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# Transformer Fault Diagnosis Method Based on Dynamic Weighted Combination Model

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***Abstract***

*The paper tried to integrate the DGA data with the gas production rate, which are the major indexes of transformer fault diagnosis. Duval's triangle method, BP neural network and IEC three-ratio method were weighted. Firstly, the paper regarded the gas production rate as the independent variables, fitted the cubic curves of the gas production rate and variance of each diagnosis method, and then defined the weights of each algorithm through the data processing method of unequal precision. At last, the dynamic weighted combination diagnosis model was established. That is, the weight is different as the gas production rate changes although the method is identical. The results of diagnosis examples show that the accuracy rate of the weighted combination model is higher than any single algorithm, and it has certain stability as well.*

***Keywords:*** *transformer fault, weighted combination model, duval's triangle, bp neural network, three-ratio method*



## 1. Introduction

Power transformer is the key equipment of the power supply system, which has important practical value for the real-time monitoring and fault diagnosis of the state of the transformer [1]. At present, the dissolve gas analysis (DGA) method of transformer oil is widely used to estimate the internal fault properties of the transformer [2], and diagnosis method like the Duval's triangle method, the three-ratio method, IEC three ratio method, etc. are considered classical. With the development of artificial intelligence technology, neural network, fuzzy theory, expert system, genetic algorithm and other methods are applied to the fault diagnosis of transformers [3-6].

There is a complex relationship between the appearance of the transformer faults and the fault mechanism, as a result a single diagnostic method usually have its limitations and there will be a diagnostic blind area to produce false positives or false negatives, generally, the diagnosis accuracy rate is between 70% and 80%. In transformer fault diagnosis, many scholars adopt a combination form with a variety of checking methods [7-12], which increases the accuracy rate of fault diagnosis to 80% - 90%.The diagnosis combination model is established for constant, that is, the model parameters are invariable in any detection. This paper introduces the ideas of the weighted combination, and emphasizes the dynamic of the weights.

The paper adopts the method of weighted combination diagnosis. Firstly, Duval's triangle method, BP neural network and IEC three-ratio method are used to diagnose the transformer state. Then the results of the three methods are weighted and combined to get the final diagnosis conclusion. The key of the research is to find the weights. Here, another index of transformer fault diagnosis-the total hydrocarbon gas production rate [13] as the independent variables is introduced. Selecting the suitable sampling points, fitting out the cubic curves of the total hydrocarbon gas production rate and variance of diagnosis method, then using the data processing method of unequal precision [14, 15] to work out the weights of each algorithm for different fault types under different gas production rates. The dynamic model has certain stability, and the accuracy rate of each type of transformer fault diagnosis is increased to more than 90% as well.

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## 2. Weighted Combination Diagnosis Model

Set each diagnostic algorithm with $A_i(i=1...n)$, according to the error theory of the unequal measurement accuracy and data processing method; give different diagnosis methods the different weights $p_i$ on the basis of its reliability, the higher reliability the greater weight in the comprehensive diagnosis. According to the fault types of the transformer, the method of determining the weight of the n kinds of diagnosis algorithms is:

$$p_1 : p_2 : ... p_i = \frac{1}{\sigma_1^2} : \frac{1}{\sigma_2^2} : ....... \frac{1}{\sigma_i^2} \; ; \quad \sum_{i=1}^{n} p_i = 1 \tag{1}$$

Where: $\sigma_i^2$ is the variance of diagnosis algorithms $A_i$ .

For multiple samples measurement data, using Bessel formula the calculated variance is more accurate, that is:

$$\sigma_i{}^2 = \frac{\sum_{j=1}^{N} (y_{ij} - y\ )^2}{N-1} \tag{2}$$

Where: $y_{ij}$ is the jth diagnostic value of the ith diagnosis algorithm $A_i$ , y is the theoretical true value, N is the number of sampling points. In view of the six main fault types of the transformer, the classification analysis is shown in Table 1.

Table 1. Fault Types of Power Transformer

| No | Fault types | ab. |
|---|---|---|
| Y1 | partial discharge | PD |
| Y2 | low energy discharge | D1 |
| Y3 | high energy discharge | D2 |
| Y4 | heat fault $t < 300°C$ | T1 |
| Y5 | heat fault $300°C < t < 700°C$ | T2 |
| Y6 | heat fault $t > 700°C$ | T3 |

For one transformer fault, the diagnostic results of the $A_i$ algorithm is:

$$\boldsymbol{s}_i = [s_{i1} \quad s_{i2} \quad ...... \quad s_{im}]^T \tag{3}$$

Where: $s_{im}(m=1,2,.....6)$ is the judgment of whether the transformer fault type is Ym by algorithm $A_i$ , if the diagnosis is Ym, set $s_{im}=1$ ,if not, set $s_{im}=0$ . Then the diagnosis conclusion matrix of the n algorithm is expressed as:

$$\boldsymbol{S} = \begin{bmatrix} s_{11} & s_{21} & \cdots & s_{n1} \\ s_{12} & s_{22} & \cdots & s_{n2} \\ \cdots & \cdots & \cdots & \cdots \\ s_{1m} & s_{2m} & & s_{nm} \end{bmatrix}^{m \times n} \tag{4}$$

For the Ym type, the weights of each diagnostic algorithm are:

$$\boldsymbol{p}_m = [p_{1m} \quad p_{2m} \quad \cdots \quad p_{nm}]^T \tag{5}$$

The weight value of the diagnosis result for the m fault types is expressed as:

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{bmatrix}^{n\times m} \quad (6)$$

It can be seen that, even the same kind of algorithm $A_i$ , the diagnostic value of different types of faults will be different. The diagnostic results of the weighted combination diagnostic model can be getting from the formula (4) and (6).

$$\boldsymbol{S}^z = \boldsymbol{S}^{m\times i} \times \boldsymbol{P}^{i\times m} \quad (7)$$

Where the main diagonal elements of $\boldsymbol{S}^z$ are:

$$S_{mm}^z = \sum_{i=1}^{N} p_{im} s_{im} \quad (8)$$

That is the weighted sum value of n diagnostic algorithm on Ym type fault. $\max\left\{S_{mm}^z\right\}(m=1,2,...6)$ is the diagnostic conclusions of weighted combination model, and also the fault type conclusion with the highest degree of confidence.

Table 2. Diagnosis Results of Duval's Triangle

| fault type | $r_a$(mL/d) | 10 | 14 | 18 | 22 | 26 | 30 | 34 | 38 | Total false number/ False rate % |
|---|---|---|---|---|---|---|---|---|---|---|
| PD | Sample number | 10 | 11 | 12 | 17 | 19 | 16 | 15 | 15 | 31 |
| | False number | 4 | 3 | 3 | 4 | 3 | 5 | 4 | 5 | 26.96 |
| D1 | Sample number | 10 | 14 | 13 | 21 | 18 | 18 | 16 | 19 | 30 |
| | False number | 3 | 3 | 3 | 5 | 5 | 4 | 3 | 4 | 23.26 |
| D2 | Sample number | 8 | 10 | 17 | 18 | 21 | 22 | 19 | 20 | 41 |
| | False number | 3 | 4 | 7 | 6 | 7 | 5 | 4 | 5 | 30.37 |
| T1 | Sample number | 12 | 17 | 20 | 19 | 16 | 15 | 12 | 8 | 21 |
| | False number | 1 | 2 | 3 | 2 | 3 | 4 | 3 | 3 | 17.65 |
| T2 | Sample number | 11 | 14 | 15 | 15 | 14 | 16 | 13 | 13 | 22 |
| | False number | 2 | 2 | 3 | 3 | 2 | 3 | 3 | 4 | 19.82 |
| T3 | Sample number | 13 | 15 | 15 | 18 | 23 | 22 | 17 | 13 | 34 |
| | False number | 4 | 4 | 5 | 5 | 5 | 4 | 4 | 3 | 25 |

Table 3. Diagnosis Results of BP Neural Network

| fault type | $r_a$(mL/d) | 10 | 14 | 18 | 22 | 26 | 30 | 34 | 38 | Total false number/ False rate % |
|---|---|---|---|---|---|---|---|---|---|---|
| PD | Sample number | 10 | 11 | 12 | 17 | 19 | 16 | 15 | 15 | 27 |
| | False number | 2 | 2 | 3 | 3 | 4 | 4 | 4 | 5 | 23.48 |
| D1 | Sample number | 10 | 14 | 13 | 21 | 18 | 18 | 16 | 19 | 25 |
| | False number | 3 | 3 | 3 | 3 | 2 | 4 | 3 | 4 | 19.38 |
| D2 | Sample number | 8 | 10 | 17 | 18 | 21 | 22 | 19 | 20 | 25 |
| | False number | 3 | 3 | 4 | 4 | 3 | 3 | 2 | 3 | 18.52 |
| T1 | Sample number | 12 | 17 | 20 | 19 | 16 | 15 | 12 | 8 | 19 |
| | False number | 2 | 3 | 2 | 2 | 2 | 3 | 2 | 3 | 15.97 |
| T2 | Sample number | 11 | 14 | 15 | 15 | 14 | 16 | 13 | 13 | 19 |
| | False number | 2 | 1 | 3 | 2 | 2 | 4 | 2 | 3 | 17.12 |
| T3 | Sample number | 13 | 15 | 15 | 18 | 23 | 22 | 17 | 13 | 33 |
| | False number | 4 | 4 | 3 | 4 | 6 | 5 | 4 | 3 | 24.26 |

**3. Determination of Variance**

In the fault diagnosis of the transformer, the development trend of the transformer can be judged by detecting the growth rate of the dissolved gas in the transformer oil [16]. In this paper, the characteristics gas content and total gas production rate from the DGA data is considered, in order to improve the reliability of diagnosis.

In this paper, the total hydrocarbon gas production rate $r_a$ is the independent variables; $\sigma_i^2$ is the variance of each fault diagnosis method. Based on a large number of samples, the change of $\sigma_i^2$ with $r_a$ is investigated. That is with the change of $r_a$, whether the reliability of the diagnostic methods will be different. If the values of $p_i$ changing, the combination model will be different. When $r_a$ is set to a fixed value $r_0$, statistics for large sample of transformer fault types is adopted, the real fault type of the transformer is set to Ym (m=1……6), then the theoretical true value $y_m$=1. If the method diagnose the transformer fault types correctly, the detection value of $A_i$ is $y_{ij}=y_m=1$, or else $y_{ij}=0$. Put the $y_{ij}$ value into formula (2), when $r_a = r_0$, the variance of diagnostic methods for Ym type is $\sigma_{im}^2$. Using sampling method, calculate $\sigma_i^2$ the variance of $A_i$ with different values of $r_a$, and fit the cubic curve of $r_a - \sigma_i^2$:

$$\sigma_i^2 = a_3 r_a^3 + a_2 r_a^2 + a_1 r_a + a_0 \tag{9}$$

In fault analysis, based on the $r_a$ and formula (9) to determine $\sigma_i^2$ of $A_i$, thus the weighted combination diagnosis model (8) can be used for comprehensive diagnosis.

**4. Sample Training**

In the paper, 745 cases with clear fault cause of transformer DGA data and total hydrocarbon gas production rate $r_a$ is collected as the test and training sample.

1. The samples were classified according to Table 1, which include 115 samples of PD fault , 129 samples of D1 fault,135 samples of D2 fault, 119 samples of T1 fault, 111 samples of T2 fault and 136 samples of T3 fault.
2. For each fault, the samples are sorted according to the size of the $r_a$, 8 points with the same interval are set to the observation point. Set $r_0$ is an observation value, $\Delta$ is the step, when $r_a \in \left( r_0 - \frac{\Delta}{2}, r_0 + \frac{\Delta}{2} \right]$, the corresponding samples are regarded as $r_0$ sample. Using Duval's triangle method, BP neural network and IEC three-ratio method for diagnosis, the statistical data is shown in Table 2, Table 3 and Table 4.

Table 4. Diagnosis results of IEC three-ratio method

| fault type | $r_a$(mL/d) | 10 | 14 | 18 | 22 | 26 | 30 | 34 | 38 | Total false number/ False rate % |
|---|---|---|---|---|---|---|---|---|---|---|
| PD | Sample number | 10 | 11 | 12 | 17 | 19 | 16 | 15 | 15 | 18 |
| | False number | 3 | 2 | 2 | 1 | 3 | 2 | 2 | 3 | 15.65 |
| D1 | Sample number | 10 | 14 | 13 | 21 | 18 | 18 | 16 | 19 | 18 |
| | False number | 2 | 3 | 3 | 3 | 2 | 2 | 1 | 2 | 13.95 |
| D2 | Sample number | 8 | 10 | 17 | 18 | 21 | 22 | 19 | 20 | 35 |
| | False number | 4 | 3 | 4 | 3 | 6 | 4 | 5 | 6 | 25.93 |
| T1 | Sample number | 12 | 17 | 20 | 19 | 16 | 15 | 12 | 8 | 14 |
| | False number | 2 | 2 | 3 | 2 | 1 | 1 | 2 | 1 | 11.76 |
| T2 | Sample number | 11 | 14 | 15 | 15 | 14 | 16 | 13 | 13 | 16 |
| | False number | 2 | 2 | 3 | 2 | 1 | 2 | 2 | 2 | 14.41 |
| T3 | Sample number | 13 | 15 | 15 | 18 | 23 | 22 | 17 | 13 | 27 |
| | False number | 4 | 3 | 4 | 3 | 5 | 3 | 3 | 2 | 19.85 |

3. Using the formula (2) to calculate variance of observation points with each method, which is shown in Table 5, Table 7.
4. According to the variance of observation points in Table 5, Table 6 and Table 7, using matlab to fit the cubic curve $r_a - \sigma_i^2$ of each fault types, which is shown in Figure 1, Figure 2 adn Figure 3 and formula (10), (11).

Table 5. Each Observation Point's σ2 of Duval's Triangle

| fault type / $r_a$(mL/d) | PD | D1 | D2 | T1 | T2 | T3 |
|---|---|---|---|---|---|---|
| 10 | 0.4444 | 0.3333 | 0.4286 | 0.0909 | 0.2 | 0.3333 |
| 14 | 0.3 | 0.2308 | 0.4444 | 0.125 | 0.1538 | 0.2857 |
| 18 | 0.2727 | 0.25 | 0.4375 | 0.1579 | 0.2143 | 0.3571 |
| 22 | 0.25 | 0.25 | 0.3529 | 0.1111 | 0.2143 | 0.2941 |
| 26 | 0.1667 | 0.2941 | 0.35 | 0.2 | 0.1538 | 0.2273 |
| 30 | 0.3333 | 0.2352 | 0.2381 | 0.2857 | 0.2 | 0.1667 |
| 34 | 0.2857 | 0.2 | 0.2222 | 0.2727 | 0.25 | 0.25 |
| 38 | 0.3571 | 0.2222 | 0.2632 | 0.4286 | 0.3333 | 0.25 |

Table 6. Each Observation Point's σ2 of BP Neural Network

| fault type / $r_a$(mL/d) | PD | D1 | D2 | T1 | T2 | T3 |
|---|---|---|---|---|---|---|
| 10 | 0.2222 | 0.3333 | 0.4286 | 0.1818 | 0.2 | 0.3333 |
| 14 | 0.2 | 0.2308 | 0.3333 | 0.1875 | 0.0769 | 0.2857 |
| 18 | 0.2727 | 0.25 | 0.25 | 0.1053 | 0.2143 | 0.2143 |
| 22 | 0.1875 | 0.15 | 0.2353 | 0.1111 | 0.1429 | 0.2353 |
| 26 | 0.2222 | 0.1176 | 0.15 | 0.1333 | 0.1538 | 0.2727 |
| 30 | 0.2667 | 0.2352 | 0.1429 | 0.2143 | 0.2667 | 0.2381 |
| 34 | 0.2857 | 0.2 | 0.1111 | 0.1818 | 0.1667 | 0.25 |
| 38 | 0.3571 | 0.3571 | 0.1579 | 0.4286 | 0.25 | 0.25 |

Table 7. Each Observation Point's σ2 of IEC Three-Ratio Method

| fault type / $r_a$(mL/d) | PD | D1 | D2 | T1 | T2 | T3 |
|---|---|---|---|---|---|---|
| 10 | 0.3333 | 0.2222 | 0.5714 | 0.1818 | 0.2 | 0.3333 |
| 14 | 0.2 | 0.2308 | 0.3333 | 0.125 | 0.1538 | 0.2143 |
| 18 | 0.1818 | 0.25 | 0.25 | 0.1579 | 0.2143 | 0.2857 |
| 22 | 0.0625 | 0.15 | 0.1765 | 0.1111 | 0.1429 | 0.1765 |
| 26 | 0.1667 | 0.1176 | 0.1765 | 0.0667 | 0.0769 | 0.2273 |
| 30 | 0.1333 | 0.1176 | 0.1905 | 0.0714 | 0.1333 | 0.1429 |
| 34 | 0.1429 | 0.0667 | 0.2778 | 0.1818 | 0.1667 | 0.1875 |
| 38 | 0.2143 | 0.1111 | 0.3158 | 0.1429 | 0.1667 | 0.1667 |

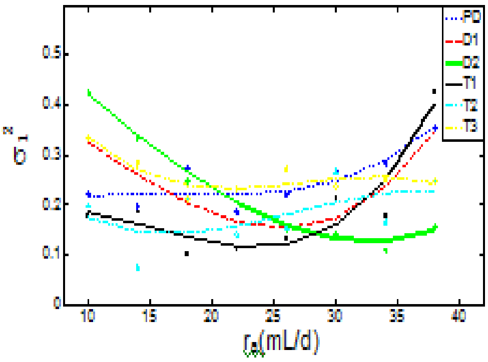


Figure 1. ra-σ1j2 Curves of Duval's Triangle

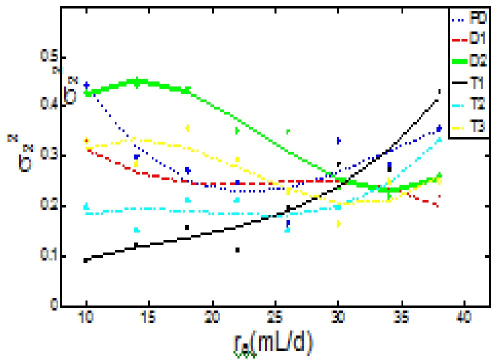


Figure 2. ra-σ2j2 Curves of BP Neural Network

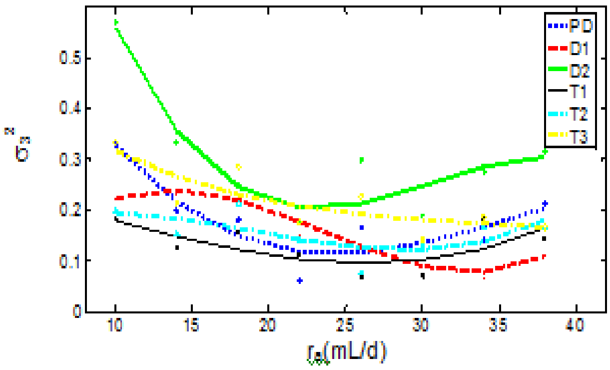


Figure 3. ra-σ3j2 Curves of IEC Three-Ratio Method

$$\begin{cases} \sigma_{11}^2 = 2.8168\times10^{-5} r_a^3 + 2.8818\times10^{-3} r_a^2 + 8.7221\times10^{-2} r_a + 1.0523 \\ \sigma_{12}^2 = 2.5742\times10^{-5} r_a^3 + 1.9067\times10^{-3} r_a^2 + 4.6003\times10^{-2} r_a + 0.60915 \\ \sigma_{13}^2 = 5.3571\times10^{-5} r_a^3 + 3.869\times10^{-3} r_a^2 + 7.6674\times10^{-2} r_a + 9.05\times10^{-3} \\ \sigma_{14}^2 = 1.8312\times10^{-5} r_a^3 + 8.9142\times10^{-4} r_a^2 + 1.9074\times10^{-2} r_a + 2.4343\times10^{-2} \\ \sigma_{15}^2 = 2.895\times10^{-5} r_a^3 + 1.6924\times10^{-3} r_a^2 + 3.0829\times10^{-2} r_a + 1.6773\times10^{-2} \\ \sigma_{16}^2 = 4.4531\times10^{-5} r_a^3 + 3.0424\times10^{-3} r_a^2 + 5.833\times10^{-2} r_a + 6.3196\times10^{-3} \end{cases} \quad (10)$$

$$\begin{cases} \sigma_{21}^2 = 1.7902\times10^{-5} r_a^3 + 9.6373\times10^{-4} r_a^2 + 1.6811\times10^{-2} r_a + 0.12862 \\ \sigma_{22}^2 = 2.0545\times10^{-5} r_a^3 + 5.6047\times10^{-4} r_a^2 + 1.183\times10^{-2} r_a + 0.47983 \\ \sigma_{23}^2 = 8.747\times10^{-6} r_a^3 + 9.2367\times10^{-5} r_a^2 + 2.2133\times10^{-2} r_a + 0.64446 \\ \sigma_{24}^2 = 3.6557\times10^{-5} r_a^3 + 1.7164\times10^{-3} r_a^2 + 1.9904\times10^{-2} r_a + 0.12165 \\ \sigma_{25}^2 = 1.9669\times10^{-5} r_a^3 + 1.59\times10^{-3} r_a^2 + 3.0829654\times10^{-2} r_a + 0.40237 \\ \sigma_{26}^2 = 2.6965\times10^{-5} r_a^3 + 2.2099\times10^{-3} r_a^2 + 5.7433\times10^{-2} r_a + 0.71562 \end{cases} \quad (11)$$

$$\begin{cases}\sigma_{31}^2 = 2.5041\times10^{-5} r_a^3 + 2.2546\times10^{-3} r_a^2 + 7.3136\times10^{-2} r_a + 0.8548\\ \sigma_{32}^2 = 4.2093\times10^{-5} r_a^3 + 2.9601\times10^{-3} r_a^2 + 5.7082\times10^{-2} r_a + 9.4544\times10^{-2}\\ \sigma_{33}^2 = 5.7832\times10^{-6} r_a^3 + 5.3237\times10^{-3} r_a^2 + 1.5336\times10^{-1} r_a + 1.6181\\ \sigma_{34}^2 = 7.197\times10^{-6} r_a^3 + 1.4512\times10^{-4} r_a^2 + 7.4056\times10^{-3} r_a + 0.26032\\ \sigma_{35}^2 = 1.8442\times10^{-5} r_a^3 + 1.0505\times10^{-3} r_a^2 + 1.4403\times10^{-2} r_a + 0.13797\\ \sigma_{36}^2 = 7.2996\times10^{-6} r_a^3 + 7.4767\times10^{-4} r_a^2 + 2.7187\times10^{-2} r_a + 0.52087\end{cases} \quad (12)$$

Obviously, when the training samples are not the same, the $r_a - \sigma_i^2$ curve will be different. In the fault diagnosis, put the $r_a$ into formula (10)-(12), the variance can be calculated. Using formula (1) to determine the weights of three diagnostic methods for the diagnosis of the same type of fault Ym, that is:

$$p_{1m} : p_{2m} : p_{3m} = \frac{1}{\sigma_{1m}^2} : \frac{1}{\sigma_{2m}^2} : \frac{1}{\sigma_{3m}^2}\text{, and } \sum_{i=1}^{n} p_{im} = 1 \quad (13)$$

Put the formula (13) into the comprehensive diagnosis model (8), the final diagnosis results will be determined.

## 5. Diagnosis Example

Using weighted combination model to diagnose T1 type transformer fault, The sample data is caused by local overheating of two-phase winding lead terminal, which belongs to the low temperature overheat fault, the DGA data of the sample are shown in Table 8.

Table 8. Components of DGA Data

| gas | H2 | CH4 | C2H2 | C2H6 | C2H2 |
|---|---|---|---|---|---|
| volume/ppm | 43.7 | 30.2 | 46.6 | 3.7 | 19.4 |

The total hydrocarbon gas production rate is 23.2mL/d, put it into formula (2), the calculated variance of each diagnosis algorithm in this state are as follows:

1) Duval's triangle method

$$\boldsymbol{\sigma}_1^2 = [0.22814 \quad 0.24669 \quad 0.35626 \quad 0.16704 \quad 0.18256 \quad 0.26545]^T$$

2) BP neural network

$$\boldsymbol{\sigma}_2^2 = [0.22346 \quad 0.16025 \quad 0.19049 \quad 0.11607 \quad 0.16481 \quad 0.23592]^T$$

3) The improved three-ratio method

$$\boldsymbol{\sigma}_3^2 = [0.11504 \quad 0.16215 \quad 0.20347 \quad 0.10027 \quad 0.13701 \quad 0.2014]^T$$

According to formula (1), (5) to get the weight matrix:

$$\boldsymbol{P} = \begin{bmatrix} 0.2497 & 0.2463 & 0.2164 & 0.2436 & 0.2907 & 0.2904\\ 0.2550 & 0.3791 & 0.4047 & 0.3506 & 0.3220 & 0.3268\\ 0.4953 & 0.3746 & 0.3789 & 0.4058 & 0.3873 & 0.3828 \end{bmatrix}$$

Using the above three algorithms to diagnose, the result is (PD, D1, T1), then the corresponding diagnosis matrix is:

$$S = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}^T$$

Put it into formula (7), which is the weighted combination diagnosis model, can get:

$$S^z = \begin{bmatrix} 0.2497 & 0.2463 & 0.2164 & 0.2436 & 0.2907 & 0.2904 \\ 0.255 & 0.3791 & 0.4047 & 0.3506 & 0.322 & 0.3268 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0.4953 & 0.3736 & 0.3789 & 0.4058 & 0.3873 & 0.3828 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Result shows that the fourth value is the largest in diagonal elements, which is 0.4058, and it correspond to the fourth fault types T1, the conclusion is consistent with the actual situation. In this paper, 477 samples of the training model is selected randomly, using the weighted combination model to diagnose, the conclusions are shown in Table 9.

Table 9. Diagnosis Results of Weighted Combination Model

| Fault type (sample size) | False number | False rate% |
|---|---|---|
| PD (63) | 6 | 9.52 |
| D1 (75) | 8 | 10.67 |
| D2 (82) | 8 | 9.76 |
| T1 (77) | 6 | 7.82 |
| T2 (85) | 8 | 9.41 |
| T3 (95) | 8 | 8.42 |

The Table 9 shows that the maximum diagnostic false rate of the weighted combination diagnosis model is 10.67%, and the minimum is 7.82%. They are better than any of the above diagnosis algorithm. Obviously, with the change of gas production rate the dynamic weighted values conforms to the objective conditions better, the correct rate of this diagnosis model is much better than that single diagnosis method.

## 6. Conclusion

In this paper, the DGA data and gas production rate, the two indexes of the transformer fault diagnosis, are combined. The diagnosis variance of Duval's triangle, BP neural network and the improved three ratio method is fitted with the total hydrocarbon gas production rate separately to produce the cubic curves. A dynamic weighted combination diagnosis model is established, that is, the weight is different as the gas production rate changes although the method is identical. The results of diagnosis examples show that the accuracy rate of the weighted combination model is higher than any single algorithm, and it increased to more than 90% in main transformer fault diagnosis, and it has certain stability as well. The model has been applied to the fault diagnosis system of a 110KV transformer.

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