Transformer Fault Diagnosis Based on BOA Optimized SVM

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Abstract: To improve the classification accuracy of transformers in different operating states, a BOA-SVM classification method for transformers in different operating states is proposed. Due to the excellent global search capability of the BOA method, in order to address the issue of the significant impact of key parameters on transformer operation status classification results in the SVM method, BOA is used to determine the key parameters of the SVM method, and the BOA-SVM model is applied to transformer operation status classification. In the end, the BOA-SVM fault diagnosis model has higher classification accuracy compared to using only the SVM model, with an average classification accuracy of 95.9%, and can effectively diagnose and classify the operating status of transformers.

Keywords: Butterfly Optimization Algorithm; SVM; Transformer; Fault Diagnosis; Parameter Optimization

1. Introduction

Transformers, as a device for changing voltage, are a key component of the current power grid[1-3]. If the abnormal state of the transformer cannot be detected in a timely manner, it will cause power outages in the line, and even explosions and fires may occur. Therefore, fault diagnosis of transformers is of great significance[4].

The commonly used method for diagnosing transformer faults is DGA in oil, However, the DGA method has problems with incomplete encoding and overly absolute encoding, resulting in a low fault diagnosis rate[5-7].

At present, the common methods of transformer operation state identification mainly include Bayesian network method, expert system, SVM,neural networks and fuzzy logic[8-12]. However, the convergence speed of neural network methods is slow and the efficiency is low. resulting in slow convergence speed and low efficiency. Fuzzy logic relies on the completeness of sample data, Bayesian theory requires many independent conditional attributes when used, and expert systems lack self-learning ability. Compared to other methods, SVM has better handling of local extremum and stronger generalization ability, but its classification performance is largely affected by parameters. Therefore, In order to accurately determine the relevant parameters of SVM, some intelligent optimization algorithms are applied to the optimization of the algorithm[13-15]. However, in practical applications, these algorithms all have certain shortcomings, such as poor local search ability of genetic algorithms, complex programming implementation, low search efficiency of artificial bee colonies, slow convergence speed, premature convergence of particle swarm optimization algorithms. The BOA stands out among many algorithms due to its fewer parameters, ease of implementation, and excellent optimization capabilities[16].

Therefore, a transformer operating state classification strategy based on BOA-SVM is proposed, which uses BOA to determine the key parameters in SVM and utilizes the BOA-SVM model for transformer operating state classification.

2. BOA

Butterflies themselves can release and perceive fragrance, which can then be used for foraging or courtship[17]. In BOA, each butterfly will produce different fragrance concentrations related to its fitness, and each butterfly will conduct local search and local search by feeling the fragrance concentrations from other butterflies around it. In BOA, each butterfly will emit different fragrance, and each butterfly will feel the fragrance concentration of other butterflies around it is also different.

The definition formula of the fragrance concentration generated by the butterfly itself is as follows:

$$f_i = cI^a \quad (1)$$

f_i is the intensity of the fragrance of other butterflies around different butterflies, C is a sensory factor, I is the intensity of stimulation, a is a power exponent that depends on morphology, and usually takes 0.1.

In the global search, each butterfly will move to the butterfly g^* with the strongest fragrance concentration it feels. The search formula is:

$$x_i^{t+1} = x_i^t + (r^2 g^* - x_i^t) f_i \quad (2)$$

Where, x_i^t is the position of the i-th butterfly when iterating t times, and g^* is the optimal solution in the current stage.

In the local search stage, it can be expressed as:

$$x_i^{t+1} = x_i^t + (r^2 x_j^t - x_k^t) f_i \quad (3)$$

Where, x_j and x_k are the j and k butterflies randomly selected from the butterfly population.

3. SVM

SVM belongs to binary classification models, and its model can be solved by solving convex quadratic programming problems.

$$\begin{cases} \max 1/\|\omega\| \\ s.t.\ y_i(\omega^T x_i + b) \ge 1, i = 1,2,\cdots,n \end{cases} \quad (4)$$

Where ω is the normal vector of the selected hyperplane, x_i is the characteristic space constructed by data samples, y_i is the result label, B is the threshold, N is the number of samples.

In practical applications, many data are nonlinear. The core of nonlinear SVM is to use kernel function to map fault data to high-dimensional space, construct optimal hyperplane and classify the data, and finally map the classified data back to low-dimensional space. This paper uses Gaussian kernel function mapping transformation, as shown in Equation (5).

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2),\ \gamma > 0 \quad (5)$$

Where, the kernel parameter γ determines the bandwidth σ of the radial basis kernel.

To maximize the interval, we only need to maximize $1/\|\omega\|$, which is equivalent to minimizing $\|\omega\|^2/2$. In order to prevent the noise from making the whole problem unsolvable, a relaxation coefficient is introduced into the constraint condition, as shown in the following formula.

$$\begin{cases} \min \frac{\|\omega\|^2}{2} + C\sum_{i=1}^{n} \varepsilon_i \\ s.t.\ y_i(\omega^T x_i + b) \ge 1 - \varepsilon_i, \varepsilon_i \ge 0, i = 1,2,\cdots,n \end{cases} \quad (6)$$

Where, C is a penalty parameter, and the parameter C reflects a trade-off between the objective function and the constraint population, ε_i is a relaxation constant.

In the above equation, the selection of (γ, C) has a significant impact on the classification performance of SVM. If not chosen properly, it will result in a decrease in classification accuracy.

In summary, the classification result of SVM is closely related to the determination of γ and C. Therefore, this article adopts the BOA algorithm to optimize the SVM parameters, achieving the best diagnostic performance of the classifier.

4. Transformer fault diagnosis based on BOA optimized SVM

4.1 Data Selection

The main components of transformer oil are hydrocarbons and other compounds. Due to the influence of various comprehensive factors, it gradually ages and decomposes, producing a series of mixed gases, and most of these gases are soluble in transformer oil. When a transformer malfunctions, the volume fraction of dissolved gases in the oil will also change accordingly. Therefore, the volume fraction of dissolved gases in oil can reflect the operation of transformers. Select the gas volume fractions of H2, CH4, C2H6, C2H4, and C2H2, as well as the gas ratios of C2H2/C2H4, CH4/H2, and C2H4/C2H6, as samples for fault diagnosis.

4.2 Fault diagnosis process

1) Data preprocessing. Due to the large volume fraction of gas and the small relative gas ratio, normalization of the sample is required.

2) Sample classification. Select a portion of the processed data samples as the training set and the remaining as the testing set.

3) Optimize SVM. Optimize the parameters

(γ, C) in SVM using BOA, and finally output the optimal parameter combination.

4) Fault diagnosis. Based on the trained SVM fault model, perform fault diagnosis on the test samples, output diagnostic results and accuracy.

4.3 Experimental analysis

This article uses 401 sets of data collected and organized from literature as fault samples, of which 255 sets are training samples and the remaining 146 sets are testing samples. According to the type of transformer fault, the samples are divided into six states. The specific situation of transformer fault samples is shown in Table 1.

Table 1. Transformer Fault Samples

Type	Number of training sets	Number of test sets
High temperature overheating	61	33
Medium low temperature overheating	39	22
High-energy discharge	55	30
Low energy discharge	48	26
partial discharge	16	13
Normal state	36	22

Transformer fault samples are trained and tested on MATLAB. The search range for parameters (γ, C) is [0.01100]. Finally, the BOA-SVM model is used to diagnose transformer faults. The results obtained are shown in Table 2.

Table 2. Fault Diagnosis Results of BOA-SVM Method

Type	Sample size	Number of correct classifications	Accuracy(%)
High temperature overheating	33	32	97
Medium low temperature overheating	22	20	90.9
High energy discharge	30	28	93.3
Low energy discharge	26	25	96.2
partial discharge	13	13	100
Normal state	22	22	100
Total	146	140	95.9

According to Table 2, the proposed method has an accuracy rate of 97% for classifying high-temperature and overheated operating states, 90.9% for classifying medium and low-temperature and overheated operating states, 93.3% for classifying high-energy discharge operating states, 96.2% for classifying low-energy discharge operating states, 100% for classifying partial discharge operating states, 100% for classifying normal states, and an average classification accuracy rate of 95.9%. In order to verify the progressiveness of BOA-SVM, it is applied to the classification of transformer operation status together with the SVM only method. The final classification results are shown in Table 3.

Table 3. Fault Diagnosis Results of SVM Method

Type	Sample size	Number of correct classifications	Accuracy(%)
High temperature overheating	33	31	93.9
Medium low temperature overheating	22	20	90.9
High energy discharge	30	26	86.7
Low energy discharge	26	24	92.3
partial discharge	13	10	76.9
Normal state	22	19	86.4
Total	146	130	89

It can be seen from Table 3 that the operation state classification accuracy of SVM model for each fault type is lower than that of BOA-SVM model, and the average accuracy of BOA-SVM is 6.9% higher than SVM.

5. Conclusion

Aiming at the problem that the setting of key parameters in SVM method has great influence on the classification of transformer operation state, this paper puts forward a new method based on BOA-SVM. The key parameters of SVM are determined by BOA, and the fault diagnosis is carried out by BOA-SVM model.

Finally, the experiment shows that the average fault classification accuracy of BOA-SVM method is 95.9%, while the average fault diagnosis rate of only using SVM is only 89%, which shows the advanced nature of the proposed BOA-SVM model.

References

[1] Yan P, Wang J B, Wang Y W Z. Transformer fault diagnosis based on MPA-RF algorithm and LIF technology. Measurement Science & Technology, 2024, 35(2):025504. 1-025504.10.

[2] Bai X, Zang Y, Li J, et al. Transformer fault diagnosis method based on two-dimensional cloud model under the condition of defective data. Electrical Engineering, 2024, 106(1). DOI:10. 1007/s00202-023-01964-7.

[3] Wang L Z, Chi J F, Ding Y Q, et al. Transformer fault diagnosis method based on SMOTE and NGO-GBDT. Scientific Reports, 2024, 14(1). DOI:10. 1038/s41598-024-57509-w.

[4] Lu W, Shi C, Fu H, et al. Research on transformer fault diagnosis based on ISOMAP and IChOA-LSSVM. IET Electric Power Applications, 2023. DOI:10. 1049/elp2.12302.

[5] Liu J, Cai B, Yan S, et al. Transformer fault diagnosis based on the improved QPSO and random forest. IOP Publishing Ltd, 2024. DOI:10. 1088/ 1361-6501/ ad574c.

[6] Rao S, Yang S, Tucci M B S. Convolutional neural networks applied to dissolved gas analysis for power transformers condition monitoring. International journal of applied electromagnetics and mechanics, 2023, 73(4): 265-281.

[7] Kaur K, Bhalla D, Singh J. Fault Diagnosis for Oil Immersed Transformer Using Certainty Factor. IEEE transactions on dielectrics and electrical insulation: A publication of the IEEE Dielectrics and Electrical Insulation Society, 2024(1):31. DOI:10. 1109/TDEI.2023.3307513.

[8] Jin Y, Wu H, Zheng J, et al. Power Transformer Fault Diagnosis Based on Improved BP Neural Network. Electronics (2079-9292), 2023, 12(16). DOI:10. 3390/ electronics12163526.

[9] Mudholkar R R, Sawant S R, Tengshe G G, et al. Fuzzy Logic Transformer Design Algorithm (FLTDA). Active and Passive Electronic Components, 1999, 22(1):17-29. DOI:10.1155/1999/53850.

[10]Wang Y, Lu F, Li H. Synthetic Fault Diagnosis Method of Power Transformer Based on Rough Set Theory and Bayesian Network. Springer, Berlin, Heidelberg, 2008. DOI:10. 1007/ 978-3-540-87734-9_ 57.

[11]Xin-Gang C, Tai-Fu L I. Research on Expert System of Transformer Insulation Fault Diagnosis Based on DGA Characteristic Parameters. Transformer, 2005.

[12]Zhao Z, Guo Y, Xu A, et al. Fault diagnosis of the transformer based on QPSO-SVM. Journal of Physics: Conference Series, 2023, 2530(1). DOI:10. 1088/1742-6596/2530/1/012026.

[13]Li Y, Bao D, Luo C, et al. An Intelligent Fault Diagnosis Method for Oil-Immersed Power Transformer Based on Adaptive Genetic Algorithm. Springer Berlin Heidelberg, 2012. DOI:10.1007/978-3-642-25553-3_21.

[14]Duan H B, Xu C F, Xing Z H. A hybrid artificial bee colony optimization and quantum evolutionary algorithm for continuous optimization problems. International Journal of Neural Systems, 2010, 20(01):39-50. DOI:10. 1142/ S012906571000222X.

[15]Zhang J, Ding Y, Zhang X, et al. A Novel Method Based on Particle Swarm Optimization Support Vector Neural Network for Transformer Fault Diagnosis// International Symposium on Neural Networks.Springer, Singapore, 2024. DOI:10. 1007/978-981-97-4399-5_51.

[16]S. S, G. K. R. Copy-Move Forgery Detection and Classification Using Improved Butterfly Optimization Algorithm-based Convolutional Neural Network. International Journal of Intelligent Engineering & Systems, 2024, 17(1). DOI:10. 22266/ ijies2024. 0229. 72.

[17]Arora S, Singh S, Yetilmezsoy K. A modified butterfly optimization algorithm for mechanical design optimization problems. Journal of the Brazilian Society of Mechanical Sciences & Engineering, 2018, 40(1):21. DOI:10. 1007/ s40430-017-0927-1.

