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FAULT DIAGNOSIS OF SUBWAY AUXILIARY INVERTER BASED ON EEMD AND SAPSO-RBFNN

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Abstract. *To improve the fault diagnosis precision of the subway auxiliary inverter, the paper proposes a fault diagnosis model on the basis of radial basis function neural network (RBFNN) and a hybrid optimization algorithm. Firstly, the paper adopts ensemble empirical mode decomposition (EEMD) to process fault signal of auxiliary inverter. Then extract effective frequency domain energy feature vectors by energy feature extraction. Thirdly, the paper optimizes the parameters of RBFNN by means of the particle swarm optimization (PSO) and simulated annealing (SA) algorithm. Finally, the fault feature vectors will be applied in the optimized RBFNN to achieve fault recognition. The experimental results show that the proposed fault diagnosis model not only achieves better classification effect and generalization ability, but also heightens the diagnosis accuracy of the subway auxiliary inverter compared with PSO-RBFNN and RBFNN.*
Keywords: Subway auxiliary inverter, Fault diagnosis, EEMD, Particle swarm optimization, Simulated annealing

1. **Introduction.** Subway auxiliary inverter is the indispensable key electrical equipment in urban rail train [1]. The serious faults of auxiliary inverter make such many facilities work improperly as cooling fan, and air compressor, which will lead to subway train unable to run normally [2]. However, the failure probability of auxiliary inverter is highest of all train facilities [3]. So it is very necessary to develop a kind of intelligent fault diagnosis system of subway auxiliary inverter.

RBF neural network with powerful learning ability and approaching capacity has been used widely in the fault diagnosis [4]. However, it is difficult to accurately select the appropriate node number of hidden layers and parameters, such as clustering center, basic width and connective weight of RBFNN. Various solutions have been put forward to tackle this problem, such as [5-8]. On the basis of the seniors' research, the paper uses SAPSO algorithm to optimize RBFNN, which not only successfully obtains the optimal structure and parameters of RBFNN, but also overcomes the disadvantages of the premature and low precision of the standard PSO.

The main text is mainly composed of the following four parts. According to the characteristics of fault signal, the first part combines EEMD with energy feature extraction method to process fault signals. In the second part, the paper details the theory of PSO, SA and SAPSO algorithm. The third part simulates and analyses the advantages of SAPSO-RBFNN algorithm. The last part is conclusion.

2. **Fault Feature Extraction Based on EEMD.**

2.1. **Fundamental of EEMD.** Ensemble empirical mode decomposition (EEMD) was put forward first by Huang and others, which is a good noise-assisted method for analyzing nonlinear and nonstationary signal [9]. Aimed at the mode mixing problem of empirical mode decomposition (EMD), EEMD adds the Gaussian white noise, whose frequency is evenly distributed, into the original signal to ensure the continuity of the signal over all scales. The decomposition process of EEMD is shown as follows.

1) Initialize the total execution times M of EMD and the amplitude coefficient η of white noise; set the current decomposition times $m = 1$ and the number of intrinsic mode functions (IMFs) $n = 1$.
2) Add random white noise $n_m(\mathrm{t})$ into the original signal $x(\mathrm{t})$, and we will obtain the new signal $x_m(\mathrm{t})$.
$$x_m(\mathrm{t}) = x(\mathrm{t}) + \eta n_m(\mathrm{t}) \tag{1}$$
3) Set $x'_m(\mathrm{t}) = x_m(\mathrm{t})$ and calculate all extreme points of $x'_m(\mathrm{t})$. Adopt cubic spline function to fit the upper and lower envelopes through respectively interpolating the maxima and minima.
4) Compute the mean of these two envelopes, symbolized by avg and calculate $h_m(\mathrm{t})$ according to the following formula.
$$h_m(\mathrm{t}) = x'_m(\mathrm{t}) - avg \tag{2}$$
5) Judge whether $h_m(\mathrm{t})$ matches the conditions of IMF. If the conditions are not met, set $x'_m(\mathrm{t}) = h_m(\mathrm{t})$ and return to the step 3) until the conditions are met.
6) Set the n-th intrinsic mode function (IMF) $c_{m,n}(\mathrm{t}) = h_m(\mathrm{t})$, and calculate the residual signal $r_{m,(n+1)}(\mathrm{t}) = r_{m,n}(\mathrm{t}) - c_{m,(n+1)}(\mathrm{t})$, where $r_{m,1}(\mathrm{t}) = x_m(\mathrm{t}) - c_{m,1}(\mathrm{t})$.
7) Judge whether terminal conditions of EMD are met. If not, set $n = n + 1$, $x_m(\mathrm{t}) = r_{m,n}(\mathrm{t})$ and return to the step 3). Otherwise, execute the next step.
8) Judge whether m is equal to M; if not, set $m = m + 1$ and return to the step 2) until m is equal to M.
9) Calculate the average of all $c_{m,i}$ of each IMF to cancel the added white noise.
$$\bar{c}_i(\mathrm{t}) = \frac{1}{M}\sum_{m=1}^{M} c_{m,i}(\mathrm{t}) \tag{3}$$
$$(i = 1, 2, \ldots, n;\ m = 1, 2, \ldots, M)$$

During the decomposition process of EEMD, the total execution times M of EMD and the amplitude coefficient η of the white noise have strong influences on the decomposition results of EEMD. So Wu and Huang suggested that if M was set to 100, the value of η should be fetched from around 0.2 [10].

2.2. **Energy feature extraction method.** We obtain n IMFs by EEMD, and each IMF represents a stationary signal of definite characteristic scale. Choose the first N IMFs, which contain the main fault characteristics. Then calculate the total energy E_i of each IMF to construct a feature vector $T = [E_1, E_2, \ldots, E_N]$. Since the calculated results are usually larger under normal circumstances, E_i needs to be dealt with normalization [11] to get a new feature vector T'.
$$T' = [E_1/E, E_2/E, \ldots, E_N/E], \quad E = \sqrt{\left(\sum_{i=1}^{N} E_i^2\right)} \tag{4}$$
The feature vector T' serves as the fault feature vector of subway auxiliary inverter.

3. **Designment of RBFNN Optimized by SAPSO.**

3.1. **Theory of PSO.** Particle swarm optimization (PSO) is based on iteration proposed by Kenndy and Eberhart in 1995 [12]. Each particle in the PSO algorithm is composed of the position vector and velocity vector, where the position vector represents the solution of optimization problem, the velocity vector decides the flight direction and speed of particle and the particle performance is determined by the fitness of objective function. In each iteration, seek the personal best solution *Pbest* and global best solution *Gbest* by calculating and comparing the fitness values. In the end, the optimal solution of this problem can be acquired by the cooperation and competition between particles.

Firstly, initialize a random group of m particles in an n-dimensional search space and suppose the total number of iterations is $k_{\max}$. The current position vector X_i^k and velocity vector V_i^k of the i-th particle are expressed as follows.

$$\begin{aligned} X_i^k &= \left[x_{i1}^k, \ldots, x_{id}^k, \ldots, x_{in}^k\right] \\ V_i^k &= \left[v_{i1}^k, \ldots, v_{id}^k, \ldots, v_{in}^k\right] \end{aligned} \tag{5}$$

where i is the number of particles, $i = 1, 2, \ldots, m$; d is the dimension of search space, $d = 1, 2, \ldots, n$; k is the number of iterations, $k = 1, 2, \ldots, k_{\max}$.

Secondly, evaluate the fitness of each particle to find the current best position of the i-th particle $Pbest_i^k$ and of the whole particle swarm $Gbest^k$.

$$\begin{aligned} Pbest_i^k &= \left[pbest_{i1}^k, \ldots, pbest_{id}^k, \ldots, pbest_{in}^k\right] \\ Gbest^k &= \left[gbest_1^k, \ldots, gbest_d^k, \ldots, gbest_n^k\right] \end{aligned} \tag{6}$$

Then update the position and velocity of each particle according to the following equation.

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 \left(pbest_{id}^k - x_{id}^k\right) + c_2 r_2 \left(pbest_d^k - x_{id}^k\right) \tag{7}$$

$$x_{id}^{k+1} = x_{id}^k + \beta v_{id}^{k+1} \tag{8}$$

In the expressions, r_1 and r_2 are random numbers between 0 and 1, which are used for maintaining the diversity of particle swarm [13]. c_1 and c_2 are learning factors, which can adjust the individuality and sociality of particles [14]. To search for the true optimal solution, the paper designs the value range of v_{id}^k, $v_{id}^k \in [v_{\min}, v_{\max}]$. β is the constraint factor of velocity. ω is the connective weight used to keep the movement inertia of the particle, and $\omega \in [\omega_{\min}, \omega_{\max}]$. Use the expression (9) to calculate the value of ω in order to balance the global searching ability with the local searching ability.

$$\omega = \omega_{\max} - k \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} \tag{9}$$

Finally, terminate the iterative process by terminal conditions we preset, such as the maximal number of iterations $k_{\max}$, the value range of fitness, etc.

3.2. **Simulated annealing algorithm.** Simulated annealing (SA) is an effective stochastic searching optimization method proposed by Metropolis [15]. It is based on Metropolis sampling criteria with the feature of mutational probability and enhances the global optimization capability by simulating the physical process of solid annealing [16]. Suppose a solution for the optimization problem is i, the fitness of i is $f(i)$ and the T is the control parameter of temperature. The solution i will be updated to j after an iteration, and $f(j)$ is the fitness of j. Formula (10) represents the receiving probability p_i that the system solution is transferred from i to j.

$$p_i = \begin{cases} 1, & f(j) > f(i) \\ \exp\left(\dfrac{f(j) - f(i)}{T}\right), & f(j) \le f(i) \end{cases} \tag{10}$$

The initial temperature T^0 of SA is represented as follows.

$$T^0 = \frac{-f(Gbest^0)}{\log(0.2)} \tag{11}$$

The initial temperature is very high. During the process of iteration, the temperature T will be gradually lowered due to the annealing rate λ until the stopping criteria are met.

The standard PSO is not fit for solving complicated multi-modal problems. The algorithm is less sensitive to environmental change and the premature problem is more likely to appear caused by particles aggregation, which may disenable us to get the actual optimal solution [17]. To solve this problem, the paper introduces the idea of simulated annealing into PSO and thus develops into a compound algorithm. During the iterative process, SA receives optimal solution with the larger probability, and takes in deteriorative solution with the smaller probability. Thereby, the new hybrid algorithm can increase the diversity of particles, decline the probability of local convergence and greatly improve convergent speed of PSO.

3.3. **Optimization of RBFNN based on SAPSO.** The paper selects RBFNN with Gaussian basis function as the fault diagnosis model of subway auxiliary inverter. RBFNN is a special artificial neural network with three-layer feedforward [18]. On the one hand, it has many advantages including simple structure, efficient convergence, etc. On the other hand, it has the disadvantage of uncertain structure and parameters in design [19]. Therefore, the paper uses K-means clustering algorithm to determine the structure of RBFNN, and then employs the modified PSO algorithm by SA algorithm to constantly optimize RBFNN in order to get the optimal parameters. The optimization process is shown as follows.

1) Collect the fault samples of auxiliary inverter and determine the node number of input layers and output layers of RBFNN.
2) Preset the parameters of RBFNN: process the samples by K-means clustering algorithm to obtain h q-dimensional clustering center vectors. Accordingly, set the node number of hidden layers to h and initialize the value range of clustering center matrix C, basic width vector σ and connective weight matrix w of output layers.
3) Initialize the parameters of PSO: spatial dimension n, learning factors c_1 and c_2, the total number of iterations $k_{\max}$, the weight of velocity β, the maximum $v_{\max}$ and minimum $v_{\min}$ of particle velocity, the maximum $w_{\max}$ and minimum $w_{\min}$ of connective weight.
   Initialize the parameters of SA: the control parameter of temperature T^0, the annealing rate λ.
4) Encode the structure of particle's position as:

$$c_{11}^k, c_{12}^k, \ldots, c_{1q}^k, \sigma_1^k, c_{21}^k, c_{22}^k, \ldots, c_{2q}^k, \sigma_2^k, \ldots, c_{h1}^k, c_{h2}^k, \ldots, c_{hq}^k, \sigma_h^k$$

   Encode the structure of particle's velocity as:

$$v_1^k, v_2^k, \ldots, v_{p\times(q+1)}^k$$

5) Determine the fitness function: take the root mean squared error between predicted output and true one as the fitness function of PSO. In the k-th iteration, if the number of fault samples is N, the node number of output layers is M, the actual output is y_{ij}^k and predictive output is $\hat{y}_{ij}^k$, the current fitness function of PSO can be expressed as:

$$f = \sqrt{\frac{1}{2}\sum_{j=1}^{N}\sum_{i=1}^{M}\left(y_{ij}^k - \hat{y}_{ij}^k\right)^2} \tag{12}$$

6) Take the initial position of particle swarm as the initial personal best solution $Pbest^0$. Calculate the fitness of each particle to select the particle position of the smallest fitness as the initial global best solution $Gbest^0$.
7) Determine the receiving probability p_i of the i-th particle as Formula (13). When $p_i > rand()$, set $Gbest^k = Pbest_i^k$. Otherwise, set $Gbest^k = Gbest^k$.

$$p_i = \exp\left(-\frac{f\left(Pbest_i^k\right) - f\left(Gbest^k\right)}{T^k}\right) \tag{13}$$

8) Update the position and velocity of particles according to Formulas (7) and (8).
9) Calculate the fitness of each particle and update $Pbest^k$ and $Gbest^k$ by comparing their fitness values.
10) Update the control parameter of temperature T according to the following formula.

$$T^{k+1} = \lambda \times T^k \tag{14}$$

11) Judge whether the iterative terminal conditions are met; if not, return to the step 7). Otherwise, execute the next step.
12) Decode the global optimal solution to obtain the optimized clustering center matrix C and basic width vector σ.
13) Calculate the connective weight matrix w of output layers by the means of least square method. Calculate the output of RBFNN according to the three parameters.

We can see from the process described above that the paper combines K-means clustering algorithm with SAPSO algorithm to train RBF neural network. This method not only solves the problem which has been in RBF neural network, but it also improves performance of RBF neural network, such as generalization ability and approximation capability.

4. **Simulation and Analysis.** The experiment takes MATLAB 2010 as the programming platform to achieve fault diagnosis of subway auxiliary inverter based on SAPSO-RBFNN, PSO-RBFNN and RBFNN. Select four common types of faults and respectively encode frequency variation as [1 0 0 0], impulsive transient as [0 1 0 0], voltage fluctuation as [0 0 1 0] and transient oscillation as [0 0 0 1], which will be taken as the output of RBFNN. Collect 32 groups of fault data and for each kind of fault, select 20 groups as the training samples and the other 12 groups as the testing samples.

Firstly, decompose the fault samples by EEMD and get several IMFs and a residual component for each group of fault samples. The decomposition results of impulsive transient are presented in Figure 1.

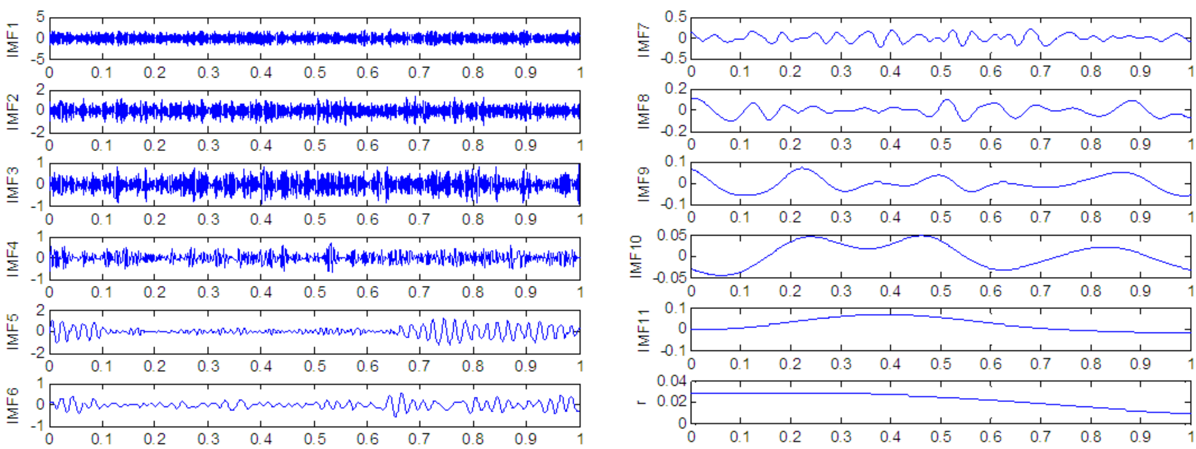

Figure 1. Decomposed results of impulsive transient signal

Secondly, the paper chooses the first six IMFs, which contain the main fault features, and process the six IMFs by energy feature extraction to obtain the normalized fault feature vectors. Parts of fault feature vectors are shown in Table 1.

Thirdly, take the fault feature vectors as the input of RBFNN, and use the K-means clustering algorithm to initialize the neural network. So we can determine the structure of RBFNN is 6-7-4. During the optimization process of SAPSO, the spatial dimension is 30, the learning factors have the same value 1.79, the total number of iterations is 140, the weight of velocity is 0.3, the value range of particle velocity is from −0.98 to 0.98,

TABLE 1. Parts of fault feature vectors

Fault type	Serial number	E_1	E_2	E_3	E_4	E_5	E_6	Fault label
Frequency variation	1	0.3330	0.1009	0.0501	0.0360	0.4409	0.0318	1 0 0 0
	2	0.2972	0.0997	0.0544	0.0312	0.4941	0.0174	1 0 0 0
	3	0.3148	0.0976	0.0399	0.0266	0.4968	0.0157	1 0 0 0
Impulsive transient	1	0.4843	0.1429	0.0634	0.0316	0.1541	0.0341	0 1 0 0
	2	0.5216	0.1576	0.0884	0.0402	0.1730	0.0086	0 1 0 0
	3	0.5467	0.1593	0.0745	0.0288	0.1515	0.0290	0 1 0 0
Voltage fluctuation	1	0.1038	0.0316	0.0146	0.2381	0.6045	0.0045	0 0 1 0
	2	0.1179	0.0322	0.0170	0.1479	0.6776	0.0036	0 0 1 0
	3	0.1330	0.0350	0.0152	0.1597	0.6496	0.0045	0 0 1 0
Transient oscillation	1	0.0151	0.0035	0.0186	0.9566	0.0043	0.0011	0 0 0 1
	2	0.0181	0.0042	0.0795	0.8955	0.0016	0.0009	0 0 0 1
	3	0.0201	0.0053	0.0507	0.9203	0.0021	0.0008	0 0 0 1

TABLE 2. Diagnosis results of SAPSO-RBFNN, PSO-RBFNN and RBFNN

Model	Frequency variation	Impulsive transient	Voltage fluctuation	Transient oscillation	Diagnosis accuracy
SAPSO-RBF	111/120	113/120	116/120	117/120	95.21%
PSO-RBF	104/120	108/120	103/120	113/120	89.17%
RBF	99/120	102/120	96/120	108/120	84.38%

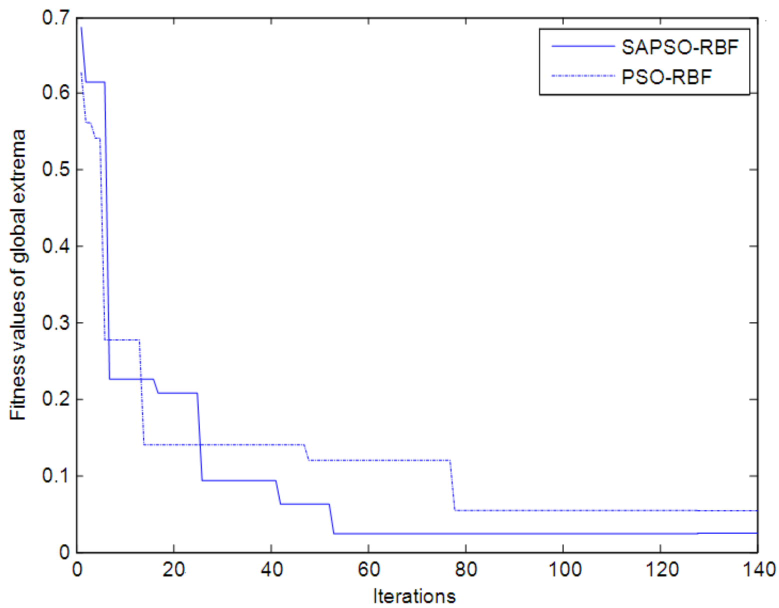

FIGURE 2. Fitness curves of global extrema in optimization process

the connective weight is in the range of $(0.15, 0.95)$ and the annealing rate is 0.55. This experiment tests ten times for each group and the diagnosis results of these three RBFNN models are given in Table 2. The fitness curves of global extrema of SAPSO-RBFNN and PSO-RBFNN during the optimization process are shown in Figure 2.

In Figure 2, the fitness of global extremum represents the error between predicted output and true one. So compared with PSO-RBFNN, the error of SAPSO-RBFNN is smaller and the convergent speed is faster. In Table 2, the diagnosis accuracy of SAPSO-RBFNN reaches 95.21%, and the actual output of SAPSO-RBFNN comes closer to the predicted one. Concluded from this experiment, SAPSO-RBF improves the diagnosis accuracy and convergent speed of PSO-RBFNN.

5. **Conclusion.** Focused on the nonstationary and nonlinear characteristics of fault signal of subway auxiliary inverter, the paper puts forward a new fault diagnostic method based on the simulated annealing particle swarm optimization algorithm and radial basis function neural network. This method combines the advantages of PSO with SA to optimize the parameters of RBFNN for overcoming the premature convergence. The experimental results have proved the higher diagnosis accuracy and faster convergent speed of SAPSO-RBFNN. However, the diagnosis accuracy of this method cannot reach 100 percent due to the complex structure of subway auxiliary inverter and the situation of multiple faults occurring simultaneously. Therefore, the method needs to be amended and improved in the future.

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