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Regular paper

Study on fault fusion diagnosis of power transformer test data analysis and symptoms

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With the continuous improvement of the level of science and technology, automation, modernization and digital technology have been important applications in the field of power transformation, providing a positive impetus for the development of power transformation to unmanned. Transformer as the key equipment in the substation, its operation safety is very important, once the failure, and has not been found in time, then it will cause unimaginable transformer accidents, resulting in human and economic losses. And transformer fault diagnosis is a problem of multi-factor fault index evaluation, so how to timely and effectively fault diagnosis of transformer is a hot topic. In view of this characteristic, D-S evidence theory is applied to it in this paper. Starting from fault fusion diagnosis, transformer experimental data and symptom phenomena are analyzed at the same time, transformer fault diagnosis is completed, reasonable and accurate diagnosis results are given, and safe operation of substation is escorted.

Keywords: Transformer; D-S evidence theory; Fault fusion diagnosis.

1. Introduction

The process of transformer fault diagnosis contains many uncertainties, such as random uncertainty and cognitive uncertainty[1-3]. Specifically, in the transformer preventive test, the monitoring data will present random uncertainty due to the difference of instrument accuracy, test environment and human intervention degree[4]. In the diagnosis of omen phenomena of transformers, the expert experience and knowledge used are cognitively uncertain[5, 6]. As for D-S evidence theory, it takes the reliability function as a measure to control the probability of some events and complete the construction of the reliability function[7, 8]. When evidence theory is more convincing than probability theory, important concepts such as "don't know" and "uncertainty" can be expressed from the perspective of cognition. It can be seen that D-S evidence theory is applied to transformer fault diagnosis in this paper. With the help of D-S evidence theory, transformer test data and symptom diagnosis results are fused to realize comprehensive diagnosis of transformer running state.

2. Notation

The notation used throughout the paper is stated below.

A	any subset of the power set
$m(A)$	basic probability distribution function of any subset of the power set
m	the basic probability distribution function

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K	the conflict degree of multiple independent evidences m_1, m_2 and m_3
α_i	the trust degree of the i body of evidence is represented by α_i
$m_i(j)$	the trust degree distribution of the JTH judgment of the i body of evidence
$m_i(\Theta)$	the trust degree of the i body of evidence
l	the number of output values of the i diagnostic module
$\xi_{0i}(k)$	the correlation coefficient
γ_{0i}	the correlation degree
ρ	the resolution coefficient
γ_{0i}	the weight value of all decision indicators

3. Basic overview of D-S evidence theory and its synthesis rules

3.1. A basic overview of D-S evidence theory

In 1967, A. P. Dempster, a mathematician at Harvard University in the United States, put forward DS evidence theory, and then his student Shafer introduced the concept of trust function, which was further improved and became a common mathematical method to solve a variety of data fusion problems, such as information fusion and decision fusion[9, 10]. D-S evidence theory exists without the support of the identification framework Θ. But the elements in Θ will repel each other, and the power set is represented by 2 PI, which represents the combination of problems. In the identification framework of D-S evidence theory Θ, all results have a certain probability, which is called Basic Probability Assignment (BPA). In general, the BPA function is also called the MASS function and is represented by M in the range [0,1], satisfying Equation 1.

$$\begin{cases} 0 \le m(A) \le 1 \\ m(\emptyset) = 0 \\ \sum_{A \subseteq \theta} m(A) = 1 \end{cases} \quad (1)$$

In Equation 1, any subset of the power set is represented by A, whose basic probability distribution function is represented by $m(A)$.

3.2. Composition rules of D-S evidence theory

Dempster's law of composition can reflect the law of the joint effect of event evidence, which is the key content of D-S evidence theory. On the same identification framework, given several different evidence's reliability function, if the conflict between these several evidence is small, then the combination rule can be used to calculate the reliability function, and the problem is regarded as the reliability function generated under the joint action of evidence. For $\forall A \subseteq \Theta$, the composite results of multiple independent evidences m_1,m_2 and m_3 can be calculated by Equation 2.

$$m(A)\begin{cases}0, A=\emptyset\\ \dfrac{\sum_{A_i\cap B_j=A} m_1(A_i)m_2(B_j)}{1-K}, A\neq\emptyset\end{cases} \quad (2)$$

In Equation 2, the basic probability distribution function is represented by m, and the conflict degree of multiple independent evidences m_1, m_2 and m_3 is represented by K. Wherein, K can be calculated by formula 3.

$$K=\sum_{A_i\cap B_j\cap C_k=\emptyset} m_1(A_i)\cdot m_2(B_j)\cdot m_3(C_k) \quad (3)$$

If the conflict is too large, it can indicate that the possibility of the same event is completely opposite, which is not conducive to the formation of the result of evidence synthesis.

4. Transformer test data and symptom fusion diagnosis method based on D-S evidence theory

4.1. Selection of transformer fusion diagnosis fault mode

The fault fusion diagnosis of power transformer test data and symptom phenomenon can be regarded as the fusion of two identical diagnosis results. Through integration, the fault diagnosis mode of power transformer fusion is shown in Figure 1.

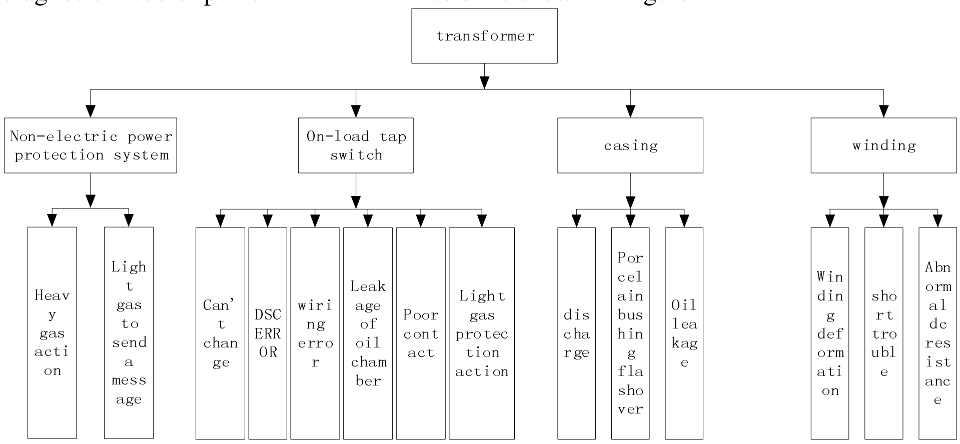

Figure 1: Transformer fusion diagnosis fault mode

4.2. Transformer fault fusion diagnosis process based on D-S evidence theory

Based on D-S evidence theory, the fusion diagnosis process of power transformer fault can be divided into three steps. The first step is to complete the construction of identification framework and evidence body. The identification framework is constructed from transformer fusion fault diagnosis mode, and the construction of evidence body is completed under the joint action of test data diagnosis matrix and omen phenomenon diagnosis matrix. Second, the basic probability distribution function of all the evidence is verified. In essence, information fusion technology is a new process of synthesizing different evidence bodies under the same framework. In this process, the determination of basic probability distribution function is the key content, which is represented by the probability converted by the weighted average probability of symptom diagnosis matrix and test data diagnosis matrix.In the fusion diagnosis of substation, the diagnostic accuracy varies with the different diagnostic methods. Therefore, there is a reliability coefficient α between data diagnosis and symptom diagnosis, and the trust degree of the evidence body can be determined by observing the coefficient. Combined with previous diagnostic experience, the reliability coefficient α of the data diagnosis matrix is set as 0.74 and the reliability coefficient of the symptom diagnosis matrix is set as 0.7 in this paper.At this point, set the JTH fault probability of the i diagnostic sub-module as $O_i(j)$, then the basic probability of the diagnostic module for fault j can be calculated by Equation 4.

$$\begin{aligned} m_i(j) &= \frac{O_i(j)\alpha}{\sum_{j=1}^{l} O_i(j)} \\ m_i(\Theta) &= 1-\alpha_i (i=1,2) \end{aligned} \tag{4}$$

In Equation 4, the trust degree of the i body of evidence is represented by α_i, and the trust degree distribution of the JTH judgment of the i body of evidence is represented by $m_i(j)$. The trust degree of the i body of evidence is represented by $m_i(\Theta)$ in the case that the allocation cannot be determined. The number of output values of the i diagnostic module is represented by l. Third, the synthesis and decision of evidence. The likelihood degree functions and reliability functions of all propositions in the identification framework are calculated separately under different evidences, and then the likelihood degree functions and reliability functions under the combined action of all evidences are calculated by D-S synthesis rule. After the confidence interval and uncertainty confidence are obtained, the reliability function value of location fault type is the largest and exceeds the uncertainty reliability function value,Where, the reliability interval is represented by $[Bel_j, pl_j]$. Combined with the actual situation of diagnosis, the difference value set here between the fault type reliability function value and other types of reliability function value should exceed 0.05, and the threshold value of the uncertain function value should be less than 0.1.

5. Determination method of transformer index parameter weight

When experts analyze and judge the weight of each evaluation index, they will be affected by many unknown factors, and the judgment results given cannot accurately reflect the importance of each index. Grey correlation analysis is a commonly used analysis method in system analysis, which can effectively find out the correlation degree among various factors. In determining the weights of link on the application of the analysis technology, can make up for the inadequacy of expert experience judgment weight, through quantitative means more experience judgment expert group of weight with a maximum of experts set, based on the differences between the two size, determine the expert group experience the connection degree of value judgment, when shown the correlation, the greater the expert experience to have consistent judgment, Furthermore, it shows that the index has a higher importance and the greater the weight. Based on this, all indicators are normalized to determine the weight corresponding to each index. The steps are as follows. First, the original data are collected and sorted to establish a grey correlation set. When there are n evaluation indicators, m experts can be organized to judge the weight value of each indicator from the perspective of experience, and the corresponding weight empirical judgment data can be obtained. Then, the matrix scale in the analytic hierarchy process can be used to determine the specific weights, and the numbers 1-5 are used to represent equally important, slightly important, obviously important, strongly important and extremely important respectively. The specific expression is shown in Equation 5.

$$\begin{aligned} X_1 &= \left(x_1(1), x_1(2), \ldots, x_1(m)\right) \\ X_2 &= \left(x_2(1), x_2(2), \ldots, x_2(m)\right) \\ &\vdots \quad \vdots \quad \vdots \\ X_n &= \left(x_n(1), x_n(2), \ldots, x_n(m)\right) \end{aligned} \tag{5}$$

In $X_1, X_2, \cdots, X_n$, the maximum weight value is found as the "common" reference weight value, and the reference data column X_0 formed can be expressed by Equation 6.

$$X_0 = \left(x_0(1), x_0(2), \cdots, x_0(m)\right) \tag{6}$$

Second, the correlation coefficient and correlation degree are calculated. The data given above are taken as the basis, and the correlation coefficient $\xi_{oi}(k)$ between the expert experience weight judgment value and the "public" reference weight can be calculated by using Equation 7, and the correlation degree γ_{oi} between the experience weight judgment value and the "public" reference weight can be calculated by using Equation 8.

$$\xi_{oi}(k) = \frac{\min\limits_i \min\limits_k |x_0(k) - x_i(k)| + \rho \max\limits_i \max\limits_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max\limits_i \max\limits_k |x_0(k) - x_i(k)|} \tag{7}$$

$$\gamma_{oi} = \frac{1}{n} \sum_{k=1}^{n} \xi_{oi}(k) \tag{8}$$

Where, the resolution coefficient is represented by ρ, $\rho \in (0, \ 1)$, and in general, $\rho = 0.5$. The weight of each evaluation index can be made clear by checking the correlation degree between the series.Third, make γ_{oi} as the weight value of all decision indicators, that is $\omega_i = \gamma_{oi}$. Fourthly, normalize the correlation degree of all factors, and calculate the weight value of each factor in the evaluation system with Equation 9.

$$\gamma_{oi} = {}^{\gamma_{ok}}/_{\gamma_{ok}} \tag{9}$$

For the convenience of understanding, this paper gives the specific process of determining the weight by the grey correlation method, as shown in Figure 2.

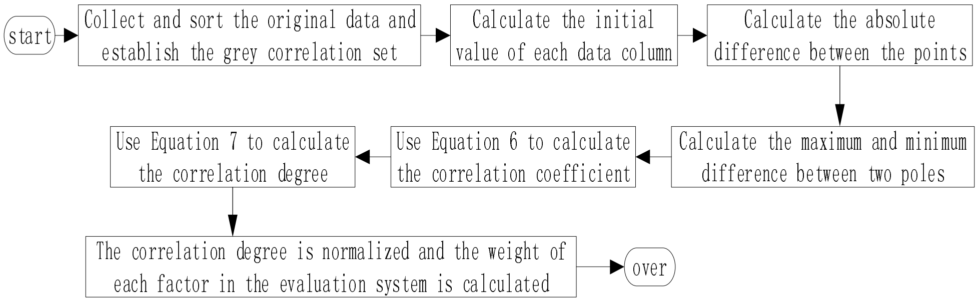

Figure 2: Grey correlation method to determine the weight process

6. Empirical Research

6.1. Data collection before the experiment and membership determination of the experiment items

In order to test the validity of D-S evidence theory in the fault fusion diagnosis of power substation, this paper takes the transformer with the model SFPSZ1-240000/220 as the research object, collects and collates its preventive test data from 2017 to 2018, as shown in Table 1, and the chromatographic tracking data of two times in 2018 is shown in Table 2.

Table 1: Transformer preventive test data in 2017-2018

A pilot project	2017	2018	Relative change
Unbalance coefficient of winding DC resistance	0.50 %	0.54 %	0.08
Absorptance	1.49	1.27	0.147
Polarization index	2.3	1.65	0.282
Windings leakage current changes	23.3 %	122.9 %	4.274
Winding dielectric loss	0.276 %	0.61 %	1.210
Dielectric loss of capacitive bushing	0.58 %	0.75 %	0.293
Capacitive sleeve capacitance	-1.3 %	-1.5 %	0.153
Core earth current	31 mA	37.7 mA	0.216
Water content in oil	16 mg/L	22 mg/L	0.375
Oil dielectric loss	1.58 %	2.44 %	0.544
Oil breakdown voltage	52 kV	49 kV	0.057
Content of glycoaldehydes in oil	0.27 mg/L	0.33 mg/L	0.222

Table 2: Chromatographic tracking data for 2 times in 2018 (μL/L)

Test date	CO	CO2	H2	CH4	C2H2	C2H4	C2H6	Total hydrocarbon
2017.06.29	32.1	313	66	7.7	1.3	10	2.6	21.6
2018.09.10	198.5	2484	94.1	28	3.4	73.6	9.2	114.2

According to the chromatographic tracking data in Table 2, the relative gas production rates of total hydrocarbon in the two tests were 2.9% and 6.2%, the absolute gas production rates of total hydrocarbon were 4.5 mL/d and 8.9 mL/d, and the absolute gas production rates of CO were 36.4 mL/d and 51.4 mL/d, respectively. Through consulting the previous maintenance records of the transformer, it was found that the transformer had been subjected to lightning overvoltage, experienced short-term emergency load, and also underwent a major repair. Through the inspection of the appearance, it was found that the surface of the cooler had been corroded, the obstruction of the breathing apparatus caused the problem of false oil level, the temperature around the winding oil level exceeded the normal value, the transformer had a slight oil leakage phenomenon, and there was a yellow discharge behavior on the casing surface. At this time from the transformer test data and symptoms of these two aspects, the fault diagnosis. According to the test data in Table 1, the membership degree of the test items was respectively calculated with the aid of membership function, and the obtained results are shown in Table 3.

Table 3: Membership degree of test items

Components	A pilot project	Membership
Capacitive sleeve	Dielectric loss of capacitive bushing	0.5963
	Capacitive sleeve capacitance	1
Winding	Windings leakage current changes	0.9978
	Absorptance	0.1925
	Winding dielectric loss	0.1056
Insulating oil	Oil dielectric loss	0.2836
	Water content in oil	1
/	Dissolved gas in oil	0.0482

After obtaining the membership degree of electrical test items of components, 5 experts were organized to score symptom phenomena, and the failure probability of symptom phenomena was determined by means of extreme value theory. The obtained results are shown in Table 4.

Table 4: Fault probability of symptom phenomena

Components	A pilot project	Failure probability
Casing	Visual	0.37
Winding	Temperature detection	0.63
Body	Visual	0.31
Non-electrical protection system - respirator	Visual	0.70
Cooling system - cooler	Visual inspection - visual inspection	0.29

6.2. Establishment of transformer test data and symptom diagnosis matrix

After determining the fault probability of symptom phenomenon, transformer test data and symptom phenomenon diagnosis matrix are constructed according to components, as shown below.

Casing test data and symptom matrix:

$$\begin{array}{cc} & \begin{array}{ccccc} \textit{Oil leakage} & \textit{humidified insulation} & \textit{Porcelain bushing flashover} & \textit{aging} & \textit{discharge} \end{array} \\ \begin{array}{c} \textit{capacitance} \\ \textit{Dielectric loss value} \end{array} & \begin{bmatrix} 0.596 & 0 & 0 & 0.596 & 0.596 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

$$\begin{array}{cc} & \begin{array}{ccc} \textit{Oil leakage} & \textit{Porcelain bushing flashover} & \textit{discharge} \end{array} \\ \textit{visual} & \begin{bmatrix} 0.37 & 0.37 & 0.37 \end{bmatrix} \end{array}$$

Winding test data and symptom matrix：

$$\begin{array}{cc} & \begin{array}{ccc} \textit{humidified insulation} & \textit{Abnormal dc resistance} & \textit{Discharge fault} \end{array} \\ \begin{array}{c} \textit{Oil chromatographic analysis} \\ \textit{absorptance} \\ \textit{Winding leakage current} \\ \textit{Winding dielectric loss value} \end{array} & \begin{bmatrix} 0.048 & 0.048 & 0.048 \\ 0.193 & 0 & 0 \\ 0.998 & 0 & 0 \\ 0.106 & 0 & 0 \end{bmatrix} \end{array}$$

$$\begin{array}{cc} & \begin{array}{ccc} \textit{Abnormal dc resistance} & \textit{Oil duct blockage} & \textit{overload} \end{array} \\ \textit{Temperature measurement} & \begin{bmatrix} 0.63 & 0.63 & 0.63 \end{bmatrix} \end{array}$$

Insulating oil test data matrix:

$$\begin{array}{cc} & \begin{array}{ccc} \textit{Aging of solid insulation} & \textit{Oil deterioration} & \textit{humidified insulation} \end{array} \\ \begin{array}{c} \textit{Oil dielectric loss value} \\ \textit{Water content in oil} \end{array} & \begin{bmatrix} 0.283 & 0.283 & 0.283 \\ 0 & 0 & 0 \end{bmatrix} \end{array}$$

Body diagnosis matrix:

$$\begin{array}{cc} & \begin{array}{cc} \textit{Oil leakage} & \textit{Box shell deformation} \end{array} \\ \textit{visual} & \begin{bmatrix} 0.31 & 0.31 \end{bmatrix} \end{array}$$

Non-electric protector-respirator diagnosis matrix:

$$\begin{array}{rcc} & \textit{Bad breathing passage} & \textit{Respiratory passage bypass} \\ \textit{visual} & [0.70 & 0.70] \end{array}$$

Cooling system-cooler diagnostic matrix:

$$\begin{array}{rccc} & \textit{Negative pressure air intake} & \textit{The oil flow loop is blocked} & \textit{All shipments} \\ \textit{visual} & [0.29 & 0.29 & 0.29] \end{array}$$

According to the above characteristic parameters, five experts built an initial weight matrix. At this time, the weights of seven test items, five symptom phenomena and dissolved gas in oil were calculated by means of the grey correlation method, as shown in Table 5.

Table 5: The weights of 7 test items and 5 symptom phenomena

Components	A pilot project	Weight
Capacitive sleeve	Dielectric loss of capacitive bushing	0.126
	Capacitive sleeve capacitance	0.147
Winding	Windings leakage current changes	0.168
	Absorptance	0.147
	Winding dielectric loss	0.147
Insulating oil	Oil dielectric loss	0.147
	Water content in oil	0.126
Casing	visual	0.25
Winding	Temperature detection	0.29
Body	Visual	0.21
Non-electrical protection system - respirator	Visual	0.13
Cooling system - cooler	Visual inspection - visual inspection	0.17
/	Dissolved gas in oil	0.9

6.3. Failure probability acquisition

Based on the test data and symptom matrix of each component, the fuzzy comprehensive evaluation method was used to carry out the weighted sum of the above seven test items and five symptom phenomena, and the fault probability of each fault mode was calculated, as shown in Table 6.

Table 6: The total failure probability of each failure mode

Components	Test data failure mode	Probability	Signs of phenomenon failure mode	Probability
Casing	Bushing flashover	0.126	Bushing flashover	0.095
	Aging	0.213	Discharge	0.095
	Discharge	0.088		
	Oil leakage	0.095		
Winding	Humidified insulation	0.249	Abnormal dc resistance	0.183
	Abnormal dc resistance	0.048	Oil duct blockage	0.183
	Discharge fault	0.048	Overload	0.183
			Oil leakage	0.088
			Humidified insulation	0.126
Insulating oil	Aging of solid insulation	0.042	/	/
	Oil deterioration	0.042	/	/
	Humidified insulation	0.167	/	/
Cooling system - cooler	/	/	Negative pressure air intake	0.051
	/	/	The oil flow loop is blocked	0.051
	/		All shipments	0.051
Non-electric protection - respirator	/	/	Bad breathing passage	0.087
	/	/	Respiratory passage bypass	0.087
Body	/	/	Oil leakage	0.067
	/	/	Box shell deformation	0.067

It can be seen from Table 6 that in the winding, the "direct resistance anomaly" is a fault common to both the test data and the symptom phenomena. In the casing, "porcelain casing flashover", "oil leakage" and "discharge" are the common faults of test data and symptoms. These faults have basically the same probability and low discrimination rate, so it is necessary to use D-S theory to carry out fault mode fusion.

6.4. Fault mode fusion based on D-S theory

Specifically, the fusion idea is as follows: firstly, the identification framework is constructed, and the direct resistance anomaly, oil leakage, flashover of porcelain casing and discharge are respectively represented by F_1, F_2, F_3 and F_4. Secondly, the basic probability distribution of each evidence body is obtained. Finally, formula 3 is used for calculation to obtain the reliability interval and diagnostic results of the identification framework under the action of isolation and fusion, as shown in Table 7 and Table 8.

Table 7: Reliability interval and diagnostic results under single action

Evidence	$m_i(\theta)$	[Bel(F_i), pl(F_i)]					
			F_1	F_2	F_3	F_4	Diagnosis
Test Data A	0.27	Bel	0.105	0.196	0.286	0.105	/
		pl	0.375	0.466	0.556	0.375	
Symptom data B	0.3	Bel	0.276	0.140	0.140	0.140	/
		pl	0.576	0.440	0.440	0.440	

Table 8: Reliability interval and diagnostic results under fusion

Evidence	$m_i(\theta)$	[Bel(F_i), pl(F_i)]					
			F_1	F_2	F_3	F_4	Diagnosis
A&B	0.076	Bel	0.250	0.229	0.331	0.132	F_3
		pl	0.326	0.305	0.407	0.208	

As can be seen from Table 8, after the D-S theory fusion, the fault F_3 has the maximum reliability function value, the confidence interval is $[0.331, 0.407]$, and the uncertainty is reduced to 0.076. At the same time, both the reliability value and the reliability interval can show good peak value and separability, which can accurately identify the transformer fault, that is, F_3 porcelain sleeve flashover. At this point, after the normalization of the reliability function, the failure probability of F_1, F_2, F_3 and F_4 is obtained as $\{0.266, 0.244, 0.350, 0.137\}$.In conclusion, the following conclusions can be drawn: First, the probability of oil leakage, porcelain casing flashover and aging failure is relatively high. Second, the probability of winding DC resistance abnormality and insulation damp fault is large. Therefore, it can be judged that there is a problem of lax sealing of the transformer, which leads to abnormal DC resistance and leads to overheating fault. At the same time, it can also judge the casing quality is not good or the sealing is not strict, which leads to the capacitor being damp and weakening the service life of the capacitor screen insulation. It needs to arrange maintenance as soon as possible. The actual situation is as follows: in 2018, after a one-month pre-test of the transformer, the power failure maintenance was carried out, and it was found that there was a loose seal between the military cap of the casing and the top of the oil tank, resulting in damp insulation. The feasibility of D-S evidence theory in the fusion diagnosis of transformer experimental data and symptom phenomena is confirmed.

7. Summary

In general, the D-S evidence theory is first expounded, and the corresponding synthesis rules are given. Secondly, starting from the selection of transformer fusion diagnosis mode, the fault fusion diagnosis method of transformer test data and symptom phenomena is systematically explained, and the calculation formula of trust distribution of evidence body is given. Finally, according to the test data and signs of fusion fault diagnosis methods and processes, to model SFPSZ1-240000/220 transformer as the research object to carry on the empirical research, finally the result shows that the transformer casing of poor quality or untight seal problems, was consistent with actual situation, and drew a satisfactory full stop for this study.

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