ABSTRACT
Power transformer condition assessment is the basis of condition-based maintenance and plays a very important role in carrying assets management and risk assessment for power system. As the heart of transmission and transformation system, power transformer’s condition has close relation with many factors, such as the production quality of itself, operation environment and so on. This paper analyzes some variables which could represent the transformer’s condition, including the data from preventative test, factory test and commission test, diagnostic test, on-line detection and monitoring, routine inspection, operation history, family defection and environment information. Some parameters which have representation are chosen as the condition variables. Artificial neuron network (ANN) and Dempster-Shafer (D-S) evidence theory are adopted to form the multi-parameter information fusion condition assessment model. Besides the static value, the change trends of some parameters are considered as an independent evidence section. Cooperating with on-line monitoring, it will be helpful to improve the accuracy and efficiency of condition assessment.

KEY WORDS
Condition assessment; multi-information fusion; D-S theory; artificial neuron network; on-line monitoring; trend analysis

1. Introduction
As “heart” of power transformation system, transformer’s condition has great influence on the security and stability of whole power system. Obtaining accurate condition information is one of the key steps to implement condition-based maintenance, which is helpful to find potential defects in time and reduce the failure probability. There are a lot of information which reflect the current condition of power transformer from different aspects, levels and degrees. It is important to make full use of the combined information and establish multi-information fusion transformer assessment model for improving the accuracy of transformer assessment. In recent years, some modern combined assessment algorithms have been studied and applied widely, such as fuzzy theory[1], grey hierarchy model[2], artificial neuron network (ANN), evidence reasoning theory[3], Bayes network[4], and so on. At present, the widely used assessment method is getting the condition score based on current value of condition parameters, then calculating the “health index” according to weighted average[5-7]. The deterioration of most defects, especial insulation defects, is a progressive procedure. Therefore, the tendency of condition parameters is also one of the important information which could reflect the condition of transformer. In recent years, as the promotion of on-line monitoring technology, there is enough data source for trend analysis. The integration of on-line monitoring and condition assessment will improve the timeliness and accuracy of condition assessment greatly. This paper extracts condition parameters from test data (including preventative test, factory test, commission test, diagnostic test, on-line detection and monitoring), routine inspection, operation history, family defection and environment information. The evaluation criterion condition functions for key condition parameters and the multi-parameter fusion assessment model which use ANN and D-S evidence theory are established. The trend of condition parameters is considered as one of the important evidence sections.

2. Condition Parameter and Condition Class
2.1 Condition Parameter
The following rules should be considered when choosing condition parameter: (1) Condition parameter should have high sensibility. The small change of apparatus condition could cause obvious variation of condition parameter. (2) It should have high reliability. The variation of condition parameter could reflect the change of apparatus condition accurately. (3) It is practical, which should be obtained easily. (4) There is independence among condition parameters, which will reflect the characteristic of transformer from different aspects. The condition information of transformer includes 4 categories: test data, operation information, historic data...
and family deficiency. Test data reflects various characteristic of transformer, which is necessary for transformer condition assessment and failure diagnosis. The data source includes preventative test, factory test, commission test, diagnostic test, on-line detection and monitoring. Dissolved gas analysis and electric test are key components of it. This paper chooses dissolved gas analysis, winding direct current resistor, winding insulation resistor and absorption factor (or polarization index), core insulation resistor, winding with bush dielectric dissipation factor and partial discharge as condition parameters. Operation information comes from routine inspection mainly, including transformer load, oil temperature, seal and leak, abnormal noise, status of cooling device, unhealthy working condition, environment information. Operation information is the recorder of transformer operation condition, which is related to the life and aging status of transformer. The oil temperature, fan running condition, load and environmental information are chosen as condition parameter. Historic information is composed of failure records, short circuit history and maintenance history. Family deficiency is the file about the similar defects on the same type of transformer produced by same factory.

2.2 Condition Class

The condition of transformer is divided into 4 classes: normal, attention, abnormal and serious. Normal condition indicates the condition parameters are stable and within the attention values described by rules. When the variation tendency of one or more condition parameters is close to attention value, but doesn’t exceed attention values, it will be considered as attention condition. Abnormal condition refers to at least one parameter varies greatly and exceed the attention value. If at least one important condition parameter severely exceeds the standard, the condition should be serious. Transformer could operate normally when it is in normal condition. When it is evaluated as attention condition, it could continue working, but need to be monitored. If the transformer is abnormal condition, it is necessary to strengthen monitoring and plan to examine and repair at right moment. If assessment result falls into serious condition, the transformer has to be stopped and checked as soon as possible.

3. Condition Evaluation Index Function

Each condition parameter reflects the condition of transformer from different aspects. Based on the absolute value or relative variation of condition parameter $x_i$ ($i=1, 2, \cdots, N$, $N$ is the amount of condition parameter), the condition information of some aspect $s_i$ ($i=1,2, \cdots, M$, $M$ is the amount of condition class) could be draw. At last, the whole condition of transformer could be obtained on the basic of each condition value $s_i$. It is one of the key steps to definite the mapping relation between $x_i$ and $s_i$ (condition evaluation function).

For most of condition parameters, the following method is usually adopted to define condition evaluation function (taking the condition parameter with minimum index for example):

$$
\begin{align*}
  s_i &= \begin{cases} 
  0 & (x_i \geq X_{imax}) \\
  1 & (x_i \leq X_{imin}) \\
  1 - \frac{x_i - X_{imin}}{X_{imax} - X_{imin}} & (X_{imin} < x_i < X_{imax}) 
  \end{cases} 
\end{align*}
$$

$x_{imax}$ and $X_{imin}$ are the maximum and minimum threshold value of condition parameter $x_i$. The condition value $s_i$ which fall into [0,1], represents the linear distance between condition parameter $x_i$ and two thresholds. In practice, the mapping between condition parameter and condition is often non-linear. The condition parameter could be divided into some sections and different linear map functions are adopted in different sections.

4. Multi-Parameter Fusion Assessment Model

Both material and structure of transformer are very complex. It often withstands some factors of electrical, heat and mechanical power together. The multi-information fusion assessment model is built based on artificial neuron network and D-S evidence theory. Combined with the classes of transformers’ condition information, various types of information are used as the input of ANN. As Figure 1, the parallel ANNs are considered as the first stage and D-S evidence theory is used as the second stage of assessment model.

![Fig.1 Multi-information Fusion Transformer Assessment Model](image-url)
4.1 Artificial Neuron Network (ANN)

Radial Base Function (RBF) network has been proven to approximate any function in order to arbitrary precision and has best uniform approximation performance. It could overcome the shortage of local minimum of traditional Back Propagation (BP) network. Therefore, it is used to the first stage of assessment model. Like BP network, RBF is one kind of forward broadcasting networks. It often has 3 layers: input, hidden and output. The outputs of the jth neuron of hidden layer is:

\[ z_j = \exp \left( -\frac{\|x-C_j\|^2}{D_j} \right) \quad j = 1,2, \ldots, p \]  

(2)

\( C_j \) is the central vector of e jth neuron of hidden layer, \( D_j \) is width vector, and \( \| \cdot \| \) is Euclidean norm.

The neuron output of hidden layer is \( Y = [y_1,y_2, \ldots, y_q]^T \),

\[ y_k = \sum_{j=1}^{p} w_{kj} z_j \quad k = 1,2, \ldots, q \]  

(3)

\( w_{kj} \) is regulation weight between kth neuron of output layer and the jth neuron of hidden layer.

In application, the condition evaluation results of acetylene concentration, hydrogen concentration dissolved in oil, content and relative gas production rate of total hydrocarbon are chosen as components of information space \( I_1 \). The information space \( I_2 \) includes coil DC resistor, coil insulation resistor, absorption factor (or polarization index), core insulation resistor and winding with bush dielectric dissipation factor. The information space \( I_3 \) is made up of the on-line monitoring recorders of partial discharge, dielectric dissipation factor, iron core grounding current and dissolved gas analysis.

The variation trend of parameters in \( I_1 \) is considered as an independent information space \( I_2 \). The first stage assessment sub-system is made up of 4 RBF networks which outputs include 4 nodes: \( S_1-S_4 \) corresponding to normal, attention, abnormal and serious conditions respectively.

As for other condition parameters, for example, routine inspection recorder, family flaw, the weighted average method could be used to get the condition information.

4.2 D-S Theory

D-S theory is one kind of uncertainty reasoning method which could fuse evidence provided by multi-evidence sources and narrow the hypotheses constantly. Having excellent decision making capacity, it has been applied in data fusion and target recognition widely [8-10].

The basic concepts of D-S theory include:

1. Basic Probability: In case \( \Theta \) is recognition frame, if set function m: \( 2^\Theta \rightarrow [0,1] \) (\( 2^\Theta \) is the power set of \( \Theta \)) meets: \( (1) m(\emptyset) = 0; \quad (2) \sum_{A \in \Theta} m(A) = 1 \), then m is the basic probability assignment in frame \( \Theta \), \( \forall A \subseteq \Theta \). m(A) is defined as basic certainty of A.

2. Belief Function: The function Bel: \( 2^\Theta \rightarrow [0,1] \) defined by \( \forall A \subseteq \Theta \), Bel(A) = \( \sum_{B \subseteq A} m(B) \) is called belief function in \( \Theta \).

3. Focal Element and Core: For \( \forall A \subseteq \Theta \), if m(A)>0, A is called focal element in belief function Bel. All the focal elements in frame \( \Theta \) are collectively called cores.

4. Plausibility: Suppose Bel: \( 2^\Theta \rightarrow [0,1] \) is belief function in frame \( \Theta \), the function \( pls: 2^\Theta \rightarrow [0,1] \) defined by \( \forall A \subseteq \Theta \), \( pls(A) = 1 - Bel(\overline{A}) = \sum_{B \cap A = \emptyset} m(B) \) is called plausibility function of Bel. \( \forall A \subseteq \Theta \), \( pls(A) \) is called the plausibility of A.

5. Belief Interval: For \( \forall A \subseteq \Theta \), interval \( [Bel(A), pls(A)] \) is called belief interval of A.

The normal expression of D-S theory combination rule is:

\[ m_1 \oplus m_2 (Z) = \frac{\sum_{X,Y} m_1 (X) \times m_2 (Y)}{1-K} \]  

(4)

\( K = \sum_{X,Y = \emptyset} m_1 (X) \times m_2 (Y) \), \( m_1 (X) \) and \( m_2 (Y) \) are basic probability of X and Y respectively. They are also called mass functions. The value of K indicates the conflict degree between combined evidences. If K=0, it is completely identical for two evidences. If K=1, the evidences are completely inconsistent. \( 0<K<1 \) indicates there are parts of conflict between two evidences.

The inference rule of D-S theory is followings. Supposing \( \exists Bel(F_i) = \max \{ Bel(F_j), F_j \in \Theta \} \), for \( \forall F_i \), if Equation (5) is meted, \( F_i \) is the inference result.

\[ \begin{cases} Bel(F_i) - Bel(F_j) > \varepsilon_1 \\ Bel(\emptyset) < \varepsilon_2 \\ Bel(F_i) > Bel(\emptyset) \end{cases} \]  

(5)

\( \varepsilon_1 \) and \( \varepsilon_2 \) are thresholds set in advance.

5. Application of Trend Analysis

The degradation of most defects, especially insulation defects, is a gradually progress. The absolute values of some statistical index and to get the future predictor of this index based on existing data. In other word, the
predictors \( \{x_{i-1}, x_{i+2}, \ldots, x_{i+9}\} \) will be get from current index series \( \{x_1, x_2, \ldots, x_t\} \). In trend analysis, linear regression algorithm is usually used to analyze smooth changing tendency. Exponent and trigonometric function regression algorithms are used to simulate tremendous and periodic change respectively. In this paper, linear regression algorithm is adopted to get the variation trend of these condition parameters. Supposing the index series is \( \{y_1, y_2, \ldots, y_n\} \) and the time series is \( \{t_1, t_2, \ldots, t_n\} \), then the linear regression function is: 

\[
y = a + bt
\]

The method of least square is used to calculate the coefficient \( a \) and \( b \).

\[
\left\{ \begin{align*}
    b &= \frac{\sum_{i=1}^{n} t_i y_i - n \bar{t} \bar{y}}{\sum_{i=1}^{n} t_i^2 - n \bar{t}^2 } \\
a &= \bar{y} - b \bar{t}
\end{align*} \right.
\]

The slope of linear regression function could be used condition parameter. The normalization pre-processing is necessary before input to ANN. As one of simplified processing methods, the averages of relative change rate of each index are chosen as condition parameters.

### 6. Case Analysis

Tab.1 is the dissolved gas analysis data from one 500kV power transformer.

<table>
<thead>
<tr>
<th>( \text{H}_2 ) (µL/L)</th>
<th>( \text{C}_2\text{H}_2 ) (µL/L)</th>
<th>( \sum(\text{C}1+\text{C}2) ) (µL/L)</th>
<th>( \Delta(\text{C}1+\text{C}2) ) (%/month)</th>
</tr>
</thead>
<tbody>
<tr>
<td>34</td>
<td>0.5</td>
<td>108.5</td>
<td>7.2</td>
</tr>
</tbody>
</table>

The data of electrical test, such as coil DC resistor, are in the normal range and are not list here. This transformer installs dissolved gas analysis and partial discharge on-line monitoring device. Tab.2 lists the monitoring recorders of hydrogen, acetylene, total hydrocarbon and partial discharge lasting 5 days. The interval is 24 hours.

<table>
<thead>
<tr>
<th>( \text{H}_2 ) (µL/L)</th>
<th>( \text{C}_2\text{H}_2 ) (µL/L)</th>
<th>( \sum(\text{C}1+\text{C}2) ) (µL/L)</th>
<th>PD (pC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>62</td>
<td>0.6</td>
<td>121.4</td>
</tr>
<tr>
<td>2</td>
<td>67</td>
<td>0.6</td>
<td>130.7</td>
</tr>
<tr>
<td>3</td>
<td>73</td>
<td>0.7</td>
<td>140.9</td>
</tr>
<tr>
<td>4</td>
<td>77</td>
<td>0.9</td>
<td>153.2</td>
</tr>
<tr>
<td>5</td>
<td>78</td>
<td>1.1</td>
<td>158.5</td>
</tr>
</tbody>
</table>

Based on on-line monitoring data, the averages of relative change rate are calculated using simplified method, as list in Tab.3.

<table>
<thead>
<tr>
<th>( \text{Index} )</th>
<th>( \text{H}_2 )</th>
<th>( \text{C}_2\text{H}_2 )</th>
<th>( \sum(\text{C}1+\text{C}2) )</th>
<th>PD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average relative change rate(%/day)</td>
<td>5.95</td>
<td>16.87</td>
<td>6.92</td>
<td>6.21</td>
</tr>
</tbody>
</table>

The condition parameters list in Tab.1 and Tab.2 are mapped into interval \([0, 1]\) according to condition evaluation index function introduced in this paper. The results are input to artificial neuron network ANN1 and ANN2 respectively. At the same time, the data in Tab.3 are input to ANN3. On the basis of experience, the reliabilities of three ANNs are set 0.8, 0.7 and 0.75 respectively. The transformed outputs of ANNs are considered as the basic probability assignment of 3 evidence sections, as list in Tab.4. Tab.5 is the probability assignment after being information fused.

| \( \text{Evidence space} \) | \( m(\Theta) \) | \( m(S) \) |
|-----------------|----------------|----------------|----------------|----------------|----------------|
| 1               | 0.2            | 0.226          | 0.377          | 0.189          | 0.008          |
| 2               | 0.3            | 0.186          | 0.335          | 0.175          | 0.004          |
| 3               | 0.25           | 0.059          | 0.555          | 0.074          | 0.063          |

If the decision rule is \( \epsilon_1=0.5 \) and \( \epsilon_2=0.1 \), three evidence sections could not give a clear conclusion before information fusion. But after being fused, the condition could be judged to \( S_2 \), attention condition. At the same time, the influence of environment factors is reduced greatly. As time going on, the on-line monitoring partial discharge increased slowly and the concentration of acetylene increased obviously. The off-line partial discharge test was performed during maintenance and the results are identical with on-line monitoring. There are discharge traces on insulation components, windings and grounding electrostatic shielding. The reason is the chamfer of bearer was stick reversely. There was a sharp point which resulted in discharge because of electric field concentration.

Similarly, total 23 power transformers were assessed by this solution by far and the results of 17 are identical with inspection conclusions. The accuracy rate is about 74%.
7. Conclusion

(1) The variation tendencies of part condition parameters are important factors influencing condition assessment conclusion of power transformer.

(2) It is very helpful to integrate transformer on-line monitoring into condition assessment, which will improve the effectiveness and accuracy of condition assessment.

(3) D-S evidence theory could eliminate the one-sidedness of some evidence sections and fuse all evidence sections effectively, which will reduce the uncertainty of assessment greatly.

Acknowledgements

This research is supported by Science and Technology Project of State Grid Corporation, China (SG10028) and Hubei Electric Power Corporation (201110101).

References


