LED Reliability Assessment Using a Novel Monte Carlo-Based Algorithm

Javad Enayati, Abolfazl Rahimnejad, *Member, IEEE*, and Stephen Andrew Gadsden, *Senior Member, IEEE*

***Abstract*—Application of Monte Carlo (MC) simulations in the statistical analysis of LED lumen maintenance is presented in this paper. Lumen maintenance data is acquired using experimental tests accomplished in the electro-optics laboratory of the Mazinoor lighting industry, which is an accredited laboratory by Iranian National Standards organization. The sampling rate and the duration of the experiments are consistent with LM-80-15 standard introduced by the Illumination Engineering Society of North America. In some cases, due to the existence of nonlinear dynamics in real trends of light flux, particularly in the first 1,000 hours, features are not completely captured using traditional reliability assessment techniques such as TM-21. In this study, a two-phase model is applied to cover features in lumen maintenance data. Furthermore, to estimate the parameters of the dedicated model in mild and severe operating conditions, a nonlinear Kalman filter-based method known as the iterated extended Kalman filter (IEKF) is used. A set of MC simulations are run to construct the probability density functions (PDFs) for the estimated parameters. Each simulation uses different values of the parameters chosen from the corresponding distribution. Finally, lifetime PDFs are constructed to extract reliability indices. All of the simulations are conducted in MATLAB and the results are compared with the conventional and well-known TM-21 approach.**

***Index Terms*—Extended Kalman filter, lumen maintenance, Monte Carlo simulation, product model, reliability assessment.**

I. Introduction

LIGHT Emitting Diodes (LEDs) are highly reliable electronic products which typically do not fail under the standard life test. Hence, LED's lifetime is estimated using prediction and statistical assessment techniques. Several issues including mis-modeling of LEDs' life trends, parameter estimation errors, and insufficient number of samples chosen for tests can result in the erroneous prediction of lifetime. Various studies have been carried out to overcome the mentioned issues. As reference for LED customers, Illuminating Engineering Society of North America (IESNA) presented the TM-21 standard method for projecting long-term lumen-maintenance information of LED-based light sources [1]. This mathematical method estimates an exponential lumen depreciation model based on life data collected by LM-80 approved process that measures the maintenance of the luminous flux for a group of LED chips at each 1000h time step [2]. Although different methodologies are presented by researchers for testing LEDs to extract reliability indices over time [3]–[6], LM-80 approach is widely accepted among LED manufacturers and customers. Furthermore, based on data obtained by LM-80, some complex models can be developed to extract a precise trend of lumen depreciation in LED-based light sources [7], [8]. Unlike the conventional TM-21 method, complex models use full data set including the first 1,000 hours fluctuated lumen data to predict lumen projection.

A comprehensive model needs to take critical information into consideration; this information, which is provided by a complete data set on LEDs' lumen maintenance trends, is relevant to the early life or low-stress operation of LEDs. The resultant model can lead to a more accurate prediction of future trends. As an appropriate and well-constructed model is extracted for lumen degradation of LED light sources, the model parameters can be estimated utilizing prognostic techniques. A review of prognostic techniques applied to estimate the model parameters of LED devices and LED systems is presented in [9], [10]. Least Squares (LS) method is the most popular approach for estimating the model parameters. Nevertheless, in most proposed models the parameter estimation process is nonlinear. The LS algorithm in its standard form suffers from poor estimation accuracy when highly nonlinear models are used [11], [12]. Moreover, LS-based methods do not provide detailed reliability information on the obtained data [13]. Field experiments demonstrated LED's failure indicators are considered as a combination of lumen maintenance and chromaticity coordinates. Hence, spectral power distribution-based methods to analyze and predict the reliability of LED light sources are introduced in [14]–[16].

Kalman Filter (KF) based approaches have been repeatedly implemented to estimate the parameters of lumen degradation models of LEDs. Since the degradation process is nonlinear and measurement noise has a non-zero mean, the application of KF is restricted. Extended KF (EKF), Unscented KF (UKF), and Cubature KF (CKF) are some variants that have been developed to overcome the above-mentioned problems [17]–[19]. EKF as a successful method, which is simply and practically implementable, can mitigate the deficiencies of the regression method employed in TM-21. Artificial

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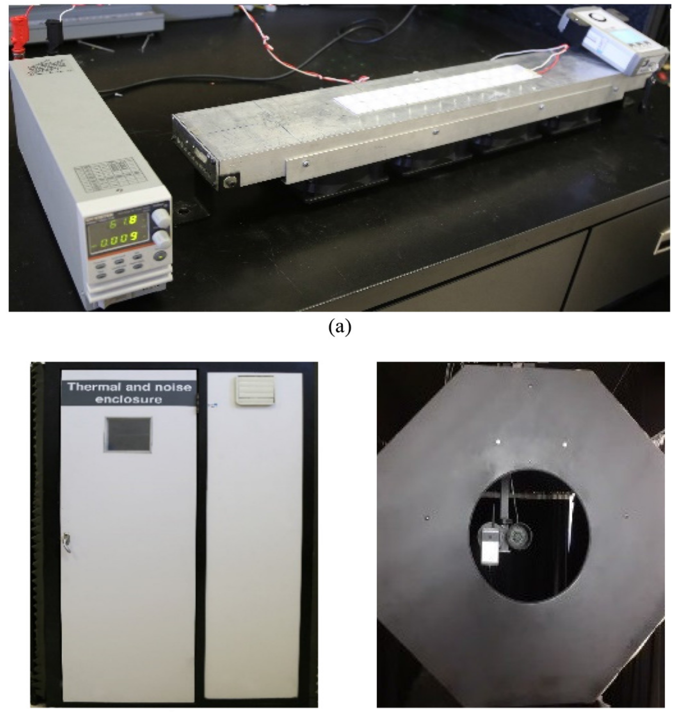
neural networks (ANNs), as an effective engineering tool, are frequently applied for parameter estimation. ANNs are also well-known in LEDs' life estimation context [20], [21]. Nevertheless, finding optimized determinants of a particular ANN, i.e., network architecture, weights, and activation functions is rarely possible. Consequently, the application of ANNs is restricted to extracting complex models for life projection of LEDs where the number of parameters in the model is high. Physics of Failure (PoF) is another well-known approach in reliability theory that engineers in different areas of science apply to model and simulate degradation processes. PoF-based methodologies use the knowledge of how failures actually occur in a product through available physical models. The physical models can be made based on different properties in LED chips such as voltage-current characteristics, lumen depreciation, leakage resistance depreciation, thermal-induced solder deformation, etc., [22]–[26].

In spite of the advantages of the physics-based reliability assessment, the establishment of physical models for the failure process requires adequate knowledge of the system which is rarely accessible in complex systems. All above-mentioned parameter estimation methods serve a fit model for extracting reliability information on various case studies. However, applicable reliability indices such as mean time to failure (MTTF), confidence interval (CI), reliability function, and useful life can be obtained by statistical analysis on the proposed models. The lack of existence of a standard statistical analysis approach has brought about more attention to novel reliability assessment techniques which is the main focus of this study.

In this paper, an optimized two-phase lumen degradation model, namely product model, is utilized for a practical case study including 20 samples of similar LEDs. The applied model uses the information of both luminous flux increment in the initial stage and its extended decay over time; thus, a full/complete data set of recorded luminous flux is utilized for the estimation of model parameters. Unlike conventional methods which mostly discard data of the first 1000 hours, applying full data set provides a more accurate analysis of future trends of the lumen degradation process. Iterated Extended Kalman Filter (IEKF) is used to estimate the parameters of the product model. The re-linearization function in IEKF enhances the accuracy of the estimation process, especially when the model has a high degree of nonlinearity and noise corruption. The main contribution of the paper relies on the statistical analysis of the estimated parameters to find the fittest probability distributions. Based on the fitted distribution functions, reliability evaluation of the studied case including MTTF, CI, reliability function, and useful life are computed by Monte Carlo (MC) simulations. The obtained results are compared to conventional IES TM-21 to show the capability of the proposed algorithm.

II. Data Extraction

To evaluate the capability of the proposed approach a set of practical test data is utilized. The luminous flux of a light source including 20 LED chips is logged using a set of photometric devices. Principles of data logging system and the required instruments are presented in this section. The investigated LED chips are 3W federal series natural white type manufactured by Edison Opto Corporation. The test data is collected for two operating conditions, i.e., mild and severe conditions. In the former, LEDs are run at 700mA and the temperature of the solder point is kept constant at 55°C; while in the latter, the LEDs current and solder point temperature are 1000mA and 105°C, respectively. In both cases, the ambient temperature is set to be 50°C. The controlling set instruments including thermal enclosure, active cooling heat sink, and electronic power supply are utilized to maintain the desired set points. Furthermore, to record optical data, the luminous flux of each chip is measured by Goniophotometer at time zero. Note that the LM-80-15 test procedure includes photoreceptors that directly measure the luminous flux for all time steps; however, we use a portable lux meter at a fixed distance and angle to each chip. Then, the corresponding changes in the luminous flux over elapsed time are computed based on relative changes in the illuminance measured by lux meter. Based on the experiments, the obtained results by the proposed data logging system have an acceptable consistency with the LM-80 test procedure. The time step for recording data is 1000 hours. This process repeats 6 times for both operating conditions and the final data is obtained for 6000 hours. The measurement instruments are shown in Fig. 1. All measurements are carried out in the electro-optics laboratory of the Mazinoor lighting industry which is an accredited laboratory by Iranian national standard organization. The normalized recorded flux data is demonstrated in Table I. Note that the data reported in the first and second rows for each sample corresponds to the mild and



(a) (b) (c)

Fig. 1. Test equipment including (a) power supply, active cooling system, LED chips, and lux meter, (b) Thermal enclosure, and (c) Goniophotometer.

TABLE I
RECORDED NORMALIZED LUMINOUS FLUX DATA OVER TIME

Sample \ Time(h)	0	1000	2000	3000	4000	5000	6000
1	100	100.2	100.5	99.9	99.5	99.0	99.0
	100	99.9	98.9	97.9	97.0	97.0	97.1
2	100	100.1	100.5	100.0	99.8	99.6	99.7
	100	100.1	99.5	98.5	98.8	98.4	98.1
3	100	100.3	100.2	99.6	99.9	99.7	99.8
	100	100.2	99.5	98.8	98.4	97.4	97.4
4	100	100.2	100.0	99.2	99.4	98.8	99.1
	100	100.3	99.2	98.4	98.2	97.3	96.7
5	100	100.5	100.1	99.4	99.2	98.8	99.0
	100	100.0	98.2	97.4	97.7	96.9	96.8
6	100	100.1	99.7	99.2	99.1	98.6	98.6
	100	100.3	99.7	98.9	98.7	97.7	97.2
7	100	100.0	100.0	99.1	98.2	98.4	98.6
	100	100.2	100.0	99.1	98.9	98.0	98.0
8	100	100.4	100.1	99.2	99.1	98.6	98.7
	100	100.1	99.0	98.2	98.2	97.5	97.4
9	100	100.3	100.0	99.6	99.4	98.9	99.2
	100	100.0	99.1	98.5	98.3	97.5	97.1
10	100	100.2	99.8	99.2	99.0	98.6	98.6
	100	100.1	99.3	98.8	99.0	98.3	98.2
11	100	100.1	99.9	99.2	99.2	98.7	98.8
	100	99.9	98.8	98.5	98.4	97.7	97.9
12	100	100.2	100.0	99.2	99.5	99.1	99.2
	100	100.0	99.5	98.9	98.7	97.8	97.7
13	100	100.0	99.7	98.9	98.9	98.5	98.6
	100	100.3	99.4	98.1	98.3	97.3	97.1
14	100	100.3	100.1	99.5	99.7	99.6	99.9
	100	100.1	99.0	98.5	98.2	97.2	96.8
15	100	100.0	99.8	99.4	99.3	98.5	98.6
	100	100.2	99.0	98.2	98.1	97.4	97.2
16	100	100.2	99.3	98.6	98.9	98.3	98.2
	100	99.9	98.8	98.0	98.3	97.7	97.7
17	100	100.0	99.9	99.2	99.2	98.7	98.6
	100	100.0	99.1	98.2	98.2	98.0	97.8
18	100	100.1	99.5	99.0	98.8	98.3	98.6
	100	100.1	99.3	98.3	98.3	97.8	97.4
19	100	100.2	100.0	99.6	99.8	99.2	99.1
	100	100.2	99.8	98.9	99.1	99.0	98.4
20	100	100.3	100.1	99.5	99.2	98.5	98.6
	100	100.0	99.4	98.2	98.1	97.7	97.5

The data reported in the first and second rows for each sample corresponds to the mild and severe operating conditions, respectively.

severe operating conditions, respectively. Further details of the applied method for analyzing the recorded data are described in the next section.

A. Preliminary Data Analysis

According to Table I, it is obvious that luminous flux in LED chips has a growing trend at first 1000 hours. This phenomenon known as the break-in period originates in some physical phenomena, such as annealing of defects in the LED epitaxial layer, reduction in contact resistances, and changes in the refractive index of materials in the light path. The break-in period has been repeatedly addressed by LED manufacturers and researchers in semiconductor science [7]. Note that some exceptions exist for the severe condition where the accelerated decreasing trend in the luminous flux overcomes the above-mentioned physical sources of the initial flux increment. Conventional methods, e.g., TM-21, neglect the increasing part of the recorded flux data to have a monotonically decreasing trend. Additionally, simple models with a low number of parameters require the elimination of the initial data (increasing part) to fit the lumen maintenance trend correctly. However, when critical information relevant to the early working hours of LED light sources is missed and its dependence on the whole test data is neglected, estimates of the parameters in the decaying phase would be unrealistic. Hence, multi-phase models with higher number of parameters could be applied to cover characteristics of both break-in and extended decay periods. While higher-order equations are applied to illustrate lumen maintenance trend, model nonlinearity increases and parameter estimation of the model would be more complex. Therefore, a suitable nonlinear estimation paradigm should be applied for such a process. Since extracting parameters of the lumen maintenance model based on the data-driven procedure is affected by the process and measurement noises, the filtering techniques to estimate parameters have been repeatedly proposed in [9], which is utilized in this study as well.

B. Reliability Analysis

Once a model is fitted to lumen maintenance of each chip, the statistical analysis can be carried out to obtain reliability indices. One of the drawbacks of conventional methods is neglecting higher statistical moments, such as variance, in the reliability analysis of the LEDs. Hence, reliability indices such as MTTF, CI, reliability function, etc., could not be obtained for the collected data set. Moreover, tens of millions of a specific LED chip are produced when it is launched into the market; however, a limited number of LED chips are just selected for the standard life test, e.g., LM-80, which may not be a suitable representative of such a large statistical population. If a simple statistical analysis is used for such a small test sample, the uncertainties in the outputs would lead to unreliable results. Thus, in some recent researches, simulation-based statistical data-driven approaches are utilized to extract reliability characteristics [27]. It should be noted that the proposed method extracts the reliability indices for the mild test condition where the longer lifetime with higher uncertainties can be obtained for LEDs.

III. Proposed Algorithm

This section presents a novel approach to statistical analysis of the lumen maintenance of a typical LED chip. This paradigm can be generalized to analyze the lumen output of all types of LEDs over time. The proposed algorithm has the capability of noise rejection of the recorded experimental data in estimating model parameters, and statistical analysis based on the extracted complex model to assess the reliability characteristics of the LEDs more accurately. Details of the proposed method are illustrated in the following subsections.

A. Lumen Maintenance Modeling

A temporary increase in luminous flux followed by a decaying trend is a common phenomenon in the lumen maintenance of most LEDs. Unclear reasons may exist behind the temporary increase in luminous flux in the initial working hours.

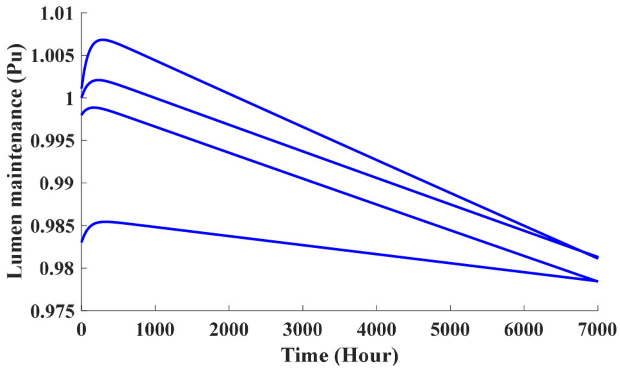


Fig. 2. Typical lumen maintenance trend corresponding to product model.

Apart from the source of the growing trend in the lumen of LEDs, this property contains the main information about the future trend of the luminous flux. Although most recent methods disregard initial hours' data, the current study emphasizes using a complete set of the recorded lumen data by applying a product model. In addition, finding an optimal model is challenging when nonlinear characteristics of LEDs are taken into consideration. The typical nonlinear model proposed in [7] is applied in this paper. For the sake of simplification, a first-order process is assumed for the first increasing phase according to (1):

$$\delta + \lambda\left(1 - e^{-\beta t}\right) \tag{1}$$

where λ corresponds to the maximum asymptotic increase in luminous flux, β is a special decay coefficient, and δ is projected initial normalized luminous flux. Moreover, for modeling the eventual decrease in lumen, an exponential term, which explicitly fits the decreasing trend, is utilized. Total product model explaining total luminous flux ϕ_t would be made by the combination of both trends as follows:

$$\begin{aligned}\phi_t &= e^{-\alpha t}\left(\delta + \lambda\left(1 - e^{-\beta t}\right)\right)\\ &= h(\alpha, \beta, \lambda, \delta)\end{aligned} \tag{2}$$

where α is the decay rate constant for the decreasing phase. As can be seen, the obtained model has four tuning parameters which should be estimated to fit the lumen properties over time. Two-phase trends for the lumen maintenance corresponding to typical values of α, β, λ, and δ are depicted in Fig. 2.

B. KF Based Parameter Estimation

The Kalman Filter (KF) in its various forms is clearly established as a fundamental tool for analyzing and solving a broad class of estimation problems [28]. The principles of the KF are illustrated in state estimation and system identification resources. In this subsection, state variable representation for parameter estimation of the nonlinear product model using Iterated Extended Kalman Filter (IEKF) is proposed. The states to be estimated are defined as:

$$X^T = [-\alpha \quad -\beta \quad \lambda \quad \delta] \tag{3}$$

where T shows the transpose of the state vector. As targeted states are constant, the discrete-time equation for states X and covariance matrix P can be simply written using a 4×4 identity transition matrix $\varphi(t_k, t_{k+1})$ without considering the process noise as follows:

$$X_{k+1,k} = \varphi(t_k, t_{k+1})X_{k,k} \tag{4}$$

$$P_{k+1,k} = \varphi(t_k, t_{k+1})P_{k,k}\varphi(t_k, t_{k+1})^T \tag{5}$$

The estimation results could be updated and improved once the measured lumen maintenance in each step is received. According to (2), measurement function h is a nonlinear function of states. Hence, first-order Taylor series expansion is used to linearize the nonlinear equation in the IEKF framework. As a result, the structure matrix H would be:

$$\begin{aligned}H = \frac{\partial h}{\partial X} = \Big[&(\delta + \lambda)\mathrm{t}e^{-\alpha \mathrm{t}} - \lambda \mathrm{t}e^{-(\alpha+\beta)\mathrm{t}},\\ &- \lambda \mathrm{t}e^{-(\alpha+\beta)\mathrm{t}}, e^{-\alpha \mathrm{t}} - e^{-(\alpha+\beta)\mathrm{t}}, e^{-\alpha \mathrm{t}}\Big]^T\end{aligned} \tag{6}$$

Since the measurements are usually corrupted by a sequence of noises with zero mean and variance ${\sigma_v}^2$, the IEKF gain matrix G_{k+1} is updated accordingly. Then, measurement update equations for state vector and covariance matrix are constructed as follows:

$$G_{k+1} = P_{k+1,k}H^T\left(H P_{k+1,k} H^T + \sigma_v^2\right)^{-1} \tag{7}$$

$$X_{k+1,k+1} = X_{k+1,k} + G_{k+1}\left[\phi_t - h\left(X_{k+1,k}\right)\right] \tag{8}$$

$$P_{k+1,k+1} = (I - G_{k+1}H)P_{k+1,k} \tag{9}$$

According to (6), the structure matrix is linearized around $X_{k+1,k}$. Furthermore, measurement information is applied for estimating $X_{k+1,k+1}$; thus, accuracy of estimation of state vector $X_{k+1,k+1}$ is improved compared to $X_{k+1,k}$. Hence, re-linearization of the structure matrix around new estimate $X_{k+1,k+1}$ reduces linearization error, and $X_{k+1,k+1}$ is recalculated applying re-linearized H matrix. This process, as the main feature of IEKF, can be repeated as many times as desired, although for most problems the majority of the possible improvement is obtained by only re-linearizing one time [29]. One of the other main features of the IEKF algorithm is its noise rejection capability as it takes the measurement noise matrix σv into account. Nevertheless, in most conventional methods the errors that originate in the measurement noise can cause notable life projection errors.

C. Monte Carlo Analysis of Results

Monte Carlo (MC) simulation is a powerful tool to investigate the statistical characteristics of stochastic variables [30]. In this paper, a MC campaign is applied to explore the optical output of a set of LED chips for finding a suitable distribution fitted to statistical properties of the lumen maintenance. For this purpose, the IEKF algorithm estimates model parameters for each LED applying data recorded in Table I. The statistical analysis is carried out for the mild test condition where a longer lifetime with higher uncertainties can be obtained for LEDs. Based on estimated parameters, the most appropriate

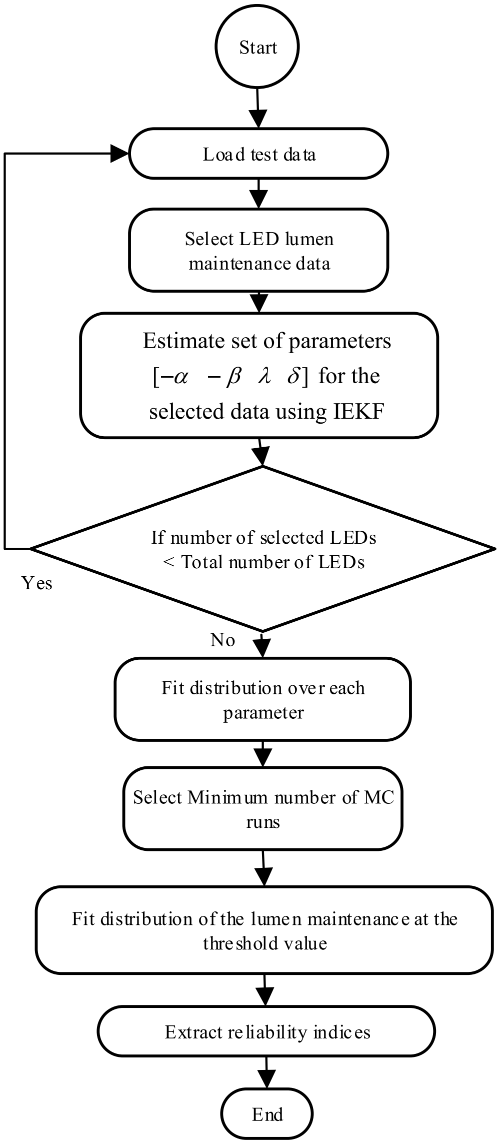


Fig. 3. Basic flowchart showing the sequence of operations in proposed approach.

TABLE II
RESULTS OF PARAMETER ESTIMATION USING IEKF

Parameter / Sample	-α (1e-5×)	-β	λ	δ
1	0.3143	0.0098	0.00777	0.99215
	0.6050	0.01014	0.00061	1.00152
2	0.1424	0.00958	0.00441	0.98310
	0.3770	0.01011	0.00212	1.00704
3	0.1080	0.01020	0.00289	0.98308
	0.6001	0.00999	0.00705	0.99814
4	0.2568	0.01028	0.00346	0.99818
	0.6951	0.00901	0.00765	1.00550
5	0.3370	0.01037	0.00669	0.99102
	0.5780	0.00631	0.00168	1.00289
6	0.3142	0.01003	0.00313	0.99978
	0.6272	0.01008	0.00935	0.99675
7	0.3690	0.01001	0.00332	0.99693
	0.4962	0.01038	0.00764	0.99942
8	0.3799	0.01054	0.00669	0.99348
	0.5251	0.00913	0.00222	1.00317
9	0.2584	0.01012	0.00471	1.00091
	0.5667	0.00944	0.00384	1.00333
10	0.3414	0.01015	0.00421	0.99757
	0.3561	0.00934	0.00190	1.00712
11	0.2909	0.01018	0.00332	0.99963
	0.3902	0.00872	0.00113	1.00133
12	0.2126	0.01024	0.00278	1.00227
	0.4860	0.01003	0.00458	0.99641
13	0.3070	0.01018	0.00168	0.99839
	0.6438	0.01016	0.00654	1.00821
14	0.0949	0.01022	0.00184	1.00236
	0.6458	0.00878	0.00541	1.00433
15	0.3178	0.01005	0.00371	0.99601
	0.5807	0.00881	0.00366	1.00139
16	0.3689	0.00926	0.00200	0.99813
	0.4092	0.00914	0.00181	1.00172
17	0.3067	0.01007	0.00331	0.99414
	0.4171	0.00974	0.00148	1.00140
18	0.3277	0.00989	0.00189	0.99846
	0.5236	0.00997	0.00353	1.00733
19	0.2215	0.01003	0.00422	0.99741
	0.3232	0.01021	0.00361	1.00238
20	0.3906	0.01031	0.00733	1.00191
	0.5155	0.01038	0.00274	1.00599

The data reported in the first and second rows for each sample corresponds to the mild and severe operating conditions, respectively.

distribution over each parameter is constructed. In each run of MC, a parameter vector [α β λ δ] is extracted from the constructed distributions; then, unique lumen maintenance is obtained based on the extracted vector. A predefined number of simulations is run to fit the distribution of lumen maintenance at a desired threshold value, e.g., L_{70} (the time at which the luminous flux reduces to 70 percent of the initial value). Based on the fitted distribution on L_{70}, the reliability function and CI bounds are obtained. These indices can be useful to determine the maintenance scheduling, preventive actions, life calculations, etc. Fig. 3 demonstrates the flowchart of the proposed algorithm. In the following section, the simulation results are presented and discussed in detail.

IV. SIMULATION RESULTS

To reveal the performance of the proposed method, the results of simulations are explored in this section. Additionally, a comparative study with conventional methods is conducted to evaluate the capability of the proposed algorithm in extracting precise reliability indices. Data presented in Table I is used as input for the algorithm. The recording process is all carried out in the electro-optics laboratory of the Mazinoor lighting industry. Based on the measurements, IEKF algorithm estimates the product model parameters and proposes a lumen maintenance trend for each LED. Utilizing the statistics of these parameters some important indices are extracted.

A. Parameter Estimation

Results of parameter estimation using IEKF algorithm according to equations (3) to (9) for both mild and severe conditions are shown in Table II. These parameters are estimated while the recorded luminous flux in Table I is assumed to be noise-free. In practice, unknown noise exists in the measured values. Errors of the measurement devices, environmental condition tolerances, and parameters' rounding can be effective sources of the measurement noise. Hence, pseudo noises are

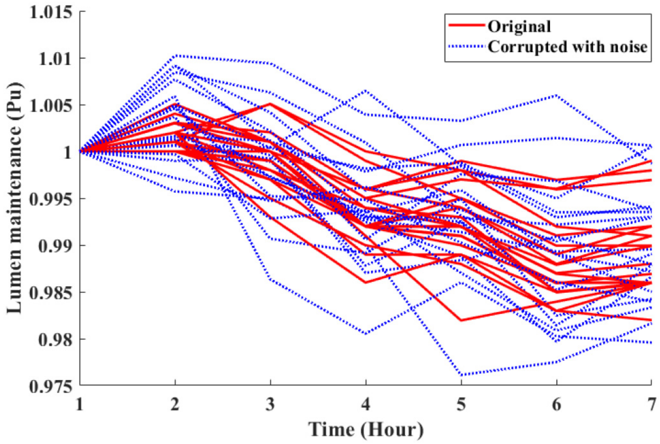


Fig. 4. Original and noise corrupted measurements, mild test condition.

TABLE III
QUALITY OF THE ESTIMATION UNDER NOISE CONDITION
(MEAN AND VARIANCE)

SNR	Parameter	-α Mean Std.	-β Mean Std.	λ Mean Std.	δ Mean Std.
No noise	Mild	0.2830e-5 7.59e-13	0.010075 8.011e-8	0.003968 3.3827e-6	0.996245 3.022e-5
	Severe	0.5181e-5 1.18e-13	0.009494 8.755e-8	0.003927 3.0481e-6	1.002769 7.476e-4
30dB	Mild	0.2830e-5 7.62e-13	0.010068 8.035e-8	0.003722 3.4859e-6	0.996312 3.031e-5
	Severe	0.5162e-5 1.19e-13	0.009011 8.812e-8	0.004000 3.0669e-6	1.002135 7.483e-4
25dB	Mild	0.2828e-5 8.01 e-13	0.010102 1.002e-7	0.003964 3.9246e-6	1.000120 3.473e-5
	Severe	0.5204e-5 1.27e-13	0.009464 8.998e-8	0.004152 3.0961e-6	1.001974 7.516e-4

added to the recorded data to investigate the performance of the proposed approach in presence of the noise corrupted measurements. Two test scenarios at signal-to-noise ratios SNR=30 dB and SNR=25 dB are applied to explore the capability of the IEKF in noisy conditions. The original and noise corrupted measurements at SNR=25 dB for the mild test condition are shown in Fig. 4. Using statistical indices, the quality of the estimation under noisy situations for both mild and severe operating conditions is reported in Table III. As observed, the mean and variance of the parameters have little change when noise is applied to the measurements. The main reason behind the stability of the IEKF in the noisy condition is its filtering capability as it takes measurement noise matrix σv into account in its formulation. To obtain the lumen maintenance for each LED, estimated parameters are applied to the product model. Furthermore, a comparative study based on Log-likelihood values is conducted between different distributions to find the fittest one to each parameter. Due to space limitation, only results of the mild test condition are presented in Fig. 5 and Table IV. The next step is to apply MC simulation to generate random variables using the selected distribution for each parameter. Each vector of parameters [α β λ δ], extracted from distributions, proposes a specific trend for lumen maintenance of the studied LEDs. Statistical analysis of the MC outputs provides important reliability information.

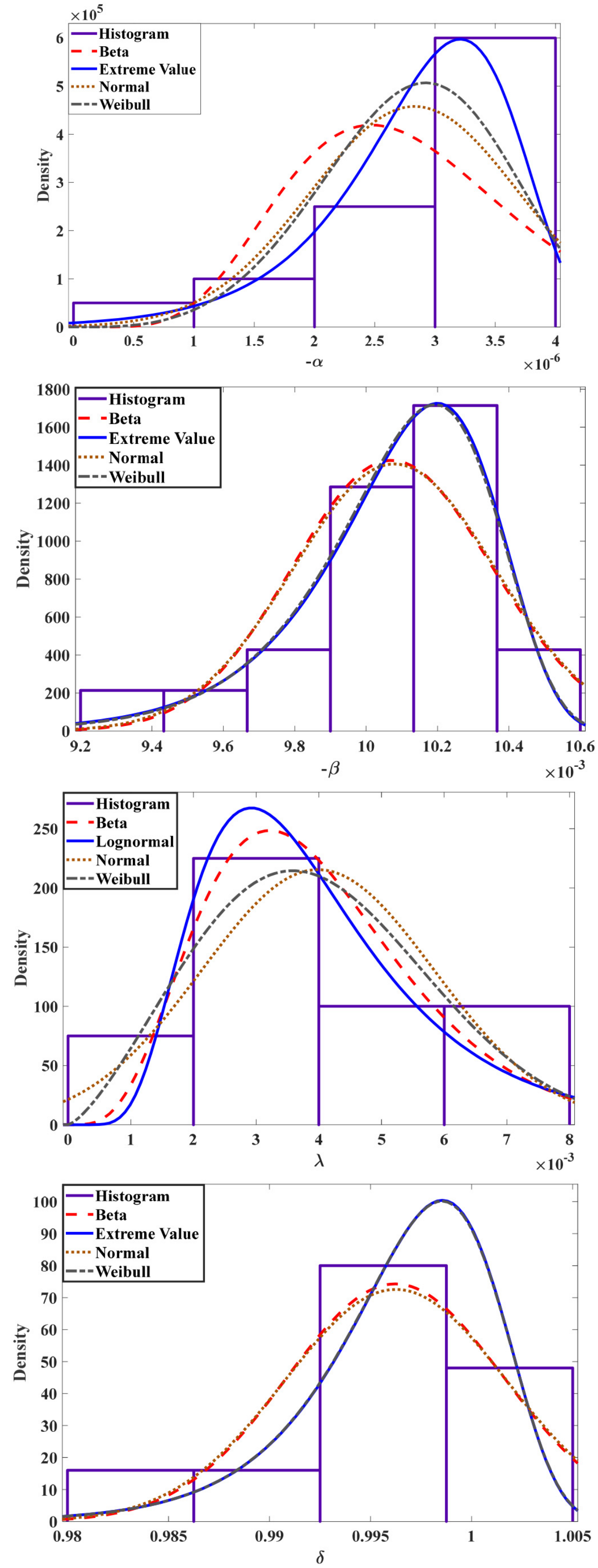


Fig. 5. Performance of fitting distributions for mild test condition, graphical comparison.

B. Useful Lifetime

To obtain the useful lifetime of LEDs, the lumen maintenance factor of 70% (L_{70}), which is accepted by most manufacturers in LED industries as a failure threshold, is

TABLE IV
PERFORMANCE OF FITTING DISTRIBUTIONS FOR MILD TEST CONDITION, NUMERICAL COMPARISON

Parameter	Distribution	Log likelihood
$-\alpha$	Beta	248.681
	Extreme value	**253.607**
	Normal	251.191
	Weibull	251.776
$-\beta$	Beta	135.434
	Extreme value	**137.942**
	Normal	135.668
	Weibull	137.940
λ	Beta	100.051
	Normal	98.078
	Log normal	**100.312**
	Weibull	99.228
δ	Beta	77.001
	Extreme value	**80.622**
	Normal	77.034
	Weibull	80.596

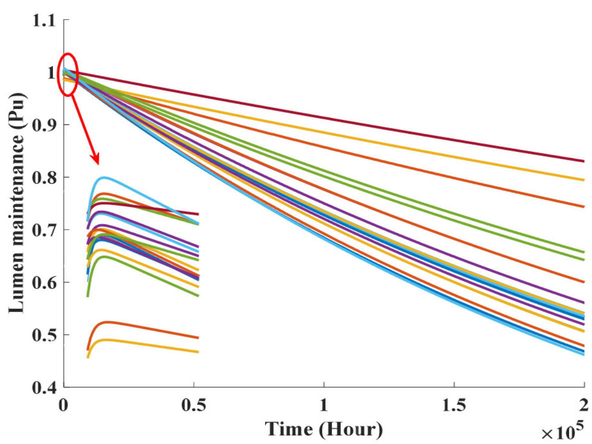


Fig. 6. Lumen maintenance results of product model for studied samples.

selected. For this case, L_{70} is calculated based on the product model. The life projection of the samples using the product model is shown in Fig. 6. The magnified results for initial hours in the graph depict that the utilized model covers the increasing phase of the lumen maintenance.

L_{70} values obtained by the proposed method and simple exponential model for mild and severe conditions are reported in Table V. For the presented algorithm, the average of parameters, given in Table II, is applied to calculate the L_{70} index. It should be mentioned that TM-21 results are calculated based on the simple exponential decaying model with least-squares curve fitting [1]. Note that extrapolating an exponential model to L_{70} gives the values presented in Tables V and VI.

According to the results given in Table II, the small decay rates are obtained for the mild test condition, where the average decay rate of α is estimated to be 2.83e-6. The minimum established value of α in the TM-21-19 is 2e-6, the values lower than which cause L_{70} of higher than 175,000 hours.

TABLE V
USEFUL LIFETIME (AVERAGE L_{70}) CALCULATED BY PROPOSED METHOD AND SIMPLE EXPONENTIAL MODEL

Index		Simple exponential model*	IEKF Product model
L_{70} (Hour)	Mild	149,600	123,900
	Severe	70291	72618

*As per TM-21, the life projections should be reported as >36000

TABLE VI
CALCULATED MTTF VALUES AND CORRESPONDING STANDARD DEVIATION BY SIMPLE EXPONENTIAL MODEL AND PROPOSED METHODS, MILD CONDITION

Index	Simple exponential model	Proposed method
MTTF (Hour)	124,400	118,700

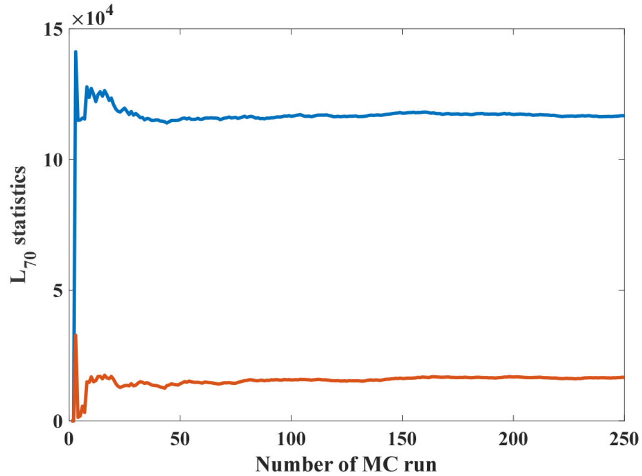
Nevertheless, other parts of the LED light system would fail before the LED chips' failure in such a condition. In practice, LEDs operates at more stringent conditions similar to severe test condition considered in this study, where the calculated lifetimes are closer to the reality. As seen, a higher average decay rate of around 5e-6 has been estimated for the severe condition in this study.

A more detailed view on the Table V shows that in the mild test condition, the difference between life projection calculated by exponential model and proposed strategy is around 21% while it decreases to 3% for the severe condition. This is caused by the fact that in the mild condition, the final luminous flux values (after 6000 hours) are close to initial ones. As well, the simple model does not account for initial lumen increment phase in the model which results in a noticeable missing information in such small variations of luminous flux. The effect of missing information decreases for higher range of variations of luminous flux as per sever condition, where the calculated results of both methods are much closer to each other.

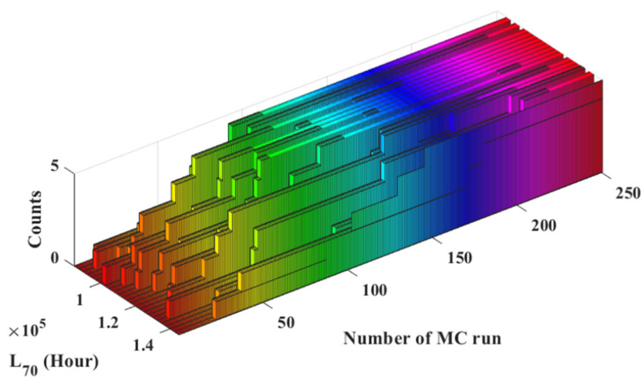
Furthermore, based on 6X rule, TM-21 mandates that rated L_{70} lifetime cannot be greater than 6 times the actual LM-80 test duration, i.e., 36,000 hours for this case study. Then, the useful lifetime corresponding to the TM-21 method presented in Table V is just a calculated value. Accordingly, the reported value should be stated >36,000 hours. To handle this issue with the limitation on the reported value, the proposed method utilizes the pseudo samples generated by MC simulation, which is further discussed in the following subsections.

C. Mean Time to Failure (MTTF)

Without considering the higher statistical moments of each test unit, little reliability information for the LEDs is obtained. Indices such as MTTF, CI, reliability function, etc., cannot be extracted by the average analysis of the units. Therefore, a MC campaign is run to generate life distribution to extract reliability indices. Since the lumen maintenance has lower decay rates in the mild test condition, the ranges of the calculated reliability indices are considerably beyond the values determined by the 6X rule. Moreover, the uncertainties corresponding to



(a)



(b)

Fig. 7. Determination of minimum MC runs by analysis of L_{70} statistics for mild test condition, (a) mean and standard deviation, and (b) distribution.

these values would be significantly high. Hence, to demonstrate the capability of the MC procedure in calculating the reliability indices, the data obtained for the mild test condition with higher uncertainties are applied in this section. The first step is generating stochastic values for the parameters of the product model. Based on the fitted distributions proposed in the previous section, a parameter vector $[\alpha\ \beta\ \lambda\ \delta\ ]$ is extracted in each run of MC simulation. To obtain the life projection for a predefined time, the parameters are applied to the product model. The minimum number of MC runs used for the final analysis is determined by examining the statistics of notable parameters such as mean value and standard deviation. For the studied case, L_{70} index statistics, demonstrated in Fig. 7, are targeted to determine the minimum number of runs. The asymptotic trend of the parameters shows that there would be few expected changes in the output of the MC analysis when performing more than 150 runs. Furthermore, it can be observed that the distribution of L_{70} does not change when MC runs exceed 150 simulations. The main reason behind this asymptotic trend is growing the population of parameters as the number of MC runs increases. As a result, the statistical characteristics become close to their true values. As previously mentioned, most LED-based industries put lumen maintenance

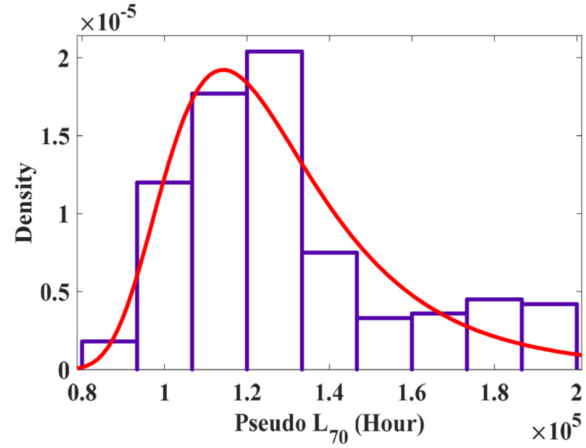


Fig. 8. Statistical analysis of pseudo L_{70} results obtained by MC simulation (250 runs) for mild test condition.

factor of 70% (L_{70}) as a failure threshold. Then, the mean value of pseudo L_{70} attained by MC simulation is the best representative of the MTTF index that is shown in Table VI. As can be seen, the MTTF calculated by the proposed methods is close to the corresponding useful lifetimes. Moreover, the proposed method provides more reliable values as a higher number of (pseudo) samples are used to extract the statistical indices which in turn reduces the uncertainties (existed in the conventional methods).

D. Reliability Prediction

Fitted probability distribution on the "pseudo L_{70}" obtained from MC simulations can be an effective data source for maintenance scheduling in LED-dependent industries. A set of 250 MC runs is considered to generate pseudo L_{70} data. The histogram and fitted distribution to obtained data are represented in Fig. 8. Statistical analysis of the results shows that the Extreme Value, amongst all investigated distributions, is the best-fitted function to illustrate the statistical features of the L_{70} data. Based on the fitted distribution the reliability function R can be obtained as follows:

$$R = 1 - CDF \tag{10}$$

where CDF is the Cumulative Density Function of the fitted Extreme Value distribution. Fig. 9 demonstrates the reliability and the 95% confidence intervals for the studied LEDs. Maximum Likelihood Estimator (MLE) is used to estimate the parameters of Extreme Value distribution, i.e., location and scale, to be fitted to the pseudo L_{70} data; then, the reliability function is obtained according to (10). MC simulation generates pseudo samples with reliability features similar to those of the real tested LEDs; hence, reliability information, i.e., reliability function, MTTF, and CI, can be obtained from a larger population. However, IES TM-21 method is limited to mean values, and no reliability analysis is provided to help LED-based industries in their maintenance scheduling, preventive actions, life prediction, etc. Obviously, such calculations

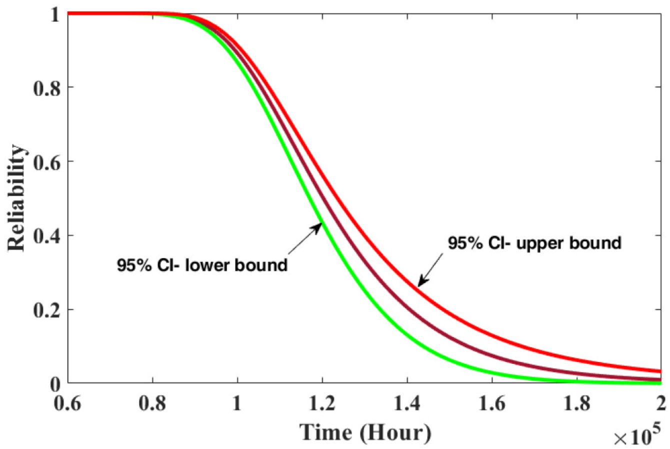


Fig. 9. Reliability prediction results for the studied mild test condition.

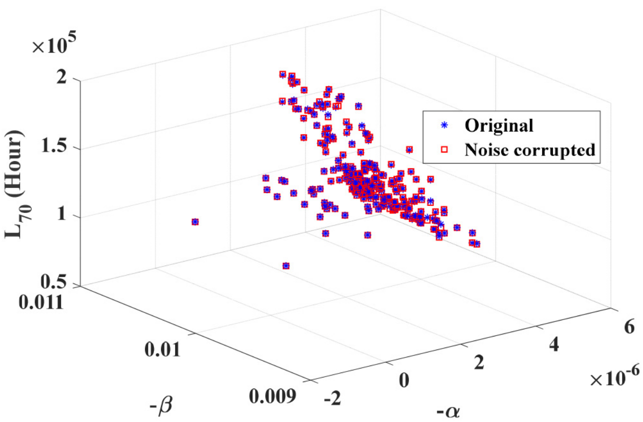


Fig. 10. MC analysis of noise effects for mild test condition.

present a straightforward way for manufacturers and customers to understand products clearly.

E. MC Analysis of Noise Effects

The effect of noise on parameter estimation was examined in Section IV-A. In this subsection, the effects of noise on principle reliability indices is investigated. For this purpose, the noise-corrupted lumen maintenance with SNR=25 dB is studied. A MC campaign with 250 runs is applied to obtain different trends of lumen maintenance. L_{70} index is extracted from each trend and compared to its noise free peer. Sensitivity analysis shows that α and β are the most affected parameters in noise presence. Nevertheless, Fig. 10 reveals no significant difference between L_{70} duals obtained in noisy and noise-free conditions for different values of α and β.

V. Conclusion

A novel algorithm for the reliability assessment of the LEDs was presented in this paper. The proposed method extracts the reliability characteristics of the LEDs based on a two-phase product model. This model was constructed using experimentally recorded data of both luminous flux increment in the initial stage and its extended decay over time. The data is logged in two distinct operating conditions, i.e., mild and severe, in which the temperature and forward currents are different. Moreover, a nonlinear KF-based algorithm, the IEKF, was utilized to capture the nonlinear characteristics of the lumen maintenance trends and mitigate data noise effects. Statistical distributions were fitted to the estimated parameters to improve the lumen maintenance model. The MC campaign was used to generate pseudo samples from dedicated distributions. These were applied to statistical analysis at threshold lumen maintenance values (L_{70}) to obtain useful reliability indices such as MTTF, CI, and reliability function. Results of the conducted simulations in MATLAB verify the capability of the proposed algorithm in the life-prediction of investigated LED chips, which can be generalized to other LED packages.

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