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Catenary Fault Identification Based on PSO-ELM

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Abstract. Catenary has been exposed outdoors for a long term, and its failure rate is very high, which has seriously affected the operation and development of traction power supply system. Due to the problems of low detection time, backward detection means and influenced by human factors in traditional catenary fault identification methods, this paper proposed a fault identification method based on PSO-ELM. This method could reduce the hidden layer nodes of traditional ELM and improve the accuracy of identification. In this paper, this method was compared with ELM, GA-ELM, BP, GA-BP and PSO-BP. A sample of catenary detection data of a power supply section in 2018 was selected. The results show that PSO-ELM is an efficient method for the fault identification of catenary.

1. Introduction
Catenary is one of the "three major components" of electrified railway, which usually erects over the railway track and arranges outdoors. It is vulnerable to the high-speed impact of locomotive pantograph, and has become a weakness of the traction power supply system. At present, catenary workers usually use inspection vehicles to detect catenary fault and make fault judgment based on their experience. This method often consumes a lot of time, and the detection time lags behind, which cannot meet the spanning and accurate detection requirements of railway[1-3]. Therefore, it is necessary to find a fast and accurate method to identify catenary faults.

In recent years, many scholars are active in fault identification. Ref. [4] proposed the principle of fault indicator to quickly identify the fault of catenary equipment, but it is not suitable for installing fault indicators in some occasions. In Ref. [5], a fault diagnosis method based on Particle Swarm Optimization (PSO) to optimize artificial neural network (ANN) for power system is introduced. But ANN needs a lot of parameters and runs for a long time. Ref. [6] introduced a classification and identification method for series arc faults by wavelet approximate entropy algorithm. However, the effect of this method is largely affected by the feature vector extraction. Ref. [7] introduced PSO and SVM to improve the fault classification performance of doubly-fed wind turbines under different operating conditions, but the process is more complicated. Ref. [8] proposed the weight method combined with extreme learning machine (ELM) in order to achieve better results in energy saving prediction of the purification tower. But the parameters of the model cannot be automatically updated and adjusted in time.
ELM is a single hidden layer feed-forward neural network with fewer parameters. It has strong fitting ability\(^9\). However, the prediction performance of traditional ELM algorithm is highly susceptible to the number of hidden layer nodes. The number of nodes is too small, the prediction accuracy is insufficient; the number of nodes is too large, the over-fitting is prone to occur. Hence, a PSO optimize ELM method for catenary fault identification is proposed. This method is compared with PSO optimize BP neural network\(^{10}\), Genetic Algorithm (GA) optimize ELM and BP neural network\(^{11-13}\) respectively. The results show that PSO-ELM greatly improves the accuracy of catenary fault identification and has certain application value.

2. Establishment of Catenary Fault Model
Catenary is an indispensable system in the development of railway, whose safe and stable operation deserves attention. In order to seek a new and fast identification method for the safe operation of catenary, common detection parameters in catenary system are selected.

2.1. Criteria for Catenary Fault Factors
In this paper, we select three parameters, like contact wire height, stagger value and locator gradient, as the research objects according to the railway technical standards.

In accordance with the railway technical standards, the contact wire height should not be higher than 6500 mm, not less than 5700 mm in the interval and intermediate station, not less than 6200 mm in the marshalling station, section station and individual larger intermediate station, and the height in the station and interval should be consistent.

The stagger value refers to the distance of contact wire from the center of pantograph at the location point. If the distance is selected properly, the friction between the pantograph and the contact wire will be uniform and the pantograph will not disengage. According to the railway technical standards, the stagger values are divided into two parts based on 120 km/h. For the section below 120 km/h, the stagger values of straight areas are 200–400 mm, and the stagger values of curve areas are 300–450 mm. For the section 120 km/h and above, whether in straight or curve areas, the stagger values are designed values ± 50 mm.

The correct installation of locating device is necessary to maintain the normal operation of pantograph and catenary, so the locator gradient should meet the requirements of railway technical standards. According to the standards, the locator gradient of the section below 120 km/h is 1/10–1/5, and under difficult conditions it is not more than 1/10–1/3.

2.2. Design of Fault Classification and Identification Indicators
Whether the parameters such as contact wire height, stagger value and locator gradient are normal or not directly affect the normal operation of catenary. The contact wire height is a significant part of the quality of catenary, which greatly affects the current receiving quality of pantograph. If the contact wire height is too high or too low, the current receiving quality will be greatly reduced, and even the scraping bow will be caused. The stagger value has a direct impact on the stability of contact wire and pantograph-catenary relationship\(^{14}\). Selecting an appropriate stagger value will effectively reduce the changes of the locator tensile force, thereby enhancing the stability of the contact wire and reducing the occurrence of pantograph-catenary faults. Conversely, if the stagger value is too large or too small, it will greatly increase the probability of pantograph-catenary failure, and is going against the stability of the contact wire\(^{15}\). The locator gradient is also an important parameter affecting the pantograph-catenary relationship. It should not only to consider the influence of topography and geomorphology based on local conditions, but also to meet the requirements of its own force and the structure of pantograph-catenary. If the gradient is too large or too small, it will cause the failure of catenary\(^{16}\).

Accurate identification of the faults caused by these three parameters will effectively reduce the occurrence of faults. Therefore, according to the railway standards, this paper identifies all data with four indicators. Indicator "1": normal data, i.e., contact wire height, stagger value and locator gradient all meet the requirements of railway standards; Indicator "2": contact wire height failure, stagger value and locator gradient meet the requirements; Indicator "3": stagger value failure, contact wire height
and locator gradient meet the requirements; Indicator "4": locator gradient failure, contact wire height and stagger value meet the requirements.

2.3. Data Preprocessing

Catenary is a complex system with many parameters and most of the parameters are non-linear. Different parameters usually have different dimensions, such as contact wire height, stagger value and locator gradient. In order to simplify the calculation, the data needs to be pre-processed and normalized to [-1,1]. When the training of the network is finished, the predicted values obtained are anti-normalized.

The mapminmax function is used for normalization, and the formula is shown as in equation (1):

\[ y = (y_{\text{max}} - y_{\text{min}}) \times \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} + y_{\text{min}} \]  

(1)

Where \( y_{\text{max}}=1 \), \( y_{\text{min}}=-1 \), \( x \) is the input data, \( x_{\text{min}} \) is the minimum value among the input data, \( x_{\text{max}} \) is the maximum value among the input data, and \( y \) is the output data.

3. Basic Theories

3.1. Extreme Learning Machine

ELM is an algorithm model proposed by Professor Guangbin Huang for solving the single hidden layer feed-forward neural networks\(^{[9,17-19]}\). It can randomly initialize the weights and offsets, which is faster and easier than traditional neural network methods. Typical ELM consists of input layer, hidden layer and output layer, as shown in figure 1.

![Figure 1. The structure of typical extreme learning machine.](image_url)

Assuming there are \( N \) random samples \((x_i, y_i)\), and \( x_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^T \in \mathbb{R}^n\), \( y_i = [y_{i1}, y_{i2}, \cdots, y_{im}]^T \in \mathbb{R}^m\), an ELM network with \( l \) hidden layer nodes can be expressed as:

\[ \sum_{j=1}^{l} \beta_j f(\omega_j \cdot x_j + b_j) = a_j, \quad j = 1, 2, \cdots, N \]  

(2)

Where \( f(x) \) is the activation function of the hidden layer, \( \omega_j \) is the input weight of the input neuron and the \( i \)-th hidden layer node, \( b_j \) is the offset of the \( i \)-th hidden layer node, and \( \omega_j \cdot x_j \) is the inner product of \( \omega_j \) and \( x_j \).

Theoretically, ELM can infinitely approximate the actual values of the sample, so that the error is minimized, that is, expressed as:

\[ \sum_{j=1}^{N} \left\| \delta_j - t_j \right\| = 0 \]  

(3)
That is, there are $\beta_i$, $\omega_i$ and $b_i$, so that

$$\sum \beta_i f(\omega_i \cdot x_j + b_i) = t_j, \quad j = 1, 2, \cdots, N$$  

(4)

Abbreviated as

$$H\beta = T$$  

(5)

Where $H$, $\beta$ and $T$ are expressed by the following equations (6)-(8), respectively.

$$H = \begin{bmatrix} f(\omega_1 \cdot x_1 + b_1) & f(\omega_2 \cdot x_1 + b_2) & \cdots & f(\omega_l \cdot x_1 + b_l) \\ f(\omega_1 \cdot x_2 + b_1) & f(\omega_2 \cdot x_2 + b_2) & \cdots & f(\omega_l \cdot x_2 + b_l) \\ \vdots & \vdots & \ddots & \vdots \\ f(\omega_1 \cdot x_N + b_1) & f(\omega_2 \cdot x_N + b_2) & \cdots & f(\omega_l \cdot x_N + b_l) \end{bmatrix}$$  

(6)

$$\beta = [\beta_1, \beta_2, \cdots, \beta_l]^T$$  

(7)

$$T = [t_1, t_2, \cdots, t_N]^T$$  

(8)

Where $H$ is the output matrix of the hidden layer, $\beta$ is the output weight, and $T$ is the expected output.

Unlike traditional gradient descent based algorithms, ELM algorithm does not need to adjust all parameters during the iteration. In the ELM algorithm, the input weight $\omega_i$ and the offset of the hidden layer node $b_i$ are randomly determined, that is, $H$ is determined. In this case, simply calculate the output weight by equation (9):

$$\hat{\beta} = H^+ T$$  

(9)

Where $H^+$ is the Moore-Penrose generalized inverse of $H$.

3.2. Particle Swarm Optimization

PSO is an iterative optimal algorithm\(^1\) proposed by Kennedy and Eberhart in 1995. It searches for the global optimal solution through continuous iteration, cooperation and competition. In PSO, each particle corresponds to an initial position and velocity, and is constantly updated during the iteration. The updating rules of each particle's position and velocity are as follows:

$$V_{ij}^{k+1} = \sigma V_{ij}^k + c_1 r_1 (P_{ij}^k - Z_{ij}^k) + c_2 r_2 (P_{ij}^k - Z_{ij}^k)$$  

(10)

$$Z_{ij}^{k+1} = Z_{ij}^k + V_{ij}^k$$  

(11)

Where $V_{ij}$ is the velocity of the $i$-th particle, $Z_{ij}$ is the position of the $i$-th particle, $\sigma$ is the inertia weight coefficient, $k$ is the current number of iterations, $P_{ij}$ is the individual optimal position of the $i$-th particle, and $P_{ij}$ is the global optimal position of the particle swarm, $c_1$ and $c_2$ are learning factors, and $r_1$ and $r_2$ are uniform random numbers within $[0, 1]$.

In order to ensure the global optimization, the inertia weight coefficient $\sigma$ should be set to a
larger number as much as possible. The inertia weight coefficient of this paper is set according to equation (12):

$$\sigma(k) = 0.9 - 0.6 \times \frac{k}{K}$$

(12)

Where $k$ is the current number of iterations and $K$ is the maximum number of iterations.

When the global optimal fitness function satisfies the requirements or the number of iterations reaches the maximum, the optimization ends. The PSO algorithm is simple and easy to operate, with less empirical parameters and faster convergence. Therefore, PSO-ELM to realize the identification of catenary fault categories is proposed.

3.3. **Specific Steps for PSO to Optimize ELM**

In this paper, PSO is used to optimize ELM, and the number of hidden layer nodes of ELM is effectively reduced under the premise of improving identification accuracy. Specific steps are as follows:

1. Determine sample data and normalize the data, including training samples, test samples, input variables and output variables;
2. Establish the network structure of PSO-ELM. In this paper, the number of input layer nodes is 3, the number of hidden layer nodes is 50, the number of output layer nodes is 1, and the "sig" function is selected as the activation function;
3. Set the parameters of PSO. In this paper, the maximum number of iterations is 100, and the inertia weight coefficient $\sigma$ is solved according to equation (12). Each iteration produces an inertia weight coefficient. The population number is set to 30, and the learning factors are set to $c_1=2.8$, $c_2=1.3$;
4. Determine the fitness value function. Calculate the fitness value of each particle, and find the individual optimal solution and the global optimal solution of the particle;
5. Initialize the position and velocity of each particle, and continuously update the position and velocity according to equations (10) and (11) during the iteration;
6. Judge whether the running result meets the requirements, that is, whether the maximum number of iterations is reached or whether a global optimal solution is generated. If the requirements are met, the iteration stops. Otherwise, go to step (4) and continue the iteration.

4. **Experimental verification**

The catenary detection data of a power supply section is selected as the data source, of which the straight segment is selected as the sample. The training samples are 640 groups and the test samples are 120 groups. According to the description in the railway technical standards of Part 2, combined with the topography of the area under the power supply section, the ranges of the three parameters are determined as follows: the contact wire height is not less than 5700mm, not higher than 6500mm; the stagger value is not less than 200mm, not higher than 400mm; the locator gradient range is 1/10~1/3 (excluding 1/3 and 1/10). Those values, which do not meet this standard, are regarded as failures. Based on the standard, each sample obtains an indicator. Among the training samples, the corresponding samples of the four indicators are all 160 groups, respectively. Among the test samples, the corresponding samples of the four indicators are all 30 groups, respectively.

In this paper, ELM, PSO-ELM, GA-ELM, BP, PSO-BP and GA-BP algorithms are used to compare the results, which are reflected by Accuracy, Mean Squared Error (MSE), Decision Coefficient ($R^2$) and Running Time ($t$).

4.1. **Algorithmic Parameter Settings for Each Algorithm**

For the ELM algorithm, a 3-layer network structure is adopted. Through repeated attempts, the "sig" function is selected as the activation function, and the hidden layer nodes are 115. The input variables are the contact wire height, the stagger value and the locator gradient, and the output variables are the
indicators mentioned in Part 2.

For the BP neural network, a 3-layer network structure is constructed. The number of input layer nodes is 3, the number of hidden layer nodes is 50, and the number of output layer nodes is 1. The total number of iterations is 100.

In the optimized process of PSO, the population size is set to 30. PSO is used to optimize ELM and BP neural network, respectively. The related parameters and variables are consistent in both the optimizations. The number of input layer nodes is 3, the number of hidden layer nodes is 50, and the number of output layer nodes is 1. The total number of iterations is 100.

In the GA optimized process, the population size is set to 10, the crossover probability is set to 0.6, the mutation probability is set to 0.1. The number of input layer nodes is 3, the number of hidden layer nodes is 50, and the number of output layer nodes is 1. The total number of iterations is 100.

4.2. Results Analysis

On the basis of the preset model parameters, the training samples are respectively trained by 6 kinds of algorithms, and the test samples are tested by them respectively. The obtained results are shown in figures 2-7.

(1) Comparison of ELM and BP neural network for catenary fault identification

Figure 2 shows the identification result of unoptimized ELM and the accuracy is 75.8333%. From figure 3, we can see the identification accuracy of unoptimized BP neural network is 77.5000%. In short, the above two algorithms have low identification results for the catenary and need to be improved.

(2) Comparison of GA-ELM and GA-BP for catenary fault identification

Figure 4 and figure 5 are the results of catenary fault identification after optimizing ELM and BP neural network by GA respectively. The accuracy of GA-ELM in figure 4 is 79.1667%, and the accuracy of GA-BP in figure 5 is 85.0000%.

(3) Comparison of PSO-ELM and PSO-BP for catenary fault identification

Figure 6 is the identification result of PSO-ELM. It can be seen from the figure that the method obtains the optimal effect, and the predicted accuracy is very high, which reaches 95.0000%. Figure 7 is the identification result of PSO-BP with an accuracy of 90.0000%, which is higher than the accuracy of the four methods shown in figures 2-5, but is less than the accuracy of PSO-ELM.

![Figure 2. Identification result of ELM.](image1)

![Figure 3. Identification result of BP neural network.](image2)
Through the comparison of the above six methods, it can be seen intuitively that PSO-ELM has the best effect, which can accurately identify various catenary fault categories. Since the effect of each operation is random, in order to reconfirm the high accuracy of PSO-ELM in the fault identification of catenary, the above six algorithms are respectively executed 10 times, as shown in table 1 - table 3.

| Serial number | MSE       | R²        | Accuracy(%) | t (s) | MSE       | R²        | Accuracy(%) | t (s) |
|---------------|-----------|-----------|-------------|-------|-----------|-----------|-------------|-------|
| 1             | 0.2413    | 0.8079    | 75.8333     | 0.58  | 0.2107    | 0.8336    | 80.0000     | 6.31  |
| 2             | 0.2369    | 0.8161    | 80.0000     | 0.53  | 0.2284    | 0.8179    | 80.8333     | 6.56  |
| 3             | 0.1828    | 0.8563    | 81.6667     | 0.57  | 0.2597    | 0.8044    | 80.0000     | 6.95  |
| 4             | 0.2089    | 0.8378    | 76.6667     | 0.57  | 0.2455    | 0.8120    | 85.0000     | 6.79  |
| 5             | 0.2166    | 0.8295    | 80.8333     | 0.55  | 0.2822    | 0.7770    | 79.1667     | 6.44  |
| 6             | 0.2018    | 0.8394    | 79.1667     | 0.55  | 0.2219    | 0.8298    | 75.8333     | 6.09  |
| 7             | 0.2492    | 0.8047    | 78.3333     | 0.54  | 0.2681    | 0.7869    | 78.3333     | 6.25  |
| 8             | 0.2305    | 0.8181    | 77.5000     | 0.58  | 0.2283    | 0.8268    | 83.3333     | 6.52  |
| 9             | 0.2459    | 0.8087    | 78.3333     | 0.56  | 0.2295    | 0.8179    | 80.0000     | 6.40  |
| 10            | 0.2424    | 0.8099    | 75.8333     | 0.59  | 0.2767    | 0.7788    | 79.1667     | 6.47  |
Based on the results of 10 runs, the average effect of each algorithm can be calculated, as shown in table 4. It is noted that the accuracy of PSO-ELM is 95.5000%, which is much higher than the accuracy of the other five algorithms. The MSE of PSO-ELM is 0.0584, which is far lower than the MSE of the other five algorithms.

Table 4. Comparison of the average effect of the six algorithms.

| Types   | Training samples | Test samples | MSE    | R²     | Accuracy(%) | t (s)   |
|---------|------------------|--------------|--------|--------|-------------|--------|
| ELM     | 640              | 120          | 0.2256 | 0.8228 | 78.4167     | 0.56   |
| GA-ELM  | 640              | 120          | 0.1826 | 0.8569 | 77.4000     | 56.40  |
| PSO-ELM | 640              | 120          | 0.0584 | 0.9534 | 95.5000     | 32.20  |
| BP      | 640              | 120          | 0.2451 | 0.8085 | 80.1667     | 6.48   |
| GA-BP   | 640              | 120          | 0.2110 | 0.8372 | 81.5000     | 429.18 |
| PSO-BP  | 640              | 120          | 0.1620 | 0.8743 | 85.3333     | 830.91 |

5. Conclusions

The fault identification of catenary detection parameters is significant to improve the pantograph-catenary relationship and ensure the safe and stable operation of catenary. In this paper, three parameters closely related to the pantograph-catenary relationship are taken as the research objects. A fault identification method based on PSO-ELM is proposed. The catenary detection data of a power supply section in 2018 is selected as the sample, and the following conclusions are drawn:

(1) The accuracy of catenary fault identification based on unoptimized ELM and BP neural network are 78.4167% and 80.1667%, respectively. Both the accuracy are low and need to be optimized.

(2) The accuracy of catenary fault identification based on GA-ELM and GA-BP are 77.4000% and 81.5000%, respectively. Both the optimized effects are poor, and the running time are long, which do not meet the requirements of catenary fault identification.

(3) The accuracy of catenary fault identification based on PSO-BP is 85.3333%, which is higher than the previous four methods. But its running time is 830.91s, which severely affects the speed of fault identification and is not suitable for the requirements of catenary fault identification.
(4) The accuracy of catenary fault identification based on PSO-ELM reaches 95.5000%, and the running time only needs 32.2s, which can meet the requirements of the catenary system to quickly and accurately identify faults. It provides a new method for catenary fault identification.

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