TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.7, July 2014, pp. 5096 ~ 5103
DOI: 10.11591/telkomnika.v12i7.5210

Transformer State Assessment Method Based on Fuzzy and Evidence Theories

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Abstract

Accurate and reliable assessment of power equipment operation state is the premise and basis for maintenance of power system state. This article builds the transformer body state assessment model based on fuzzy and evidence theories taking 500kV oil-immersed transformer as the object of research. The representative parameters in preventive test are selected as state assessment indicators by making reference to the factory values and threshold-crossing values of which the indicator normalization is carried out to determine the degrees of membership of each indicator relative to different state assessment levels using fuzzy evaluation method. These indicators are divided into three sub-evidence bodies, i.e. gas dissolved in oil, oilation test and electrical test, and information combination of these three sub-evidence bodies is carried out using evidence theory to further assess the operation state of transformer body. The effectiveness of this assessment model applied in state assessment of transformer body is verified by example analysis of the data of a 500kV transformer. This assessment model has clear ideas and doesn't need too much historical data; it provides a new method for transformer state assessment.

Keywords: *power transformer, fuzzy evaluation, evidence theory, state assessment*

1. Introduction

Along with the continuous improvement of power transmission and transformation voltage grades and grid capacities, the safe and stable operation of power system is facing great challenges. As the core equipment of power transmission and transformation system, the operation state of power transformer directly affects the safe operation level of the whole power system. Accurate and reliable assessment of operation state of power transformer to discover the potential hazards of transformer and reduce the probability of transformer faults is helpful to improve the safe operation level of the whole grid.

It can be known from the transformer state evaluation indicators given by literature [1] that: the amount of information of power transformer state is large and reflects the operation state of transformer on different levels. However, due to the inaccuracy of measurement and imperfection of evaluation criteria, there is great uncertainty of the state assessment of transformer. And based on this, research of transformer state assessment methods has been conducted by many scholars at home and abroad. Bayesian network [2-3] assessment method takes the historical, current and future states of transformer into comprehensive consideration to determine the comprehensive state of transformer by Bayesian network. But this assessment method needs a large amount of historical data as training sample of Bayesian network. Support vector machine [4-6] assessment method with good fitting and generalization capabilities can map the highly non-linear input and output functions and can well appropriate the mapping of transformer operation state from state information. This method also needs certain samples for training and excessively hardens the treatment of assessment state boundary. Grey target theory [7] rates the state of transformer in standard fault free mode and uses the grey target contribution degree as the weight of quantity of state. Fuzzy comprehensive evaluation method conducts fuzzy evaluation normalization of each assessment indicator to obtain the membership vector and then conducts compositional operation of membership vectors of all indicators to obtain the comprehensive evaluation result. In addition, there are literatures assessing the state of transformer through matter-element theory [11], cloud theory [12], set pair analysis [13] and core vector space [14] methods, etc. The application

Received November 26, 2013; Revised March 20, 2014; Accepted April 2, 2014

of these methods greatly facilitates and develops the transformer state assessment research, and these methods also play an important role in actual applications.

Evidence theory [15-16] is an important uncertainty inference method; it attaches importance to the subjectivity of evidence estimation as well as emphasizes the objectivity of evidence. It effectively combines the different information through accumulation of evidences and continuous shrinkage of the set of assumptions and has strong decision treatment capability. With 500kV oil-immersed transformer as the object of research, this article considers the transformer state assessment as a multi-attribute decision-making problem and builds the transformer body state assessment model based on fuzzy and evidence theories according to the selected transformer body state assessment parameters which are representative parameters in preventative test and are divided into three sub-evidence bodies according to characteristics.

2. Selection of Assessment Indicators

A relevant industrial standard divides the transformer into five parts, i.e. body, bushing shell, tapping switch, cooling system, non-electric quantity protection and conducts the state assessment respectively. This article specifically assesses the state of insulation of transformer body, and it can be a reference for state assessment methods of other parts.

The following principles shall be followed by the selection of assessment indicators: (1) High sensitivity, i.e. the minor change of equipment state shall be able to cause the significant change of quantity of state; (2) High reliability, i.e. the change of assessment indicator shall be able to accurately reflect the change of equipment state; (3) Practicability, i.e. the assessment indicators shall be convenient for testing; (4) Various assessment indicators shall be independent of each other and reflect the features of transformer from different aspects as much as possible. And based on this, the quantities of part states of gas dissolved in oil, oilation test and electrical test of transformer body are selected as the assessment indicators in this article. As shown in Table 1:

Table 1 Transformer Body State Assessment Indicators

Transformer Body State	Gas dissolved in oil	Total hydrocarbon content
		Hydrogen content
		Acetylene content
	Oilation test	Oil dielectric loss
		Oil breakdown voltage
		Moisture in oil
		Furfural
	Electrical test	Direct current resistance unbalance rate
		Winding dielectric loss
		Polarization index
		Iron core grounding current

3. Indicator Quantization and State Division

3.1. Assessment Indicator Normalization

Power transformer body is a very complicated system. Various assessment indicators reflect the operation state of transformer from different sides and different assessment indicators have different unit measures. Before the assessment of transformer body state by comprehensive use of these assessment indicators, normalization of assessment indicators shall be conducted. In this article, the normalization of assessment indicators is conducted by use of relative cracking degrees. As for the assessment indicators of which the indicator values are the smaller the better, such as content of hydrogen in oil, the calculation of relative cracking degrees is carried out using formula (1):

$$x_{nr} = \begin{cases} 0 & x_r \le x_0 \\ \dfrac{x_r - x_0}{x_1 - x_0} & x_0 < x_r \le x_1 \\ 1 & x_r > x_1 \end{cases} \qquad (1)$$

$$x_{nr} = \begin{cases} 1 & x_r \le x_1 \\ \dfrac{x_0 - x_r}{x_0 - x_1} & x_1 < x_r \le x_0 \\ 0 & x_r > x_0 \end{cases} \quad (2)$$

As for the assessment indicators of which the indicator values are the larger the better, such as oil breakdown voltage, the calculation of relative cracking degrees is carried out using formula (2).

In formulas (1) and (2), x_r is the actual measured value of assessment indicator e_r, x_{nr} is the normalized value, x_0 and x_1 are normalized threshold values. x_1 is determined by preventive test procedure, and the expression of actual measure value of assessment indicator beyond the stipulated value shall arouse the attention. x_1 is the factory value of assessment indicator. According to the transformer assessment guidelines and field survey data, the threshold values of various assessment indicators of 500kV transformer body are shown in Table 2.

Table 2. Normalized Threshold Values of State Assessment Indicators

Assessment Indicator	x_0	x_1
Total hydrocarbon content (uL/L)	50	150
Hydrogen content (uL/L)	30	150
Acetylene content (uL/L)	0	5
Oil dielectric loss (%)	0	2
Oil breakdown voltage (kV)	70	50
Moisture in oil (mg/L)	0	15
Furfural (mg/L)	0	4
Direct current resistance unbalance rate (%)	0	2
Winding dielectric loss ((%)	0	0.6
Polarization index	2	1.5
Iron core grounding current (A)	0	0.1

3.2. State Grading

The transformer state is generally divided into four state grades: normal state S1, attention state S2, abnormal state S3 and serious state S4. Normal state means that: various assessment indicators of transformer are stable and within the warning values and attention values stipulated by the procedure, the transformer can operate normally; attention state means that: the changing trends of one or more assessment indicators develop approaching the standard limit values but haven't exceeded the standard limit values, the transformer can continue the operation and the monitoring shall be enhanced; abnormal state means that: a certain assessment indicator has relatively large change and has exceeded or slightly exceeded the standard limit value, the operation shall be monitored and repair shall be scheduled to be carried out as appropriate; serious state means that: an important assessment indicator has seriously exceeded the standard limit value, and power-off repair shall be scheduled to be carried out as soon as possible.

4. Transformer Body State Assessment Model Applying Fuzzy and Evidence Theories

According to the assessment indicator selection method in Section 1, the assessment indicators of transformer body are divided into the quantities of part states of three sub-evidence bodies, i.e.: gas dissolved in oil (sub-evidence body 1), oilation test (sub-evidence body 2) and electrical test (sub-evidence body 3). Each sub-evidence body consists of several assessment indicators (Table 1). The working steps of transformer body state assessment model based on fuzzy and evidence theories are: 1) Obtain the actual values of various assessment indicators and conduct the normalization, determine the degree of membership of each assessment indicator to the state of transformer using fuzzy theory; 2) Determine the degree of membership of each sub-evidence body to the state of transformer; 3) Conduct the evidence inference of each sub-evidence body using evidence theory to obtain the assessment state of transformer body. The detailed working process of assessment model is shown in Figure 1.

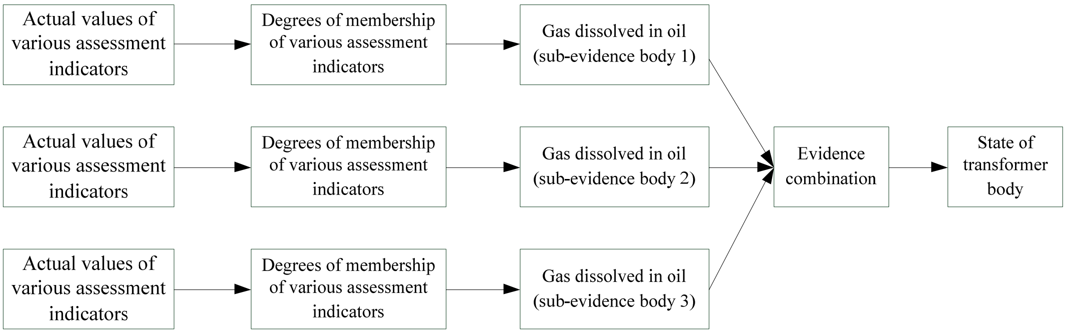

Figure 1. Transformer Body State Assessment Model

4.1. Degree of Membership of Assessment Indicator

This article determines the states of various assessment indicators using fuzzy evaluation method which overcomes the problem of excessive hardening of assessment state boundary treatment of other evaluation methods. According to fuzzy mathematic theory, the information of different state grades of assessment indicators can be expressed by membership functions. The common membership functions are triangular membership function, trapezoidal membership function, semi-trapezoid and semi-ridge combination membership function. Triangular membership function is relatively rough in the determination of state grade, while trapezoidal membership function is easy to cause information loss. This article uses semi-trapezoid and semi-ridge combination membership function to determine the information of different state grades of various assessment indicators, and the membership function is defined as:

$$\mu_1(x_{nr}) = \begin{cases} 1 & x_{nr} \le a_1 \\ \frac{1}{2} - \frac{1}{2}\sin[\frac{\pi}{a_2 - a_1}(x_{nr} - \frac{a_1 + a_2}{2})] & a_1 < x_{nr} \le a_2 \\ 0 & x_{nr} > a_2 \end{cases} \quad (3)$$

$$\mu_2(x_{nr}) = \begin{cases} \frac{1}{2} + \frac{1}{2}\sin[\frac{\pi}{a_2 - a_1}(x_{nr} - \frac{a_1 + a_2}{2})] & a_1 < x_{nr} \le a_2 \\ 1 & a_2 < x_{nr} \le a_3 \\ \frac{1}{2} - \frac{1}{2}\sin[\frac{\pi}{a_4 - a_3}(x_{nr} - \frac{a_3 + a_4}{2})] & a_3 < x_{nr} \le a_4 \end{cases} \quad (4)$$

$$\mu_3(x_{nr}) = \begin{cases} \frac{1}{2} + \frac{1}{2}\sin[\frac{\pi}{a_4 - a_3}(x_{nr} - \frac{a_3 + a_4}{2})] & a_3 < x_{nr} \le a_4 \\ 1 & a_4 < x_{nr} \le a_5 \\ \frac{1}{2} - \frac{1}{2}\sin[\frac{\pi}{a_6 - a_5}(x_{nr} - \frac{a_5 + a_6}{2})] & a_5 < x_{nr} \le a_6 \end{cases} \quad (5)$$

$$\mu_4(x_{nr}) = \begin{cases} 0 & x_{nr} \le a_5 \\ \frac{1}{2} + \frac{1}{2}\sin[\frac{\pi}{a_6 - a_5}(x_{nr} - \frac{a_5 + a_6}{2})] & a_5 < x_{nr} \le a_6 \\ 1 & x_{nr} > a_6 \end{cases} \quad (6)$$

In formulas (3)~(6), x_{nr} is the normalized value of assessment indicator e_r; $\mu_1(x_{nr})$~$\mu 4(x_{nr})$ are the degrees of membership of assessment indicator er relative to four different state grades S1~S4. a_1~a_6 are boundary values between different state grades. According to relevant fuzzy rules, the values of a1~a6 are selected as 1/10, 3/10, 4/10, 6/10, 7/10 and 9/10.

4.2. Degree of Membership of Sub-evidence Body

The degrees of membership $\mu_1(x_{nr})$~$\mu_4(x_{nr})$ of assessment indicator er relative to four different state grades can be determined from formulas (3)~(6). The mathematical expression of degree of membership of sub-evidence body is:

$$\mu_i(E_j) = \sum_{r=1}^{m} \mu_i(x_{nr})\omega(x_r) \tag{7}$$

In which, $\mu_i(E_j)$ is the degree of membership of sub-evidence body *j* relative to state grade *i*. $\mu_i(x_{nr})$ is the degree of membership of assessment indicator er in sub-evidence body *j* relative to state grade *i*. $\omega(x_r)$ is the weight of indicator er. The weight of each indicator is determined using expert decision method. In this article, the state of transformer is divided into four grades, therefore, the values selected for i are 1, 2, 3 and 4. As there are three sub-evidence bodies in assessment model, the values selected for j are 1, 2 and 3. m is the number of assessment indicators in sub-evidence body; as obtained from Table 1: the numbers of assessment indicators in various sub-evidence bodies in assessment model are respectively: 3, 4 and 4. The weights of assessment indicator er in various sub-evidence bodies are:

Gas dissolved in oil: {0.2697, 0.1780, 0.5223}
Oilation test: {0.1710, 0.1964, 0.1964, 0.4362}
Electrical test: {0.2828, 0.1720, 0.1720, 0.3732}

4.3. Evidence Combination Theory

Evidence combination theory, also known as DS theory, is an uncertainty inference and treatment method. Evidence combination theory is based on the combination of evidences and updating of belief functions and describes the uncertainty through the concepts such as identification frame, basic belief distribution function, belief function, plausibility and confidence interval [17].

4.3.1. Basic Definitions

The basic definitions of evidence combination theory are as follows:

Definition 1: assume that: Θ is the identification frame and the basic belief distribution function m is the mapping from the set 2^Θ→[0,1], and $A \subseteq \Theta$. If ① $m(\phi) = 0$ and ② $\sum_{A\subseteq\Theta} m(A) = 1$ are satisfied, m(A) is called the basic belief distribution function of event A and expresses the degree of belief of evidence to A. All the sets satisfying m(A)>0 are called focal elements, and the union of all the focal elements in frame Θ is called the core.

Definition 2: the function Bel: 2^Θ→[0,1] defined by $\forall A \subseteq \Theta$ and $Bel(A) = \sum_{B\subseteq A} m(B)$ is called the confidence function on Θ and expresses the degree of belief to the trueness of A.

Definition 3: assume Bel: 2^Θ→[0,1] to be the confidence function on Θ, for $\forall A \subseteq \Theta$; the function Pls: 2^Θ→[0,1] defined by $Pls(A) = 1 - Bel(\overline{A})$ is called the plausibility function of Bel.

Definition 4: for $\forall A \subseteq \Theta$, the interval [Bel(A), pls(A)] is called the confidence interval of A.

4.3.2. Evidence Combination

Considering that different sub-evidence bodies have different relative importance, confidence function α is introduced to correct the confidence distribution before evidence combination.

$$\begin{cases} m'(A) = \alpha m(A) \\ m'(\Theta) = 1 - \alpha \end{cases} \tag{8}$$

m'(A) is the corrected confidence function value; m'(Θ) is the confidence distribution of uncertain evidence.

Given the confidence functions of different evidence bodies in the same identification frame, the combined confidence function can be calculated using the combination rule. The basic combination rule is as follows:

$$(m_1 \oplus \cdots \oplus m_n)(A) = \frac{\sum_{A_1 \cap \cdots \cap A_n = A} m_1(A_1) \times \cdots \times m_n(A_n)}{1 - \sum_{A_1 \cap \cdots \cap A_n = \varnothing} m_1(A_1) \times \cdots \times m_n(A_n)} \quad (9)$$

After the combined confidence function of different sub-evidence bodies has been determined, the assessment target determination can be conducted using the corresponding inference rule. The basic inference rule is as follows:

$$\begin{cases} m(F_i) - m(F_j) > \varepsilon_1 \\ m(\Theta) < \varepsilon_2 \\ m(F_i) > m(\Theta) \end{cases} \quad (10)$$

F_i is the state grade obtained by the assessment; m(F_i) is the confidence function value of assessment result; m(F_j) is the confidence function values of other states; m(Θ) is the uncertain confidence function value; ε_1 and ε_2 are threshold values predefined according to expertise and technical standards. In this article, the values selected for ε_1 and ε_2 are 0.5 and 0.1 respectively.

5. Example Analysis

The assessment object is the transformer with model of ODFPS-250000/500 in a transformer substation of Hubei Provincial Electric Power Company, the preventative test data of this transformer in May 2010 are selected for the assessment of the state of transformer body. The actual values of its various indicators, i.e. gas dissolved in oil, oilation test and electrical test are shown in Table 3:

Table 3. Preventative Test Data of Transformer

Sub-evidence Body	Assessment Indicator	Measured Value
Gas dissolved in oil	Total hydrocarbon content (uL/L)	70.1
	Hydrogen content (uL/L)	60.5
	Acetylene content (uL/L)	3.6
Oilation test	Oil dielectric loss (%)	0.5
	Oil breakdown voltage (kV)	67.1
	Moisture in oil (mg/L)	9
	Furfural (mg/L)	3.01
Electrical test	Direct current resistance unbalance rate (%)	1
	Winding dielectric loss ((%)	0.53
	Polarization index	1.9
	Iron core grounding current (A)	0.065

Table 4. Confidence Function Values of Sub-evidence Bodies before the Correction

Sub-evidence Body	m(A)			
	S1	S2	S3	S4
1	0.1548	0.2929	0.5095	0.0128
2	0.1979	0.1695	0.5625	0.0701
3	0.0860	0.2274	0.5175	0.1691

Table 5. Confidence Function Values of Sub-evidence Bodies after the Correction

Sub-evidence Body	m(Θ)	m(A)			
		S1	S2	S3	S4
1	0.1000	0.1393	0.2636	0.4586	0.0115
2	0.4653	0.1058	0.0906	0.3008	0.0375
3	0.1700	0.0714	0.1887	0.4296	0.1403

The normalization of measured values of indicators is conducted using the calculation formula of relative cracking degrees and the threshold values of various assessment indicators in Section 2. Then, the degrees of membership of each assessment indicator relative to various state grades are obtained based on fuzzy evaluation method to further obtain the degrees of membership of each sub-evidence body relative to various state grades; Table 4 and Table 5 respectively show the confidence function values of various sub-evidence bodies before and after the correction.

According to the inference rule in formula (10), the maximum confidence function value of sub-evidence body 1 is 0.4586 with difference of less than ε_1 from all the other confidence function values; therefore, the operation state of transformer body can't be determined by the information of sub-evidence body 1 alone. Similarly, neither sub-evidence body 2 nor sub-evidence body 3 can determine the operation state of transformer body by themselves. Therefore, evidence combination is conducted for the three sub-evidence bodies and the confidence function values are obtained, as shown in Table 6:

Table 6 Confidence Function Values after Evidence Combination

Transformer Body	m(Θ)	m(A)			
		S1	S2	S3	S4
1&2&3	0.0222	0.0705	0.1816	0.6990	0.0267

Table 6 shows the confidence distribution of three sub-evidence bodies after evidence combination. It can be seen that: the confidence function value of state S3 is 0.6990 with difference of more than ε_1 from the confidence function values of all the other states; the uncertain evidence confidence function value is 0.0222 and is less than ε_2, in addition, the confidence function value of state S3 is more than the uncertain evidence confidence value. Therefore, it can be obtained from the inference rule that: the transformer is in state S3, i.e. abnormal state. The actual situation is that: there are high temperature overheating traces around the coil of this transformer and there has been arc discharge phenomenon, therefore, the operation of this transformer shall be monitored and the repair shall be scheduled to be carried out as appropriate; thus, the correctness of the assessment method in this article is verified.

6. Conclusion

This article selects the representative parameters in preventive test of transformer as assessment indicators for state assessment and divides these indicators into three different sub-evidence bodies to assess the operation state of transformer body by use of assessment model based on fuzzy and evidence theories. It can be obtained from the research in this article that: 1) The use of fuzzy evaluation method in treatment of uncertainty problem can overcome the problem of excessive hardening of assessment state treatment of other evaluation methods; 2) Evidence theory can overcome the one-sidedness of evidence body in a certain aspect and effectively combine the information of various evidence bodies to allow the state assessment results to be more specific and greatly reduce the assessment uncertainty; 3) The transformer body state assessment model based on fuzzy and evidence theories has clear principles and easily accessible assessment indicators, it can accurately assess the operation state of transformer body without requiring a large amount of empirical data. This assessment model is also applicable to all the other transformer parts or other power equipments.

Acknowledgements

This work was supported by Science and Technology Program of Shanxi Power Corporation (No. KJ [2011] 333) and National Basic Research Program of China (973) Program (No.2009CB724507)

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