Transformers Condition Evaluation Based on Bayesian Classifier

Xin Zhang\(^1\)*, Jianglin Li\(^2\), Guangzhen Liu\(^3\), Liqing Liu\(^1\), Hao Ma\(^1\) and Tiankai Yang\(^4\)

\(^1\)Electric Power Research Institute, State Grid Tianjin Electric Power Corporation, Tianjin 300384, China
\(^2\)XJ Group Corporation, Xuchang 461000, China
\(^3\)State Grid Tianjin Electric Power Corporation, Tianjin 300010, China
\(^4\)School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China

\(*\)Corresponding author e-mail: zhangxin_sgcc@126.com

Abstract. Higher requirements was put forward to accurate and efficient transformer condition assessment by the large-scale promotion of condition overhaul. Core indicators reflecting the running state of transformer were selected to establish transformer evaluation indicators system with analysis on transformer on-line monitoring, live detection and electrical test, and then the indicator scoring method and subordinating degree function of indicator score and transformer state were given. On this basis Bayesian theory was introduced briefly and a transformer condition assessment method based on Bayesian classifier was presented considering transformer monitoring and test data, the current data included, on multiple time dimensions. Finally, through analysis on transformers actual monitoring data in some power network, accurate assessment of transformer running state was made and the practicability and accuracy of this method was verified.

1. Introduction

With the development of power grid scale and the improvement of equipment quality, the maintenance of power transformers has changed from the traditional regular maintenance mode to the state-based maintenance mode, and the transformer state assessment is the basis and key to state-based maintenance [1, 2]. However, the transformer is an integrated system, with various defect types and complex mechanisms. The transformer condition monitoring has many test items and characteristic indexes. The result of the state assessment is not a simple binary judgment of “Pass” or “Fail”, so the transformer state assessment is an analytical process with randomness and ambiguity.

At present, transformer state assessment methods are mainly divided into uncertainty analysis method and combination model method. These methods have enriched the study of transformer state evaluation, but only through the operation monitoring data of a certain time section of the transformer for state assessment, did not take into account the historical state of the transformer and the impact of family defects on the current state.
In this paper, Bayesian theory is introduced into the field of transformer evaluation and a transformer layered state evaluation system is established. A transformer state assessment model based on Bayesian classifier is proposed, and a transformer state assessment method considering historical state and state change trend is formed.

2. Layered State Evaluation System

2.1. Transformer status evaluation indicators

In the current power grid, transformer oil is mostly used to insulate and dissipate heat in large-scale transformers. Oil chromatography analysis and oiling experiments can find early potential failures of transformers and accurately determine the current insulation state of transformers.

By conducting electrical tests on transformers to measure insulation degradation levels quantitatively, it is also possible to find early transformer defects and evaluate transformer status. Therefore, from the three aspects of oil chromatographic analysis, oiling experiments and electrical test, 12 feature quantities were selected to build a transformer state assessment system, shown as Fig.1.

![Figure 1. Transformer condition assessment system](image)

2.2. Indicators scoring model and membership function

The scores of each indicator's monitoring results use a percentage grading system, and then the correlation between scores and insulation status (positive or negative correlation) is used to normalize the index scores by using the ascending half ladder and the descending half ladder models.

A score of 0 indicates the good condition value of some type product (factory test/handover test value of the transformer), a score of 1 indicates the worst state that the transformer insulation completely damaged, and 0.5 indicates the critical value to be noted. The index score table and its meaning are shown in Table 1.
Table 1. Transformer state classification and score

| Indicator scores | State classification | State description | Maintenance strategy |
|------------------|----------------------|-------------------|----------------------|
| 0~0.2            | Normal state (A)     | Indicator is stable within the warning value and the attention value | Extended maintenance |
| 0.2~0.5          | Attention state (B)  | Indicator approaching standard limits or has a tendency to standard limits | Attention monitoring |
| 0.5~0.8          | Abnormal state (C)   | Indicator has significant changes and has approached or exceeded the standard limits | Timely maintenance |
| 0.8~1            | Severe state (D)     | Indicator seriously exceeds the standard limit | Instant maintenance |

However, the indicator scores and transformer states are not mapped one by one, and they have a certain degree of probability. In order to deal with the problem of boundary transitions in different states, a fuzzy distribution method is used to establish a segmented membership function for each state. In combination with practical experience, this paper uses the distribution function of the combination of the semi-ladder and the semi-rural to establish a membership set of index scores for various states.

3. Application of Bayesian classifier in state assessment

3.1. Bayesian classification theory

Bayesian Network (BN) is an indefinite knowledge expression model with a well-expressed framework and flexible reasoning capabilities. Today it has become the mainstream method for uncertain knowledge representation and inference technology in the field of artificial intelligence [3, 4].

Bayesian networks can be represented with directed acyclic graphs. Each random variable node is conditionally independent of any node subset made up of other descendant nodes given its parent. Applying conditional independence to chain rules is available:

$$P(X) = \prod_{i=1}^{n} P(X_i | X_{i-1},...,X_1) = \prod_{i=1}^{n} P(X_i | Pa_i)$$

(1)

In the formula, $X_i$ is the node associated with the random variable $X$, and $Pa_i$ is the combination of all the values of its parent node. Formula (1) shows that the Bayesian network can express the joint probability distribution of variables and greatly simplify the joint probability distribution of variables. According to above Bayesian theorem, a classification model based on statistical methods can be established, namely Bayesian classifier. For instance data sets (Bayesian training set) $D = \{X_1, X_2, ..., X_n\}$ and class variables $C = \{c_1, c_2, ..., c_m\}$, the probability that an instance $I_i = \{x_1, x_2, ..., x_n\}$ belongs to class $c_j$ is denoted by Bayes theorem as

$$P(c_j | x_1, x_2, ..., x_n) = \frac{P(x_1, x_2, ..., x_n | c_j)P(c_j)}{P(x_1, x_2, ..., x_n)}$$

(2)

In formula (2), $\alpha$ is a regularization factor, $P(c_j)$ is the prior probability of class $c_j$, and $P(x_1, x_2, ..., x_n | c_j)$ is the posterior probability of class $c_j$, reflecting the influence of sample data on class $c_j$.

Transformer state evaluation, from the mathematical point of view, is to establish the mapping function between the evaluation index and the transformer state, and its essence is the classification process to determine of the class variable (transformer state) according to the attribute variable (the
transformer state characterization indicators). In combination with the above analysis, Naïve Bayesian (NB) classifier is used to evaluate transformer status in many Bayesian classifiers.

The NB classifier belongs to a two-layer Bayesian network and contains only one parent node and several mutually independent child nodes, as shown in Fig. 2.

![Figure 2. NB classifier diagram](image)

On the basis of formula (2), the following reasoning can be obtained for the single-layer independence of NB classifier. In formula (3), $c_j$ that maximizes $P(c_j | x_1, x_2, ..., x_n)$ is the category to which case $(x_1, x_2, ..., x_n)$ belongs.

$$P(c_j | x_1, x_2, ..., x_n) = \alpha P(c_j) \prod_{i=1}^{n} P(x_i | c_j)$$

3.2. Realization of state assessment based on Bayesian classifier

In the common transformer state hierarchy model, the evaluation basis is the current transformer index data, which is the monitoring information of the same time section. However, the actual state of the transformer is not only related to the current measured index. The historical data of the integrated transformer can observe the charge trend and speed of each index, so as to more accurately assess the state of the transformer [5].

The transformer state assessment based on the Bayesian classifier can link the prior probability with the posterior probability, and comprehensively consider the monitoring information of multiple time sections of the transformer. Therefore, each index value is predicted and the future state of the transformer is obtained through the historical and current monitoring information firstly. Then, the comprehensive state of the transformer is evaluated by using the index data of the transformer history, present and future time sections, shown as Fig.3.

The part of the dashed line box in Fig. 4 indicates the process of determining the transformer state of a certain time according to the monitoring index value, the state evaluation model and membership function described in Section 2. This state is used as a random variable node in a Bayesian network to perform a state assessment based on a Bayesian classifier.

Set $\xi_{ijk} = P(X_j = X_{ij}^k | Pa')$, in which $Pa$ represents the parent node of the random variable $X_j$, namely transformer history, present and future time segments. Possible values of each parent node include 4 states: normal (A), attention (B), abnormal (C) and severe (D). $Pa'$ represents the $j$-th value combination in the parent node's value combination (a total of $4^3 = 64$ combinations).

$X_{ij}^k$ represents the $k$-th possible value of $c$ (a total of 4 states, denoted as $r = 4$ ). According to the conditional expectation estimation method, the learning formula of Bayesian network conditional probability table can be obtained:

$$E(\xi_{ijk}) = \frac{\alpha_k + N_{ijk}}{\sum_{k=1}^{r} (\alpha_k + N_{ijk})}$$ (4)
In the formula (4), $N_{ij}$ refers to the number of samples when the parent node of node $X_i$ takes the $j$-th combination of values and $X_i$ is the $k$-th state in the Bayesian classifier training set. $\alpha_i$ represents expert knowledge, which can be given by an expert or a Bayesian assumption.

4. Examples
The statistics of all 110kV transformers in some area of Shaanxi Province are shown in Table 2.

**Table 2.** State statistics of 110 kV transformers in some area

| Transformer synthesize state | A  | B  | C  | D  |
|-----------------------------|----|----|----|----|
| Transformer number          | 29 | 112| 34 | 18 |

Using the total of 193 transformer operation data and the synthesize state in Tab. 3 as the training set, the Bayesian classifier is operated as a self-learning function.

There is a 63MVA three-volt transformer in this area with a rated voltage of 110/35/10.5kV. The tertiary oil chromatographic data is shown in Table 3.

**Table 3. Transformer oil chromatographic analysis data**

| Date        | H$_2$ | CH$_4$ | C$_2$H$_6$ | C$_2$H$_4$ | C$_2$H$_2$ | CO  | CO$_2$ |
|-------------|-------|--------|------------|------------|------------|-----|--------|
| 2014/5/11   | 46    | 39     | 4.3        | 21.9       | 12         | 309 | 251    |
| 2014/5/19   | 89.5  | 37     | 4.5        | 34         | 57.9       | 423.9| 354    |
| 2014/6/13   | 215.5 | 41     | 4.5        | 51.8       | 66.5       | 467.7| 1246   |

Using the three analysis data to predict the data of future indicators, and taking the data of date 1 and date 2 as average values as historical data, taking date 3 data as current data, and the result is: the history, current and future states of the transformer are B, C, and C, respectively. The results are shown in Tab. 4.

**Table 4. Transformer condition assessment result**

| History state | Current state | Future state | Synthesize state |
|---------------|---------------|--------------|------------------|
| B             | C             | C            | A 0.092          |
|               |               |              | B 0.143          |
|               |               |              | C 0.202          |
|               |               |              | D 0.563          |

Tab. 4 shows that this transformer is most likely to be in a serious state and should be repaired as soon as possible. After the inspection by the hanging hood, the transformer does have the fault of insulation damage between the windings and the short circuit between the windings, which is consistent with the result of the state assessment based on the Bayesian classifier.

5. Conclusion
The operating status of the transformer is not only related to the current monitoring data, but also related to historical data, status change trends, family defects and so on. This paper analyses the data types that reflect transformer states. From the three aspects of oil chromatography analysis, oil chemistry test and electrical test, a transformer state evaluation system with 12 characteristic quantities is constructed.

The Bayesian classifier is used to apply the transformer monitoring data of multiple time sections to the state evaluation, realizing the transformers synthesize state evaluation in different states such as different time dimensions, multiple indicator dimensions, and missing or redundant indicator data. This method based on Bayesian classifier for transformer state assessment has been proved to be effective and has high accuracy after actual verification.
Acknowledgments
This work was financially supported by SGCC Science and Technology Project “KJ18-1-44 Research and application of key technologies for intelligent decision”.

References
[1] LIAO Ruijin, YANG Lijun, ZHENG Hanbo, et al. Reviews on oil-paper insulation thermal aging in power transformers [J]. Transactions of China Electrotechnical Society, 2012, 27 (5): 1-12.
[2] LI Li, ZHANG Deng, XIE Longjun, et al. A condition assessment method of power transformers based on association rules and variable weight coefficients [J]. Proceedings of the CSEE, 2013, 33 (24): 152-159.
[3] Chen-Fu Chien, Shi-Lin Chen, Yih-Shin Lin. Using Bayesian network for fault location on distribution feeder [J]. IEEE Transactions on Power Delivery, 2002, 17 (3): 785~793.
[4] Charniak E. Bayesian Networks without Tears [J]. AI Magazine, 1991, 12 (4): 50-63.
[5] ZHANG Y, DING X, LIU Y, et al. An artificial neural network approach to transformer fault diagnosis [J]. IEEE Transactions on Power Delivery, 1996, 11 (4): 1836-1841.