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# Predicting Lumen Degradation of Light Emitting Diodes Using Hybrid Particle Filter Trained Neural Networks

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**ABSTRACT** High power white light emitting diodes (LEDs) are the widely opted eco-friendly alternate light source over incandescent lamps due to their lower power consumption and longer lifetime. The emerging market demand for LEDs brings about the critical need for adequate reliability testing and lifetime prognosis as they are predominantly used in uncontrolled environments. The common wear-out failure modes of LEDs include light output (luminosity) degradation and color shift. Commercially available LEDs have prolonged lifetime of about 70,000h which makes it impractical to obtain real-time degradation data, which subsequently complicates the ability to accurately predict the lumen maintenance life. Several attempts have been made by researchers to develop physics of failure models and / or data driven models for predicting the remaining useful life (RUL) of LEDs. However, these methods lack generalizability and do not address the prediction uncertainties caused by unit-to-unit variation. This calls for the need to develop robust prediction algorithms capable of handling variations in degradation trends due to manufacturing process, system design and environmental / operating conditions. This study proposes a hybrid prognostic approach which combines particle filters (PF) and neural networks (NN). The run-to-failure trend of one LED in a lot is used to model a feedforward neural network and the model parameters are optimized using the particle filter algorithm. The PF trained NN model is further used for RUL prediction for other LED devices in the lot enabling variations to be accounted for and naturally embedded into the prognostic framework. The accuracy of proposed hybrid approach was evaluated using RMSE as the performance metric.

**INDEX TERMS** Hybrid prognostic algorithm, particle filters, neural networks, remaining useful life, light emitting diodes (LEDs).

## I. INTRODUCTION

Light Emitting Diodes (LEDs) are rapidly dominating the global markets for solid state lighting (SSL) replacing traditional light sources such as incandescent bulbs and fluorescent lamps. LEDs are energy efficient, environment friendly and have low health impact due to low UV radiation [1]. Unlike traditional light sources, the efficiency of LEDs does not depend on its shape or size which makes them a perfect choice for aviation lighting, television display backlighting, automobile headlamps, general illumination etc. Although LEDs are not used in safety critical applications, there is still a clear need for better reliability studies in order to meet the performance expectations of the end-use solutions that leverage on them.

Prognostics is the study of predicting the remaining useful life of a system or a device under regular operating use conditions. Prognostic methodologies have been successfully applied to several engineering systems or devices such as lithium-ion batteries [2]–[4], bearings [5], [6], gears [7], [8], composite materials [9] etc. Applying prognostic methodologies on LEDs for predicting the lumen maintenance life benefits the manufacturers as well as the users by shortening qualification testing time and enabling faster time to market.

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The common failure modes of LEDs discussed in literature are light output degradation and color shift beyond a predefined user-defined threshold. Based on reliability studies, the Alliance for Solid-State Illumination Systems and Technologies (ASSIST) categorizes the lumen lifetime as L50 (light output decline by 50% with reference to the initial light output) or L70 (70% light output degradation with reference to initial light output) [10]. Also, many leading LED manufacturers such as Philips®Lumileds and CREE strictly adhere to IES (Illuminating Engineering Society) recommended TM-21 regression methods as the standard protocol for predicting the lifetime of LED products. The TM-21 method is a mathematical formulation wherein an exponential curve is fit to the lumen degradation data between 1000h to 6000h and subsequently, the exponential model is extrapolated to determine the lifetime of the LEDs. Thus, it has become a common practice among researchers to compare their method against the TM-21 protocol. However, TM-21 is incapable of projecting lumen degradation data under multiple operating/loading conditions. Also, TM-21 projection method requires at least 6000 hours of lumen depreciation data to be precisely collected at sampling intervals of 1000 hours. Hence, TM-21 method cannot be used as a robust lifetime estimation tool as data collected from longer / shorter streams cannot be directly utilized for projection.

Prognostic algorithms are broadly categorized as model-based methods, data-driven methods and hybrid approaches. For model-based methods, complete understanding of the system failure mechanisms, operating conditions and influence of environmental factors are imperative. Based on information about system behavior, a physical / empirical / phenomenological model that represents the system best is used for predicting the future behavior of the system. Data driven methods, on the other hand, identify underlying degradation patterns/trends in the failure data and use that information to predict the future state of the system/device.

Amongst model-based methods, filtering-based prognostic approaches are commonly used for predicting the RUL of electronic devices. However, they were not the popular choice for prognosis on LEDs. To name a few, Fan *et al.* [11] modeled the lumen degradation data of high-power white LEDs using a nonlinear exponential model and used an unscented Kalman filter prognostic approach to predict the lumen maintenance life. The authors extended their work to predict the chromaticity shift in phosphor converted white LEDs [12]. In this case, the chromaticity state shift was modeled using a dual-exponential model. The prediction results of both the proposed methods were found be more accurate than the prediction using the TM-21 standard. However, Kalman filter based methods are severely limited by the assumptions of linearity and Gaussian noise. Hence, Fan *et al.* [13] further developed a particle filter based prognostic approach which can be applied on non-linear systems with non-Gaussian noise and proposed this as a replacement to the TM-21 standard regression method. A single term exponential model was used to formulate the damage evolution model describing the LED lumen degradation. Compared to the TM-21 method, the PF based prognostic approach predicted the lumen maintenance life with a prediction error of less than 5%.

Data-driven methods, on the other hand, are considered as black-box methods as they rely on statistical and pattern recognition approaches and do not require specific failure models. Apart from the least square regression method recommended in TM-21 standards, several adaptations of non-linear regression models such as inverse power law model [14], Arrhenius model [15] and Weibull functions [16] were employed for predicting the RUL of LEDs. Chang *et al.* [17] developed a relevance vector machine (RVM) regression model to capture the transient degradation dynamics caused by unit-to-unit variations. The authors used similarity weights as a measure to deduce the degree of affinity between two different degradation trends. Their results showed that the LED qualification testing time can be reduced drastically from 6000 hours to 210 hours.

Duong *et al.* [18] proposed yet another prognostic method using multi-output Gaussian process regression (MO-GPR). The authors used two sets of experimental data under different operating conditions from Ref. [17] to test the proposed MO-GPR method. The basic idea of the proposed method was to implicitly learn the correlation between the degradation traces and use that information to optimize the hyperparameters of the MO-GPR. The results were compared against the prediction results using particle filters and proved to be effective even when there were very few historical data available for training and when the data were not regularly sampled. However, the prediction accuracy of all the above-mentioned regression-based methods was compromised due to uncertainties in operating/loading conditions and discontinuities in data collection. Alternatively, Liu *et al.* [19] used two different artificial neural network (ANN) model for predicting the lifetime of multi-chip high power LED light source. The first ANN was used to quantify the temperature distribution of high-power white LEDs from the finite element model (FEM) simulations and the second ANN was subsequently used for lifetime predictions.

The implementation of prognostic methodologies for LEDs is particularly challenging owing to the lack of standard and uniform criteria for evaluating the performance of LEDs. Though lumen degradation and color shift are the common failure mechanisms accounted for in literature, these failures can be triggered by several/combined long-term decays due to chip degradation, encapsulate degradation and phosphor degradation etc. Also, these failure mechanisms are difficult to distinguish which poses hindrance to the development of failure-specific physical models as well as obtaining training data that clearly define the underlying state of the system.

One effective approach to address the above-mentioned concerns is to use hybrid prognostic methods which integrate the strengths of physics of failure models with the versatility of data-driven methods. Hybrid prognostic algorithms have been successfully applied on several electronic devices [20]–[23], mechanical systems [8], [24], [25] and microelectromechanical systems [26]. Sutharssan *et al.* [27] attempted to propose a fusion prognostic approach for LEDs by combining the logistic regression method with Kalman filters. However, it was a mere conceptual description and the authors stopped short of providing any substantial prediction results.

In this work, we propose a new hybrid prognostic approach combining particle filters and neural networks for estimating the RUL of LEDs. Particle filters proved to be a more robust approach for LED prognosis with its ability to predict the RUL distribution along with confidence intervals over a deterministic lifetime prediction, which is less effective and often subject to large margin of error when it comes to risk-informed decision making for maintenance or replacements. In order to overcome the lack of availability of sophisticated physics-informed damage evolution models to capture all the intricacies of the degradation traces in the PF framework and also accounting for the fact that certain unique degradation patterns may be process / manufacturing / equipment use related and nothing in particular to do with the physics involved, we propose to use the neural network architecture as a surrogate model. The choice of neural network model over other statistical models such as ARIMA was made to describe the often-complex non-monotonic degradation time dynamics of LEDs under consideration. The failure modes in LEDs can range from chip level defects such as dislocations or dark spots to system level degradation such as degradation of the cooling element used in an array of LEDs to lower the junction temperature. Thus, the lumen degradation of LEDs is influenced by several factors such as materials, thermal properties and operating conditions. In order to model such highly non-linear degradation trend, neural network models would be best suited because of their ability to capture and learn complex patterns. To the best of our knowledge, this is the first attempt to propose a PF-NN hybrid algorithm for LED prognosis.

This paper is organized as follows. In Section II, the LED lumen degradation data used in this work is explained along with appropriate NN model selection methods. In Section III, conventional prognostic approaches namely the feedforward neural network model and standard particle filter algorithm are introduced and the prediction results using these conventional methods for LED lumen degradation dataset is presented. In Section IV, the proposed hybrid prognostic approach integrating particle filters and neural networks is introduced and the prediction results for two LEDs using the proposed approach are presented in Section V. Finally, Section VI summarizes the present study and also provides possible recommendations for future work.

## II. DEGRADATION DATASET AND MODEL SELECTION

### A. LUMEN DEGRADATION DATASET

The experimental results obtained by Chang *et al.* in Ref. [17] are used as the degradation dataset in this work. Sixteen high power LEDs each with a rating of 3W and maximum junction temperature of 135°C were placed in a temperature chamber. Aging tests were conducted for all 16 LEDs inside the thermal chamber with a drive current of 450mA at 55°C. The test conditions were regulated such that the temperature inside the chamber does not exceed the maximum junction temperature of the LEDs. The lumen degradation data for 3 out of the 16 LEDs based on the L70 failure criteria are shown in Fig. 1(a). LED-1 was used for training and LED-2 and LED-3 were used as the test dataset in our study. In both the neural network and particle filter-based analyses which will be shown in the subsequent sections, we set the failure threshold to be 75%.

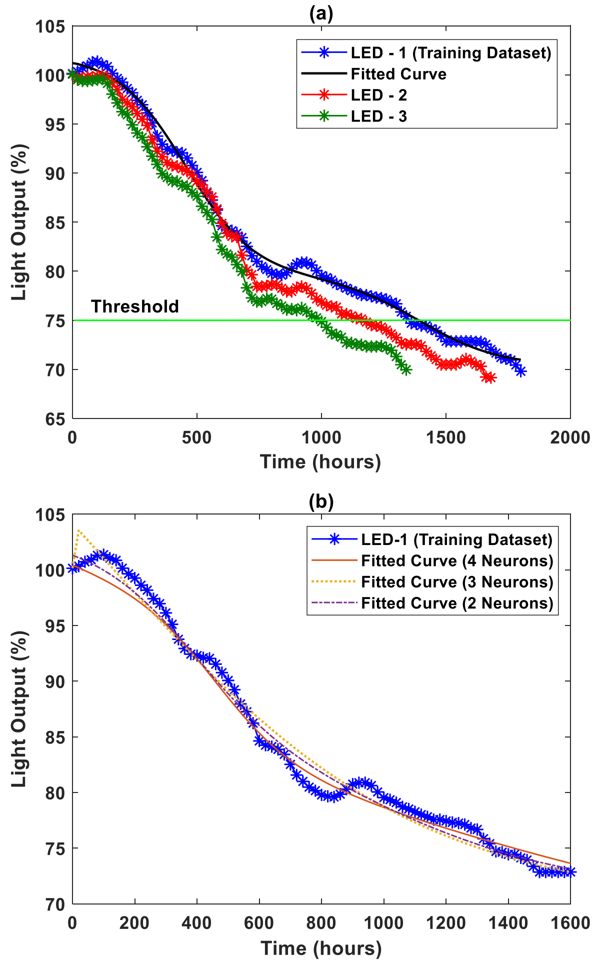


**FIGURE 1. (a) The LED lumen degradation dataset of 3 LEDs obtained from Ref. [17]. The black curve represents the fitted curve for LED-1 using NN degradation model (b) The fitted curve for LED-1 using 2,3 and 4 hidden neurons.**

### B. NN MODEL ARCHITECTURE SELECTION

Selecting an appropriate NN model entails the selection of a network architecture with optimum number of hidden neurons. Ideally, the number of neurons with the best fit to the training data is chosen. The network size should be large enough to fit the data well and at the same time small enough to reduce overfitting. Thus, the choice of network size affects the performance of the network model. However, there aren't

**TABLE 1.** BIC analysis of different NN model architectures comprising of different number of hidden neurons.

| No. of Hidden Neurons | No. of Parameters to be estimated | BIC Value |
|---|---|---|
| 2 | 7 | 7.9538 |
| 3 | 10 | 7.8662 |
| **4** | **13** | **7.8604** |
| 5 | 16 | 8.3024 |
| 6 | 19 | 8.1415 |

any hard-and-fast rules in literature for proper NN model selection. Hence, for the purpose of our study, we resort to Bayesian Information Criteria (BIC) to select the network size. The key idea behind choosing BIC as the metric for model selection is that BIC measures the 'in-sample' fit (i.e., model fitness to the training data) but also penalizes the model based on number of parameters to be estimated by the model. BIC is defined as

$$BIC = q * ln\,(n) - 2 * ln(\hat{L}) \tag{1}$$

where $\hat{L}$ is the maximized value of the likelihood function of the model, $n$ is the size of the training dataset and $q$ is the number of parameters to be estimated by the model. In this study, the training data is fit into model equations with number of hidden neurons varying from 2 to 6 (keeping the number of hidden layers confined to 1). The likelihood function of the corresponding fitted curve is used for BIC analysis. The model with minimum BIC value is considered as the best suited model. The curve fitting results for training dataset (LED-1) using 2, 3 and 4 neurons are shown in Fig.1(b). The BIC values pertaining to different network size are shown in Table 1. Based on the BIC analysis, 4 hidden neurons were chosen as the appropriate network size for our study.

## III. PROGNOSTIC ANALYSIS USING STANDARD NEURAL NETWORK AND PARTICLE FILTERS

### A. FEEDFORWARD NEURAL NETWORKS (FFNN)

In this work, a Multi-Layer Perceptron (MLP) with one hidden layer and four hidden neurons was chosen for the purpose of prognosis. For RUL estimation, the feed-forward neural network (FFNN) model operates in two modes – Training and Prediction. In the training mode, run-to-failure data of one of the LED devices in the sample lot is fed as input to the network model. The input signal is connected to each of the neurons in the hidden layer and is characterized by weight ($w_i^j$) and bias ($b_i^j$) coefficients. While training the network model, the network parameters ($w_i^j$ and $b_i^j$) are initialized with arbitrary values and a backpropagation learning algorithm is used to iteratively adjust the weight and bias values. The network parameters are adjusted to reduce the mean squared error value (MSE) till the parameters converge to an optimal value.

In the prediction mode, the NN model with network parameters estimated in the training mode are used to predict the failure trend of the test device. The schematic of the network

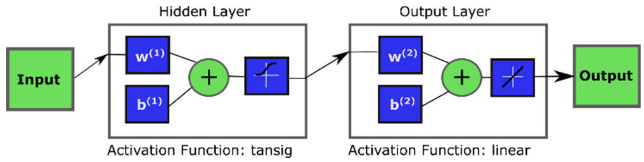


**FIGURE 2.** The schematic representation of Multi-Layer Perceptron (MLP) neural networks.

architecture used in this work is shown in Fig.2. The MLP network is characterized by a sigmoidal activation function between the input and hidden layer and a linear activation function between the hidden and output layer. The sigmoid activation function can be expressed as

$$h_i = \frac{1}{1 + e^{-(w_i^{(1)} * k + b_i^{(1)})}} \tag{2}$$

where $w_i^{(1)}$ and $b_i^{(1)}$ are the weight and bias values corresponding to the input node and $k$ is the time in hours. The time $k$ for LED lumen degradation is fed into the NN model as input. It is to be noted that the time $k$ here is not an index of time data but the actual value of time itself. The Levenberg-Marquart (LM) learning algorithm is used for training the network model and the predicted output of the network can be expressed as:

$$g((w, b)\,, k) = f(\sum_{i=1}^{M} (h\left(\left(k * w_i^{(1)} + b_i^{(1)}\right) w_i^{(2)}\right) + b_i^{(2)}) \tag{3}$$

where $w_i^{(2)}$ and $b_i^{(2)}$ are the weight and bias values associated with the hidden layer, $w_i^{(1)}$ and $b_i^{(1)}$ are the weight and bias values corresponding to the input node and M is the number of hidden neurons in the NN network. The input layer activation function is represented by $h(.)$ and the network output $g(.)$ gives the predicted light output with respect to time $k$ (in hours).

### B. STANDARD PARTICLE FILTER (SPF)

Particle Filters (PF) are a class of non-linear filters based on sequential Monte Carlo methods. The schematic representation of the prognostic framework using particle filters is shown in Fig. 3. In Bayesian filtering techniques, the system state is represented by a probability density function (pdf). The basic idea of particle filters is to approximate the system state pdf by a set of weighted particles. The initial prior distribution is generated based on user knowledge of system behavior and the underlying failure mechanisms. A suitable physical / empirical model which best describes the system dynamics is chosen as the degradation model. The weighted particles are propagated through the degradation model.

The degradation model parameters are recursively updated for all the available measurement data as per Bayes theorem. This process is called state estimation.

Once the model parameters are tuned to best represent the dynamics of the system, the degradation model is extrapolated to predict the future state of the system. A suitable

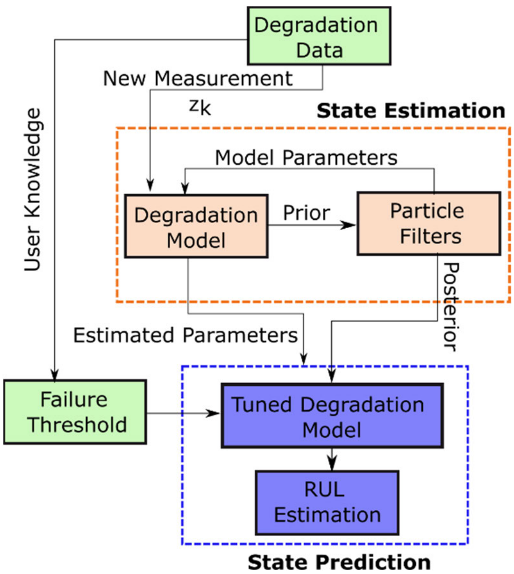


**FIGURE 3.** The schematic representation of particle filter prognostic framework.

failure threshold is assumed based on prior knowledge of the system and the model is propagated with respect to time till the failure threshold is reached. This process is called state prediction.

In this work, the neural network model described in Eqn. (3) is used as the underlying degradation model representing the system dynamics. Thus, the state transition and measurement function of the PF algorithm can be expressed as

$$x_k = x_{k-1} + \omega_{k-1} \tag{4}$$

$$z_k = g(x_k, k) + \varepsilon_k \tag{5}$$

where $x_k$ and $x_{k-1}$ refer to the current and previous state respectively and $\boldsymbol{\omega}_{k-1}$ is the process noise. The state transition function $g$, which is where the physical failure model is usually induced in an incremental form, is now replaced by the NN degradation model represented by Eqn. (3) and $\boldsymbol{\varepsilon_k}$ is the measurement noise.

### C. RUL ESTIMATION USING FFNN AND STANDARD PF

For FFNN method, LED-1 dataset was used for training a NN model of 4 hidden neurons using the LM algorithm. The trained NN model was used to predict the degradation behavior of LED-2 and LED-3. The network model was executed for 50 repetitions with 50 random arbitrary initial values for weights and biases. The prediction results for LED-2 using FFNN is shown in Fig.4(a). It is evident from the prediction results that the degradation traces mostly follow the training dataset barring a few traces which follow the actual degradation data of LED-2 depicted by the black curve in Fig.4(a).

In this work, the choice of 4 hidden neurons was made based on BIC analysis as already explained in the previous section. The network size of 4 hidden neurons had the best fit with minimum BIC values. The curve fitting results are shown in Fig.1(b). From literature, it can also be inferred those 4 or 5 hidden neurons are an optimal choice for RUL prediction in systems with two-phase degradation trends [28]. Thus, despite introducing considerable complexity into the network model, the trained FFNN model failed to capture the true degradation trend of the test dataset and the prediction traces only followed the training dataset, not the test dataset.

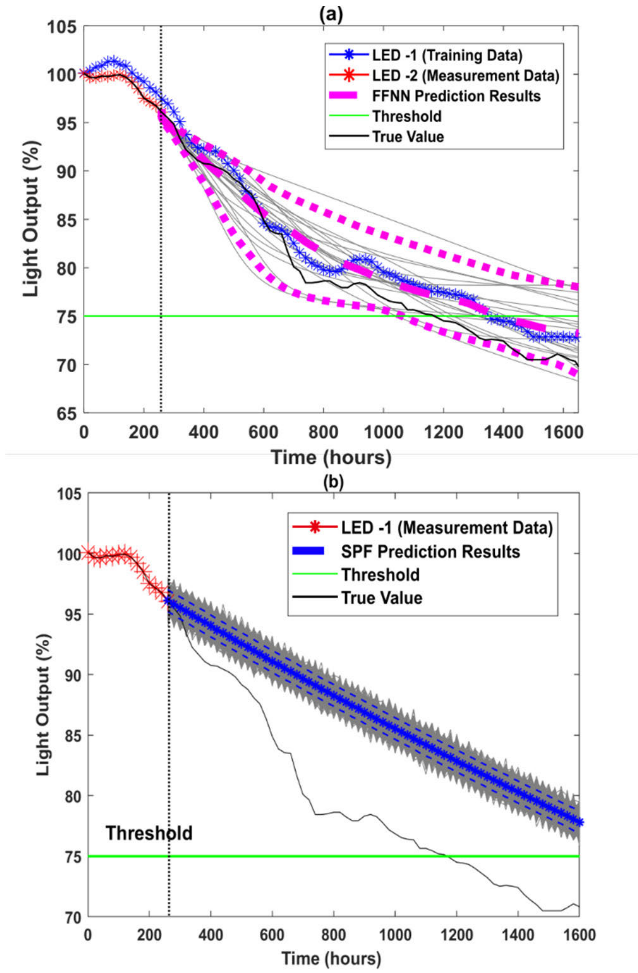


**FIGURE 4.** The prediction curves using the standard prognostic approaches (a) feedforward neural network (FFNN) model and (b) standard particle filter (SPF) algorithm. The gray lines in (a) and (b) represent the prediction traces using 50 repetitions of NN and 5000 particles, respectively.

As an alternative to the data-driven analysis, we now analyze the dataset using the PF framework. The initial parameter guess for the state transition model for the PF was obtained from curve fitting results.

The NN model (4 hidden neurons) equation expressed in Eqn. (3) was formulated as an incremental luminosity degradation model for PF. The algorithm was executed with 5000 particles and the prediction traces for all 5000 particles are shown in Fig. 4(b).

The results clearly indicate highly unsatisfactory performance as the degradation traces completely diverge away from the actual failure data depicted by the black curve in

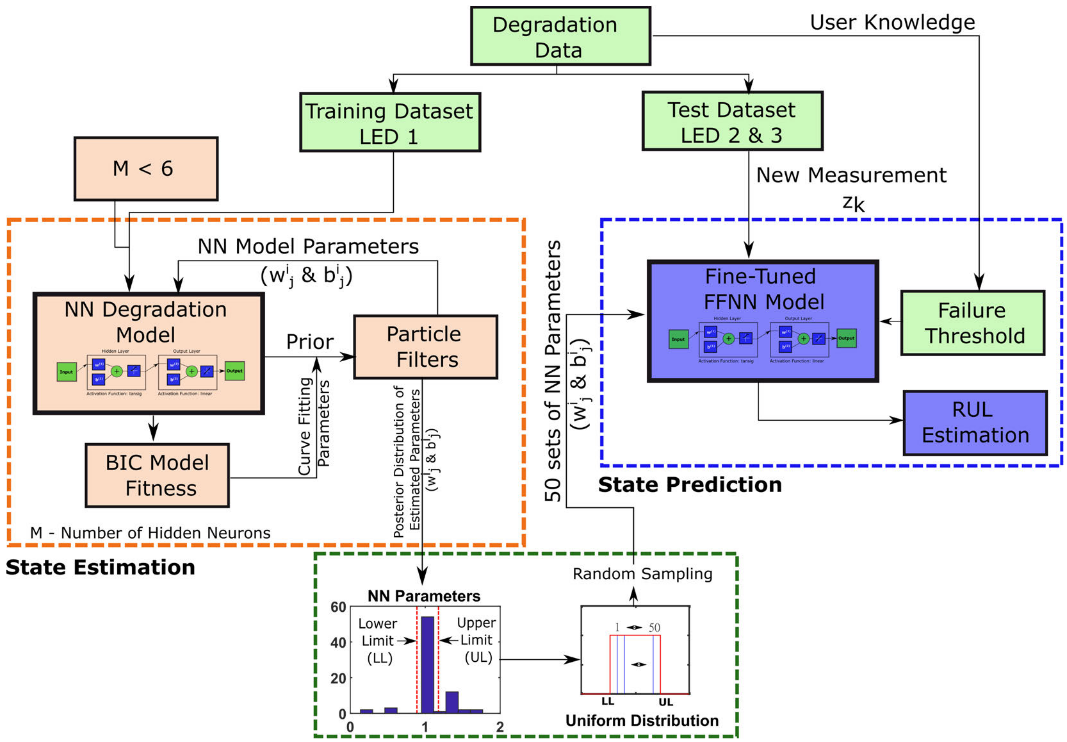


**FIGURE 5.** The schematic representation of the proposed particle filter trained neural network prognostic approach (HyA).

Fig.4(b). The accuracy and performance of the PF algorithm primarily depends on the model accuracy. Even though a NN model with adequate complexity (4 hidden neurons) is used as the degradation model here, 260 hours of available data is insufficient for the algorithm to estimate the large number of model parameters (13 of them) accurately. Also, the PF algorithm inherently suffers from weight decay problems due to particle degeneracy and impoverishment thereby hampering the diversity of the predicted posterior parameter distributions which could also affect its performance.

The incompetency of the two standard (FFNN and Standard PF) prognostic approaches are evident from the prediction results shown in Fig. 4. Moreover, it is to be noted that the degradation trends shown in Fig.1(a) were obtained under specific testing conditions and a change in testing conditions such as a lower drive current or a higher temperature can further alter the lumen degradation behavior of LEDs. Such scenarios can further worsen the performance of conventional prognostic approaches. In order to address these issues, we propose a hybrid particle filter trained neural network model which has the capability to overcome the generalization bottleneck faced by conventional approaches.

## IV. PROPOSED HYBRID PROGNOSTIC FRAMEWORK

The overall flowchart of the proposed hybrid particle filter trained neural network framework (HyA) is shown in Fig. 5. The proposed hybrid approach works in two-stages – (A) *State Estimation* and (B) *State Prediction*. Similar to conventional prognostic approaches discussed in Section III, LED-1 dataset is used for training the NN model and curve fitting parameters of LED-1 dataset were used to generate the initial prior distribution for the PF algorithm. A uniform distribution with $\pm$ 3% bounds of the true parameter value obtained from curve fitting were generated and this was fed into the PF algorithm as the initial parameter guess values. The NN model parameters i.e., weight and bias coefficients then get optimized using the PF algorithm. PF algorithm recursively updates the model parameters using the degradation model expressed in Eqn. (3) till the actual End-of-Life of LED-1. These steps enable the degradation model to estimate the state parameters closer to the actual / true value and hence referred to as the *state estimation* stage of our overall HyA framework.

Appropriate initialization of the weight and bias coefficients is crucial for a proper convergence of the NN model. In this work, the PF estimated model parameters were fed into the *State Prediction* stage of HyA. This ensures that the NN model used for state prediction in PF is configured with informed values of weight and bias coefficients as a replacement to an arbitrary assignment of weights and biases. To elaborate further, the posterior distribution of the NN parameters is represented using a histogram. The bin with the highest frequency is selected and the corresponding bin width were identified and labelled as lower limit (LL) and upper limit (UL) as shown in Fig. 5. A uniform distribution with the upper and lower limits for each of the model parameters (weights and biases) were generated and 50 sets of random samples from that uniform

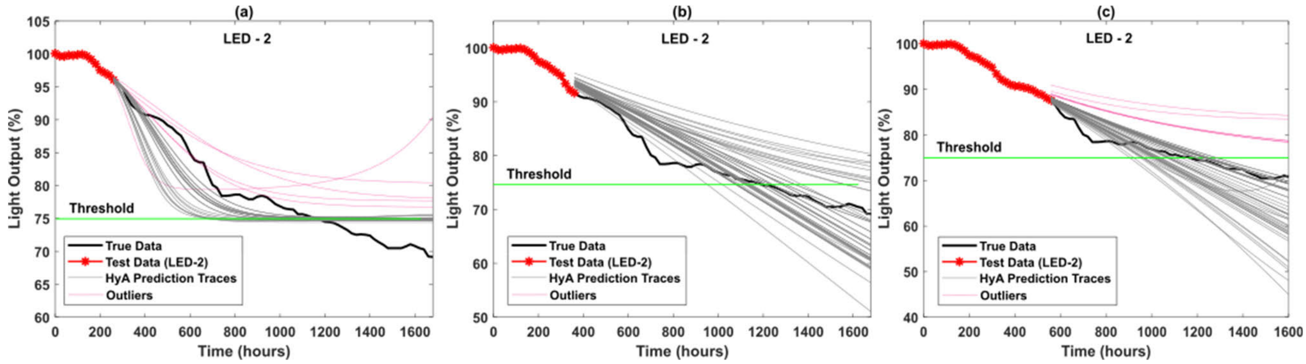

**FIGURE 6.** The lumen degradation prediction curves for LED-2 using the proposed hybrid prognostic approach (HyA) at (a) 260h, (b) 360h and (c) 560h. The gray lines represent the prediction traces for 50 repetitions and the dotted magenta lines are the obvious classified outliers.

distribution were fed into the NN model as initial weight / bias coefficients.

The tuned NN model was executed for 50 repetitions and each repetition was configured with one combination of the random sample generated from the uniform distribution of NN parameters as the initial parameter guess values. In other words, the NN model is now being fed with a non-deterministic pseudo-distribution of weights and biases represented by the 50 values (instead of a single point value that is commonly assigned in general, that too arbitrarily).

The informed initial parameter configuration of the NN in the HyA framework constrains the NN model parameters to hover around closer to the true values (of the training dataset) thus enabling better as well as faster convergence for prognostication on the test dataset. Finally, the tuned FFNN degradation model was further fine-tuned on-the-fly for all the available measurement data from the test dataset using the LM algorithm. The failure threshold was set to be at 75% of the initial luminosity and with this definition, the RUL distribution for the test LED was estimated.

## V. RESULTS AND DISCUSSION

### A. RUL PREDICTION USING HyA

The run-to-failure data of LED-1 was chosen for training as stated in the previous sections. The HyA was executed for 50 repetitions and for each repetition, the weights and biases for NN were sampled from the uniform distribution approximation to the highest frequency bin of the PF parameter posterior distribution. The prediction results for LED-2 at 260 hours and 360 hours, are shown in Fig. 6(a) and Fig. 6(b), respectively. For 260 hours, the predictions were unable to capture the actual degradation trend even though only 5 repetitions were needed to be classified as unsuccessful/outliers. A particular repetition was considered to be successful if the prediction trace falls within the $2\sigma$ bounds of the predictions. Additionally, if the prediction trace follows a monotonically increasing trend, then it was considered an outlier as well. The outliers based on the above-mentioned criterion are represented by dotted (shown in magenta) lines in Fig. 6. The divergent or exponentially increasing trends observed in few of the traces can be attributed to weight decay (overfitting / underfitting) while training the NN model in the state prediction stage of HyA. Very large or very small weights can cause the output function to be rough and produce outputs which are beyond the actual range of the data at a given time instant.

However, for 360 hours, the prediction results clearly shows that most of the prediction traces manage to capture the entire degradation trend. Also, all the 50 repetitions were found to be successful with no monotonically increasing trends and all the predictions traces with the 2 $\sigma$ bounds as shown in Fig. 6(b). Barring a few traces, the prediction error for about 45 out of 50 traces were found to be within acceptable limits. Subsequently, with the availability of a greater number of measurement data in the test dataset up to 560 hours, the prediction success rate improved as shown in Fig. 6(c). Almost 46 out of 50 traces were able to trace the actual degradation trend. The confidence interval of the prediction traces of successful repetitions were found to be narrower compared to the predictions at 360 hours indicating that with the availability of more data, the NN model learns the degradation trend better (as one should expect).

The remaining useful life of the LED can be estimated by

$$RUL_i = EOL - k \tag{6}$$

where i refers to the NN repetition count, EOL is the actual end of life of the LED and k is the failure threshold. The true RUL of a device is the difference between End-of-life of the device and the prediction starting point.

The RUL distribution for LED-2 is plotted in Fig. 7. The RUL values corresponding to successful repetitions (removing the obvious outliers) were chosen for the purpose. The actual end-of-life of LED-2 based on assumed failure threshold (75% light output) was found to be 1180 hours. Thus, the true RUL for 260 hours as the prediction starting point falls at 920 hours. The RUL distribution at 260 hours is shown in Fig. 7(a). A large RUL prediction error of about 250 hours can be observed at 260 hours due to weight decay and the

**TABLE 2.** Comparison of RMSE Values with confidence interval (Represented by the 5th and 95th Percentile) for Different Prediction Methods for Test Data Sets, LED-2 & LED-3 at 260h, 360H and 560h.

| Prognostic Method | LED - 2 | | | | | | | | | LED - 3 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 260h | | | 360h | | | 560h | | | 260h | | | 360h | | | 560h | | |
| | 5th | 50th | 95th | 5th | 50th | 95th | 5th | 50th | 95th | 5th | 50th | 95th | 5th | 50th | 95th | 5th | 50th | 95th |
| **PF** | 14.01 | 14.63 | 15.21 | 8.32 | 8.58 | 8.94 | 8.33 | 8.98 | 9.16 | 11.88 | 12.05 | 12.05 | 9.22 | 9.97 | 10.05 | 8 | 8.33 | 8.58 |
| **FFNN** | 4.12 | 6.58 | 10.45 | 2.97 | 6.01 | 12.08 | 2.14 | 4.37 | 6.66 | 2.06 | 5.98 | 10.43 | 1.43 | 5.12 | 9.78 | 1.09 | 3.77 | 8.96 |
| **HyA** | 3.49 | 7.03 | 6.08 | 3.69 | 5.63 | 7.19 | 0.99 | 2.56 | 4.02 | 2.88 | 5.52 | 8.00 | 1.11 | 3.98 | 7.43 | 2.97 | 3.03 | 4.32 |

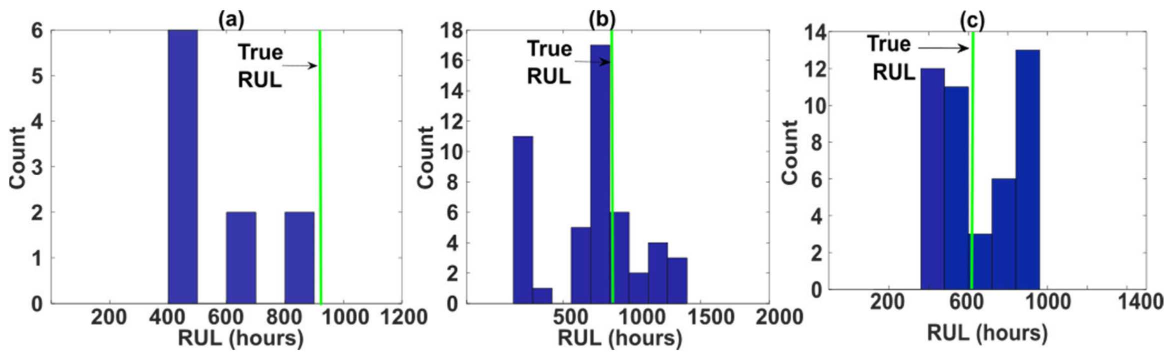


**FIGURE 7.** The prediction RUL distribution for LED-2 using the proposed hybrid prognostic approach (HyA) at (a) 260h, (b) 360h and (b) 560h. The green lines represent the true RUL at the respective prediction starting points.

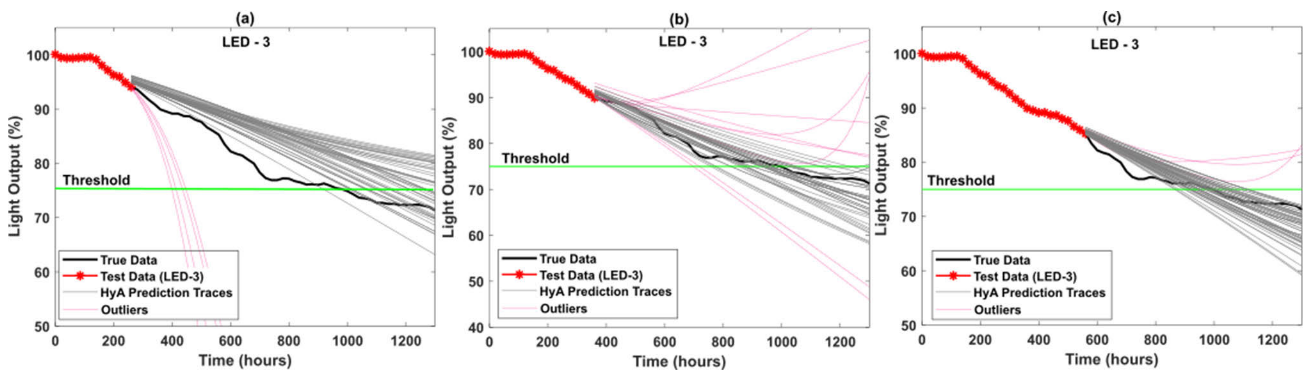


**FIGURE 8.** The lumen degradation prediction curves for LED-3 using the proposed hybrid prognostic approach (HyA) at (a) 260h, (b) 360h and (c) 560h. The gray lines represent the prediction traces for 50 repetitions and the dotted magenta lines are the obvious classified outliers.

wide confidence interval discussed earlier. However, the RUL prediction error reduced drastically to 10 hours for predictions made at 560 hours as shown in Fig. 7(c).For LED-3 on the other hand, the prediction results were found to be better and more accurate than LED-2. The prediction results for LED-3 at 260 hours, 360 hours and 560 hours are shown in Figs. 8(a), 8(b) and 8(c) respectively. The corresponding RUL distributions for LED-3 is shown in Fig. 9. The actual end-of-life of LED-3 was at 1000 hours and hence the true RUL corresponding to the three different prediction starting points mentioned above were 740 hours, 640 hours and 440 hours respectively.

The RUL prediction error were determined to be below 20 hours for all three prediction starting points and there were no weight decay issues observed in the prediction results. The NN weight and bias evolution using standard FFNN and HyA are discussed in detail in subsection C. It is to be noted that HyA predictions do not detect the sharp kink in the degradation trend at 750 hours for both LED-2 and LED-3. This leaves room for further improvement to optimize the proposed approach by using a more complex NN architecture such as RNN or LSTM.

Predictions at 760 hours were performed as well for both the LEDs and the proposed method outperformed conventional approaches with very good prediction accuracy. For the sake of brevity, the results are not discussed in this work. Of the 3 LEDs considered in this work, LED-3 was found to degrade rapidly. However, the prediction results for LED-3

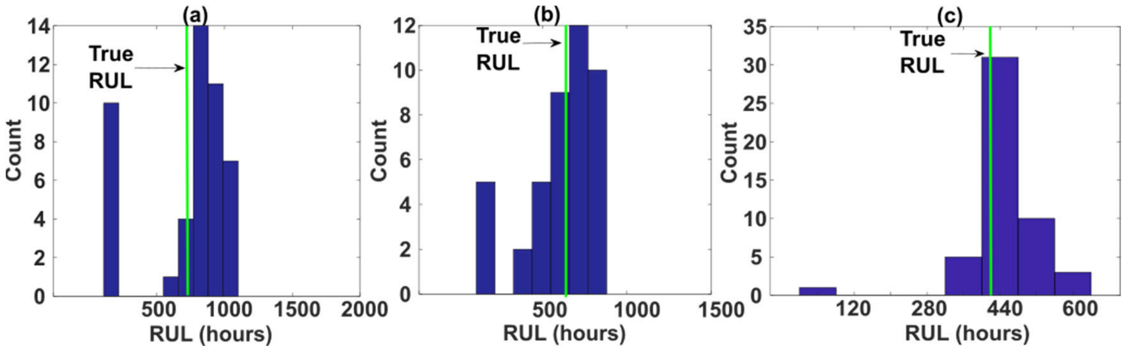


**FIGURE 9.** The prediction RUL distribution for LED-3 using the proposed hybrid prognostic approach (HyA) at (a) 260h, (b) 360h and (b) 560h. The green lines represent the true RUL at the respective prediction starting points.

using the proposed hybrid approach were found to be even better than that of LED-2. Thus, it can be concluded that the proposed approach efficiently captures rapidly deteriorating non- exponential trends and has the ability to handle unit-to-unit variations effectively.

## B. PERFORMANCE EVALUATION

The commonly used prognostic performances metrics are root mean squared error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE). MAPE and MAE gives the absolute error between the true and predicted values whereas RMSE gives the standard deviation of the residuals. MAPE and MAE are not sensitive to outliers compared to RMSE values. So, RMSE is comparatively a more stringent metric than MAPE and MAE. Hence, we use root mean square (RMSE) as the performance metric to compare the prognostic abilities of FFNN and standard PF with the proposed HyA approach. RMSE is a measure of deviation of predicted values from the actual degradation data and can be expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=T}^{n}(x_{predicted} - x_{true})_k^2} \tag{7}$$

where $n$ is the size of the training dataset, $T$ is the prediction starting point and $k$ is the time (in hours). The RMSE values with its confidence intervals (represented by the 5$^{th}$ and 95$^{th}$ percentile values) for all three prognostic approaches for both LED-2 and LED-3 are listed in Table 2 for the three prediction time instants of $\{260, 360, 560\}$ hours. From Table 2, it can be inferred that the proposed hybrid algorithm (HyA) in general clearly outperforms both the conventional prognostic approaches with a considerably low value of RMSE.

Computational time is yet another important aspect to consider while developing prognostic approaches. From Table 3, it can be observed that standard particle filters with 5000 particles offer the fastest prognosis. However, the prediction accuracy of PF is poor for two-phase degradation phenomena. Similarly, the standard FFNN takes an average of 22 seconds for execution; however, it has poor performance in terms of RMSE values. Thus, HyA proves to be an affordable choice of prognostic algorithm for achieving good performance accuracy with a moderate computational load. It is to be noted that the simulations were executed in a DELL workstation (Model- Inspiron 14 – 5459) with 16GB RAM and Intel Core i5 processor.

**TABLE 3.** Comparison of Computational Time for Different Prediction Methods for Test Data Sets for LED-2 & LED-3.

| Method | Computational Time at 360 hours (secs) | |
|---|---|---|
| | LED-2 | LED-3 |
| PF | 8.81 | 8.32 |
| FFNN | 23.45 | 21.43 |
| HyA | 44.08 | 43.75 |

It is to be noted that there is only one prior study that we can make some comparison of our results with, which is the study that reported the raw data used in this work, Ref. [17]. The authors in Ref. [17] use a simpler definition of the prediction error purely based on the predicted and true RUL and taking that less stringent definition (for the sake of comparison), the average error reported in their work for the LED data sets studied here is $\sim$2.47%. In comparison, the average error in RUL prediction based on our HyA framework is $\sim$ 1.67%. This further illustrates the robustness of our framework.

## C. NN MODEL PARAMETER EVOLUTION TRACKING

In order to understand the proposed HyA approach further, we investigated the parameter evolution during NN training process based on the backpropagation learning algorithm. We observed the individual trend for all the 13 parameters in the NN degradation model used in this work. The weights and bias values are the learnable parameters of the NN model. Although the existence of one unique set of optimum NN parameters which best approximates the degradation data is improbable, we can deduce a set or a band of NN parameters which best fits the data. We performed two different case studies to understand the NN parameter evolution w.r.t time during training.

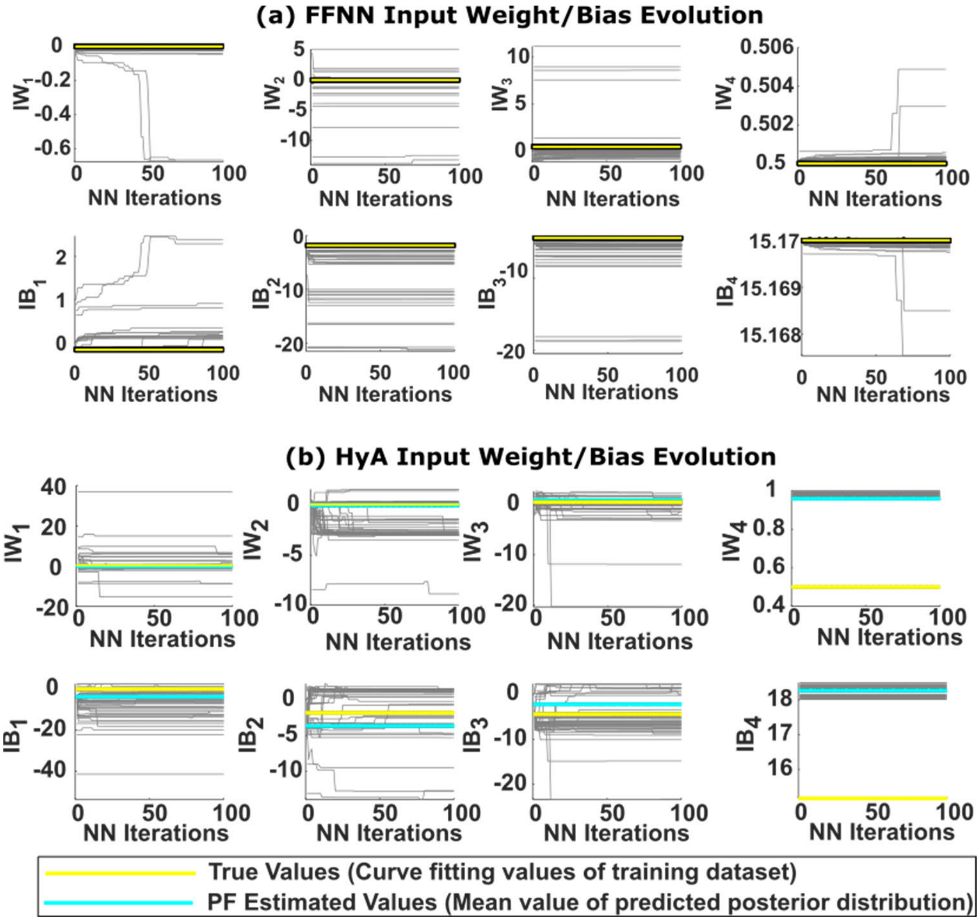


**FIGURE 10.** The NN input weight and input bias evolution on the test data set for (a) FFNN with deterministic initial parameter values and (b) HyA using stochastic PF estimated initial parameter values. The gray lines represent the parameter evolution traces for 50 repetitions. The yellow lines represent the true values from curve fitting and the cyan lines represent the mean of the PF estimated parameter values.

### 1) CASE STUDY 1 – NN PARAMETER EVOLUTION WITH DETERMINISTIC INITIAL PARAMETER VALUES

Traditionally, the initial parameters values in a standard FFNN model are arbitrarily assigned and the network parameters evolve during backpropagation to obtain the desired output. A standard FFNN model with one hidden layer and 4 hidden neurons was formulated. The backpropagation learning occurs in our NN model using the LM algorithm as it has a faster convergence rate compared to gradient descent. Also, LM algorithm has the ability to find an optimal solution even if the initial parameter values are far from the true parameter values.

The LED – 1 dataset was used for training the FFNN and for this, the deterministic curve fit parameter values of LED – 1 using Eqn. (3) were set as the initial deterministic seed values for the weights and biases in the FFNN. The NN model was then trained using LM algorithm and the trained model was used to predict the degradation trend of the test dataset (LED -2). The NN model was trained with maximum number of iterations set at 100 i.e., 100 iterations of backpropagation. The motive behind choosing 100 iterations was to enable the NN model to learn the degradation trend better with the expectation that the model parameters would eventually converge closer to the true values. The trained NN model was executed for 50 repetitions for predicting the degradation state of the test dataset and for each repetition, the initial parameter values were configured to be the deterministic curve fit extracted values of the training dataset. The parameter evolutions for the test dataset during backpropagation (training) were obtained. The input side weight and bias evolution trends are shown in Fig. 10(a).

The yellow line represents the assumed true parameter value from curve fitting results of LED – 1 (training dataset). It can be seen that the input side parameters (grey line traces) for the test dataset (LED – 2) before backpropagation hover around the true values. However, after backpropagation, the output side weight and bias values were found to be erratic and failed to converge towards the true values as shown in Fig.11(a). Since the output layer information is critical as it represents the desired output (lumen output in our case study) from the network, it can be concluded that the FFNN fails to train the model with one run-to-failure training dataset effectively and hence produces poor predictions subsequently for test datasets LED-2 and LED-3.

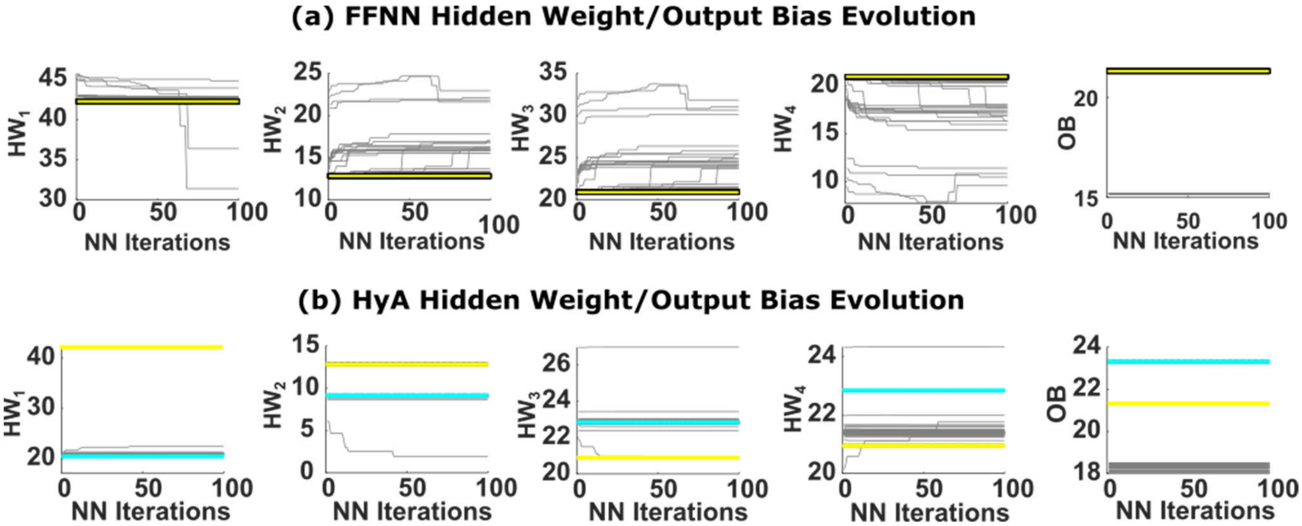


**FIGURE 11.** The NN hidden weight and output bias evolution on the test data set for (a) FFNN with deterministic initial parameter values and (b) HyA using stochastic PF estimated initial parameter values. The gray lines represent the parameter evolution traces for 50 repetitions. The yellow lines represent the true values from curve fitting and the cyan lines represent the mean of the PF estimated parameter values.

### 2) CASE STUDY 2 – NN PARAMETER EVOLUTION WITH STOCHASTIC INITIAL PARAMETER VALUES FROM PF ALGORITHM

The NN parameter evolutions for the proposed HyA algorithm were also analyzed for comparison. In this case, 50 set of network parameters obtained from the posterior distribution of PF algorithm (on the training data set) were used to configure the NN model. The NN model was trained for 100 iterations and the trained model was executed for 50 repetitions. Unlike the standard FFNN model which is configured with deterministic initial parameter values for each repetition, the proposed HyA is configured with one new set of PF trained network parameter values for each repetition. This attributes to an informed initial parameter configuration each and every time the algorithm is executed. From Fig. 10(b), it can be seen that the input side parameters vary drastically for all 50 repetitions. However, after training, the output side weight and bias values converge towards the mean of the PF estimated values (cyan line) as shown in Fig. 11(b). The cyan line represents the mean of the PF estimated values and the yellow line represent the true values obtained from curve fitting. We may infer from the NN parameter evolution in Fig. 11(b) that the variance in the parameter evolution traces for HyA is lower than that observed for standard FFFN shown in Fig.10(b). Thus, it can be concluded that the proposed HyA algorithm optimizes the model parameters efficiently. The outliers found in the prediction traces in Figures 6 and 8 using the proposed HyA can be attributed to the few NN parameter evolution traces which are astray (divergent) from the PF estimated values as seen in Figs. 10(b) and 11(b).

## VI. CONCLUSION

In this work, a hybrid prognostic approach integrating particle filters and neural networks has been proposed to predict the lumen degradation of high-power white LEDs. A feedforward neural network model was formulated to capture the light output degradation of LED using curve fitting functions. A uniform distribution of curve fitted parameters within ±3% bounds was used for the initial prior distribution in the particle filter algorithm. The lumen degradation data of 3 LEDs from literature were used to test the performance of the proposed approach. The PF algorithm was used to obtain the posterior distribution of the NN model parameters comprising of weights and bias coefficients for the training dataset, LED-1. The tuned NN model imbibing the PF estimated model parameter distributions was further used to predict the remaining lumen maintenance life of other two LED test datasets. To the best of our knowledge, the proposed approach is the first of its kind to be tested for LED lumen degradation prediction. The prediction results of the proposed HyA were compared with the conventional standard FFNN and standard PF approaches. The proposed method proved to be more effective, efficient and adaptable compared to the conventional purely data and purely model-based approaches using RMSE and computational time as the metrics for comparison.

Based on our in-depth study, it can be concluded that the proposed approach is a powerful methodology to address the prognostic concerns of systems/devices showing significant unit-to-unit variations, non-monotonicity and even perhaps varying operating conditions in their degradation profiles. Note that the accuracy of the prognosis very much depends on the choice of several parameters for the NN and PF which include the number of hidden layers, number of neurons and type of activation function (for NN) and the number of particles, resampling strategy, underlying degradation model as well as initial prior distribution (for PF). We have accounted for all these considerations in our work and chosen the optimal NN architecture by making use of the BIC metric.

For future work, we intend to introduce suitable weight regularization methods to the proposed hybrid algorithm. This can be done by using suitable resampling/roughening methods within the particle filter algorithm in order to avoid particle degeneracy and impoverishment. Also, our current proposed method uses a purely mathematical empirical degradation model formulation using the NN architecture as the only foundation. In order to capture the inflections in the degradation pattern and the overall trend, a suitable physics informed model could be used as a surrogate model so that the NN is only used to capture the residuals and inflections while the overall trend envelope is captured by the physical / phenomenological laws of degradation, which might enable even simpler NN architectures to be used with fewer model parameters to be learnt without compromising on the effectiveness of degradation pattern capture and resulting in further improvisation of the RUL prediction accuracy.

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