OWA Operator-Based Fuzzy Comprehensive Assessment Of Transformer Condition

Liping Shi
School of Information and Electrical Engineering
China University of Mining and Technology, Xuzhou, Jiangsu, China
shiliping98@126.com

Hongxia Xie
School of Computer science and Technology
China University of Mining & Technology, Xuzhou, Jiangsu, China
xiehx@cumt.edu.cn

***Abstract*—The indicators system and indicators normalization method for the condition assessment of Transformer is developed and membership function of the indicators is established. The establishment of Expert Weight is decided jointly by subjective weight and objective weight which is based on entropy weight thoughts, while the indicators weight is gained by the weight which is derived from the standard Analytic Hierarchy Process and the expert weight. A comprehensive condition assessment model of transformer based on OWA(Ordered Weighted Averaging) operator and fuzzy assessment is proposed and divided into two layers, fuzzy polymerization is adopted for the second layer sub-indicators to get the fuzzy membership of the first layer main indicators, while OWA operator polymerized with the final comprehensive condition assessment of the transformer is adopted for the main indicators of the first layer. In order to fully consider the impact of indicators weight and membership on the condition assessment result, a fuzzy polymerization conversion function based on OWA operator is introduced in the model, so as to integrate the attribute information from various important information sources. Case analysis indicates that the condition assessment of transformer can be carried out by this method; the reasonable and objective conclusion is close to the true condition of transformer.**

***Index Terms*—condition assessment; OWA Ooperator; fuzzy sets; entropy**

I INTRODUCTION

For transformer condition assessment, basically, the existing methods, such as routing inspection, on-line monitoring and historical data are used to acquire device status data which are used to comprehensively assess the running condition of the transformer, then providing suggestion for transformer maintenance and optimizing maintenance plan. In essence, the transformer condition assessment is typically a multi-attribute decision-making problem, and one of the main research directions is how to build a scientific evaluation indicator system and determine a reasonable and effective evaluation methods[2].

In the condition assessment of the power transformer, the evaluation indicator weights are often combined with evidential reasoning method[2], fuzzy decision-making method [13, 17], ideal point method [11], matter-element method [18, 19], and information fusion method [12] to assess the operational status of the power transformer. These methods generally require the establishment of an assessment indicator hierarchy of transformer condition. The first layer usually contains electrical test, oil test, maintenance records and other indicators while in the second or third layer, the evaluation indicators are slightly different. Then the relative importance of each indicator is decided by experts to calculate the weight of each indicator, and the composition operations are conducted for weighted indicator values. There are many application area of condition assessment. A membership degree Back-Propagation network (MDBP) for water quality assessment with combining fuzzy mathematics and artificial neural network[6]. Jiang [1] introduced a cloud-based assessment model which was combined with Analytic Hierarchy Process (AHP) method and fuzzy theory, and then the multi-level fuzzy comprehensive assessment was used to evaluate the dam failure risk. Yang [10] apply the Analytic Hierarchy Process and Fuzzy Comprehensive Evaluation methods in crime prevention system. in which the assessment results are consistent with the reality and this method can be reasonably used for the effectiveness evaluation of crime prevention system.

This paper proposed the Ordered Weighted Averaging (OWA) operator be applied to assess the transformer condition. OWA operator was proposed by an American well-known scholar, Yager in 1988[7]. The basic idea of the method is since the weight sequence is only related to the location of the indicators, in the problem-solving process, indicator data for decision-making should be sorted from big to small in order to calculate the weight of data at each position, and then weighting combination should be conducted. Since the introduction of the method, it is widely used in expert systems, mathematical programming, neural networks, image compression, multi-attribute decision-making and many other areas[15]. When using OWA operator for decision making, most of these applications only sort in accordance with the attribute values without taking into account the effects of

doi:10.4304/jcp.9.4.956-965

decision-making indicator weights on decision-making results.

In this paper, in order to facilitate the assessing process, a two-level assessing model, including fuzzy model and OWA operator-based decision-making model is developed, which benefits from the fuzzy properties and the capabilities of OWA operator combination . Consider of the fundamental and commonly used means to evaluate transformer conditions. Employed are the transformer preventive tests including the electrical test, oil test, oil chromatographic analysis and other indicators. A OWA operator-based decision-making procedure for condition assessments is then presented to illustrate how to use the model to address an assessing issue. The case study shows that the model is capable of providing a meaningful and effective condition assessment.

The rest of the paper is organized as follows. Section Ⅱ gives the methods of ordered weighted averaging operator. In Section 3, the indicators weights in OWA aggregation using fuzzy model is presented, as well as the simulation model. Section 4 describes condition assessment of power transformers using OWA and fuzzy approach. Section 5 describes the application of the proposed method to the condition assessment of a power transformer in a coal mine, and concluding remarks finally.

II ORDERED WEIGHTED AVERAGING (OWA) OPERATOR

OWA operator was proposed by Professor Yager [7]:

Definition 1:OWA operator is the mapping F in N-dimensional space: $R^n \rightarrow R$,if:

$$F(a_1,..,a_n)=\sum_{i=1}^{n} w_i b_i \ . \qquad (1)$$

Wherein, b_i is the *i-th* largest data element in the vector $(a_1,\ldots, a_n)$ *while* $W=(w_1,\ldots, w_n)^T$ is mapping F related weighted vector. If $W\in[0,1]$ and $\sum_{i=1}^{n} w_i = 1$, then F is called OWA operator.

Now consider the function ind (k) as the *k-th* largest value in the vector a_i, then the OWA operator can be represented as:

$$F(a_1,...,a_n)=\sum_{i=1}^{n} w_i a_{ind(i)} \ . \qquad (2)$$

Different values of weighted vector W result in different OWA operators.

Definition 2: Suppose $\alpha(W)$ as the optimistic degree of the decision maker or the and/or degree of OWA operator,

$$\alpha(W)=\sum_{i=1}^{n} w_i \frac{n-i}{n-1} \ . \qquad (3)$$

It demonstrates $\alpha(W) \in [0,1]$.

In the multi-attribute decision-making, it can be demonstrated that:

When W=(1,0,0,…,0), $\alpha(W)$=1 represents the decision maker is the most optimistic and OWA is the largest (or) operator;

When W=(0,0,0,…,1), $\alpha(W)$=0 represents the decision maker is the most pessimistic and OWA is the smallest (and) operator;

When $W=(1/n, 1/n, 1/n,\ldots, 1/n)$, $\alpha(W)$=0.5,OWA is the averaging operator.

It can be seen from the above that when W gets near to "or" operation, $\alpha(W)$ will be closer to 1; when W gets near to "and" operation, $\alpha(W)$ will be closer to 0.

III INDICATORS WEIGHTS IN OWA AGGREGATION USING FUZZY MODEL

When assessing the transformer condition, we need to consider the weights of the assessment attributes. Since the attributes are weighted, OWA operator cannot be directly used to solve the status value of the transformer without processing data. To convert the membership $C_i(x)$ of weighted data through fuzzy model.

(1) The Acquisition of Weighted Vector

Professor Yager[9] proposed in 1997 the BUM function to determine the weight vector W. This function has the following characteristics:

f:[0,1]→[0,1], where $f(0)=0$, $f(1)=1$ and if $x>y$, then $f(x)>f(y)$.

Functions satisfying the above conditions are also called BUM function. The way to use BUM function to get the weighted vector is:

$$w_i = f(j/n)-f((j-1)/n) \qquad (j=1,2,...,n) \ .(4)$$

You can prove that w_i $\sum_{i=1}^{n} w_i = 1$, which meets the condition of OWA operator.

(2) Indicator Membership Conversion

In this paper, the fuzzy operation was used to conduct compositional operation to indicator weights and the indicator membership so as to use OWA operator. Suppose C_1, ...,C_n as evaluation indicator, and its corresponding weight $u_i \in [0,1]$, x represents transformer condition, $C_i(x)$ represents the membership of the i-th decision attribute C_i to condition x. Suppose $a_i(x) = G(u_i, Ci(xe))$, and G is a fuzzy conversion function, then $a_i(x)$ is the composite value that contains indicator weight and indicator membership.

Based on the above description, the decision scheme value of the OWA operator with indicator weight can be drawn:

$$\begin{aligned} C(x) &= F((u_1,c_1(x)),\ldots,(u_n,c_n(x)) \\ &= \sum_{i=1}^{n} w_i a_{ind(i)}(x) \end{aligned} \ . \qquad (5)$$

In this paper, conversion function G is constructed with the method of literature[8]:

$G_{max}(u_i,C_i(x))=T(u_i,C_i(x))= u_iC_i(x)$

$G_{min}(u_i,C_i(x))=S(u_i,C_i(x))=1-u_i+ u_iC_i(x)$

$G_{avg}(u_i,C_i(x))= (n/U)u_iC_i(x)$

Wherein, $U = \sum_{i=1}^{n} u_i$

The form of G depends on OWA aggregate function F, and OWA Operator in turn depends on the weighting vector W. Different W results in different types of aggregate, therefore different conversion function G should be used. Since a can represent different OWA operator, $\alpha(W)$ can be considered as parameters in constructing transformation function G . According to known $G_{\max}$, $G_{\min}$ and G_{avg}, fuzzy model can be used to construct conversion function G. Fuzzy rules are as follows:

If the value of α is high, then $G(u_i, C_i(x)) = G_{max}(u_i, C_i(x))$

If the value of α is medium, then $G(u_i, C_i(x)) = G_{avg}(u_i, C_i(x))$

If the value of α is low, then $G(u_i, C_i(x)) = G_{min}(u_i, C_i(x))$

Based on these inference rules, suppose $high(\alpha)$ represents the α value is high, $medium(\alpha)$ indicates that the α value is medium, $low(\alpha)$ expressed low α value, then the given OWA operator α is known, the conversion function G is:

$$G(u_i, C_i(x)) = \frac{a+b+c}{d}. \tag{6}$$

wherein,
$$a = high(\alpha)G_{max}(u_i, C_i(x))$$
$$b = medium(\alpha)G_{avgx}(u_i, C_i(x))$$
$$c = low(\alpha)G_{min}(u_i, C_i(x))$$
$$d = high(\alpha) + medium(\alpha) + low(\alpha) = 1$$

The fuzzy subsets of *high, low, medium* are defined as follows:

$$high(\alpha) = \begin{cases} 0 & \alpha \le 0.5 \\ \sin^2(\alpha\pi) & \alpha \ge 0.5 \end{cases}. \tag{7}$$

$$medium(\alpha) = \cos^2(\alpha\pi). \tag{8}$$

$$low(\alpha) = \begin{cases} \sin^2(\alpha\pi) & \alpha \le 0.5 \\ 0 & \alpha \ge 0.5 \end{cases}. \tag{9}$$

According to this classification, $G(u_i, C_i(x))$ is as follows:

$$G(u_i, C_i(x)) = \begin{cases} u+v & \alpha \le 0.5 \\ w+u & \alpha \ge 0.5 \end{cases}. \tag{10}$$

wherein,
$$u = cos^2(\alpha\pi)G_{avg}(u_i, C_i(x))$$
$$v = sin^2(\alpha\pi)G_{min}(u_i, C_i(x))$$
$$w = sin^2(\alpha\pi)G_{max}(u_i, C_i(x)).$$

IV Condition Assessment of Power Transformers Using OWA and Fuzzy Approach

A. Evaluation Indicator System and Normalization

Taking into account the diversity of transformer assessment condition and the vagueness of the influence on assessment results, transformer condition assessment model divides assessment indicator into different levels[13, 14, 16, 17, 21]. As shown in *Figure 1,* the model reflects the transformer running condition from different levels, to varying degrees, and from different side, including electrical test, oil test, oil chromatographic analysis and other indicators.

Since there are many factors affecting the transformer, the selected assessment indicators include quantitative and qualitative indicators. The measuring units of the indicators are different and the indicator values are quite different. If these indicators are directly used for the assessment, those indicators with big order of magnitude will become main factors while the condition of the transformer is loosely related to the order of magnitude of the indicator value, therefore, we need to conduct normalization according to the measuring unit and order of magnitude of the indicators and acquire more objective results.

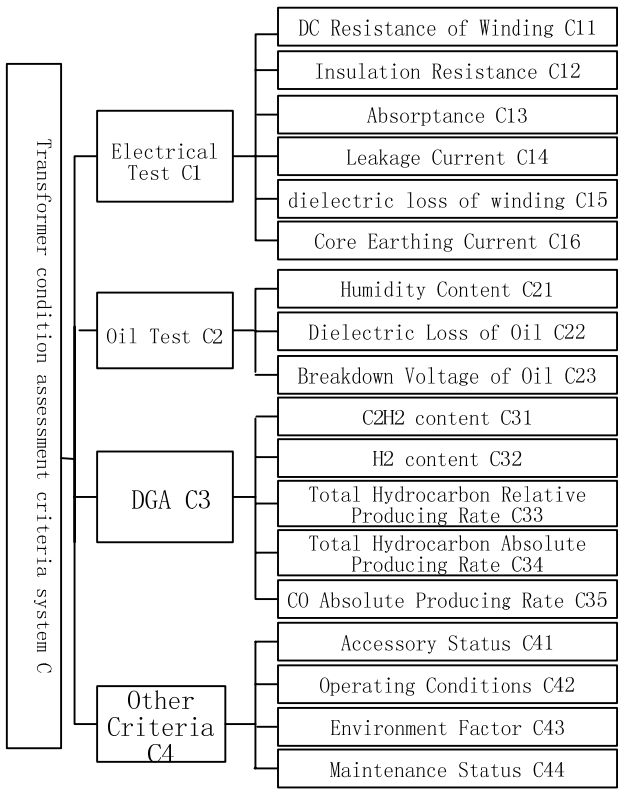

Figure 1 Hierarchy structure of assessment indicators

Quantitative indicators are mainly established in the process of normalization based on the threshold of the assessment indicators[14, 17].

The normalized formula of each indicator is shown in Table Ⅰ.

TABLE I

QUANTITATIVE INDICATORS NORMALIZATION

quantitative indicators	normalized formula	quantitative indicators	normalized formula
C11 /%	(1.8-*n*)/ 1.8	C22 /%	(4-*n*)/ 4
C12 /MΩ	(*n*-800)/800	C23 /kv	(*n*-30)/30
C13 /%	(*n*-1.1)/2-1.1	C31 /μL/L	(5-*n*)/5
C14 /μA	(80-*n*)/80	C32 /μL/L	(150-*n*)/150
C15 /%	(0.8-*n*)/0.8	C33 /%	(10-*n*)/10
C16 /A	(0.1-*n*)/0.1	C34 /mL/d	(12-*n*)/12
C21/ mg/L	(25-*n*)/25	C35e /mL/d	(100-*n*)/100

B. Evaluation Indicator Membership Function

The assessment condition of the transformer is divided into four types[13]: "Good", "General", "Caution", "Severe". Establish the corresponding set of conditions: $X = \{x_1 = \text{Good}, x_2 = \text{General}, x_3 = \text{Caution}, x_4 = \text{Severe}\}$.

The membership of the *i*-th indicator Ci under a first level indicator to the transformer's archetype condition x_j is set as $u_{ij}(j=1,2,3,4)$ and all the membership of the secondary level indicator constitutes the blurring evaluation matrix of corresponding first level indicator. Taking oil test as an example, its evaluation matrix is:

$$U_{C_1} = \begin{bmatrix} u_{11} & u_{12} & u_{13} & u_{14} \\ u_{21} & u_{22} & u_{23} & u_{24} \\ u_{31} & u_{32} & u_{33} & u_{34} \end{bmatrix}$$

Through fuzzy evaluation or OWA operator evaluation of the secondary indicators a first level indicator evaluation matrix can be obtained. In the same way, the condition assessment matrix of the transformer can be obtained.

(1) Membership Function of Quantitative Indicators

Liao Ruijin, etc[2, 14]. pointed out that, taking into account the boundaries of the assessment levels should be an interval of the fuzziness between assessment levels, the triangle subordinate function or trapezoidal method can be adopted. However, when modeling the fuzziness between the condition levels of the transformer, the triangular membership function method is sketchy while the trapezoid function will cause the loss of data. In order to obtain more accurate information, this paper adopted the methods mentioned in the literature[2, 14] to process, that is to use membership function which is half trapezoidal and half rhombic.

Membership function of good condition level x_1:

$$\mu_1(x_i) = \begin{cases} 0 & x_i < k_2 \\ \frac{1}{2} + \frac{1}{2} sin(\pi \frac{x_i - (k_1 + k_2)/2}{k_1 - k_2}) & k_2 \le x_i < k_1 \\ 1 & x_i \ge k_1 \end{cases} . \quad (11)$$

Membership function of general condition level x_2:

$$\mu_2(x_i) = \begin{cases} 0 & x_i < k_4 \quad or \quad x_i \ge k_1 \\ \frac{1}{2} + \frac{1}{2} sin\, \pi(\frac{x_i - (k_3 + k_4)/2}{k_3 - k_4}) & k_4 \le x_i < k_3 \\ 1 & k_3 \le x_i < k_2 \\ \frac{1}{2} - \frac{1}{2} sin(\pi \frac{x_i - (k_1 + k_2)/2}{k_1 - k_2}) & k_2 \le x_i < k_1 \end{cases} . \quad (12)$$

Membership function of attention condition level x_3:

$$\mu_3(x_i) = \begin{cases} 0 & x_i < k_6 \quad or \quad x_i \ge k_3 \\ \frac{1}{2} + \frac{1}{2} \sin(\pi \frac{(x_i - (k_5 + k_6)/2)}{k_5 - k_6}) & k_6 \le x_i < k_5 \\ 1 & k_5 \le x_i < k_4 \\ \frac{1}{2} - \frac{1}{2} \sin(\pi \frac{x_i - (k_3 + k_4)/2}{k_3 - k_4}) & k_4 \le x_i < k_3 \end{cases} \quad (13)$$

Membership function of severe condition level x_4:

$$\mu_4(x_i) = \begin{cases} 1 & 0 \le x_i < k_6 \\ \frac{1}{2} - \frac{1}{2} \sin(\pi \frac{x_i - (k_5 + k_6)/2}{k_5 - k_6}) & k_6 \le x_i < k_5 \\ 0 & x_i \ge k_5 \end{cases} \quad (14)$$

According to the calculation and validation, k_1=12/13,k_2=10/13,k_3=8/13,k_4=6/13,k_5=4/13,k_6=2/13.

(2)Membership Function of Qualitative Indicators

The transformer's attachment condition, overhaul condition, operational condition and environment factors are qualitative indicators. The operational condition only has qualitative description and it is difficult to provide quantitative value directly but experts gave qualitative description through experience. The expert scoring method was used in this paper in normalization process of the qualitative indicators, with the scoring interval being [0,1]. The better the transformer's condition, the higher the scoring value and the closer it is to 1.

For the transformer's operating conditions, various factors need to be comprehensively taken into account, including transformer load, running temperature rise, close-in short circuit, suffered voltage conditions. Suppose there are *m* experts, then the final weight should be $w_i(i=1,2,\ldots,m)$ and the value of the qualitative indicator C_j is:

$$C_j = \sum_{i=1}^{n} w_i c_{ji} . \quad (15)$$

where c_{ji} means the scoring of the indicator *j* by the *i-th* expert.

After figuring out the value of C_j, apply the above formulas(11)~(14) to calculate the membership of the indicator C_j.

C. Evaluation Indicator Weights

The weights reflect the role and status of the evaluation indicators in the transformer condition assessment and objectively reflect the relative importance of each indicator. The different indicators play different roles in the condition assessment of the transformer. In order to make the transformer assessment condition get close to the real running condition, the indicators should be attached with corresponding weights according to their

importance. Therefore what plays a key role in the transformer condition assessment is how to reasonably calculate and determine the weight of each indicator.

(1)Weights Determined by Group Decision-making Expert

In the transformer condition assessment, in order to ensure accuracy, objectivity and comprehensiveness of the assessment, an panel should be established by industry experts or technicians to comprehensively evaluate and determine the attributes of evaluation indicator, so it is necessary to introduce multi-attribute group decision-making method.

Typically, multi-attribute group decision-making weights contain two parts: experts weight and target weight. In this paper, according to professional title, length of service, the degree of being well-known of each expert in the panel, the subjective weights of the experts are determined and the expert's subjective weights are calculated with the thought of entropy weight according to the degree of deviation between the actual indicator weight and the optimal weight evaluated by different experts. Then the final weight of the expert is obtained with linear weighting method by integrating subjective and objective weights of the experts.

1) Determination of the Experts' Subjective Weight

This paper, by comprehensively analyzing the degree of being well-known, professional title length of service and judgment basis of the experts, determined the score sheet of experts' subjective weights as shown in Table Ⅱ.

Suppose the *i*-th expert's subjective weighting score is:

$$R_i = \sum_{i=1}^{n} x_i w_i \ . \tag{16}$$

TABLE Ⅱ
SCORE OF EXPERTS SUBJECTIVE WEIGHTS

Indicators X_i	Weight(x_i)	Level	S(w_i)
Domain familiarity X_1	2	Very familiar	4
		familiar	3
		more familiar	2
		Generally familiar	1
Title X_2	4	Full professor	4
		Associate professor	3
		intermediate title	2
		Junior Title	1
Working age X_3	3	Over 30 years	4
		20—30 years	3
		10—20 years	2
		Less than 10 years	1
Judgment X_4	1	Theoretical analysis	4
		Production experience analysis	3
		Reference academic paper	2
		Similar activities contrast	1

After normalizing the subjective weights of the experts we get:

$$r_i = \frac{R_i}{\sum_{i=1}^{n} R_i} \ . \tag{17}$$

Where *n* is the number of experts.

The panel consisted of six experts. According to the above scoring indicators, we got the panel's score table as shown in TableⅢ.

TABLEⅢ
EXPERTS SCORE TABLE

Experts	X_1	X_2	X_3	X_4
E1	4	4	4	4
E2	4	4	3	3
E3	3	4	3	3
E4	3	3	4	4
E5	3	3	3	3
E6	3	2	1	2

According to Table 2, Table 3, the expert subjective weight score formula (16) and normalized formula (17), the panel's subjective weight(SW) and normalized weitht(NW) score table can be obtained, as shown in Table Ⅳ

TABLE Ⅳ
WEIGHTS OF EXPERTS

Experts	E1	E2	E3	E4	E5	E6
SW	40	37	33	33	30	22
NW	0.2051	0.1897	0.1692	0.1692	0.1538	0.1128

2) Determination of the Expert Objective Weights Based on Entropy Weight

For multi-attribute decision-making problems, the entropy theory is used to determine the weight of each assessment indicator[5][20] . This paper uses this technology to determine the objective weight of the panel.

As for the determination of each assessment indicator in the transformer assessment model, suppose certain assessment indicator contains n sub-indicators and the panel consists of m experts, we acquire the m × n-order weight matrix:

$$U = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ u_{m1} & u_{m2} & \dots & u_{mn} \end{bmatrix} \tag{18}$$

The u_{ij} represents the i-th expert's scoring on the j-th evaluation indicator weight, $u_{ij} \in [1,4]$,the larger the value of u_{ij}, the larger its relative weight.

Definition 4 (expert entropy): After m decision-makers grade for the importance of the *n*-th evaluation indicator, the weight matrix obtained is as shown in formula (18). It is called (m, n) the weight evaluation problem for short, so the entropy of the i-th decision-maker can be defined as:

$$H_i = -k \sum_{j=1}^{n} g_{i,j} \, ln \, g_{i,j} \qquad i = 1,2,\dots,m \ . \tag{19}$$

where $g_{i,j} = \dfrac{u_{i,j}}{\sum_{j=1}^{n} u_{i,j}}$, $k = \dfrac{1}{ln\, n}$

and assuming when g_i, $g_{i,j}\ln g_{i,j}=0$.

Definition 5 (expert entropy weight): As for the (m, n) weight evaluation problem, the entropy weight of the i-th expert γ_i can be defined as:

$$\gamma_i = \frac{1 - H_i}{m - \sum_{i=1}^{m} H_i} \ . \tag{20}$$

The vagueness and uncertainty of the indicators can be measured by entropy. According to Shannon information entropy principle, the smaller the entropy of the decision-making experts, the larger the entropy weight of the decision-making experts, showing that the more objective the indicator ratings given by the experts. Entropy weight reflects the effects of the objective information when the experts assesses indicators, therefore, the results are objective weights while subjective weights can reflect the preferences of the experts to the assessment indicators. Entropy weight-based objective and subjective weight can reflect both expert's objective information for decision-making and the subjective preferences of the experts.

Consider the normalized value of the expert's entropy weight as the objective weight, denoted as O_i:

$$O_i = \frac{\gamma_i}{\sum_{i=1}^{m} \gamma_i}. \tag{21}$$

According to the obtained expert subjective weight R_i and objective weight γ_i, the i-th expert's comprehensive weight can be obtained with the linear weighting method:

$$\lambda_i = \alpha R_i + \beta O_i \qquad i = 1,2,...,m. \tag{22}$$

wherein α + β = 1, α, β are respectively the degree of preferences to subjective weight and the objective weight. In this paper, α = 0.55 and β = 0.45.

Taking oil chromatographic analysis of the second-level indicators, the relative importance of the second-level indicators given by experts is as shown in Table Ⅴ.

TABLE Ⅴ
RELATIVE IMPORTANCE OF DGA

Experts	C32	C32	C33	C34	C35
E1	4	1	2	2	1
E2	4	1	3	2	2
E3	3	1	2	1	1
E4	3	2	2	2	1
E5	3	1	2	2	1
E6	3	1	3	2	1

According to the definition of entropy (19) and entropy weight(20) (21), the objective weight(OW) with DGA is as shown in Table Ⅵ.

TABLE Ⅵ
EXPERT OBJECTIVE WEIGHTS OF DGA

	E1	E2	E3	E4	E5	E6
Entropy Hi	0.9139	0.9426	0.9284	0.9675	0.9463	0.9350
OW	0.2351	0.1566	0.1955	0.0887	0.1466	0.1775

Similarly, the panel objective weights of the oil experiment, electrical test and other indicators are as shown in Table Ⅶ:

TABLE Ⅶ
THE OTHER SUB-INDICATORS EXPERTS OBJECTIVE WEIGHTS

	E1	E2	E3	E4	E5	E6
C2	0.1717	0.1717	0.2937	0.1197	0.1300	0.1132
C1	0.1264	0.0852	0.1032	0.1613	0.1450	0.3788
C4	0.2013	0.1709	0.2013	0.1437	0.1961	0.0867

According to the expert comprehensive weight computational (22), Table Ⅳ, Table Ⅵ and Table Ⅶ, the sub-indicators expert comprehensive weight can be drawn as shown in Table Ⅷ.

TABLE Ⅷ
EXPERTS COMPREHENSIVE WEIGHTS OF SUB-INDICATORS

	E1	E2	E3	E4	E5	E6
C1	0.1698	0.1427	0.1395	0.1657	0.1498	0.2325
C2	0.1902	0.1816	0.2252	0.1469	0.1431	0.1130
C3	0.2186	0.1748	0.1810	0.1330	0.1507	0.1419
C4	0.2035	0.1812	0.1836	0.1577	0.1728	0.1011

Similarly, the expert comprehensive weights of the first-level indicators are as shown in Table Ⅸ.

TABLE Ⅸ
EXPERTS COMPREHENSIVE WEIGHTS OF MAIN INDICATORS

	E1	E2	E3	E4	E5	E6
Main indicators	0.1968	0.2156	0.1789	0.1449	0.1528	0.1108

(2) Determination of Valuation Indicator Weight

After the establishment of the evaluation indicator hierarchy, according to many experts' Analytic Hierarchy Process (AHP[3, 4]), the weights of indicators at all levels are established.

Take oil chromatographic analysis as an example, construct judgment matrix according to Table 5,

$$W = \begin{bmatrix} 1 & 5 & 3 & 3 & 5 \\ 1/5 & 1 & 1/2 & 1/2 & 1 \\ 1/3 & 2 & 1 & 1 & 2 \\ 1/3 & 2 & 1 & 1 & 2 \\ 1/5 & 1 & 1/2 & 1/2 & 1 \end{bmatrix}$$

Obtain the largest eigen value λmax = 5.0053, the corresponding eigenvector A=[0.8686 0.1613 0.3110 0.3110 0.1613]^T; when n = 5, RI = 1.12, then CI = 0.0013.

CR = CI / RI = 0.0011 <0.1 through consistency check.

Similarly, the weight distributions of other experts are as shown in Table Ⅹ.

TABLE Ⅹ
AHP RESULTS OF OIL CHROMATOGRAPHIC SUB-INDICATORS

Experts	Eigen vector	λmax	CI	CR
E1	[0.86860.16130.3110 0.3110 0.1613]^T	5.0053	0.0013	0.0011
E2	[0.7945 0.1424 0.4630 0.25890.2589]^T	5.0173	0.0043	0.0038
E3	[0.7790 0.2443 0.4627 0.2443 0.2443]^T	5.0100	0.0025	0.0022
E4	[0.7226 0.3815 0.3815 0.3815 0.2028]^T	5.0100	0.0025	0.0022
E5	[0.74520.2207 0.4166 0.4166 0.2207]^T	5.0133	0.0033	0.0030
E6	[0.6143 0.1831 0.6143 0.3254 0.3254]^T	5.0133	0.0033	0.0030

According to Table 8 ~Table 10 Weighted averaging method, the decision-making weight W of the panel about the oil chromatographic analysis can be obtained:

W=[0.3928 0.1084 0.2200 0.1615 0.1173]^T.

Similarly, other indicators' weights can also be computed. Due to the limited space of this paper, only the final results are shown in Table Ⅺ.

TABLE XI
WEIGHTS OF ASSESSMENT INDICATORS

Main indicators	Weight	sub-indicators weight
C1	0.807	{0.1892,0.0964,0.1135,0.1717,0.24,0.1892}
C2	0.853	{0.4206,0.3703,0.2091}
C3	1	{0.3928,0.1084,0.2200,0.1615,0.1173}
C4	0.325	{0.4285,0.2871,0.1038,0.1807}

D. Indicator Missing Weight Adjustment

In the transformer condition assessment, if the assessment indicators information of the transformer is complete and accurate, and it is easy to obtain satisfactory condition assessment results in most cases, however sometimes some indicators are not available due to backward data acquisition technology and equipment operation, then part of the evaluation indicators will be unavailable. At this time, it is necessary to adjust the weights of the existing indicators. This paper adopted Deng's correlation proposed by Professor Deng Julong, with the calculation steps being as follows:

Step 1: Since the indicators are a single-factor sequence, it is unnecessary to obtain the initial values of the data sequence. Suppose X_0 as the weight of the missing indicator C_0 in an assessment program and $X_1,X_2,...,X_n$ as the weights of the existing indicators $C_1,C_2,...,C_n$.

Step 2: difference sequence

$$\Delta_i = |X_0 - X_i|, i = 0,1,2,...,n$$

Step 3: maximum and minimum difference of two poles denoted as:

$$D = \max_i \max_l \Delta_i, \quad d = \min_i \min_l \Delta_i$$

Step 4: correlation coefficient

$$\gamma_{oi} = \frac{d + \varphi D}{\Delta_i + \varphi D}, \varphi \in (0,1), i = 1,2,...,n. \quad (23)$$

Since the data sequence is a sequence of single factor, γ_{oi} is denoted as the gray correlation between the missing indicator X_0 and existing indicators X_i.

When the indicator C_0 is missing, the weight of the indicator C_i is adjusted as:

$$X_i' = X_i + \frac{\gamma_{oi}}{\sum_{i=1}^{n} \gamma_{oi}} X_0. \quad (24)$$

X_i' is the weight after indicator C_i is adjusted and X_i is the weight before the indicator C_i is adjusted. If too many indicators/key indicators are missing, it will lead to incorrect evaluation results.

E. Weighted OWA Operator-based Transformer Condition Fuzzy Assessment Steps

According to the previous description, this paper advances a fuzzy comprehensive evaluation model of weighted OWA operator-based transformer. This model presented integrates the fuzzy evaluation method and weighted OWA operator and the main steps of the model are as follows:

Step 1: Build a assessment indicator system for the transformer condition assessment model. Based on the actually measured data and the normalized formula (see Table 1), the initial data of the assessment indicators are obtained through normalization process. By AHP, the weight of each indicator is determined. Suppose A_i as the secondary indicator weight matrix under the first indicator i.

Step 2: Build a set of conditions of the transformer: "Good", "General", "Caution" and "Severe". Establish the corresponding set of conditions: $X=\{x_1,x_2,x_3,x_4\}$, wherein x_1 = Good, x_2 = Average, x_3 = Caution, x_4 = Severe.

Step 3: Based on the formula (11) to (14), calculate the membership of the secondary indicators to the transformer condition set X and get the following fuzzy evaluation matrix.

$$C_i = \begin{bmatrix} C_{i1} \\ \vdots \\ C_{ij} \end{bmatrix} = \begin{bmatrix} c_{11} & ,..., & c_{14} \\ \vdots & \vdots & \vdots \\ c_{j1} & ,..., & c_{j4} \end{bmatrix}$$

Where C_i represents first-level indicator, C_{ij} represents the evaluation of the secondary-level indicator j under the first-level indicator C_i. Suppose the secondary-level indicator weight matrix under the indicator C_i is $A_i=(a_1,a_2,...,a_j)$, then the judgment result of the indicator C_i is $R_i=A_i\&C$, where & means the generalized fuzzy operator. This paper selected weighted averaging operator to conduct fuzzy evaluation represented by M (+, ·), namely $R_i = \sum_{i=1}^{j} a_i c_{ij} (j = 1,2,...,4)$. This method considers not only all the information of a single indicator but also the influence of main indicators on the transformer condition, which is more consistent with the actual situation. The fuzzy evaluation matrix of the first-level indicator is obtained through the processing.

$$R = \begin{bmatrix} R_1 \\ R_2 \\ R_3 \\ R_4 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & r_{14} \\ r_{21} & r_{22} & r_{23} & r_{24} \\ r_{31} & r_{32} & r_{33} & r_{34} \\ r_{41} & r_{42} & r_{43} & r_{44} \end{bmatrix}$$

Corresponding weight value matrix $A=(a_1,a_2,a_3,a_4)$.

Step 4: Calculate the weighting vector W of the first-level indicators, obtain the value of α (W) by the formula (3) and the value of *high(α),medium(α),low(α)* according to the formula (7) (8) (9).

Step 5: According to the first-level indicator matrix R, the first-level indicator weight vector A and the formula (3-10), the fuzzy conversion values of the evaluation indicators in the OWA operators are obtained. According to the thought of weighted OWA operator, map the condition sets of the transformer with the programs of OWA operator, $X=\{x_1,x_2,x_3,x_4\}$, then $x_1=(r_{11},r_{21},r_{31},r_{41})^T$ and sort the programs in descending order according to the component values of them, resulting in program $G=\{g_1,g_2,g_3,g_4\}$,$g_1=(g_{ind(1)1}, ..., g_{ind(j)1})^T$ (j=1,2,…,4),wherein $g_{ind(j)1}$ means the j-th largest element in $(g_{11},g_{21},g_{31},g_{41})$, then the decision-making program matrix is:

$$G=\begin{bmatrix} g_{ind(1)1} & g_{ind(1)2} & g_{ind(1)3} & g_{ind(1)4} \\ g_{ind(2)1} & g_{ind(2)2} & g_{ind(2)3} & g_{ind(2)4} \\ g_{ind(3)1} & g_{ind(3)2} & g_{ind(3)3} & g_{ind(3)4} \\ g_{ind(4)1} & g_{ind(4)2} & g_{ind(4)3} & g_{ind(4)4} \end{bmatrix}$$

Step 6: Calculate the decision-making value D_i (i=1,2,3,4) of each program according to the formula (5) and sort programs according to the decision-making values, finally, take the program whose decision-making value is greater as the decision-making program.

V CASE STUDY

At Jiangzhuang coal mine of Zaozhuang Mining Group, the main transformer capacity is 12.5MVA, the voltage level is 35kV, and the model is SZ11-12500/35. In 2010, the insulating data of oil test and preventive test are as shown in Table Ⅻ. The oil dissolved gas analysis results are as shown in Table XIII. The resulted are calculated by the method presented in this paper.

TABLE Ⅻ
THE DATA OF PREVENTIVE TESTS IN 2010

Test item	Test value	Test item	Test value
C11 /%	0.39	C16/A	0.012
C13/%	1.87	C21/ mg/L	4
C14/μA	15	C22 /%	0.86
C15/%	0.2	C23/kV	55

TABLE XIII
RESULTS OF OIL DISSOLVED GAS CHROMATOGRAPHIC

Gas	Assay value	Gas	Assay value
C31/μL/L	0.35	C34/mL/d	1.46
C32/μL/L	18	C35/mL/d	13.6
C33/%	0.98		

Operational history and maintenance records of the transformer: general overhaul difficulty, without major repairs, 2 minor repairs, leaving a slight defect, no suffering of over-voltage. The main questions of the attachments: there are rust and dirt on the cooler's surface. The transformer was put into operation from 1999 to 2010, its operating life up to 11 years. The operating environment temperature is around 25℃, the air quality is relatively good and the pollution level is two.

The normalized value of the quantitative data can be calculated according to Table 1 and the membership function of the quantitative data can be calculated by using the normalized value according to the formula (11), (12), (13), (14). The results are as shown in Table XIV Quantitative data normalized value and membership.

TABLE XIV
QUANTITATIVE DATA NORMALIZED VALUE AND MEMBERSHIP VALUE

Test item	Test value	Normalized value	Membership value
C11 /%	0.39	0.7833	[0.0205 0.9795 0 0]
C13/%	1.87	0.8556	[0.59580.4042 0 0]
C14/μA	15	0.8125	[0.1828 0.8172 0 0]
C15 /%	0.28	0.8133	[0.1892 0.8108 0 0]
C16 /A	0.012	0.88	[0.8187 0.1813 0 0]
C21/ mg/L	7	0.8	[0.0955 0.9045 0 0]
C22 /%	0.86	0.785	[0.0257 0.9743 0 0]
C23 /kv	55	0.8333	[0.3703 0.6297 0 0]
C31/μL/L	0.73	0.854	[0.5798 0.4202 0 0]
C32/μL/L	32	0.7867	[0.0315 0.9685 0 0]
C33/%	1.78	0.822	[0.2633 0.7367 0 0]
C34/mL/d	1.46	0.8783	[0.8051 0.1949 0 0]
C35/mL/d	19.6	0.804	[0.1208 0.8792 0 0]

Based on expert scoring and the formula (11) to (15), the qualitative indicators scoring and membership values are shown in Table XV.

TABLE XV
THE QUALITATIVE INDICATORS MEMBERSHIP VALUE

Qualitative indicators	Score	Membership value
C41	0.5819	[0 0.8876 0.1124 0]
C42	0.7385	[0.0953 0.9047 0 0]
C43	0.7657	[0.0013 0.9987 0 0]
C44	0.7269	[0 1 0 0]

There is no insulation resistance indicator in electrical test of the indicators. According to the adjustment method of indicator lack of weights in Section 4.4 of this paper, adjust the weights. When the indicator is not missing, the indicator weight sequence is X_i=[0.1892,0.0964,0.1135,0.1717,0.24,0.1892], supposing the missing indicator x_0=0.0964, the other related data sequence x_1=0.1892 ,x_2=0.1135 ,x_3=0.1717,x_4=0.24,x_5=0.1892. Then the difference sequence is:

$$\Delta x=[0.7036 \quad 0.0171 \quad 0.0753 \quad 0.1436 \quad 0.0928].$$

The maximum and minimum differences are:

D=0.7036, d=0.0171.

The relevancy of the missing indicator weight and other indicator weight can be calculated according to the formula (23):

$$\gamma=[0.3495 \quad 1.0000 \quad 0.8637 \quad 0.7447 \quad 0.8297]$$

The weight values after adjusting the indicators can be calculated according to the formula (24), and then normalized the values:

$$u=[0.2089 \quad 0.1291 \quad 0.1905 \quad 0.2625 \quad 0.2089]$$

According to the weighted average algorithm in Section 4.5, using the weights obtained in Section 4.3 (Table 11) and the missing weight adjustment, obtain the condition matrix C of the first-level indicator.

$$C=\begin{bmatrix} 0.3367 & 0.6632 & 0 & 0 \\ 0.1271 & 0.8729 & 0 & 0 \\ 0.4333 & 0.5667 & 0 & 0 \\ 0.0275 & 0.9244 & 0.0482 & 0 \end{bmatrix}$$

In C, from the first line to the fourth line are respectively electrical test, oil test, oil chromatographic analysis and condition values of other indicators.

Suppose the first-level indicator weighting vector W = [0.4 0.3 0.2 0.1], then according to the formula (3) α = 0.67 and the formula (7) (8) (9), it can be obtained that:

$high(\alpha)$ = 0.7409, $medium(\alpha)$ =0.2591,$low(\alpha)$ = 0

U = 0.807+1+0.853+0.325=2.985, then we can get G_{max} and G_{avg}.

The fuzzy conversion function is:

$G(u_i,C_i(x))$=0.7409*$G_{\max}(u_i,C_i(x))$+0.2591*$G_{avg}(u_i,C_i(x)$),OWA decision-making matrix G can be obtained by G_{max} and G_{avg}:

$$G=\begin{bmatrix}0.4022 & 0.9498 & 0.0022 & 0\\ 0.2957 & 0.5824 & 0 & 0\\ 0.1383 & 0.526 & 0 & 0\\ 0.0097 & 0.3418 & 0 & 0\end{bmatrix}$$

The final score D of each program is obtained by (5):

$$D=\begin{bmatrix}0.2782 & 0.6940 & 0.0009 & 0\end{bmatrix}$$

Therefore, D2 is the maximum value, the condition being "General", indicating that individual assessment indicator value of the transformer is not in the normal range, but others are normal, the likelihood of failure is relatively small and the transformer can continue to run. There are no failure during the actual operation of the transformer. This is consistent with the assessment results of the proposed model in this paper.

VI SUMMARY

In this paper, an indicator system of transformer condition assessment was built and the membership function of the indicator was established for the multi-attribute decision making problems of transformer condition assessment. This paper adopted a method that combined the subjective weight and objective weight. The comprehensive assessment model of the transformer condition was proposed, which integrated OWA operator and fuzzy evaluation. The model is divided into two layers, fuzzy aggregation method was used for the secondary-level sub-indicator to obtain the fuzzy membership of the first-level main indicators which adopted the final comprehensive evaluation of the transformer condition. To fully take into account the influence of indicator weight and indicator membership on the assessment results, this paper introduced a OWA-based fuzzy aggregation conversion function to integrate the attribute information of a number of different sources of information. Case study shows that this approach can be convenient to assess transformer condition with reasonable and objective conclusion which is close to the true running condition of the transformer.

ACKNOWLEDGMENT

This work was supported by the Research Fund for the Doctoral Program of Higher Education of China under grant 20110095110014 and by the Key (Key grant) Project of Chinese Ministry of Education under grant 311021.

REFERENCES

[1] Jiang Ying, Zhang Qiuwen. A Fuzzy Comprehensive Assessment System of Dam Failure Risk Based on Cloud Model. Journal of Computers [J], 2013, 8(4).

[2] Liao Ruijin, Zheng Hanbo, Grzybowski S.et al. An Integrated Decision-Making Model for Condition Assessment of Power Transformers Using Fuzzy Approach and Evidential Reasoning. IEEE Transactions on Power Delivery [J], 2011, 26(2):1111-1118.

[3] Saaty Thomas L. Analytic Hierarchy Process [Generic]. Generic]. Ed.Eds; John Wiley & Sons, Ltd, 2005, Vol.

[4] Saaty Thomas L., Vargas Luis G., Saaty Thomas L.et al. The Seven Pillars of the Analytic Hierarchy Process [Book Section]. International Series in Operations Research & Management Science [Book Section]. Ed.Eds.; Springer US, 2001,Vol. 34(pp 27-46.

[5] Shannon C. E. A mathematical theory of communication. ACM SIGMOBILE Mobile Computing and Communications Review [J], 2001, 5(1):3-55.

[6] Xue Ming. A Novel Water Quality Assessment Method Based on Combination BP Neural Network Model and Fuzzy System. Journal of Computers [J], 2013, 8(6).

[7] Yager R. R. On ordered weighted averaging aggregation operators in multicriteria decision making. IEEE Transactions on Man and Cybernetics Systems [J], 1988, 18(1):183-190.

[8] Yager R. R. Criteria importances in OWA aggregation: an application of fuzzy modeling[C]. Proceedings of the Sixth IEEE International Conference on Fuzzy Systems, 1997:1677-1682.

[9] Yager Ronald. Prioritized OWA aggregation. Fuzzy Optimization and Decision Making [J], 2009, 8:245-262.

[10] Yang Zhigang. Research on the Effectiveness Evaluation and Risk Optimization of Crime Prevention System Based on Fuzzy Theory and AHP Model. Journal of Computers [J], 2011, 6(2).

[11] Wen-Qing C, Xin-Ye L. Integrated Condition Assessment of Power Transformer Based on Improved TOPSIS [J]. High Voltage Apparatus, 2009, 6): 120-123.

[12] LIAO R J, HUANG F L, YANG L J, et al. Calculation Method of Power Transformer Condition Assessment Index Weight Using Unascertained Theory [J]. High Voltage Engineering, 2010, 9): 2219-2224.

[13] Rui-jin L, Qian W, Si-jia L, et al. Condition Assessment Model for Power Transformer in Service Based on Fuzzy Synthetic Evaluation[J]. Automation of Electric Power Systems, 2008, 3): 70-75.

[14] Yu-xiang Liao. Study on the Comprehensive Assessment Model of Transformer Operation Condition [D].Chongqing: Chongqing University, 2006.

[15] Yi L, Xiao-guang G, Guang-zhong L, et al. Weighted Attribute Information Fusion Based on OWA Aggregation Operator [J]. Chinese Journal of Scientific Instrument, 2006,3): 322-325.

[16] Si-jia L. Study on Grading Assessment Model for Power Transformer Operation Condition [D]. Chongqing: Chongqing University, 2008.

[17] Qian W. Study of the Comprehensive Assessment Method for the Power Transformer Condition in Service with Fuzzy Theory [D]. Chongqing:Chongqing university, 2005.

[18] [XIONG H, SUN C X, DU P, et al. Synthetic Assessment of Power Transformer Condition Based on Matter-element Theory[J]. Journal of Chongqing University (Natural Science Edition), 2006,10): 24-28.

[19] YANG L, YU F, BAO Y. Classification evaluation of transformer insulation condition based on matter-element theory[J]. Electric Power Automation Equipment, 2010,6): 55-59.

[20] Hui-ren Z, Pi-e Z, Wan-feng Q, et al. Mulitiple Attribute Group Decision-making Approach Based on Entropy and Maximizing Deviations [J]. Soft Science, 2008, 3): 20-22.

[21] Cheng-zhi Z. Study on Key Technologies of Optimal maintenance for Transmission & Distribution Equipments [D]. Hangzhou: Zhejiang University, 2008.

Liping Shi is born in 1964, Ph.D. She is a professor at School of Information and Electrical Engineering in CUMT. Her research interests are coal mine mechanical and electrical equipment and automation, application of power electronics in power systems, and equipment and power grid operation and fault diagnosis. She has published more than 30 research papers in journals and international conferences and she has won more than 10 the provincial scientific research award .Now she preside research fund for the Doctoral Program of Higher Education of China under grant 20110095110014 and by the Key (Key grant) Project of Chinese Ministry of Education under grant 311021.

Hongxia Xie is born in 1980, Ph.D. She is currently a lecture at school of Computer Science and Technology, CUMT. Her research interests are in maintenance, fault diagnosis, distributed parallel processing, data mining, and neural network.