DIAGNOSIS OF TRANSFORMER FAULTS USING FEATURE EXTRACTION AND AUTOMATIC DIVISION BASED FUZZY CLUSTERING

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Abstract - Power transformer which has an important influence on the entire power transmission system is related to the safety and stability of the entire power system. However, transformer may fail if it works for a long time. In order to improve the accuracy of fault diagnosis and guarantee system security, an optimal fuzzy clustering method was put forward to diagnose faults. The relationships between characteristic gas in power transformer oil and different fault types were analyzed, and fuzzy clustering was optimized to improve the algorithm convergence speed. It was found that the accuracy of fault diagnosis based on analysis using optimal fuzzy clustering algorithm was 92.23%, suggesting an increase of 23.3% compared to the traditional gas feature based fault diagnosis. The method can accurately diagnose faults of power transformers and ensure the stability of electric system.

Keywords: Power transformer, Feature extraction, Fuzzy clustering, Fault diagnosis.

1. Introduction

With the development of social economic level and science technology, demands of different industries on electric power are increasing, which puts new requirements on electric power system. The power transformer plays a vital role in the whole power system, and it is a necessary factor for the effective operation of power system. Failure of power transformer will cause considerable economic impact on the operation of power grid [1,2].

Power transformer failure will cause huge cost; therefore, an effective transformer fault diagnosis method is of great significances to the stable and safe operation of power system. In the study of Abu-Siada et al. [3], a online technology which could detect power transformer faults through establishing voltage-current track diagram to solve the problem of dependence of frequency response analysis on experts. Seifeddine et al. [4] put forward an intelligent fault classification based power transformer dissolved gas analysis. Power transformer faults were classified using neural network, and it was verified being able to significantly improve transformer faults diagnosis preciseness. In the study of Yang et al. [5], the application of artificial intelligent system in the diagnosis of transformer faults was introduced, and it was verified being accurate in diagnosing transformer faults. Zheng R. et al. [6] put forward a two-stage classifier cascaded power transformer fault diagnosis algorithm for the single-power and multi-power transformer fault diagnosis. The experiment suggested that it could enhance the accuracy of transformer fault diagnosis. Xiang et al. [7] applied back-propagation (BP) neural network algorithm in the diagnosis of transformer faults and enhanced the accuracy of network training through optimizing the search direction of BP neural network. Examples were demonstrated to verify that the method could effectively diagnose transformer fault. Li et al. [8] put forward a weighted fuzzy kernel clustering based power transformer fault diagnosis method and verified its accuracy through experiments. In this study, the features of gas in power transformer oil were extracted, and the fuzzy clustering algorithm was optimized to enhance its accuracy. The optimized method was compared with the traditional fault diagnosis method to verify its effectiveness.

2. Analysis of Gas in Power Transformer Oil and Fault Diagnosis

Power transformer mostly has an oil-immersed structure, and its insulativity depends on insulating oil and insulation paper. Due to long-time operation, transformer oil is decomposed and aged under the influence of electricity and heat and generates low-molecular hydrocarbon gas, CO and CO2. Those gases were dissolved in transformer oil. The emergence of these gases is the inevitable result of transformer operation. If the transformer fault lasts for a long time, the gas produced by the thermal decomposition will be fused with the transformer oil, and the rest will rise up and swap out N2 and O2 dissolved in the oil. In the case of sudden transformer failure, the bubbles with relatively large volume flow fast in the oil; as a result the gases are separated out, and a large number of bubbles generate and enter into the oil storage tank and replay of transformer, leading to gas alarming or trip.

The gases in transformer include air, gases generated during normal operation and gases generated during failure. When transformer fails, chemical groups such as CH3, Ch2 and CH and carbon-carbon bond in transformer oil molecules are damaged under the influence of electricity and heat, and hydrocarbon chemical bond breaks. Moreover the generated free radicals recombine to be hydrogen and some low-module hydrocarbon gases.

The changes of gas are different under the influence of temperature. Alkane will be thoroughly decomposed to low-module hydrocarbon when the temperature is 300 C during failure. With the increase of the temperature, olefin, aromatic hydrocarbon and cycloalkanes are decomposed. Different temperature during failure will lead to different categories of hydrocarbon gases in the oil.
Transformer faults roughly include overheating fault, high energy discharge fault and spark discharge fault, which are correlated to the content of dissolved gases in the oil. Therefore analyzing the dissolved gases in the oil can help determination on transformer faults. Dissolved gas analysis is one of the common methods currently [10].

3. Feature Extraction Method

The dissolved gases in the transformer oil contain five kinds of characteristic gases. Different content of gases indicate different transformer faults. Moreover there is non-linear coupling relationship between different gases. Therefore feature extraction can help find out abnormal data for further identification in fault diagnosis. In this study, an improved kernel principal component analysis was put forward to analyze sample data.

Suppose sample data as $X = \{x_1, x_2, x_3, \cdots x_N\}$ and $y = W^T\lambda$, then $u = Wy$

was the reconstruction signal of original sample data X, i.e. $e = x - u$. Then the error reconstruction function of sample data is:

$$J(W) = E\|x-u\|^2 = \frac{1}{N}\sum_{i=1}^{N}\left\|x_i - WW^T x_i\right\|^2 \tag{1}$$

The optimization of error reconstruction function aimed at reducing signal loss after dimensionality reduction of sample data. Therefore the minimum error reconstruction function J(W) meant that W was equivalent to the Principal Components Analysis subspace of input sample data X, i.e. the principle component of X. Therefore reconstruction of error function could be used for determining whether random sample data were outliers.

Here space was input, and the abnormal value of space was identified using the given threshold ε >0.

$$e(x_i) = \left\|x_i - WW^T x_i\right\|^2 > \varepsilon \tag{2}$$

The existence of abnormal value in the data set which was obtained by mapping sample data set to high-dimensional space via kernel principle component analysis was determined using the minimum error principle of characteristic space signal reconstruction. The data set in high-dimensional space $\Phi(x)$ was substituted to equation (2), then we have

$$e(\Phi(x_i)) = \left\|\Phi(x_i) - WW^T\Phi(x_i)\right\|^2 \tag{3}$$

In equation (3), the form of non-linear function $\Phi(x_i)$ is unknown; hence error reconstruction could not be performed directly. Thus equation (3) was expanded after squaring, and moreover kernel function $K(x_i, x_j) = \Phi(x_i)\cdot\Phi(x_j)$ was introduced.

The result was as follows.

$$\begin{aligned} e(\Phi(x_i)) &= \Phi(x_i)\Phi(x_j) - 2WW^T\Phi(x_i)\Phi(x_j) + (WW^T)(WW^T)\Phi(x_j)\Phi(x_i) \\ &= K(x_i, x_j) - 2WW^T K(x_i, x_j) + (WW^T)^2 K(x_i, x_j) \end{aligned} \tag{4}$$

The value of reconstruction error could be calculated, and the outliner could be determined using equation (4).

4. The Basis of Fuzzy Clustering Theory

Clustering analysis can divided data objects into different groups in which objects were highly similar with the objects in the same group and highly dissimilar with the objects in other groups.

In actual problems, there are usually fuzzy boundaries or overlapping between sample data. Therefore fuzzy clustering analysis is needed.

Fuzzy c-means is a common kind of fuzzy clustering algorithm. Suppose there was a clustering sample set $x_k \in R^s(k = 1,2,3,\ldots, N)$, in which s stands for the feature dimension of the samples and c stands for the number of categories of the samples.

Then an intra-class weighed error quadratic sum could be found as target function.

$$J_m(U,V)=\sum_{i=1}^{c}\sum_{j=1}^{N}(u_{ij})^m(d_{ij})^2 \tag{5}$$

where $U=[u_{ij}]$ is fuzzy membership matrix, $u_{ij}\in[0,1]$ stands for the fuzzy membership of j-th data to i-th class, $V=[v_1,v_2,\cdots,v_c]$ is clustering center matrix, $m\in[1,\infty]$ stands for smoothing parameter, usually between 1.5 and 5, and d_{ij} stands for the distance between x_j and v_i.

Suppose the partial derivative of J_m with respect to v_i and u_{ij} as 0, then the iterative formulas of the membership degree and clustering center were as follows.

$$u_{ij}=\left(\frac{d_{ij}^2}{\sum_{k=1}^{c}d_{kj}^2}\right)^{-\frac{1}{m-1}} \tag{6}$$

$$v_i=\sum_{j=1}^{N}u_{ij}^m x_j \Big/ \sum_{j=1}^{N}u_{ij}^m \tag{7}$$

The detailed procedures of the algorithm were as follows.

Firstly clustering number c, smoothing parameter m and iterative stopping error ε were given. Then clustering center v_i was initialized. Finally the iterative operation was performed according to formula (6) and (7) until $\|v_i(k)-v_i(k-1)\|\le\varepsilon$.

5. The Optimized Fuzzy Clustering Algorithm

To overcome the disturbance of noise, a kernel function based dot density weighed fuzzy clustering algorithm was put forward. The dot density of every sample point X_i was defined as:

$$f_i=\sum_{j=1,j\ne i}^{N}\frac{1}{d_{ij}} \tag{8}$$

where $d_{ij}=\|x_i-x_j\|$, i.e. the Euclidean distance between two sample points. The weight of every point could be obtained by normalizing f_i.

$$w_i=\frac{f_i}{\sum_{j=1}^{N}f_j} \qquad 1\le i\le N \tag{9}$$

The iterative formulas of the membership degree and clustering center of dot center weighted fuzzy c-means were as follows.

$$u_{ij}=\left(d_{ij}^2 \Big/ \sum_{k=1}^{c}d_{jk}^2\right)^{-\frac{1}{m-1}} \tag{10}$$

$$v_i=\left(\sum_{j=1}^{N}w_j u_{ij}^m x_j\right)\Big/\left(\sum_{j=1}^{N}w_j u_{ij}^m\right) \tag{11}$$

Gaussian kernel function was introduced to the algorithm.

$$k(x,y)=\exp\left(-\frac{\|x-y\|^2}{2\delta^2}\right) \tag{12}$$

where δ stands for the width of Gaussian function.

The distance between two samples points in the high-dimensional space which applied kernel function was as follows.

$$d_{ij}=K(x_i,x_i)-2K(x_i,x_j)+K(x_j,x_j) \tag{13}$$

Then the computational formula of dot density was:

$$f_i=\sum_{j=1,j\ne i}^{N}\frac{1}{K(x_i,x_i)-2K(x_i,x_j)+K(x_j,x_j)} \tag{14}$$

The concrete realization procedures of the algorithm were as follows.

Firstly the initial clustering number c and initial clustering center v(0) were determined using semi-supervised method. The smoothing parameter and threshold of stopping iteration ε were given.

Next the dot density of the kernel space was obtained using equation (14). Equation (9) was substituted to obtain the feature weight of different dimensions of failure sample set.

The membership degree and clustering centers were updated according to equation (10) and (11).

Procedure 2 and 3 were repeated until $\|v_i(k)-v_i(k-1)\|\le\varepsilon$.

6. Instance Analysis

Five gases H_2, CH_4, C_2H_6, C_2H_4 and C_2H_2 were selected as feature vectors.

The concentrations of the gases in the transformer oil were taken as the sample set of fault diagnosis. Moreover 106 groups of dissolved gas analysis data samples corresponding to the categories of transformer faults were collected, including 17 groups of data in normal state, 16 groups of data corresponding to low-temperature superheat fault, 21 groups of data corresponding to moderate-temperature superheat fault, 24 groups of data corresponding to high-temperature superheat fault, 11 groups of data corresponding to low-energy discharge fault and 17 groups of data corresponding to high-energy discharge fault. To ensure the accuracy of fault diagnosis, the samples were selected in the same form, and the operation environment was also similar. Part of the sample data is as follows.

Table 1 Part of the sample data

Proportion of H_2	Proportion of CH_4	Proportion of C_2H_6	Proportion of C_2H_4	Proportion of C_2H_2	Actual fault
0.50	0.35	0.07	0.06	0.01	Normal
0.41	0.27	0.12	0.11	0.03	Normal
0.56	0.41	0.08	0.02	0	Low-temperature superheat
0.45	0.31	0.12	0.14	0	Low-temperature superheat
0.22	0.35	0.13	0.19	0.06	Moderate-temperature superheat
0.04	0.25	0.06	0.72	0	High-temperature superheat
0.58	0.17	0.05	0.07	0.08	Low-energy discharge
0.46	0.09	0.03	0.21	0.24	High-energy discharge
0.47	0.12	0.04	0.32	0.17	High-energy discharge

Abnormal data among the 106 groups of sample data needed to be eliminated according to the improved kernel principle component analysis based feature extraction. It was found that one group of data corresponding to moderate-temperature superheat fault and two groups of data corresponding to high-temperature superheat fault were abnormal. Classification was performed after the three groups of data were eliminated.

Then clustering analysis was performed on the samples using the optimized fuzzy clustering algorithm. Smoothing parameter m was set as 1.5, the width of Gaussian kernel function was set as 2, and convergence threshold was set as 1×106.

The samples were classified according to the algorithm, and the classification results are shown in Table 2.

Table 2 The classification results of the samples after eliminating of abnormal data

Category of faults	Number of samples	Correctly classified samples	Wrongly classified samples	Accuracy (%)	Overall accuracy (%)
Normal	17	17	0	100	92.23
Low-temperature superheat	16	15	1	93.75	
Moderate-temperature superheat	20	18	2	90.00	
High-temperature overheat	22	20	2	90.91	
Low-energy discharge	11	10	1	90.91	
High-energy discharge	17	15	2	88.24	

Then the three groups of abnormal data were put into the samples, and all the samples were classified in the same way. The results are shown in Table 3.

Table 3 The classification results of the samples without eliminating of abnormal data

Category of fault	Number of samples	Correctly classified samples	Wrongly classified samples	Accuracy (%)	Overall accuracy (%)
N	17	17	0	100	89.62
Low-temperature superheat	16	15	1	93.75	
Moderate-temperature superheat	21	18	3	85.71	
High-temperature superheat	24	20	4	83.33	
Low-energy discharge	11	10	1	90.91	
High-energy discharge	17	15	2	88.24	

Besides the eight groups of samples showed in Table 2, the wrongly classified samples also included a group of data corresponding to moderate-temperature superheat fault and two groups of data corresponding to high-temperature superheat fault, i.e. the three groups of abnormal data which were eliminated by the improved kernel principle component analysis based feature extraction.

Therefore the overall accuracy of the classification of transformer faults decreased to 89.63%, which was 2.61% lower compared to the accuracy of classification after the abnormal data were eliminated.

The existence of abnormal data in samples could cause large impacts on the fault diagnostic results. Therefore the improved kernel principle component analysis based feature extraction is effective for improving the accuracy of fault diagnosis.

Then the samples in which the abnormal data had been eliminated were classified using the traditional fuzzy clustering algorithm and the improved algorithm. The results are shown in Figure 1.

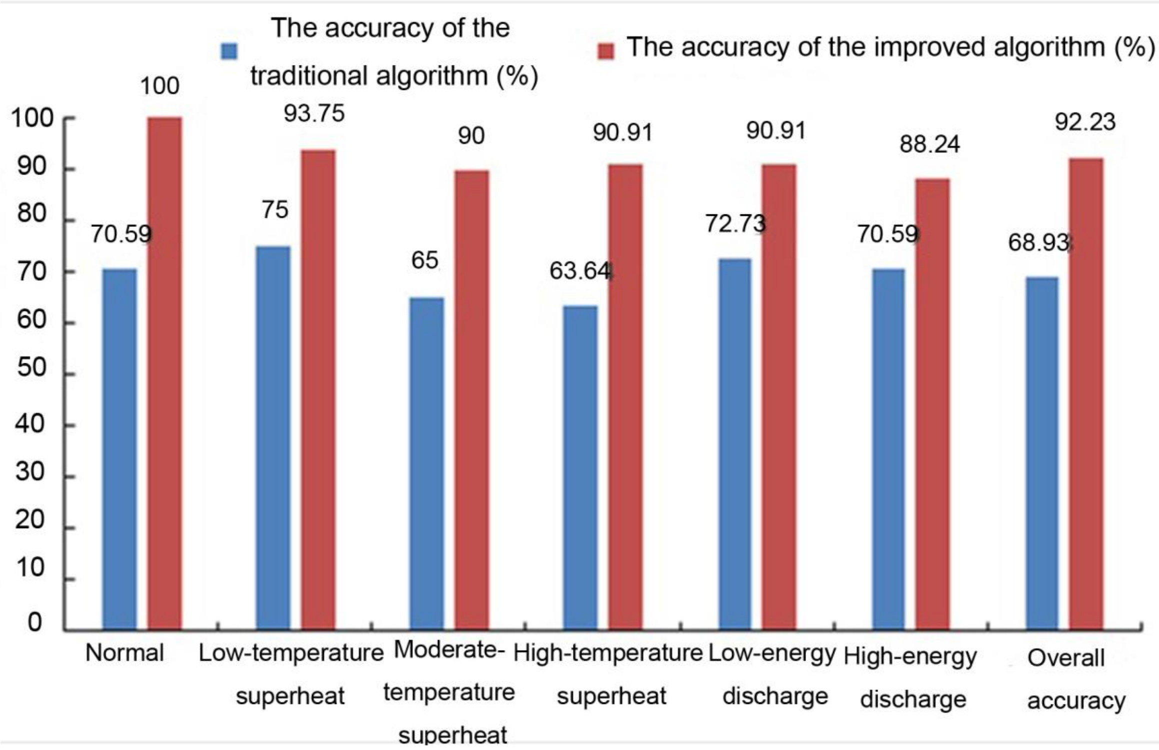

Figure 1: Comparison of accuracy between the traditional and improved algorithms

The comparison suggested that the improved algorithm was more accurate than the traditional algorithm in the classification of transformer classification. The overall accuracy of the improved algorithm was 92.23%, which was higher than 23.3% of the traditional algorithm. The accuracy of the traditional algorithm would be much lower if the abnormal data were not eliminated through feature extraction. The comparison indicated that the fault diagnosis method based on feature extraction and the optimized fuzzy algorithm was effective and highly accurate.

7. Discussion and Conclusion

With the development of industry, electrical equipment failure has increasingly become the focus.

Ensuring the operation of power system is very important. It is urgent to reduce failure of power transformer as one of most important power transformer. More and more methods have been applied in transformer fault diagnosis, and the accuracy has also been improved gradually. Božić et al. [11] put forward a dissolved gas analysis based power transformer fault diagnosis logistic regression method and verified its favorable performance in diagnosing faults. Mani et al. [12] diagnosed several transformer faults with intuitive fuzzy expert system and found that it was effective. In the study of Sahri et al. [13], genetic algorithm was combined with support vector machine, which improved the effect of fault diagnosis. Xiong et al. [14] applied the improved PSO-BP neural network in the diagnosis of power transformer faults and moreover verified the accuracy of the method.

Dissolved gas analysis is one of the effective means for the diagnosis of oil immersible power transformer. Feature extraction is usually used in dissolved gas analysis. The current feature extraction method is poor in processing abnormal values among data, which will cause large impacts on fault diagnosis. In this study, an improved kernel principle component analysis was put forward. After the data was mapped to high-dimensional space nonlinearly, signal reconstruction is performed on feature vectors. Then whether the data was outliers was determined. Abnormal data were eliminated.

The analysis on the sample data using the improved kernel principle component analysis based feature extraction suggested that the accuracy of fault diagnosis was improved after the two groups of abnormal data were eliminated.

After the abnormal data were eliminated, the sample data were identified using fuzzy clustering method. Fuzzy clustering has favorable performance in diagnosing faults and can perform better when combining with other methods, for example, fuzzy c-means in combination with support vector machine [15], fuzzy c-means in combination with artificial immune network [16] and fuzzy c-means in combination with probabilistic neural network [17]. In this study, a kernel function based dot density weighted fuzzy clustering algorithm was put forward. The membership degree was processed by reasonable weighting adjustment during clustering.

The accuracy of the improved diagnostic method was 93.23%, which was much higher than that of the traditional diagnostic method. It indicated that the new method was feasible in the diagnosis of transformer faults. Diagnosis of power transformer faults can help early discovery and treatment of faults to prevent further deterioration. In this study, the gases in the power transformer oil were analyzed, the abnormal data were eliminated through feature extraction, and fuzzy clustering was optimized to enhance the convergence speed.

The results demonstrated that the optimized algorithm performed will in diagnosing transformer faults, and its accuracy was significantly higher than that of the traditional diagnostic method. This work is of great significance to the stable operation of electrical power system.

References

[1] De A R R L, De Azevedo C C, De Sousa R M. “Power Transformer Top Oil Temperature Estimation with GA and PSO Methods,” Energy & Power Engineering, 2012, 4(1):41-46.

[2] Barbosa D, Netto U C, Coury D V, Oleskovicz M. “Power Transformer Differential Protection Based on Clarke's Transform and Fuzzy Systems,” IEEE Transactions on Power Delivery, 2011, 26(2):1212-1220.

[3] Abu-Siada A, Islam S. “A Novel Online Technique to Detect Power Transformer Winding Faults,” IEEE Transactions on Power Delivery, 2012, 27(2):849-857.

[4] Seifeddine S, Khmais B, Abdelkader C. “Power transformer fault diagnosis based on dissolved gas analysis by artificial neural network,” First International Conference on Renewable Energies and Vehicular Technology, 2012:230-236.

[5] Yang Q P, Li M Q, Mu X Y, Wang J. “Application of Artificial Intelligence (AI) in Power Transformer Fault Diagnosis,” International Conference on Artificial Intelligence and Computational Intelligence. IEEE, 2010:442-445.

[6] Zheng R, Zhao J, Zhao T, Li M. “Power Transformer Fault Diagnosis Based on Genetic Support Vector Machine and Gray Artificial Immune Algorithm,” Proceedings of the CSEE, 2011, 31(7):56-63.

[7] Xiang W Q, Hua Z, Wang H, Xie XZ. “Application of BP neural network with L-M algorithm in power transformer fault diagnosis,” Power System Protection & Control, 2011, 88(8):170-174.

[8] Li J, Zhang Q, Wang K, Wang JY, Zhou TC, Zhang YY. "Optimal dissolved gas ratios selected by genetic algorithm for power transformer fault diagnosis based on support vector machine," IEEE Transactions on Dielectrics & Electrical Insulation, 2016, 23(2):1198-1206.

[9] Fu Y, Tian Z N, Jiang Y R, Cao JL. "Power Transformer Fault Diagnosis Using Weighted Fuzzy Kernel Clustering," High Voltage Engineering, 2010, 36(2):371-374.

[10] Ahmed M R, Geliel M A, Khalil A. "Power transformer fault diagnosis using fuzzy logic technique based on dissolved gas analysis," Control & Automation. IEEE, 2013:584 - 589.

[11] M. Božić, M. Stojanović, Z. Stajić, Vukić D. "Power transformer fault diagnosis based on dissolved gas analysis with logistic regression," Przeglad Elektrotechniczny, 2013, 89(6):83-87.

[12] Mani G, Jerome J. "Intuitionistic Fuzzy Expert System based Fault Diagnosis using Dissolved Gas Analysis for Power Transformer," Journal of Electrical Engineering & Technology, 2014, 9(6):2058-2064.

[13] Sahri Z, Yusof R. "Fault diagnosis of power transformer using optimally selected DGA features and SVM," Control Conference, 2015:1-5.

[14] Xiong Z Y, Yang Q B, Zhang Y F. "Improved PSO-BP neural network for power transformer fault diagnosis: Improved PSO-BP neural network for power transformer fault diagnosis," Journal of Computer Applications, 2010, 30(3):783-785.

[15] Sun H Q, Xue Z H, Du Y, Sun LH, Sun KJ. "Power transformer fault diagnosis based on fuzzy C-means clustering and multi-class SVM," International Conference on Machine Learning and Cybernetics. IEEE, 2010:2266-2269.

[16] Wang F Z, Shao S M, Dong P F. "Research on Transformer Fault Diagnosis Method Based on Artificial Immune Network and Fuzzy C-Means Clustering Algorithm," Applied Mechanics & Materials, 2014, 574:468-473.

[17] Hsieh JC, Tai CC, Su MS, Lin YH. "Identification of Partial Discharge Location Using Probabilistic Neural Networks and the Fuzzy C-means Clustering Approach," Electric Machines & Power Systems, 2014, 42(1):60-69.