LED Landscape Lighting Equipment Fault Diagnosis Research

Zhihong Tian1,*, Yuwei Zhao1, Zicheng Zheng1, Xiangang Meng2
1College of Electronic Information and Automation Tianjin University of Science & Technology Tianjin, China
2Glory Wisdom (Tianjin) Engineering Design Co. Ltd Tianjin, China

*Corresponding author: zhtian@tust.edu.cn

Abstract. Aiming at the fault diagnosis characteristics of LED landscape lighting equipment, a class of genetic algorithm improved particle swarm optimization optimized wavelet neural network model is constructed. This fusion algorithm introduces the idea of cross factors and inertia weights in the genetic algorithm to the basic particle swarm optimization algorithm, and adjusts for the traits of the standard wavelet neural network that has a slow convergence rate and might fall into local extreme values. The simulation results prove that this fusion algorithm can be efficaciously applied to the fault diagnosis of LED landscape lighting equipment and meet the needs of real-time monitoring of equipment.

1. Introduction
LED landscape lighting makes this dim night bright and colorful, and becomes a unique "business card" for the city's foreign exchange and cooperation. Because the working environment of equipment is mostly exposed outdoors, the actual work site still needs to rely on simple equipment and the experience of technicians to check the failure of LED landscape lighting equipment, but this situation is accompanied by huge risks [1]. In view of this situation, it is of great significance to develop a high-efficiency LED landscape lighting fault diagnosis system based on modern fault diagnosis theory and technology, linked together the newest accomplishments results of neural networks.

In the scope of fault diagnosis, neural networks are very suitable for erecting "non-linear mapping" bridges between fault phenomena and fault mechanisms based on their efficient learning ability and adaptability [2-3]. This forward network optimizes the parameters according to the error, but it is also accompanied by the risk of converging to a local minimum [4]. The wavelet neural network is an extension of this basic network, and the wavelet analysis is grafted on the basic network at the excitation function of the hidden layer to achieve a higher convergence rate [5]. This paper introduces the standard particle swarm algorithm to improve, and then incorporate the idea of cross factors and inertial weights from genetic algorithms, constructed a new optimization algorithm for LED landscape lighting fault diagnosis.

2. Fault diagnosis systemse
LED landscape lighting equipment is a relatively complicated system, which is composed of three basic components: driving power supply, transmission line and LED lamps. And a large amount of data show
that the driving power supply is the main cause of LED equipment failure [6]. Taking LED drive power as the key object of fault diagnosis, judging whether it is invalid can well evaluate the overall working state of LED landscape lighting equipment [7]. There are 6 main detection indicators: input voltage adjustment rate (%), input current adjustment rate (%), total power deviation rate (%), output current adjustment rate (%), output power accuracy (%) and output ripple current rate (%).

In actual work, LED landscape lighting equipment rarely fails at multiple points at the same time, and this multiple fault conditions usually occur due to multiple points of failure caused by the failure of one point passed to other parts. Therefore, this article focuses on the determination of the single fault point fault state, the location of the data sampling point shown in Fig.1.

![Fig 1. Data Sampling Points of LED Landscape Lighting Equipment](image)

By comparing these real-time data with the normal operation data, the LED equipment is judged working status. Among them, the parameter in the normal range can be characterized by the value "1"; the value in the abnormal range is labelled by the value "0"; the arbitrary value is marked by "*". The fault symptom and source code table is shown in Table 1.

| Number | T1 | T2 | T3 | Fault location      | Coding |
|--------|----|----|----|---------------------|--------|
| 1      | 0  | *  | *  | Input failure       | 100    |
| 2      | 1  | 0  | *  | Drive power failure | 010    |
| 3      | 1  | 1  | 0  | Output failure      | 001    |
| 4      | 1  | 1  | 1  | normal status       | 000    |

3. Construction of wavelet neural network

The wavelet neural network integrates the advantages of wavelet analysis and artificial neural network [8]. It has both a large amount of data processing and self-learning ability by the neural network, and has the localized properties of wavelet transform. So, it has a strong approximation ability and a fast convergence speed, and can avoid the danger of falling into local optimization. The three layers of the compact structure wavelet neural network is shown in Fig.2, and its parameter table shown in Table 2.

![Fig 2. Structure Diagram of Three Layer Wavelet Neural Network](image)
Table 2. Parameter comparison table

| Symbols          | Meaning or effect                                      |
|------------------|-------------------------------------------------------|
| $m(k = 1, 2, \ldots, m)$ | Number of input layer nodes                           |
| $n(j = 1, 2, \ldots, n)$ | Number of hidden layer nodes                          |
| $N(i = 1, 2, \ldots, N)$ | Number of output layer nodes                          |
| $s_k$            | Input sample of the kth of input layer                |
| $y_i$            | The actual output value of the ith node of output layer |
| $\tilde{y}_i$    | The expected output value of the ith node of output layer |
| $a_{kj}$         | Connection weight between input layer node k and hidden layer node j |
| $a_{ji}$         | Connection weight between hidden layer node j and output layer node i |
| $a_j$            | The scaling parameters of the jth node of hidden layer |
| $b_j$            | The shifting parameters of the jth node of hidden layer |
| Mexican Hat function | Wavelet function                                    |
| Sigmoid function | Activation function                                  |

Through forward calculation, the input of the jth wavelet element of the hidden layer is:

$$s_j = \sum_{k=1}^{m} \omega_{kj} x_k, j = 1, 2, \ldots, n$$  \hspace{1cm} (1)

The output of the jth wavelet element is:

$$h_j = \psi_{a_j,b_j}(s_j) = \frac{1}{\sqrt{a_j}} \left(1 - \left(\frac{s_j - b_j}{a_j}\right)^2\right)e^{-\frac{(s_j-b_j)^2}{2a_j^2}}$$  \hspace{1cm} (2)

The output of the jth wavelet element is:

$$y_j = \frac{1}{1 + e^{-h_j}}, \quad i = 1, 2, \ldots, N$$  \hspace{1cm} (3)

The error energy function is:

$$E = \frac{1}{N} \sum_{i=1}^{N} (\tilde{y}_i - y_i)^2$$  \hspace{1cm} (4)

After clarifying the structure of the wavelet neural network, the next step is to explore the appropriate value of each parameter $\{\omega_{kj}, a_i, b_i, \omega_{ji}\}$ in the network, which was depended entirely on the degree of optimization of the training algorithm, to build a good wavelet neural network. So, seeking a reliable and efficient training algorithm is the key to building an algorithm model [9].

4. Optimization of wavelet neural network

The neural network is a collection of weights, and improper selection will result in the final training curve not converging to the expected value, or it will take more training time to approximate the expected value. Generally speaking, a good initial weight should satisfy two conditions:
The activation value of each layer of the neuron is not saturated; 
the activation value of each layer of the neuron is not zero.

The particle swarm optimization algorithm (PSO) can efficaciously correct the defect that the neural network might fall into the local optimum. However, in the actual use of PSO, it can be found that PSO can’t avoid falling into local optimum in some special cases [10]. Therefore, this paper introduces the cross thoughts of genetic algorithm into PSO, and innovates the concepts of inertial weight factor \( \omega \) and individual average extremum \( P_{ad} \), in order to optimize the population segmentation strategy to improve the search accuracy of algorithm and avoid falling into the local optimal value. The basic formula of genetic algorithm improved particle swarm optimization (GA-PSO) is as follows:

1) Basic formula for optimizing PSO:

\[
\begin{align*}
\dot{v}_{id} &= \omega (k+1)v_{id} + c_1 r_1 (p_{ad} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \\
x_{id} &= x_{id} + v_{id}
\end{align*}
\]  

(5)

Where, \( P_{ad} = (p_{1d} + p_{2d} + \ldots + p_{nd})/n \), \( d=1, 2, \ldots, D \).

2) Introduce the cross factor of genetic algorithm:

\[
\begin{align*}
x_i^{t+1} &= P_c x_i^t + (1-P_c)x_j^t \\
x_j^{t+1} &= P_c x_j^t + (1-P_c)x_i^t
\end{align*}
\]  

(6)

3) Introduce the Inertia weight factor:

\[
\omega(k+1) = (\omega_{init} - \omega_{end}) \ast \frac{(k_{max} - k)}{k_{max}} + \omega_{end}
\]  

(7)

The steps of GA-PSO can be divided into the following eight stages, and the flow chart can be shown in Fig.3:

Fig 3. Algorithm flow chart of GA-PSO-WNN
1) Determine the number of neurons in each layer of the wavelet neural network, initialize the parameters and use \( \{ \omega_{kj}, a_j, b_j, \omega_{ji} \} \) to vectorize the individual description.

2) Define the fitness in PSO, calculate the fitness by (4), and take the minimum value \( J_{\text{min}} \) by means of sorting.

3) Set the initial parameters in the particle swarm. The maximum number of iterations is \( T_{\text{max}} = 1500 \). The target error value is \( E_{\text{goal}} = 10^{-3} \). Set the cognitive learning coefficient \( C_1 = 1.4962 \) and the social learning coefficient learning factor \( C_2 = 1.4962 \). The upper and lower limits of the weight factor \( \omega \) is \([0.1,0.8]\). The genetic cross coefficient \( P_c = 0.9 \).

4) With the change of \( T \), the vector \( X \) and \( V \) of each particle are updated by (5), and the fitness value of each particle is calculated by (4). The optimal solution \( P_{\text{id}} \) of each particle as of the \( T \)th iteration is recorded and used to calculate the individual average extremum \( P_{\text{ad}} \). The optimal solution \( P_{\text{gd}} \) of the population as of the \( T \)th iteration is recorded.

5) Introduce the crossover factor of genetic algorithm into PSO, and use (6) to complete the hybridization operation.

6) Calculate and update the weighting factor \( \omega \) by (7).

7) Judge whether the algorithm reaches the termination condition, which \( T > T_{\text{max}} \) or \( E < E_{\text{goal}} \). If the termination conditions are met, carry out 8); if any one of the termination conditions is not met, switch back to operation 4).

8) The iterative operation is stopped, the global optimal solution is generated, and the most ideal wavelet neural network is obtained by using this solution set.

5. Fault diagnosis of LED landscape lighting based on wavelet neural network

5.1. Determine input
In accordance with the LED equipment failure indexes in Chapter II, input nodes \( t \) is 6. In order to refine the effective information in the raw data, first, the original input data is preprocessed to obtain valid input data. And then the membership is solved for these data. Finally, the membership is used as the input, that is:

\[
\text{input}_i = \frac{1}{1 + e^{-\frac{x_i - X_i}{\epsilon_i}}}, \quad i = 1, 2, \cdots, 6
\]  \hspace{1cm} (8)

Where, \( \text{input}_i \) represents the input value after processing; \( x_i \) represents the actual value of the \( i \)th indicator; \( X_i \) represents the preset alarm value of the \( i \)th indicator.

5.2. Determine output
In view of the three-level structure of LED equipment, it is appropriate to select three types of typical fault states as the output variables, which contain input failure (\( O_1 \)), drive power failure (\( O_2 \)) and output failure (\( O_3 \)), that is, output nodes \( n \) is 3.

5.3. Determine hidden layer nodes
The design of the hidden layer nodes \( m \) is determined using empirical formulas:

\[
m = \sqrt{t + n + p}, \quad p \in [1, 10]
\]  \hspace{1cm} (9)

For the 6 input 3 output wavelet neural network, \( m = 12 \) is the best.
5.4. Fault diagnosis results and analysis

This experiment verifies the three types of wavelet neural network algorithms in Matlab: standard wavelet neural network (BP-WNN), standard particle swarm optimization wavelet neural network (PSO-WNN) and genetic algorithm improved particle swarm optimization wavelet neural network (GA-PSO-WNN). Select the best one-time training result to draw a graph, and use the graph to intuitively represent the training error curve of wavelet neural network under three different algorithms. The result is shown in Fig.4.

Among the three training error curves, the number of iterations needed to achieve the preset accuracy is 1095, 938 and 442 respectively. The following conclusions can be drawn from the analysis of these data:

1) BP-WNN needs to carry out the longest iterative calculation, the reason behind it is that it only has the ability of nonlinear mapping, and it most likely fall into the situation of local extremum.

2) The convergence curve of PSO-WNN shows a clear deceleration trend in the later period, which is due to the stagnation of PSO, that is, the optimization stagnation caused by all particles tending to the same when the particles are in the later stage of the iteration process.

3) The number of iterations required for GA-PSO-WNN to reach the preset accuracy is the smallest, and the convergence speed is significantly better than the other two types of algorithms, which can better achieve the preset goal in fault diagnosis.

The trained network is applied to the fault prediction of LED landscape lighting equipment, and the predicted results are compared with the actual fault types, so that the accuracy of this network in fault diagnosis can be obtained. For verify the actual performance of GA-PSO-WNN, BP-WNN and PSO-WNN are also applied to the LED landscape lighting equipment fault test sample set, and the output results of these three algorithms are compared. Some results are shown in Table 3.
Table 3. Output Results Comparison of Three Types of Algorithm

| Number | Perfect Output (O1 O2 O3) | Algorithm        | Diagnostic Result | Error Diagnosis | Fault Location |
|--------|---------------------------|-------------------|-------------------|-----------------|----------------|
|        |                           |                   | O1    | O2    | O3    |                   |                  |
| 1      | 1 0 0                     | GA-PSO-WNN        | 1.0017 | 0.0113 | 0.0043 | 0.0058           | Input failure    |
|        |                           | BP-WNN            | 0.8473 | 0.0418 | 0.0971 | 0.0972           |                  |
|        |                           | PSO-WNN           | 0.9231 | 0.0594 | 0.0060 | 0.0474           |                  |
| 2      | 0 1 0                     | GA-PSO-WNN        | 0.0231 | 1.0031 | 0.0407 | 0.0023           | Drive power failure |
|        |                           | BP-WNN            | 0.1446 | 0.7328 | 0.3212 | 0.2444           |                  |
|        |                           | PSO-WNN           | 0.0387 | 0.8672 | 0.2510 | 0.1408           |                  |
| 3      | 0 0 1                     | GA-PSO-WNN        | 0.0173 | 0.0012 | 1.0023 | 0.0069           | Output failure   |
|        |                           | BP-WNN            | 0.0795 | 0.0914 | 0.8907 | 0.0934           |                  |
|        |                           | PSO-WNN           | 0.0294 | 0.0183 | 0.9829 | 0.0216           |                  |

It can be seen from Table III that the fault diagnosis error of GA-PSO-WNN constructed in this paper is less than that of BP-WNN or PSO-WNN, that is to say, this new algorithm has excellent optimization effect on wavelet neural network, making it have higher convergence rate and generalization performance in the fault diagnosis of LED landscape lighting equipment.

6. Conclusion
Aiming at the requirements of LED landscape lighting fault diagnosis, this paper proposes the GA-PSO to wavelet neural network optimization, which effectively avoids the risk of standard wavelet neural network convergence rate difference and local minimum convergence. The simulation results prove that: this new algorithm has the characteristics of high precision and high efficiency compared with the traditional algorithm, which effectively improves the diagnostic performance of LED landscape lighting fault diagnosis. However, it still needs to be pointed out here that this paper only discusses the situation of single point fault, and the diagnosis of compound fault is the focus of the next exploration.

References
[1] DAI Dan, CHEN Yinsheng, “Development Status and Development Trend of LED Lighting Technology,” Building Electricty, pp.14-20, December 2014.
[2] QI Jiyang, ZHU Chang’an, “Research on intelligent fault diagnosis method of the equipments,” Chinese Journal of Scientific Instrument, vol.27, pp.1270-1275, October 2006.
[3] CHEN Ru-qing, “Comparison Between Two Fault Diagnosis Methods Based on Network,” Proceedings of the CSEE, vol.25, pp.112-115, August 2005.
[4] XIE Xiangfeng, LEI Dian, SUN Chengbo, “Research of Fault Diagnosis Method of Switch Power Supply Based on BP Neural,” Electronic Measurement Technology, vol.35, pp.11-16, August 2012.
[5] ZHUANG Zhemin, YIN Guohua, LI Fenlan, JIANG Zhongwei, “Wind turbine fault diagnosis based on wavelet neural network,” Transactions of China Electrotechnical Society, vol.24, pp.224-228, April 2009.
[6] LEI Han, Narendran N, “An Accelerated Test Method for Predicting the Useful Life of an LED Driver,” Power Electronics IEEE Transactions on, vol.26, pp.2249-2257, August 2011.
[7] ZHOU Yuege, ZHU Yi, LI Xiang, ZHAI Guo-fu, “Performance reliability assessment of LED drivers for lighting,” Electric Machines and Control, vol.18, pp.99-104, September 2014.
[8] Delyon B, Juditsky A, Benveniste A, “Accuracy Analysis for Wavelet Approximations,” IEEE Transactions on Neural Networks, vol.6, pp.332-348, February 1995.
[9] Ooyen A V, Nienhuis B, “Improving the convergence of the back-propagation algorithm,” Neural Networks, vol.5, pp.465-471, March 1992.
[10] LIU Jinyang, GUO M Z, DENG C, “GeesePSO: an efficient improvement to particle swarm...
optimization,” Computer Science, vol.33, pp.166-168, 2006.