A Transformer Fault Diagnosis Method Based on Bayesian Network

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ABSTRACT: This paper summarizes the fault types and fault hazards of the transformer, and combs the corresponding relationship between the transformer fault types and the fault symptoms, which provides reference for the transformer fault diagnosis and state maintenance. Based on the analysis of the existing transformer fault diagnosis, the transformer fault diagnosis based on Bayesian network is mainly studied. Bayesian network has advantages in machine learning, data reasoning and so on. It has been widely applied in the field of fault diagnosis. In this paper, the QMR model of transformer fault diagnosis is established by using the principle of Bayesian network and the relationship between fault type and fault feature, and the model is used to diagnose the specific fault. Then the paper further analyzes the result of fault diagnosis in order to prove the correctness and validity of Bayesian network.

1. INTRODUCTION
Power transformer is an important equipment in power system. It has important functions of changing voltage and transmitting power. Its operating state is directly related to the safe and stable operation of power system, and has important research value. Once a transformer fails, it may cause catastrophic consequences, increase the risk of power outages in the power grid, cause inconvenience to people's production and life, and bring huge economic losses to the national economy. In recent years, due to the improvement of transformer manufacturing process and material improvement, the reliability rate has increased significantly, but some accidents still affect the safe operation of the power grid. Therefore, it is important to find out the hidden dangers of the transformer in advance and prevent it
from happening. It is of great significance to solve the problem of transformer slow-deformation and prevent the occurrence and expansion of transformer accidents[1]. With the advancement of computer technology, intelligent diagnosis methods are gradually applied to transformer fault diagnosis. Traditional fault detection methods are combined with data mining to develop artificial intelligence processing[2], genetic algorithms, support vector machines[3], neural networks[4], Bayesian networks[5], etc. Bayesian network, also known as reliability network, can intuitively express the probability distribution and conditional independence between transformer fault and feature quantity, learn network structure and probability table from data, and is widely used in equipment fault diagnosis. The Bayesian network effectively integrates expert experience and fault data from the field to facilitate next-step decisions.

2. TRANSFORMER TYPICAL FAULT

2.1 Winding Fault
The cause of transformer winding failure is mainly due to external short-circuit impact, poor manufacturing process, insulation moisture, and insulation aging. Through the analysis after the fault, such a conclusion is obtained, which directly causes the various faults of the transformer to be related to the winding deformation. When the transformer is short-circuited, the short-circuit current will generate a leakage magnetic field around the winding. Under the action of the electromagnetic force, the winding may be distorted and deformed.[6] The cumulative effect will further develop the deformation. When the secondary over-current is again suffered, the insulation may be breakdown, causing faults such as short-circuit between turns, short-circuit between phases.

2.2 Core Failure
Multi-point grounding of the iron core has an important influence on the deterioration process of the transformer. It will cause overheating of the oil and windings, further aging the oil-paper insulation, and generate flammable gas at the same time as the wood blocks and the clamps in the transformer are carbonized. According to the statistical data, about 30% of the total fault of the transformer is the core ground fault, which is the third place in the accident.[7]

2.3 Current Loop Overheat Fault
The heat generated during normal operation of the transformer is different from the overheat fault. The overheat fault mainly includes local overheating abnormalities such as overheating of the conductor, overheating of the tap changer, overheating of the low voltage winding and the casing connection, resulting in decomposition of the insulating oil paper and even carbonization of the paperboard.

2.4 Insulation Fault
Products formed after insulation aging such as furfural, furfural, etc., will have an irreversible effect on electrical equipment, reducing the tensile strength of insulating paper, reducing the volume resistivity of insulating paper, breakdown voltage, and reducing the life of insulation. Insulation is a major cause of insulation damage, which can lead to insulation discharge and breakdown failure, and increase the age of cellulose. Dendritic discharge failures are mainly caused by insulation moisture and insulation defects.[8]

2.5 Discharge Failure
Discharge is an important factor causing dielectric breakdown, which may cause insulation breakdown. After being impacted by the discharge particle, local breakdown may occur in the insulation. At the same time, the active gas such as nitrogen oxide and ozone released during discharge reacts with the nitric acid, which is corrosive, causing further expansion of the fault; high-pressure gas is generated during discharge. The impact causes a new cracking point in the insulation; the radiation with strong energy generated by the discharge process may cause the insulation to become brittle.
3. FAULT DIAGNOSIS BAYESIAN NETWORK MODEL

3.1 Bayesian Formula

3.1.1 Bayesian rule
According to probability theory
\[
P(B | A) = \frac{P(A, B)}{P(A)}
\]
(1)

We can be obtained by the formula 1
\[
P(B | A) = \frac{P(A | B)P(B)}{P(A)}
\]
(2)
P(B) is the prior probability and P(B|A) is the posterior probability. This formula is the basis of the Bayesian network. We can think that A represents a special state quantity and B represents a fault type, thus establishing a Bayesian network model.

3.1.2 Independence rule
in case:
\[
P(A | B) = P(A | B, C)
\]
(3)

Then the variables A and C are independent, that is, when B is known, the probability of A is independent of C.

3.1.3 Chain rule
If \( P(X_1, X_2, \ldots, X_n) \) is the joint probability distribution of \( X_1, X_2, \ldots, X_n \), then
\[
P(X_1, X_2, \ldots, X_n) = P(X_1 | X_2, \ldots, X_n)P(X_2 | X_3, \ldots, X_n)\ldots P(X_n | X_1)P(X_1)
\]
(4)

This formula is called a chain rule, and this rule can express the joint probability distribution with conditional probability. The representation method will change due to the ordering of the variables.

3.2 Typical Bayesian Network
Bayesian networks represent variables in graphical mode. The lines between the graphs represent probability information, and the probability distribution and independence between variables are visually expressed.

It can be used to mine potential relationships and diagnose faults. The Bayesian network consists of a directed acyclic graph and a probability table. In the model established in this paper, each parent node represents a transformer fault type variable and each child node represents a fault symptom variable. In the case of a dependency, that is, when the feature quantity can reflect a certain fault type, the directed edge points to the fault feature quantity (child node) by the fault type (parent node), and is represented by a single-line arrow (see Figure 1). The probability of the fault type (parent node) is the prior probability, and the fault feature quantity (child node) is the conditional probability.

3.3 Bayesian Network QMR Model
The Bayesian network combines existing data with expert systems by probabilistic representation of correlation and causality between data. The QMR model is a typical application of Bayesian. The network model has a two-layer structure, one is the fault category and the other is the fault feature.
The QMR-DT model has been widely used in medical diagnosis, and has achieved excellent results with the improvement of the algorithm.
Transformer fault diagnosis is similar to QMR-DT diagnosis, which diagnoses defects based on the symptoms of the disease, which is the characteristic quantity of the fault.

The digraph multiple fault diagnosis problem consists of the following:

1. Transformer fault diagnosis QMR model is a two-layer directed acyclic graph. Each of the nodes in the first layer represents the transformer fault and each of the notes in the second layer represents the feature quantity that may be observed to be present or absent.
2. The relationship between the fault type and the feature quantity is determined and a QMR model between the transformer fault and the feature quantity is established. According to the expert knowledge, the association matrix $M$ is established, and the fault feature quantity associated with the corresponding fault in the matrix is $1$, otherwise is $0$.

3. Connect the associated fault and feature quantity nodes with arrows, and give the prior probability of the fault type and the conditional probability between the associated nodes according to the existing data and expert experience knowledge. According to Bayesian reasoning and calculation, get the type of fault when the known fault feature quantity is obtained.

4. THE QUICKSCORE ALGORITHM

The aim of the quickscore algorithm is to compute the probability of each transformer fault $f_i$, $i=1, 2, \ldots, n$, given a set of abnormal characteristic quantity $q^+ \in Q^+$ and normal characteristic quantity $q^- \in Q^-$. We assume that the nodes are noisy-or nodes and faults are marginally independent. Also, we assume that characteristic quantities are conditionally independent given any fault instance, where an instance is an assignment of present or absent to each fault.

We first compute the probability that a single quantity will be normal. Pearl noted the equivalence

$$p(q^-) = \prod_{i=1}^{n} \left[ p(q | only f_i) p(f_i^-) + p(f_i^-) \right]$$  \hspace{1cm} (5)

When we compute the probability that the set of normal quantities $Q^-$ are observed. We have

$$p(Q^-) = \prod_{i=1}^{n} \left[ \prod_{q \in Q} p(q | only f_i) p(f_i^-) + p(f_i^-) \right]$$  \hspace{1cm} (6)

The situation is more complex for abnormal quantities. According to the literature\[11]\)

$$p(Q^+) = \sum_{Q^- \in 2^{Q^-}} (-1)^{|Q^-|} \prod_{i=1}^{n} \left[ \prod_{q \in Q} p(q | only f_i) p(f_i^+) + p(f_i^+) \right]$$  \hspace{1cm} (7)

Where $2^{Q^-}$ denotes the power set of $Q^-$, and $|Q|$ denotes the number of elements in set $Q$.

In the most general case where some quantities are normal and some are abnormal, we can combine equation 6 and equation 7 to obtain

$$p(Q^+, Q^-) = \sum_{Q^- \in 2^{Q^-}} (-1)^{|Q^-|} \prod_{i=1}^{n} \left[ \prod_{q \in Q} p(q | only f_i) p(f_i^+) + p(f_i^+) \right]$$  \hspace{1cm} (8)

We first compute $p(Q^+, Q^-)$, then compute $p(f_i, Q^+, Q^-)$ by setting $p(f_i^-) = 1$ in equation 8. The sought-after probability is then by the product rule of probability.

$$p(d | Q^+, Q^-) = \frac{p(d, Q^+, Q^-)}{p(Q^+, Q^-)}$$  \hspace{1cm} (9)

5. CASE STUDIES AND RESULTS ANALYSIS

Table 1 and table 2 summarize components and denotations in the Bayesian Network for transformer fault. We should note that fault types and quantities in table may not cover all the conditions. In figure 4, the cause nodes of the network consist of nine potential faults which may occur in transformer, and 24 characteristic quantities are presented in the network. The causal relationship between different fault types and quantities was reported by literature\[12]\).

To verify the correctness of the proposed method, a transformer is taken for example. In table 3, $0$ represents the quantity is normal and $1$ represent the quantity is abnormal. The symptom information is input into the built-in Bayesian network, and the quickscore inference method is used to solve the probability corresponding to each fault of the transformer under such conditions, as shown in Table 4.

It can be inferred from Table 4 that the winding fault is the fault with the highest probability of occurrence among the nine faults, and the Bayesian network diagnosis result is the winding fault.
Through the field winding inspection of the transformer, it is found that the transformer winding has a deformation fault, which is consistent with the Bayesian network inference results.

Table 1 Power transformer fault type

| Node Number | Fault Type          | Node Number | Fault Type          |
|-------------|---------------------|-------------|---------------------|
| 1           | Winding fault       | 6           | Insulation aging    |
| 2           | Core failure        | 7           | Insulation oil degradation |
| 3           | Current loop overheating | 8       | Partial discharge   |
| 4           | Insulation moisture | 9           | Oil-flow discharge  |
| 5           | Arc discharge       |             |                     |

Table 2 Characteristic Quantity

| Node Number | Characteristic Quantity | Node Number | Characteristic Quantity               |
|-------------|-------------------------|-------------|---------------------------------------|
| 10          | Insulating oil dielectric loss | 22         | CO relative gas production rate       |
| 11          | Water content in oil    | 23         | CO2 relative gas production rate      |
| 12          | Oil breakdown voltage  | 24         | Increment of winding short-circuit impedance |
| 13          | Insulation resistance absorption ratio | 25         | Winding insulation loss               |
| 14          | Polarization index     | 26         | Increment of winding capacitance initial value |
| 15          | Volume resistivity     | 27         | Acetylene content                    |
| 16          | Hydrogen content       | 28         | Partial discharge                    |
| 17          | Core grounding current | 29         | Total oil dissolved gas content      |
| 18          | Iron core insulation resistance | 30         | Methane content                     |
| 19          | Ethane content         | 31         | Neutral point oil flow electrostatic current |
| 20          | Ethylene content       | 32         | Furfural content                    |
| 21          | Increment of winding DC impedance | 33         | Cardboard polymerization degree     |
Table 3 Characteristic Quantity

| Node Number | Characteristic Quantity | Node Number | Characteristic Quantity | Node Number | Characteristic Quantity |
|-------------|-------------------------|-------------|-------------------------|-------------|-------------------------|
| 10          | 0                       | 18          | 0                       | 26          | 1                       |
| 11          | 0                       | 19          | 0                       | 27          | 0                       |
| 12          | 0                       | 20          | 0                       | 28          | 0                       |
| 13          | 0                       | 21          | 0                       | 29          | 0                       |
| 14          | 0                       | 22          | 0                       | 30          | 0                       |
| 15          | 0                       | 23          | 0                       | 31          | 0                       |
| 16          | 1                       | 24          | 1                       | 32          | 0                       |
| 17          | 0                       | 25          | 1                       | 33          | 0                       |

Table 4 Fault probability results

| Fault Type               | Fault probability |
|--------------------------|-------------------|
| Winding fault            | 1.0000            |
| Core failure             | 0.1100            |
| Current loop overheating | 0.1300            |
| Insulation moisture      | 0.1400            |
| Arc discharge            | 0.3845            |
| Insulation aging         | 0.1650            |
| Insulation oil degradation| 0.2300            |
| Partial discharge        | 0.1905            |
| Oil-flow discharge       | 0.1400            |

Figure 1. Typical Bayesian network.

Figure 2. Bayesian inference form.

Figure 3. The structure of QMR model.
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