.

3.2.4. Machine learning and AI-based methods

Sutharssan in [86] introduced a simple neural network with two hidden neurons for high-power white LED lifetime prediction. Clustering approaches, such as the one proposed in [87], have been applied to identify anomalies in LED behavior based on SPD response. [88] presents a novel machine-learning approach integrating a feature extractor and a novelty detector for electrode image processing. SVM models in [89] extend applications to spatial modulation visible light communication. [90] utilizes a long short-term memory recurrent neural network for UV LED lifespan prediction. [91] introduces Correlation-Driven Neural Networks, surpassing standard methods in correlating solder properties with LED reliability. Recently, M. S. Ibrahim et al. [4] prepared a complete review of ML and Digital Twin methods for diagnostics and prognostics of LEDs. This review includes Markovian models and Bayesian networks, SVM for LED fault detection and lifetime prediction. In [92], a wavelet neural network efficiently detects water-drop defects in LED chips and in [93] the authors employed a Wiener process to model mid-power white LED degradation while exploring ML models to predict the junction temperature from LEDs optical characteristics. In the recent study [94], the authors explored the use of Long short-term memory and convolutional neural networks for anomaly detection and RUL prediction in accelerated degradation tests. Their experiments with high-power white LEDs revealed that the ML can achieve comparable accuracy to the IESNA TM-21 method but with a 70% reduction in the training data. In [95] the authors proposed an automated optical inspection method for LED defect detection using unsupervised generative adversarial neural networks. Kim et al. [96] presented an inverse design of organic light-emitting diode structure based on deep neural networks and [97] investigated active learning approach to predict degradation pathways of an organic semiconductor used in organic LEDs whilst [98] used extreme gradient boosting (XGBoost) and LightGBM stacked ML models to predict the electron blocking layer of AlGaN/AlGaN superlattice under various conditions. [99], predicted the lifetime of power MOSFET devices using various ML algorithms. The results show that the LSTM and GRU have a better performance for this specific task.

3.2.5. Probabilistic graphical models

There is only a very limited number of works that attempted the use of Probabilistic graphical models to assess the reliability and durability of LED lamps and systems. For instance,e [100] discusses a k-out-of-n methodology for graph-based system reliability analysis, whilst a Petri Net model was developed in [101] to study real-time correction methods for LED chip sorting. Recently, a Bayesian network approach for system-level reliability assessment of high-power light-emitting diode lamps [102] was proposed and the luminous flux degradation and reliability modeled by Gamma processes and Weibull distributions. The Bayesian network was employed for the system-level reliability assessment and defined from a directed acyclic graph of the system structure and informed by a failure mode analysis. The applicability of this approach is then demonstrated in a real-life example.

3.3. Model updating and data feedback

Generally speaking, model and data feedback occurs when the outputs of a model and/or new observations are forwarded back as inputs as part of a chain of cause-and-effect that forms a circuit or loop. Newly gathered information and monitoring data must be embedded within

PHM frameworks to regularly update models, reduce uncertainties, and enhance predictive performance. These tools are essential to reduce epistemic uncertainty in the model predictions and definition. Several methods based on this feedback loop paradigm include, among others, Reinforcement Learning approaches, ensemble-based model bootstrapping, bagging and boosting [98], and Bayesian calibration and model updating methods, see e.g., [103–106]. While a comprehensive review of these approaches exceeds the scope of this work, a brief overview of some key aspects and features of these methods is presented next.

3.3.1. Reinforcement learning methods

In Reinforcement Learning (RL), the parameters of a model/agent are updated through by collecting trajectories of observations, actions, rewards and new observations. Deep RL have been successfully applied for PHM in various engineering fields, like in flow part management problems, for optimal maintenance and operational planning of energy systems [107], RUL prediction [108–110]. However, the exploration of RL frameworks to enhance PHM and L_p prediction in LEDs remains an unexplored area.

3.3.2. Bayesian model updating

Bayesian inference combines prior knowledge expressed through a prior distribution with a likelihood function derived from observed data, generating a posterior distribution of quantities of interest for a given model class. Bayes' theorem defines the posterior probability as the product of the likelihood and prior, divided by a normalizing constant as follows [103]:

$$\mathbb{P}[\theta|\mathcal{D},\mathcal{M}] = \frac{\mathbb{P}[\mathcal{D}|\theta,\mathcal{M}] \cdot \mathbb{P}[\theta|\mathcal{M}]}{\mathbb{P}[\mathcal{D}|\mathcal{M}]}, \tag{13}$$

where θ are the unknown factors to be inferred, i.e., the parameters defining a PHM model class $\mathcal{M}$. $\mathbb{P}[\theta|\mathcal{M}]$ represents the prior (background belief/knowledge on how the quantities θ varies), $\mathbb{P}[\mathcal{D}|\theta,\mathcal{M}]$ is the likelihood, i.e., the probability that the available data $\mathcal{D}$ explain θ. The probability $\mathbb{P}[\theta|\mathcal{D}]$ defines the posterior distribution of θ given the available observations and it can be updated when more data are collected. The quantity $\mathbb{P}[\mathcal{D}]$ represents a normalizing constant (marginal likelihood) and is an analytically intractable multidimensional integral over θ. Hence, numerical methods have been developed to approximate Bayes' theorem, e.g. approximated Bayesian computations defining the following updating rule:

$$\mathbb{P}[\theta|\mathcal{D},\mathcal{M}] \propto \mathbb{P}[\mathcal{D}|\theta,\mathcal{M}] \cdot \mathbb{P}[\theta|\mathcal{M}]. \tag{14}$$

For examples of Bayesian updating and calibration approaches for LED the interested reader is reminded to e.g., [74,75,102].

3.4. Summary of the reviewed models for PHM

Machine Learning (ML) and Artificial Intelligence (AI) methods excel in handling complex data and providing accurate predictions. However, their reliance on extensive, high-quality data and computational resources may limit applicability in reliability and LED degradation modeling. On the other hand, well-established statistical methods like survival models offer insights into failure time relationships but may be sensitive to assumptions and outliers. Filter-based approaches prove computationally efficient for real-time fault detection but may lag in predicting future failures compared to ML and statistical methods. Stochastic processes, including Gamma, Poisson, and Wiener models, contribute to LED reliability modeling but may demand advanced identification and likelihood estimation methods. Combining these tools in hybrid Prognostics and Health Management (PHM) frameworks with physical system knowledge can yield valuable insights. The choice of method and framework should align with the specific application and available data, potentially involving a blend of methods, model ensembles, and hybrid approaches for enhanced accuracy and reliability. For a comprehensive exploration of hybrid frameworks integrating physics-based models with data-driven deep learning algorithms, particularly in safety-critical systems, readers are directed to [111].

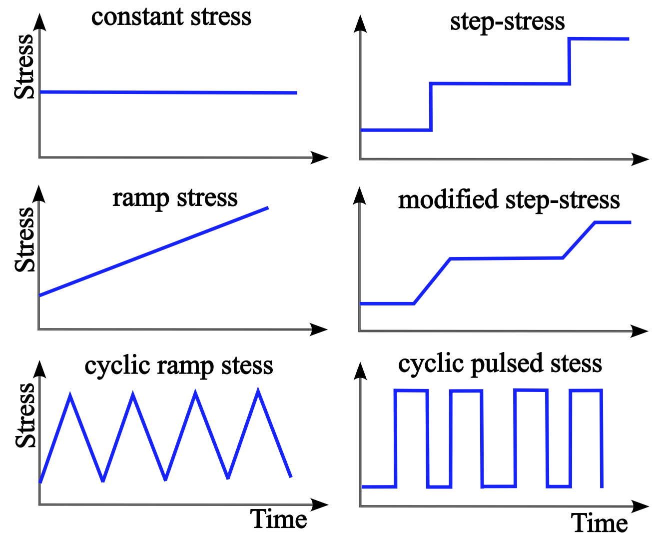

Fig. 3. An example ATs classifications based on the stress profile.
Source: Adapted from [7].

4. Epistemic uncertainty reduction by accelerated aging

Reliability data for LEDs in the context of reliability analysis often comprises use-rate trajectories rather than traditional time-to-event (failure) data, due to the infrequent failures of highly reliable LEDs. To reduce epistemic uncertainty and provide better quality data, accelerated degradation and testing methods play a crucial role. Despite challenges posed by the slow degradation of LEDs even under moderately high temperatures [112], ATs are recommended by industry standards, such as the one of the Next Generation Lighting Industry Alliance [11]. In fact, given the slow degradation, achieving meaningful test results requires accurate measurements and specialized metering devices. Instrumentation and physical measures (absorbance, intensity, chromatography) for accelerated testing physics-based analysis of LEDs are extensively reviewed in [24].

The synergy of ATs and PHM proves beneficial in enhancing LED product reliability and reducing testing costs and different classes of ATs can be applied. For instance, Accelerated Binary Tests, Accelerated Life Tests, Accelerated Repeated Measures Degradation Tests, and Accelerated Destructive Degradation Tests, can be used. Four main types of ATs are defined based on the loading (stress) profile, namely: constant, step, progressive stress, and cyclic stress tests. Fig. 3 illustrates examples of ATs classification based on the stress profiles and the reader is reminded to [6,7], for a detailed discussion of statistical models and challenges of the different approaches.

4.1. Constant stress (CS) test

Constant stress tests, particularly with purely thermal acceleration, is a mature methodology for LED lighting product assessment. Preliminary estimation of LED activation energy typically involves analyzing at least two different temperature levels. Combinations of thermal and electrical stress, maintaining elevated temperature and current levels throughout the test, are also generally explored. In [113], a method involves collecting flux degradation data from multiple stress levels, fitting a Weibull distribution function to characterize the LED-based light bars' lifetime. [114] employs iso-thermal and iso-current stress tests, using statistical analysis of thermal resistance (R_{th}) to compute junction temperature. [115] studies the effect of serial resistance on power luminosity degradation through a constant-stress test, addressing both degradation and catastrophic failure mechanisms. In [116], accelerated tests using constant humidity and temperature are performed to speed up LED aging, analyzing transmittance, spectral intensity, and luminous flux.

4.2. Step stress (SS) test

Step-stress tests are employed to demonstrate the reliability and durability of LED products by collecting degradation data over incremental stress levels. Nelson's equivalent cumulative damage theory and analysis method for the lifetime of products from step-stress data are presented in [117]. [118] introduces a nonlinear Wiener-process-based step-stress ADT that can account for temporal variability, unit-to-unit variability, and measurement errors. A comparison of step-stress approaches with constant stress experiments in [64] indicates comparable service life estimation accuracy with higher sample efficiency for the former. [119] applies a step-temperature and step-humidity approach in a simulation study to accelerate aging, while [120] employs step-stress to age high-power LED lamps, extending modeling via a subsystem isolation method. Optimal Design of Experiments approaches to stress tests have been proposed in works like [121,122]. These methods often require defining a target model and are based on the maximum likelihood function and Fisher information matrix. Other works dealing with step-stress tests for LEDs include [64,123], which proposes a progressive stress test using cumulative exposure and progressive temperature levels to estimate luminous flux first passage time.

4.3. Cyclic stress (CyS) test

Cyclic stress tests, involving power cycling and on/off cycles, subject solder joints to thermal and mechanical stresses. Industry standards like JESD22A104-B [3] are used for defining such experiments, especially in the lighting industry. Other standards exist, see e.g., [14,124,125]. Various studies have explored power cycling and thermal cycling for LEDs and microelectronics. For example, [126] investigated accelerated thermal aging of LEDs, while Magnien et al. [127] studied thermal resistance in LED modules. [128] investigated thermal fatigue life of Au80Sn20 eutectic and silver paste applying three driving currents and characterizing the thermal fatigue life of the die-attached materials according to the Coffin–Manson relationship. Electrical and optical fatigue in organic light-emitting diodes were investigated in,e.g., [129]. Machine learning-based lifetime prediction for solder joints was developed by Samavatian et al. [91]. Additionally, crack growth due to repeated temperature cycles and the effect of temperature/power cycling on visible crack formation and electromigration were studied [130,131].

4.4. On measurements and standard in the LED industry

LED aging factors can be measured using a large variety of metering techniques, for instance, monitoring physical quantities such as acoustic, chromatic, and thermal properties or electrical, thermal, vibrational and mechanical readings. Complementarily, high-definition imagery can support micro-crack detection in an offline monitoring set-up. Following, we present a list that exemplifies some of the technologies applied for LED reliability and durability analysis: Scanning acoustic microscopy (SAM), differential scanning calorimetry, dynamic mechanical analysis, thermogravimetric analyses, ultraviolet–visible, thermomechanical analysis [132], scanning acoustic microscopy (SAM), and scanning electron microscopy analyses X-ray imaging [133], Leakage current analysis [134], combined SAM and X-ray spectroscopy, environmental tests of vibration, reflectivity analyses [135], and photoelectron spectroscopy.

4.5. Summary of the reviewed accelerated life tests for LEDs

Tables 1 and 2 provide an overview of research articles on accelerated degradation experiments for LED reliability testing. While top-tier LEDs often exceed 100,000 h, lack of degradation data pose challenges for verifying PHM models and reducing epistemic uncertainty further. Conducting a reliability qualification test spanning over 100,000 h lacks practicality, as it would extend well beyond a decade before the LED could be qualified and introduced to the market. Hence, ATs are require to reduce epistemic uncertainty by collecting degradation data in shorter time (generally less than 10,000 h).

Table 1
Overview of stress test classified based on loading profile, stressors, the degradation indicator, and use of an optimal DoE approach.

Ref.	Load profile			Stressors			Aging factor			ODoE
	CS	SS	CyS	T	I_f	RH	ϕ	$\Delta uv'$	R_{th}	
[113]	✓	.	.	✓	✓	.	✓	.	.	.
[114]	✓	.	.	✓	✓	.	✓	✓	.	.
[115]	✓	.	.	✓	✓	✓	✓	.	.	.
[136]	✓	.	.	✓	✓	.	✓	.	.	✓
[45]	✓	.	.	✓	✓	.	✓	.	.	.
[116]	✓	.	.	✓	.	✓	✓	.	.	.
[137]	✓	.	.	✓	.	✓	✓	✓	.	.
[138]	✓	.	.	✓	.	✓	✓	.	.	.
[75]	✓	.	.	✓	.	.	✓	✓	.	.
[131]	✓	.	.	✓	.	.	.	✓	.	.
[139]	✓	.	.	✓	✓	.	✓	✓	.	.
[140]	✓	✓	.	✓	.	.	✓	.	.	.
[64]	✓	✓	.	✓	.	.	✓	.	.	.
[141]	.	✓	.	✓	.	.	✓	.	.	.
[119]	.	✓	.	✓	.	.	✓	.	.	.
[120]	.	✓	.	✓	.	.	✓	.	.	.
[121]	.	✓	.	✓	.	.	✓	.	.	✓
[142]	.	✓	.	✓	.	.	✓	.	.	✓
[143]	.	✓	.	✓	.	.	✓	.	.	.
[123]	.	✓	.	✓	.	.	✓	.	.	.
[127]	.	.	✓	✓	✓.	.	.	.	✓	.
[126]	.	.	✓	✓	✓	.	✓	.	.	.
[128]	.	.	✓	✓	.	.	.	.	✓	.
[129]	.	.	✓	✓	✓	.	.	✓	.	.
[91]	.	.	✓	✓	.	.	.	.	.	.

Works on ATs are categorized in this paper based on stress profiles (CS, SS, Cys), stressors (temperature, current, humidity), degradation indicators (flux, color shift, thermal resistance), and consideration of availability of optimal DoE approaches. Notice that most studies focus on constant-stress or step-stress tests, with flux depreciation and temperature as primary degradation and accelerating factors. Limited exploration of cyclic stress testing and minimal consideration of humidity effects are observed. Notably, many works do not employ statistically optimal experimental designs, presenting an area for improvement in future LED reliability testing and PHM research. Addressing interactions between stressors is crucial, as factors like temperature and current dependencies impact LED device degradation, requiring accurate predictions for enhanced reliability and product design.

5. Epistemic uncertainty reduction via optimized testing

Optimal test design is paramount to providing good-quality data, reducing uncertainty and, in turn, enhancing the accuracy and reliability of PHM models and predictions. It enables the development of improved explanatory models, capable of describing causal relationships between, e.g., the occurrence of failures and degradation and the role of LED features and external stressors. However, testing LEDs under different stress conditions may require a substantial effort given the number of possible combinations. Typically, experiments are designed by domain experts who select multiple combinations of explanatory variables (such as LED features and stressors) based on their perceived significance in elucidating the variability observed in a dependent measured quantity. Additionally, feasibility constraints, such as maximum test duration, sample size limitations, or budgetary/physical restrictions, are implicitly or explicitly considered. However, experimental designs solely relying on expert opinion may result in suboptimal resource utilization, leading to sampling biases toward specific factors perceived as the most critical ones [144]. Consequently, such biases may give rise to exorbitantly expensive experiments, inaccurate or misguided

Table 2
Physics-of-Failure (PoF), Data-drive (DD), and Hybrid PHM models categorized based on the experiment type, e.g., experimental degradation or simulated experiment, the device analyzed, the number of samples and the number of acceleration levels (stressors combinations).

	N levels	Samples	Experiment	Duration	Device	PHM	Models
[45]	3	30	Experim.	6000 [h]	LED lamps	Hybrid	Exp. decay and Arrhenius
[64]	2	20	Experim.	500 [h]	LED packages	DD	Wiener/Brownian process
[75]	1	1	Exp. and Sim.	3000 [h]	LED lamps	Hybrid	Bayesian calibration
[91]	18	–	Sim. FEM	1000 [h]	Solder joints	Hybrid	Neural network
[113]	4	15	Experim.	5000 [h]	LEDs bars	DD	Nonlin. Rand. Coef.
[114]	–	4	Experim.	2500 [h]	3 HP-LED	PoF	Arrhenius and TTF
[115]	7	15	Experim.	507 [h]	AlGaInP LEDs	Hybrid	Weibull and Peck
[116]	4	–	Experim.	1200 [h]	LED modules	Hybrid	Weibull and Peck model
[119]	3	5	Sim. Multi-Physics	2000 [h]	LED bulb	PoF	Exp. decay and Arrhenius
[120]	3	8	Experim.	1258 [h]	LED lamps	PoF	Exp. decay and Arrhenius
[121]	5	22	Simulated	9118 [h]	LED lamps	DD	Wiener process
[123]	5	15	Simulated	9118 [h]	LED module	DD	Wiener/Brownian process
[126]	5	16	Experim.	20 [k-cycles]	LED module	PB	Structure fun./fatigue
[127]	4	1	Experim.	18 [k-cycles]	Blue flip-chip LEDs	PoF	Thermal impedance model
[128]	3	5	Experim.	120 [h]	HP-LED	PB	Fatigue Coffin–Manson
[129]	4	20	Experim.	473 [h]	Organic LED	PoF	Fatigue model
[131]	8	4	Experim.	8665 [h]	HP LED	PoF	Blacks model
[136]	9	1	Experim.	2500 [h]	Organic LED	DD	Parametric L1 with interactions
[137]	3	20	Experim.	2000 [h]	LED devices	Hybrid	Wiener process
[138]	5	7–14	Experim.	528 [h]	AlGainP LEDs	Hybrid	Peck and Arrhenius model
[140]	4	9	Experim.	2000 [h]	LED Lamp-cup Bulb	Hybrid	Weibull/Log-Norm
[141]	3	10	Experim.	1050 [h]	LED lamps	Hybrid	Weibull and Arrhenius
[142]	10	30	Simulated	Optimized	LED generic	DD	Stochastic diffusion process
[143]	3	68	Simulation	3500 [h]	Organic LED	DD	Generalized linear mixed model
[139]	4	4	Experim.	6000 [h]	COB Module	PoF	Arrhenius model

conclusions regarding variable importance and possible interactions between variables, or the presence of nonlinearity within the process, thereby severely compromising the validity of the obtained results.

The theory of Design of Experiments provides a comprehensive framework comprising formal methods to investigate these intricate relationships (see e.g., [145,146] for textbook overviews). In [147], simulation-based results of more than 30 different DoE methods are compared to a full-factorial design, used as the reference ground truth, for their ability to characterize complex systems and processes. A decision tree chart for DoE selection is proposed and the considered DoE protocols include screening methods such as the fraction factorial and Plackett–Burman designs and optimization designs such as the Central Composite Designs, Box–Behnken designs, and Taguchi designs. The uncertainty is reduced by selecting controllable factors and sample sizes and with a model summarizing the expert opinions on the relationship between controllable factors, uncontrollable factors, and dependent variables. The DOE techniques were originally developed in an agricultural context in the 1920's and later further developed in an industrial context. The first application in reliability is [148]. The well-known reliability monographs [149,150] include treatments of DoE in the context of reliability. These classical DOE methods use saturated first-order and second-order linear models and assume a regular experimental region. For situations in which these assumptions do not apply such as when resources are limited or when hard constraints must be imposed on the experiment (due to limited budget, time, or physical limitations), more sophisticated methods have been developed. For instance, if the experimental region does not have a regular shape, if the number of experiments chosen by a classical design is too large, or if the studied models deviate from the usual first or second-order ones.

So-called Optimal Design of Experiments (ODoE) methods seek a statistically optimal experimental setup that maximizes the use of available resources and minimizes the uncertainty in the parameters or predictions of a statistical model. This results in models with better statistical power, reduced bias in the estimates of the model parameters, and generally higher accuracy and generalization. The mathematical theory behind ODoE is much more involved than classical DoE, but see e.g., [151] for a tutorial and [152,153] for accessible textbook introductions to ODoE. The Fisher information is often used to define optimality criteria for ODoE. Once the statistical criterion has been optimized, the resulting design minimizes the uncertainty in the model's predictions and parameters. Metrics built from the information matrix minimize the uncertainty in the model parameters and predictions, hence better characterizing the process.

5.1. Maximum likelihood and Fisher information

Let us consider a data set $\mathcal{D} = \{\mathbf{x}_i, y_i\}_{i=1}^{n}$, and a parameter vector $\theta \in \mathbb{R}^{n_\theta}$ of a model $y = M(x;\theta)$ that must be estimated from $\mathcal{D}$, e.g., the parameter of a degradation model or a lifetime model. A well-established approach to estimate the parameters of the models is via the maximum likelihood estimator method, that is, an estimate $\hat{\theta}$ can be obtained from the available data by minimizing the log-likelihood as follows:

$$\hat{\theta} = \arg\max_{\theta\in\theta} \ \log \mathcal{L}(\theta|\mathcal{D}), \tag{15}$$

where $\log \mathcal{L}(\theta|\mathcal{D}) = \ln(\mathcal{L}(\theta|\mathcal{D}))$ is the logarithm of a likelihood function, e.g., $\mathcal{L}(\theta|\mathcal{D}) = \prod_{i=1}^{n} f(y_i|M(x_i;\theta))$. Once the parameters have been estimated, it is natural to ask what the level of epistemic uncertainty affecting $\hat{\theta}$ and the prediction accuracy of $M(x;\hat{\theta})$ for new data are. The epistemic uncertainty affecting $\hat{\theta}$ can be formally estimated using the variance–covariance matrix of the estimate or, equivalently, computing the Fisher information matrix. The Fisher information quantifies the information carried by a random variable X about the unknown model parameter θ to be quantified, e.g., the distribution parameters of a lifetime distribution $f_T(t;\theta)$, the fitting coefficients of a regression model and so on. Let $f(X;\theta)$ be the probability density/mass function (or probability mass function) for y for parameter vector θ. The Fisher information matrix is the expectation of the score function, i.e., the expected value of the partial derivative of the log-likelihood function with respect to θ:

$$\mathcal{I}(\theta) = \mathbb{E}\left[\left(\frac{\partial}{\partial\theta}\log\mathcal{L}(\theta)\right)^2\right] \tag{16}$$

where $\log \mathcal{L}(\theta) = \ln f(X;\theta)$ is the log-likelihood of the model with parameters θ. For twice differentiable log-likelihood functions and under certain regularity conditions, then the Fisher information may also be written as $\mathcal{I}(\theta) = -\mathbb{E}\left[\frac{\partial^2}{\partial^2\theta}\ln f(X;\theta)\right]$. For a vector of design parameters $\theta = (\theta_1, \theta_2, \ldots, \theta_{n_\theta})$ the Fisher information is a $n_\theta \times n_\theta$ matrix defined as follows, $[\mathcal{I}(\theta)]_{i,j} = -\mathbb{E}\left[\frac{\partial^2}{\partial\theta_i\partial\theta_j} \ \ln f(X;\theta)\right]$, where the

indices of rows and columns are indicated by the subscript i and j, respectively. The observed information for a parameter estimator $\hat{\theta}$ is given by $\mathcal{J}(\hat{\theta}) = -\nabla\nabla^{\top} \log \mathcal{L}(\theta)|_{\theta=\hat{\theta}} = -H(\log \mathcal{L}(\hat{\theta}))$, and H is the Hessian matrix of the log-likelihood function. The Fisher information matrix is the expectation of the observed information:

$$\mathcal{I}(\theta) = \int_{\mathbb{R}} \mathcal{J}(\hat{\theta}) f(x;\theta) dx = \mathbb{E}_x[-H(\log \mathcal{L}(\theta))].$$

Also, note that in two independent experiments indexed as e_1 and e_2, the Fisher information matrix enjoys additivity, $\mathcal{I}_{e1,e2} = \mathcal{I}_{e1} + \mathcal{I}_{e2}$. Clearly, since the Cramèr–Rao bound ensures the Fisher information defines a lower bound on the variance of an unbiased estimator of the model parameter $var(\hat{\theta}) \geq \frac{1}{\mathcal{I}(\theta)}$, information fusion from independent experiments can provide a clear benefit in terms of model uncertainty reduction.

5.2. Optimization problem and optimality criterion

We define a candidate design as $\zeta = \{\mathbf{x}_i, \omega_i\}_{i=1}^{n_e}$, where $\mathbf{x} \in \mathcal{X} \subset \mathbb{R}^{n_x}$ are n_x-dimensional vectors of controllable experimental factors in a support space $\mathcal{X}$ and ω are weights associated with n_e experimental conditions. Experimental factors and their space, $\mathcal{X}$, are generally defined based on various constraints, e.g., budget constraints, physical constraints, and other techno-economical considerations. The weight ω defines the percentage of samples that must be allocated on $\mathbf{x}_i$ and is generally proportional to the available resources and budget. Then the total number of distinct experiments is denoted with n_e whilst the total number of samples with n, such that $\sum_{i=1}^{n_e} n\omega_i = n$, $0 < \omega_i \leq 1$ for all $i = 1,\dots,n_e$, and $\sum_{i=1}^{n_e} \omega_i = 1$. The goal of ODoE methods is to identify an optimal experimental setup that maximizes the statistical information conveyed by the data. Mathematically, ODoE seeks an optimal ζ via the following minimization problem:

$$\zeta^{\star} = \arg\min_{\zeta \in \Psi} \gamma(\mathcal{I}(\zeta,\theta)), \quad \text{subject to} \sum_{i=1}^{n_e} \omega_i = 1, \quad 0 \leq \omega_i, \ \forall i \tag{17}$$

where $\Psi = \mathcal{X} \times [0,1]^{n_e}$ is the set of candidate experimental designs, $\zeta^{\star}$ is the optimized design, and $\gamma(\cdot)$ is a scalar transformation on the Fisher information matrix that defined the objective function, i.e., a so-called optimality criterion. We will discuss different options for the criteria $\gamma(\cdot)$ next.

A decision rule serves as a guide for optimizing an experiment, aligning with its purpose and the analyst's expectations. Various criteria exist in the literature, typically based on statistical indicators derived from the information matrix or the variance–covariance matrix of θ (the inverse of the information matrix). Table 3 provides a succinct overview of some widely-used metrics and their interpretations. For instance, the A- and D-optimality criteria aim to minimize the trace and determinant of the inverse information matrix, respectively. Where the A-optimality reduces the average variance of parameter estimates by minimizing the trace and D-optimality minimizes the overall "size" of the Fisher information,i.e., minimizing the model uncertainty as the volume of the confidence ellipsoid centered around the θ estimate (proportional to the determinant). Note that, in full generality, the information matrix $\mathcal{I}(\zeta,\theta)$ has been assumed dependent on both the design of experiment ζ and a vector of model parameters θ. This is often the case for ODoE for nonlinear models, which are known to be optimal only locally, i.e., in correspondence of θ. For instance, we can denote by ζ_θ^D a design is ζ that is locally D-optimal in the sense that it minimizes the D criterion under the assumption that θ is the true model parameter.

Table 3
A summary of the commonly applied optimal metrics for ODoE.

Criteria name:	Objective $\min_{\zeta}$:	Interpretation. It minimizes:
A-optimal	$\mathbf{Tr}(\mathcal{I}(\zeta;\theta)^{-1})$	the average variance of the estimator
C-optimal	$\mathbf{c}^T \mathcal{I}(\zeta;\theta)^{-1}\mathbf{c}$	the variance of a linear combination of θ
D-optimal	$\mathbf{Det}(\mathcal{I}(\zeta;\theta)^{-1})$	the volume of the ellipsoidal confidence region
E-optimal	$\lambda_{max}(\mathcal{I}(\zeta;\theta)^{-1})$	the diameter of the confidence ellipsoid
G-optimal	$\max_{X\in\mathcal{X}} \mathbf{x}^T \mathcal{I}^{-1}(\zeta;\theta)\mathbf{x}$	the maximum variance of the estimator

5.3. Optimal designs for reliability tests

There is a growing literature on ODoE methods for reliability testing in general and LED testing in particular. [142] tried to find an optimal design of step-stress accelerated degradation tests with multiple stresses and multiple degradation measures. In step-stress accelerated degradation tests, the testing units are tested for a time t_i for a certain stress condition S_i, next the stress level is changed to S_{i+1} and the unit is tested for a time of t_{i+1}. The objective was to find a design plan, such that the prediction accuracy is optimized while minimizing the costs. They provide a simulation-based approach to finding the optimal design [154] found D-optimal designs for lifetime experiments with exponential distribution and censoring. The case where products fail according to an exponential distribution was examined, and the products were tested for a fixed time. It is important to note that the set of products either failed or did not, so no degradation process was considered. [155] discuss the D-optimal design of accelerated life tests with two stress factors and their interaction. A general method was proposed that could be extended to more than two stresses. The maximum likelihood estimator and the expected Fisher information matrix were used to minimize the variance of the predicted variables. Minimizing the determinant of the Fisher matrix minimizes the variance of the model parameters. [156] discuss optimal step-stress ALT plans for exponentially distributed lifetimes in which stresses are not changed simultaneously but at a fine rate. The optimality criterion is the variance of the logarithm of the mean life time. [121] derive optimal step-stress plans for several optimality criteria when the degradation process is assumed to be a Wiener process. In many cases, simulations in previous research indicated that the optimal plans are relatively simple in the sense that they only use minimum and maximum stress levels. This is confirmed by performing a formal analysis. [122] study optimal step-stress designs for generalized Wiener processes in order to allow features such as nonlinearity and item-to-item variability. The optimality criterion is a combination of the asymptotic variance of the mean and variance of lifetimes. [157] study optimal designs for nonlinear mixed effect models in which they optimize the quantile of the lifetime distribution, which is of great practical importance for tests in the spirit of LM-80 tests. [158] present a software package written in the statistical software R, which produces optimal designs for several of the optimality criteria discussed in Section 5.

6. Conclusions

This paper reviewed Prognostics and Health Management models, accelerated life testing and optimal experimental design for LEDs. This survey accelerated degradation tests for LED, focusing on constant-stress, step-stress, and cyclic-stress degradation methods. Albeit Optimal DoE can be particularly useful for accelerated testing since it can help quantify and reduce the uncertainty in the models used for PHM, these approaches are often not adopted in practice. By using a well-designed DoE, it is possible to systematically vary the factors that are most likely to influence the response variable, thereby enabling the identification of the key drivers affecting the reliability and degradation of the LEDs. Optimal DoE approaches can improve the PHM models significantly, reducing the uncertainty associated with the models and predicted lifetime. Additionally, DoE can help

optimize the AT test plan, reducing the testing time and the number of samples required with substantial economic benefits. Therefore, optimal DoE practices in accelerated testing can further enhance the reliability of PHM frameworks and lead to more cost-effective testing and monitoring strategies. Among the reviewed approaches for modeling accelerated degradation of LEDs, we noticed that (often), the combined effect of multiple aging factors neglected. Only one or two aging factors are considered simultaneously, often focusing on only one degradation indicator (where luminous flux depreciation is the most used). The duration of AT experiments rarely exceeds 10,000 h, and the lifetime of top-tier LED can extend way beyond 100,000 h (more than a decade). Hence, degradation data under normal conditions are generally unavailable, and this hampers the validation of models that translate relevant stressors observed in an 'accelerated' environment back to 'normal' operational conditions. In other words, there is an inherent lack of data usable to verify the functional map transforming a lifetime distribution from an accelerated stress domain back to a normal operational domain. Furthermore, because optimal DoE approaches are often not used, degradation data are collected agnostically from the used PHM model class. Neglecting the model during data collection may result in longer testing times, inefficient sampling, and ineffective usage of the available resources. Based on this, we argue there is significant room for improvement in the design and implementation of data collection strategies and PHM models for LEDs' lifetime prognosis. To conclude, further research is needed to address the limitations of the most commonly accelerated degradation tests for LED and PHM models. Therese is a need to prescribe more comprehensive data collection strategies and combine these strategies with pre-existing data, knowledge from experts, and cutting-edge PHM models with uncertainty quantification capabilities. These sophisticated PHM frameworks must account for various predictive models and possibly consider ensemble approaches, multiple degradation mechanisms, multiple aging indicators, and heterogeneous data sources. It is essential for the research in LED reliability to move beyond conventional metrics like flux and color, as they can lead to sampling inefficiencies and significant increases in testing times and experimental costs. Finally, model-based optimal DoE methods must be considered as they can reduce testing costs and minimize the epistemic uncertainty affecting prognostic models and LED lifetime predictions.

CRediT authorship contribution statement

Roberto Rocchetta: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation, Visualization. **Elisa Perrone:** Writing – review & editing, Resources. **Alexander Herzog:** Writing – review & editing, Resources. **Pierre Dersin:** Writing – review & editing. **Alessandro Di Bucchianico:** Writing – review & editing, Project administration, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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