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Street Lamp Fault Diagnosis System Based on Extreme Learning Machine

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Abstract. In view of the construction of urban lighting system needs a lot of manpower deployment, especially for its fault diagnosis problem management. This paper proposes a fault model detection and diagnosis subsystem based on the extreme learning machine for street lamps system. The subsystem is part of the event rule response system which is based on the complex event processing technology framework. The system can handle a large amount of sensor data, perform filtering, carry out complex data processing and decision making. The experimental results show that the proposed street lamp fault diagnosis system based on extreme learning machine can diagnose the street lamp fault effectively and respond to it automatically.

1. Introduction

With the continuous advancement of urbanization, more and more high demands are placed on urban lighting construction for illumination for streets and infrastructure in the cities [1]. In the urban lighting system, the troubleshooting and repair of the system has become the most important requirement or part of the system e.g. the rapid response to urban lighting failure. Better urban lighting system will showcase how comprehensive the urban infrastructure of a given city. Most of the existing road lighting maintenance management is about exercising reactive maintenance process e.g. replacing broken lamps. In the maintenance process, the circuit cables and the road lighting equipment are often inspected using specific tools and require a large amount of human efforts. These things cost a lot and very slow to carry out. So, it is sometime impossible to do a timely investigation of existing faulty street lights. Because of these drawbacks of traditional manual maintenance, Xiao-hua Zhang et al.[2] proposed a street lamp monitoring system based on configuration technology. The main detection method is based on analysing the sensor output value of the existing smart lighting device, and judging the rules through expert knowledge, once the rules are met. The system uses the Internet of Things technology to raise an alarm. The detection strategy is limited by the expert's judgment of the faults. With the development of neural network algorithms, neural network-based fault diagnosis models have emerged. Yong Dong et al.[3] proposed a diagnostic model for computer hard disk fault diagnosis using BP neural network, SVN, decision tree, and Bayesian. They pointed out that such methods rely on the accuracies of the parameters used in the diagnosis, so the result is not what you

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are looking for. At present, the research on street lamp fault diagnosis is still in its infancy, there are opportunities to study and research in this area.

Therefore, this paper proposes a street lamp fault detection system based on the extreme learning machine algorithm. The contribution lies in the extraction of sensor data from the existing smart lighting facilities, the fault model which is constructed by using the extreme learning machine, and the deployment of the event rule response system based on the CEP framework. In this system, the speed and efficiency of the detection and diagnosis are improved.

2. Street Lamp Fault Diagnosis System based on ELM

Nowadays, the urban lighting system is mainly composed of two parts: electrical power distribution system unit and infrastructure and management unit as shown in Figure 1(A)[4]. Therefore, the faults management of urban lighting system are typically divided into power distribution system faults and the faults of the street lamp nodes. This paper mainly deals with the main circuit fault of the street lamp nodes.

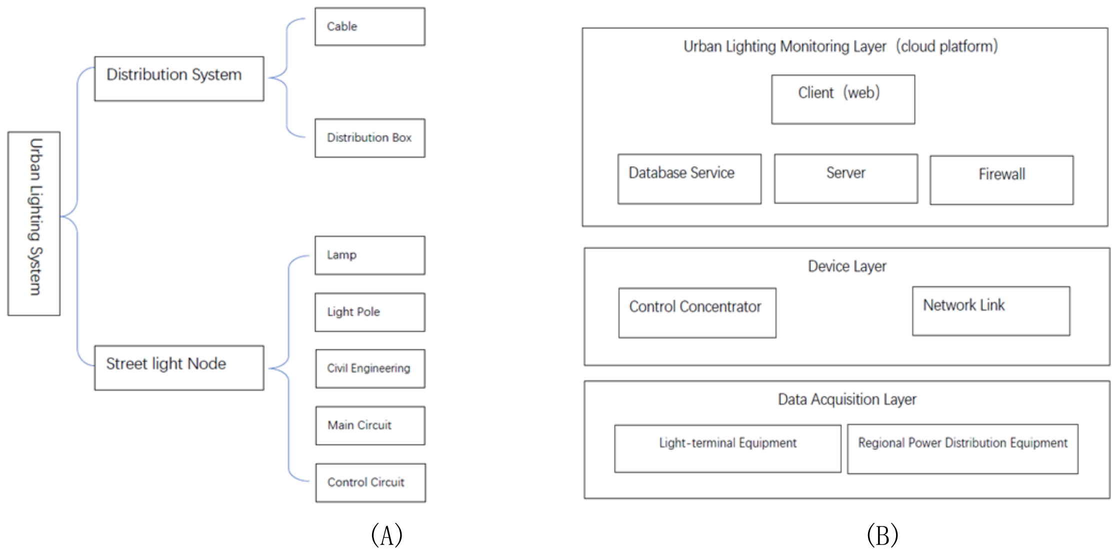

Figure 1. The street lamp Block diagram of (A) the fault(B) the city lighting system

Due to the variety of components of the main circuit of the node, the types of faults are also complicated. Therefore, a comprehensive control system is needed to manage the faults in the street lights system, hence facilitating the analysis and diagnosis of the street lights' faults. Figure 1(B) shows the overall structure of the system where the streetlight diagnostic system is located.

The streetlight diagnosis system is deployed in the monitoring layer and the data collection layer collects the corresponding sensor data, whereas the device layer integrates and reports the data. The diagnosis system makes a diagnosis response by using the trained model for the reported data. Thereby the diagnosis and response to the fault of the street lamp node is realized [5].

2.1. *Extreme Learning Machine*

Extreme learning machine is a new type of feedforward neural network (SLFNs). Its algorithm can overcome the shortcomings of multiple iterations in classical neural network algorithms during training. Only a simple linear regression is required to obtain relatively satisfactory requirements. This produces good outcomes and faster training time [6].

Guangbin Huang et al. [7]conducted an in-depth study on the finite set input of feedforward neural networks. It is found that for the finite set of Q different samples, if the activation function of the feedforward neural network is an infinitely differentiable function of arbitrary intervals, then the hiddenness of SLFNs The Q layer requires up to Q neurons to be able to approach the Q samples infinitely. This finding also shows that the learning ability of SLFNs is independent of the weight of the input layer to the hidden layer, and only relates to the weight of the hidden layer to the output layer. Therefore, they designed a new type of feedforward neural network, the Extreme Learning Machine

(ELM).

The network structure diagram of SLFNs is as shown in Figure.2. ELM is composed of input layer, hidden layer and output layer like SLFNs. Input layer, only one hidden layer and output layer are fully connected through neurons [8].

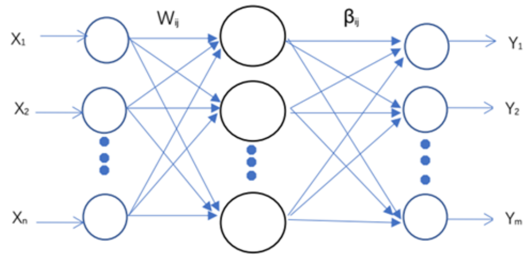

Figure 2. The network diagram of ELM

When the input layer has n neurons and the hidden layer has 1 neuron, the connection weight w of the input layer and the hidden layer is as follows

$$W = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \dots & \dots & \dots & \dots \\ w_{l1} & w_{l2} & \dots & w_{ln} \end{bmatrix}_{l\times n} \quad (1)$$

Where: w_{ji} represents the connection weight of the i-th neuron of the input layer and the j-th neuron of the hidden layer.

When the output layer has m neurons, the hidden layer has 1 neuron, and the connection weight β of the output layer neurons and the hidden layer neurons is as follows

$$\beta = \begin{bmatrix} \beta_{11} & \beta_{12} & \dots & \beta_{1m} \\ \beta_{21} & \beta_{22} & \dots & \beta_{2m} \\ \dots & \dots & \dots & \dots \\ \beta_{l1} & \beta_{l2} & \dots & \beta_{lm} \end{bmatrix}_{l\times m} \quad (2)$$

Where: β_{jk} represents the connection weight of the j-th neuron of the hidden layer and the k-th neuron of the output layer.

When the threshold $b = [b_1 b_2 \dots b_l]^T_{1\times l}$ of the hidden layer neurons is set, the training set input matrix and the Y output matrices with Q samples are established.

Then, according to Figure 3, the output T of the network is $T = [t_1, t_2, \dots, t_Q]_{m\times Q}$, so each vector t_j in the T matrix is

$$t_j = \begin{bmatrix} t_{1j} \\ t_{2j} \\ \vdots \\ t_{mj} \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{l} \beta_{i1} g(w_i x_j + b_i) \\ \sum_{i=1}^{l} \beta_{i2} g(w_i x_j + b_i) \\ \vdots \\ \sum_{i=1}^{l} \beta_{im} g(w_i x_j + b_i) \end{bmatrix} (j = 1, 2, \dots, Q) \quad (3)$$

Among them, $w_i = [w_{i1}, w_{i2}, \dots, w_{in}]$; $x_j = [x_{1j}, x_{2j}, \dots, x_{nj}]^T$, g(x) is an excitation function, which can be "Sigmoid", "Sine", etc.

The above formula can be written as $H\beta = T'$, Where: T' is the transposition of the matrix T; H is the output matrix of the ELM hidden layer. Therefore, the specific form of H is as follows:

$$H = \begin{bmatrix} g(w_1 \bullet x_1 + b_1) & g(w_2 \bullet x_1 + b_2) & \cdots & g(w_l \bullet x_1 + b_l) \\ g(w_1 \bullet x_2 + b_1) & g(w_2 \bullet x_2 + b_2) & \cdots & g(w_l \bullet x_2 + b_l) \\ \cdots & \cdots & \cdots & \cdots \\ g(w_1 \bullet x_Q + b_1) & g(w_2 \bullet x_Q + b_2) & \cdots & g(w_l \bullet x_Q + b_l) \end{bmatrix}_{Q\times l} \quad (4)$$

In fact, the number of neurons in the hidden layer is unlikely to be equal to the number of training samples. Let E be the sum of the squares of the errors of the ELM. Therefore, the optimal value of the network weight finally solved is such that E=||Hβ-Y||.The value is the smallest. Huang et al [9] have given the following two theorems through the study of SLFNs, which is the theoretical basis for the realization of ELM.

Theorem 1: Given any Q different samples $((x_i,t_i)$, where $x_i=[x_{i1},x_{i2},...,x_{in}]T\in R$, $t_i=[t_{i1},t_{i2},...,t_{in}]T\in R)$, and when the activation function g(x) is infinitely differentiable in arbitrary intervals, arbitrarily assigning $w_i\in R$ and $b_i\in R$, then for SLFNs with Q hidden layer neurons, the hidden layer matrix H is reversible, and ||Hβ-T'||=0.

Theorem 2: Given any Q different samples $((x_i, t_i)$, where $x_i=[x_{i1},x_{i2},...,x_{in}]T\in R$, $t_i=[t_{i1},t_{i2},...,t_{in}]T\in R)$, given arbitrary small error ε>0, and when the activation function g(x) is infinitely differentiable in any interval, arbitrarily assigning $w_i\in R$ and bi∈R, then for SLFNs with K(K<Q) hidden layer neurons, its hidden layer matrix H is reversible, and ||Hβ-T'||< ε . Through the above theorem, extreme learning determines the weight of the output layer by training the sample [10].

Solving the solution of the equation by the method of least squares is

$$\hat{\beta} = \arg\min \|H\beta - Y\| = H^{+}Y \quad (5)$$

Where: H^+ is the Moore-Penrose generalized inverse matrix of the hidden layer matrix H, scilicet:

$$H^{+} = (H^{T}H)^{-1}H^{T} \quad (6)$$

The algorithm of the extreme learning machine is divided into the following three steps:

(1) determining the number of neurons in the hidden layer, randomly setting the connection weight w of the input layer and the hidden layer and the threshold b of the implicit neuron;

(2) selecting an infinitely differentiable function as the activation function of the hidden layer neurons, and then calculating the hidden layer output matrix H;

(3) Calculate the output layer weight $\hat{\beta}$

2.2. Intelligent street lamp main circuit failure analysis

The main circuit of the smart street lamp is a system board based on the STM32 micro control chip. In essence it is an analogy control circuit. Therefore, the system board part circuit-Sallen-key filter is the most fault analysis. Figure 3 (A)is the Sallen-key filter. Assume that when one of the layers C1, C2, R1, R2, and R3 has a problem, it will have a great impact on the overall circuit. As shown in the following Figure 3 (B), R3 normal and fault affect the output voltage, so through the different components in the circuit The excitation at different frequencies obtains the corresponding output voltage as a model parameter for fault diagnosis [11].

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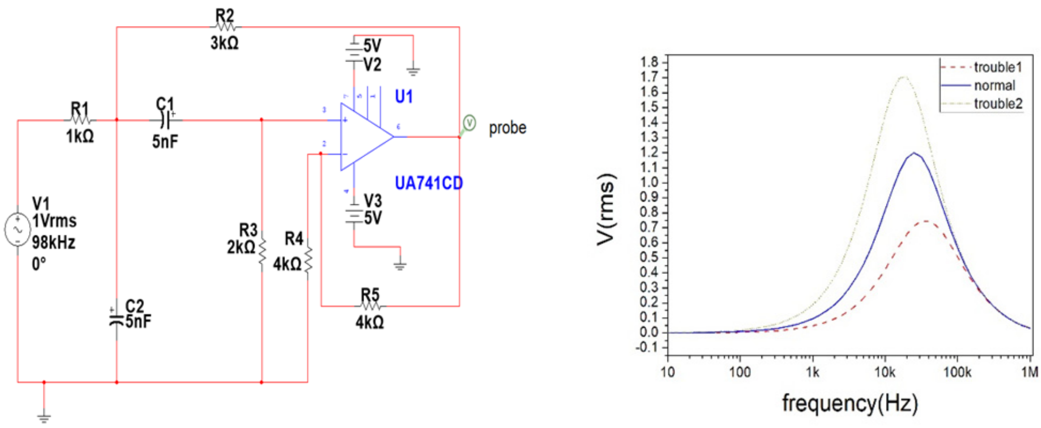

(A) (B)

Figure 3. The sallen-key filter of **(A)** Schematic diagram **(B)**Voltage output curve of the resistance R3

2.3. Fault extraction based on principal component analysis
The value of the output voltage at different frequencies is the key data used for fault analysis. These voltages become the main constituents of the dimensional factors of the sampled data. Due to too many sampling parameters for different frequencies, these would affect the learning rate and training accuracy of the ELM. Therefore, it is necessary to reduce the dimensionality of the sampled data. PCA is a dimensionality reduction method that combines maximum variance, minimum error and coordinate axis correlation. Its purpose is to map n-dimensional features to k-dimensional. (k<n), this k-dimensional is a completely new orthogonal factor. This k-dimensional factor is called the principal element and is a reconstructed k-dimensional factor, rather than simply removing the remaining n-k dimensional factors from the n-dimensional factors [12].

The calculation process of PCA is as follows:

(1)Data standardization

Its purpose is to eliminate the differences caused by dimensions (i.e. units). Common data normalization methods include Min-Max scaling and Z-score standardization. PCA usually adopts zero-mean normalization method.

(2)Calculate the covariance matrix

Let the standardized data matrix be X and find the covariance variance moment.

(3) Find the eigenvalues and eigenvectors of the covariance matrix

The eigenvalues are sorted from large to small, and the cumulative contribution rate is calculated according to the principal element contribution rate. Usually the cumulative contribution rate is greater than 95%.

(4)Project the sample points onto the selected feature vector

Suppose the number of samples is m, the number of features is n, the normalized sample matrix is DataAdjust(m*n), the covariance matrix is n*n, and the matrix of selected k eigenvectors is EigenVectors(n*k). Then the projected data FinalData is

$$FinalData(m*k) = DataAdjust(m*n) \times EigenVectors(n*k) \tag{7}$$

3. Event Rule Response System
The responsibility of the event rule response system is to obtain basic data information (such as various data values of the sensor, gateway information, device login information, etc.) from the system, and integrate such information through filtering and processing correspondingly according to the processed information. The event response system is designed according to the Complex Event Processing Technology (CEP) framework, and its framework is shown in Figure 4[13].

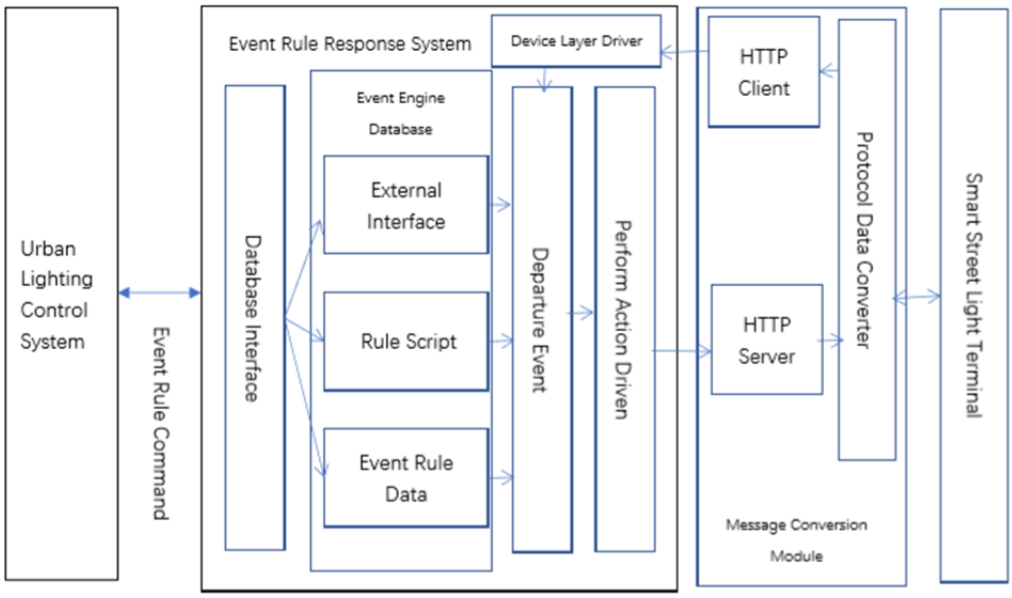

Figure 4. Framework of event rule response system

First, the web-based event rule response system responds to the urban lighting control system by writing the event, rule and interface to the corresponding parts in the event engine database. These rules are then sent to the database interface module through the JSON message format for unpacking. The corresponding data is sent to the event engine database where it is registered. When the smart street lamp terminal reports the collected data to the message conversion module, the original binary data reported will be processed by the protocol data converter. Then the processed data will be delivered to the device layer driver through the HTTP client. The driver converts the JSON message of the event information and the data information to corresponding event name and event parameter information and transmits the converted information to the trigger event engine for judgment. When the reported event and data are matched it triggers event condition of the event engine database and the corresponding action event instruction is sent to the execution action driver according to the previously defined event rule database. The execution action driver is combined according to the corresponding execution instruction to send the corresponding message to the device layer HTTP server[14].

3.1. Trigger Event Rule Response Mechanism

Figure 5 is a logic flow diagram of a trigger event rule response mechanism. The mechanism is developed based on the SQLite library, and the rule script library is based on the lua programming language, designed specifically for writing the rule script. It is often necessary to design a customized linkage scheme between the sensor and the actuator according to a certain scenario on the project. The main problem with many existing solutions is that each type of solution is designed independently and does not have versatility and scalability. Therefore, a trigger event rule response mechanism is provided to solve this problem. The linkage scheme of the sensor and the actuator according to the multi-scene is realized by storing the rule or the rule pointer in the corresponding database. If you have a new scenario, just add the corresponding database event policy. Of course, if you want to modify or delete the event strategy, you only need to modify and delete the database.

The streetlight fault diagnosis system is deployed based on the trigger event rule response mechanism, and the message reported by the sensor parameter is set as a trigger event. When the event rule is activated, the set rule script is executed i.e. the street lamp fault discrimination script This script will input the reported parameters into the established diagnostic fault model and will return the processing result when the system made a decision. The event rule will respond to the above results by making a corresponding warning response. All the operations in this process are implemented by registering the external interface. Therefore, the external interface of the fault diagnosis system only needs to register two types of external interfaces for obtaining parameter data and alarms [15].

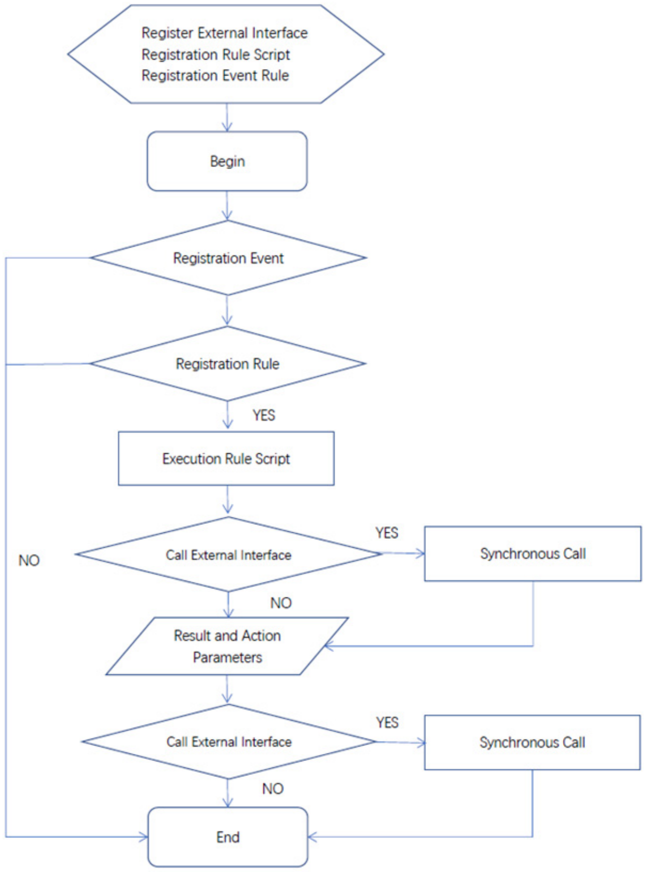

Figure5. Flow diagram of the event rule response mechanism

4. Experimental results and analysis

In this experiment, the Sallen-key filter in the street lamp is used as the test fault circuit. By performing soft fault processing on some components in the circuit, the value of R2 and R3 is less than the normal value of 10%~50%. Fault, 10%~50% higher than the normal value is expressed as a large soft fault. Similarly, the value of C1 and C2 is less than the normal value of 5%~50%, which is expressed as a small soft fault, which is 5% higher than the normal value. 50% is expressed as a large soft fault. The test sample was 200 and the test data was 50. 1KHz, 8KHz, 18KHz, 48KHz, 68KHz, and 98KHz are selected as the characteristic sampling points, and some samples are shown in Table 1.

Table 1. Sample eigenvalues

	R2↑	R2↓	R3↑	R3↓	C1↑	C1↓	Normal
1K	0.1238	0.0860	0.1200	0.0684	0.1223	0.0749	0.0948
8K	0.7927	0.7949	1.0138	0.6035	0.9865	0.6648	0.7946
18K	0.9982	1.2347	1.3669	0.9086	1.2816	0.9883	1.0953
48K	0.8347	1.0178	1.0205	0.8654	0.9803	0.8689	0.8863
68K	0.7035	0.7839	0.7890	0.7203	0.7754	0.6954	0.7045
98K	0.5521	0.5499	0.5749	0.5473	0.5478	0.5250	0.5173

The new eigenvalues obtained by PCA are shown in Table 2.

Table 2. New eigenvalues

	R2↑	R2↓	R3↑	R3↓	C1↑	C1↓	Normal
eigenvalues1	-0.1294	0.1047	0.3377	-0.3012	0.2450	-0.2100	-0.0468
eigenvalues2	0.0957	0.1098	0.0022	-0.0395	0.0374	-0.0166	0.0306
eigenvalues3	0.0181	0.0010	0.0085	0.0266	0.0044	-0.0219	-0.0366

Firstly, the number and the accuracy of different number of hidden layer nodes are tested. The test results can be seen from Figure 6. As the number of hidden layer nodes approaches the number of training samples, the accuracy rate is higher.

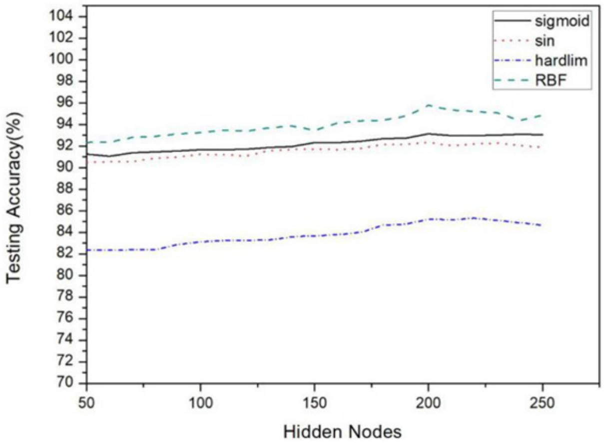

Figure 6. Graph of the number and accuracy of hidden layers

The raw data and the eigenvalues recombined by the principal component analysis method are brought into the ELM system for classification, wherein Table 3 shows the diagnostic accuracy and time of the different excitation functions[16].

Table.3 Diagnostic accuracy and time of different excitation functions

	Sigmoid	**Sin**	**Hardlim**	**RBF**
Training time (s)	0.4213	0.4352	0.4950	0.4322
Test time (s)	0.0245	0.0437	0.0447	0.0196
Training accuracy	95.19%	96.55%	91.23%	96.73%
Test sample accuracy	93.24%	92.17%	85.36%	95.78%

It can be seen from Table 3 that the speed and accuracy of the excitation function RBF are the best in such learning, so RBF is selected as the excitation function of the ELM in the data processing comparison experiment. Table 4 shows the comparison of the diagnostic accuracy and time after PCA processing with the unprocessed data through the extreme learning machine training test.

Table.4 Comparison table of results for different processing of raw data

	Unprocessed data		**Processed by PCA**	
	ELM- Sigmoid	**ELM- RBF**	**ELM- Sigmoid**	**ELM- RBF**
Training time (s)	0.4213	0.4322	0.2745	0.3722
Test time (s)	0.0245	0.0196	0.0169	0.0138
Training accuracy	95.19%	96.73%	95.32%	97.76%
Test sample accuracy	93.24%	95.78%	93.74%	98.96%

It can be seen from the table that through the pre-processing of the original data, the diagnostic accuracy is improved, and the training accuracy is also improved. Furthermore this also improved the training time and test time. The table shows that the light fault detection system based on ELM that incorporated the PCA processing mechanism for the original data can effectively and quickly detect the main circuit fault of the street lamp node. In this case it was found that the detection efficiency is higher and faster time taken.

5. Conclusion

This paper proposes a system that combines the ELM with main principle component analysis for detecting and diagnosing the problem of street lamp faults. Based from the experiment, the system was found to have a high diagnostic rate and higher accuracies. The solution was found that accuracy increased by one percent than normal detection and diagnosis approach. And the solution was found to be 29.59% faster than normal detection and diagnosis approach.The study proposes a new feasible solution for street lamp fault detection and diagnosis that has good applicability to the street lamp system.

Acknowledgments
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