Fault Diagnosis of Oil-immersed Transformer Based on Belief Rule Base

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Abstract: This paper establishes a diagnostic model based on the Belief Rule Base (BRB) by using the fault gas data type and fault type judgment value in the oil immersed transformer fault. The traditional Constraint Processing Method (TCPM) in BRB has a great impact on fault accuracy. Therefore, this paper proposes an Adaptive Constraint Processing Method (ACPM) for the constraints of BRB parameters, and uses the Seeker Optimization Algorithm (SOA) to optimize the BRB parameters to construct ACPM- SOA-BRB diagnostic model. In addition, in order to improve the diagnostic efficiency of the BRB model, this paper achieves a reasonable simplification of the BRB model structure by reducing the fault gas type and reducing the training model parameters. Experimental results verify the effectiveness of ACPM-SOA-BRB.

Keywords: confidence rule base; oil-immersed transformer; fault diagnosis; constraint processing; crowd search algorithm

1 Introduction

The transformer is the core link in ensuring the continuous normal operation of the power system. Therefore, in order to ensure the normal operation of the transformer, the initial diagnosis of the transformer fault becomes very important. Traditional oil-immersed transformer fault diagnosis techniques include Duval triangle method [1], key gas method [2] and ratio method [3]. These methods are simple and easy, but lack complex nonlinearity between transformer fault data and fault types. The effective characterization and processing of relationships, the accuracy and reliability of diagnostic results need to be improved.

Therefore, researchers also use Artificial Intelligence (AI) methods to analyze early failures of oil-immersed transformers. These methods include artificial neural networks (ANN) [4], support vector machines (SVW) [5], rough set theory [6], and so on. However, existing AI methods also have some limitations. For example, artificial neural networks are prone to fall into local optimum and over-fitting [6]; support vector machines have slow convergence and long training time [6]; rough sets largely ignore the information characteristics of ratio rules [7].

In response to the shortcomings of the AI method, the researchers proposed some improvement measures. Yang et al. [8]introduced an adaptive genetic algorithm combining probabilities and mutation probabilities in probabilistic neural networks, optimized the smoothing parameters and increased the prediction accuracy of probabilistic neural networks. Wang et al. [6]used association rules combined with rough set theory to improve the ability to mine massive data. Zhang et al. [9]proposed a transformer diagnosis model based on improved support vector machine classification and particle swarm optimization (PSO) algorithm, which improved the convergence ability of support vector machine. It can be seen from the above research that for nonlinear non-convex models such as neural networks and support vector machines, the intelligent optimization algorithm can be used to determine the model parameters, so as to obtain an effective diagnosis model.

The Belief Rule Base (BRB) is an expert system that effectively models data with nonlinear, fuzzy relationships [10]. The BRB system is a kind of AI method, which is composed of a series of traditional IF-THEN rules with confidence, premise attributes and rule weights. Therefore, BRB has a strong ability to characterize nonlinear causal relationships.

In view of the modeling advantages of BRB, this paper proposes a fault diagnosis model for oil-immersed transformer based on BRB. The core idea of the diagnostic model is to first use the BRB method to establish a confidence rule relationship between fault data and fault types of different dissolved gases in the transformer, and then use Evidential Reasoning (ER) to convert the input into an output fault type. The value is finally compared with the actual observed fault type judgment value to determine the true fault type and achieve the purpose of fault detection. The traditional Constraint Processing Method (TCPM) in BRB has a great impact on fault accuracy. Therefore, in this paper, an adaptive Constraint Processing Method (ACPM) is proposed for the constraints of BRB parameters, and the BRB parameters are optimized by the Seeker Optimization Algorithm (SOA). Construct the ACPM-SOA-BRB diagnostic model. In addition, in order to improve the diagnostic efficiency of the BRB model, this paper achieves a reasonable simplification of the BRB model structure by reducing the fault gas type and reducing the training model parameters. Experimental results verify the effectiveness of ACPM-SOA-BRB.

The remainder of this paper is organized as follows: In Section 2, a BRB-based transformer diagnostic model and diagnostic process are described. In Section 3, the BRB-based transformer fault diagnosis training model and algorithm are described. Section 4 is an analysis and comparison of fault diagnosis examples for oil-immersed transformers. We conclude this article with conclusions in Section 5.

2 BRB-based transformer diagnostic model and diagnostic process

2.1 BRB-based transformer diagnostic model structure

The BRB system is essentially an expert system. Assuming that a BRB has a total of L confidence rules, the vector form represented by the k th rule of the BRB model is:

$$\begin{aligned} R_K:\ & \text{If } x \text{ is } \mathrm{A}^k \\ & \text{Then } D \\ & \text{With belief degree } \beta^k \end{aligned} \tag{1}$$

Where, $x=\left[x_1, x_2, \cdots, x_M\right]$, x is expressed as the input vector of the BRB system, that is, the vector consisting of five oil-immersed transformer fault gas data in the diagnostic model, $x_i\left(i=1,2,\cdots,M\right)$ represents the i th premise attribute. M represents the number of confidence rules in the BRB; A^k represents a set of reference values input by the k th rule,and $\mathrm{A}^k=\left\{\mathrm{A}_1^k, \mathrm{A}_2^k, \cdots, \mathrm{A}_M^k\right\}, k=1,2,\cdots,L$, L represents the number of confidence rules in the BRB; D represents the result vector, $D=\left[D_1, D_2, \cdots, D_N\right]$, N indicates the number of evaluation results; β^k indicates a vector consisting of confidence, $\beta^k=\left[\beta_{1,k}, \beta_{2,k}, \cdots, \beta_{N,k}\right]$. In the diagnostic model, the initial β^k is given by the expert, and $\sum_{j=1}^{N}\beta_{j,k}=1$.

2. 2 ER method based on BRB transformer diagnosis model

The ER algorithm combines the confidence rules in the BRB by evidence reasoning, and obtains the estimated value $\hat{\beta}_j$ of the fault diagnosis by inputting the information, thereby obtaining the final output $S\left(x\right)$ of the BRB system. The reasoning step of the ER algorithm mainly includes the following three parts:

Step1 conversion method of different input information

In the calculation of the confidence rule base activation weight, first determine the confidence level $\alpha_{i,j}^k$, $i=1,2,\cdots,M$, $k=1,2,\cdots,L$. The specific conversion formula is as follows (2)-(4):

$$\alpha_{i,j}^k=\frac{\gamma_{i,j+1}^k-x_i}{\gamma_{i,j+1}^k-\gamma_{i,j}^k}, \gamma_{i,j}^k \le x_i \le \gamma_{i,j+1}^k, j=1,2,\cdots,J_i-1 \tag{2}$$

$$\alpha_{i,j+1}^k=1-\alpha_{i,j}^k, j=1,2,\cdots,J_i-1 \tag{3}$$

$$\alpha_{i,s}^k=0, s=1,2,\cdots,J_i, s\ne j, j+1 \tag{4}$$

Where $\gamma_{i,j}^{k}$ indicates that the k th rule given by the expert corresponds to the reference value of input x_i; and J_i indicates the number of reference values given by the expert.

Step2 confidence rule library activation weight calculation

Enter the information x, then the corresponding activation weight ω_k of the k-th rule is calculated as shown in equation (5):

$$\omega_k = \frac{\theta_k \prod_{i=1}^{M} \left(\alpha_i^k\right)^{\delta_i}}{\sum_{l=1}^{L} \theta_l \prod_{i=1}^{M} \left(\alpha_i^l\right)^{\delta_i}}, k = 1, 2, \cdots, L, i = 1, 2, \cdots M \tag{5}$$

Where $\omega_k \in [0,1]$ and θ_k represent the rule weights of Rule θ_k, the initial δ_i is given by the expert, and δ_i is the i th premise attribute weight.

Step3 Inferential calculation of ER parsing algorithm

$$\hat{\beta}_j = \frac{\mu \times \left[\prod_{k=1}^{L} \left(\omega_k \beta_{j,k} + 1 - \omega_k \sum_{i=1}^{N} \beta_{j,k} \right) - \prod_{k=1}^{L} \left(1 - \omega_k \sum_{i=1}^{N} \beta_{j,k} \right) \right]}{1 - \mu \times \left[\prod_{k=1}^{L} (1 - \omega_k) \right]} \tag{6}$$

$$\mu = \left[\sum_{j=1}^{N} \prod_{k=1}^{L} \left(\omega_k \beta_{j,k} + 1 - \omega_k \sum_{i=1}^{N} \beta_{j,k} \right) - (N-1) \prod_{k=1}^{L} \left(1 - \omega_k \sum_{i=1}^{N} \beta_{j,k} \right) \right]^{-1} \tag{7}$$

The ER parsing algorithm combines all the rules in the BRB to obtain the final output $S(x)$ of the BRB as:

$$S(x) = \left\{ \left(D_j, \hat{\beta}_j \right), j = 1, 2, \cdots, N \right\} \tag{8}$$

In the formulae (6) to (8), $\hat{\beta}_j$ indicates the confidence level of the relative evaluation result D_j.

3 BRB-based transformer fault diagnosis training model and algorithm

3. 1 BRB-based transformer fault diagnosis training model

The difference between the estimated output fault type of the transformer fault diagnosis model and the fault type of the actual output is determined by the error of the actual fault type confidence level $\beta_{i(m)}$ and the estimated output confidence level $\hat{\beta}_{i(m)}$. For a given set of actual input and output detection values $\left(x_{i(m)}, \beta_{i(m)}\right)$, the estimated output value $\hat{\beta}_{i(m)}$ can be found by equations (2)-(7), so that the average error from multiple sets of data is:

$$\xi(V)=\frac{1}{T}\sum_{m=1}^{T}abs\left(\beta_{i(m)}-\hat{\beta}_{i(m)}\right) \tag{9}$$

In the formula, $V=\left[\theta_k,\beta_{j,k},\delta_h\right]^{\mathrm{T}}$ represents a column vector composed of BRB system parameters (ie, decision variables to be optimized), and T represents the number of training data, i indicating the i th rule.

In order to reduce the error between the fault type judgment result obtained by the actual system and the fault type diagnosis result obtained by the SOA-BRB diagnostic model, the objective function of the transformer fault diagnosis training model corresponding to the optimization problem is:

$$\min_{V}\{\xi(V)\} \tag{10}$$

In the formula, the constraints of the model are as shown in equations (11)-(14):

$$0\le\theta_k\le 1, k=1,2,\cdots,L \tag{11}$$

$$0\le\beta_{j,k}\le 1, j=1,2,\cdots,N, k=1,2,\cdots,L \tag{12}$$

$$\sum_{j=1}^{N}\beta_{j,k}=1, k=1,2,\cdots,L \tag{13}$$

$$0\le\delta_h\le 1, h=1,2,\cdots,M \tag{14}$$

3. 2 Reduction of fault gas type and simplification of training model

The BRB model structure has strong nonlinearity, and the number of model parameters becomes significant larger as the scale of the problem increases. This makes it more difficult to optimize the BRB model parameters. For the optimization problem of this paper, the reduced fault gas type and simplified training model can effectively control the complexity of the corresponding optimization problem [12]. The reduction and simplification process is as follows:

First, according to the estimation method of confidence level $\hat{\beta}_j$ in Sections 2.1 and 2.2 (ie, equations (1) to (6)), the fault diagnosis training model of Section 3.1 is established using five fault gas data (ie, equation (10) to Equation (14)), and use SOA to optimize the training model parameters to obtain the model parameter $\theta_k,\beta_{j,k},\delta_h$; then, select the three fault gas data corresponding to the three largest values of the premise attribute weight δ_h as the transformer fault diagnosis Data; further, the selected three fault gas premise attribute weights δ_h are set to 1, so that the decision variable or the optimization variable $V=\left[\theta_k,\beta_{j,k},\delta_h\right]^{\mathrm{T}}$ is reduced to $V=\left[\theta_k,\beta_{j,k}\right]^{\mathrm{T}}$, and the activation weight of the BRB is simplified by the formula (5) as follows:

$$\omega_k=\frac{\theta_k\prod_{i=1}^{M}\alpha_i^k}{\sum_{l=1}^{L}\theta_l\prod_{i=1}^{M}\alpha_i^l},k=1,2,\cdots,L,i=1,2,\cdots,M \tag{15}$$

3. 3 SOA optimization algorithm

Implementing the SOA algorithm requires three phases as shown below:

The first stage: the determination of the search direction

The SOA algorithm acquires social experience and cognitive experience by simulating human social learning and cognitive learning, and uses these experiences to simulate three kinds of behaviors (self-interested behavior, altruistic behavior, and pre-action behavior) to determine the individual's search direction.

Through the analysis and modeling of self-interested behavior, altruistic behavior and pre-action behavior, the search direction of the ith search individual is determined by the following three directions:

$$\text{Self-interested direction：}\ \vec{d}_{i,ego}(t)=\vec{p}_{i,best}-\vec{x}_i(t) \tag{16}$$

$$\text{Altruistic direction : }\vec{d}_{i,alt}(t)=\vec{g}_{i,best}-\vec{x}_i(t) \tag{17}$$

$$\text{Pre-direction: }\vec{d}_{i,pro}(t)=\vec{x}_i(t_1)-\vec{x}_i(t_2) \tag{18}$$

The search direction of the ith search individual is determined by the three-direction random weighted geometric mean shown in equations (16)-(18), as shown in the following equation:

$$\vec{d}_i(t)=sign\left(\omega*\vec{d}_{i,pro}+\varphi_1*\vec{d}_{i,ego}+\varphi_2*\vec{d}_{i,alt}\right) \tag{19}$$

In equations (16)-(18), t is the current evolutionary algebra, $t_1,t_2\epsilon\{t,t-1,t-2\}$; $\vec{x}_i(t_1)$ and $\vec{x}_i(t_2)$ are the optimal positions in $\left\{\vec{x}_i(t-2),\vec{x}_i(t-1),\vec{x}_i(t)\right\}$; $\vec{g}_{i,best}$ is the historical optimal solution position of the neighborhood of the ith search individual, $\vec{p}_{i,best}$ is the historical optimal solution position of the ith search individual search, and $sign(\bullet)$ is the symbol function of each dimension of the input vector; φ_1 and φ_2 It is a real number randomly selected within $[0,1]$,and ω is the inertia weight that linearly decreases from 0.9 to 0.1 with evolutionary algebra.

Second stage: determination of search step size

The determination of the ith search individual search step size is a fuzzy inference behavior based on the uncertainty between the objective function and the step size. The fuzzy variable of the search step is represented by a Gaussian membership function. The Gaussian membership of the population location is represented by equations (20)-(21):

$$u_i = u_{\max} - \frac{m - I_i}{m - I}\left(u_{\max} - u_{\min}\right), i = 1, 2, \cdots, m \tag{20}$$

$$u_{ij} = rand\left(u_i, 1\right),\ j = 1, 2, \cdots, D \tag{21}$$

In equations (20)-(21), $u_{\min} = 0.0111$; $u_{\max} = 1$; u_i is the membership degree of the objective function value i; u_{ij} is the membership degree of the j -dimensional space objective function i, $u_{ij} \in \left[u_i, 1\right]$; I_i is the population function value in descending order of $x_i\left(t\right)$ Sequence number; m is the population size; D is the search space dimension.

The first search individual search step is as shown in equation (23):

$$\alpha_{ij} = \delta_{ij}\sqrt{-\ln\left(u_{ij}\right)} \tag{22}$$

$$\overrightarrow{\delta_{ij}} = \omega \bullet abs\left(\vec{x}_{\min} - \vec{x}_{\max}\right) \tag{23}$$

$$\omega = \left(T_{\max} - t\right) / T_{\max} \tag{24}$$

In equations (22)-(24), α_{ij} is the step size of the j -dimensional space; δ_{ij} is the Gaussian membership function parameter; $\vec{x}_{\min}$ and $\vec{x}_{\max}$ are the positions of the same subgroup with the minimum and maximum function values, respectively. t and T are the current number of iterations and the maximum number of iterations, respectively.

Stage 3: Search for individual location updates

When the i search individual search direction and the search step size are determined, the position update formula is as shown in the following equations (25)-(26):

$$\Delta x_{ij}\left(x+1\right) = \alpha_{ij}\left(t\right) d_{ij}\left(t\right) \tag{25}$$

$$x_{ij}\left(t+1\right) = x_{ij}\left(t\right) + \Delta_{ij}\left(t+1\right) \tag{26}$$

In the formula (26), $x_{ij}\left(t+1\right)$ indicates the position of the i th search individual in the j th-dimensional search direction at the $t+1$ th generation.

3. 4 Adaptive constraint processing method ACPM

Constraint processing is an important research field, which is widely used and has achieved good results, such as product configuration, task planning and scheduling, and spatial reasoning [13]. In view of this, it is necessary to properly handle the constraints of the oil-immersed transformer fault diagnosis model to improve the efficiency of the BRB structure for parameter adjustment.

It can be seen from Section 2 2.1 of this paper that the processing method of the constraint condition of the traditional oil-immersed transformer fault diagnosis model is transformed into the following equations (27)-(29):

$$\theta_k = \begin{cases} 0, \theta_k \le 0 \\ 1, \theta_k > 1 \end{cases} \tag{27}$$

$$\beta_{j,k} = \begin{cases} 0, \beta_{j,k} \le 0 \\ 1, \beta_{j,k} > 1 \end{cases} \tag{28}$$

$$\beta^k = \left[\beta_{1,k}, \beta_{2,k}, \cdots, \beta_{N,k}\right] / \sum_{j=1}^{N} \beta_{j,k} \tag{29}$$

In this paper, the traditional oil-immersed transformer fault diagnosis model constraint processing method (Eq. (27)-(28)) is changed to the adaptive constraint processing method. The specific description is as shown in equations (30)-(31):

$$\theta_k = \begin{cases} \frac{1}{2}|\theta_k|, \theta_k \le 0 \\ \frac{1}{\theta_k}, \theta_k > 1 \end{cases} \tag{30}$$

$$\beta_{j,k} = \begin{cases} \frac{1}{2}|\beta_{j,k}|, \beta_{j,k} \le 0 \\ \frac{1}{\beta_{j,k}}, \beta_{j,k} > 1 \end{cases} \tag{31}$$

3. 5 Construction of ACPM-SOA-BRB

According to the above description of the oil-immersed transformer fault diagnosis optimization training model and the SOA optimization algorithm, the specific implementation steps of the oil-immersed transformer fault diagnosis model based on the confidence rule base (in conjunction with Figure 2) are as follows:

Step 1: Convert the fault gas data into experimental sample data and group them into training data and test data.

Step 2: Establish a BRB-based oil immersed transformer fault diagnosis model.

Step 3: Parameter initialization of the oil immersed transformer fault diagnosis model:

Step 3.1: θ_k is randomly selected randomly between $[0,1]$.

Step 3.2: Enter the training sample data, and convert the experimental sample data into the corresponding confidence $\beta_{j,k}$ by the equations (2)-(4).

Step 4: Optimize the initialization parameters of the BRB using SOA:

Step 4.1: Determine the search direction of each search individual using equations (16)-(19).

Step 4.2: Determine the search step size of the search individual using equations (20)-(24).

Step 4.3: Update the location of each search individual using equations (25)-(36).

Step 5: Calculate the objective function $\min_{V}\{\xi(V)\}$.

Step 6: Determine whether the number of iterations of the AUS-SOA reaches the maximum number of iterations. If the termination condition is met, the rule weight θ_k and the confidence level $\beta_{j,k}$ are output, and the fourth step is returned.

Step 7: Enter the test sample data and output the diagnosis result $S(x)$.

4 Analysis and comparison of fault diagnosis examples for oil-immersed transformers

4. 1 Example Description

In this paper, the 48 sets of transformer fault gas data that have been published are collected and reduced as experimental data, of which 33 groups are used as training data (training set) and 15 groups are used as test data (test set). These diagnostic data include the working state of the transformer five, that is, normal state (N), low-energy discharge (LE-D), medium temperature and low temperature overheating (ML-T), arc discharge. (Arc discharge, AD) and high temperature overheating (HT). The five operating states of normal state, low energy discharge, medium and low temperature overheating, arc discharge and high energy overheating are denoted as {10000}, {01000}, {00100}, {00010} and {00001}, respectively.

Table 1 Reference values of the volume fraction of five fault gases

Fault gas	Fault gas volume fraction reference value /10^{-6}L				
	S	JS	M	JB	B
H_2	0	7	16	40	76
CH_4	2	10	30	60	100
C_2H_6		0	7	18	45
C_2H_4	1	7	28	52	70
C_2H_2		0	7	17	28

From Table 1, it can be found that the number of confidence rules L is 5*5*4*5*4=2000.

To construct the BRB fault diagnosis model, first set the reference value of the volume fraction of the five fault gases. The types of reference values are divided into five types: small (S), small (JS), medium (M), large (JB), and large (B), that is, $\mathrm{D}=(\mathrm{D}_1,\mathrm{D}_2\cdots\mathrm{D}_5)=(\mathrm{S,JS,M,JB,B})$. Five reference values are selected for H_2, CH_4, and C_2H_4, namely, small (S), small (JS), medium (M), large (JB), and large (B). Four reference values were selected for C2H6 and C_2H_2, namely, smaller (JS), medium (M), larger (JB), and large (B). The types and quantified values of the volume fraction reference values of the five fault gases are shown in Table 1.

4. 2 Reduction of fault gas type and simplification of the training mode

The 45 sets of transformer fault gas data collected in this paper were used as training data. Initialization θ_k , $\beta_{j,k}$ and δ_h , this paper takes the method of random selection to determine the values of θ_k , $\beta_{j,k}$ and δ_h , and then trains the BRB transformer fault diagnosis model through SOA algorithm. The initial parameter of the SOA algorithm is set to $\omega_{\max}=0.9, \omega_{\min}=0.1; u_{\max}=0.95, u_{\min}=0.0111$. The population number is 60 and the evolutionary algebra (the number of iterations) is 500. To ensure the validity of the premise attribute weight training results, the average value of the 10 training results is taken as the final training result. The weight of the premise attribute after training is shown in Table 2.

Table 2 Prerequisite attribute weight training results

Fault gas	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2
Weights	0.403 4	0.465 1	0.337 2	0.477 9	0.391 6

According to the weight training results of the five fault gases shown in Table 2, three fault gas data with the largest weight value are selected as experimental data. After the fault gas data type is reduced, the five premise attributes are converted into three premise attributes, namely {H_2, CH_4, C_2H_4}, and the premise attribute weight is set to 1, and the rule number of the confidence rule base becomes 5* 5*5=125.

4. 3 Diagnostic results of BRB-based fault diagnosis model

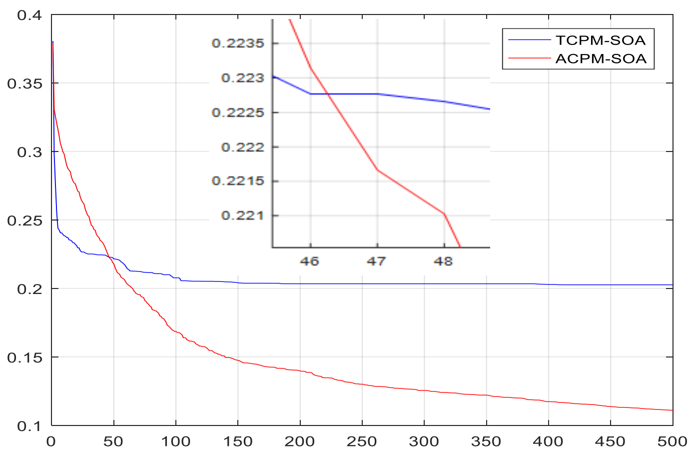

Figure 1 TCPM-SOA and ACPM-SOA fitness curve

The fault gas data of 33 groups of oil-immersed transformers collected in this paper are approximately reduced as training data. θ_k , $\beta_{j,k}$ This paper adopts the method of selected by experts from $[0,1]$ to determine the values of θ_k initial and

$\beta_{j,k}$,and then substitutes the training data, and uses the SOA algorithm to optimize the training of the BRB model. The parameter setting and the number of iterations of the SOA algorithm are the same as those of 4.2. Based on the BRB-based transformer fault diagnosis model, under the ACPM condition and SOA algorithm optimization, the fault diagnosis accuracy rate of the training set is about 91%.

In addition, the paper also proposes the fitness curve (mean error) of the SOA algorithm under the traditional constraint processing method (TCPM-SOA) and the adaptive constraint processing method (ACPM-SOA) to further verify and implement the traditional constraint processing method (TCPM).). The BRB diagnostic model with Adaptive Constraint Processing (ACPM) is more efficient than the BRB diagnostic model. Figure 1 is a graph of the fitness average after 20 runs of the algorithm. It can be seen from Fig. 1 that when the number of iterations exceeds 46 generations, the adaptability of the SOA algorithm under ACPM is continuously reduced. When iterating to 500 generations, it is close to 0.1, and in the case of TCPM, it is close to 0.2. Obviously, adaptive constraint processing is more efficient than traditional constraint processing.

Table 3 Comparison of test set diagnostic results

Instance number	Troubleshooting result				Actual fault type
	SVM	IEC three-ratio	TCPM-SOA -BRB	ACPM-SOA -BRB	
1	N	N	N	N	N
2	N	N	N	N	N
3	LE-D	LE-D	LE-D	LE-D	LE-D
4	LE-D	**AD**	LE-D	LE-D	LE-D
5	LE-D	**AD**	LE-D	LE-D	LE-D
6	**HT**	**HT**	ML-T	ML-T	ML-T
7	**HT**	*	ML-T	**LE-D**	ML-T
8	ML-T	*	ML-T	ML-T	ML-T
9	AD	AD	**LE-D**	AD	AD
10	AD	AD	AD	AD	AD
11	AD	AD	**LE-D**	AD	AD
12	**ML-T**	HT	HT	HT	HT
13	HT	HT	HT	HT	HT
14	**ML-T**	HT	HT	HT	HT
15	HT	*	**ML-T**	HT	HT
Correct rate /%	73.3	60	80	86.7	

Note: The bold part is the diagnosis result of the wrong score, and * indicates that the diagnosis result is missing.

4. 4 Analysis of fault diagnosis results of test sets

The fault gas data of 15 sets of oil-immersed transformers collected in this paper are taken as test data. The rule weight and confidence of the BRB system obtained after ACPM-SOA training in 3.3 be used as the rule weight and initial confidence of the test data. In this paper, the fault diagnosis results of the reduced test set under the BRM-based oil-immersed transformer fault diagnosis model under the TCPM-SOA-BRB model and the ACPM-SOA-BRB model are given. In addition, the paper also gives the fault diagnosis results. The diagnostic results of the reduced test set under the standard support vector machine(svm) and the test results of the test set before the subtraction are calculated under the IEC three-ratio method [14].

Table 3 shows the transformer fault diagnosis results of the test set data under different diagnostic methods. From the diagnostic results of the test data set, the correct rate of the support vector machine and IEC three-ratio method diagnosis results are less than 80%. The correct rate of TCPM-SOA-BRB diagnosis was 80%, and the correct rate of ACPM-SOA-BRB diagnosis was 86.7%. The experimental results show that the ACPM-SOA-BRB diagnostic model is more effective than some traditional transformer fault diagnosis techniques, and it is verified that the ACPM-SOA-BRB diagnostic model is more effective than the TCPM-SOA-BRB diagnostic model.

5 Conclusions

The BRB-based oil immersed transformer fault diagnosis model proposed in this paper. Firstly, the parameters of the BRB model are optimized by introducing the SOA algorithm. According to the obtained premise attribute weights, the fault gas type reduction and the training model parameters are reduced, thus achieving a reasonable simplification of the BRB model structure. Then, under the ACPM, the simplified BRB transformer fault diagnosis model is trained by SOA algorithm, and the diagnostic model ACPM-SOA-BRB is obtained. The experimental results verify that the diagnostic effect of the ACPM-SOA-BRB diagnostic model is better than several existing diagnostic methods.

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