Fault Diagnosis of Power Transformer in Mine

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Abstract. In view of the ambiguity of power system transformer faults in mines, the traditional gas analysis method cannot directly judge the possibility of fault occurrence based on gas concentration. A fault diagnosis method for mine transformers based on intuitionistic fuzzy Petri nets is proposed. The relationship between characteristic gas and fault is described by intuitionistic fuzzy set, and a new type of intuitive fault diagnosis model is established. The membership degree and non-affiliation degree are introduced into the model. The intuitionistic fuzzy inference algorithm is designed. By obtaining and processing the specific parameters such as the weight of the connecting arc and the threshold of the transition in the fault diagnosis model, the fault diagnosis process is transformed into the intuitionistic fuzzy inference process using the intuitionistic fuzzy Petri net. Finally, the membership degree and non-affiliation degree of each fault are obtained to judge the possibility of fault occurrence. It is verified by the fact that the above-mentioned mine transformer fault reasoning method can quickly judge the possibility of fault occurrence according to the concentration of gas.

1. Introduction
The Mine-used transformer is an important part of the mine power system, and its reliability directly affects the production safety of the mine. Oil-immersed transformers account for a high proportion of mine transformers because of their unique advantages. How to better diagnose them is a subject worth studying. In literature [1-3], the traditional fuzzy Petri net method is used to study the reliability of the transformer, but the diagnostic accuracy is not ideal. The literature [4] starts from the dissolved gas in the transformer oil, and it is of certain reference significance to judge the source of the fault by quantitative analysis of the gas.

With the development of artificial intelligence, various artificial intelligence algorithms such as artificial neural network [5-9], expert system, fuzzy support vector machine have been widely used in transformer fault diagnosis. The application has achieved certain results. In [7], the bat algorithm is used to optimize the parameters and weights of BP neural network, and the optimized parameters are applied to the BP neural network diagnosis model. The iterative convergence is fast, the efficiency is high, but the steps are more complicated. In [8], the Elman network algorithm is used to optimize the initial parameters of the Petri net model, which improves the accuracy of fault diagnosis, but it is impossible to determine which fault is most likely to occur. Literature [10] combines the traditional three-ratio method with statistical methods to construct an expert system for diagnosis, which improves the accuracy of fault diagnosis, but the statistics are time-consuming and labor-intensive.

None of the above methods can directly judge the possibility of fault occurrence based on the concentration of gas. Therefore, this paper proposes a fault diagnosis method for mine transformer based on intuitionistic fuzzy Petri net. The relationship between the gas content in the transformer oil and the
fault is represented by the intuitionistic fuzzy set, and the mine transformer intuitive fault diagnosis model is established. Then the membership degree and non-membership degree are introduced into the model, and the fault diagnosis process is transformed into the use of intuition. The intuitionistic fuzzy inference process of fuzzy Petri nets is presented by means of matrix operations. The simulation results show that the mine transformer fault reasoning method can quickly judge the probability of fault occurrence according to the gas concentration.

2. Mine-used transformer diagnostic system principle
Transformer oil is a mixture of hydrocarbon molecules of many different molecular weights. The pyrolysis gas production of transformer oil depends on the different stability of hydrocarbon molecules with different chemical bond structures at high temperatures.

When a transformer occurs inside and there is a latent fault, hydrocarbons will oxidize/crack, some C-H bonds and C-C bonds are broken to form unstable H, CH, CH2, CH, C and other free radicals. These radicals are rapidly recombined by complex chemical reactions, eventually producing hydrogen and low molecular hydrocarbon gases. Such as methane, Ethane, ethylene, acetylene, etc., may also form solid particles of carbon and a hydrocarbon polymer (X wax). Carbon solid particles and hydrocarbon polymers can be deposited inside the equipment. In the early stage of the failure, the formed gas is dissolved in the oil; when the fault energy is large, it is also possible to aggregate the free gas.

The principle of internal fault judgment of mining transformers is based on the above characteristics of gas production. Different faults, due to different energy at the fault point, different temperatures and different insulation materials involved, their gas production is also different:

1) The paper is generally overheated, the main characteristic gases are: CH4, C2H4, and the secondary characteristic gas: C2H2.
2) Oil and paper are severely overheated, the main characteristic gases are: CH4, C2H4, and secondary characteristic gases: C2H2, CO, CO2.
3) Spark discharge in oil, main characteristic gas: H2, C2H2.
4) Arc discharge in oil, main characteristic gases: H2, C2H2, secondary characteristic gases: CH4, C2H4.
5) Partial discharge in oil, main characteristic gases: H2, CH4, CO, secondary characteristic gases: C2H2, CO2.

Due to the complex gas content in the transformer oil, the traditional method of fault diagnosis method cannot determine the nature and state of the fault well. It is impossible to quantitatively judge the faults at a certain moment according to the content of various gases, and which faults occur. The possibility is small. To this end, a fault diagnosis modeling method for mining transformers based on IFPN is proposed.

3. IFPN-BASED MINE-USED TRANSFORMER FAULT DIAGNOSIS MODELING METHOD
Atanassov K T adds membership and non-affiliation in the traditional Zadeh fuzzy set, and extends the fuzzy set theory to better describe some uncertain information. If X is a given universe A is an intuitionistic fuzzy set on X, then the intuitionistic fuzzy set of X is defined as follows

\[ A = \{ < x, \mu_A(x), \gamma_A(x) > | x \in X \} \]

Where \( \mu_A(x) \) is the membership function of set A, \( X \rightarrow [0,1] \), \( \gamma_A(x) \) is the non-membership function of set A, \( X \rightarrow [0,1] \). For any element \( x \in X \) on set A, there is \( 0 \leq \mu_A(x) + \gamma_A(x) \leq 1 \).

The internal mechanism of the transformer is complex, and the mapping between the fault feature quantity and the fault type is fuzzy \cite{14}, which is very suitable for fault diagnosis using Intuitionistic Fuzzy Petri Net (IFPN).

3.1. Intuitionistic Fuzzy Petri Net Definition
Intuitionistic fuzzy Petri nets can be expressed as:

\[ \text{IFPN} = (P,T,I,O,W,\tau,S) \]

where:

1) \( P = \{ p_1, p_2, ..., p_n \} \), representing a finite set of libraries.
\[ \mathcal{T} = \{ t_1, t_2, \ldots, t_n \} \], which represents a finite set of transitions, each of which has a corresponding intuitionistic fuzzy rule.

3) \( I = \{ w_{ij} \} \) is the weighted input matrix \((i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)\), which represents the input weight of the transition to the library. When the input library of the transition \( t_j \) is \( p_i \), \( w_{ij} \) is equal to the weight of \( p_i \) to \( t_j \). When the input library of the transition \( t_j \) is not \( p_i \), \([w_{ij}] = 0\).

4) \( O = \{ b_{ij} \} \) is the output matrix, indicating the reliability of the output arc \((i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)\). When the output library of the transition \( t_j \) is the library \( p_i \), \( b_{ij} \) is equal to \( c_j \), and \( c_j \) is the intuitionistic fuzzy number, which represents the credibility of the transition \( t_j \), which can be expressed as \( c_j = (\mu_{cj}, \gamma_{cj}) \), \((j = 1, 2, \ldots, m)\), where \( \mu_{cj} \) is the membership degree of the credibility of the transition \( t_j \), and \( \gamma_{cj} \) is the non-affiliation degree of the credibility of the transition \( t_j \). If the library \( p_i \) is not the output library of the transition \( t_j \), then \( b_{ij} = (0, 1) \).

5) \( W \) is the connected arc weight function, which is divided into the input arc weight function \( W_i \) and the output arc weight function \( W_o \). \( W_i \) is equal to the weight set on the transition of the input library; \( W_o \) is the intuitionistic fuzzy number \((\mu_0, \gamma_0)\), indicating The credibility of the arc connected to the output library, \( \mu_0 \) is the membership degree of the transition credibility, and \( \gamma_0 \) is the non-affiliation degree of the credibility of the transition.

6) \( \tau = \{ \lambda_1, \lambda_2, \ldots, \lambda_n \}^T \) is the upper threshold of transition, where \( \lambda_j \) is the intuitionistic fuzzy number, which can be expressed as \( \lambda_j = (\alpha_j, \beta_j), \ (j = 1, 2, \ldots, m) \), \( \alpha_j > 0 \) is the threshold of the change credibility, and \( \beta_j \geq 0 \) is the threshold of the non-confidence of the transition.

7) \( S = [S(p_1), S(p_2), \ldots, S(p_n)]^T \) is an n-dimensional column vector representing the token value (identification) of the library node, and \( S(p_i) \) is the intuitionistic fuzzy number \((\mu_i, \gamma_i)\), \( \mu_i \) is the membership degree of the \( p_i \) confidence of the library, and \( \gamma_i \) is the non-affiliation degree of the \( p_i \) confidence of the library \((i = 1, 2, \ldots, n)\). \( s_0 = [s_0(p_1), s_0(p_2), \ldots, s_0(p_n)]^T \), which represents the initial token value of the library node.

3.2. Intuitionistic fuzzy production rules
The intuitionistic fuzzy production rule is a tool for intuitionistic fuzzy Petri net knowledge representation. Each change of the intuitionistic fuzzy Petri net can be used as an intuitionistic fuzzy production rule. The input library of the transition is the antecedent proposition of the intuitionistic fuzzy rule, and the output library of the transition is the conclusion proposition of the intuitionistic fuzzy rule. The fuzzy production rule used in this paper is the intuitionistic fuzzy production rule

\[
\text{IF } d_1 \text{ AND } d_2 \ldots \text{AND } d_n \text{ THEN } d_k \]

\[ (\lambda, W_{11}, W_{12}, \ldots, W_{kn}, W_0) \]

Among them, \( d_n \) is the premise proposition, and \( d_k \) is the result proposition. In actual application, it can be replaced by the library. \( \lambda \) is the transition threshold; \( W_{11}, W_{12}, \ldots, W_{kn} \) are the weights of the input arc, respectively, and the weight is equivalent to the influence factor. Different weights represent the influence of the gas content in the mine transformer oil on the fault result;

\( W_0 \) is the weight set on the output arc, indicating the credibility of the rule. The corresponding structure diagram is shown in Figure 1.
3.3. IFPN based reasoning method

Fuzzy reasoning based on intuitionistic fuzzy Petri nets is an uncertainty reasoning, which is mainly used to describe the fuzzy concept of "non-this" and has parallel dynamic reasoning ability. In the process of reasoning, the weight of the connecting arc and the threshold of the transition are determined by using the content of all gases at a certain moment of the mining transformer, and the weighted input matrix $L_{5 \times 11}$, the output matrix $O_{5 \times 11}$, the transition threshold vector $\tau$, and the library are obtained. The initial identification vector $S_0$. The transformer fault diagnosis model has 11 libraries and 5 transitions. The reasoning algorithm is as follows:

Input: weighted input matrix $L_{5 \times 11}$; output matrix $O_{5 \times 11}$; transition threshold vector $\tau$; library initial identification vector $S_0$;

Output: The identification vector of the library $S$.

Step 1: Initialize each matrix, determine the input matrix and output matrix values, let $k = 0$, initialize the identification vector value, $S_k = S_0$;

Step 2: Calculate the reserve potential energy $H$ of the change of the library, the intuitionistic fuzzy value $H = I^T \cdot S_k$;

Step 3: Compare $H$ with the threshold $\tau$ and let $\varepsilon = H \land \tau$. It can be seen that $\varepsilon$ should be an $m$-dimensional intuitionistic fuzzy vector of $(0,1)$ or $(1,0)$, then let $\varphi = H \land \varepsilon$, the premise fuzzy value of the transition is successfully excited, where $\varphi$ is an $m$-dimensional intuitionistic fuzzy column vector;

Step 4: Calculate the fuzzy value of the output library after one reasoning: $\theta = 0 \land \varphi$;

Step 5: Calculate $S_{k+1}$: $S_{k+1} = S_k \lor \theta$;

Step 6: Determine the size of $S_{k+1}$ and $S_k$. If $S_{k+1} = S_k$, the reasoning ends, otherwise let $k = k + 1$, return to step 2, continue the reasoning, until the end.

3.4. Matrix operators used by the algorithm

Based on the IFPN inference process as a matrix operation, several matrix operations are as follows:

1) $\otimes$: $C = A \otimes B \Rightarrow \max (a_{ik} \cdot b_{kj}) = c_{ij}, 1 \leq k \leq s, A, B, C$ are $n \times s, s \times m, n \times m$ dimensional intuitionistic fuzzy matrix;

2) $\oplus$: $C = A \oplus B \Rightarrow \min (a_{ij} + b_{ij}), A, B, C$ are $n \times m$ dimensional intuitionistic fuzzy matrices, according to intuitionistic fuzzy logic, $(\max (\mu(a_{ij}) + \mu(b_{ij})), \min (\gamma(a_{ij}) \cdot \gamma(b_{ij})))$

3) $\odot$: $C = A \odot B \Rightarrow a_{ij} \cdot b_{ij} = c_{ij}, A, B, C$ are $n \times m$ dimensional intuitionistic fuzzy matrices, according to intuitionistic fuzzy logic, $a_{ij} \cdot b_{ij} = (\mu(a_{ij}) \cdot \mu(b_{ij}), \gamma(a_{ij}) + \gamma(b_{ij}) - \gamma(a_{ij}) \cdot \gamma(b_{ij}))$;

4) $\ominus$: $C = A \ominus B \Rightarrow \begin{cases} 1, a_{ij} \geq b_{ij} \\ 0, a_{ij} \leq b_{ij} \end{cases}$

Where $a_{ij} \geq b_{ij} \Rightarrow \mu(a_{ij}) \geq \mu(b_{ij})$ and $\gamma(a_{ij}) \leq \gamma(b_{ij})$. 

Figure 1. Combined fuzzy production.
3.5. Process based on IFPN mine-used transformer fault diagnosis method
Based on the IFPN mine transformer fault diagnosis method, it is divided into the following steps:

1) Determine the input library, output library, and transition of the transformer fault.
2) According to the content of characteristic gas in the mining transformer oil at a certain time, set the threshold value of the weight and transition of the IFPN connecting arc, and establish the IFPN-based mining transformer fault fuzzy production rule.
3) Establish a fault diagnosis reasoning model for mine transformer based on IFPN based on fuzzy production rules.
4) Determine the input and output matrix, and the initial identification vector of the library, and use the fuzzy inference algorithm to diagnose the fault diagnosis model.
5) Find the reasoning results and analyze the results.

4. Experimental and simulation proof

4.1. Model Construction
Based on the data provided in [8], the fault diagnosis model of mine transformer based on intuitionistic fuzzy Petri net is constructed. The weights obtained by Elman network algorithm are optimized as shown in Table 1.

| Arc | Weight | Arc | Weight | Arc | Weight |
|-----|--------|-----|--------|-----|--------|
| $W_{11}$ | 0.4998 | $W_{25}$ | 0.3001 | $W_{43}$ | 0.0839 |
| $W_{12}$ | 0.1967 | $W_{26}$ | 0.0121 | $W_{45}$ | 0.1758 |
| $W_{15}$ | 0.3008 | $W_{33}$ | 0.5896 | $W_{46}$ | 0.4961 |
| $W_{23}$ | 0.5116 | $W_{36}$ | 0.4702 | $W_{51}$ | 0.6182 |
| $W_{24}$ | 0.1993 | $W_{42}$ | 0.3596 | $W_{53}$ | 0.3886 |

According to the main gases CH$_4$, C$_2$H$_4$, H$_2$, C$_2$H$_2$, CO, CO$_2$ generated in the transformer oil as input reservoirs, corresponding to $P_1$, $P_2$, $P_3$, $P_4$, $P_5$, $P_6$, respectively, five faults of the transformer: oil and paper are generally overheated, Oil and paper are severely overheated, arc discharge in oil, arc discharge in oil as input reservoirs, corresponding to $P_7$, $P_9$, $P_9$, $P_{10}$, and $P_{11}$, respectively. The fault fuzzy production rule is as follows:

- $R_1$: if CH$_4$ is slightly higher ($W_{11}(0.4998)$) and C$_2$H$_4$ is lower ($W_{12}(0.1967)$) and CO$_2$ is lower ($W_{15}(0.3008)$) then oil and paper are generally overheated ($W_0(0.7,0.28)$);
- $R_2$: if H$_2$ high ($W_{23}(0.5116)$) and CO high ($W_{24}(0.1993)$) and CO$_2$ high ($W_{25}(0.300)$) C$_2$H$_2$ is not high ($W_{26}(0.0121)$) then oil and paper Severe overheating ($W_0(0.7,0.28)$);
- $R_3$: if H$_2$ is higher ($W_{33}(0.5896)$) C$_2$H$_2$ is slightly higher ($W_{36}(0.4702)$) then spark discharge in oil ($W_0(0.7,0.28)$);
- $R_4$: if C$_2$H$_4$ is slightly higher ($W_{42}(0.3596)$) and H$_2$ is higher ($W_{43}(0.0839)$) and CO$_2$ is higher ($W_{45}(0.1758)$) and C$_2$H$_2$ is higher ($W_{46}(0.4961)$) then oil Medium arc discharge ($W_0(0.7,0.28)$);
- $R_5$: if CH$_4$ is slightly higher ($W_{51}(0.6182)$) and H$_2$ is higher ($W_{53}(0.3886)$) then partial discharge in oil ($W_0(0.7,0.28)$);

Transform the above fuzzy production rule into the IFPN reasoning model, as shown in Figure 2.
4.2. Example verification

The algorithm is applied to the IFPN fault diagnosis reasoning model in Figure 2. The diagnostic reasoning process is as follows:

First, let $k = 0$, according to the data in the fault diagnosis reasoning model, the input matrix $I$, the output matrix $O$, the initial identification matrix $S_0$ and the transition threshold $\tau$ are determined according to the definition of the intuitionistic fuzzy Petri net and the intuitionistic fuzzy production rule.

$$I = \begin{bmatrix}
0.4998 & 0.1976 & 0 & 0 & 0.3008 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

$$S_0 = [(1,0)(0.56,0.4)(0.8,0.15)(0.3,0.65)(0.49,0.45)(0.7,0.24)(0.1,0.1)(0.1)(0.1)(0.1)]^T$$

Let $k = 0$, initialize $S_k = S_0$

$$H = I^T \cdot S_0 = [(0.757,0.214)(0.625,0.344)(0.8,0.196)(0.7,0.274)(0.929,0.058)]^T$$

$$O = \begin{bmatrix}
(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.7,0.28) & (0.1) & (0.1) & (0.1) & (0.1)
(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.7,0.28) & (0.1) & (0.1) & (0.1) & (0.1)
(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.7,0.28) & (0.1) & (0.1) & (0.1) & (0.1)
(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.1)(0.7,0.28) & (0.1) & (0.1) & (0.1) & (0.1)
\end{bmatrix}$$

$$\varepsilon = H \otimes \phi = [(0.757,0.214)(0.625,0.344)(0.8,0.196)(0.7,0.274)(0.929,0.058)]^T$$

$$\theta = O \otimes \phi = [(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)(0.0,0.344)]^T$$

$$S_1 = S_0 \oplus \theta = [(1,0)(0.56,0.344)(0.8,0.15)(0.3,0.344)(0.49,0.344)(0.7,0.24)(0.53,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)(0.49,0.344)]^T$$

According to the above method, we can get:

$$S_2 = [(1,0)(0.56,0.3)(0.8,0.15)(0.3,0.344)(0.49,0.3)(0.7,0.24)(0.53,0.3)(0.438,0.3)(0.56,0.3)(0.49,0.251)(0.65,0.3)]^T$$

$$S_3 = [(1,0)(0.56,0.3)(0.8,0.15)(0.3,0.3)(0.49,0.3)(0.7,0.24)(0.53,0.3)(0.438,0.3)(0.56,0.3)(0.49,0.293)(0.65,0.3)]^T$$

$$S_3 = S_2$$, the reasoning ends.

It can be seen from the results that the library with the highest degree of membership in the possible failure is $P_{11}$, and its identifier is $P_{11} = (0.65, 0.3)$, which indicates that the fault "partial discharge"
corresponding to the $P_{11}$ of the library is most likely to occur. The library with the least degree of membership in the possible failures is $P_8$, which is identified as $P_8 = (0.438, 0.3)$; This indicates that the fault of the library $P_8$ corresponding to the “oil and paper severe overheating” is the least likely.

5. Conclusion
For oil-immersed transformers working in mines with high coal dust content for a long time, this paper proposes a fault diagnosis method for mine transformers based on intuitionistic fuzzy Petri nets. The conclusions are as follows:

1) Mine-used transformer fault diagnosis method based on intuitionistic fuzzy Petri nets introduce information such as membership degree and non-affiliation degree into the traditional Petri net model, and realize the intuitionistic fuzzy inference algorithm through matrix operation, which is more conducive to computer programming, and the reasoning process is more efficient, reasoning results can get more information.

2) The diagnostic model can directly determine the fault of the transformer by analyzing the gas in the transformer oil, and obtain the membership degree and non-affiliation degree of each fault cause, which provides a new fault for oil-immersed transformer fault diagnosis idea.

References
[1] Li Jianglin, etc. A FPN-based substation fault reasoning mechanism [J]. Power System Protection and Control, 2012, 40(17): 13-18.
[2] Dai Chenxi, etc. High-speed rail traction transformer based on model and fuzzy Petri net fusion disability diagnosis [J]. Power System Protection and Control, 2016, 44(11): 26-32.
[3] Wang Jinyuan, Ji Yanchao. Fuzzy Petri network knowledge representation method and its application in obstacle diagnosis [J]. Journal of China Electrical Engineering, 2003, 23(1): 122-126.
[4] S Okabe, G Ueta. Partial discharge criterion in AC test of oil immersed transformer and gas filled transformer in terms of harmful partial discharge level and signal transmission rate [J]. IEEE Trans on Dielectrics and Electrical Insulation, 2012, 19(4): 1431-1439.
[5] Zhang Yifei, etc. Oil-immersed transformer model based on chemical reaction optimization neural network and fusion DGA algorithm [J]. Journal of Shandong University of Science and Technology, 2017, 3(3): 70-74.
[6] Li Shiguang, etc. Fault diagnosis of mine transformer based on optimized fuzzy Petri net [J]. Industrial and mining automation, 2017, 43(5): 54-57.
[7] Shi Ruifeng, etc. Fault diagnosis expert system for dissolved gas power transformer in oil [J]. Journal of Power Systems and Automation, 2014, 26(12): 49-54.