IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 28, 2017, accepted September 22, 2017, date of publication October 10, 2017, date of current version November 7, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2761802

Multidimensional Data-Driven Life Prediction Method for White LEDs Based on BP-NN and Improved-Adaboost Algorithm

KAIYUAN LU, WENJIN ZHANG, AND BO SUN, (Member, IEEE)
School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China
Corresponding author: Bo Sun (e-mail: sunbo@buaa.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 61673037.

ABSTRACT In view of the light-emitting diode (LED) and its life prediction, despite its currently wide use, IES TM-21-11 parametric life prediction method is incapable to extrapolate under multidimensional conditions (include working environmental conditions). This paper presents a multidimensional back propagation-neural network (BP-NN) based life prediction method which considers different driving currents and ambient temperatures. In this method, parameters such as temperature, electric current, initial chromaticity coordinates and initial luminous flux serve as the inputs, while life serves as the output. Since the traditional NN can easily get trapped in local minima and be affected by low precision, the BP-NN method is improved using Adaboost algorithm. The expected life predicted by the improved method is compared with that of traditional BP-NN and IES TM-21-11. The LED lamps of different power grades are compared for verification purposes. The results show that when predicting LED's lifetime, the improved method reduces the average relative error by on average by 54% compared with traditional BP-NN. However, the improved method takes 63.6% longer to operate, which requires the users to choose an appropriate model in accordance with particular operating conditions.

INDEX TERMS White LED, life prediction, Adaboost, BP neural network, multidimensional data.

I. INTRODUCTION

In recent years, solid state lighting is widely used in various areas of industry and life and has become a hotspot of academic research. As a new generation of light source, LED is leading a new revolution in the area of lighting [1], [2], with its advantages such as low driving voltage, high efficiency, long life and low cost. With the gradual increase of LED lamps' service life, to make the accurate life prediction is expected to gain extensive attention gradually.

At present, the LED life prediction methods driven by data mainly include Statistical Regression Method, Bayes Net Method, Finite Element Method, Kalman Filtering Method, Particle Filtering Method and Neural Network Method [3]. As for Statistical Regression Method, Qu *et al.* [4] use Weibull analysis to facilitate the lifetime models in LED lamp accelerated degradation testing and get a great effect. However, the method requires relatively strict premise condition and accurately understanding of physical structure.; Bayesian Network Method [5] is good at dealing with complex causal relationship between the dependent variable and the incomplete data sets, but it still needs to know the failure mechanism and the prior distribution in advance; Finite Element Method simulation [6] is carried out to obtain the ambient temperature in the LED driver; Kalman Filtering Method [7] is a recursive algorithm taking the minimum mean square error as the estimated criteria, but only when the system state equation and observation equation are both close to linear and continuous, the predicted results can be close to the real values; Particle Filtering technology [8] shows superiority in nonlinear and non-Gaussian system, which determines its wide application range is very wide. However the main problem is that it needs to use a large number of samples to approximate the posterior probability density of system. Neural network [9] is a mathematical model based on human brain's neurons structure and work style. With extremely high adaptive and learning ability, it can well fit all kinds of nonlinear function. Besides, the BP-NN is a kind of multilayer feed forward network trained according to the error back propagation algorithm. Though the BP-NN is currently one of the most widely used neural network model, it can easily come across local optimum and slow convergence speed due to its subjective factors.

According to the current study, the LED junction temperature is the key parameters affecting the service life of the LED [10], [11]. In the case of other conditions unchanged, a certain increase of both current and ambient temperature raise the junction temperature, which result in an acceleration to the aging of LED lamps as well [12], [13]. Therefore the current and environment temperature have been chosen as the work and environmental parameters into the model' inputs, with the other three crucial product characteristic parameters as chromaticity coordinates u', v' and luminous flux into the model' inputs as well. All the inputs are collected from the initial conditions.

Thus the factors affecting the service life of white LED can be summarized as luminous flux, chromaticity coordinates, current, temperature, *et al.*, among which luminous flux and chromaticity coordinates, as the indicators judging LED's life, have a direct influence and current and temperature, as the two most important work and environmental parameters, have a key and complex influence on the attenuation process of luminous flux and chromaticity coordinates [14].

Given that the IES TM-21-11 standard [15] current widely used to calculate the time to reach 70% of the initial luminous flux which can be called to a parametric failure. Under different temperature conditions only based on the same current, and other relevant life prediction researches [16]–[18] also carried out under one dimension, a multidimensional life prediction method for white-lighting LED is proposed. For sample data acquisition, it needs to undertake continuous measurement for a long time under multiple conditions. Therefore under the same condition, the sample data acquired is little and the failure process of different products is not completely consistent. Furthermore, given the nonlinear relationship between input and output, it is appropriate to choose relatively mature BP-NN algorithm.

BP-NN algorithm has its own advantages such as being rapid, direct, and accurate. With its simple structure, plenty of adjustable parameters, large amount of training algorithms and good maneuverability, BP-NN algorithm has earned wide attention and application in such fields as multidimensional biology [19], chemistry [20], mechanical engineering [21] and reliability evaluation [22] in recent years. But for the LED field, the application of BP-NN algorithm is still not too much. Sutharssan [7] uses a simple neural network model to implement the LED life prediction, the model including a hidden layer and two neurons nodes in hidden layer. Chen and Hsu [22] propose a neural-network-based recognition system for automatic light emitting diode (LED) inspection. Two types of neural-networks, back-propagation neural-network (BP-NN) and radial basis function network (RBFN) are proposed and tested. The proposed neural-network approach is successfully demonstrated by real data sets and can be effectively developed as a system for a practical application purpose. However, the research on life prediction containing multidimensional parameters such as temperature and current has not yet been carried out.

In this study, two life prediction methods driven by multidimensional data for white LED are proposed. Five relative parameters as the inputs, the models are respectively established by traditional BP-NN and Adaboost-improved BP-NN algorithm to predict white LED lamps' life which is the output of them. Moreover, the results are compared with the parametric life expectancy computed by IES TM-21-11 and multiple sets of data are contrasted to explore the white LED life prediction method driven by multidimensional data under different conditions. Finally, the usage scenarios are proposed according to the accuracy and time from comparison results, and the weight of influence of each input parameters on the output life is analyzed to offer reference for further research.

II. PREDICTION METHOD BASED ON BP-NN

A. THE IES TM-21-11 LIFE PREDICTION METHOD

IES TM-21-11 is a frequently-used method of projecting long term lumen maintenance of a LED light source based on 6,000 hours (or more) of lumen depreciation data collected from per LM-80-2008 report [23]. Owing to its standardization and convenience, it has been widely used in industry area [24].

The time to reach 70% of the initial luminous flux obtained by IES TM-21-11 method is widely used as a parametric failure of LED light, which is taken as a parametric life standard in this paper. This time is just used as an appropriate reference data to compare the performance of the following two methods. IES TM-21-11 method makes the curve fitting for the data in accordance with index least squares method. The fitting curve that light source decays over time is shown as equation (1), in which $\Phi(t)$ is averaged normalized luminous flux output at time t, t is operating time in hours, B is projected initial constant derived by the least squares curve fit and α is decay rate constant derived by the least squares curve fit.

$$\Phi(t) = B\, exp(-\alpha t) \tag{1}$$

Use the equation (2) to project the lumen maintenance life. L_{70} is the lumen maintenance life expressed in hours where 70 is the percentage of initial lumen output that is maintained.

$$L_{70} = \frac{\ln(B/0.7)}{\alpha} \tag{2}$$

However, TM-21-11 parametric life prediction method can only be applied to fixed current and temperature, the value given by LM-80-2008 reports, and cannot go for the values beyond the reports. For example, one LM-80-2008 report contains two sets of data: 20 °C/0.5A and 60 °C/1A, and needs to predict the life time of 40°C/0.75A, which is unavailable by the TM-21-11 parametric life prediction method. So the multidimensional parameters-driven life prediction method is required to come up.

B. THE BP-NN LIFE PREDICTION METHOD

The BP neural network adopts the method of error backward propagation to train weights, with the function of approximating nonlinear continuous rational function. For this white LED life prediction, through the establishment of model, this method can predict the lifetime with multidimensional input parameters, rather than the fixed ones, as a workaround to the limit of TM-21-11 method.

In the process of signal's forward annotating, the input signal passes from the input layer to the output layer through hidden layer. The topological structure of the white-lighting LED's life prediction model based on BP-NN is shown in Figure 1.

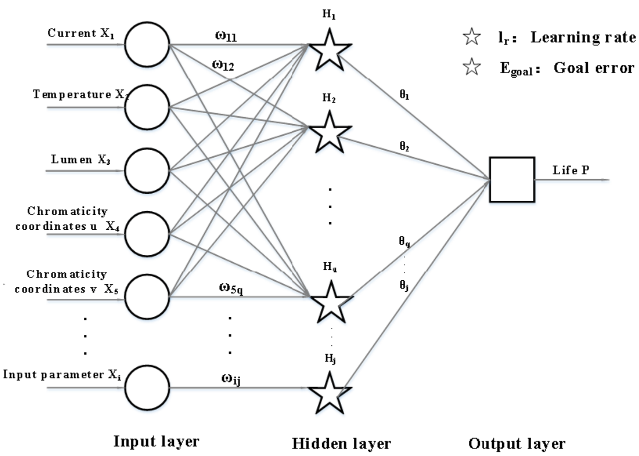


FIGURE 1. The topological structure of BP neural network.

The parameters such as electric current (X_1), temperature (X_2), luminous flux (X_3), chromaticity coordinates u′ (X_4) and chromaticity coordinates v′ (X_5) are taken as the input and life serves as the output. ω_{ij} is the weight connecting input neurons with hidden layer neurons. θ_j is the weight connecting hidden layer neurons with output neurons. i and j represent the neurons in input layer and hidden layer respectively. As the threshold value of hidden layer's node, α_j can make the graphics of the activation function to move around, thus increasing the possibility of solving the problem. The output H_j of hidden layer can be calculated by equation (3) :

$$H_j = f(\sum_{i=1} \omega_{ij} X_i - \alpha_j) \tag{3}$$

Since the linear model is not expressive enough, the excitation function is included in the network to add to the nonlinear factors. The common nonlinear excitation function includes jump function, quasi-linear function, hyperbolic tangent tansig function, sigmoid function, *etc*. Given that the nonlinear and convergence speed of the model is slow, it is the most suitable to use sigmoid function in areas of logsig function as the excitation function in hidden layers, the formula of which is shown as equation (4) :

$$f\,(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

b_j is the threshold value of the output layer node(the initial value of α_j and β_j is random). After the output value H_j in implicit layer is plugged in equation (5), the LED life prediction value P can be calculated as:

$$P = \sum_{j=1} H_j \theta_j - \beta_j \tag{5}$$

When the learning rate l_r is larger, the weight changes greater and the convergence happen faster. But if the learning rate is too large, oscillation of system will occur. Therefore, on condition that oscillation won't take place, larger learning rate is always the better. Among the commonly used learning rate ranging from 0.05 to 0.1, 0.1 is more appropriate for this network. In the process of modeling, the difference between predicted value P and expected value of parametric life at TM-21-11 standard is defined as the error E_{rrk}. Conduct back-propagation of inserted parameters of corrected network and retrain the network until E_{rrk} is less than E_{goal}, and then the training of BP neural network is completed.

III. IMPROVED PREDICTION METHOD BASED ON ADABOOST

A. THE FUNDAMENTALS OF ADABOOST ALGORITHM

Despite its low accuracy, the neural network has an advantage in predicting multidimensional data, therefore to improve it turns into the priority of further researches. In theory, the recognition method that repeats simple features is called the weak learning algorithm, whose accuracy is only slightly higher than that by chance. In contrast, the algorithm with high accuracy which can get finished in a short period of time is called the strong learning algorithm. So in the case of knowing only weak learning algorithm, it has become concern to researchers to find a strong learning algorithm. In this way, Adaboost algorithm [25] arises.

Adaboost algorithm is an iterative algorithm with its core idea of attaching great importance to samples with great prediction error and weak learner [26] with excellent performance. Current researches and application of Adaboost algorithm are mainly focused on its classification, but in recent years, there have been some application in its prediction [27], [28]. For making prediction, Adaboost algorithm makes the different weak predictors integrated into strong predictors and complement with each other through training them, enabling the integrated strong predictor to possess large applicability. Especially in the case of BP neural network as a weak predictor, the algorithm also optimizes its weakness such as local optimum and overfitting.

B. THE BP NEURAL NETWORK ALGORITHM BASED ON ADABOOST

In this paper, the BP neural network is taken as a weak predictor. After its repeatedly training LED sample data and combining multiple weak BP neural network predictors through Adaboost algorithm, a strong predictor [29] is formed. The process of LED life prediction by the improved BP neural network based on Adaboost algorithm is shown in Figure 2.

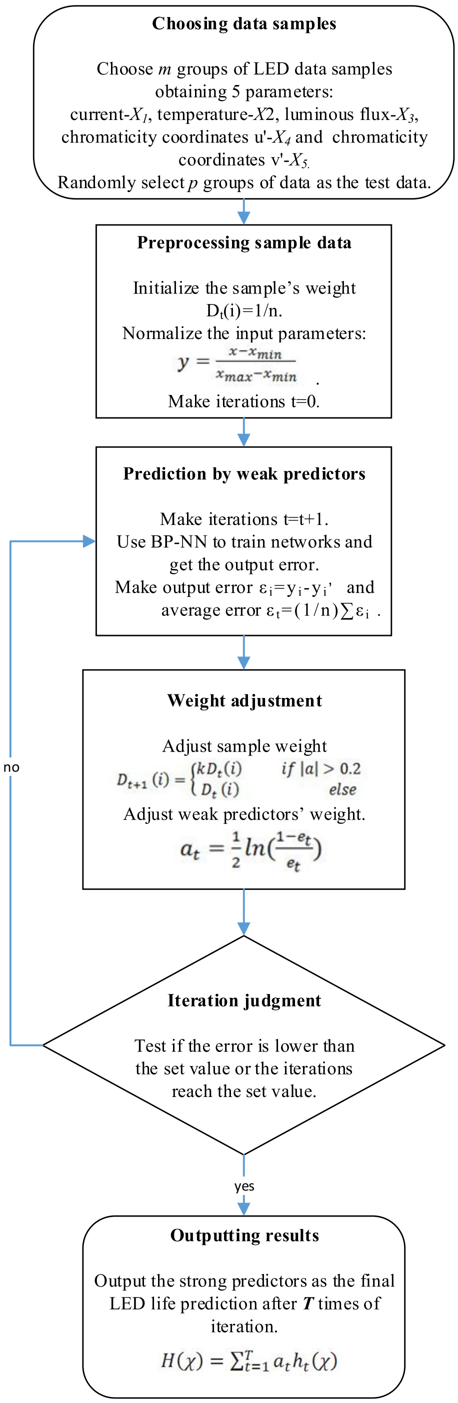


FIGURE 2. The flow chart of LED life prediction improved by Adaboost.

As the Figure 2 shown, first of all, in the phase of obtaining sample data, m sets of TM-08-80 reports' testing data concerning LED lamps from various manufacturers are selected, among which m sets are training samples and p sets are testing samples.

Secondly, in the stage of preprocessing sample data, for samples containing n initial input parameters, the system sets the sample's weight in t times of iterations as $D_t(i)$. Then the system determines the structure of neural network initializes the threshold value of BP neural network and normalizes the parameters such as current, temperature, luminous flux and chromaticity coordinates u′, v′ in the training samples.

Then after the use of BP neural network as a weak predictor for training, the output error ε_i, average error ε_t and forecasting model $h_t(x)$ are obtained, with y_i being the parametric life expectancy of training sample at TM-21-11 standard and y_i' being the predicted output of weak predictor's model. In the stage of adjusting sample weight, as the distribution weight adjustment coefficient, k is generally 1.1. This model also adjust the weight of weak predictor according to the average error ε_t at the same time, ensuring that the predictors with fewer errors take up greater weight and total weight reaches 1.

Finally, when the error is less than the set value or the number of iterations is higher than the set value, once iteration ends, the weak predictor $h_t(x)$ integrates into strong predictor $H(x)$.

IV. CASE STUDY

A. CASE DESCRIPTION

The study selects two authentic samples. which encompass a high-power LED sample group (sample 1) and a mid-power LED sample group (sample 2). The interval of each group of test lasts 1000h and the test time is more than 6000h. In each group of samples, 5 input parameters are chosen respectively including electric current, ambient temperature, initial luminous flux value and the initial chromaticity coordinates u′, v′ (CIE 1976). The former 6 groups of training sample contain mutually crisscross data such as 55°C, 85 °C, 105 °C, 120 °C and 0.35 A, 0.7A and the later training sample contains 6 groups of data such as 55 °C, 85 °C, 105 °C, 100mA and 200mA. They both randomly choose 1 set of sample as a test sample respectively. By choosing test samples from two different manufacturers, the adaptability of algorithm to different samples can be examined. In making comparative analysis of two kinds of algorithm, their strength and weakness and the effectiveness of their multidimensional prediction can be verified.

The data values of two training samples' parameters in the process of IES TM-21-11 calculation are listed in Table 1. After the life expectancy is gotten, the Table 2 lists the complete output and standard output data of the two training samples, among which Data 6 and Data 12 are the test sample data. As the validation data, they do not attend the training.

B. BP-NN MODELING AND RESULTS

The chromaticity coordinates are in 10^{-1} order of magnitude and life expectancy value is between 10^4 orders of magnitude. With parameters' units and physical quantities being different, the sample data are normalized to avoid that some parameters in too high or low orders of magnitude are ignored. After model comparisons, when learning rate $l_r = 0.1$, learning objectives $E_{goal} = 10^{-3}$ and the number of nodes in hidden layer is 5, network mean square error and the number of iterations are ideal.

TABLE 1. The statistical table of current, temperature and the life expectancy.

Sample	Current (A)	Temperature (°C)	α	B	Life expectancy(h)
Sample 1	0.35	55	1.0506	2.36E-06	172300.5
		85	1.0510	3.13E-06	129926.0
		120	1.0220	5.80E-06	63741.7
	0.7	55	1.0008	2.16E-06	165459.2
		85	1.0129	6.90E-06	53578.4
		105	1.0172	8.53E-06	43803.2
Sample 2	0.1	55	0.9943	2.92E-06	120129.6
		85	0.9864	2.47E-06	138668.1
		105	0.9869	7.41E-06	46379.7
	0.2	55	0.9950	4.25E-06	82652.7
		85	0.9867	5.12E-06	67004.8
		105	0.9663	8.51E-06	37895.3

TABLE 2. List of sample data.

		Current (A)	Initial luminous flux(lm)	Initial chromaticity coordinates u	Initial chromaticity coordinates v	Life expectancy (h)
Sample 1	Data 1	0.35	66.7	0.2417	0.5138	172300.5
	Data 2	0.35	67.6	0.2374	0.5074	129926.0
	Data 3	0.35	69.9	0.2346	0.5079	63741.7
	Data 4	0.7	124.9	0.2304	0.5117	165459.2
	Data 5	0.7	120.4	0.233	0.5103	53578.4
	Data 6	0.7	132.9	0.2359	0.5048	43803.2
Sample 2	Data 7	0.1	61.9	0.2586	0.5250	120129.6
	Data 8	0.1	61.6	0.2601	0.5260	138668.1
	Data 9	0.1	61.7	0.2580	0.5240	46379.7
	Data 10	0.2	115.6	0.2573	0.5221	82652.7
	Data 11	0.2	112.3	0.2586	0.5233	67004.8
	Data 12	0.2	113.7	0.2574	0.5249	37895.3

As shown in Figure 3, the horizontal coordinates in the graph represent the number of iterations, and the vertical axis represents mean square error. After model's self-learning

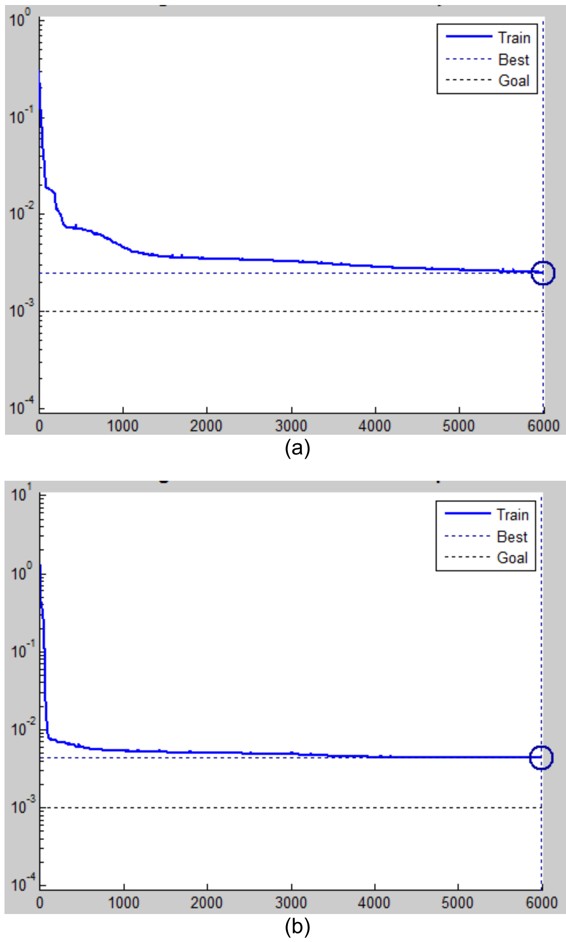


FIGURE 3. The training convergence curves of BP neural network. (a) Sample 1. (b) Sample 2.

for 6000 times, mean square error of two sets of data are 2.08×10^{-3} and 4.34×10^{-3} respectively, indicating that when the error between predicted life and expected life output by model after its training narrowed gradually to the target, the model can be used.

Figure 4 is the effect picture of two sets of samples' BP-NN network training return. The correlation coefficient R stand for how well it fits with its scope being (0, 1). The closer R is to 1, the better the equation fits. As shown in chart, the correlation coefficient of two samples reaches 99.995% and 100% respectively, indicating that equation has great ability to explain life value and model fitting proceeds well.

Finally, when the model validation and life prediction of two LED new samples proceed, the users can put five input parameters into the model after their being normalized and make the output value anti-normalized. In this way, the predicted life can be achieved. The results of the test sample are shown in Table 3.

C. ADABOOST-IMPROVED BP-NN MODELING AND RESULTS

By taking BP neural network as a weak predictor and training two groups of LED test samples in Table 1, the prediction

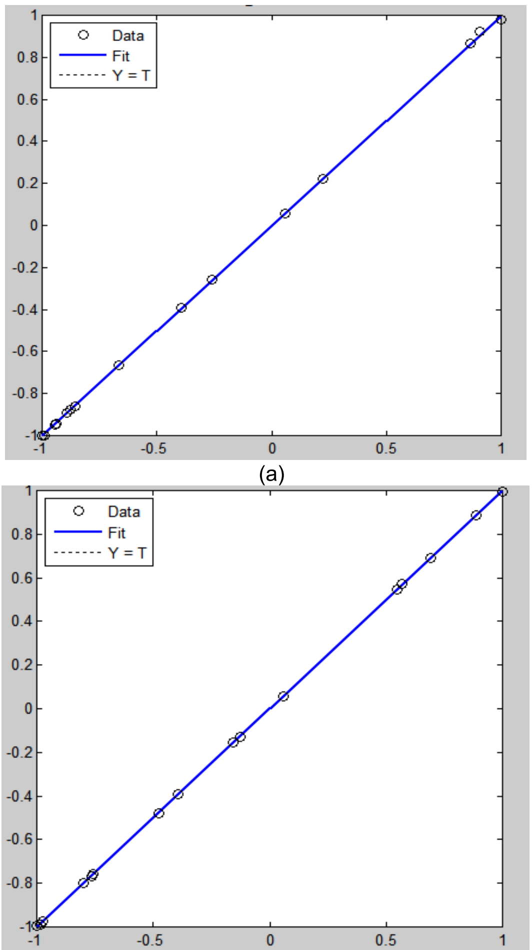


FIGURE 4. The effect of network training regression. (a) Sample 1. (b) Sample 2.

TABLE 3. Test sample's error.

	Test Data 6			Test Data 12		
Statistics	Life time (h)	Ea[a] (h)	Er[b]	Life time (h)	Ea (h)	Er
TM-21-11 expected life	43803.2	0	**0%**	37895.3	0	**0%**
BP-NN model	46707.5	2904.3	**6.63%**	35231.3	2664	**7.03%**
Improved-Adaboost	42813.2	989.95	**2.26%**	36356.8	1538.5	**4.06%**

[a]Ea: Absolute value of error with expected value

[b]Er: Relative value of error with expected value

results can be gotten. Then through adjusting the weight value of test samples according to the results, one set of BP weak predictors and their weights can be obtained. The model takes

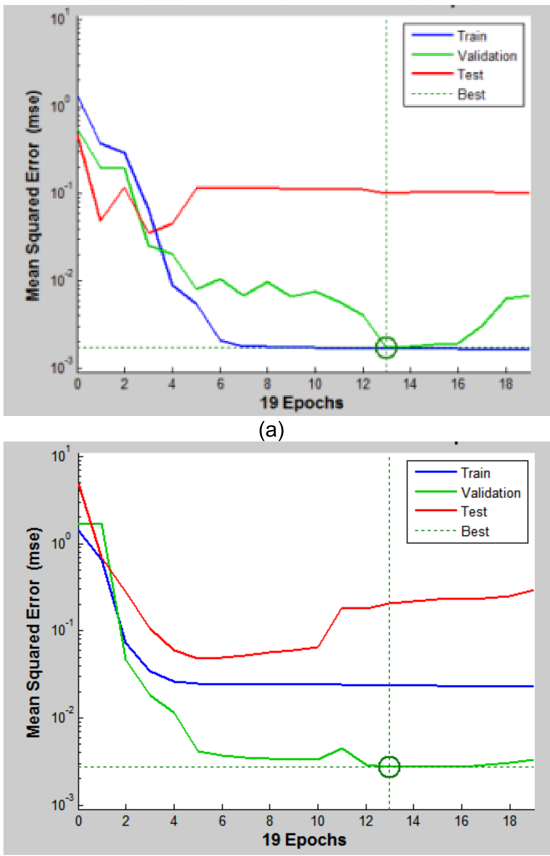


FIGURE 5. The curves of iterations and training errors. (a) Sample 1. (b) Sample 2.

the result with error exceeding 1000h as the sample required to strengthen learning. After repeated training, 10 BP neural network weak predictors are earned. Finally through outputting strong predictors by the use of Adaboost algorithm, the predicted life value is output.

Each time when the model gets training, the system will automatically put part of results into the neural network for validation. After processing the results and expected life to get the error, the system will determine whether the error tends to stay stable after the multi-step iterations. If the error never falls or rises, the system will stop the training in case of over-learning. Figure 5 shows two weak predictors whose weight values at are the largest during 10 times of iterations. The horizontal coordinates in the graph represent the number of iterations, and the vertical axis represents mean square error. From the graph it can be seen that both declining curves of error mean square predicted by two neural networks turns flat within twenty steps. Both networks start to converge and the best values validating the performance arise in the 13th step of iterations, showing that it is appropriate to select 20 times of iteration during the period of BP neural network's weak prediction.

As seen from the Figure 6, the overall R predicted by strong predictors is 0.985 and 0.974 respectively with fine regression

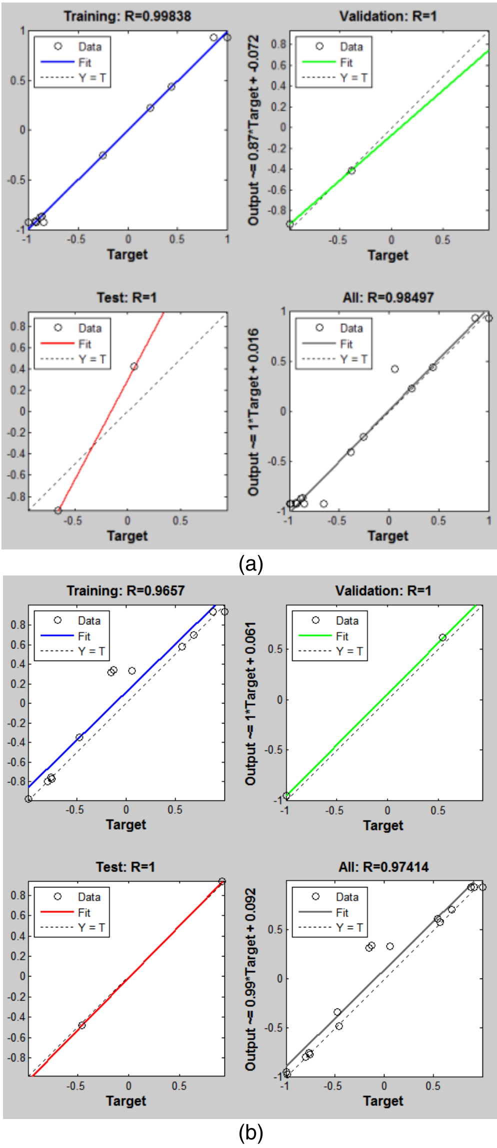


FIGURE 6. State of prediction regression. (a) Sample 1. (b) Sample 2.

TABLE 4. List of prediction errors of two models.

	Error of BP-NN model （h）	Error of Adaboost-improved model （h）	**Relative value of reduced error**
Test Data 6	2904.3	989.95	**66%**
Test Data 12	2664.0	1538.5	**42%**

TABLE 5. List of operation time of two models.

	Average operation time of BP - NN model (s)	Average operation time of Adaboost-improved model (s)	**Relative value of increased operation time**
Test Data 6	5.4	13.5	**60.0%**
Test Data 12	3.8	11.6	**67.2%**

TABLE 6. List of simulate sample data and outcome.

	X_1(A)	X_2(℃)	X_3(lm)	X_4	X_5	L_1(h)	L_2(h)
simulate sample 1	0.50	80	100	0.23	0.51	100875.3	82816.7
simulate sample 2	0.60	100	110	0.22	0.5	75687.8	62916.3
simulate sample 3	0.12	60	80	0.25	0.52	133837	119789.1
simulate sample 4	0.18	90	100	0.26	0.53	78651.9	69853.5

forecasting results. The statistical results of predicted life, expected life and error are shown in Table 3.

V. DISCUSSION

A. COMPARISON BETWEEN TWO MODELS

1) In terms of prediction precision, Adaboost-improved model is superior to the BP-NN model, with the former's error reduced by 54% on average than the latter, as shown in Table 4.
2) In terms of the operation time, BP-NN model is superior to the Adaboost improved model. As shown in Table 5, error reaching 10^{-3} as the standard, it can be seen that Adaboost-improved model takes more time by 63.6% on average to operate by using the Matlab software to make tests.

In the training, error and validation error of test sample are gradually on the decrease and local optimum and over fitting never happen in BP-NN model. But as for the prediction precision, Adaboost-improved model is obviously superior to the BP-NN model, while in terms of the operation time, BP-NN model has more advantages.

B. PREDICTION PROCESS UNDER NEW CONDITIONS

For LED life prediction under whatever electric current and temperature conditions, the traditional methods such as TM-21-11 don't work. But these two experimental methods can both undertake valid prediction. For instance, to implement life prediction under other conditions, which has not appeared in products' original data, the users simply need to make field measurements of initial luminous flux, initial chromaticity coordinate u′ and v′ on the basis of establishing model. Normalize the 5 parameters and put them respectively into the above two solidified model, which weights and threshold value have been fixed, after being trained, the predicted life is output. As shown in Table 6, X_1-X_5 represent the current, temperature, luminous flux, chromaticity coordinates u′ and v′; L_1 and L_2 represent the prediction results of the BP-NN model and Adaboost-improved model, respectively. Four groups of simulate sample data are in the range of product parameters and the prediction results are calculated according to chapter II. This method shortens the time to make fast multidimensional LED life prediction in engineering and lowers the difficulty of prediction, possessing great practical value for application.

C. THE WEIGHT OF EACH INPUT PARAMETER

As for the key parameters such as electric current, temperature, chromaticity and luminous flux, it is also of concern to the researchers how their influences weigh on the LED life.

Garson [30] has put forward a method after derivation that evaluating the weight of each input parameter's impact on the output based on neural network connection weights and threshold value. This method is similar to the fact that by the analysis of Radial Basis Function (RBF) neural network's principal components, we can get the percentage of contribution to the output by the multi-parameter neural network's input parameters. As shown in Figure 1, for the output node number of BP-NN model is 1, the input parameter's contribution percentage formula can be simplified into the equation (6).

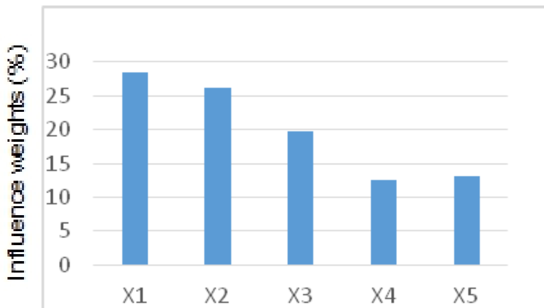


FIGURE 7. **Influence weights of input parameters on the life (%).**

In this formula, I_s is the s^{th} input parameter's weight of influence on the output, i, j, k respectively stand for the input layer, hidden layer and output layer nodes. i, j, k respectively show the node number of hidden layer and output layer, ω_{ij}, θ_j respectively indicate the connection weights from input to neurons in hidden layer and from hidden layer to neurons in output layer.

$$I_s = \frac{\sum_{j=1}^{J}\left(|\omega_{sj}|/\sum_{i=1}^{I}|\omega_{ij}|\right)\times|\theta_j|}{\sum_{i=1}^{I}\left\{\sum_{j=1}^{J}\left(|\omega_{ij}|/\sum_{i=1}^{I}|\omega_{ij}|\right)\times|\theta_j|\right\}} \tag{6}$$

The distribution histogram of input parameters' influence weight on the LED life according to the above formula is shown in Figure 7, in which the *X1-X5* respectively mean the electric current, temperature, luminous flux, chromaticity coordinate u' and chromaticity coordinate v'. It can be seen that as the two most important influence factors, electric current and temperature play a vital role on life. Besides, luminous flux and chromaticity also have certain impact on life.

VI. CONCLUSION

In view of the present studies on white LED life prediction, the research on the prediction method driven by multidimensional data is still lacking. Therefore the authors put forward the BP neural network and Adaboost-improved BP neural network prediction methods which make use of such related parameters as electric current and temperature, with product data from various power grades contrasted. Both methods take temperature, electric current, initial chrominance and initial luminous flux as the input, the service life as the output. They establish model based on LM-80-2008 report data and make prediction. The results show that:

1) In terms of prediction precision, Adaboost-improved model is superior to the BP-NN model, with the former's error reduced by 54% on average than the latter. But in view of the operation time, Adaboost-improved model has a disadvantage, which takes more time by 63.6% on average.

2) Compared with other life prediction methods based on LM-80-2008 report, the proposed methods can analyze multidimensional data under different conditions, which means input parameters need not long time measurements made in the laboratory environment, only in the present state of measurement can predict life. The study greatly shortens the time of LED forecast has great practical application value. The part B of section ćõ also provides the process and result.

3) With regards to the different input parameters' influences on the LED life, from the above data it can be seen, as the two most important influence factors, electric current and temperature play vital roles on life. Besides, luminous flux and chromaticity also have certain impact on life.

REFERENCES

[1] G. Lozano, S. R. K. Rodriguez, M. A. Verschuuren, and J. G. Rivas, "Metallic nanostructures for efficient LED lighting," *Light Sci. Appl.*, vol. 5, p. e16080, Jun. 2016.

[2] R. Zhang, W.-D. Zhong, K. Qian, and D. Wu, "Image sensor based visible light positioning system with improved positioning algorithm," *IEEE Access*, vol. 5, pp. 6087–6094, 2017.

[3] B. Sun, X. Jiang, K.-C. Yung, J. Fan, and M. G. Pecht, "A review of prognostic techniques for high-power white LEDs," *IEEE Trans. Power Electron.*, vol. 32, no. 8, pp. 6338–6362, Aug. 2017.

[4] X. Qu, H. Wang, X. Zhan, F. Blaabjerg, and H. S.-H. Chung, "A lifetime prediction method for LEDs considering real mission profiles," *IEEE Trans. Power Electron.*, vol. 32, no. 11, pp. 8718–8727, Nov. 2017.

[5] P. Lall, J. Wei, and P. Sakalaukus, "Bayesian models for life prediction and fault-mode classification in solid state lamps," in *Proc. Int. Conf. Thermal, Mech. Multi-Phys. Simulation Experim. Microelectron. Microsyst.*, Apr. 2015, pp. 1–13.

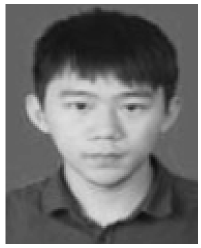
[6] H. Niu, H. Wang, X. Ye, S. Wang, and F. Blaabjerg, "Converter-level FEM simulation for lifetime prediction of an LED driver with improved thermal modelling," *Microelectron. Rel.*, vols. 76–77, pp. 117–122, Sep. 2017.

[7] T. Sutharssan, *Prognostics and Health Management of Light Emitting Diodes*, vol. 21. London, U.K.: Univ. Greenwich, 2012, pp. 688–691.

[8] P. Lall, H. Zhang, and L. Davis, "Assessment of lumen degradation and remaining life of LEDs using particle filter," in *Proc. ASME Int. Techn. Conf. Exhibit. Packag. Integr. Electron. Photon. Microsyst.*, 2013, pp. 1–13.

[9] B. H. M. Sadeghi, "A BP-neural network predictor model for plastic injection molding process," *J. Mater. Process. Technol.*, vol. 103, no. 3, pp. 411–416, Jul. 2000.

[10] H.-K. Fu, C.-W. Lin, T.-T. Chen, C.-L. Chen, P.-T. Chou, and C.-J. Sun, "Investigation of dynamic color deviation mechanisms of high power light-emitting diode," *Microelectron. Rel.*, vol. 52, no. 5, pp. 866–871, May 2012.
[11] P. Lall, P. Sakalaukus, and L. Davis, "Reliability and failure modes of solid-state lighting electrical drivers subjected to accelerated aging," *IEEE Access*, vol. 3, pp. 531–542, 2015.
[12] Y. Ma, R. Hu, X. Yu, W. Shu, and X. Luo, "A modified bidirectional thermal resistance model for junction and phosphor temperature estimation in phosphor-converted light-emitting diodes," *Int. J. Heat Mass Transf.*, vol. 106, pp. 1–6, Mar. 2017.
[13] H. Mirgolbabaee, S. T. Ledari, and D. D. Ganji, "Heat transfer analysis of a fin with temperature-dependent thermal conductivity and heat transfer coefficient," *New Trends Math. Sci.*, vol. 3, no. 2, pp. 55–69, 2015.
[14] L. Lohaus, E. Leicht, S. Dietrich, R. Wunderlich, and S. Heinen, "Advanced color control for multicolor LED illumination systems with parametric optimization," in *Proc. Conf. IEEE Ind. Electron. Soc. (IECON)*, Nov. 2013, pp. 3305–3310.
[15] *Projecting Long-Term Lumen Maintenance of LED Light Sources*, document IES TM-21-11, 2011.
[16] J. Fan, K. C. Yung, and M. Pecht, "Physics-of-failure-based prognostics and health management for high-power white light-emitting diode lighting," *IEEE Trans. Device Mater. Rel.*, vol. 11, no. 3, pp. 407–416, Sep. 2011.
[17] P. Lall, H. Zhang, and J. Davis, "Prognostication of LED remaining useful life and color stability in the presence of contamination," in *Proc. IEEE Conf. Prognostics Health Manage.*, Jun. 2015, pp. 1–8.
[18] T. Sutharssan, S. Stoyanov, C. Bailey, and Y. Rosunally, "Prognostics and health monitoring of high power LED," *Micromachines*, vol. 3, no. 1, pp. 78–100, 2012.
[19] Y. Zhang, J. Yang, S. Wang, Z. Dong, and P. Phillips, "Pathological brain detection in MRI scanning via Hu moment invariants and machine learning," *J. Experim. Theoret. Artif. Intell.*, vol. 29, pp. 299–312, Jan. 2016.
[20] B. Dan, K. Chen, L. Xiong, Z. Rong, and J. Yi, "Research on multi-BP NN-based control model for molten iron desulfurization," in *Proc. World Congr. Intell. Control Autom. (Wcica)*, 2008, pp. 6133–6137.
[21] B.-J. Ge, W. Guo, and D.-H. Zhang, "Application of BP neural network in turbo-generator harmonic analysis under negative-sequence loss conditions," in *Proc. Int. Conf. Meas., Inf. Control*, Aug. 2013, pp. 959–963.
[22] W.-C. Chen and S.-W. Hsu, "A neural-network approach for an automatic LED inspection system," *Expert Syst. Appl.*, vol. 33, no. 2, pp. 531–537, 2007.
[23] *Approved Method for Lumen Maintenance Testing of LED Light Source*, document IES-LM-80-08, 2008.
[24] H. Ganev and T. Q. Khanh, "Degradation of high-power LEDs—Luminous flux and TM 21 life time," in *Proc. 11th China Int. Forum Solid State Lighting (SSLCHINA)*, Nov. 2014, pp. 141–143.
[25] Y. Freund, "An adaptive version of the boost by majority algorithm," *Mach. Learn.*, vol. 43, no. 3, pp. 293–318, Jun. 2001.
[26] Y. Freund, "Boosting a weak learning algorithm by majority," *Inf. Comput.*, vol. 121, no. 2, pp. 256–285, Sep. 1995.
[27] P. Yao, Z. Wang, H. Jiang, and Z. Liu, "Fault condition prognostic for rotating machinery based on new WEEMD and adaptive boosting regression algorithm," *Develop. Biol.*, vol. 296, no. 1, pp. 49–137, 2013.
[28] L. Zhou and K. K. Lai, "AdaBoost models for corporate bankruptcy prediction with missing data," *Comput. Econ.*, vol. 50, no. 1, pp. 69–94, 2017.
[29] S. Cungen and Z. Wenzhen, "Economic analysis on tax model based on BP neural network," in *Proc. Int. Conf. Commun., Circuits Syst. (ICCCAS)*, Jul. 2009, pp. 569–572.
[30] G. D. Garson, "Interpreting neural-network connection weights," *Expert*, vol. 6, no. 4, pp. 46–51, 1991.



KAIYUAN LU received the B.S. degree in instrument science and technology engineering from Beihang University, Beijing, China. He is currently pursuing the M.S. degree in reliability and systems engineering with the School of Reliability and Systems Engineering, Beihang University. His research interests include prognostics and health management for LED lighting and electronics, physics of failure, and reliability of electronics.

WENJIN ZHANG received the M.S. and Ph.D. degree in aircraft design engineering from the Beihang University. He is currently a Professor and a Vice General Engineer with the School of Reliability and Systems Engineering, Beihang University, Beijing, China. He is a Vice General Reliability Engineer of the AVIC Helicopter. He is a reliability expert member of the China Association for Quality. His current research interests include reliability system engineering, prognostics and health management, and integrated logistic support modeling and simulation.

BO SUN (M'07) received the B.S. degree in mechanical engineering from the Beijing Institute of Mechanical Industry, Beijing, China, in 2001, the Ph.D. degree in reliability engineering and systems engineering from Beihang University, Beijing, China, in 2007. He is currently an Associate Professor and a member of the Faculty of Systems Engineering, School of Reliability and Systems Engineering, Beihang University, Beijing, China. He is a supervisor of M.S. students and teaches three courses for undergraduate and master students. His current research interests include prognostics and health management, physics of failure, reliability of electronics, reliability engineering, and integrated design of product reliability and performance.

Dr. Sun is a member of the editorial board of the International Journal of Prognostics and Health Management. He has led over ten projects supported by NSFC, industries, and companies. In the past few years, he has also participated in over ten projects supported by government and national commissions. He has published over 70 papers and three book chapters. He has served as a Reviewer for the IEEE Transactions on Reliability, Reliability Engineering and System Safety, Journal of Thermal Analysis and Calorimetry, Quality and Reliability Engineering International, the Annual Conference of the PHM Society 2009–2016, and the IEEE Prognostics and System Health Management Conference from 2012 to 2015, a Session Chair with the Annual Conference of the PHM Society in 2011 and the IEEE Prognostics and System Health Management Conference from 2012 to 2015, and a technical committee member for the first International Conference on Reliability Systems Engineering and the 2015 IEEE Prognostics and System Health Management Conference.