Fault Detection for ZPW-2000A Jointless Track Circuit Based on Deep Belief Network Optimized by Grey Wolf Optimizer Algorithm

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Abstract. At present, the fault detection for jointless track circuit still depends on the experience of electrical personnel, which leads to low maintenance efficiency and the phenomenon of misjudgment and missed judgment. A fault detection method for track circuit based on deep belief network (DBN) is proposed in this paper. According to the working principle and transmission characteristics of track circuit, 12 voltage and current monitoring parameters are selected to detect 15 types of track circuit fault. However, the selection of structural parameters for deep belief network is time-consuming, so grey wolf optimizer algorithm (GWO) is proposed to optimize DBN, which can adaptively select the number of neurons in each hidden layer. The simulation results show that by introducing the GWO algorithm to optimize the DBN detection model, the fault classification accuracy of the ZPW-2000A jointless track circuit can reach 96.96%, which significantly improves the fault detection level of the track circuit.

1. Introduction
Track circuit is used to check the occupation, clearance, and integrity of trains, and it is an important part of railway signal equipment. However, due to the complex composition of track circuit and the harsh and changeable working environment, the probability of fault is high and the types of faults diverse in the actual operation process, which seriously affects the railway transportation efficiency and operation safety. At present, the fault detection of track circuit depends on the experience of the electrical personnel to analyze the collected data, which will lead to the fault cannot be dealt in time and the maintenance efficiency is low. Therefore, it is very important to use intelligent algorithm to analyze the data collected by track circuit, and to mine its deep feature to assist the electrical personnel in fault detection.

With the rapid development of computer technology and artificial intelligence, intelligent algorithms have been applied to the research of track circuit fault detection. Wang et al.\textsuperscript{[1]} combined neural network with fuzzy logic to construct an interval type-2 neuro fuzzy system to realize intelligent detection of track circuit fault modes. Aiming at the low accuracy of single fault detection, Li et al.\textsuperscript{[2]} proposed to fuse the detection results of BP neural network and fuzzy comprehensive evaluation with D-S evidence theory to achieve high detection accuracy. Xie et al.\textsuperscript{[3]} used deep belief network to train the fault data, and BPNN to fine-tune the network to achieve the effective detection of track circuit.

In this paper, based on the common fault modes in the application of track circuit, the DBN is introduced to establish the fault detection model. At the same time, in order to avoid the influence of...
artificial selection of structural parameters on the ability of DBN feature extraction, GWO is used to optimize the structural parameters of DBN to improve the fault detection accuracy of the model.

2. ZPW-2000A track circuit

2.1. Working principle
ZPW-2000A track circuit is divided into main track and small track. The transmitter of the main track generates 18 kinds of low frequency and 8 kinds of carrier frequency signals, which are transmitted to the corresponding main track and the small track in the syntonic section. The signal returns to the receiving end of the track circuit through the rail, and is sent to the receiver of this section through the syntonic section, matching transformer, and cable channel. The small track signal in the syntonic section is processed by the adjacent track circuit receiver in front of the operation, and the processing results are sent to the receiver in this section. The receiver of this section judges whether the section is occupied or not by the main track signal and the small track signal in the syntonic section.

2.2. Monitoring quantity of track circuit
The data of track circuit in normal condition is easy to obtain from the centralized signal monitoring system, but it is difficult to obtain the data of track circuit in different fault conditions. Therefore, the equivalent model of the ZPW-2000A track circuit can be established to obtain the required data through simulation. Table 1 shows the relevant monitoring quantity for fault diagnosis of ZPW-2000A jointless track circuit.

| Monitoring quantity | Symbol | Monitoring quantity | Symbol |
|---------------------|--------|---------------------|--------|
| Transmitting voltage | M1     | Current at receiver end TU1 | M7     |
| Transmitting current | M2     | Current at receiver end SVA | M8     |
| Cable side transmission voltage | M3 | Current at receiver end TU2 | M9     |
| Current at transmitter end TU1 | M4 | Cable side reception voltage | M10    |
| Current at transmitter end SVA | M5 | Main rail input voltage | M11    |
| Current at transmitter end TU2 | M6 | Main rail output voltage | M12    |

2.3. Fault modes of track circuit
According to the field investigation and consulting the literature on ZPW-2000A track circuit fault detection, the fault modes of track circuit are summarized as shown in Table 2.

| Symbol | Fault mode | Remarks | Symbol | Fault mode | Remarks |
|--------|------------|---------|--------|------------|---------|
| F1     | Normal     | Track circuit is normal | F9     | SPT digital cable failure at the receiver end | Outdoor receiving terminal |
| F2     | SPT digital cable failure at the transmitter end | Outdoor delivery terminal | F10    | Transmitter failure | Indoor delivery terminal |
| F3     | Transmitter end TU1 failure | Outdoor delivery terminal | F11    | Transmitter end cable simulation network failure | |
| F4     | Transmitter end SVA failure | Outdoor delivery terminal | F12    | Receiver end cable simulation network failure | Indoor receiving terminal |
| F5     | Transmitter end TU2 failure | | F13    | Receiver end attenuator failure | |
| F6     | Receiver end TU1 failure | Outdoor receiving terminal | F14    | Receiver failure | Rail line |
| F7     | Receiver end SVA failure | | F15    | Compensation capacitance fault | |
| F8     | Receiver end TU2 failure | | | | |
3. Fault detection for track circuit based on DBN optimized by GWO

3.1. DBN
The structure of DBN is a neural network with multiple hidden layers, which is composed of multiple restricted Boltzmann machines (RBM)[4]. Fig.1 shows the structure of DBN model, which is composed of three RBM and softmax layers. Each RBM is composed of an input layer and a hidden layer. Input neurons \( v \) and hidden neurons \( h \) are connected by weight \( W \), and neurons in the same layer are independent of each other.

![Fig.1 The structure of DBN](image)

RBM is the basic unit structure of DBN, so the essence of DBN training is to train RBM. RBM is a probability graph model based on energy, but because its expected value of distribution is not easy to obtain[5], the contrast divergence algorithm[6] is used to train RBM, as shown in Fig.2. Firstly, the training data is delivered to \( v^{(0)} \), and the state \( h^{(0)} \) of hidden layer neurons is obtained by CD-K algorithm, and then the state of input layer neurons \( v^{(1)} \) is obtained, and a reconstruction is completed.

![Fig.2 The training process of RBM](image)

The training process of DBN can be divided into two parts:
(1) RBM forward stack learning. The data of input is extracted from the deep distribution through a series of nonlinear transformations, which is unsupervised learning. The parameters of the model obtained by unsupervised learning process can be applied in the following supervised learning model.
(2) Reverse fine-tuning process. Because RBM forward stack learning can only ensure the best relationship of mapping between input and output of each layer, the error in the training process will accumulate with the increase of training layers. So the reverse fine-tuning method is adopted to fine-tune the connection weight and bias of each layer from the last layer of DBN network to minimize the error.

3.2. The structure parameters of DBN optimized by GWO
The basic idea of GWO is that randomly generated \( N \) grey wolves are scattered in the search space. In the search process, the optimal individual \( \alpha \) wolf and the second and third optimal individuals \( \beta \) and \( \delta \) wolves constantly update the position of prey, that is, the global optimal solution[7]. The other wolves in the group constantly update the distance between the prey, so that the group can search, encirclement and attack the prey until the optimal solution is captured. Compared with other genetic algorithms, GWO has the advantages of less input parameters, strong robustness, and fast convergence speed.
Due to the artificial selection of DBN structure, there are problems such as the performance degradation of the detection model, the increase of the classification error rate, and the enumeration method is time-consuming and labor-intensive, so this paper uses GWO to optimize the structure parameters of DBN.

The parameters to be optimized include the number of neurons in each hidden layers $m_1, m_2, m_3$ and the learning rate $\eta \in (0,1)$.

The proposed methodology of GWO-DBN works in the following steps:

Step 1: The equivalent model of track circuit is established, and the fault data of different track circuit faults are collected to form the fault data set. Due to the different fault modes, there are differences in their manifestations. Different modes of data have different dimensions, so it is necessary to normalize the fault data set.

Step 2: According to the proportion, the fault data set are divided into training set data and test set data.

Step 3: The number of hidden layer neurons $m_1, m_2, m_3$ and the learning rate $\eta$ are encoded into real vector forms, establishing the one-to-one relationship of mapping with grey wolf individuals in the population, and the initialization operation is carried out.

Step 4: The fitness values of all individuals are calculated, and the wolves of $\alpha, \beta$ and $\delta$ are marked.

Step 5: The positions of all individuals are updated according to the positions of $\alpha, \beta$ and $\delta$ wolves.

$$D_k = |C_k \cdot X_k(t) - X(t)|, \quad k = \alpha, \beta, \delta$$

$$X_i(t + 1) = X_k(t) - A_i \cdot D_i, \quad i = 1, 2, 3$$

$$X(t + 1) = \frac{X_1 + X_2 + X_3}{3}$$

Where $X_k$ is the optimal position of three grey wolves in the current population, $X$ is the position vector of the other candidates, $D_k$ is the distance between current candidate wolf and optimal wolf.

Step 6: Update fitness values for all individuals.

Step 7: When the error of the training sample is within the allowable limit of the set error or the number of iterations reaches the maximum, the optimal position will be output. Otherwise, go to step 4 and re-update the position of wolves until the requirements are met.

Step 8: The optimized DBN network is used to train test set data and output fault detection classification results.

4. Simulation

4.1. Fault sample

In the simulation, $M_1$-${M}_{12}$ in Table 1 is taken as the monitoring quantity of the fault detection model, and the fault data of the 15 fault modes in Table 2 can be obtained through the simulating track circuit equivalent model. There are 15000 fault samples $F_1$-$F_{15}$, 1000 for each fault type. Among them, 800 are training sets and 200 are test sets.

4.2. The parameters of GWO-DBN model

Since the fault detection model of track circuit is based on $M_1$-${M}_{12}$ as the monitoring quantity, the number of neurons in the input layer of is 12, and there are 15 fault modes $F_1$-$F_{15}$, so the number of neurons in the output layer of is 15.

The parameters of DBN network optimized by GWO are shown in Table 3.

In the training process of DBN network model, the number of iterations will also affect the accuracy of fault detection. Fig.3 shows the relationship between track circuit fault detection and iterations in 5-layer GWO-DBN.
Table 3  The parameters of GWO-DBN

| Parameter                  | Quantity |
|----------------------------|----------|
| Neurons in the input layer | 12       |
| RBM layers                 | 3        |
| Iterations of RBM          | 150      |
| $m_1$                      | 12       |
| $m_2$                      | 12       |
| $m_3$                      | 13       |
| Neurons in the output layer| 15       |
| Learning rate of DBN       | $8.6 \times 10^{-4}$ |

Fig.3  Influence of iterations on detection accuracy

It can be seen from Fig.3, when the initial number of iterations is less than 24, the fault accuracy is less than 50%, but with the gradual increase of the number of iterations, the fault accuracy increases. When the number of iterations reaches 200, the classification accuracy tends to be stable.

4.3. Simulation results

Through the optimization and training of DBN network structure parameters by GWO, the test set data is input into the detection model to verify the correctness of the model.

Fig.4  The fault classification results of GWO-DBN

The accuracy rate of fault detection in different fault modes is shown in Table 4.

Table 4  Detection accuracy in different fault modes

| Fault modes | Accuracy/% | Fault modes | Accuracy/% |
|-------------|------------|-------------|------------|
| F1          | 95.2       | F9          | 99.6       |
| F2          | 97.8       | F10         | 100        |
| F3          | 98.9       | F11         | 98.9       |
| F4          | 100        | F12         | 97.9       |
| F5          | 98.6       | F13         | 86.5       |
| F6          | 94.9       | F14         | 89.3       |
| F7          | 100        | F15         | 96.8       |
| F8          | 100        |             |            |
It can be seen from Fig.4 and Table 4, when the GWO-DBN network model is used for fault detection, the average fault detection accuracy reaches 96.96%, and the detection accuracy of each fault type is higher than 86%, indicating that the classification performance of the model is better and the fault detection accuracy is higher. According to the comparative data in Fig.5, after using GWO to optimize the DBN structure parameters, the overall detection accuracy of the track circuit fault detection model is improved.

Fig.5 Performance of fault detection models

5. Conclusion
Due to the randomness and complexity of ZPW-2000A track circuit fault, DBN neural network is used to detection fault. But the artificial selection of DBN network structure parameters will affect the detection accuracy, so GWO is selected to optimize the DBN network structure parameters. The proposed method can adaptively select the optimal number of neurons and learning rate of each hidden layer. The simulation results show that DBN detection model optimized by GWO can extract the deep features of different fault modes to detect the fault, and achieves a higher fault accuracy.

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