Transformer Fault Detection Method Based on RCMDE and POA-LSSVM

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Abstract: To improve the feature extraction capability and fault detection accuracy for transformers, a new transformer fault detection approach is introduced. This approach combines refined composite multiscale dispersion entropy (RCMDE) for feature extraction with pelican optimization algorithm (POA)-optimized least squares support vector machine (LSSVM) for classification tasks. Specifically, RCMDE is employed to capture the sound signals of transformers under various operating conditions and calculate their corresponding entropy features. Given that the classification performance of LSSVM is highly sensitive to parameter settings, POA is utilized to optimize these parameters, thereby establishing a robust POA-LSSVM model. The fault features extracted are then classified by utilizing the optimized model. Experimental outcomes indicate that the proposed method attains a comprehensive fault detection accuracy of 96.67%.

Keywords: RCMDE; POA; LSSVM; Rransformer; Fault Detection

1. Introduction

Distribution transformers are one of the most widely used devices in power systems and are deployed outdoors for operation throughout the year. Due to the influence of harsh environmental conditions and variable climates and other complex factors, this equipment frequently experiences faults [1]. According to statistics, there are as many as several thousand power accidents caused by transformer faults every year, which not only result in severe economic losses but also pose a risk of casualties. Therefore, conducting research on the condition assessment of distribution transformers has significant practical significance [2].

Due to the harsh working conditions of the transformer, the materials and structural components inside the transformer are prone to performance degradation, which can lead to problems such as partial discharge or abnormal sounds. While the transformer is in operation, whether a fault occurs or it is in an abnormal operating state, abnormal sounds will be produced, where the abnormal information of the equipment is contained [3]. Therefore, by analyzing the sound signals of the transformer, extracting the fault features therein, and researching the corresponding fault diagnosis methods, it is helpful to detect potential fault hazards in a timely manner.

Transformer sound signals are complex nonlinear signals. Entropy-based nonlinear signal feature extraction techniques have found extensive application in the domain of equipment fault diagnosis [4]. Common information entropies include fuzzy entropy, permutation entropy, and dispersion entropy methods, etc. Where fuzzy entropy is prone to generating unreliable entropy values when dealing with short-time signals, permutation entropy, although simple to calculate, neglects the relationship between amplitudes. Dispersion entropy overcomes the shortcomings of the former two methods, has a relatively high computational efficiency, and is less affected by sudden signal changes. However, all the above methods are single-scale. Therefore, Azami et al. proposed RCMDE, which not only can calculate entropy values at multiple time scales but also reduces the influence of data length on entropy values through refined processing.

LSSVM is an improved form of SVM [5]. Unlike traditional SVM, LSSVM effectively reduces computational complexity by using equality constraints instead of inequality constraints. Compared with solving quadratic programming problems, solving linear equations is more efficient, which makes LSSVM exhibit superior performance when dealing with large-scale datasets. In practical applications, to achieve better classification and regression results, it is usually necessary to combine LSSVM with optimization algorithms to determine the best parameter configuration. The Pelican Optimization Algorithm is a recently developed meta-heuristic approach that features a straightforward structure, low computational complexity, and robust global search capabilities. In this study, this algorithm is employed to fine-tune the parameters of the LSSVM.

In order to improve the extraction of transformer fault features and the precision of fault detection, this paper introduces a transformer fault detection method that combines RCMDE with POA-optimized LSSVM. Initially, the transformer feature data is processed using RCMDE, and POA is utilized to optimize the relevant parameters of LSSVM, namely the kernel parameter g and the penalty coefficient C. The obtained fault feature data is then used for fault detection by POA-LSSVM.

2. Theoretical Basis

2.1 RCMDE

The REMDE is an enhanced approach that originates from dispersion entropy. RCMDE adopts a brand-new calculation approach. Firstly, it calculates the occurrence probability of each dispersion pattern in every coarse-grained sequence. Then, it averages these probability values. Eventually, the RCMDE value is obtained [6]. This process effectively avoids the potential data loss issue that may occur during the coarse-graining operation in the traditional DE method, thereby enhancing the accuracy of the calculation results. This makes the RCMDE method more advantageous in terms of both efficiency and precision.

Regarding the original signal $u=\{u_1,u_2,u_3,\cdots,u_L\}$ with a length of L, it can be equally divided into several small segments starting from u_1 with a period of τ, and the mean value of each segment is computed. Subsequently, the average values of each segment are combined to form a coarse-grained sequence, where the k th coarse-grained sequence can be expressed as:

$$x_{k,j}^{\tau}=\frac{1}{\tau}\sum_{b=k+\tau(j-1)}^{k+j\tau-1}u_b \tag{1}$$

Subsequently, compute the probability of each coarse-grained scattering pattern λ and then average these probability values.

1) By using the normal distribution function, map the sequence $x_{k,j}=\{x_j, j=1,2,\cdots,N\}$ to $y=\{y_j, j=1,2,\cdots,N\}$, where y_j is:

$$y_j=\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{x_j}e^{[-(t-\theta)^2]/(2\sigma^2)}dt \tag{2}$$

Where, θ is the mean value.

2) Use a linear algorithm to map y_j to the range of $[1,2,\cdots,c]$, which is specifically expressed as:

$$z_j^c=R(c\cdot y_j+0.5) \tag{3}$$

Where, $R(\cdot)$ is the rounding operation.

3) Using the embedding dimension m and time delay d, determine the resulting time series:

$$z_i^{m,c}=\{z_i^c, z_{i+d}^c,\cdots,z_{i+(m-1)d}^c\} \tag{4}$$

4) Assuming that the dispersion pattern corresponding to each time series $z_i^{m,c}$ is $\lambda v_0 v_1\cdots v_{m-1}$, if conditions $z_i^c=v_0$, $z_{i+d}^c=v_1$, and $z_{i+(m-1)d}^c=v_{m-1}$ are met, then the dispersion pattern corresponding to $z_{i+(m-1)d}^c=v_{m-1}$ is $\lambda_{v_0v_1\cdots v_{m-1}}$.

5) Calculate the occurrence probability $P(\lambda_{v_0v_1\cdots v_{m-1}})$ of each dispersion pattern $\lambda_{v_0,v_1,\cdots v_{m-1}}$:

$$P(\lambda_{v_0v_1\cdots v_{m-1}})=\frac{num(\lambda_{v_0v_1\cdots v_{m-1}})}{N-(M-1)d} \tag{5}$$

6) For each scale corresponding to τ, RCMDE can be defined as:

$$\delta_{RCMDE}(X,m,c,d,\tau)=-\sum_{\lambda=1}^{c^m}\overline{P}(\lambda_{v_0v_1\cdots v_{m-1}})\cdot \ln[\overline{P}(\lambda_{v_0v_1\cdots v_{m-1}})] \tag{6}$$

2.2 POA

POA is a new meta-heuristic optimization algorithm that draws inspiration from the group hunting behavior of pelicans [7]. By simulating the hunting process of pelicans and constructing a corresponding mathematical model, the algorithm seeks to identify the optimal solution to the problem. This approach features fewer input parameters, faster convergence, an effective balance between global exploration and local exploitation, and a straightforward, easy-to-implement process. In the iterative process of the algorithm, each pelican individual corresponds to a potential solution, and its updates and explorations are directed by the fitness value of the current solution. By facilitating collaboration and information sharing among individuals, the algorithm jointly seeks the optimal solution. Continuous iterative search and position adjustments enable the POA to gradually converge toward the global optimum, providing an efficient and flexible method for solving practical problems.

The POA updates candidate solutions by simulating the behaviors and strategies of pelicans during the hunting process. The algorithm divides the hunting strategy into two phases: exploration and exploitation, which are mathematically modeled as follows:

2.2.1 Initialization

The mathematical description of the pelican population initialization is as follows:

$$x_{i,j} = l_j + rand(u_j - l_j) \tag{7}$$

Where, N represents the pelican population size. In the Pelican Optimization Algorithm, the objective function value for each pelican individual can be determined using the objective function, whereas the objective function value of the entire pelican population can be expressed in vector form as:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N*1} \tag{8}$$

2.2.2 Exploration Stage

At this stage, pelicans will locate the position of their prey and move towards it. By simulating the behavioral strategies of pelicans, the algorithm is able to explore the search space and identify various regions with the assistance of POA. The core of this method lies in enhancing the algorithm's precise search ability by randomly generating the location of the prey. The above concepts and the movement strategy of pelicans are as follows:

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + rand(P_j - Ix_{i,j}), F_p < F_i \\ x_{i,j} + rand(x_{i,j} - P_j), else \end{cases} \tag{9}$$

2.2.3 Development Stage

In the development phase, as pelicans get closer to the water surface, they extend their wings to force the prey upward and utilize their throat pouches to gather the prey. This strategy can effectively increase the number of prey captured within the attack area. Through the simulation of pelicans' hunting behavior, POA is able to converge more effectively toward high-quality solutions within the hunting area, thus improving local search and exploitation abilities. The algorithm needs to evaluate the points around the pelican to find better solutions. The hunting process of pelicans can be simulated by the following mathematical formula.

$$x_{i,j}^{P_2} = x_{i,j} + R(1 - \frac{t}{T})(2rand - 1)x_{i,j} \tag{10}$$

Where, $R = 0.2$ is a constant, $R(1 - \frac{t}{T})$ is the neighborhood radius of the population size. As the algorithm progresses, this coefficient will gradually decrease, causing the neighborhood radius of each member to shrink accordingly. This way, a more detailed scan of the area near each member can be conducted, which helps the algorithm approach the global optimal solution more closely. After completing the above search and capture process, the pelicans will launch another attack and hunt, entering the iterative calculation stage. During this process, the optimal position needs to be continuously updated, and the positions of the pelican group should be constantly adjusted. Based on the previously obtained design variables and objective function values, the new optimal position is selected to replace the original one, and the iterative calculation continues until the optimal solution is found. Finally, the iteration is stopped and the calculation results are output.

2.3 LSSVM

LSSVM is an extension of the conventional SVM, developed to tackle the high computational complexity that SVM faces when solving practical problems. A key advancement of LSSVM lies in converting the inequality constraints of SVM into equality constraints. Regarding optimization techniques, while SVM relies on quadratic programming to solve the loss function, LSSVM employs a least squares linear system instead. This modification not only simplifies the solution process but also enhances the efficiency of LSSVM in handling large-scale datasets. Moreover, LSSVM retains the effectiveness of SVM for classification and regression tasks while preserving its capability to tackle nonlinear problems.

The LSSVM method performs well in dealing with small sample problems and is highly suitable for small sample scenarios such as transformer fault diagnosis. Additionally, when solving classification problems, LSSVM requires the selection of an appropriate kernel function. Currently, the Radial Basis Function (RBF) kernel is widely used, which handles the non-linear relationship between features and labels by mapping samples to a high-dimensional space. In LSSVM, the parameters g of the RBF kernel and the penalty coefficient C play a crucial role in classification performance. This paper combines the improved BOA algorithm with the cross-validation method to optimize and determine the kernel parameter g and the penalty coefficient C, thereby enhancing the classification effect of the model.

3. Experimental Analysis

3.1 Experimental Data

To verify the effectiveness of the proposed RCMDE and POA-optimized LSSVM transformer fault detection approach, this paper utilizes the IET TC 10 database as the experimental dataset. The selected transformer experimental data consist of six categories: medium and low-temperature overheating, partial discharge, high-energy discharge, high-temperature overheating, low-energy discharge, and normal state. A total of 300 data samples are collected to form the dataset, with 240 samples allocated for model optimization and training, while the remaining 60 samples are reserved for testing the model's performance. The precise categorization of the experimental dataset is displayed in Table 1.

3.2 Results Analysis

The selected data is subjected to feature extraction by RCMDE, where the parameter selection of RCMDE is $d=1, m=3, c=6, \tau=30$. The fault features obtained after processing by RCMDE method are used for fault detection and classification by POA-LSSVM. Where, in the process of fault feature classification by POA on LSSVM, the range of values for the kernel parameter g and the penalty coefficient C are both $[0.01,500]$. The final classification outcomes are illustrated in Figure 1.

Table 1. Classification of Experimental Data Sets

Type	Number	Training set	Test set
Medium and low temperature superheating	1	40	10
Partial discharge	2	40	10
High-energy discharge	3	40	10
High-temperature overheating	4	40	10
Low-energy discharge	5	40	10
Normal state	6	40	10

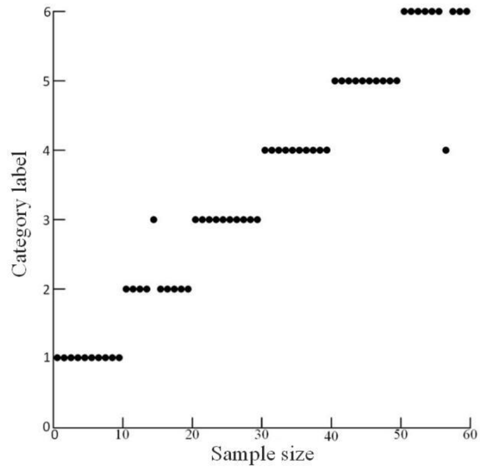

Figure 1. Fault Detection Outcomes Using RCMDE-POA-LSSVM

As can be seen from Figure 1, among the six types of operation states, only two samples were classified wrongly. One partial discharge sample was wrongly classified as high-energy discharge, and one normal state sample was wrongly classified as high-temperature overheating. The overall fault detection accuracy rate was 96.67%. To validate the advantages of the proposed method, it was compared with DE-POA-LSSVM, RCMDE-SSA-LSSVM, and RCMDE-GWO-LSSVM, and all were applied to fault detection. Where, SSA is the Sparrow Search Algorithm (SSA), and GWO is the Grey Wolf Optimizer (GWO). The fault detection outcomes of the other three methods are presented in Figures 2-4 respectively.

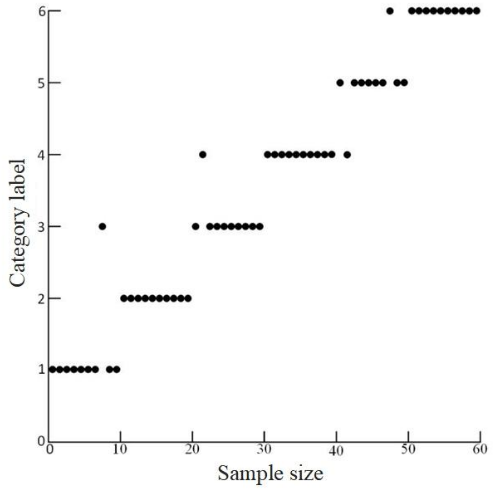

Figure 2. Fault Detection Outcomes Using DE-POA-LSSVM

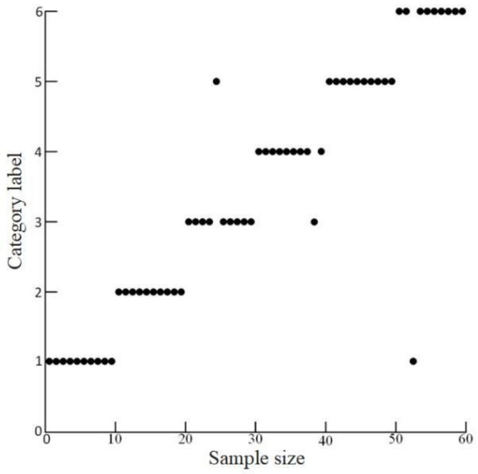

Figure 3. Fault Detection Outcomes Using RCMDE-SSA-LSSVM

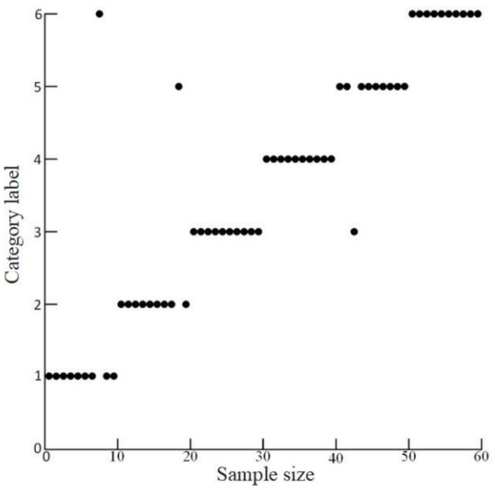

Figure 4. Fault Detection Outcomes Using RCMDE-GWO-LSSVM

As can be seen from Figure 2-4, the final comprehensive fault detection accuracy rate of the fault detection result adopting DE-POA-LSSVM is 93.33%, while the final comprehensive fault detection accuracy rates of the methods adopting RCMDE-SSA-LSSVM and RCMDE-GWO-LSSVM are both 95%, which are considerably lower than those of the RCMDE-POA-LSSVM-based method proposed in this paper. This confirms the superiority of the proposed approach.

4. Conclusion

Targeting the challenges of extracting fault features in transformers and the low accuracy in fault detection, a new method for transformer fault detection based on RCMDE and POA-optimized LSSVM is proposed. Initially, RCMDE is utilized to extract features from the transformer data. To address the issue that the relevant parameters of LSSVM affect its fault classification performance, POA is proposed to optimize the parameters, establishing the POA-LSSVM model. The feature components obtained through feature extraction are used for fault detection by the POA-LSSVM model, and the results are compared with those of DE-POA-LSSVM, RCMDE-SSA-LSSVM, and RCMDE-GWO-LSSVM. The results indicate that the proposed method achieves the highest comprehensive fault detection accuracy at 96.67%.

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