Application of Particle Swarm Optimization Algorithm in Power Transformer Fault Diagnosis

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Abstract. Fault diagnosis of power transformer is indispensable for power system reliability. To improve the function of fault diagnosis and overcome the “code absence” problem of the traditional ratio method, this paper presents a novel approach for oil chromatographic fault diagnosis based on particle swarm optimization algorithm. The PSO algorithm is used to obtain the optimal three-ratio value that can best represent various fault types of power transformers, and then the change trend of the characteristic gas of the power transformer is analyzed to predict the possible faults. Combining the stereogram method and the optimal three-ratio method, A comprehensive fault diagnosis method for based on oil chromatographic distraction is obtained. In the end, simulation of the actual oil chromatographic data of the transformer verifies the accuracy and effectiveness of the proposed method.

Keywords: Power transformer; Fault diagnosis; PSO; Oil chromatographic analysis.

1. Introduction
The stable operation of the power transformer is indispensable for the entire power system. When the transformer equipment fails or is abnormal, it is necessary to discover the failure in time and determine the location and cause of the failure.

In engineering practice, an effective method used to determine whether a transformer fault occurs is dissolved gas analysis (DGA) [3-5]. The three-ratio is a widely used DGA method that uses the generational rate of gas to determine fault types. However, the ratio method has some limitations, such as codes absence, inaccurate diagnosis and lack of formulation. therefore, artificial intelligence technologies such as support vector machines [6-8], fuzzy clustering [9,10], neural network algorithms [11], and particle swarm optimization [12-14] are used to adjust parameters and further improve the performance of fault diagnosis capabilities in power transformer. The principle of particle swarm algorithm is relatively simple, few parameters to be set, and easy to achieve through programming. Therefore, this paper uses particle swarm optimization algorithm to calculate the optimal three-ratio of transformer faults, and finally obtains a comprehensive fault diagnosis model of transformer based on PSO algorithm.
2. Basic PSO Algorithm
Set a swarm composed of \( n \) particles in D-dimensional space. The position and velocity of the particle \( i \) in D-dimensional space is \( x_i \) and \( v_i \).

\[
x_i = (x_{i1}, \ldots, x_{id}, \ldots, x_{iD}) \quad 1 \leq i \leq n, 1 \leq d \leq D
\]

\[
v_i = (v_{i1}, \ldots, v_{id}, \ldots, v_{iD}) \quad 1 \leq i \leq n, 1 \leq d \leq D
\]

The best position of particle \( i \) in the solution space as \( P_i = (p_{i1}, p_{i2}, \ldots, p_{id}) \), and the optimal position of the particle swarm is \( P_g = (p_{g1}, p_{g2}, \ldots, p_{gd}) \). The evolution equation of the particle swarm:

\[
v_{id}^{k+1} = w v_{id}^{k} + c_1 r_1 (P_{id}^k - x_{id}^k) + c_2 r_2 (P_{gd}^k - x_{id}^k)
\]

\[
x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}
\]

Parameters \( c_1 \) and \( c_2 \) are nonnegative learning factors, \( w \) is inertia weight vector, \( r_1 \) and \( r_2 \) are random variables with the scope of zero to one, \( k \) is the iteration. The range of the \( d \) particle position and velocity are \([\, \text{dMIN}_d, \, \text{dMAX}_d\,]\) and \([\, \text{vMIN}_d, \, \text{vMAX}_d\,]\).

3. Optimal Three-ratio Based on PSO Algorithm
Set the sample as a consisting of 1 dimensional vector \( Y_i \), \( Y = \{Y_i; i=1, 2, \ldots, n\} \), and perform sample \( Y \) according to the fault type \( C = \{C_1, C_2, \ldots, C_m\} \).

\[
Y = \bigcup_{i=1}^{m} C_i
\]

The total inter-class discrete sum:

\[
J_c = \sum_{i=1}^{m} \sum_{Z_k \in C_i} d(Y_i, Z_k)
\]

In the above equation, \( Z_k \) is the center of the \( k \) cluster, \( d(Y_i, Z_k) \) is the distance from the sample to the cluster center, and \( J_c \) is the sum of the distances from all samples to the corresponding cluster center:

\[
d(Y_i, Z_k) = \sqrt{\sum_{j=1}^{n} (Y_{ij} - Z_{kj})^2}
\]

The smaller the \( J_c \) value, the more the corresponding cluster center can represent fault type. The specific process of finding various faults through particle swarm optimization is shown in Figure 1.
4. Comprehensive Diagnostic Method of Oil Chromatography

4.1. Analysis of Gas Change Rate

The generational rate of gas is related to the temperature of fault point and the energy consumption of the fault when a transformer fails. If only the absolute value of the characteristic gas is analyzed, it is difficult to correctly determine the severity of the fault. Therefore, it is necessary to consider the gas production rate of the characteristic gas when analyzing the fault. The average value of the characteristic gas $x$ per operation day is the absolute gas generation rate of the gas $γ_x$:

$$γ_x = \frac{(C_{x2} - C_{x1}) \cdot m}{\Delta t \cdot \rho}$$  \hspace{1cm} (8)

Where $C_{x1}$, $C_{x2}$ are the concentrations of the gas $x$ measured in the first and second sampling; $m$ is the total oil quantity of the equipment; $\Delta t$ is the operating time in the sampling; and $\rho$ is the density of the oil.

The alert values of the characteristic gas generation rate are shown in Table 1.

| Types | Open Type | Diaphragm Type |
|-------|-----------|----------------|
| THC   | 6         | 12             |
| C₂H₂  | 0.1       | 0.2            |
| H₂    | 5         | 10             |

Table 1. Alert value for absolute gas generation rate.
The content of various characteristic gases on the n day is predicted by the gas generation rate. The gas content $C^n_x$ of the characteristic gas $x$ on the n day is:

$$C^n_x = C_x + (1 + \gamma_x)^n$$

Where $C_x$ is the last measured concentration of the characteristic gas $x$ in the transformer oil measured.

The content of various characteristic gases can be predicted, and the transformer can be predicted according to the oil chromatography analysis method.

### 4.2. Oil Chromatography Based on PSO Algorithm

The power transformer fault diagnosis can be combined into four types: medium and low temperature overheating, high temperature overheating, low energy discharge, and high energy discharge. The steps for comprehensive diagnosis of transformer oil chromatography based on the PSO algorithm are as follows:

- **Step 1:** Calculate the characteristic gas dissolution rate in the transformer oil. If it exceeds the value, it means that the transformer is faulty.
- **Step 2:** The PSO algorithm is used to calculate the optimal three ratios of the four types of faults in the transformer.
- **Step 3:** For the analysis of transformer oil chromatography, first use the stereogram method. If the failure cannot be judged due to the "code absence" problem, then use the improved three-ratio method to re-analyze.
- **Step 4:** When the improved three-ratio method cannot judge a fault due to "code absence", the distances of the three three-ratio samples to the various optimal three-ratio values are calculated respectively, and the fault type corresponding to the optimal three-ratio with the smallest distance is selected.
- **Step 5:** Calculate the gas generation rate of the characteristic gas in the oil, analyze the severity of the transformer failure, predict the possible failure of the transformer, and take corresponding protective measures.
- **Step 6:** When the oil chromatogram judges that it is a thermal fault, and the DC resistance of the three-phase winding is unbalanced, it can be judged that the wire cake is broken. If the current of the core ground wire exceeds the standard, or the core-to-earth insulation is reduced, then the core-to-ground fault; if the DC resistance of the winding exceeds the standard, the joint is not well welded and the conductive area is small.

### 5. Verification

This paper uses collected oil chromatographic data that has proven to be faulty and fully reflects the type of transformer faults, and verifies the accuracy and effectiveness of the proposed method for transformer fault diagnosis through simulation calculations. In the particle swarm optimization algorithm, the inertia weight $w$ is 0.729, the learning factor $c_1$ and $c_2$ are set to 1.4962, the number of iterations is 1000, and the number of individuals in the population is 30. The optimal three ratios of the four kinds of faults obtained by the PSO algorithm are shown in Table 2. The results of sexual verification are shown in Table 3.

| Fault types                      | $C_2H_2/C_2H_4$ | $C_2H_4/C_2H_6$ | $CH_4/H_2$ |
|---------------------------------|-----------------|-----------------|------------|
| Low energy discharge            | 1.055           | 0.333           | 6.404      |
| High energy discharge           | 0.790           | 0.393           | 8.1124     |
| Medium and low temperature      | 0.040           | 2.587           | 3.716      |
| overheating                     |                 |                 |            |
| High temperature overheating    | 0.011           | 1.913           | 5.067      |
Table 3. Algorithm validation results.

| No. | H₂ | CH₄ | C₂H₆ | C₂H₄ | C₂H₂ | The code of three-ratio | PSO triple ratio | Real Fault |
|-----|----|-----|------|------|------|------------------------|-----------------|------------|
| 1   | 58 | 290 | 373  | 149  | 0    | Medium temperature     | Medium temperature | Partial iron core heating |
| 2   | 93 | 58  | 37   | 43   | 0    | None code              | Medium temperature | The upper yoke are grounded |
| 3   | 160| 130 | 96   | 33   | 0    | Low temperature        | Low temperature   | Short circuits between some core silicon steel sheets |
| 4   | 2300| 0   | 5    | 116  | 0    | Partial discharge      | Partial discharge | The capacitor core is loosely rolled, and many steam drums between paper layers. |
| 5   | 1565| 93  | 47   | 34   | 0    | None code              | Partial discharge | Loose insulation partition between clamp and pressure pole |
| 6   | 130| 270 | 500  | 67   | 3    | High temperature       | Medium temperature | The positioning pin is not turned over and has a melting point |
| 7   | 180| 180 | 4    | 74   | 3    | Arc discharge and overheating | Arc discharge and overheating | Interver short circuit |
| 8   | 4824| 29272| 16647| 5052 | 3.5  | High temperature       | High temperature  | Partial short-circuit fault |
| 9   | 180| 175 | 50   | 75   | 4    | Low temperature        | Low temperature   | Poor contact of the tap-changer |
| 10  | 60 | 139 | 430  | 21   | 4.6  | High temperature       | High temperature  | Two points of the iron core are grounded to generate circulating currents and cause high temperature heat |
| 11  | 610| 1200| 1800 | 300  | 6    | High temperature       | High temperature  | Neutral lead has overheating |
| 12  | 259| 863 | 994  | 393  | 6    | Medium temperature     | Medium temperature | Low temperature bushing conductive rod and nut pad overheating, visible heat traces |
| 13  | 73 | 520 | 1230 | 140  | 7    | High temperature       | High temperature  | The iron pallet is short-circuited to the iron core and has a melting point |
| 14  | 135| 466 | 502  | 70   | 9    | High temperature       | High temperature  | High-voltage B-phase tap-changer burned out |
| 15  | 56 | 13  | 2.4  | 22   | 22.13 | Arc discharge           | Arc discharge     | W-phase 4-layer enclosures have traces of creepage |
| 16  | 218| 195 | 217  | 35   | 33   | Arc discharge           | Arc discharge     | Obvious discharge marks between the high-voltage and the low-voltage winding |
| 17  | 500| 4400| 5590 | 500  | 34   | High temperature       | High temperature  | The primary circuit changes the pressure ratio, the joint nut is loose, and the nut and the piece are melted |
| 18  | 170| 24  | 17   | 7    | 54   | Low energy discharge   | Low energy discharge | High-voltage lead discharges the sleeve conductive tube |
| 19  | 980| 73  | 12   | 0    | 58   | Partial discharge      | Partial discharge | The bushing is not grounded |
| 20  | 80 | 20  | 20   | 6    | 62   | Low energy discharge   | Low energy discharge | Bare lead discharges to sleeve conductive tube |
| 21  | 60 | 40  | 110  | 10   | 70   | Arc discharge           | Arc discharge     | The tap-changer has an arc |
| 22  | 707| 115 | 55   | 11   | 81   | Arc discharge           | Arc discharge     | Scorched insulation paper partially scattered on the bottom of the box |
As the table shown, the accuracy of the optimal three-ratio based on particle swarm proposed in this paper is higher, which is in line with the situation of on-site maintenance confirmation such as hanging hoods, and can well compensate for the defects such as "code absence" of improved three-ratio.

6. Conclusion
This paper focuses on fault diagnosis methods of transformers analyzed by oil chromatography. The PSO optimization algorithm is used to calculate the optimal three-ratio value that can best represent various fault types of power transformers, and then the rate of change of the characteristic gas of the power transformer is analyzed to predict the possible failures. Combining the stereogram method and the optimal three-ratio method, A comprehensive DGA method for power transformers based on oil chromatography analysis was obtained. Finally, by simulating the actual oil chromatographic data of the transformer, it can be seen from the simulation results that the method proposed in this paper can improve the accuracy of fault judgment and overcome the "code absence" problem of the traditional ratio method, which can be used for engineering transformer fault diagnosis in practice.

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