OWA Operator-Based Fuzzy Comprehensive Assessment Of Transformer Condition

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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 Operator; 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 method[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...
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: \( \mathbb{R}^n \rightarrow \mathbb{R} \), if:

\[
F(a_1,\ldots,a_n) = \sum_{i=1}^{n} w_i a_i . \tag{1}
\]

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:

\[
F(a_1,\ldots,a_n) = \sum_{i=1}^{n} w_i a_{ind(i)} . \tag{2}
\]

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,

\[
\alpha(W) = \sum_{i=1}^{n} w_i \frac{n-i}{n-1} . \tag{3}
\]

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

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

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

When \( W=\{0,0,0,\ldots,1\} \), \( \alpha(W)=0 \) 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:

\[
f:[0,1] \rightarrow [0,1], \text{where } f(0) = 0, f(1) = 1 \text{ if } x \geq y, \text{ then } f(1) > f(y).
\]

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

\[
w_i = f(j/n) - f((j-1)/n) \quad (j = 1,2,\ldots,n). \tag{4}
\]

You can prove that \( \sum_{i=1}^{n} w_i = 1 \), 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 \( C_1, \ldots, C_n \) 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 \( a_i(x) = G(u_i, C_i(x)) \), 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:

\[
C(x) = F((u_1,C_1(x)),\ldots,(u_n,C_n(x))) = \sum_{i=1}^{n} w_i a_{ind(i)} (x) . \tag{5}
\]

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

\[
G_{\text{max}}(u,C(x))=T(u,C(x))=u C(x)
\]
\[
G_{\text{min}}(u,C(x))=S(u,C(x))=1-u C(x)
\]
\[
G_{\text{avg}}(u,C(x))=\frac{(n-1)u+C(x)}{n}.
\]
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 \( G_{\text{max}}, G_{\text{min}} \) and \( G_{\text{avg}} \), fuzzy model can be used to construct conversion function G. Fuzzy rules are as follows:

If the value of \( a \) is high, then \( G(u_i, C_i(x)) = G_{\text{max}}(u_i, C_i(x)) \)

If the value of \( a \) is medium, then \( G(u_i, C_i(x)) = G_{\text{avg}}(u_i, C_i(x)) \)

If the value of \( a \) is low, then \( G(u_i, C_i(x)) = G_{\text{min}}(u_i, C_i(x)) \)

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

\[
G(u_i, C_i(x)) = \frac{a + b + c}{d}.
\]

\[
a = \text{high}(\alpha)G_{\text{max}}(u_i, C_i(x))
\]

\[
b = \text{medium}(\alpha)G_{\text{avg}}(u_i, C_i(x))
\]

\[
c = \text{low}(\alpha)G_{\text{min}}(u_i, C_i(x))
\]

\[
d = \text{high}(\alpha) + \text{medium}(\alpha) + \text{low}(\alpha) = 1
\]

The fuzzy subsets of \( \text{high}, \text{low}, \text{medium} \) are defined as follows:

\[
\text{high}(\alpha) = \begin{cases} 
0 & \alpha \leq 0.5 \\
\sin^2(\alpha \pi) & \alpha > 0.5
\end{cases}
\]

\[
\text{medium}(\alpha) = \cos^2(\alpha \pi)
\]

\[
\text{low}(\alpha) = \begin{cases} 
\sin^2(\alpha \pi) & \alpha \leq 0.5 \\
0 & \alpha > 0.5
\end{cases}
\]

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

\[
G(u_i, C_i(x)) = \begin{cases} 
u + w & \alpha \leq 0.5 \\
u + w & \alpha > 0.5
\end{cases}
\]

\[
u = \cos^2(\alpha \pi)G_{\text{avg}}(u_i, C_i(x))
\]

\[
w = \sin^2(\alpha \pi)G_{\text{min}}(u_i, C_i(x))
\]

\[
u = \sin^2(\alpha \pi)G_{\text{max}}(u_i, C_i(x))
\]

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.

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 1.
B. Evaluation Indicator Membership Function

The assessment condition of the transformer is divided into four types: "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 \( C_i \) 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:

\[
\begin{bmatrix}
 u_{11} & u_{12} & u_{13} & u_{14} \\
 u_{21} & u_{22} & u_{23} & u_{24} \\
 u_{31} & u_{32} & u_{33} & u_{34} \\
 u_{41} & u_{42} & u_{43} & u_{44}
\end{bmatrix}
\]

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 \( x_1 \):

\[
\mu_1(x_j) = \begin{cases} 
0 & x_j < k_2 \\
\frac{1}{2} + \frac{1}{2} \sin \frac{x_j - (k_3 + k_4)}{k_1 - k_2} & k_2 \leq x_j < k_1 \end{cases}
\]

(11)

Membership function of general condition level \( x_2 \):

\[
\mu_2(x_j) = \begin{cases} 
0 & x_j < k_4 \\
\frac{1}{2} - \frac{1}{2} \sin \frac{x_j - (k_3 + k_4)}{k_1 - k_2} & k_4 \leq x_j < k_3 \\
1 & k_3 \leq x_j < k_2 \\
\frac{1}{2} - \frac{1}{2} \sin \frac{x_j - (k_3 + k_4)}{k_1 - k_2} & k_2 \leq x_j < k_1
\end{cases}
\]

(12)

Membership function of attention condition level \( x_3 \):

\[
\mu_3(x_j) = \begin{cases} 
0 & x_j < k_6 \\
\frac{1}{2} - \frac{1}{2} \sin \frac{x_j - (k_3 + k_4)}{k_5 - k_6} & k_6 \leq x_j < k_5 \\
1 & k_5 \leq x_j < k_4 \\
\frac{1}{2} - \frac{1}{2} \sin \frac{x_j - (k_3 + k_4)}{k_5 - k_6} & k_4 \leq x_j < k_3
\end{cases}
\]

(13)

Membership function of severe condition level \( x_4 \):

\[
\mu_4(x_j) = \begin{cases} 
0 & x_j < k_6 \\
\frac{1}{2} - \frac{1}{2} \sin \frac{x_j - (k_3 + k_4)}{k_5 - k_6} & k_6 \leq x_j < k_4 \\
1 & k_4 \leq x_j < k_3
\end{cases}
\]

(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 \( w = (i=1, 2, ..., m) \) and the value of the qualitative indicator \( C_j \) is:

\[
C_j = \sum_{i=1}^{m} w_i c_{ji}.
\]

(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:

$$R_i = \sum_{j=1}^{n} x_{ij}w_{ij}.$$  \hspace{1cm} (16)

<table>
<thead>
<tr>
<th>Indicators $X_i$</th>
<th>Weight$(x_{ij})$</th>
<th>Level</th>
<th>S$(w_{ij})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domain familiarity $X_1$</td>
<td>2</td>
<td>Very familiar</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>familiar</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>more familiar</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Generally familiar</td>
<td>1</td>
</tr>
<tr>
<td>Title $X_2$</td>
<td>4</td>
<td>Full professor</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Associate professor</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>intermediate title</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Junior Title</td>
<td>1</td>
</tr>
<tr>
<td>Working age $X_3$</td>
<td>3</td>
<td>Over 30 years</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20—30 years</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less than 10 years</td>
<td>1</td>
</tr>
<tr>
<td>Judgment $X_4$</td>
<td>1</td>
<td>Theoretical analysis</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Production experience analysis</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Reference academic paper</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Similar activities contrast</td>
<td>1</td>
</tr>
</tbody>
</table>

After normalizing the subjective weights of the experts we get:

$$r_i = \frac{R_i}{\sum_{i=1}^{n} R_i}.$$  \hspace{1cm} (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 Table III.

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 weight(NW) score table can be obtained, as shown in Table IV.

<table>
<thead>
<tr>
<th>WEIghts of EXPERTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experts</td>
</tr>
<tr>
<td>SW</td>
</tr>
</tbody>
</table>

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:

$$U = \begin{bmatrix} u_{11} & u_{12} & \ldots & u_{1n} \\ u_{21} & u_{22} & \ldots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{m1} & u_{m2} & \ldots & u_{mn} \end{bmatrix}.$$  \hspace{1cm} (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 matrix.

The entropy of the i-th indicator is defined as:

$$H_i = -k \sum_{j=1}^{n} g_{i,j} \ln g_{i,j}, \hspace{1cm} i = 1,2,\ldots,m.$$  \hspace{1cm} (19)

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

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

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

$$\gamma_i = \frac{1 - H_i}{m - \sum_{i=1}^{m} H_i}.$$  \hspace{1cm} (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 assess indicators, therefore, the results are objective weights while subjective weights can reflect the preferences of the experts to the assessment indicators. Entropy subjective weights can reflect the preferences of the experts to the assessment indicators. Entropy weight reflects the effects of the objective information when the experts assess indicators, according to the obtained expert subjective weight $R_i$, the subjective weight of the experts can be obtained with the linear weighting method:

$$O_i = \gamma_i = \sum_{j=1}^{m} \lambda_{ij} \gamma_j$$

(21)

According to the obtained expert subjective weight $R_i$ and objective weight $\gamma_i$, the i-th expert’s comprehensive weight can be obtained with the linear weighting method:

$$\lambda_i = \alpha R_i + \beta O_i \quad i = 1,2,\ldots,m$$

(22)

wherein $\alpha + \beta = 1$, $\alpha$, $\beta$ are respectively the degree of preferences to subjective weight and the objective weight. In this paper, $\alpha = 0.55$ and $\beta = 0.45$.

Taking oil chromatographic analysis of the experiment, electrical test and other indicators as shown in Table

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

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.

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

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:

$$W = \left[ \begin{array}{c} 1.53 \ 1.53 \ 1.53 \ 1.53 \ 1.53 \end{array} \right]$$

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.
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 proposal 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 \( X_{1}, X_{2}, \ldots, X_{n} \) as the weights of the existing indicators \( C_{1}, C_{2}, \ldots, C_{n} \).

Step 2: difference sequence
\[ \Delta_{i} = [X_{0} - X_{i}], i = 0,1,2,\ldots,n \]

Step 3: maximum and minimum difference of two poles denoted as:
\[ D = \max_{i} \Delta_{i}, \quad d = \min_{i} \Delta_{i} \]

Step 4: correlation coefficient
\[ \gamma_{oi} = \frac{d + \phi D}{\Delta_{i} + \phi D}, \quad \phi \in (0,1), i = 1,2,\ldots,n. \quad (23) \]

Since the data sequence is a sequence of single factor, \( \gamma_{oi} \) 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:
\[ X'_{i} = X_{i} + \frac{\gamma_{oi}}{\sum_{i} \gamma_{oi}} X_{0}. \quad (24) \]

\( X'_{i} \) 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 \( x_{1} = \text{Good}, x_{2} = \text{Average}, x_{3} = \text{Caution}, x_{4} = \text{Severe} \).

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.

\[ C_i = \begin{bmatrix} c_{i1} & \ldots & c_{i4} \\ \vdots & \ddots & \vdots \\ c_{ij} & \ldots & c_{i4} \end{bmatrix} \]

Where \( C_{ij} \) 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 \( A_{i} = (a_{1}, a_{2}, \ldots, a_{n}) \), 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 \( M (\cdot , \cdot ) \), namely \( R_{i} = \sum_{j=1}^{4} a_{ij} \cdot x_{j} \) \( (j = 1,2,\ldots,4) \). 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.

Step 4: Calculate the weighting vector \( W \) of the first-level indicators, obtain the value of \( \alpha \) (W) by the formula (3) and the value of \( \alpha \) (high(\( A \)), medium(\( A \)), low(\( A \))) 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 \( x_{j} = (r_{j1}, r_{j2}, r_{j3}, r_{j4})^{T} \) and sort the programs in descending order according to the component values of them, resulting in program \( G = \{g_{j1}, g_{j2}, g_{j3}, g_{j4}\} \), where \( g_{j} \) = the j-th largest element in \( \{g_{j1}, g_{j2}, g_{j3}, g_{j4}\} \), then the decision-making program matrix is:
and sort programs according to the decision-making value is greater as the decision-making program.

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 results are calculated by the method presented in this paper.

TABLE XII

<table>
<thead>
<tr>
<th>Test item</th>
<th>Test value</th>
<th>Normalized value</th>
<th>Membership value</th>
</tr>
</thead>
<tbody>
<tr>
<td>C11 %</td>
<td>0.39</td>
<td>0.7833</td>
<td>[0.0205, 0.9795]</td>
</tr>
<tr>
<td>C14/µA</td>
<td>1.87</td>
<td>0.8536</td>
<td>[0.5958, 0.8042]</td>
</tr>
<tr>
<td>C15%</td>
<td>0.28</td>
<td>0.8133</td>
<td>[0.1892, 0.8106]</td>
</tr>
<tr>
<td>C16 /A</td>
<td>0.012</td>
<td>0.88</td>
<td>[0.0197, 0.9803]</td>
</tr>
<tr>
<td>C21/ mg/L</td>
<td>7</td>
<td>0.8</td>
<td>[0.0928, 0.1436]</td>
</tr>
<tr>
<td>C22 %</td>
<td>0.86</td>
<td>0.7853</td>
<td>[0.0257, 0.9743]</td>
</tr>
<tr>
<td>C23 /kv</td>
<td>55</td>
<td>0.8333</td>
<td>[0.3703, 0.6297]</td>
</tr>
<tr>
<td>C31/ µL/L</td>
<td>0.35</td>
<td>0.7346</td>
<td>[0.0027, 0.9244]</td>
</tr>
<tr>
<td>C32/µL/L</td>
<td>18</td>
<td>0.8443</td>
<td>[0.0092, 0.9908]</td>
</tr>
<tr>
<td>C33%</td>
<td>0.98</td>
<td>0.86</td>
<td>[0.8187, 0.9047]</td>
</tr>
</tbody>
</table>

TABLE XIII

<table>
<thead>
<tr>
<th>Gas</th>
<th>Assay value</th>
<th>Gas</th>
<th>Assay value</th>
</tr>
</thead>
<tbody>
<tr>
<td>C31/ µL/L</td>
<td>0.35</td>
<td>C34/µL/L</td>
<td>1.46</td>
</tr>
<tr>
<td>C32/µL/L</td>
<td>18</td>
<td>C35/ µL/L</td>
<td>13.6</td>
</tr>
<tr>
<td>C33%</td>
<td>0.98</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 transformer: general overhaul difficulty, without major overhaul, the environment temperature is around 25°C, the air quality is relatively good and the pollution level is two.

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

TABLE XIV

<table>
<thead>
<tr>
<th>Test item</th>
<th>Test value</th>
<th>Normalized value</th>
<th>Membership value</th>
</tr>
</thead>
<tbody>
<tr>
<td>C11 %</td>
<td>0.39</td>
<td>0.7833</td>
<td>[0.0205, 0.9795]</td>
</tr>
<tr>
<td>C13%</td>
<td>1.87</td>
<td>0.8536</td>
<td>[0.5958, 0.8042]</td>
</tr>
<tr>
<td>C14/µA</td>
<td>15</td>
<td>0.8125</td>
<td>[0.1828, 0.8172]</td>
</tr>
<tr>
<td>C15 %</td>
<td>0.28</td>
<td>0.8133</td>
<td>[0.1892, 0.8106]</td>
</tr>
<tr>
<td>C16 /A</td>
<td>0.012</td>
<td>0.88</td>
<td>[0.0197, 0.9803]</td>
</tr>
<tr>
<td>C21/ mg/L</td>
<td>7</td>
<td>0.8</td>
<td>[0.0928, 0.1436]</td>
</tr>
<tr>
<td>C22 %</td>
<td>0.86</td>
<td>0.7853</td>
<td>[0.0257, 0.9743]</td>
</tr>
<tr>
<td>C23 /kv</td>
<td>55</td>
<td>0.8333</td>
<td>[0.3703, 0.6297]</td>
</tr>
<tr>
<td>C31/ µL/L</td>
<td>0.35</td>
<td>0.7346</td>
<td>[0.0027, 0.9244]</td>
</tr>
<tr>
<td>C32/µL/L</td>
<td>18</td>
<td>0.8443</td>
<td>[0.0092, 0.9908]</td>
</tr>
<tr>
<td>C33%</td>
<td>0.98</td>
<td>0.86</td>
<td>[0.8187, 0.9047]</td>
</tr>
</tbody>
</table>

There are 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 $X=[0.1892, 0.0964, 0.1135, 0.1717, 0.24, 0.1892]$, the related data sequence $x=[0.1892, 0.0964]$, the other related data sequence $x=[0.1717, 0.24]$, then according to the formula (7) (8) (9), it can be obtained that: $\gamma = 0.3495$.

The maximum and minimum differences are: $D=0.7036$, $d=0.0171$.

According to the weighted average algorithm in Section 4.5, using the weights obtained in Section 4.3 (Table XI) 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) $\alpha = 0.67$ and the formula (7) (8) (9), it can be obtained that: $\alpha = 0.7409$, medium(1)=0.2591, low(1)=0. The formula (23):

$C = \begin{bmatrix}
0.3367 & 0.6632 & 0 & 0 \\
0.1271 & 0.8729 & 0 & 0 \\
0.4333 & 0.5667 & 0 & 0 \\
0.0275 & 0.9244 & 0.0482 & 0
\end{bmatrix}$
There are no failure during the actual operation of the relatively small and the transformer can continue to run. Others are normal, the likelihood of failure is 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.

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REFERENCES

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