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Overview of high-power LED life prediction algorithms

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Life prediction significantly influences the reliability of LED light sources. While high-power LED light sources theoretically offer a lifespan of up to 100,000 h, irreversible damage to components leads to light failure, substantially reducing their actual lifespan. Consequently, accurate life prediction is pivotal for manufacturers to cut costs and enhance economic efficiency. This necessity aligns with the interests of communities, governments, and consumers. Currently, the most extensively employed prediction methods are based on traditional physical models and data-driven approaches. The focal point of current research lies in realizing model fusion, presenting both a hotspot and a challenge. To elucidate the relationships, advantages, and disadvantages of different algorithms and establish the groundwork for LED life prediction algorithm development, this paper first introduces material properties and the light decay model of high-power LED light sources. Subsequently, it discusses the principles and methods of the physical model concerning light source reliability. The paper also presents a review and comparison of recent domestic and foreign light source life prediction models. Finally, it provides insights into the expected future development trends in life prediction.

KEYWORDS

high-power LED, optical decay, data-driven, life prediction, prediction models

1 Introduction

The pressing issue of carbon emissions has garnered attention globally because of the effects of urbanization and global warming on humanity. Data from the International Energy Agency reveals a staggering 15.6-fold increase in the world's annual carbon emissions over the 120-year period from 1900 to 2020 (Wang et al., 2023). Recognizing the urgency, countries advocate for a green and low-carbon economic development model to expedite the reduction of greenhouse gas emissions. Cities, being the focal point of human activity, are particularly vulnerable to climate change, making them pivotal in the strategy to diminish carbon emissions and address climate concerns. China's 14th Five-Year Plan concentrated efforts on building an ecological civilization, emphasizing carbon emissions reduction, pollution reduction, and the shift from quantitative to qualitative improvements in the ecological environment (Zhao et al., 2022). This strategic initiative aims to combat challenges posed by environmental pollution and achieve sustainable and high-quality economic development.

More than half of China's total national carbon dioxide emissions stem from thermal power generation, with lighting accounting for ~20% of this consumption and steadily rising to 40% over time (Petkovic et al., 2022). Aligned with the strategic goals of "carbon peak and carbon neutrality," the imperatives of energy conservation, emission reduction, and green development underscore the need to curtail lighting power consumption. This reduction is pivotal in attaining the ambitious "double carbon" goal. High-power LEDs, emerging as the premier green light source of the new generation, are gradually replacing conventional lighting sources due to their attributes of low power consumption, high light efficiency, brightness, and a minimal carbon footprint (Unión-Sánchez et al., 2022). Their widespread applications in both indoor and outdoor settings (Chang et al., 2012) underscore their importance, with the lifespan of LED light sources emerging as a critical factor in energy economy and environmental sustainability (Padmasali and Kini, 2020). However, despite advancements in technology, conventional statistical techniques such as least squares, maximum likelihood estimation, and polynomials persist in the rated life prediction of LED light sources. This approach involves constructing a probability model based on the computation of a physical statistical model, utilizing probability distribution to characterize data regularities for life prediction and light source analysis. Nevertheless, this method is ill-suited for scenarios with high-dimensional and nonlinear features due to stringent distribution requirements and high standards for data quality. Maximum likelihood estimation, influenced by assumptions about data distribution and extreme values, adds complexity, especially when applying the least squares method for linear regression of luminous flux. Estimating regression parameters for polynomials is imperative, as unpredictable changes in random parameters result in extended prediction times, low model efficiency, and diminished prediction accuracy. Consequently, comprehensive testing of accelerated aging life, immunity to electromagnetic interference, weather resistance, and other factors directly impacting the life of light sources is essential before conducting an in-depth analysis of LED life.

An array of life prediction algorithms has emerged in recent years, primarily classified into two categories: traditional prediction models and machine learning prediction models, all aimed at achieving accurate and efficient life prediction of LED light sources (Illuminating Engineering Society, 2015). Within this landscape, traditional algorithms (Shi et al., 2020; Zhang J. et al., 2022; Zhang and Zhang, 2023) rely on physical and mathematical models to attain predictions, exhibiting low accuracy and a straightforward model structure. In response to the shortcomings of individual models, a common strategy involves the use of multi-parameter degradation models, traditional physical models (Cai et al., 2021; Cui et al., 2022), regression models (Kang et al., 2020), Markov chain (Song et al., 2021; Dvorzak et al., 2022), Bayesian networks (Dvorzak et al., 2022), and other random probability methods. However, these methods often entail lengthy prediction times, intricate networks, and low efficiency. Machine learning, on the other hand, leverages extensive training data, utilizing the gradient descent method to minimize the loss function and obtain optimal model parameters for life prediction. Examples include the adaptive neuro-fuzzy inference system (ANFIS) (Kyak et al., 2021), long short-term memory network (LSTM) (Pugalenthi et al., 2021; Zhang L. J. et al., 2023), LSTM and multi-representation domain adaptation (LSTM-MRAN) (Lyu et al., 2022), width-based learning system and LSTM (B-LSTM) (Wang et al., 2022), multi-dimensional deep neural network (MDNN) (Yang et al., 2022), multi-neural network fusion (Kumari et al., 2021; Ma and Mao, 2021; Hu et al., 2023). In the realm of LED life prediction applications, machine learning stands out for its swift forecasting times, superior accuracy, and efficiency. Nonetheless, the machine learning network is not without its drawbacks, encompassing extended training times and over-computation, where the quality of training data and network architecture significantly impacts prediction accuracy.

In conclusion, the future trajectory points toward realizing LED light source life forecasting through the application of machine learning fusion algorithms. Much of the current literature focuses on LED packaging and drive life forecasting, facing challenges in data collection, high prediction costs, and infrequent prediction times due to excessive precision in considering influencing elements. Presently, the examined prediction techniques can materialize predictions derived from machine learning and statistical model dimensions, albeit with limitations in accuracy, generalization, and adaptation. To reduce the cost of light source life prediction, enhance precision and real-time functionality, and establish logical relationships between various algorithms, this work commences with an exploration of light decay impacting factors. Subsequently, the introduction covers light attenuation, reliability, and accelerated life models. The following section reviews conventional algorithms, Bayesian networks, and artificial neural network algorithms, emphasizing the development trend, particularly focusing on deep learning and model fusion algorithms. The final section encapsulates the advantages and drawbacks of various algorithms while outlining prospects for the implementation of quick, cost-effective, and highly accurate prediction algorithms from the perspectives of manufacturers, governments, and researchers.

2 Light decay model of the light source

The theoretical lifespan of an LED light source can extend up to one hundred thousand hours, yet the practical application life merely encompasses 30%-50% of this theoretical value. Examining the index analysis of light source reliability is crucial for conserving lighting power, mitigating environmental pollution and light pollution, and advancing the development of a national low-carbon economy (Pang and Cai, 2021). The light source life serves as a pivotal technical parameter for evaluating the reliability and quality of a light source, necessitating research into life prediction (Lee and Kim, 2021). Accelerated aging life tests demonstrate that factors such as temperature, humidity, and chemical corrosion induce light decay (Feuk et al., 2021), impacting the overall service life of the light source. Therefore, this chapter initiates by elucidating the influence of LED device materials on the light source's lifespan, delving into the characteristics of different devices, and encapsulating the future development trends. Ultimately, a mathematical model is formulated based on the principles of light source decay, establishing a robust theoretical foundation for subsequent life prediction algorithms.

2.1 Luminescence mechanism and materials of light source

The LED light source consists of several PN junctions. When subjected to a forward bias power supply, the holes in the P region collide with the electrons in the N region, generating energy to release light energy (Tsai et al., 2022). The material of the light source device significantly influences its performance.

(1) Traditional LED chips employ materials such as gallium phosphide (GaP), gallium aluminum arsenic (GaAlAs), gallium arsenide (GaAs), gallium nitride (GaN) (Kulkarni et al., 2023) and others. Defects in the PN junction, such as material quality and dislocation factors, result in issues like impurity ionization, excitation scattering, and lattice scattering (Lee et al., 2023). These problems lead to a sharp decline in internal quantum efficiency, significantly impacting the chip's lifespan. Chips commonly use structures like GaN, AlGaAs/GaAs quantum wells, quaternary AlGaInP/GaAs, InGaN/GaN (Li et al., 2023) periodic quantum wells. N-GaN chips, due to their small size, are prone to short circuits, diminishing high-temperature resistance and lifespan. AlGaAs/GaAs chips, using GaAs substrate, absorb light intensely, adversely affecting the light source's lifespan. GaN chips on sapphire substrates are widely adopted in various lighting applications, benefitting from high mechanical strength, easy processing, cleaning, mature technology, and stability. Future chip materials should address issues of poor reliability, high cost, and inadequate heat dissipation, aiming to enhance electrical efficiency and light extraction efficiency to minimize power consumption.

(2) Phosphor materials. Phosphor materials, crucial in addressing issues of light decay and color shift caused by phosphor heating (Zhang L. et al., 2023), significantly impact light source lifespan. Traditional phosphor materials often utilize blue chips to excite yellow phosphors (Baheti et al., 2023). While this method has mature technology and low cost, light sources using this material suffer from high color temperature, low color rendering index, and low luminous efficiency. Tricolor phosphors (red, green, and blue) excited by ultraviolet light chips are frequently employed for high luminous efficiency, uniform color, and luminosity distribution (Cheng et al., 2024). However, this material is highly sensitive to temperature changes. With the growing demand for white LEDs, scholars are increasingly focusing on graphite-like carbon nitride (g-C_3N_4) blue phosphors, which offer high chemical stability, moderate bandwidth, and no pollution (Maged et al., 2023). This material exhibits high light efficiency, thermal stability, and a prolonged light source life, marking it as a future research trend.

(3) Packaging materials. The transmittance and refractive index of LED packaging materials significantly impact the luminous efficiency and brightness of the light source. Additionally, their heat dissipation performance has a direct effect on the chip's temperature (Wan et al., 2023), thereby influencing the lifespan. Epoxy resin, favored for its low cost and high hardness, is widely used in light source packaging. However, its poor heat resistance makes it unsuitable for high-power light source packaging. Silicone materials, characterized by high transparency and heat resistance, find extensive use in high-power LED packaging (Chen et al., 2023). However, the material's low refractive index results in light source life loss. With the robust development of the new energy industry, the future trend involves the development of composite materials such as silicone, epoxy resin, with high refractive index, high transmittance, and anti-aging properties.

The performance of the LED light source material is shown in Table 1.

2.2 Light decay model of light source

Every light source undergoes varying degrees of light decay with prolonged use, leading to a reduction in luminous flux. Ultimately, this diminishes the brightness of the light source, making it insufficient or unsuitable for the entire product lifespan. As per LM-80 standards, the light source parameter is considered failed when the luminous flux drops to 70% (L70) or 50% (L50) of its initial value. Ornamental lighting is typically based on a 50% threshold, while ordinary lighting adheres to the 70% threshold.

LED light degradation is influenced by numerous factors, including structure, environmental conditions (corrosion), temperature, humidity, packing materials, packaging technology, and electrical parameters (current, voltage) (Cui et al., 2022). Regardless of the influencing element, the light output diminishes over time. As illustrated in Figure 1, the lumen curve is depicted, with the average value of the normalized light output from the LM-80 report forming the basis for the LED light source's light output data. This integrates LM-80 data, widely used in industry standards, and the prediction method specified by TM-21 to calculate the life value. The light flux attenuation rate begins at zero, gradually dropping as the light source ages. In other words, the lifetime Lp decreases to p% of the initial value when the luminous flux decreases to p% of its starting value. The light source is deemed faulty when the luminous flux falls to 70% of its initial value, marking the light source's life threshold according to LM-80. Hence, a crucial variable influencing the life forecast is the degree of light flux attenuation.

The mathematical models for luminous flux attenuation encompass the exponential model, three-parameter model, and empirical formula model. General lighting commonly employs the exponential model (Ke et al., 2023) and empirical model (Lyu et al., 2022), as depicted in Equation (1).

$$ø(t) = ø_0 e^{-at} \tag{1}$$

where $ø(t)$ represents the attenuated luminous flux value after the light source is ignited for time t. $ø_o$ denotes the initial luminous flux value, a is the attenuation coefficient of luminous flux, and t denotes the duration of the light source after ignition.

The blue light decay model aligns with the three-parameter model (Hoole et al., 2019; Zhang et al., 2019, 2020), as shown in Equation (2).

$$1 - \frac{øt}{ø_o} = aln(\frac{t}{t_o}) \tag{2}$$

where $ø(t)$ is the luminous flux value of ignition time t, $ø_o$ is the luminous flux value at time t_o, a is the fitting coefficient, as shown in Equation (3).

$$t_0 = A \times I_F^{-\beta} \tag{3}$$

TABLE 1 Summary of light source material properties.

Device	Application material	Performance characteristics	Development trend
Chip	GaN; AlGaAs/GaAs quantum wells; Quaternary AlGaInP/GaAs; InGaN/GaN periodic quantum wells	GaN crystal growth poses difficulties, with N-type susceptibility to short circuits and P-type facing challenges in achieving compatibility; The AlGaAs/GaAs quantum well chip encounters issues where the substrate significantly absorbs light. Additionally, the quaternary AlGaInP/GaAs chip exhibits low luminous efficiency and inadequate heat dissipation performance; For the InGaN/GaN chip, lattice dislocation and low internal quantum efficiency persist	Reduce the ohmic resistance and body resistance of the chip to improve the electrical efficiency; Perfect surface roughening and laser stripping technology; Research and development of thin film chips, photonic crystals, and AC chip technologies
Phosphor powder	YAG phosphor + blue light chip; The red-green-blue tricolor phosphor + Ultraviolet light chip; Composite phosphors	YAG phosphor presents challenges with high white color temperature, low color rendering index, and dazzling effects; Tricolor phosphors exhibit low white light efficiency; Composite phosphors, however, demonstrate good thermal stability.	Ongoing research involves the development of fluorescent glass, fluorescent film, and new fluorescent materials, aiming to address existing challenges and enhance overall performance
Packaging materials	Epoxy resin; Silicone; Silicone/Epoxy resin	High hardness, easy to aging; Good heat resistance, low refractive index; Good heat resistance, high refractive index	Research and development of epoxy resin composites; Research and Development of Silicone Composites and Nanocomposites

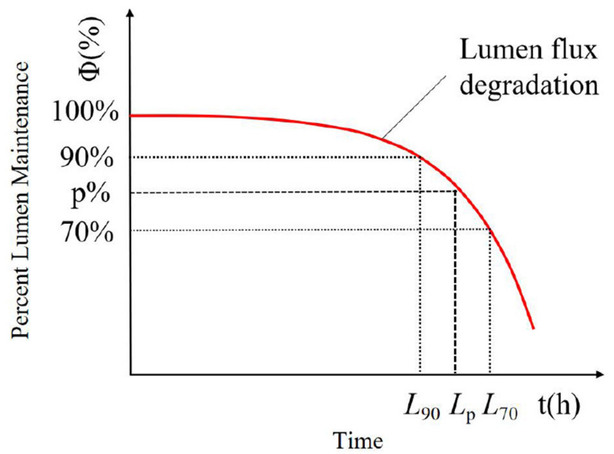

FIGURE 1
Lumen decay curve (Kyak et al., 2021).

where A and β are experimental coefficients, I_F is the current value when the time is t_F.

An empirical model of luminous flux attenuation was developed based on the following formula (4) (dos Santos et al., 2020):

$$\varnothing(t) = d_1 + jd_2 + j(d_3 + jd_4)ln(t) \quad (4)$$

where $\varnothing(t)$ represents the value of luminous flux at ignition time t, d_1, d_2, d_3 and d_4 are independent of current and time, j is the input current density, and t is the ignition time. Table 2 summarizes the advantages and disadvantages of the light decay models.

3 Light source model and discussion

The ability of a product to perform its designated functions within specified conditions and timeframes is termed reliability (Li F. et al., 2020). With each alteration to the required parameters, reliability diminishes until the product's performance reaches a point of failure. Failures can be categorized as either destructive or parameter-based (Liu W.-G. et al., 2020). Destructive failure leads to the product ceasing to function due to various causes, while parameter failure involves a decline in the product's performance index but continued operation. This study investigated parameter failure, specifically from the perspective of luminous flux L70 and light attenuation.

TABLE 2 Advantages and disadvantages of the light decay model.

Model classification	Defect	Merit
Exponential model	Low precision	Fewer parameters, easy to model
Three-parameter model	Interference between parameters	Simple model
Empirical model	Low precision	High fitting accuracy

3.1 Light source reliability model

After extensive statistical data analyses and calculations, commonly used reliability distribution models include the Index (Qin et al., 2022), Lognormal (Botev et al., 2019), Weibull (Ahmad and Ghazal, 2020; Albassam et al., 2023), and Gamma distribution (Iriarte et al., 2020; Ozonur and Paul, 2022). The characteristics of these reliability models are outlined in Table 3.

The graphical representations of these reliability distributions are depicted in Figure 2. To estimate the light source's lifetime, random variables are arranged in an exponential distribution (Kalita et al., 2023). Figure 2A illustrates that the exponential distribution, commonly used for characterizing the distribution of random variables related to "life," indicates that the probability

TABLE 3 Reliability model characteristics.

Model classification	Feature
Exponential distribution	The product accidentally fails and the failure rate is constant, with no memory
Lognormal distribution	The distribution curve always shows a right deviation, and there is a greater possibility of upward and smaller downward
Weibull distribution	The number of parameters is variable, and the specific situation can be changed into exponential, logarithmic normal, approximate normal, etc.
Gamma distribution	The distribution is skewed and features additivity and scalability. The value of parameter α is varied and can be turned into an exponential distribution

of random variables is solely tied to the time interval, not the starting point in time. This results in a considerable variance. This approach, popular in LED life prediction, considers only one or two influencing factor parameters, like temperature and current, making the model straightforward. The lognormal distribution (Leech et al., 2023), shown in Figure 2B, is chosen when considering the influence of time on the distribution. Due to independent expansions of random variables producing a multiplicative cumulative impact, this approach aligns with the data distribution of light source reliability, offering minimal prediction costs and broad applications. It is often applied to predict the life of LED light sources prone to stress failures, such as lead fracture, solder joint failure, and chemical corrosion. The Weibull distribution (Shama et al., 2023), a continuous probability distribution with roots in statistics, provides great flexibility and extensive applicability. Figure 2C displays the Weibull distribution probability density diagram, with $\beta = 1$ and α adjusted to various values, exhibiting characteristics resembling the logarithmic and exponential normal distributions when $\alpha \leq 1$, and resembling the γ distribution when $\alpha > 1.5$. This model depicts a reliability "bathtub" curve with three stages: early failure, random failure, and aging failure. However, its structure is more complex than that of the exponential and lognormal distributions. The γ distribution (Xu H. et al., 2022), another continuous probability function based on statistics, is depicted in Figure 2D. This method allows alterations to the shape and scale parameters, modifying the curve's height, width, and shape. When the shape parameter is 1, it approximates an exponential distribution. This model boasts high prediction accuracy, significant generalization capacity, and ease of adjustment in its parameters.

3.2 Accelerated life model of light source

The term "accelerated life" signifies the expedited aging process a product undergoes to approximate an extended lifespan. According to the LM-80 standard, an LED's lifespan is estimated to be around 10 years or nearly 6,000 hours. This method of accelerating aging to predict the life of light sources has gained recognition from governments, businesses, and researchers, currently serving as an industry testing standard. Commonly employed acceleration models, such as Arrhenius (Nohut, 2021), inverse power law (Ning et al., 2022), Eyring (Yang and Riggleman, 2022), and polynomials (Nandi, 2020). Arrhenius derives its life acceleration model from activation energy, focusing solely on thermal acceleration factors as the degradation stress. This model predominantly considers temperature as the degradation stress when estimating the lifespan of electrical devices. The inverse power law model, inversely related to the strength of degradation stress, predicts life by establishing a reciprocal power relationship that explains the deterioration of voltage, current, power, and other characteristics of the LED light source. The Eyring model employs a single temperature stress as an acceleration condition model, with the Generalized Eyring model being utilized when humidity or current stress characterizes the degrading product characteristics. To address the nonlinear relationship within a dataset, the polynomial model is frequently employed. Utilizing least squares and interpolation, this model fits the data set, and the resulting curves are used to project the LED light source's expected lifespan.

In addition to the aforementioned fundamental models, most recent accelerated life models are noteworthy. The Hallberg-Peck (Xiao-Dong et al., 2017) for predicting product life because it accounts for temperature and humidity. The Lawson model (Qinyan, 1990), a temperature and humidity acceleration model, is effective in predicting the shelf life of items where humidity is both the primary and supplemental factor. For military devices, MIL-HDBK-217 (Temsamani et al., 2017), a manual-based dependability prediction approach, effectively estimates product life, considering environmental factors, electrical stress, and temperature cycles. T-NT (Lee et al., 2010) is designed to predict product life under the combined effects of temperature stress and non-thermal stress, encompassing factors such as voltage, current, humidity, and pressure. The index model (Wang and Xian, 2021), following an exponential distribution, can predict the life of a random variable failure rate that is time-independent. The Coffin-Manson model (Gao et al., 2022), designed for products failing because of fatigue at varying temperatures, employs a temperature cycle impact acceleration model. Figure 3 displays the flow of the aforementioned four acceleration models.

3.3 Development status and review of prediction algorithms

3.3.1 Traditional model algorithm

The inception of life prediction algorithms marked the application of the least squares method, known for its superior fitting degree. To reduce test time and costs, Zhang et al. (2012) employed the lognormal function to portray LED lifespan distribution and utilized the least squares method (LSM) to compute lifetime values. Sun et al. (2018) integrated failure physics and reliability theory, applying the least squares approach to fitting data for forecasting LED life. Despite its high fitting precision, the least squares method is challenged by poor accuracy and a complex calculation process.

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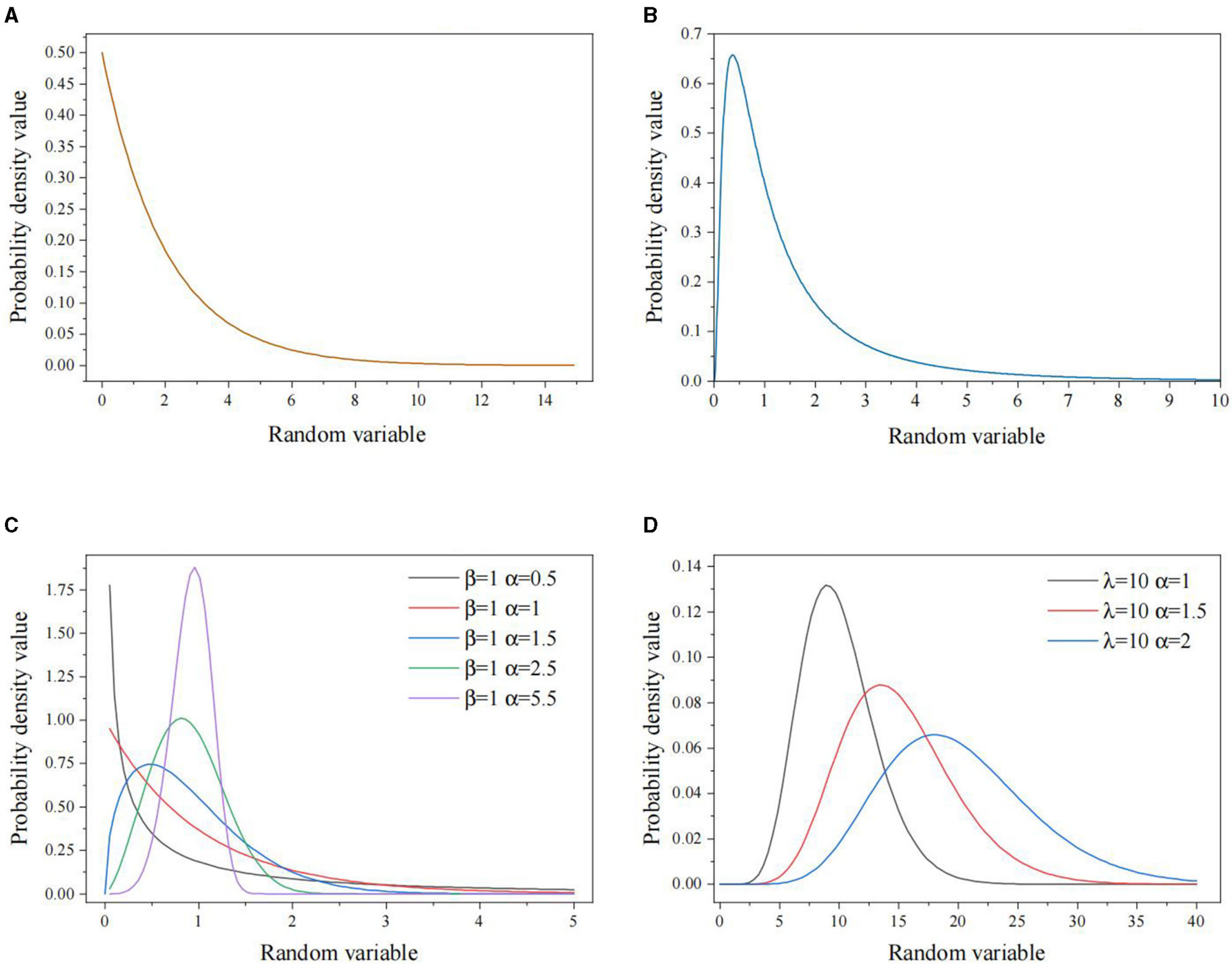

FIGURE 2
Distribution of four models. **(A)** Index distribution graph. **(B)** Lognormal distribution graph. **(C)** Weibull distribution graph. **(D)** Γ distribution graph.

The demand for parameter fitting and extrapolation under the least squares method contributes to low precision. To enhance prediction accuracy, the maximum likelihood estimation method, relying solely on parameter estimation and eliminating the need for extrapolation, is favored. Tsai et al. (2012) assessed life percentiles for life value determination, modeling LED deterioration through the Wiener process and employing the maximum likelihood estimation approach. Ibrahim et al. (2018) validated luminous flux degradation data through modeling and experimentation, utilizing the γ process for degradation characterization along with the maximum likelihood technique for parameter estimation. Evaluating luminous flux degradation and predicting light source lifetime, Ibrahim et al. (2019) combined the maximum likelihood estimation approach with gamma distribution degradation (GDD). Truong et al. (2022) introduced a stochastic difference equation (SDE) based on the self-heating (current stress) phenomenon and maximum likelihood estimate (MLC). The rate of LED light source deterioration is influenced by various factors, with linear regression often falling short due to its neglect of minor effect parameters. Nonlinear regression emerges as a more accurate alternative.

Nonlinear regression algorithms for life prediction frequently incorporate model combinations. Zhang et al. (2016) devised the Weibull-approximated luminous flux attenuation model (WRALDM) for forecasting, highlighting the three-parameter Weibull function's superior accuracy over the single-parameter version. Fan et al. (2021) integrated the accelerated life model with the γ process of random components. They demonstrated that the γ process had more accuracy for light decay and that the least squares regression (LSR) had higher accuracy for color shift degradation when used to characterize the degradation. Tan et al. (2021) compared the Eyring and Black models for accelerated life prediction, finding the Eyring model to offer optimal forecast accuracy and consistency when utilizing temperature and current as degrading stresses. While traditional nonlinear regression surpasses linear regression in accuracy, its complexity leads to more intricate computations and diminished accuracy. The typical linear model, with its poor fitting processing impact and low prediction accuracy due to the significant nonlinear relationship between independent and dependent variables in the LED life prediction model, contrasts with the nonlinear model. Founded

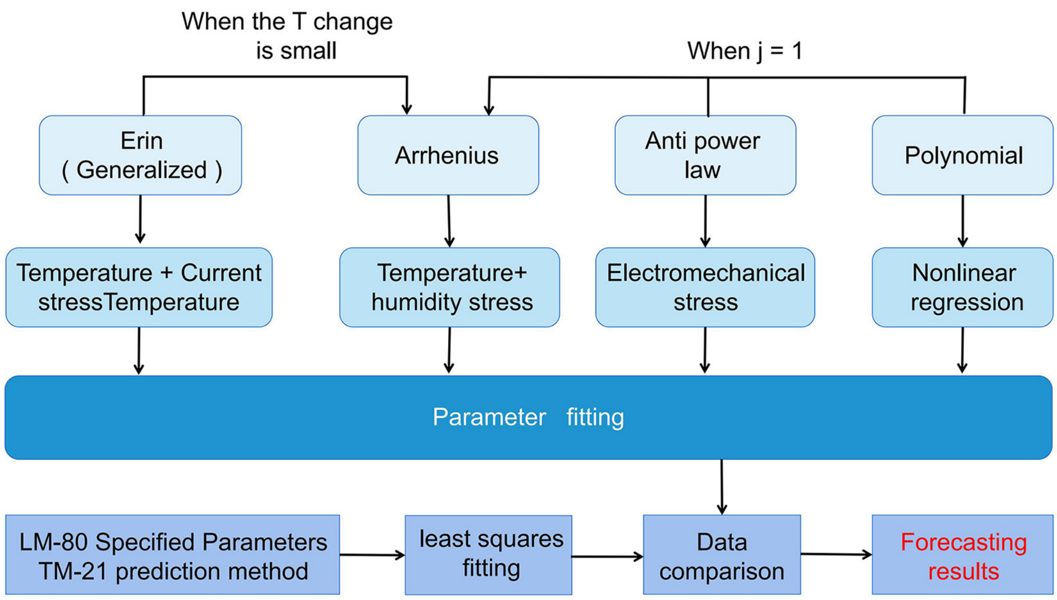

FIGURE 3
Life prediction model transformation flow chart.

on a substantial dataset and established through a mathematical statistics approach, the nonlinear regression prediction model is better suited for LED life prediction, offering high precision, efficiency, and robust generalization capabilities.

3.3.2 Filtering network

The Bayesian network, known for its ease of modeling and practical utility, proves adaptable to multivariate data. Pan and Balakrishnan (2011) employ the γ process, linking it with degradation information and assuming two associated performance characteristics for the product. Bayesian parameter estimation is then utilized to estimate the life value. Ibrahim et al. (2021) predict the lifespan of a lamp system through a Bayesian network (BN), incorporating the γ process and the Weibull distribution. Their analysis demonstrates that as the lamp system diminishes in size, the luminous flux is affected by the light source, driver, diffuser, and reflector. Before constructing the static Bayesian network, knowledge of the probability between states is crucial. Otherwise, significant parameter errors arise, making the network architecture more intricate and less efficient. The addition of a temporal component through dynamic Bayesian network incorporation addresses this challenge, enhancing predictive accuracy by considering temporal changes that align the degradation curve more closely with the actual light source degradation. Lall and Wei (2015) utilize a linear system Kalman filter (KF) and a nonlinear system extended Kalman filter (EKF) for LED life prediction. Investigating chromaticity variations of white LEDs, Fan et al. (2014a) employ data-driven techniques. The recursive nonlinear filter, specifically the unscented Kalman filter, more accurately acquires chromaticity state than the data extrapolation fitting state of the nonlinear least squares method. Accuracy in simulation results requires consideration of temperature stress influence and the incorporation of two noises during initialization to prevent forecast accuracy skewing.

Fan et al. (2014b) utilized the nonlinear filter, specifically the recursive unscented Kalman filter method, to predict the LED lumen maintenance rate based on data. The inferred lifetime demonstrated higher accuracy than the least squares regression method of TM-21. Padmasali and Kini (2017) estimated the EKF of the true state recursive algorithm based on noise measurements to predict the L70 life of LEDs. Trung et al. (2018) illustrated the accuracy and superiority of expectation maximization (EM) (real-time or offline) by predicting the lifetime of LEDs using the EM technique in conjunction with parameter values derived via Kalman smoothing. As a single stress is more likely to be the light source degradation component, collecting light source degradation data necessitates discrete input data. Simultaneously, the accuracy of life prediction will be impacted by the nonlinear transition of the system into linearity. The accuracy of the Kalman filter, based on KF, EKF, and UKF, varies from poor to high. The primary applications for the Kalman filter are the Gaussian noise probability model and linear systems, rendering it inappropriate for nonlinear and non-Gaussian filtering models.

The particle filter excels with non-Gaussian and non-linear noise models, utilizing certain known data to forecast future data. It is a Bayesian filtering algorithm that approximates using the Monte Carlo method, which relies on discrete samples of the posterior probability distribution. To forecast the lumen maintenance life of LEDs, Fan et al. (2015) developed a nonlinear filtering prediction approach based on Sequential Monte Carlo (SMC) and Bayesian dynamic recursive particle filter (PF). Investigating the remaining useful life (RUL) of airport ground lighting (AGL), Ruknudeen and Asokan (2017) employed PF and onboard diagnostics to determine L70. Enayati et al. (2021) devised a probability density function (PDF) for LED life prediction using the Monte Carlo algorithm (MC) and Nonlinear Kalman filter (IEKF). However, this approach requires advance estimating (preliminary assumptions), which proves counterproductive for identifying new products, and involves a significant amount of computation, making it impractical for online real-time monitoring.

3.3.3 Neural network

With the rapid advancement of artificial intelligence, the research and development of nanogenerators (Yang et al., 2023; Yu X. et al., 2023), new sensors (Lan, 2023), new energy batteries (Yu M. et al., 2023) and other devices have promoted and other devices have propelled the growth of intelligent production and smart living. This progress further supports national initiatives for low-carbon emission reduction (Zhou et al., 2024) and the green economy. Within this context, innovations in LED light source devices and materials continue to emerge, and the parameters associated with LED light sources are intricate and random. The conventional life prediction methods based on accelerated aging tests impose stringent requirements on environmental conditions. In practical applications, high-power light sources encounter random and uncertain conditions such as temperature and humidity, leading to decreased accuracy and poor generalization of prediction results. As artificial intelligence and deep learning continue to evolve, neural networks have expanded beyond image processing to include life prediction. The model's principle is depicted in Figure 4. The network input comprises parameters related to the light source device and the application environment, and an adaptive prediction model based on artificial neuron connections is obtained through model training. By inputting parameter data from the light source under testing, adaptive life prediction results can be derived. Consequently, the prediction model is no longer confined by application environment or material type conditions. Due to its high prediction accuracy, fast operation speed, robust generalization ability, and potent nonlinear fitting capabilities, scholars widely employ neural networks in recent years.

3.3.3.1 Single neural network

An artificial neural network (ANN), composed of numerous neurons, represents an algorithmic model for distributed parallel information processing grounded in statistical mathematics. Several successful examples in LED life prediction involve the application of neural networks such as LSTM (Jing et al., 2020), ANFIS (Kyak et al., 2021), and Recurrent neural network (RNN) (Yuan et al., 2021).

Kyak et al. (2021) achieved a nonlinear and highly precise LED light source life prediction approach by constructing a database with 6,000 hours of standard data using an Adaptive Neuro-Fuzzy Inference System (ANFIS). Examples illustrate the effectiveness of the hybrid learning algorithm model in the realm of nonlinear LED life prediction, combining fuzzy logic with artificial neural networks. Liu et al. (2019) employed a Lifetime Neural Network (Lifetime ANN), a finite element approach, and a photoelectric thermal neural network (PETANN). This methodology reduces the time required for system life prediction, enhances prediction accuracy, and obviates the need for repetitive PET testing and life calculations through neural network training. The nonlinear challenge of LED life prediction is effectively addressed by ANFIS, amalgamating the successful classification performance of neural networks with the flexible adaptation of fuzzy logic.

Jing et al. (2020) predicted the UV LED life using a Long Short-Term Memory (LSTM). It is evident that, on average, the prediction accuracy of the LSTM neural network surpasses that of NLS regression fitting by 29.7%. Employing the Harris hawks optimization (HHO) algorithm and LSTM recurrent neural networks (RNNs), Ma et al. (2023) realized the life prediction of supercapacitors with a small root mean square error. Yuan et al. (2021) devised a gated network with a two-step learning algorithm to accelerate the learning process. They also established a correlation between the thermal aging load and the luminous output of LED products to achieve the prediction goal. The recombination of the gated network with most neural networks is possible due to its exceptional flexibility and compatibility. This study underscores the benefits of the gated neural network, including easy convergence, high prediction accuracy, flexible algorithm integration, and substantial practical value, in comparison to the outcomes of artificial neural networks, RNNs, and LSTM. By contrasting the statistical approach with the artificial neural network, Zippelius et al. (2020) successfully forecasted defects using transient thermal analysis (TTA) data of LED solder connections in a temperature shock test. The experimental findings highlight the value and enhanced accuracy of LSTM-ANN. The LSTM-ANN network and statistical technique prove to be more flexible and practical, providing higher accuracy in point prediction and step length prediction compared to the 0.025 thresholds in the curve diagram and intersection point.

To impart the model with a memory function, the gated neural network utilizes the architecture of an output, updating, and forgetting gate. By sharing weights, the issue of gradient disappearance is resolved, resulting in less training process instability and faster model training. The advantages of this method include its minimal prediction error, good compatibility, and flexible use. Based on recurrent neural networks, LSTM addresses the issues of gradient explosion and disappearance, which is advantageous for extracting time series features, reducing the model's parameter count, enhancing the model's capacity for generalization, and improving the accuracy of life prediction.

3.3.3.2 Model fusion network

The structure of a single neural network departs significantly from expectations and suffers from an excessively extended training period due to the absence of original data, dispersion, and data normalization. To address these drawbacks, the model fusion network, primarily categorized into two schemes—combining a classical physical model with a neural network and fusing several neural networks—emerges as a solution. The future development trend in the field of life prediction revolves around the amalgamation of multiple neural networks to enhance prediction accuracy and feature expression capabilities.

(1) Physical-neural network

The classic physical model, relying on a single algorithm, faces challenges in achieving prediction accuracy and time demands in real-world scenarios. The inherent advantages of the neural

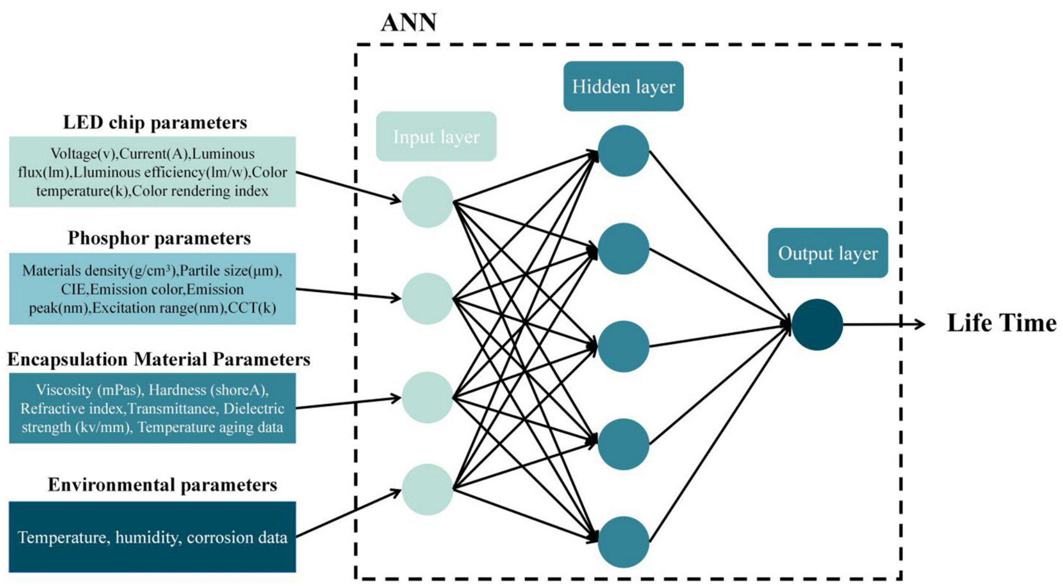

FIGURE 4
Neural network prediction model diagram.

network can compensate for these shortcomings, especially given the vast degradation data of the classic model that aligns with the needs of neural network applications. Integrating these two approaches enhances their respective strengths, and this heterogeneous integration approach has found success in the field of life prediction.

Pugalenthi et al. (2021) implemented the particle filter technique to refine model parameters and predict the remaining usable life of LEDs using the hybrid model (HyA) of Particle Filter (PF) and Neural Network (NN). The particle filter, a nonlinear filter utilizing a weighted particle approximation state, is based on the sequential Monte Carlo approach. It updates the degradation model's parameters recursively through weighted particle degradation model propagation, forecasting the state based on the time before the system reaches the failure threshold. Combining the neural network (NN) and particle filter (PF) methods, the Hybrid Particle Filter Training Neural Network Framework (HYA) is optimized. The prediction results show that HYA outperforms conventional single prediction models in LED life prediction, showcasing improved convergence and faster speed. Lu et al. (2017) introduced the ADAOST iterative method, integrating predictions from weak BP neural networks. The adaptive improved model of the ADAOST algorithm is compared with the traditional (BP-NN), revealing that the enhanced BP-NN optimizes the local optimum and over-fitting when compared to the conventional BP-NN model. Zhang J. S. et al. (2023) introduced a novel parallel hybrid neural network technique based on spatial and temporal information, consisting of a bidirectional gated recurrent unit (BiGRU) and a deep convolutional neural network (DCNN). The results demonstrate higher prediction accuracy. Yang et al. (2021) coupled the data-driven Ada-MEA-GRNN model of the enhanced AdaBoost algorithm with the MEA-GRNN network of generalized regression neural network (GRNN) and mind evolutionary algorithm (MEA), showing high precision and lower overall error compared to GRNN and other BP neural network models. Cao et al. (2020) merged the two techniques using temperature and current as inputs, showing through histograms and tables that the GA-BP network is somewhat more accurate and stable than the BP network.

Through the manipulation of parameters such as weight, bias coefficient, and threshold in time, space, or efficiency, the fusion of the physical model and the neural network suitably configures the model. This effectively prevents overfitting, bringing the fusion model closer to the true value throughout the prediction process. The resulting model exhibits high prediction accuracy, good generalization capacity, and ease of convergence.

(2) Multi-neural network fusion

Within machine learning methods, the neural network stands out as a potent learning algorithm. However, inherent structural and operational principles pose challenges in a single network, including difficulty in feature extraction, managing the number of hidden layer nodes, convergence issues, limited user communication, and information loss. To overcome these limitations, a powerful joint network algorithm is devised through the combination of multiple neural networks. Each network leverages its strengths within the fusion algorithm, contributing to its optimal capabilities. Various techniques of neural network fusion have demonstrated superior performance in real-world applications, particularly in LED life prediction. The advantages of these algorithms include high prediction accuracy, reduced learning times, and stable networks.

Da Costa et al. (2020) employed a fused long-term and short-term neural network (LSTM-DANN) model, training the domain invariant function of an adversarial neural network (DANN), to forecast the Remaining Useful Life (RUL) in the target domain. The outcomes validate the efficacy of this approach. For laser remaining usable life prediction, Abdelli et al. (2021) introduced a novel hybrid model (CNN-LSTM) by merging a Convolutional Neural Network (CNN), adept at extracting local spatial characteristics, with two parallel Long Short-Term Memory (LSTM) models suitable for capturing sequential data dependence. This composite model outperforms numerous machine learning models, including Support Vector Regression (SVR), Random Forest (RF), Multi-Layer Perceptron (MLP), CNN, and LSTM, projecting values extremely close to the true RUL. Keshun et al. (2023) utilized a three-dimensional enhanced hybrid neural network comprised of CNN and BILSTM. This hybrid model offers strong resilience, generalization, interpretability, and practicability. Using a hybrid kNN and FNN technique, Yuan (2021) integrated SSL lamps under various degradation processes to create a dataset. The kNN + FNN model demonstrated better prediction accuracy, accelerated convergence, and avoided over-fitting compared to kNN alone. ANNS and SNNS models were amalgamated into a multi-scale, multi-domain HNNS framework by Zhao R. et al. (2022). This fusion avoids the drawbacks of complex, inefficient, and unmanageable direct coupling hybrid structures, fully capitalizing on the benefits of a single model, enhancing adaptability, and expanding the model's scope of use.

A symbol of societal progress is lighting, and by extending the light source's lifespan, users replace them less frequently, leading to reduced material usage in light source production and the prevention of the release of toxic compounds that are challenging to break down. Hence, both domestic and international academics express significant interest in light source life forecasting. Meeting societal, governmental, and consumer demands, a higher forecast accuracy and faster prediction times would aid manufacturers in cost reduction and improving light efficiency, yielding other economic benefits. In the face of evolving technologies like machine learning, simple models like linear or regression cannot adequately characterize the deterioration process of some LED light sources, failing to meet consumer expectations. In response, an innovative life prediction model with exceptional accuracy, robust real-time performance, and extensive generalization ability is continually evolving. The combination of several models synergizes various techniques, preventing the model from reaching a local maximum. Considering time, space, and other dimensions significantly enhances the efficiency, training speed, generalization capacity, and prediction accuracy of the fusion method. In conclusion, Table 4 presents a comparative analysis of commonly used life prediction algorithms with accelerated stress and benefits from recent years.

3.4 Prediction algorithm summary

The landscape of prediction algorithms encompasses model fusion and various complex types, creating challenges in comprehending the logical connections between these algorithms. To elucidate the inclusion relationships among these algorithms, Figure 5 illustrates a concept map structure classification of diverse prediction algorithms (Sun et al., 2017).

The widely adopted TM-21 standard serves as a foundational framework for many manufacturers and researchers. It outlines the least squares regression prediction approach, initially employed in LED life prediction. This technique relies on the linear correlation between luminous flux and the temporal variable. The computation is straightforward and precisely fits the parameter curve. However, the application of the least squares approach is constrained, as the predominant components contributing to the LED light decay process exhibit nonlinearity.

Maximum likelihood estimation (Lu et al., 2017) is implemented based on statistical techniques to maximize the probability of parameter occurrence within the correlation probability density function of the sample set. This algorithm surpasses the least squares approach by accommodating nonlinear relationships. However, the computation complexity increases, and significant inaccuracies arise when dealing with discrete distribution data and limited data volume. The exponential model posits that luminous flux follows an exponential distribution over time. Represented by the exponential distribution function (Xu L.-H. et al., 2022), this memoryless continuous probability distribution exhibits rapid convergence and a straightforward structure, making it widely utilized. However, due to its lack of memory, prediction accuracy is compromised by solely considering the time interval.

The time series probability model is articulated through a Bayesian network known as a dynamic Bayesian network (DBN) (Zhao and Zhang, 2020). The derivation and computation of dynamic Bayesian steps involve infinite integrals, considerably complicating the algorithm's implementation (Takeuchi, 2021). Assuming linear and nonlinear state transition and observation functions, the DBN can be transformed into a KF (Azarnova and Polukhin, 2020), EKF (Liu H. et al., 2020), and UKF (Zhang G. Y. et al., 2022). A numerical integral derived from the infinite integral allows translation into a PF (Xia et al., 2020).

The challenge of predicting model parameters finds a resolution in the particle filter (PF) technique. Its advantage lies in its extensive applicability to state space models of nonlinear and non-Gaussian systems. Simultaneously, optimal prediction accuracy is achieved when a sufficient amount of known data is available (Zhou et al., 2022). The essence of PF is sequential importance sampling, grounded in Monte Carlo resampling. However, challenges arise when confronted with excessive data, complexity in the Monte Carlo resampling procedure, and the susceptibility of the iterative weight in sequential importance sampling to degradation (Chen et al., 2020). The future trajectory of the algorithm's development hinges on refining the sampling process and determining the ideal number of samples to uphold the optimal solution and stability of PF. Additionally, enhanced PF algorithms like UPF, RBPF, and EPF, amalgamating more than two algorithms, are progressively evolving and maturing.

Neural networks, known for their cost-effectiveness, quick training periods, and minimal input sample requirements as nonlinear fitting systems (Li X. et al., 2020), face challenges due to the unknown number of neurons. This uncertainty can lead to gradient vanishing or exploding, impacting the model's generalization capacity and prediction accuracy (Lu et al., 2017). Mitigating these issues involves significantly augmenting training data, incorporating a dropout layer (Gao et al., 2021) and normalization layer, utilizing an optimization technique with swift convergence, and implementing model fusion.

TABLE 4 **Comparison of commonly used life prediction algorithms in recent years.**

Algorithm	Published year	Temperature stress	Current stresses	Humidity stress	Degradation model	Parameter distribution or life model	Model data requirements	Merit
UKF (Fan et al., 2014b)	2014	√	√		Exponential model	Least square curve fitting method estimation	Luminous flux degradation data; Chromaticity coordinates; Positive voltage	Short prediction time and simple calculation
PF (Fan et al., 2015)	2015	√			Exponential model	Sequential Monte Carlo and Monte Carlo algorithm	Luminous flux degradation data; Noise data	High prediction accuracy
Weibull (Zhang et al., 2016)	2016	√	√	√	Three-parameter Weibull function approximation method	Weibull distribution, normal distribution, lognormal distribution/maximum likelihood method	The position, shape, and scale parameters are obtained by extrapolating the luminous flux degradation data of LM-80 standard temperature, humidity, and current	Wide confidence interval and high prediction accuracy
BP-NN (Lu et al., 2017)	2017	√	√		Exponential model	BP-NN/Adaboost Improved BP	Sample parameters in the LM-80 standard, including current, ambient temperature, initial luminous flux, and initial chromaticity coordinates	Strong generalization ability and a simple model
Maximum likelihood estimation method (Ibrahim et al., 2018)	2018	√	√		γ-based model	γ Distribution Degradation	Luminous flux degradation data	Simple calculation and high precision
NLS (Ibrahim et al., 2019)	2019	√	√		γ-based model	Maximum likelihood method/moment method	Luminous flux degradation data; Color temperature	Simple model
ANFIS (Kyak et al., 2021)	2020	√	√		Exponential model	Least square method/ANFIS	Sample parameters in the LM-80 standard, including current, ambient temperature, initial luminous flux, and initial chromaticity coordinates	Short training time
LSTM (Jing et al., 2020)	2020	√	√		Fitting by NLS curve	Two-parameter Weibull	Spectral density degradation data; The flux of light; Temperature	Considers time-series characteristics and has high prediction accuracy
BN (Ibrahim et al., 2021)	2021	√			γ process	Weibull	The flux of light; chromaticity Coordinates; Spectral power; Color rendering index; Color temperature	Good compatibility
MC (Enayati et al., 2021)	2021	√	√		Exponential model	Iterative extended Kalman filter	Luminous flux degradation data; Noise data	Simple model parameters and easy to obtain
Physical-neural network (Pugalenthi et al., 2021; Yang et al., 2021)	2021	√	√	√	Experimental data published in the literature	Machine learning model	The flux of light; chromaticity Coordinates; Spectral power; Color rendering index; Color temperature	High prediction accuracy and short prediction time
Multi-neural network fusion (Abdelli et al., 2021; Yuan, 2021)	2021	√	√	√	Observed data	Model fusion of statistics and machine learning	Luminous flux degradation data; Noise data	Strong generalization ability, fast convergence speed, and good model stability

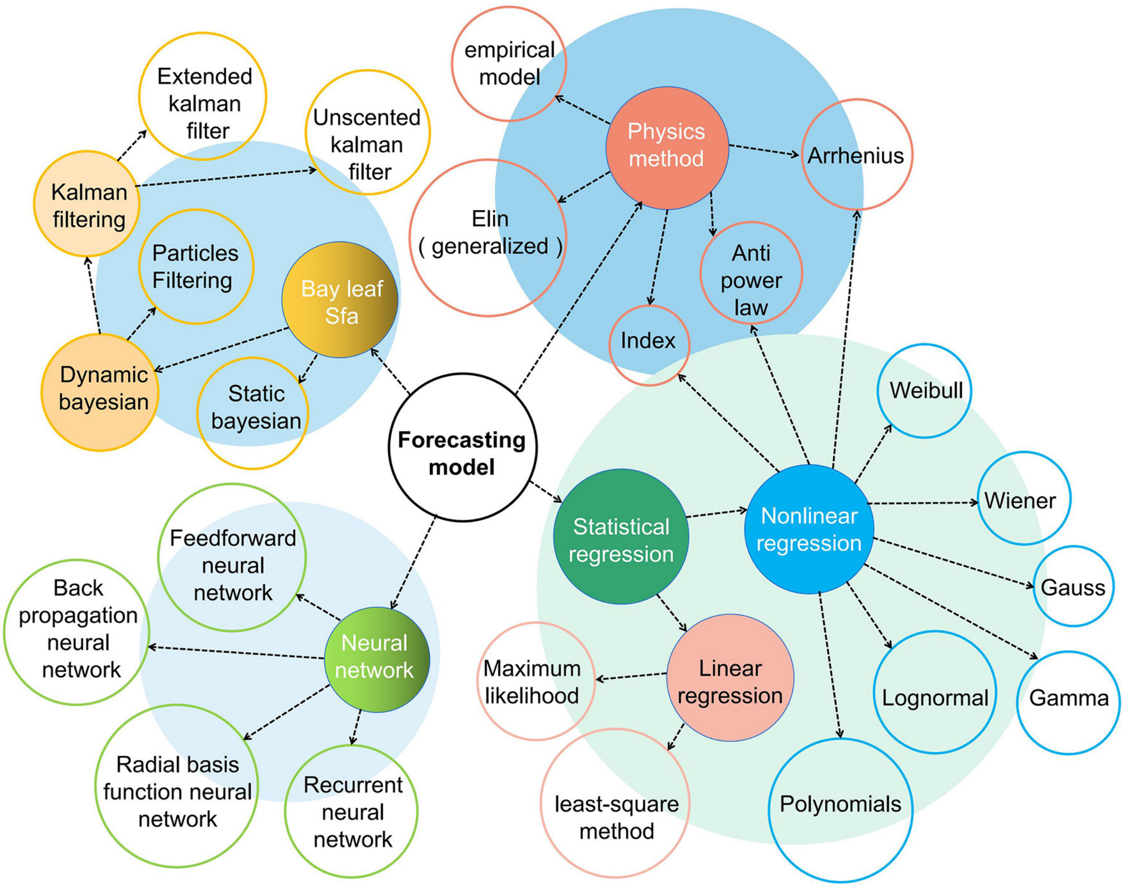

FIGURE 5
LED life prediction algorithm structure.

The landscape of deep learning continually evolves with advancements in computer technology. The current hurdle is the gradient disappearance and explosion issue arising from the deepening of network layers. Single models, addressing either temporal or geographical dimensions, suffer from weak generalization and resilience, diminished prediction accuracy, and challenges in meeting precise life prediction requirements. To cater to the needs of LED manufacturers advancing their products rapidly, the model fusion method can integrate modules such as convolution, attention mechanisms, and residuals. This enhances the model's generalization capacity and prediction accuracy while upholding stability. Consequently, the model fusion algorithm emerges as the future direction for LED life prediction.

In summary, Table 5 presents a review of the extensively used techniques for LED life prediction.

4 Prospect of algorithm

The conventional TM-21 regression technique falls short of adequately describing the rapid failure of light sources, and the duration and accuracy of predictions cannot meet present demands. Unreasonable modeling and parameter estimates pose challenges for recent artificial intelligence-based prediction techniques. Divergent machine learning algorithms grapple with inadequate training data, resulting in significant prediction variations and poor accuracy. In summary, the application of machine learning algorithms to LED light source life prediction technology is undoubtedly the future development trend, given their broad applicability and rapid evolution. Potential future development directions include:

(1) Development of models for highly accurate predictions

Researchers are advised to undertake thorough investigations into light source life prediction, approaching the subject from multiple angles. This effort aims to propel the green lighting initiative forward and elevate the benchmarks for urban green, low-carbon lighting construction, and intelligent control.

① Construction of influencing factor model

The creation of an influencing factor model involves determining the contribution of various factors to prediction outcomes. This is achieved through a thorough investigation of key drivers, luminaires, connecting components, and other relevant elements affecting the luminosity degradation of LED light sources. Employing conventional physics and statistical regression

TABLE 5 Summary of commonly used algorithms.

Method	Question	Solution
Least-square method	Ineffective for nonlinear fitting	Linearization of model
Maximum likelihood estimation	Difficulty in selecting the probability model	Increase the number of input samples
Exponential model	Only considers the time interval	Set the time start from 0
UKF	Inapplicable to degenerate nonlinear or noise non-Gaussian processes	Using particle filter
PF	Complex sampling or weight degradation	Employ adaptive sampling or improved particle filter algorithms (EPF, UPF, RBPF, etc.)
Single neural network	Limited network layers, insufficient data input, lengthy training time	Increase the number of network layers; Enhance input data quality; Introduce the dropout layer
Multi-neural network fusion	Complex network and modeling, lengthy training time	Optimize and fusion algorithm; Introduce large models (Transformer, Informer, etc.)

procedures will markedly enhance the accuracy and prediction algorithm speed of life prediction technology. This, in turn, will guide the rapidly advancing field of LED production technology, fostering a positive feedback loop.

② Deepen model fusion algorithm

Despite the superior efficiency and accuracy demonstrated by BPNN, LSTM, ANFIS, and MDNN over earlier algorithms, there remains a disparity in people's expectations regarding prediction speed and accuracy. In terms of both accuracy and efficiency, the model fusion method significantly outperforms the single-life prediction approach. This method has the capability to reduce the time required for processing nonlinear and intricate data samples, thereby enhancing prediction accuracy.

(2) Enhancing green, energy-saving light sources by production companies

Production companies must intensify efforts in advancing green, energy-saving technologies and developing intelligent lighting products aligned with the principles of "green lighting." This entails a commitment to high efficiency, energy conservation, environmental sustainability, safety, and comfort. Companies should actively contribute to urban intelligent construction while gradually phasing out outdated production capacities. The integration of state-of-the-art machinery, the Internet of Things, and big data technology facilitates a comprehensive assessment of light source performance, enhancing efficiency, and reducing raw material energy consumption. This sets the stage for the creation of green lighting and the development of intelligent cities.

(3) Government advocacy for a low-carbon lighting industry standard system

The government plays a pivotal role in achieving the "double carbon" goal, accelerating the low-carbon transformation of energy consumption, and attaining the national strategic objective of "carbon peak, carbon neutrality." Utilizing life forecast results from LED light sources as theoretical guidance, the government can formulate energy-saving and carbon-reducing lighting regulations. These policies can drive various industries toward carbon neutrality, laying the groundwork for the industrial sector's carbon peak by 2030. Currently, the durability of an LED is influenced by various factors such as drivers, packaging, heat dissipation treatment, and lead welding techniques. Variability in product quality among manufacturers significantly impacts the progress of low-carbon lighting technology. To achieve the "dual-carbon" goal and ensure high-quality, sustainable growth in the lighting industry, the government should establish a green, energy-saving, and low-carbon light source manufacturing standard system in the lighting sector. It should actively support energy conservation and emission reduction across the entire value chain, guiding the lighting industry toward a circular economy model.

In conclusion, challenges in the current life prediction model algorithm include difficult data collection, overly specific influencing elements, expensive prediction costs, and low prediction frequency. The statistical model and machine learning dimensions predominantly contribute to the model's low accuracy, limited generalization capacity, and inadequate adaptability. Therefore, to enhance feature expression by considering time and channel dimensions, the future model should integrate the influencing factor decomposition model and the principal component analysis method to screen significant driving factors as model input. Additionally, combining traditional and deep learning algorithms will minimize model complexity and enhance generalizability. This approach provides technical support for fostering the green economy and optimizing the country's industrial structure.

Author contributions

GS: Writing – original draft, Methodology, Investigation, Conceptualization. YB: Writing – review & editing, Supervision. ZZ: Writing – review & editing, Conceptualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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