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Application of Grey Relational Analysis in Code Absence of DGA for Transformer

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ABSTRACT. Three-ratio method is one of the effective methods for latent fault diagnosis of power transformers, but there is a lack of code in this method. According to the DGA data collected in this paper, it is found that the variation trend of the characteristic gas in the same fault samples is the same, and the variation trend of different fault features is obviously different. In this paper, by excavate the changing trend of each data in DGA, using the grey relational theory and using the DGA fault identification method based on grey relational analysis, the fault diagnosis of code absence power transformers in DGA is carried out. It makes up for the deficiency of the three ratio method and improves the accuracy of transformer fault diagnosis. The research results have important theoretical value and practical value of engineering. It can be popularized vigorously and bring great economic benefits to the power system and the society.

1. Introduction

The use of Dissolved Gases Analysis (DGA) in oil-filled transformer has become the main method for the diagnosis of transformer faults in various countries in the world [1]. It can not only find the early latent faults of transformer, but also diagnose transformer without cutting off the equipment. International electrician electrical committee recommended three ratio method based on the analysis of gases dissolved in transformer oil. It has been widely applied to discover the hidden faults of transformer and has played an important role in it [2].

The diagnosis process of the three-ratio method generally follows the guidelines of dissolved gas analysis and judgment in transformer oil. In the guideline (GB1T7252-1987) there is 18 codes absence. With the accumulation of operating experience and example verification, the initial assessment method of three ratio in our country had been improved, making this method more complete. The guideline was revised in 2001 (GB1T7252-2001), adding code of compound fault type. However, the revised guideline still fails to provide corresponding judgment criteria for failure code type 011 [3].

This paper combines the grey system theory with the characteristic that the gas variation trend of the same fault type of transformer is consistent [4-7].By comparing the grey correlation coefficient between the characteristic gas of the 011 code fault and characteristic gas of each fault, the type of the 011 code fault is determined, which is an effective exploration of the DGA code absence type.

2. Gas law in transformer fault

In order to analyze and study the transformer fault diagnosis method, also to overcome the defects of misjudgment near the ratio boundary and code absence. For the collected DGA data, the three-ratio

encoding of the DGA data was calculated and classified according to the code. In this paper, the collected 012 code DGA data is taken as an example [8-10], and the DGA data is plotted and analyzed. The DGA data is shown in table 1, and the data increase and decrease trend is shown in figure 1.The units of hydrogen(H_2) and ethylene(C_2H_4) in the figure are 10uL/L, which is reduced to one-tenth of the original value, and the other three gases are uL/L.

Table 1. Collected fault data coded as 012

| number	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	code	Fault type
1	39	3.8	5.6	69	0	3.9	High temperature overheating
2	102.96	6.62	2.21	10.24	0.24	10.296	Overheating of bare metal
3	117	2.29	1.5	76.4	0	11.7	Solid insulation aging
4	67	5.1	0.77	3.85	0	6.7	spark discharge
5	117.8	1.8	2.67	62.8	0	11.78	Solid insulation aging
6	145.2	5.6	5.6	115.5	0	14.52	Solid insulation aging
7	120.4	4	0	78.7	0	12.04	Solid insulation aging
8	147.6	8.2	2	118.2	0	14.76	Solid insulation aging
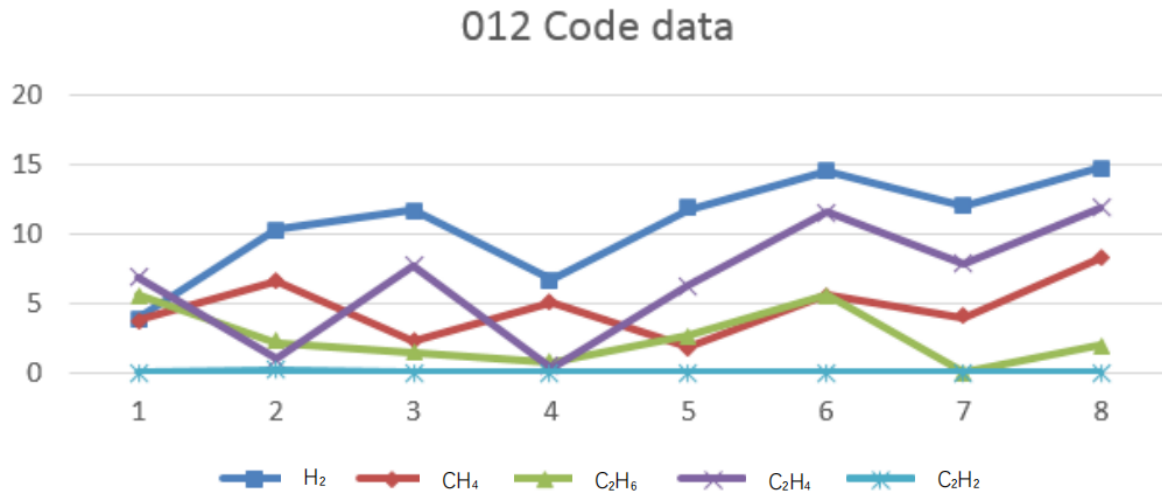
Figure 1. 012 code data

In Figure 1, the changing laws of five gases encoded as 012, such as hydrogen and methane, are not characteristic. From one data to another, various gases have increased and decrease. Such as from first data to fifth data, the increase or decrease trend of methane (CH_4) and ethylene (C_2H_4) is completely opposite. But from fifth data to eighth data, all kinds of gases show the same increase or decrease.

Carefully inspecting the data of the 012 code, we can find that the 012 coded data fault types are not uniform, there are three kinds of fault, such as overheating fault, discharge fault, solid insulation aging. In terms of solid insulation aging data 5 to 8, the gas fold line shows the same increase or decrease trend.

The above situation shows that there is a great correlation between the increase and decrease rule of characteristic gas and the type of fault when there is a fault in the transformer. That is, the same fault occurs from one data to another, and the five gases tend to increase at the same time or decrease at the same time. The data collected in different fault types often show a cross fold line, manifesting a poor correlation. Therefore, the grey correlation analysis method can be used for fault diagnosis.

3. Brief introduction of grey correlation analysis method

Correlation is a measure of the relevance between things and factors [11]. It provides the basis for the factor analysis and prediction precision analysis by finding the correlation from the random time series, and provides the basis for the decision. The grey relational degree is the measure of the comparison between the sequence and the sequence [12-14].

For sequence sets:

$$X_i = \left(x_i(1), x_i(2), \cdots, x_i(n) \right), \quad i = 0,1,2,\cdots,m \tag{1}$$

$$\gamma(x_0(k), \ x_i(k)) = \frac{\min_i \min_k \Delta_{0i}(k) + \zeta \max_i \max_k \Delta_{0i}(k)}{\Delta_{0i}(k) + \zeta \max_i \max_k \Delta_{0i}(k)}$$ is called the correlation coefficient between xi(k)

and x0(k). $\Delta_{0i}(k)$ is the absolute difference between xi(k) and x0(k). $\Delta_{0i}(k) = \left| x_0(k) - x_i(k) \right|$

$\zeta \in [0, \ 1]$ is the resolution coefficient.

$$\gamma(x_0, \ x_i) = \frac{1}{n} \sum_{k=1}^{n} \gamma(x_0(k), \ x_i(k)) \ k = 0,1,2,\cdots,n$$ is the correlation between sequence x_i and

x_0.

4. Steps of fault diagnosis method

It is necessary to establish data sets of various types of faults, including low temperature, medium temperature, high temperature overheating, partial discharge, spark discharge, arc discharge and complex type of fault type, by comparing collected data with the data of the known fault types and comparing the increase or decrease between various fault gases. Then the correlation degree is calculated, and the results are compared and discriminated. The concrete steps are as follows:

The first step is to build all kinds of fault data sets by using the data of known fault types. The data to be detected are inserted into each dataset to participate in the code calculation. Data pre-processing is conducted to reduce difference due to gas content difference. Through the statistical analysis of a large number of fault data, the proportion of each gas in each fault is calculated as shown in Table 3. Before calculating the correlation degree, all data are divided by the ratio in Table 2.

The second step: calculate the correlation coefficient between any two data I and j in the data. $\gamma(i,j)_{H_2}$, $\gamma(i,j)_{CH_4}$, $\gamma(i,j)_{C_2H_6}$, $\gamma(i,j)_{C_2H_4}$, $\gamma(i,j)_{C_2H_2}$. $\gamma(i,j)_\psi$ indicates the average value of the correlation coefficient between the gas ψ and the remaining four fault gases in the five broken lines between data i and data j.

Table 2. The proportion of the gas

Fault type	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2
Low temperature overheating	0.3820	0.3113	0.1056	0.1932	0.0079
Medium temperature overheating	0.0737	0.3689	0.2174	0.3392	0.0008
High temperature overheating	0.1329	0.2437	0.0937	0.5194	0.0103
Partial discharge	0.8907	0.0564	0.0412	0.0117	0.0001

Low energy discharge	0.5936	0.1000	0.0254	0.0571	0.2239
Arc discharge	0.3941	0.1478	0.0300	0.1965	0.2316

The third step is to calculate the correlation degree of each data to the fault type. $\gamma(i)_{H_2}$, $\gamma(i)_{CH_4}$,

$\gamma(i)_{C_2H_6}$, $\gamma(i)_{C_2H_4}$, $\gamma(i)_{C_2H_2}$, $\gamma(i)_\psi = \dfrac{1}{n-1}\sum\limits_{j=1, j\neq i}^{n-1}\gamma(i,j)_\psi$.

Fourth step: calculating the characteristic correlation of the fault ζ : $\gamma(\zeta)_\psi$.

$$\gamma(\zeta)_\psi = \frac{1}{n}\sum_{i=1}^{n}\gamma(i)_\psi \tag{2}$$

The fifth step is to calculate the correlation between the detected data 0 and the fault ζ :

$$\gamma(\zeta) = 1 - \frac{1}{5}\sum_\psi \left|\gamma(\zeta)_\psi - \gamma(0)_\psi\right| \tag{3}$$

Comparing the correlation $\gamma(\zeta)$ of detected data to each fault , the fault with biggest correlation is the fault.

5. Example verification analysis

From the processed oil coded data, 10 datas of the 011 coded data are analyzed, including 7 partial discharge datas, 2 overheating datas and 1 low energy discharge data, as shown in Table 3 [15-18].

The above method is used to discriminate and analyze the fault data. The the fault type of low temperature overheating data of 011 code were inserted into each fault set data one by one for graph analysis .When the low temperature overheating data set is inserted, the fault line can increase and decrease without crossing. When insert the rest of the fault type of the data set, there is always a intersection of the broken line as shown in figure 2,where data is inserted into the partial discharge (figure 2, the hydrogen unit for 10 ul/L, numerical shrink for one over ten, facilitate mapping analysis).

Table 3. Collected fault data coded as 011

| H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	code	Fault type
89.3	1.8	0.2	0.7	0.0	011	Partial discharge
123.5	2.64	0.56	0.8	0.0	011	Partial discharge
213.3	19.8	3.83	5.83	0.0	011	Partial discharge
420.0	37.3	14.9	30.0	0.2	011	Partial discharge
700.0	60.0	20.0	40.0	0.0	011	Partial discharge
1043.2	62	22.7	42.1	0.0	011	Partial discharge
538.3	12.6	8.7	14.1	0.3	011	Partial discharge
1680.0	0.0	1.8	2.1	0.0	011	Low energy discharge
3319.0	36.5	31.5	39.3	0.0	011	Overheating of solid insulation
565.0	53.0	34.0	47.0	0.0	011	Low temperature overheating
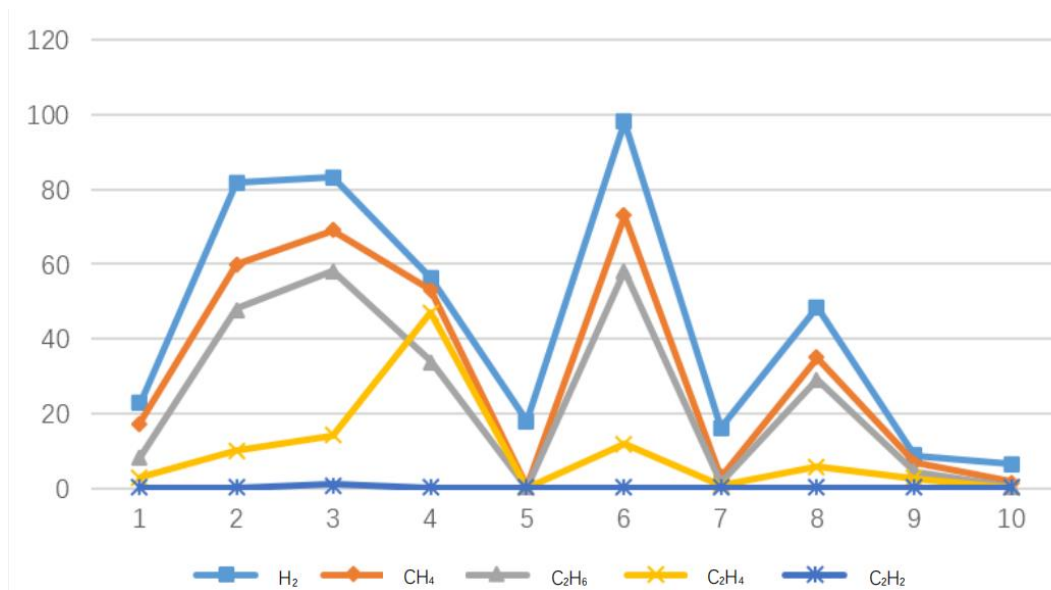
Figure 2. Low temperature overheating data of 011 code inserted in partial discharge dataset

It can be seen that when the low temperature overheating of 011 code faults are inserted into the fourth sets of data, the acetylene (C_2H_4) changes in the opposite trend, making the correlation of the inserted data decrease, which shows that the fault characteristic gas data has a smaller correlation with the partial discharge fault. Compared with the fault data sets, it can be concluded that the grey correlation with low temperature overheating is the highest and can be judged as low temperature overheating fault. The results are shown in Table 4.

Table 4. Data correlation diagnosis result of 011 code

Fault type	correlation	Fault type	correlation
Low temperature overheating	0.8972	Partial discharge	0.0753
Medium temperature overheating	0.4512	Low energy discharge	0.0958
High temperature overheating	0.3146	Arc discharge	0.0851

The result is low temperature overheating fault, which is consistent with the actual situation.

6. Conclusion
The three-ratio method determines the fault by the ratio method, which greatly reduces the information represented by DGA data. Based on the original data of DGA, this paper makes full use of the information represented by DGA data, and uses the calculation of grey relational to describe the law of DGA data increase and decrease, and can obtain the correlation between the unknown fault gas data and the various types of fault gas data, and can determine the data of the unknown fault by comparing the correlation. An example shows that this method can overcome the lack of codes in the three-ratio method. By calculating the correlation of the known fault type data set, the fault identification is carried out. The diagnosis effect is related to the data set, and the more comprehensive the data set is, the better the diagnosis effect is.

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