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A Power Transformers Fault Diagnosis Model Based on Three DGA Ratios and PSO Optimization SVM

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Abstract. In order to make up for the shortcomings of existing transformer fault diagnosis methods in dissolved gas-in-oil analysis (DGA) feature selection and parameter optimization, a transformer fault diagnosis model based on the three DGA ratios and particle swarm optimization (PSO) optimize support vector machine (SVM) is proposed. Using transforming support vector machine to the nonlinear and multi-classification SVM, establishing the particle swarm optimization to optimize the SVM multi classification model, and conducting transformer fault diagnosis combined with the cross validation principle. The fault diagnosis results show that the average accuracy of test method is better than the standard support vector machine and genetic algorithm support vector machine, and the proposed method can effectively improve the accuracy of transformer fault diagnosis is proved.

1. Introduction

An oil-immersed power transformer is the core equipment for electric energy conversion in the electric power system. A fault in a transformer may result in not only substantial repair cost but also power interruptions to thousands of customers, therefore it is essential to assess its working condition online and detect the potential fault as soon as possible [1].

In the past few years, some monitoring methods, including windings displacement [2] and hot spot temperature [3], were applied to detect faults of oil-immersed power transformers, however DGA is still a more convenient and effective online monitoring method comparing to the above methods [4]. To dig the potential fault law from the gases content, some new fault diagnosis methods, including fuzzy logic [5] and support vector machine (SVM) [6], have been proposed in the recent years. In these methods, SVM is an effective method and is wildly applied in classification problems (fault diagnosis of transformers based on DGA is often considered as a classification problem) [7] because its advantages of small sample learning, global optimization, and structural risk minimization [8]. In general, some parameters have great influence on the performance of support vector machines (SVM), including kernel function, penalty coefficient C and kernel parameter gamma. These parameters are uncertain and should be optimized by artificial intelligence (AI) method. Some AI methods such as ICA, GA, were used to optimize the two parameters in the classification problems and receive a good performance. PSO, firstly put forward by Eberhart and Kennedy in 1995 [9], is an effective AI optimization algorithm for optimizing the SVM parameters because this algorithm has good global convergence solutions and efficient local search ability. Therefore, in this paper, a new support vector machine model based on particle swarm optimization was proposed to find out whether the approach can detect faults of transformers accurately and effectively.
2. Transform SVM and Select Kernel Function

2.1. Selection of DGA Feature
At present, the main methods of transformer fault diagnosis are using all the data of DGA (H\(_2\), CH\(_4\), C\(_2\)H\(_2\), C\(_2\)H\(_4\), CO, CO\(_2\)) or part of DGA data as the characteristic quantity to diagnose faults. Literature [10] indicates that the three ratios of C\(_2\)H\(_2\)/C\(_2\)H\(_4\), CH\(_4\)/H\(_2\) and C\(_2\)H\(_4\)/C\(_2\)H\(_6\) gas ratios are more closely associated with the operation of the transformer. These three ratios are the most representative ratio characteristics. Therefore, this paper uses the three gas ratios as DGA feature pairs for fault diagnosis.

2.2. Transform the Linear SVM to the Nonlinear SVM
In order to solve the following quadratic programming in (1), the concept of SVM is introduced.

\[
\min \Phi(\omega, \xi) = \frac{1}{2} [\omega]^T [\omega] + C \sum_{i=1}^{l} \xi_i \\
\text{s.t.} \begin{cases} 
y_i [\omega^T \varphi(x_i) + b] \geq 1 - \xi_i \\
\xi_i \geq 0, i = 1, 2, \ldots, l
\end{cases}
\]

(1)

In the above formula, \(\xi_i\) is the slack variable and \(C\) is the penalty parameter. Therefore, formula (2) shows the Lagrange function simulation.

\[
L(\omega, b, \xi, \alpha, \beta) = \Phi(\omega, \xi) - \sum_{i=1}^{l} \alpha_i \{ y_i [\omega^T \varphi(x_i) + b] - 1 + \xi_i \} - \sum_{i=1}^{l} \beta_i \xi_i
\]

(2)

In the formula, the Lagrange multiplier is \(\alpha_i\) and \(\beta_i\). The Lagrangian function is transformed to the following quadratic programming (QP) problem (3) with the constraints in (4).

\[
\max \Psi(\alpha) = -\frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j) + \sum_{i=1}^{l} \alpha_i
\]

(3)

\[
f(x) = \text{sign} \left[ \sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b \right]
\]

(4)

In the formula (3), \(K(x_i, x) = \varphi(x_i) \varphi(x)\) represents a kernel function.

At last, the formula (5) represents the nonlinear two-class classifier.

\[
f(x) = \text{sign} \left[ \sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b \right]
\]

(5)

2.3. Transform the Two-Class SVM to the Multiple-Class SVM
The standard SVM is a typical two classification classifier, namely "either this or that, but the transformer fault classification is a multiple-class classification problem. Therefore, it needs to extend the two classification support vector machine to multi classification support vector machine for solving multiple-class classification problems. The OAO (one against one) scheme is a good method [11] for transforming and extending, so the schemes are adopted this method in the next section.

2.4. Establishment of the Optimal Objective Function
After obtaining the model of the nonlinear-multiple classification SVM, the selection of kernel function of SVM is important for establishing the optimal objective function. The RBF is a real valued function that depends only on the specific value of the distance. The RBF kernel function, shown in equation (6), is effective and needs less parameters setting, so it is used in the paper.
\[
K(x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2), \gamma > 0 \tag{6}
\]

In formula (6), \(\gamma\) is a free parameter in the RBF kernel function and it is inversely proportional to the width of RBF. This parameter needs to be optimized, and the punishment coefficient \(C\) for support vector machines also needs to be optimized. This paper intends to optimize these two parameters through the particle swarm optimization. Combining the RBF kernel functions with SVM, we can build the RBF-SVR model. The structure of RBF-SVR is shown in Fig. 1.

3. The Particle Swarm Optimization Optimizes the SVM Parameter

The particle swarm optimization (PSO) is a popular population-based heuristic algorithm that simulates the social behavior of individuals such as birds flocking, a school of fish swimming or a colony of ants moving to a potential position to achieve particular objectives in a multidimensional space. PSO is found to have the extensive capability of global optimization for its simple concept, easy implementation, scalability, robustness, and fast convergence [12].

PSO is mathematically modeled as follows:

\[
v_{sd}(t+1) = v_{sd}(t) + c_1(t)r_1(t)(p_{sd}(t) - x_{sd}(t)) + c_2(t)r_2(t)(p_{sd}(t) - x_{sd}(t)) \tag{7}
\]

\[
x_{sd}(t+1) = x_{sd}(t) + v_{sd}(t+1) \tag{8}
\]

In Equations (7) and (8) above, \(t\) is the number of generations; The random variable \(t\) is subject to a uniform distribution in the \((0, 1)\) interval; \(c_1(t)\) and \(c_2(t)\) is the acceleration constant; \(x_{sd}(t)\) is the position of the \(s\) particle for the \(t\) generation; \(p_{sd}(t)\) is the optimal location for all particles in the \(t\) generation.

The flow of PSO for parameters optimization can described as follows [13]:

1. Initialize the parameters of SVM;
2. A group of initial particles are randomly generated within the range of parameters, and the prediction error of SVM is chosen as the fitness value;
3. Update the individual fitness values and global fitness values of particles;
4. Update the position and speed of particles;
5. Determine if the termination condition is satisfied. If meeting the accuracy requirements or achieving the maximum number of iterations, end the operation, otherwise, continue to perform. Fig. 2 is the flow chart of PSO-SVM fault diagnosis.

**Figure 1.** Structure diagram of RBF-SVR model.

**Figure 2.** Flow chart of PSO-SVM fault diagnosis.
4. Fault Diagnosis of Power Transformers Based on PSOSVM
This paper collects DGA data from IEC TC 10. The data contains 118 samples, which matched with five diagnosis types, i.e. low-energy discharge, high-energy discharge, thermal fault of low and medium temperature, thermal fault of high temperature and normal condition.

The 118 samples were randomly divided into the training sample set containing 90 samples and the test sample set containing 28 samples. The input of the classifier is the three ratios of \( \frac{C_2H_2}{C_2H_4} \), \( \frac{CH_4}{H_2} \) and \( \frac{C_2H_4}{C_2H_6} \) gas ratios. All input data were normalized in the range of [0 1] before training to improve the generalization performance of SVM.

The target of PSO is to realize the process of the optimization of the parameters. When the candidate parameters \( C \) and \( \gamma \) are set, they vary in the range of two fixed ranges, \([10^5 10^7]\) and \([10^{-2} 10^2]\), respectively. The parameters of the PSO algorithm used in this paper are as follows: the number of populations and the number of initial particles were fixed to 30 and 8, respectively; the dimension of the optimized function was set to 2; the maximum number of generations was 10.

The Variation curves of PSO fitness are shown in Fig. 3. At last, the optimal parameters of the multi class support vector machine classifier based on PSO algorithm are \( C = 504.0727 \), \( \gamma = 4.2139 \).

According to the selected two parameters, the OAO-nonlinear multiple classification SVM classifier is trained and applied for fault diagnosis of transformers. Fig. 4 shows the testing results of 28 samples for fault diagnosis. Apparently, only 4 samples were classified incorrectly and the classification accuracy of test samples hit 85.71% (24/28). The possible reason of the error may be that the four cases are bad data with measuring error.

**Figure 3.** Variation curves of PSO fitness.  
**Figure 4.** Classification accuracy of testing samples.

In order to compare with other fault diagnosis methods, the standard SVM, GA-SVM and the method of this paper are used to do the fault diagnosis experiments respectively.

| Methods  | Accuracy  |  |  |  |  |  |
|----------|-----------|  |  |  |  |  |
| SVM      | 72.22%    | 57.14%    |  |  |  |  |
| GA-SVM   | 80.00%    | 60.71%    |  |  |  |  |
| This paper | 81.15%    | 85.71%    |  |  |  |  |

In order to compare with other fault diagnosis methods, the standard SVM, particle swarm optimization support vector machines (SVM) and the method of this paper are used to do the fault diagnosis experiments respectively.

5. Conclusion
A novel method combing particle swarm optimization with SVM for fault diagnosis of oil-immersed transformers is proposed in this paper. It is shown that the proposed method can provide the high accuracy fault diagnosis model of the transformer oil-dissolved gases on the basis of the field test results. The method could be served as an effective tool for the assessments of transformer condition. Conclusions can be summarized as follows:

Three classification approaches were studied for fault diagnosis of transformers. The classification accuracy of the three approaches, including SVM, GASVM and PSOSVM, reaches 57.14%, 60.71%, 85.71%, respectively. The comparing results demonstrate that the proposed PSOSVM approach has better performance than the other two approaches.

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