Optimization of KELM for Transformer Fault Diagnosis Based on Dung Beetle Optimizer Algorithm

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Abstract: Aiming at the problem of inaccurate classification accuracy of existing fault classification models, a Dung Beetle Optimizer (DBO) method is proposed to optimize the Kernel Extreme Learning Machine (KELM) for transformer pattern recognition. Firstly, to address the issue of the KELM method being greatly affected by parameter values during fault classification. The kernel function and regularization coefficient of KELM are determined by using DBO to establish a DBO-KELM diagnosis model, and the fault diagnosis is carried out by using the optimized DBO-KELM diagnosis model, and compared with ABC-KELM and GWO-KELM. The final experimental results show that the diagnosis effect of DBO-KELM is better and the accuracy is higher.

Keywords: DBO; KELM; Sparrow Search Algorithm; Transformer; Fault Diagnosis

1. Introduction

Transformers are important voltage conversion components in the composition of the power grid, and they are also a prerequisite for ensuring the safe and stable operation of the power grid [1-3]. Dissolved gas analysis (DGA) technology is one of the commonly used transformer pattern recognition methods. The volume fraction ratio of dissolved gas in oil will change with the operation state. By analyzing the gas, faults can be detected in a timely manner. However, traditional DGA methods are complex to operate and have low fault recognition rates, so the uncoded ratio method is often used to solve problems [4].

Due to the influence of parameter determination in common classifiers on fault classification, artificial intelligence algorithms have been introduced into the field of fault recognition. Common fault recognition methods include SVM, BP neural networks, ELM, etc [5-7]. SVM is essentially a binary classifier, and its classification performance is greatly affected by parameter selection [8]. It performs poorly in multi classification tasks. BP neural network is slow in convergence, easy to fall into local optimum, sensitive to initial parameters and low in diagnostic accuracy.[9]. ELM solves the problem of slow convergence speed, fast learning speed, and strong generalization ability, but the randomness of parameter selection in ELM can affect the classification of transformer faults [10]. KELM introduces kernel function into ELM, which not only solves the shortcomings of ELM, but also has strong robustness, which minimizes the influence of parameter setting on model classification effect and improves the accuracy of fault classification. However, the selection of kernel parameters and regularization coefficients in KELM model has great influence on the performance of the algorithm, so it is necessary to optimize its parameter selection [11].

Through the above analysis, this article presents a pattern recognition method of transformer operation state based on DBO and KELM. Firstly, the key parameters of KELM are determined by DBO, and the mode identification of transformer operation state is carried out by DBO-KELM model.

2. DBO

The DBO algorithm achieves the search for the optimal value of the population through the cooperation and information sharing among dung beetles [12].

(1) Rolling behavior

The dung beetle moves in a straight line in a given direction in the search space, and its position is:

$$P_i^{t+1} = P_i^t + a \times k \times P_i^{t-1} + b \times (P_i^t - P_w) \quad (1)$$

Among them, P_i^{t+1} is the position, and a is the direction deviation coefficient, with the value of 1 indicating that the direction has not deviated, and with the value of -1 indicating that the direction has deviated. $b = 0.3$ is a constant. P_w is the worst position in the world.

(2) Dancing behavior

When encountering obstacles in the process of bowling, the bowling dung beetle will update its position through dancing, and the position update formula at this time will be changed to the following formula:

$$P_i^{t+1} = P_i^t + tan\,(\theta)\left|P_i^t - P_i^{t-1}\right| \quad (2)$$

Where θ is the deflection angle, $\theta \in (0,\pi)$, and when $\theta \in \frac{\pi}{2}$, the dung beetle position does not need to be updated.

(3) Reproductive behavior

The female dung beetle in the population determines its spawning area according to the boundary selection strategy expressed by the following formula.

$$\begin{cases} L_b^* = max\,(P^* \times (1-R), L_b) \\ U_b^* = min\,(P^* \times (1+R), U_b) \end{cases} \quad (3)$$

Where P^* is the current local optimal position, L_b^* and U_b^* are the upper and lower bounds of the spawning range. L_b and U_b are the upper and lower bounds of the optimization problem, and U_b is the upper limit of the optimization problem. The specific location of breeding dung beetles is:

$$B_i^{t+1} = P^* + b_1 \times (B_i^t - L_b^*) + b_2 \times (B_i^t - U_b^*) \quad (4)$$

Where D is the dimension.

(4) Foraging behavior

For newborn dung beetles, feed in the best feeding area according to the following formula:

$$\begin{cases} L_b^{best} = max\,(P^{best} \times (1-R), L_b) \\ U_b^{best} = min\,(P^{best} \times (1+R), U_b) \end{cases} \quad (5)$$

Where P^{best} is the current optimal position, The specific location of foraging dung beetles is:

$$M_i^{t+1} = M_i^t + C_1 \times (M_i^t - L_b^{best}) + C_2 \times (M_i^t - U_b^{best}) \quad (6)$$

3. KELM

The introduction of kernel functions enables algorithms to reduce computational complexity and improve the accuracy and robustness of classification models [13-15].

For transformer sample data $x_i, i = 1,2,\cdots,N$. The following equation can be obtained:

$$\begin{cases} f(x) = h(x)p = Hp \\ p = H^T(\frac{I}{C} + HH^T)^{-1}T \end{cases} \quad (7)$$

Among them, x is the input and $f(x)$ is the output.

By defining the kernel matrix of KELM, we can obtain:

$$\begin{cases} K_{ELM} = HH^T \\ K_{ELMij} = h(x_i)h(x_j) = K(x_i, x_j) \end{cases} \quad (8)$$

Where x_i and x_j are training samples. $K(x_i, x_j)$ is a Gaussian kernel function.

$$K(x_i, x_j) =- exp\,(\frac{\left\|x_i - x_j\right\|^2}{g^2} \quad (9)$$

Where g is the nuclear parameter. Therefore, the output of KELM can be obtained as:

$$f(x) = h(x)b^* = h(x)H^T(HH^T + \frac{I}{c})^{-1}s = \begin{bmatrix} K(x, x_l) \\ \vdots \\ K(x, x_n) \end{bmatrix} \left(KELM + \frac{I}{c}\right)^{-1} s \quad (10)$$

4. Steps for Optimizing KELM Based on DBO

Normalize DGA data set of transformer and divide it into training set and test set.

(1) Initialize DBO parameters, and define conditional parameters such as the number of iterations, maximum, dimension, upper boundary and lower boundary of dung beetle population. Calculate the objective function value of the current dung beetle population position.

(2) Determine the new position of the beetle based on equations (1), (2), (4), and (6).

1) Judging whether the position of each updated dung beetle exceeds the boundary. Update the current optimal solution and its objective function value. And

(3) Determine whether the convergence condition is met. If satisfied, output the optimal parameters. If not, repeat step 3).

(4) Obtain the optimal combination of KELM parameters, and train KELM for transformer fault diagnosis.

5. Transformer Fault Diagnosis Based on DBO Optimized KELM

5.1 Data Feature Selection

According to the references, a total of 330 sets of DGA sample data for power transformers are selected. Among them, the first 270 groups are training sets and the last 60 groups are test sets to test the performance of the model. According to the volume fraction of five gases, transformer faults are divided into six types, as shown in Table 1.

Table 1. Transformer Fault Types and Sample Distribution

Fault Type	Training sample	Test sample
Low energy discharge	45	10
Medium low temperature overheating	45	10
High temperature overheating	45	10
High energy discharge	45	10
Partial discharge	45	10
Normal state	45	10

5.2 Transformer Fault Diagnosis

The key parameters of KELM are determined by DBO algorithm according to the above training samples, and the mode identification of transformer operation state is carried out by DBO-KELM model. To verify the effectiveness of the proposed DBO-KELM method, this paper compares it with ABC-KELM and GWO-KELM to validate its effectiveness. The population size of the optimization algorithms for the three diagnostic models is 20, the dimension is 1, and the maximum number of iterations is 50. The upper bound of DBO, ABC, and GWO methods is 5, and the lower bound is 0.01. In the test samples, samples 1-10 are low-energy discharges, samples 11-20 are medium low temperature overheating, samples 21-30 are high temperature overheating, samples 31-40 are high-energy discharges, samples 41-50 are partial discharges, and samples 51-60 are normal states. The final running state pattern recognition result are shown in Figure 1-3.

From Figure 1, it can be seen that out of 60 test samples, 3 samples have classification errors. The accuracy of low-energy discharge fault diagnosis is 90%, The classification results of low-temperature overheating operation state are 90%, high-temperature overheating operation state is 90%, high-energy discharge operation state is 100%, partial discharge operation state is 100%, normal operation state is 100%, and comprehensive fault classification result is 95%. From Figure 2, it can be seen that out of 60 test samples, 4 samples have classification errors. The accuracy of low-energy discharge fault diagnosis is 90%, The classification results of low-temperature overheating operation state are 100%, high-temperature overheating operation state is 90%, high-energy discharge operation state is 90%, partial discharge operation state is 100%, normal operation state is 90%, and comprehensive fault classification result is 93.33%. From Figure 3, it can be seen that out of 60 test samples, 5 samples have classification errors. The accuracy of low-energy discharge fault diagnosis is 80%, The classification results of low temperature overheating operation state are 100%, high temperature overheating operation state are 100%, high energy discharge operation state is 90%, partial discharge operation state is 90%, normal operation state is 90%, and comprehensive fault classification result is 91.67%. The above experimental results directly verify the advanced nature of the proposed transformer fault classification method.

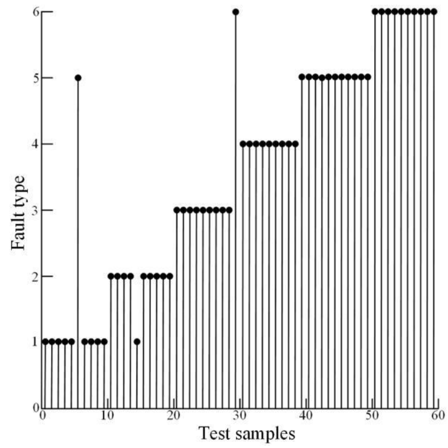

Figure 1. Fault Diagnosis Results of DBO-KELM

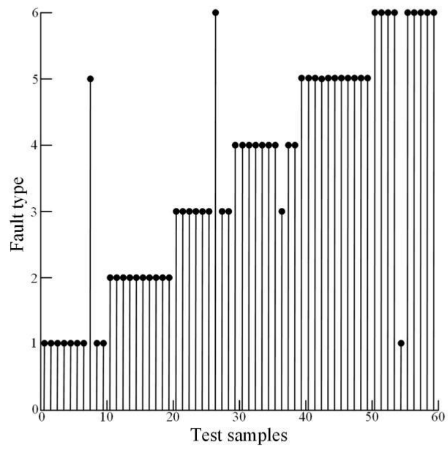

Figure 2. Fault Diagnosis Results of ABC-KELM

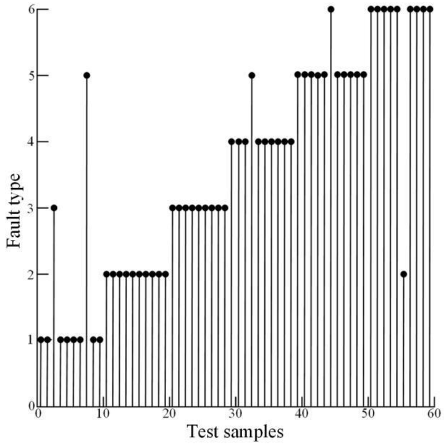

Figure 3. Fault Diagnosis Results of GWO-KELM

6. Conclusion

In order to solve the problems of transformer operation state pattern recognition and fault classification, a DBO-KELM transformer operation state pattern recognition method is proposed. Aiming at the problem that the key parameters in KELM model affect the accuracy of fault classification, the parameters of KELM are determined by DBO algorithm, and the running state pattern recognition is carried out after training with training samples by DBO-KELM method. The final experimental results show that the comprehensive fault classification result of DBO-KELM method is 95%, while that of ABC-KELM model is 93.33%, and that of GWO-KELM model is 91.67%, which shows that DBO-KELM method is advanced.

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