A Refined Classification Method for Transformer Fault Diagnosis

Le Luan, Wenxiong Mo, Hongbin Wang, Lingming Kong and Kai Zhou

Electric Power Test & Research Institute, Guangzhou Power Supply Bureau Co. Ltd, Guangzhou 510000, P. R. China

Abstract. Dissolved gas analysis is one of the most effective methods for diagnosing transformer faults. The traditional method for oil-immersed transformer fault diagnosis can only recognize several types of defects and has a low accuracy rate. In order to improve the classification effectiveness, a refined classification method for transformer fault diagnosis is proposed. It can detect more types of faults with a higher accuracy rate. The proposed method is based on the probability-output relevance vector machine, and a three-layer four-classifier model is constructed to analyse the different diagnostic results of different kinds of input data. In this model, a binomial tree is used to transfer the multi-classification problem to four binary classification problems; each classifier is a binary classifier used to distinguish the transformer type between two types of error. The proposed method is employed for analysis of 100 DGA samples consisting of characteristic gas content. The experimental result shows that this method has a high diagnostic rate and can diagnose 11 kinds of operation state.

1. Introduction

The transformer is one of the most vital equipment in the network. There will be a severe economic loss in the power network if it fails [1]. Correct fault classification can help us to prevent and reduce the probability of transformer failure. Thus, a refined classification of power transformer fault diagnosis is necessary.

Many methods have been applied in transformer fault diagnoses, such as insulating oil characteristic test, resistance test, moisture analysis, and dissolved gas analysis [2]. Among these methods, dissolved gas analysis (DGA) is the most widely used method to identify the faults in oil-filled power transformers [3]. This method diagnoses the transformer fault based on the analysis of dissolved gas concentration in the transformer oil [4]. The gases in the transformer oil mainly include hydrocarbons, such as methane, ethane, ethylene, acetylene and other gases, such as hydrogen, carbon monoxide and carbon dioxide [5]. In practice, because of the diversity, the DGA data may have relatively large uncertainty for the same type of fault. Therefore, there will be some defect in using the DGA data directly [6]. However, the DGA ratios are less influenced by the uncertainty. Several traditional transformer fault diagnosis methods have been proposed to help in fault identification, including IEC three-ratio method and Duval triangle method [7, 8]. Three-ratio method is operated by computing the key gas ratios and mapping the ratios to predefined fault patterns [9]. Duval triangle method establishes the Duval triangle to diagnose the fault type according to the content of three kinds of gas (CH₄, C₂H₄ and C₂H₂). These methods are established according to a lot of experimental results and have been used for a long period. However, transformers are very complex systems with uncertainty factors and information, and the fault diagnostic rate and the number of fault classifications of these methods are not satisfactory [10]. Three-ratio method has code defect, critical value criterion of defects and other issues [11]. Duval triangle method cannot diagnose the normal
operation state of the transformer. Both of them can only recognize several types of faults and has a low accuracy rate. With the development of artificial intelligence and machine learning, artificial neural network (ANN), support vector machine (SVM), and other techniques have been applied to power transformer fault diagnosis. Some achievements have been made, but some limitations remain. For example, SVM has outstanding performance in dealing with a small amount, high dimension data and over-fitting problem, but the kernel function of the vector machine must satisfy the Mercer condition [12]. ANN has a highly nonlinear fitting and self-adaptive ability, but the network structure is hard to determine [13]. All of these problems can be solved by using the relevance vector machine (RVM).

This paper proposes a refined classification method for transformer fault diagnosis. It can improve the accuracy rate of transformer faults diagnosis and provide more classifications of transformer faults. The proposed method is based on the probability-output relevance vector machine. In this method, the characteristic gas content is used as the input data, and a three-layer four-classification model is constructed to analyze the different diagnostic results of different input characterizing vectors. Each of these classifiers is used to distinguish the fault type between two types of errors, such as thermal faults and electrical faults. To test which kind of input data leading to a better diagnostic result, both of the normalized characteristic gas content and the characteristic gas content ratio are used as the input data of each classifier. To improve the classification effectiveness, the output of the three-layer four-classifier model is revised by performing probability calculation.

The rest of the paper is organized as follows: Section 2 introduces the related methods. Section 3 explains the proposed method in detail. Section 4 gives the experimental results and discusses the results. Section 5 concludes the paper.

2. Related Work
2.1. Dissolved Gas Analysis
Dissolved gas analysis is a kind of technology used to detect the dissolved gas in insulating oil of the transformer [14]. In the initial state of the power transformer, many gases are dissolving in insulating oil. The main gas is air which mainly consists of oxygen and nitrogen. Except for thermal faults and electrical faults, the dissolved gas in transformer oil is related to the sealing degree of the transformer as well. If the sealing degree is low, the dissolved gas will decompose some hydrogen, carbon oxide and some other impurities due to the oxidation and ageing function caused by the heating and discharging process in insulating oil and polymer materials.

The transformer oil will generate a lot of hydrocarbons if the transformer breaks down. Among these hydrocarbon molecules, methane (CH₄), ethane (C₂H₆), ethylene (C₂H₄) and acetylene (C₂H₂) are the characteristic gases. Therefore, the concentration of these gases, such as H₂, CH₄, C₂H₆, C₂H₄, and C₂H₂ can be used for power transformer faults analysis based on DGA. If the transformer fails, the emergence of these gases will change with the type of these faults. For example, if thermal faults are happening on a transformer, at low temperatures, H₂ and CH₄ are the main components of the dissolved gas in transformer oil. As temperature goes on, CH₄ and C₂H₄ come to be the characteristic gases at the medium temperature. C₂H₂ will be generated in insulating oil at high temperatures. If electrical faults are happening on a transformer, the main components in insulating oil are H₂ and CH₄ as partial discharging. The characteristic gases are C₂H₂ and H₂ when low energy discharge happens. As high energy discharge occurs, the main gases are C₂H₄, H₂ and a relative amount of CH₄ and C₂H₄ in most cases.

2.2. Traditional Methods
Many experiments have proved that the ratio of dissolved gas content in transformer oil is related to the degree of discharge and the temperature when the transformer breaks down. According to these experiments, researchers have provided several traditional diagnosis methods, such as three-ratio method and Duval triangle method.

Three-ratio method, based on the relationship among dissolved gas content in oil with discharge magnitude and temperature, selects two kinds of gases from the five characteristic gases to form three ratios. Each of these ratios has a corresponding code. The type of faults can be diagnosed according to
different ratios. This method eliminates the influence of the volume effect of the oil and has a high diagnostic rate. Table 1 shows the fault diagnosing method based on codes. If the range of gas content is less than 0.1, the coding of three ratios is 010; if it is between 0.1 and 1, the coding of them is 100; if it is between 1 and 3, the coding of three ratios is 121; otherwise, the coding is 222.

| Coding pattern | Fault type                      |
|----------------|--------------------------------|
| \( C_2H_2 \)  | \( CH_4 \) | \( C_2H_4 \) |
| \( C_2H_4 \)  | \( H_2 \)  | \( C_2H_6 \) |
| 0              | 1          |               |
| 2              | 0          |               |
| 0, 1, 2        | 2          |               |
| 1              | 0          |               |
| 2              | 0, 1, 2    |               |
| 1              | 0, 1, 2    |               |
| 2              | 0, 1, 2    |               |
| 2              | 0, 1, 2    |               |

Duval triangle method is a recommended method that diagnoses transformer faults with \( CH_4, C_2H_4, \) and \( C_2H_2 \). This method establishes a triangle which is called Duval triangle to diagnose the fault type according to the ratios between these three kinds of gases.

In the Duval triangle, the ratio of each kind of gas is used to locate the region in the triangle and recognize the fault type according to the located region.

The experimental results show that the three-ratio method cannot diagnose the normal operation state, and there is no corresponding coding pattern. In addition, the improved three-ratio method still lacks two sets of coding patterns which are 000 and 011, and the three-ratio method’s diagnostic results lack high-energy discharge state and high-energy discharge with overheating state. The accuracy rate of diagnosis is only 72%. Also, the David triangle does not contain the normal operation state region, so it is easy to cause misjudgment as diagnosing the normal operation state. The diagnostic rate of this method is 69%. In the next section, a probability-output RVM transformer fault diagnosis method is proposed.

3. Proposed Method
This section proposes a probability-output relevance vector machine (RVM) transformer fault diagnosis method.

The fault mechanism of the oil-immersed transformer is very complex, and there are many types of these faults. However, all of the faults can be attributed to thermal faults or electrical faults. Therefore, in the analysis of transformer faults, the operation state can be divided into the following five types: normal operation state, low-energy discharge, high-energy discharge, medium-low temperature heating and high-temperature overheating. From this, the transformer faults analysis is a multi-classification problem. In this paper, the binomial tree method is used to build the model. It means that the five-classification problem has been transformed into a three-level four-classifier problem. Each of these classifiers is a binary classifier.

There are three layers in this RVM model. It consists of four classifiers and five operation states. The classifier (RVM1) in the first layer diagnose whether the transformer is failed or not. If it fails, the classifier (RVM2) in the second layer is used to distinguish whether the fault is the thermal fault or the electrical fault. In the third layer, RVM3 is used to diagnose whether the electrical fault belongs to
low-energy discharge or high-energy discharge and RVM4 is used to diagnose whether the thermal fault belongs to low-temperature heating or high-temperature heating.

As constructing classifier RVM1, the target value of the normal state is 1, and the target value of the failure state is 0. When the probability output of RVM1 is larger than 0.5, the diagnostic result is normal; otherwise, it fails. When RVM2 is constructed, the target value of the electrical fault is 1, and the target value of the thermal fault is 0. Similarly, when classifier RVM3 is used, the target value of low-energy discharge is 1, and the target value of high-energy discharge is 0. When the classifier RVM4 is constructed, the target value of medium-low temperature overheating is 1, and that of high temperature overheating is 0.

It assumes that \( x = [x_1, x_2, \cdots, x_n]^T \) is the input matrix of RVM model, \( x_i, i \in \{1, \cdots, n\} \) represents the characteristic variable which is characteristic gas content or the ratio of them, \( y = [y_1, y_2, \cdots, y_n]^T \) is the target output, \( h(x, \omega) \) is the output of RVM model, \( \omega_i, i \in \{1, \cdots, n\} \) is the weight of each relevant vector, \( \varphi(x, x_i) \) is a core function. In this paper, this function is set as Bernoulli function which is \( \varphi(x, x_i) = p^x (1 - p)^{1-p}, x = 0,1. \)

In order to get the target output, the output of the RVM model can be calculated

\[
    h(x, \omega) = \sum_{i=1}^{n} \omega_i \varphi(x, x_i) + \omega_0 \quad (1)
\]

Equation (1) refers to the model output with the core function of the relevant vector and its weight.

The target output can be objected

\[
    y_n = h(x, \omega) + \varepsilon_n \quad (2)
\]

where \( \varepsilon_n \) is the bias unit of noises. \( \varepsilon_n \) subjects to the distribution as

\[
    P(y_n | \omega, \sigma^2) = N(h(x_i, \omega_i), \sigma^2) \quad (3)
\]

where \( N(h(x_i, \omega_i), \sigma^2) \) is a normal distribution.

Let \( y = [y_1, y_2, \cdots, y_n]^T \) be independent identically distributed vectors, the likelihood function of the training sample can be calculated as

\[
    P(y | \omega, \sigma^2) = \prod_{i=0}^{n} N(y_i | h(x_i, \omega), \sigma^2) \quad (4)
\]

In order to prevent over-learning, let the weight \( \omega \) subject to the distribution:

\[
    P(\omega | \alpha) = \prod_{l=0}^{n} N(\omega_i | 0, \alpha^{-1}) \quad (5)
\]

where \( \alpha \) is the \( n+1 \)-dimensional hyper-parameter vector.

Therefore, the \( \omega \)-solving problem can be reduced to a \( \alpha \)-solving problem. According to Bayesian theory, we can get the probability of posterior distribution:

\[
    P(\omega, \alpha, \sigma^2 | y) = P(\omega | y, \alpha, \sigma^2) P(\alpha, \sigma^2 | y) \quad (6)
\]

This problem has been reduced to the hyper-parameter vector \( \alpha \) and solving the problem. Our goal is to find the values of \( \alpha \) and \( \sigma^2 \) which lead to the maximum of the probability of posterior distribution. We use an iterative method to get the approximate values of \( \alpha \) and \( \sigma^2 \). When the iterative number is large enough, most hyper-parameter vectors tend to be infinities, and its relevance weight \( \omega_i \) tends to be zero. The rest \( \alpha \) converges to a limited value, and the corresponding input vector \( x_i, i \in \{1, \cdots, n\} \) is called a relevance vector. After getting the weight vector and relevance vector, the model output value \( h(x, \omega) \) can be obtained according to equation (1).
According to the transformer fault diagnosis model, the output probabilities of four classifiers belong to different fault states. These probabilities are represented by $P(RVM1)$, $P(RVM2)$, $P(RVM3)$, $P(RVM4)$, where $P(RVM1)$ represents the normal probability of diagnosis, $P(RVM2)$ represents the probability of electrical fault, $P(RVM3)$ represents the probability of low energy discharging and $P(RVM4)$ indicates the probability of heating at medium-low temperature. From this, the rate of the following four states are evaluated as:

The probability of low-energy discharge under electrical faults:

$$P(D_1) = P(RVM1) \times P(RVM3) \tag{7}$$

The probability of high-energy discharge under electrical faults:

$$P(D_2) = P(RVM2) \times (1 - P(RVM3)) \tag{8}$$

The probability of medium-low temperature heating under thermal faults:

$$P(T_1) = P(RVM4) \times (1 - P(RVM2)) \tag{9}$$

The probability of high-temperature overheating under thermal faults:

$$P(T_2) = (1 - P(RVM4)) \times (1 - P(RVM2)) \tag{10}$$

Comparing the probabilities of the four states and sorting them from the largest one to the smallest one, the first two states with larger probabilities are selected. If the difference between these two states is small, both of the two states are considered to be the transformer’s fault states. If the two states happen to be low-energy discharge and high-energy discharge, the fault state is attributed to an electrical fault. If the two states are the middle-low temperature heating and high-temperature overheating, finally the fault state is classified as a thermal fault. From this, it can be concluded that the optimized fault diagnosis method can diagnose 11 kinds of operation states, namely normal state, electrical fault, thermal fault, low-energy discharge, high-energy discharge, medium-low temperature heating, high-temperature overheating, medium-low temperature heating with low-energy discharge, medium-low temperature heating with high-energy discharge, high-temperature overheating with low-energy discharge and high-temperature overheating with high-energy discharge.

4. Experimental Results

According to a large number of research experiments, it has been proved that both characteristic gas content and the ratio of characteristic gas content have a certain relationship with the operation state of the transformer. Therefore, there are two cases for selecting characteristic variables. This paper constructs different models corresponding to different characteristic variables. The results of them are different.

4.1. The Characteristic Gas Content Is Chosen As the Input Data

The characteristic gas content is selected as the input data by five kinds of characteristic gas content: $H_2$, $CH_4$, $C_2H_6$, $C_2H_4$ and $C_2H_2$. The original gas content data should be normalized by the normalization formula to improve the accuracy rate of fault diagnosis.

$$x_{\text{new}} = C_{\text{min}} + \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} (C_{\text{max}} - C_{\text{min}}) \tag{11}$$

where $x_{\text{new}}$ is the normalized data, $x_{\text{min}}$ is the minimum value of gas content, $x_{\text{max}}$ is the maximum value of gas content, $C_{\text{max}}$ is the upper bound of the normalized gas content and $C_{\text{min}}$ is the lower bound of the normalized gas content.

4.2. The Ratio of Characteristic Gas Content Is Chosen As the Input Data

In the data of characteristic gas content ratio, the ratio of $H_2$, $CH_4$, $C_2H_6$, $C_2H_4$ and $C_2H_2$ to the total gas content is selected as the characteristic variable. Because the ratio of the five characteristic gases content is between 0 and 1, the five gas content ratios can be directly used as input data.

After constructing four classifiers and training them with 200 samples, the binary tree method is used to test 100 samples and get the overall testing result. Part of the result is shown in table 2. In this
table, 1 represents the normal state, 2 represents electrical fault, 3 represents thermal fault, 4 represents low-energy discharge, 5 represents high-energy discharge, 6 represents medium-low temperature heating, 7 is high-temperature overheating, 8 represents medium-low temperature heating with low-energy discharge, 9 represents medium-low temperature heating with high-energy discharge, 10 represents high-temperature overheating with low-energy discharge, and 11 represents high-temperature overheating with high-energy discharge. The testing result in table 2 shows the result of each case. For example, 7, 6 shows that when the normalized characteristic gas content is used as the input data, the testing result is 7 and when the ratio of characteristic content is used as the input data, the testing result is 6.

In the experiment, 100 samples are tested. When normalized characteristic gas content and ratio of characteristic gas content are used as the input data, the diagnostic rates are increased to 90% and 86%. Table 2 shows that when we use normalized characteristic gas content as the input data, the accuracy rate is always higher than the another one.

**Table 2.** Overall testing result of the proposed method

| H₂  | CH₄  | C₂H₆ | C₂H₄ | C₂H₂ | Fault type | Testing result |
|-----|------|------|------|------|------------|----------------|
| 30  | 110  | 137  | 52   | 22.3 | 1          | 1, 1           |
| 66  | 8.27 | 8.21 | 9.21 | 8.21 | 4          | 4, 4           |
| 59  | 10.4 | 4    | 10   | 12.7 | 4          | 4, 5           |
| 44.431 | 7.9976 | 1.6588 | 19.254 | 26.659 | 5          | 5, 5           |
| 79  | 18   | 7    | 71   | 8    | 5          | 5, 7           |
| 160 | 130  | 33   | 96   | 0    | 6          | 6, 6           |
| 4.32 | 193  | 118  | 125  | 0    | 6          | 6, 6           |
| 1.9632 | 29.08 | 11.288 | 57.669 | 0    | 7          | 7, 7           |
| 27.441 | 35.009 | 5.7435 | 29.355 | 2.3612 | 7          | 10, 10         |
| 9   | 89   | 496  | 19   | 0    | 3          | 3, 3           |
| 9.21 | 20.67 | 17.81 | 15.33 | 0    | 3          | 3, 3           |
| 1046 | 223  | 41   | 485  | 656  | 2          | 5, 2           |
| 1229 | 417  | 82   | 1045 | 1432 | 2          | 2, 5           |
| 10.7 | 26.1 | 75.9 | 11.2 | 10.4 | 9          | 9, 8           |
| 20  | 25.5 | 1.4  | 12.6 | 13.2 | 9          | 9, 9           |
| 109 | 42   | 5    | 40   | 14   | 10         | 11, 10         |
| 86  | 110  | 18   | 92   | 7.4  | 10, 10     |                |

Compared with traditional fault diagnosis methods, the proposed probability-output RVM transformer fault diagnosis method has a relatively high accuracy rate. It also can diagnose more types of faults than traditional diagnosis methods. Table 3 shows the accuracy rates of all of the methods.

**Table 3.** Accuracy rate of each method

|               | Three-ratio method | Duval triangle method | Proposed method |
|---------------|--------------------|-----------------------|-----------------|
| Accuracy rate | 72%                | 69%                   | 90%             |

5. Conclusions

In this paper, a refined classification method based on probability-output RVM for transformer fault diagnosis is proposed. There are three main conclusions: First, a probability-output RVM transformer diagnosis method is proposed and a three-layer four-classifier fault diagnosis model is constructed. Second, the experimental results show that this method is effective and refined. Third, according to the comparison with traditional methods based on DGA, the fault diagnosing accuracy of the proposed method is increased by nearly 20% and it also provides more categories for transformer faults diagnosis.
6. Acknowledgement
This work is supported by the Science and Technology Project of China Southern Power Grid Co. Ltd. 080037KK52170051 (GZHKJXM20170104).

7. References
[1] Huang X B, Wang X and Tian Y 2018 Condition Monitoring and Diagnosis (CMD) (Perth) pp 1–5
[2] Wang L K, Zhao X Y, Pei J N and Tang G Y 2016 Transformer fault diagnosis using continuous sparse autoencoder Springplus 5 448
[3] Fan J, Wang F, Sun Q, Bin F, Liang F and Xiao X 2017 Hybrid RVM-ANFIS algorithm for transformer fault diagnosis IET Gen. Trans. Dist 11 3637–43
[4] Zope N, Ali S I, Padmanaban S, Bhaskar M S and Mihet-Popa L 2018 Int. Conf. on Industrial Technology (Lyon) pp 1160–64
[5] Xiao G W, Yu C T, Chen W G, Jin L F and Tang S R 2017 13th IEEE Int. Conf. on Electronic Measurement & Instruments (Yangzhou) pp 220–227
[6] Dai J J, Song H, Sheng G H and Jiang X C 2017 Dissolved gas analysis of insulating oil for power transformer fault diagnosis with deep belief network IEEE Trans. Dielectr. Electr. Insul. 24 2828–35
[7] Barbosa T M, Ferrira J G, Finocchio M A F and Endo W 2017 Development of an application based on the Duval triangle method IEEE Latin America Trans. 15 1439–46
[8] Duval M and Lamarre L 2017 Electrical Insulation Conf. (Baltimore) pp 279–281
[9] Gouda O E, EI-Hoshy S H and Tamaly H H E L 2018 Proposed three ratios technique for the interpretation of mineral oil transformers based dissolved gas analysis IET Gen. Trans. Dist. 12 2650–61
[10] Cheng L and Yu T 2018 Dissolved Gas Analysis principle-based intelligent approaches to fault diagnosis and decision making for large oil-immersed power transformers: a survey Energies 11 913
[11] Kari T and Gao W 2017 Power transformer fault diagnosis using FCM and improved PCA The Journal of Engineering 2017 2605–08
[12] Li J Z, Zhang Q G, Wang K, Wang J Y, Zhou T C and Zhang Y Y 2016 Optimal dissolved gas ratios selected by genetic algorithm for power transformer fault diagnosis based on support vector machine IEEE Trans. Dielectr. Electr. Insul. 23 1198–1206
[13] [Ma H, Ekanayake C and Saha T K 2012 Power transformer fault diagnosis under measurement originated uncertainties IEEE Trans. Dielectr. Electr. Insul. 19 1982–90
[14] Wang X, Wang Z, Liu Q, Willison G, Walker D and Smith P W R 2017 Dissolved gas analysis (DGA) of mineral oil under thermal faults with tube heating method IEEE 19th Int. Conf. pp1-4