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Diagnosis of transformer faults using multi-class AdaBoost algorithm

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ABSTRACT

Low fault diagnosis accuracy is caused by the ineffectiveness of traditional shallow machine learning methods un exploring the connection between the oil-immersed transformer fault data. In response, this study suggests a method for diagnosing transformer faults based on multi-class adaBoost algorithms solves this issue. First, the SVM and the adaBoost algorithm are linked. The SVM is improved by the adaBoost approach, and the transformer defect data is thoroughly investigated. The IPSO is then used to optimize the SVM's parameters when the dynamic weight is added to the PSO algorithm. This is accomplished by updating the particle inertia weight in real-time. Lastly, by examining the relationship between the type of fault and the dissolved gas in the transformer oil, the uncoded ratio technique develops a novel gas set collaboration. The feature vector used as the input is produced using the enhanced ratio approach. The diagnosis method suggested in this paper has a significant increase in diagnostic accuracy when compared to conventional methods, according to simulations using 419 collection of transformer fault data and 117 groups of IECTC10 standard data that were gathered in China. Additionally, it has a fast confluence speed and a powerful search capability.

Keywords: *Support Vector Machines, Enhanced Particle Swarm Optimization, Power Transformers, The Dga Feature, and The Multi-Class Adaboost Algorithm Are Some of the Terms Used in Fault Detection*

1. INTRODUCTION

Power transmission and conversion are two crucial tasks carried out by the oil-immersed transformer, which is an important part of the electrical system. It will result in significant economic losses once the fault is present. As a result, transformer fault diagnosis is done to quickly discover concealed flaws and carry out maintenance in accordance with the fault type. Reduced losses and damage from transformer failure, along with more stable and dependable power grid operation, are of utmost importance [1]. The insulation began to age and fracture, and the transformer oil eventually dissolved it. The oil-immersed transformer produces very little gas while it is operating normally. Hydrogen (H2), methane (CH4), ethane (C2H4), and ethylene are the primary ingredients of these gases. (C2H2), acetylene (C2H6), carbon dioxide (CO2), and others [2]. Specific gas components will quickly grow when transformers have various defects.

As an illustration, the contents of H2 and C2H2 will increase during high-energy discharge, whereas the ratio of CH4 and C2H4 will rise rapidly during overheating of insulating oil. The defects of several transformer types are displayed here. A significant link between the shift in gas composition is visible. Dissolved gas analysis (DGA) technology is often used for online diagnosis of oil-immersed transformers because it is electromagnetic interference-free, adaptable, and useful and utilizes non-electrical quantities as diagnostic markers. Some experts suggested that basic principles based on the DGA, such as the three-ratio [3], Rogers ratio method [4], Duval triangle approach [5], and others, have had a considerable impact. They all nevertheless have excessive absolute coding restrictions and insufficient state coding. Practical applications of such problems are constrained in several ways [7]. Bayesian theory, fuzzy algorithms, the normal cloud model [8–13], etc. These techniques have produced particular diagnostic effects, but they have also addressed some of the issues with traditional algorithm boundaries, which are too rigid and susceptible to overfitting. The complicated features of the gas production mechanism, the small quantity of sample data, and the low dimensionality of the sample data, along with the transformer failure, were a problem. The above-mentioned single machine learning method's performance in diagnosing transformer faults is mediocre because it is unable to completely uncover the relationship between the transformer fault gas data. Due to its limited ability to properly uncover the connection between the transformer fault gas data, the aforementioned single machine learning algorithm performs only mediocrely in the diagnosis of transformer faults.

In order to solve this issue, the whole learning adaboost [14, 15] algorithm builds numerous weak classifiers through numerous repetitions, modifies the weight of the samples used in the next-generation classifier in accordance with the classification outcomes, performs deep mining on the samples by giving each sample a different weight, and finally weights voting to produce a strong classifier for the diagnosis of transformer faults. Zhou and coworkers [16–18] used decision tree algorithms, utmost learning machines, cloud diagnosis models, and other weak classifiers before using the AdaBoost approach to identify transformer faults. Although the AdaBoost method increases sample diversity because there are fewer fault samples from large oil-immersed transformers, the accuracy of cloud models, decision trees, and other algorithms is correlated with the number of training samples. However, setting SVM hyperparameters necessitates prior empirical knowledge, and choosing the best hyperparameters is still a challenge. open question in allied scientific domains. Zhang [8] set the SVM hyperparameters using the enhanced krill algorithm and genetic algorithm and got good results. Hyperparameter accuracy and optimization efficiency still need to be improved. In order to improve the core parameters and penalty factors of the SVM, this research suggests an IPSO. In order to improve the SVM's classification performance, it integrates the AdaBoost technique with SVM to produce numerous IPSO SVM poor classifiers through repetitions. Additionally, it conducts in-depth mining of transformer fault data.

2. OIL-IMMERSED TRANSFORMER FAULT DIAGNOSIS MODEL

SVM is used as a poor classifier to pre-classify data about transformer faults. The complicated gas generation method of transformer failure data makes it hard to have a positive impact, though. As a way to improve SVM, we employ the AdaBoost algorithm. The underlying idea behind the Multiple weak classifiers are trained using the AdaBoost algorithm, and each classifier is given a weight. A strong classifier is created by combining the classification outcomes from each classifier and weighting them. How to fully train each weak classifier and distribute weights to it is the key to this algorithm.

Adaboost Algorithm

AdaBoost learns the first weak classifier by giving the training samples starting weights. After training, in order to give misclassified data more consideration, the sample weights are continuously altered based on the classification results of the weak classifier samples. Finally, the sample weights are changed in accordance with the overall weak classifier findings. In order to adapt the training procedure for the weak classifier and train each classifier individually in order to create the strong classifier, the weight of the weak classifier is adjusted using the test mistake. The strong classifier is then created using the final weak classifier weight. When there are n training examples, for a binary classification model with T weak classifiers, the strong classifier generated by integration is:

$$F(x) = sign(f(x)) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right) \qquad (1)$$

The weak classifier's weight, denoted by the symbol t, and classification outcome, denoted by the symbol ht (x), are both included in the formula.

Weak Classifier Model Based on SVM Algorithm

A tiny sample size, a challenging gas collection process, and a complex gas production mechanism characterize the transformer fault data. Neural networks are an example of a multi-layer machine learning technique that has produced successful outcomes in many different domains. On small samples of multidimensional data, SVM has a strong classification impact. however, they still require a lot of sample data and are not appropriate for diagnosing transformer faults. In Figure 1, the SVM weak classifier-based AdaBoost method model is depicted.

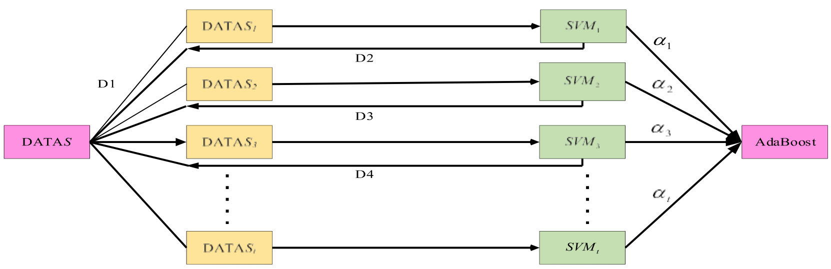

Figure 1. AdaBoost design

Transformer fault detection is a two-class issue that can be classified in a linear, indivisible manner using standard SVM. The nonlinear, multi-class change of SVM is therefore required. To maximize classification, SVM seeks a hyperplane. In order to ensure that the classification is accurate, it ensures that each sample point can be adequately removed from the hyperplane. As a result, the following is the goal function of the SVM nonlinear model:

$$\min \phi(\omega, \xi) = \frac{1}{2}\|\omega\|^2 + c\sum_{i=1}^{l}\xi_i$$
$$s.t. \begin{cases} y_i\left[\omega^T\varphi(x_i) + \lambda\right] \geq 1 - \xi_i \\ \xi_i \geq 0, \quad i = 1, 2, \ldots, l \end{cases} \qquad (2)$$

3. BASED ON AN IMPROVED PARTICLE SWARM ALGORITHM, PARAMETER OPTIMIZATION OF WEAK CLASSIFIER

The accuracy using SVM classification is influenced by the parameter choices made. The essence of SVM model optimization is choosing Some parameters that are appropriate from a wide range. The SVM parameters are optimized in this paper to create the model IPSO-SVM using the Improved Optimization Using Particle Swarm (IPSO) algorithm.

The individual extremum of each particle in the classic optimization using a swarm of particles technique is recorded and shared with the other particles in the entire swarm of tiny particles. Every particle looks for the best an answer in the space of optimization separately. The current global optimal solution for the complete swarm of particles is considered to be each person's extremity with what is best in class. The search capability of the method is unstable during the optimization process, making it simple to reach the regionally optimal. Finding the ideal solution frequently necessitates several iterations. The inertia weight affects how well it can search. The capacity to perform a global search is stronger when the value is higher, and the ability to perform a local search is stronger when the value is smaller. The disadvantages of the conventional particle swarm optimization quantitative inertia weight is enhanced to a time-changing inertia weight, and by utilizing the linearly varying weight, the inertia weight is reduced linearly from the greatest value to the minimum value. This improves the accuracy of the area under search now and speeds up algorithm convergence.

4. FEATURE VECTOR SELECTION

CO, CO2, H2, CH4, C2H6, C2H4, and C2H2 are all present within the oil -immersed transformer's DGA data. Making a decision eigenvector is also crucial in order to minimize the impact of data mistake on diagnosis accuracy. The typical gases created by overheating problem include CH4 and C2H6, which is the sum of typically more than 80% of all hydrocarbons [21, 22] are found in this compound., according to condition-based maintenance for the power grid's equipment requirements and practical expertise. The fraction of C2H6 will increase the temperature at the point of failure rises. When the temperature is below 200 C, C2H2 often won't be created [23].

When the temperature is below 500 °C, the amount of C2H2 in the total hydrocarbon does not exceed 2%. When the temperature is severely elevated, the C2H2 content does not rise above 6%. In addition to the aforementioned gases, a significant amount of CO and CO2 are also created when a Solid insulating material are involved in the overheat fault. [24], which has a significant impact on the outcomes of identification of the overheat fault. Fault gas generation from high energy discharge is identification of the overheat fault. Fault gas generation from high energy discharge is rapid, the There is a lot of gas, the predominant hydrocarbons in the gas if H2 and C2H2, followed by a significant amount of C2H6 and CH4 [25]. C2H2 typically makes up 20–70% of the total hydrocarbon, while H2 makes up 30–90%. Typically, the information contained in C2H6 in comparison to that of CH4. Low energy discharge faults typically have low overall hydrocarbon contents, with H2 and CH4 making up the majority of them. This is because of the low discharge energy. Although C2H2 will also be formed as the discharge energy density rises, the amount of C2H2 Generally, hydrocarbons are often the smallest percentage is less than 2%. primary distinction c between a fault that discharges high energy and a fault that discharges little energy [25].

The internal problems of transformers are classified into five categories by Low and medium temperature overheating, according DL/T 722-2000 and IEC 60599-2015 (T1-T2), Low energy discharge (D1), high energy discharge (D2), and partial discharge (T3), all of which occur at high temperatures. (PD). Figure 5 illustrates using three dimensions depiction of fault kinds and various DGA indices based on the 419 data sets relating to household transformer faults that were gathered. In the diagram, fault types 1 through 5 correspond to the flaws with the designations PD, D1, D2, T1, T2, and T3. As demonstrates the picture, most discharge faults have very high H2 concentrations, although there are no clear patterns in the visualization diagram's depiction of the distribution of thermal faults. The H2 concentration is a good indicator of the discharge defect, while the CH4 content from an incomplete discharge generally low. The concentrations of various DGA indicators were also visualized in three dimensions by creating distribution maps. C2H6 and C2H2 can accurately measure the temperature range of a thermal fault, and can efficiently differentiate between high-energy discharge and low-energy discharge faults. C2H2 the concentration of C2H4 is higher in high-energy discharge and low-energy discharge faults, while the contents of partial discharge and thermal fault are smaller. is higher in high-energy discharge and low-energy discharge faults. Five of them—H2, CH4, C2H6, C2H4, and C2H2—are chosen as eigenvectors, and the gas concentrations of these five are recorded as C(H2), C(CH4), C(C2H6), C(C2H4) and C(C2H2).

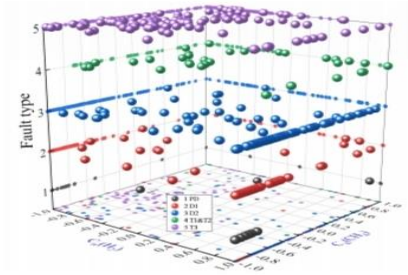

Figure 2. Visualization of Domestic Info

Due to the wide range in gas output, it is required to make the data more consistent and utilize gas concentration that has been normalized as the main feature because it may directly affect the model's ability to diagnose faults.

It is hard to effectively detect defects using only the normalized gas volume concentration indicated above as the data feature, despite the fact that there is a relationship between the different types of gas. In the context of DGA fault diagnosis, petrol fraction ratio is often used to represent more specific feature information. By several experiments and a literature analysis, the traditional ratio strategy is improved, and a unique ratio method is offered. The traditional ratio strategy often involves coding, but the new ratio method only needs the gas concentration ratio. The association between features and fault types can be more clearly demonstrated by the percentage of significant gas in total gas or total hydrocarbon concentration. The aforementioned gases were combined in nine different ratios. The DGA eigenvectors based on the new ratio approach are shown in Table 1. The ratios of the four different carbonaceous gases CH4, C2H2, C2H4, and C2H6 to total hydrocarbon are characteristics 4 through 7, and the three ratios of the three-ratio technique are one of them. The ratio of single gas to total hydrocarbon concentration can more effectively show the relationship between various fault types. For instance, feature 8-9's C2H4 and CH4 concentrations may be able to tell partial discharge faults apart from the other two types of discharge faults.

The type of overheated fault that the transformer is experiencing can also be determined using the percentage content of C2H2. The concentration of H2 is essential for determining all discharge defects. The total concentration of carbonaceous gases is given by Cn (CxHx).

In order to optimize the SVM's hyperparameters, the second part uses both the IPSO algorithm and the global search approach. The sort of transformer data used in the simulation and its source are first described in the simulation experiment's first part. The fourth section combines the AdaBoost algorithm with the SVM optimized by the IPSO algorithm to the final classification model and compares it with the model presented in the literature. The objective is to more effectively utilize the weak classifier SVM's classification abilities. A comparison of the IPSO algorithm and the Grey Wolf Optimizer (GWO) shows that it is superior. In the third section, different input feature vectors are compared to show how superior the improved ratio approaches are.

Example Sample

Problems with transformers can be either internal or external. This article focuses on the five internal problem types that are stated in the IEC 60599-2015 and DL/T 722-2000 regulations. The sample of the calculation example is composed of 117 sets of IECTC10 standard data and 419 sets of transformer failure data that were gathered in China. For the simulation, used to assess and compare AdaBoost, the 117 sets of IECTC10 fault data are divided into 87 training samples and 30 test samples. In order to test the classification ability, fault diagnosis performance, and generalization performance of the diagnosis approach, 419 sets of transformer failure data from China are employed.

SVM Prarmeter Optimization

In order to more clearly highlight the impact of the penalty factors c and kernel parameters g on the accuracy of SVM and to narrow the optimization range of the IPSO algorithm, a global search algorithm is used to optimize the initial range in which the hyperparameters may have optimal solutions. The model diagnosis accuracy rate at different parameters is shown as a curve plane and contour map in Figure 6, with the logarithmic form serving as the coordinate axis. According to the graph, the degree of yellow is inversely connected with both the SVM model diagnosis accuracy rate and the optimization of the SVM parameters. The SVM is less accurate at making diagnoses the more potent the effect and the darker the purple.

The training result is frequently better when the penalty factor is between [23, 210] and [25, 25], as shown in Figure 6. The best value of the kernel parameter is [25, 25]. This region is chosen as the IPSO optimization algorithm's border. The recommended IPSO method is used to precisely optimize the SVM parameters. The following initial values are used during simulation for the IPSO algorithm's parameters: The population size is set to 50, the maximum iterations are set to 50, the learning factors C1 and C2 are set to 1.5 and 1.7, respectively, and the maximum is set to 0.9. The minimum is set to 0.4.

Table 1. Based on an improved ratio technique, DGA characteristics

Number	DGA feature	Number	DGA feature
1	$C_n(C_2H_4)/C_n(C_2H_2)$	8	$C_n(C_2H_4+CH_4)/C_n(C_xH_x)$
2	$C_n(C_2H_4)/C_n(C_2H_6)$	9	$C_n(H_2)/C_n(H_2+C_xH_x)$
3	$C_n(CH_4)/C_n(H_2)$	10	$C_n(CH_4)/C_n(H_2+C_xH_x)$
4	$C_n(CH_4)/C_n(C_xH_x)$	11	$C_n(C_2H_2)/C_n(H_2+C_xH_x)$
5	$C_n(C_2H_2)/C_n(C_xH_x)$	12	$C_n(C_2H_4)/C_n(H_2+C_xH_x)$
6	$C_n(C_2H_4)/C_n(C_xH_x)$	13	$C_n(C_2H6)/C_n(H_2+C_xH_x)$
7	$C_n(C_2H_6)/C_n(C_xH_x)$		

5. SUMMARIZE

In this research, the AdaBoost method is used to enhance the improved particle swarm optimization (IPSO) optimized support vector machine (SVM) transformer failure diagnosis model. Applying the uncoded ratio method to create a new gas combination as the defining parameters of the fault model and establishing an improved ratio method as the input feature vector, one can perform fault diagnosis with domestic transformer data by examining the correlation between the dissolved gas in the transformer oil and the fault type.

Using the IPSO-SVM fault detection model enhanced by the AdaBoost algorithm, the type of transformer fault may be effectively and precisely diagnosed. Comparing it to the traditional SVM and AdaBoost method reveals that it has a higher classification accuracy.

Local optimum and premature convergence are common with the traditional PSO technique throughout the optimization process. The linearly falling weights improve the search performance of the PSO algorithm by substituting the quantitative weights of the conventional PSO method. By contrasting the IPSO approach with the traditional PSO algorithm, the IPSO method's improved search capabilities are shown.

The DGA fault data analysis demonstrates that, when compared to the DGA fault gas data, the suggested improved ratio methodology is substantially more accurate than the conventional ratio method.

6. RESULTS

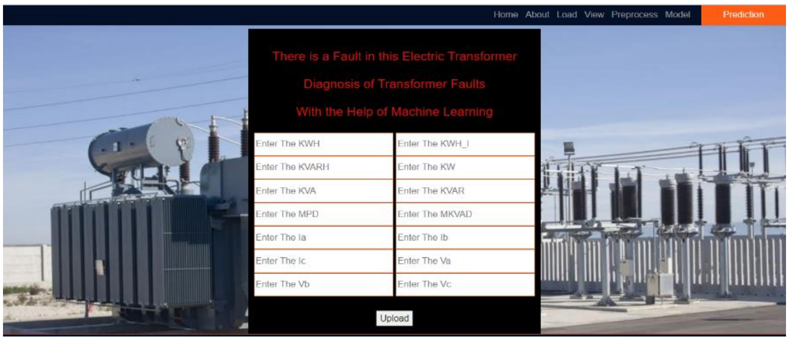

Figure 3. Transformer fault detection

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