A NOVEL FAULT DIAGNOSIS METHOD OF SHUNT MALFUNCTION FOR JOINTLESS TRACK CIRCUIT

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Abstract: *The track circuit shunt malfunction will lead to the train delays and even serious accidents such as train collision which have serious effects on safe operation of trains and transport efficiency of railway. In this paper the locomotive signal induced voltage model is established based on uniform transmission line theory. On this basis, the fault features extraction is achieved through empirical mode decomposition (EMD) method because of its adaptive advantage. The induction voltage amplitude envelope (IVAE) signals are decomposed into several intrinsic mode functions (IMFs) and the IMF energy moments are used as the fault characteristic information. The least squares support vector machines (LS-SVMs) are built to realize the multi-class classification by introducing the minimal output coding. In addition, the optimal parameters of LS-SVM model are obtained by using the improved PSO algorithm and the generalization performance is enhanced through the cross validation. The experiment shows that the fault diagnosis method for track circuit. proposed in this paper is effective.*

Keywords: *track circuit; shunt malfunction; fault diagnosis; empirical mode decomposition; IMF energy moment; improved PSO algorithm; least squares support vector machine*

I. INTRODUCTION

Track circuit is one of the key equipment in railway signaling system. The type ZPW-2000 track circuit which is widely adopted in China high-speed railway is used to realize train occupancy detection and transfer control information to trains [1]. Due to rail rust and other reasons, the track relay cannot fall normally when train enters. This phenomenon is called shunt malfunction. The shunt malfunction may lead to train delays and even serious accidents such as train collision. Hence, the transportation efficiency and safety are influenced directly by the performance of track circuit. However, the track circuit fault diagnosis depends on the experience of maintenance personnel in the field maintenance. As a result, misdiagnosis often happens. It is of immediate significance to provide a fault diagnosis system for maintenance personnel.

With the development of computer and information technology the expert system [2], artificial neural network [3-5], D-S classifier [6], artificial immune algorithm [7] are adopted to identify faults for track circuit. These methods provide new ideas for development of track circuit fault diagnosis. However, due to the complexity of track circuit structure and diversity of failure mechanism the accuracy of fault diagnosis should be further improved. Therefore, a new fault diagnosis method for track circuit based on fault feature extraction using intrinsic mode function energy moment and least squares support vector machine is put forward in this paper.

II. MODELING OF THE LOCOMOTIVE SIGNAL INDUCTION VOLTAGE

Theoretically, the rail line can be regard as a lossy uniform transmission line. And its transmission characteristics can be described using equivalent four terminal network (EFTN) [8]. The equivalent circuit of jointless track circuit is shown in Fig. 1. The electrical insulated joint consists of tune unit BA1, BA2, air core coil SVA and part of the steel rails. Z_{ca} is the connection impedance of electrical insulated equipment and steel rail. Z_T is the equivalent impedance between transmitter and electrical insulation equipment. Z_R is the equivalent impedance between receiver and electrical insulation equipment. R_f is the equivalent resistance of the train wheel. C_t is the compensation capacitor. Z_r is the connection impedance of compensation capacitor and steel rail. Z_{rcv} is the equivalent resistance of receiving end. The track signal generated by the transmitter flows into the receiver through the transmission cable, tuning unit and the rail. When a train enters the track section the track circuit is short-circuited, then most of the track signal flows back through the axles and wheels. Meanwhile, the antennas in the track circuit reader (TCR) generate the corresponding induction voltages. Afterwards, the target speed can be extracted to the on-board security computer by analog to digital sampling, signal demodulation, and decoding.

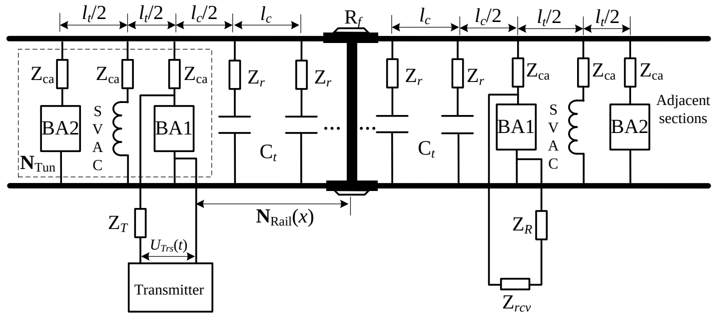

Figure 1. *The equivalent circuit model of the jointless track circuit*

Then the EFTN of the track circuit in shunt state can be given by:

$$N_{Tc}(x) = N_{Tun} \cdot N_{Rail}(x) \tag{1}$$

where, $\mathbf{N}_{Tun}$ is the EFTN of electrical insulated joint. $\mathbf{N}_{Rail}(x)$ is the EFTN of the rail line from the sending end to the shunting position x by train. Thus, the induction voltage amplitude of the on-board locomotive signal antenna $A_{IV}(x)$ can be given by

$$A_{IV}(x) = a \cdot \frac{A_{Trs}}{\left(\left|N_{Tc11}(x)R_f + N_{Tc12}(x)\right|\right)} \tag{2}$$

where, A_{Trs} is the amplitude of sending voltage. The constant coefficient a is decided by the characteristic parameters of the antenna and the circuit configuration of the locomotive signal recorder [9].

The rail line can be considered as a series of compensation units which are cascaded with each other. A single compensation unit can be expressed as

$$N_{cp} = N_g\left(l/2\right) \cdot N_{Ct} \cdot N_g\left(l/2\right) \tag{3}$$

where, $\mathbf{N}_{Ct}$ is the EFTN of compensation capacitor which can be given by

$$N_{Ct} = \begin{bmatrix} 1 & 0 \\ j\omega C_t & 1 \end{bmatrix} \tag{4}$$

$\mathbf{N}_g(l_c/2)$ is the EFTN the rail line which is half the length of the compensation unit which can be expressed as

$$N_g(l) = \begin{bmatrix} ch(\dot{\gamma}l) & \dot{Z}_c \cdot sh(\dot{\gamma}l) \\ sh(\dot{\gamma}l)/\dot{Z}_c & ch(\dot{\gamma}l) \end{bmatrix} \tag{5}$$

where, Z_c, γ are the characteristic impedance and propagation constant of the rail and l is the length.

Then the EFTN of the rail line can be given by

$$N_{Rail}\left(x\right) = \begin{cases} \left(N_{Cp}\right)^n \cdot N_g\left(x - n \cdot l_c\right), & 0 \le x < l_c/2 \\ \left(N_{Cp}\right)^{n-1} \cdot N_g \cdot N_{Ct} & \\ \cdot N_g\left(l_c/2 - n \cdot l + x\right), & l_c/2 \le x < l_c \end{cases} \tag{6}$$

where, n is the number of compensation capacitors from the sending end to the shunting position.

According to the construction of electrical insulated joints $\mathbf{N}_{Tun}$ can be expressed as

$$N_{Tun} = N_{BA1} \cdot N_g\left(l_t/2\right) \cdot N_{SVA} \cdot N_g\left(l_t/2\right) \cdot N_{BA2} \tag{7}$$

where,

$$N_{BA2} = \begin{bmatrix} 1 & 0 \\ 1/(Z_{ca} + Z_{BA2}) & 1 \end{bmatrix} \tag{8-a}$$

$$N_{SVA} = \begin{bmatrix} 1 & 0 \\ 1/(Z_{ca} + Z_{SVA}) & 1 \end{bmatrix} \tag{8-b}$$

$$N_{BA1} = \begin{bmatrix} 1 + \dfrac{Z_{ca}}{Z_{BA1}} & Z_{ca} + Z_T + \dfrac{Z_{ca} \cdot Z_T}{Z_{BA1}} \\ \dfrac{1}{Z_{BA1}} & 1 + \dfrac{Z_T}{Z_{BA1}} \end{bmatrix} \tag{8-c}$$

Taking an example of a track circuit in Beijing Railway Bureau. The total length of the track circuit is 1.23km and the basic parameters are shown in Table 1, where f_c is the frequency of the track signal. As space is limited, the connection impedances tested in the lab are not listed in this paper. Then the induced voltage amplitude envelopes (IVAEs) can be calculated using the model mentioned above and the results are shown in Fig. 2.

Table 1. *Basic parameters of the track circuit*

f_c	A_{Trs}	C_t	l_c	l_t	n	R_d
2300Hz	115.4V	40μF	80m	29m	15	1Ω·km

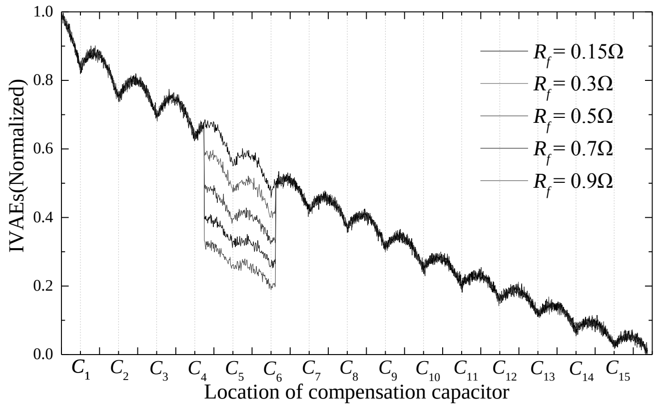

Figure 2. *The induction voltage amplitude envelopes of the track circuit*

When the track circuit is in normal condition (R_f = 0.15Ω) due to the compensation capacitors the induced voltage amplitude envelope decays wavily from the sending end to the receiving end. Each trough corresponds with the location of each compensation capacitor. When the train passes through the location of poor shunting the IVAEs decrease. And the larger the R_f, the smaller the IVAEs.

III. MULTI-CLASS LS-SVM ALGORITHM

Given the sample set $\{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}$, the sample x_i (i=1, 2,…, l) correspond to category $y_i \in \{-1, 1\}$. Then optimal classified super-plane satisfies the following conditions.

$$\begin{cases} \omega^T x_i + b \geq 1, & y_i = 1 \\ \omega^T x_i + b \leq -1, & y_i = -1 \end{cases} \tag{9}$$

where, ω is the normal vector of super-plane. b is the offset.

The LS-SVM nonlinear classification model can be obtained through solving the optimization function $\Phi_{min}(\omega, e_i)$ [10]

$$\Phi_{min}\left(\omega, e_i\right) = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{l} e_i^2 \tag{10}$$

where, C is the regularization parameter. e_i is the slack variable.

The formula (10) should satisfy the following equation.

$$yi\left(\omega^T\varphi\left(x_i\right)+b\right)=1-e_i \tag{11}$$

where, $\varphi(\cdot)$ is a mostly non-linear function, which maps the data into a higher dimensional feature space.

The Lagrangian can be defined as

$$\begin{aligned} L\left(\omega,b,e_i,\alpha_i\right) &= \frac{1}{2}\left\|\omega\right\|^2+\frac{1}{2}C\sum_{i=1}^{l}e_i^2 \\ &-\sum_{i=1}^{l}\alpha_i\left(y_i\left(\omega^T\varphi\left(x_i\right)+b\right)-1+e_i\right) \end{aligned} \tag{12}$$

where, α_i parameters are the Lagrange multipliers. The solution concludes in a constrained optimization with the conditions:

$$\begin{cases} \dfrac{\partial L}{\partial \omega}=0\Rightarrow \omega=\sum_{i=1}^{l}\alpha_i y_i\varphi\left(x_i\right) \\ \dfrac{\partial L}{\partial b}=0\Rightarrow 0=\sum_{i=1}^{l}\alpha_i y_i \\ \dfrac{\partial L}{\partial e_i}=0\Rightarrow \alpha_i=Ce_i \\ \dfrac{\partial L}{\partial \alpha_i}=0\Rightarrow y_i\left(\omega^T\varphi\left(x_i\right)+b\right)-1+e_i=0 \end{cases} \tag{13}$$

Combine equation (12) and (13) the following linear equation set is obtained.

$$\begin{gathered} \begin{bmatrix} 0 & y^T \\ y & \Omega+C^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ I \end{bmatrix} \\ y=\left[d_1,d_1,\cdots,d_m\right],\alpha=\left[\alpha_1,\alpha_2,\cdots,\alpha_m\right], \\ I=\left[1,1,\cdots,1\right],\Omega_{i,j}=y_i y_j K\left(x_i,x_j\right). \end{gathered} \tag{14}$$

where, $K(x_i, x_j)$ is kernel function of LS-SVM. Then the classification decision function of LS-SVM can be given by:

$$f\left(x\right)=\operatorname{sgn}\left(\sum_{i=1}^{l}\alpha_i y_i K\left(x,xi\right)+b\right) \tag{15}$$

where, x is the samples. The kernel function of LS-SVM must be positive definite and satisfy the Mercer theorem.

The multi-classification of LS-SVM can be achieved through multi-objective optimization or combinatorial coding method. Therefore, all classification problems can be solved once through the multi-objective optimization method. But the number of unsolved variables is larger and the solution process is more complicated [11]. Among the combinatorial coding methods the minimal output coding (MOC) method is easy to implement and the calculated amount is minimal [12]. Hence, the multi-classification is realized through constructing multiple LS-SVM combining the MOC method in this paper. Aiming at the multi-classification problem a unique coding $c_k = [y_{k1}, \cdots, y_{kj}, \cdots, y_{Nm}]$ is assigned to each class k in the MOC method. The output digit of MOC can be expressed as

$$N_m = [\log_2 F] \tag{16}$$

where, F is the number of classes.

For a new sample under test the classification results of N_m uncorrelated classifiers constitute a code s_0. Calculate the hamming distance of all codes and F coding. The class whose hamming distance is minimal is the class of the under test sample.

IV. FAULT DIAGNOSIS MODEL BASED ON IMF ENERGY MOMENT AND LS-SVM

The empirical mode decomposition (EMD) algorithm is an adaptive time-frequency analysis for signals. The original signal is decomposed into several narrow-band signals and each narrow-band signal is called intrinsic mode functions (IMFs). The decomposition results can be consisted of several IMFs and a residual signal [13].

$$s(t) = \sum_{i=1}^{D} \mathrm{imf}_i(t) + r_n(t) \tag{17}$$

Each IMF contains characteristic information of some frequency ranges. When the device malfunctions the energies of the induction voltage amplitude envelope signals will change. The IMF energy moment method considers not only the magnitudes of IMF energy but also the distribution of IMF energy with the time parameter t. Therefore, in comparison to the traditional IMF energy method the IMF energy moment can reveal the energy distribution characteristics better and it’s beneficial to failure feature extraction [14]. In order to capture the fault information hidden in the signals preferably. The feature extraction method based on IMF energy moment is adopted in this paper to extract fault features. The IMF energy moment can be expressed as

$$E_i = \sum_{k=1}^{n} (k \cdot \Delta t) \left| \mathrm{imf}_i (k \cdot \Delta t) \right|^2 \tag{18}$$

where, Δt is the sampling period. n is the sampling number. k is the sampling point. imf is the intrinsic mode function.

The IMF energy moments are used to construct a fault feature vector and the feature vector is normalized by equation (19).

$$T = [E_1, E_2, E_3, \cdots E_D] \Big/ \sum_{i}^{D} E_i \tag{19}$$

Different kernel functions will generate different LS-SVM models. Research and experiments show that the LS-SVM model has a better generalization performance when the Gauss RBF function is adopted as the kernel function [10,12]. However, there are two parameters (σ and γ) in the LS-SVM model based on Gauss RBF function need to be optimized. γ corresponds to the penalty factor C in the LS-SVM model. It decides the magnitude of the training errors and the strength of the generalization ability. σ^2 reflects the distribution characteristics of the training sample data. Therefore, the advanced particle swarm optimization (PSO) is used to seek the optimal parameter values of LS-SVM.

The PSO is an iterative optimization algorithm [15]. The PSO initializes S particles in the solution space firstly. Every particle has three features such as location, velocity and fitness. The magnitude of fitness value decides the merit of the particle. The group consisted of S particles flies in the d-dimensional space with a certain velocity $V_s = [v_{s1}, v_{s2}, \cdots, v_{sd}]^T$ ($s = 1, 2, \cdots, d$). Each particle updates its location through tracking the individual extremums $P_s = [p_{s1}, p_{s2}, \cdots, p_{sd}]^T$, individual extremums $P_g = [p_{g1}, p_{g2}, \cdots, p_{gd}]^T$ and velocities. The update formula of the velocity and location can be given by

$$\begin{aligned} v_{sd}(t+1) = {} & v_{sd}(t) + c_1 r_1 \left(p_{sd}(t) - x_{sd}(t)\right) \\ & + c_2 r_2 \left(p_{sd}(t) - x_{sd}(t)\right) \end{aligned} \tag{20}$$

$$x_{sd}(t+1) = x_{sd}(t) + v_{sd}(t+1) \tag{21}$$

where, t is the evolutionary algebra. c_1 and c_2 are acceleration factors. r_1 and r_2 are the random variables subjected to uniformly distribution. $x_{sd}(t)$ is the location of the particle.

In practical application the basic PSO algorithm falls into local optima easily. Aiming at this, the dynamic modulation strategy of nonlinear weights is introduced in this paper. The advanced PSO algorithm can be expressed as

$$\begin{aligned} v_{sd}(t+1) = {} & w(t) v_{sd}(t) + c_1 r_1 \left(p_{sd}(t) - x_{sd}(t)\right) \\ & + c_2 r_2 \left(p_{sd}(t) - x_{sd}(t)\right) \end{aligned} \tag{22}$$

$$w(t) = \left[(t_{max} - t)^m / t_{max}{}^m\right](w_{max} - w_{min}) + w_{min} \tag{23}$$

where, w_{max} is the initial inertia weight. w_{min} is the final inertia weight. t_{max} is the maximum iteration. $w(t)$ is the current weight. m is the nonlinear adjustment factor.

The track circuit fault diagnosis is realized based on IMF energy moment and LS-SVM in this paper. The fitness function of PSO can be given by

$$F = \frac{1}{p} \sum_{q=1}^{p} \left(\frac{l_{Tq}}{l_q} \times 100\% \right) \tag{24}$$

where, l_{Tq} is the number of the samples which are classified correctly in the q-th validation set. l_q is the samples number of the validation set. The overall design of fault diagnosis algorithm is given below:

Calculate the IVAEs according to the basic electrical parameters of track circuit. In addition, in consideration of the interference to the locomotive signal caused by the environment. Add the white gauss noise with 35 dB signal-to-noise ratio. Considering the imperfect matching in sending-end caused by aging of track circuit equipment the matching degree control parameter S is introduced in this paper.

Decompose the sample data by EMD and several IMFs are obtained. Calculate the IMF energy moments using equation (18) and treat them as the fault feature vector.

Optimize the parameters of LS-SVM using advanced PSO and establish LS-SVM classification model in combination with CV principle.

Put the normalized feature set into the LS-SVM diagnostic model and the final diagnosis results can be obtained.

V. INSTANCE ANALYSIS OF TRACK CIRCUIT FAULT DIAGNOSIS

The sample set with 140 groups of data is achieved through the locomotive signal induced voltage model. 100 groups of data are served as training samples and the others are test samples. Each group of data is decomposed by EMD. The decomposition results of IVAE signal when $R_f = 0.5\Omega$ is shown in Fig. 3. Calculate the energy moments of the first five IMF components using equation (18) and construct a 5-d fault feature vector **T** base on the IMF energy moments. The IMF energy moments of induction voltage amplitude envelope signals are shown in Fig. 4.

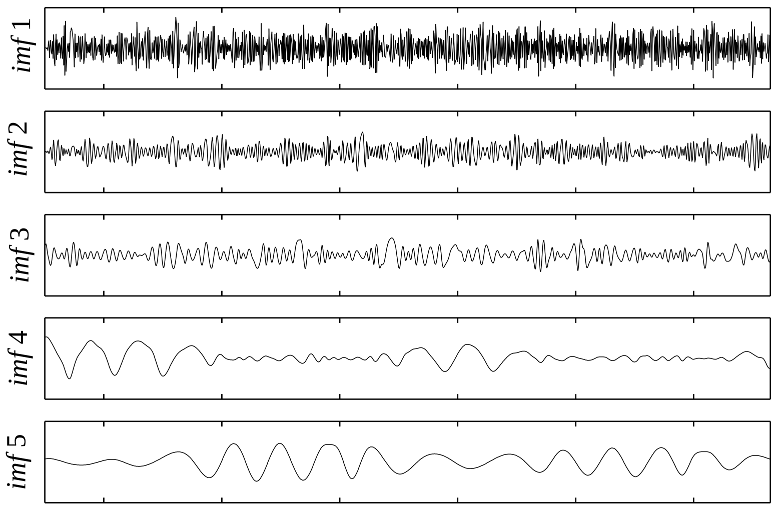

Figure 3. *EMD decomposition results of the IVAE signal when Rf = 0.5Ω*

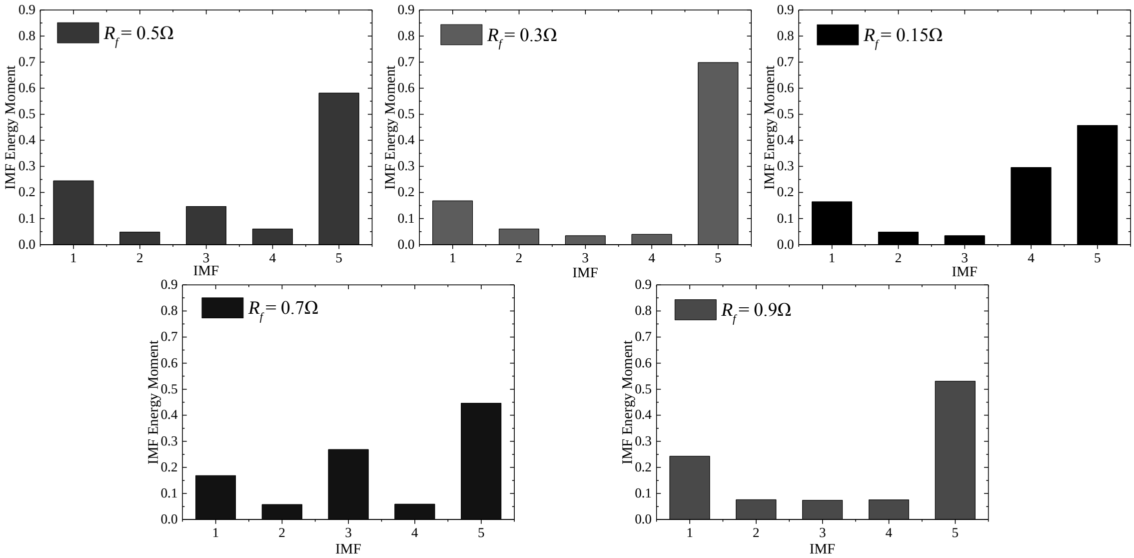

Figure 4. *IMF energy moments of the induction voltage amplitude envelope signal*

The search range of the parameters C and σ are set within [0.1, 200] and [0.01, 10] respectively in this paper. The maximum generation of PSO is 300. The number of particle swarm is 10. $w_{max} = 0.9$, $w_{min} = 0.1$. $c_{1a} = 2.5$, $c_{2a} = 0.5$, $c_{1b} = 0.5$, $c_{2b} = 2.5$. The fitness convergence curve of the parameter optimization for LS-SVM fault diagnosis model using advanced PSO algorithm is shown in Fig. 5. The optimal parameters C = 19.5721 and σ^2 = 0.3945 are obtained. It can be seen from figure 5 that the fitness curve converges faster in the first 100 evolution cycles and later flattens. Finally, the convergence level remains the same and it means the parameter optimization is achieved.

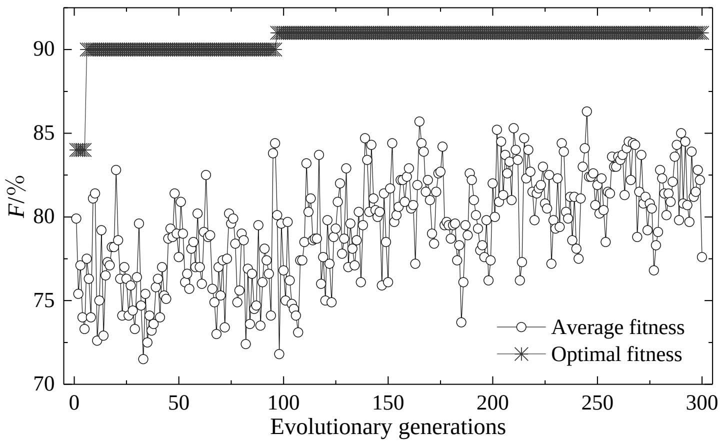

Figure 5. *Fitness curve of particle swarm optimization*

The track circuit fault diagnosis results using the method proposed in this paper is shown in Fig. 6. The diagnosis accuracies reach 92% and 90% respectively. It shows that the fault diagnosis method for track circuit proposed in this paper is effective.

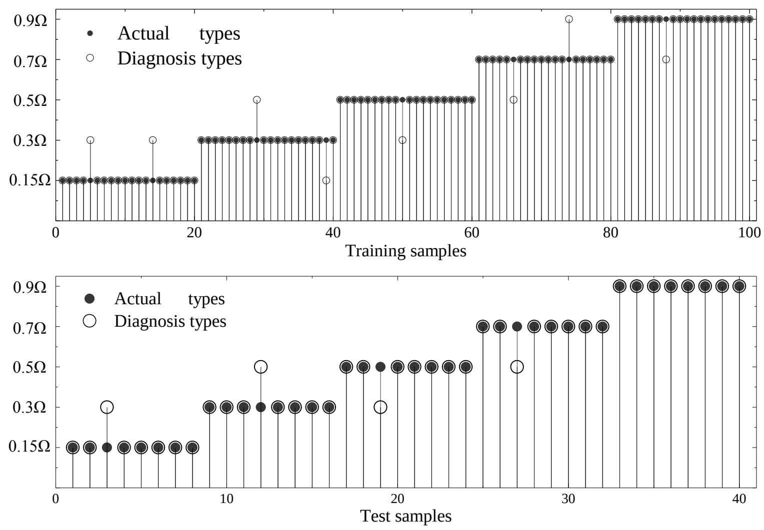

Figure 6. *Results of track circuit fault diagnosis*

VI. CONCLUSIONS

The locomotive signal induced voltage model was established based on transmission-line theory in this paper. The locomotive signal induced voltages of track circuit in normal and fault condition were simulated. On this basis the EMD decomposition was performed. The energy moments of the IMFs of induction voltage amplitude envelope signals were calculated. A 5-dimension fault feature vector **T** was constructed through each IMF energy moment. The LS-SVM classification models were established to realize fault diagnosis for track circuit. The advanced PSO algorithm was introduced to obtain the optimal parameters of LS-SVM. The results show that the diagnostic accuracy using the method proposed in this paper reaches 90%.

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