Transformer Fault Diagnosis Method Based on SSA-Optimized SVM

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Abstract: Aiming at the problem of low accuracy in current transformer fault diagnosis methods, a transformer fault diagnosis method based on the Sparrow Search Algorithm (SSA) optimized Support Vector Machine (SVM) model is proposed. Firstly, the Kernel Principal Component Analysis (KPCA) method is used to process the high-dimensional data of transformer fault features to reduce the dimension and weaken the interference of data sparsity on the results. To address the issue that the kernel function parameters and penalty coefficients in SVM have a significant impact on the fault classification effect, it is proposed to use SSA to optimize the parameters of SVM to determine the best parameter combination and establish the SSA-SVM fault diagnosis model. The obtained data is divided into training and test sets. The training set is used to train the SSA-SVM fault diagnosis model, and the test set sample data is input into the trained model for fault diagnosis. To verify the effectiveness of this method, it is compared with several common fault diagnosis methods. The results show that the proposed fault diagnosis method has significantly higher fault recognition accuracy than other models, verifying its advanced nature.

Keywords: KPCA; SVM; SSA; Transformer; Fault Diagnosis

1. Introduction

Transformers are key components in the power transformation system and play a crucial role in the safe and stable operation of the power grid. During long-term operation, transformers may suffer irreversible damage. The continuous accumulation of these abnormal damages will gradually weaken the performance of in-service transformers, thereby affecting the normal operation of substations and the overall stability of the power grid[1]. Monitoring the fault characteristics of transformers and achieving accurate and efficient diagnosis of their fault types is of great significance for ensuring the safe and stable operation of the power grid[2].

Taking the oil-immersed transformer, which is widely used at present, as an example, when the oil-immersed transformer malfunctions, the concentration of the main gases dissolved in its insulating oil will change significantly. Dissolved gases analysis (DGA) is a commonly used method in traditional transformer fault diagnosis, where it includes the Dornenburg ratio method, Roger four-ratio method and IEC three-ratio method, etc[3]. However, these methods generally have the problem of incomplete or redundant feature information, which has a certain impact on the accuracy of fault diagnosis.

In recent years, with the continuous development of intelligent optimization technology, methods such as extreme learning machine, random forest and neural network have gradually become the hotspots in the research field. However, these methods generally rely on large-scale data samples, and the system structures they build are relatively complex. In addition, when there is a large amount of noise in the dataset, the model is prone to overfitting, which in turn leads to a decline in fault diagnosis performance.

SVM has a relatively low demand for data samples, which is highly compatible with the limited amount of transformer fault data. However, the classification accuracy of SVM is largely influenced by the selection of kernel parameter g and penalty factor C. Manually determining these parameters has become difficult to meet the accuracy requirements of fault diagnosis. With the continuous development of intelligent optimization algorithms, these algorithms have been widely applied in the field of parameter optimization. As an emerging swarm intelligence optimization algorithm, SSA has excellent global optimization capabilities. Therefore, this paper adopts this algorithm to optimize the parameters of SVM to determine the best parameter combination.

Based on the above analysis, this paper proposes a transformer fault diagnosis method based on KPCA and SSA-optimized SVM. Firstly, KPCA is used to reduce the dimension of the transformer fault feature data to simplify the operation. In view of the fact that the classification accuracy of SVM is largely affected by the selection of kernel parameter g and penalty factor C, the SSA method is introduced to optimize it, determine the optimal parameter combination, and establish the SSA-SVM fault diagnosis model. To verify the effectiveness of the proposed method, it is compared with the GA-SVM and GWO-SVM models to demonstrate its superiority.

2. Theoretical Basis

2.1 KPCA

Principal component analysis has the drawback of projection, which can lead to a reduction in the distinctiveness of data, making data points blend together and difficult to distinguish. Additionally, principal component analysis requires the calculation of the covariance matrix, which has a relatively high computational complexity[4]. In contrast, KPCA is a nonlinear dimensionality reduction method based on kernel functions. Its core idea is to first transform samples to a high-dimensional space through mapping, and then apply linear dimensionality reduction techniques in the high-dimensional space for processing.

Transformer fault data can be represented by the available matrix $X_{m\times n}$, where it contains m groups of n-dimensional data. The original data is mapped to a high-dimensional space through the kernel function $\varphi(X)$. Subsequently, the covariance matrix of the data is calculated, and the eigenvalues λ and eigenvectors w_i are further solved, with the specific form shown in formula (1). The kernel matrix K can be solved by using the kernel function, and its expression is shown in formula (2). After centering the kernel matrix, formula (3) can be obtained, where l_n is an $n\times n$ matrix, and all elements are $1/n$. In this paper, based on the cumulative contribution rate reaching 85%, the first d eigenvectors corresponding to the eigenvalues are selected, and they are used as the data set after dimensionality reduction, as detailed in formula (4).

$$\varphi(X)\varphi(X)^T w_i = \lambda w_i \tag{1}$$

$$K = \varphi(X)T\varphi(X) = \begin{bmatrix} k(x^{(1)},x^{(1)}) & \cdots & k(x^{(1)},x^{(n)}) \\ \vdots & \ddots & \vdots \\ k(x^{(n)},x^{(1)}) & \cdots & k(x^{(n)},x^{(n)}) \end{bmatrix} \tag{2}$$

$$K' = K - l_n K - K l_n + l_n^T K l_n \tag{3}$$

$$Y = K^T \cdot \left[\frac{1}{\sqrt{\lambda_1}} w_1, \frac{1}{\sqrt{\lambda_2}} w_2, \cdots, \frac{1}{\sqrt{\lambda_d}} w_d \right] \tag{4}$$

2.2 SSA

SSA effectively enhances the exploration and exploitation capabilities of the search space by simulating the foraging and anti-predation behaviors of sparrows. Compared with algorithms such as the bat algorithm, grey wolf optimization algorithm, and whale optimization algorithm, SSA demonstrates superior performance in terms of search accuracy, convergence speed, stability, and escaping local optima, and possesses outstanding global optimization capabilities[5-7].

The food-seeking process of sparrows involves two behavioral strategies, namely the discoverer and the joiner. Where, the main task of the discoverer is to search for food, providing the group with the area and direction for foraging, while the joiner acquires food by following the guidance of the discoverer. These two roles can be interchanged, and any individual can become a discoverer as long as it finds food. However, the ratio of discoverers to joiners remains constant throughout the process. The position of the discoverer can be obtained by the following formula:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \exp(-i/\alpha iter_{\max}) & R_2 < S_T \\ X_{i,j}^t + QL & R_2 \ge S_T \end{cases} \tag{5}$$

Where, $X_{i,j}^t$ represents the position of the discoverer i. The joiner makes decisions by observing the behaviors of other sparrows. If the discoverer finds food, the joiner will immediately leave the current position to compete for the food; if the competition is unsuccessful, it will continue to wait for an opportunity. Its position is:

$$X_{i,j}^{t+1}=\begin{cases}Q\exp(\dfrac{X_w^t-X_{i,j}^t}{i^2}) & i>n/2\\ X_P^{t+1}+\left|X_{i,j}^t-X_P^{t+1}\right|A^{+}L & i\le n/2\end{cases} \tag{6}$$

Where A is a $1\times d$ matrix and n is the number of sparrows. When a sparrow senses danger, it will send a warning signal to the group. After receiving the signal, other sparrows will quickly take anti-predation actions. At the time of danger warning, its position is:

$$X_{i,j}^{t+1}=\begin{cases}X_b^t+\beta\left|X_{i,j}^t-X_b^t\right| & f_i>f_b\\ X_{i,j}^t+k\dfrac{\left|X_{i,j}^t-X_w^t\right|}{(f_i-f_w)+\varepsilon} & f_i=f_b\end{cases} \tag{7}$$

Where, ε is a constant and k is a random number ranging between $[-1,1]$.

2.3 SVM

As a machine learning algorithm, SVM has been widely applied in classification and regression problems[8-10]. When constructing an SVM model, it is necessary to optimize and adjust the penalty parameter and kernel parameter. Compared with traditional methods, SVM effectively avoids the problem of local minima by minimizing structural risk, thereby enhancing the generalization ability of the model. SVM is a binary classification model, and its core idea is to transform the problem into the task of solving convex quadratic programming. The learning strategy of this model lies in maximizing the margin, specifically:

$$\begin{cases}\max 1/\|\omega\|\\ s.t.\ \ y_i(\omega^T x_i+b)\ge 1\end{cases} \tag{8}$$

Where, $i=1,2,\cdots,n$. As the characteristic data of the transformer has a strong nonlinearity, the key of SVM lies in mapping the fault data to a high-dimensional space through the kernel function, and constructing the optimal hyperplane in this space to achieve data classification. After the classification is completed, the data is mapped back to the low-dimensional space. In this paper, the Gaussian kernel function is adopted for mapping transformation, as shown in Equation (9).

$$k(x_i,x_j)=\exp(-g\left\|x_i-x_j\right\|^2),g>0 \tag{9}$$

Where, g is the kernel parameter. To avoid the problem being unsolvable due to the influence of noise, a relaxation coefficient is introduced in the constraint condition, as shown in Equation (10).

$$\begin{cases}\min\dfrac{\|\omega\|^2}{2}+C\sum_{i=1}^{n}\varepsilon_i\\ s.t.\ \ y_i(\omega^T x_i+b)\ge 1-\varepsilon_i,\varepsilon_i\ge 0\end{cases} \tag{10}$$

Where, $i=1,2,\cdots,n$, 2. C is the penalty function.

From the above analysis, it can be seen that the classification effect of the SVM model is significantly influenced by the key parameters, namely the penalty function C and the kernel parameter g . If only relying on manual selection, it is impossible to guarantee a stable classification effect. Therefore, this paper adopts SSA to optimize and determine the key parameters of SVM.

3. SSA-SVM Fault Diagnosis Process

The proposed transformer fault diagnosis process based on KPCA-SSA-SVM is as follows:

Step 1: preprocessing, initialize the parameters of SSA and number and classify the obtained DGA data.

Step 2: feature extraction, use the KPCA method to reduce the dimension of the fault feature data and use it as the basis for subsequent fault data analysis.

Step 3: take the fault data as the input variable and normalize it to be constrained within the range of [0, 1].

Step 4: Optimize and determine the key parameters C and g of SVM using SSA.

Step 5: Check if the maximum number of iterations has been reached. If not, return to Step 4, if it has been reached, output the parameters C and g.

Step 6: Fault diagnosis. Build the SSA-SVM fault classification model, train the model with the training set data, and input the test set into the SSA-SVM model for fault classification.

4. Experimental Analysis

To verify the correctness and accuracy of the above-mentioned fault diagnosis method, 300 sets of characteristic gas data in transformer oil were collected. The specific sample data are shown in Table 1. These characteristic gas data cover various fault types of transformers. The parameters of SVM were optimized by SSA, and simulation experiments were carried out on the MATLAB platform to complete the training and diagnosis of characteristic fault data samples.

Table 1. Distribution of Transformer Fault Sample Data

Status	Category label	Training set	Test set
Normal	1	50	10
Medium and low temperature superheating	2	50	10
High-temperature overheating	3	50	10
High-energy discharge	4	50	10
Low-energy discharge	5	50	10

To reduce the data dimension while retaining the majority of fault features, this paper uses KPCA to conduct the dimension reduction processing on the data. The principal components with the cumulative contribution rate exceeding 90% and ranking at the top are selected as the model input quantity for the next step of fault diagnosis. SSA is utilized to optimize and determine the parameters of SVM, and the best parameters C and g are obtained to establish the SSA-SVM model. The training set samples are used to train the SSA-SVM model, and the test set is input into the SSA-SVM model for fault classification. The results obtained are shown in Figure 1.

As shown in Figure 1, among the five operation status samples of the transformer, there are two samples that are misclassified. Where, one sample of medium and low temperature overheating is wrongly classified as high temperature overheating, and one sample of low energy discharge is wrongly classified as high energy discharge. The overall accuracy rate of fault diagnosis is 96%.

To verify the effectiveness of the proposed method, the method proposed in this paper is compared with the transformer fault diagnosis methods of Genetic Algorithm (GA) optimized SVM and Grey Wolf Optimization (GWO) optimized SVM. They are all applied to the transformer fault diagnosis. To ensure the fairness of the experiment, all other experimental conditions are consistent. The final fault diagnosis results are respectively shown in Figure 2 and Figure 3.

As can be seen from Figure 2, there are 4 samples classified wrongly in the fault diagnosis results based on GA-SVM, and its comprehensive fault diagnosis accuracy rate is 92%. As can be seen from Figure 3, there are 3 samples classified wrongly in the fault diagnosis results based on GWO-SVM, and its comprehensive fault diagnosis accuracy rate is 94%, while the comprehensive fault diagnosis accuracy rate of the proposed SSA-SVM is 96%, which verifies the advanced nature of the proposed method.

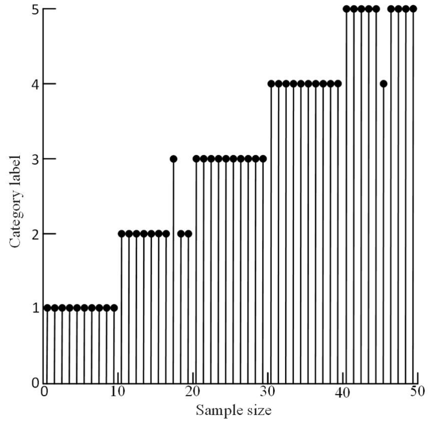

Figure 1. Fault diagnosis results based on SSA-SVM

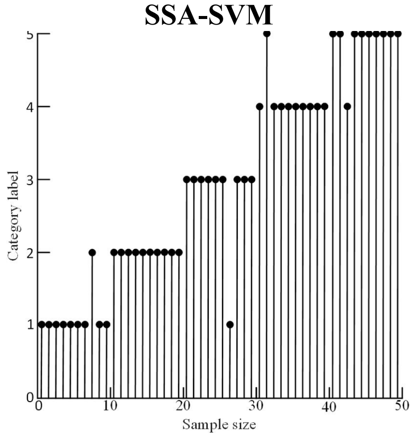

Figure 2. Fault diagnosis results based on GA-SVM

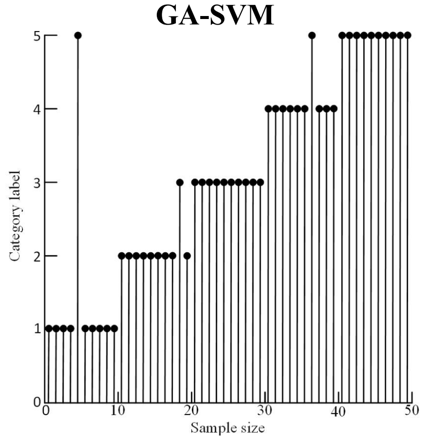

Figure 3. Fault diagnosis results based on GWO-SVM

5. Conclusion

To improve the accuracy of transformer fault diagnosis, a new method based on KPCA-SSA-SVM is proposed. Firstly, KPCA is used to reduce the dimension of transformer fault feature data. In view of the problem that the SVM classification model is greatly affected by parameter settings in the classification process, SSA is proposed to optimize and determine its parameters, and an SSA-SVM fault diagnosis model is established. After dividing the feature data into training set and test set, the SSA-SVM model is trained with the training set and the model validity is verified with the test set. The final comprehensive fault diagnosis accuracy rate is 96%. To verify the advanced nature of the proposed method, it is compared with the GA-SVM and GWO-SVM methods. The comprehensive fault diagnosis accuracy rates of the two methods are both lower than that of the proposed method, indicating that the proposed method can be applied to transformer fault diagnosis.

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