Adaptive Neural Fuzzy Petri Net Algorithm for Motor Fault Diagnosis

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Abstract. This study aimed to improve the application of fuzzy Petri net to fault diagnosis of motor systems. An adaptive Neural Fuzzy Petri Network Algorithm based on the traditional Petri net theory, fuzzy theory, and neural network algorithm is proposed and applied to the diagnosis of motor faults. The transition confidence is replaced by a Gaussian function to solve the uncertainty of fault propagation. Combined with the BP neural network, fault diagnosis parameters are adaptively trained. Finally, the Neural Fuzzy Petri Net Algorithm is applied to the fault diagnosis of a three-phase asynchronous motor, considering its fault operation mechanism and fault characteristics. The results show that the algorithm can diagnose the fault of the three-phase asynchronous motor with satisfactory accuracy and adaptability.

1. Introduction
A motor system which is comprised by a large number of functional modules with uncertain and nonlinear characteristics causes will be crashed by some small faults [1]. As a type of motor system, the three-phase asynchronous motor is used in all aspects of production and life. Accurate and timely detection of faults is particularly important because a small fault will lead the motor to unnormal state. Existing fault diagnosis methods of motors mainly include two types: quantitative analysis and qualitative analysis. The quantitative analysis method includes analytical model and data driven approaches. Although quantitative analysis methods support fault analysis based on feature components, the accuracy of fault detection is often reduced by interference signals in motor systems. Therefore, the fault diagnosis requirements of motors are difficult to meet by using quantitative analysis methods.

Qualitative analysis is a method of building a system model based on internal knowledge, and it can be divided into the graph theory method, expert system, and qualitative simulation [2]. However, accurate system models cannot be constructed by using simple qualitative analysis because of the redundant nature of motor systems. Therefore, the Petri net modeling method with qualitative and quantitative analyses was selected in this study for fault diagnosis of motor systems. Qualitative analysis was applied to establish the system model according to the characteristics of Petri net and quantitative analysis was applied to obtain the fuzzy probability.

Petri net is a combined model that constructs directed graphs by using component relationships in the target system, which can accurately handle the sequence, concurrency, and conflict relationships of discrete events [3]. With increased research in China and abroad, the application of Petri nets to fault detection of motor systems has gradually increased and good diagnosis have been obtained in recent years. Sheng et al. [4] defined the probability transition method of faulty Petri nets to solve the
drawbacks of the conventional method of fault diagnosis by using Petri nets, which considers only the state of the place with uncertain fault propagation, but not the mechanism of transitions in probability. Considering the shortage of faulty Petri net and fuzzy Petri net (FPN) in the process of fault diagnosis and reasoning, Ding and Qin [5] proposed the concept of fuzzy fault Petri net and its modeling method, which improved the effectiveness and practicability of the method by forward reasoning and backward reasoning. Several studies [6, 7, 8] proposed the construction of a modified state class diagram, fully utilized the key role of Petri nets in real-time systems and established a considerable Petri net. Furthermore, some studies [9, 10, 11] established the colored Petri net model by using colored Petri net and the modeling tool CPN Tools, which improved the efficiency of fault diagnosis and the intuitiveness of the model. Kong and Li [12] and Liu et al. [13] combined Petri net and fuzzy reasoning knowledge, which improved the dynamic adaptive ability of the algorithm, effectively solved some random and uncertain fault problems, and greatly improved the ability to locate fault sources in the process of backward reasoning. However, its mathematical reasoning that relies on the logic stepping calculation method was cumbersome and computationally intensive. Zhang et al. [14] performed rigorous mathematical reasoning on FPN and gave the matrix-based reasoning process, which laid a solid theoretical foundation for the development of the application of FPN. However, the acquisition of the initial value of the weight still depended on expert experience and the adaptability was poor.

In order to solve the problem of poor accuracy and adaptability of traditional fault diagnosis methods, this paper proposes a fault diagnosis method based on Neural Fuzzy Petri Net (NFPN).

2. Neural fuzzy Petri net

Traditional Petri net is a way to study the network structure based on the known logical relationship between input and output in the system. It has been widely used in the field of fault diagnosis in recent years.

In motor systems, the relationship between different modules is fuzzy and uncertain, therefore, it is extracted fault information that has fuzzy characteristics in the event of a fault. Traditional Petri nets cannot handle such type of data. In a previous study [15], the fuzzy theory was introduced into the Petri net to obtain FPN, which was applied to the fault diagnosis of the three-phase asynchronous motor [16].

The application of FPN in fault diagnosis can solve the fuzzy characteristics of complex systems, but the parameters obtained only by expert experience will seriously affect the accuracy of diagnosis, and the applicability of this method will be greatly reduced with the increase of system complexity. In order to solve the problem of poor adaptability in the process of fault diagnosis of FPN, NFPN is defined as a 9-tuple according to the characteristics of FPN theory and BP neural network algorithm. Compared with the FPN, the proposed method can effectively solve the problem of inaccuracy of fault diagnosis caused by relying on the expert experience to assign parameters, and greatly improve the adaptability of the algorithm.

\[ S_{NFPN} = (P, T, I, O, M, W, \alpha, F, B) \]

- \( P = \{p_1, p_2, \ldots, p_n\}^T \), \( P \) represents a set of places.
- \( T = \{t_1, t_2, \ldots, t_m\}^T \), \( T \) represents a set of transitions.
- \( I = (\delta_{ij})_{n \times m} \) is an input matrix describing the mapping of transitions to places. For the input matrix element \( \delta_{ij} \in \{0, 1\} \). If \( P_i \) is the input of \( t_j \), \( \delta_{ij} = 1 \). If \( P_i \) is not an input of \( t_j \), \( \delta_{ij} = 0 \). \( i = 1, 2, \ldots, n \) and \( j = 1, 2, \ldots, m \).
- \( O = (\gamma_{ij})_{n \times m} \) is an output matrix describing the mapping of places to transitions. For the output matrix element \( \gamma_{ij} \in \{0, 1\} \). If \( t_j \) is the input of \( P_i \), \( \gamma_{ij} = 1 \). If \( t_j \) is not an input of \( P_i \), \( \gamma_{ij} = 0 \). \( i = 1, 2, \ldots, n \) and \( j = 1, 2, \ldots, m \).
- \( M = (m_1, m_2, \ldots, m_n) \), represents a distribution vector of marked places, which is the distribution of tokens in the Petri net.
- \( W = (\omega_{ij})_{n \times m} \) is a weight matrix representing the impact of input places on transitions. \( \sum_{i=1}^{n} \omega_{ij} = 1 \), for \( i = 1, 2, \ldots, n \) and \( j = 1, 2, \ldots, m \).
• \( \alpha = (\alpha_1, \alpha_2, \cdots, \alpha_n) \) is the place value vector, where \( \alpha_i \in [0,1] \) is the place value.

• \( F = \{f_1, f_2, \cdots, f_n\} \) represents the collection of the minimum cut set failure rate of the place.

• \( B = \{b_1, b_2, \cdots, b_m\} \) is a transition influence factor vector representing the ability to influence the transition on output place.

3. NFPN learning and diagnosis

In [15, 17], the concept of traditional NFPN was proposed, a constant parameter is used to represent the influence degree of different modules. However, the relationship between different modules is often nonlinear in complex systems, so the range of \([0, 1]\) is used to indicate the influence degree is more reasonable. In order to achieve this purpose, this paper uses Gauss function instead of traditional transition confidence, and reflects the influence degree of different modules by adjusting the value of transition influence factor.

3.1. Forward reasoning

Motor systems involve multiple mapping relationships between the physical structure of the device and the faults, faults of the device, and faults. The faults are redundant and diverse in the process of propagation, and they have various modes, such as one cause with one effect, one cause with multiple effects, multiple causes with one effect, and competition [18].

In order to judge the value of the place in NFPN, a Gaussian function \( \frac{1}{e^{10b(x-1)^2}} \) was applied to reflect the effect of transitions on the output place on the basis of laboratory results. Meanwhile, for the characteristics of the competitive characteristics in the fault diagnosis process of Petri net, the competition operator is introduced, and the matrix inference method is combined to improve the computational efficiency of the algorithm. The improved value reasoning is based on the following formula.

\[
\alpha_{k+1} = \alpha_k \oplus \left[ \nabla \left( \frac{x_k}{e^{10b(x_k - 1)^2}} \right)^T \otimes O^T \right] \tag{1}
\]

According to the requirements of the NFPN algorithm fault diagnosis, when \( \alpha_{k+1} = \alpha_k \) the reasoning is over, otherwise it continues to derive \( \alpha_{k+1} \) from \( \alpha_k \), and \( \alpha_0 \) is the initial value specified by the system.

\( X_k = (x_1, x_2, \cdots, x_m) \) is an m-dimensional vector that is the sum of the marked place value and the corresponding weight product.

\[
X_k = (\alpha_k \ast M_k) \cdot W \tag{2}
\]

To determine the transition trigger, the Sigmoid function is cited:

\[
s = \frac{1}{1 + e^{-b(x-\lambda)}} \tag{3}
\]

\( S_k = (s_1, s_2, \cdots, s_m) \) is the pre-trigger matrix of the transition, where \( b \) is plus infinity and \( \lambda \) is the transition threshold. If \( x \geq \lambda \), then \( s(x) = 1 \), otherwise \( s(x) = 0 \).

The forward dynamic fault reasoning process of NFPN reflects the propagation direction of the system fault. Tokens reflect the occurrence of system faults. As the transition is triggered, a token will be passed from the input place to the output place. The fault propagation reasoning formula is as follows.

\[
M_{k+1} = M_k \oplus \left[ \frac{1}{1 + e^{-b([S_k \circ O^T] - 1)}} \right] \tag{4}
\]

The change in \( M_{k+1} \) reflects the change of token in the system, and \( M_0 \) is the initial value of the system.

3.2. Self-learning ability

In NFPN, the weight reflects the degree of influence of the input place on its transition, and the transition confidence reflects the degree of influence of the transition on its output place. In the process of fault propagation, these two values together reflect the ability of fault propagation. In complex systems, the
transmission process of faults from the transition to the output place is often nonlinear. In order to accurately reflect the fault propagation ability, the empirically significant transition confidence was replaced by the Gaussian function, and the process of fault propagation was simulated under actual conditions by changing the value of the transition influence factor. The weight adaptive learning process based on BP neural network is shown in figure 1.

![Figure 1. Flow chart of adaptive learning based on BP neural network.](image)

Error back propagation function is defined as [19]:

$$E = \frac{1}{2} \left( \alpha(P_i) - \alpha^E(P_i) \right)^2$$  \hspace{1cm} (5)

Where $\alpha(P_i)$ is the actual value of the output place, and $\alpha^E(P_i)$ is the expected value of the output place. The modifier gradient of the weight is as follows [20]:

$$\frac{\partial E}{\partial \omega_{ij}} = \frac{\partial E}{\partial \alpha(P_i)} \frac{\partial \alpha(P_i)}{\partial \omega_{ij}}$$  \hspace{1cm} (6)

$$\Delta \omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}}$$  \hspace{1cm} (7)

$$\omega_{ij}' = \Delta \omega_{ij} + \omega_{ij}$$  \hspace{1cm} (8)

$$\omega_i' = \frac{|\omega_{ij}|}{\left(\sum_{i=1}^{m} |\omega_{ij}| \right)}$$  \hspace{1cm} (9)

The modified gradient of the transition influence factor is as follows:

$$\frac{\partial E}{\partial b_j} = \frac{\partial E}{\partial \alpha(P_i)} \frac{\partial \alpha(P_i)}{\partial b_j}$$  \hspace{1cm} (10)

$$\Delta b_j = -\eta \frac{\partial E}{\partial b_j}$$  \hspace{1cm} (11)

$$b_j' = \Delta b_j + b_j$$  \hspace{1cm} (12)

By iterative calculation, the training is over when the error back propagation value $E$ is within the allowable error range.

4. NFPN learning and diagnosis

4.1. Fault data collection and processing

There are various causes of failure regarding the three-phase asynchronous motor because its internal structure is complicated. This paper proposes a combination of FMEA and FPN to analyse fault data to accurately extract the fault characteristics of the motor and establish a realistic fault model. The event table of place of the motor complex system is shown in table 1 [21].

In this study, the Bayes method was introduced to handle the probability of failure based on the event table of the place, and the expected place value was determined. This method could effectively realize the conversion knowledge and experience to rules accurately, which is helpful in solving the problem
of empiricism of assignment and realizes accurate fault diagnosis of the motor. This ultimately ensures the safe and reliable operation of the motor.

Table 1. Event table of places.

| Code | Meaning                                      | Code  | Meaning                                      |
|------|----------------------------------------------|-------|----------------------------------------------|
| P_1  | Phase winding resistance becomes smaller     | P_23  | Motor overload or irregular impact load     |
| P_2  | Rotor winding short circuit                  | P_24  | Excessive bearing wear                       |
| P_3  | Overload of motor                            | P_25  | Motor holding shaft                          |
| P_4  | Fuse melt failure                            | P_26  | Bearing locking device failure               |
| P_5  | Shaft seal ring structure damage             | P_27  | Rotor core deformation                       |
| P_6  | Oil seal material overheated                 | P_28  | Magnetic slot wedge fracture or              |
|      |                                              |       | detachment                                   |
| P_7  | Seal surface axis roughness value is too    | P_29  | Rotor winding open circuit                   |
|      | large                                       |       |                                              |
| P_8  | Temperature is too high                      | P_30  | Junction box joint loosening                 |
| P_9  | Exciting current is too large                | P_31  | Poor contact of the power control loop switch|
| P_{10}| A phase current is too large                 | P_{12}| Rotor winding mechanical failure             |
| P_{11}| Rotational speed abnormality                 | P_{33}| The central line of motor is not consistent with the center line of shearer. |
| P_{12}| Loss of phase voltage                       | P_{34}| Axial movement of rotor                      |
| P_{13}| Rotating shaft have foreign body             | P_{35}| Spring attachment device failure             |
| P_{14}| Oil entering the motor                      | P_{36}| Scratching of motor                          |
| P_{15}| Bearing is thermally expanded               | P_{37}| Stator current increase                      |
| P_{16}| Motor overheating                            | P_{38}| Excessive pressure drop                      |
| P_{17}| Motor in Open-phase State                   | P_{39}| Excessive operational shock of motor         |
| P_{18}| Motor rotation is abnormal or card machine  | P_{40}| Excessive noise of bearing                   |
| P_{19}| Motor insulation aging                       | P_{41}| The motor turns weak or does not rotate and buzz. |
| P_{20}| Reduction of lubricating oil content         | P_{42}| Motor running abnormal sound                 |
| P_{21}| Curved ring and axis hole produce friction   | P_{43}| Motor failure                                |
| P_{22}| Motor winding insulation burned              |       |                                              |

4.2. NFPN Model for the Three-Phase Asynchronous Motor

Through the analysis of the structure and fault of the three-phase asynchronous motor, the NFPN model of the motor shown in figure 2 is established.
5. Method implementation
Take the "motor winding insulation burned" and "motor holding shaft" as examples for the reasoning analysis.

5.1. Initial value determination
The initial value of the place is:
\[ \alpha_0 = (0.87, 0.6, 0.83, 0.89, 0.73, 0.88, 0.72, 0.82, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.9, 0, 0) \]
The transition threshold is set to 0.5.
Initial values of the transition influence factors are all set to 0.3. Meanwhile, the error back-propagation function of BP neural network is used to search for excellence for the initial weight and the influence factor of the transition. In order to clearly demonstrate the training of BP neural network on the weight and transition influencing factors, the process of input for places P1, P2, P3, and P4 affecting the output place P10 and P11 is taken as an example. The expected value of the place is \( \alpha^E(P_{10}) = 0.667 \) and \( \alpha^E(P_{11}) = 0.732 \), the maximum learning step is \( t = 2000 \), and the learning rate is \( \eta = 0.1 \). The maximum allowable error of E is \( 1 \times 10^{-3} \). Through training, the maximum allowable error curve, weight training curve, and transition influence factor training curve can be obtained, as shown in figure 3, figure 4, and figure 5, respectively.
The figures clearly show that E1 and E2 are smaller than the maximum allowable error of \( 1 \times 10^{-3} \) after 2000 iterations, which satisfies the error requirement.
Adjusted weights: \( \omega_{1,2} = 0.590, \omega_{2,2} = 0.410, \omega_{2,3} = 0.259, \omega_{3,3} = 0.358, \omega_{4,3} = 0.383, \omega_{9,9} = 0.554, \omega_{10,9} = 0.446, \omega_{12,12} = 0.483, \omega_{13,12} = 0.517 \).
5.2. Forward reasoning
Assume that "rotor winding short circuit", "motor overload", "fuse melt failure", "shaft seal ring structure damage", and "oil seal material overheating" are detected.

According to the requirement of forward reasoning, $\alpha_k$ is the final place value vector when $\alpha_{k+1} = \alpha_k$.

$\alpha_4=(0.87, 0.6, 0.83, 0.73, 0.88, 0.72, 0.82, 0.069, 0.727, 0.859, 0.642, 0.848, 0.0, 0.592, 0.818, 0.624, 0.811, 0.804, 0.0, 0.752, 0.9, 0.738, 0.613)$
The final failure prediction information is obtained when $\alpha_5 = \alpha_4$, where the place value indicates the probability that failure may occur.

### 5.3. Validation of accuracy

To verify the accuracy of the algorithm, the proposed algorithm was compared with that in [15], and the results are shown in Table 2.

| Diagnosis method | Basic Faults | Faults Detected | Terminal fault | Expected fault probability | Diagnostic fault probability | Accuracy |
|------------------|--------------|-----------------|----------------|---------------------------|------------------------------|----------|
| FFPN             | P_4          | P_{12}, P_{17}, P_{22} | P_{22}          | 0.830                     | 0.427                        | 51%      |
|                  | P_1, P_3     | P_9             | P_9            | 0.768                     | 0.696                        | 91%      |
|                  | P_1, P_2, P_3 | P_{9}, P_{16}, P_{13} | P_{16}          | 0.512                     | 0.602                        | 85%      |
| NFPN             | P_4          | P_{12}, P_{17}, P_{22} | P_{22}          | 0.830                     | 0.746                        | 90%      |
|                  | P_1, P_3     | P_9             | P_9            | 0.768                     | 0.705                        | 92%      |
|                  | P_1, P_2, P_3 | P_{9}, P_{16}, P_{13} | P_{16}          | 0.512                     | 0.438                        | 86%      |

The results in Table 2 show that both FFPN and NFPN can accurately diagnose the fault location, but the fault diagnosis result of NFPN is more accurate than that of FFPN. Furthermore, the fault diagnosis parameters adjusted by BP neural network ensures a detection accuracy of over 80% under different fault conditions, which overcomes low adaptability problem of FFPN has poor attributable to the experience of expert. Therefore, the NFPN fault diagnosis method proposed in this paper has high accuracy and adaptability, and it can meet the fault diagnosis requirements of complex systems.

### 6. Conclusions

In this study, BP neural network was combined with FPN to develop the NFPN method. This method was applied to the fault diagnosis of the complex system of the three-phase asynchronous motor. The following conclusion can be drawn:

- The Gaussian function was used to replace the traditional transition confidence in the NFPN to reflect the impact of the transition on the output place. Furthermore, the weights and transition influence factors were adjusted by error back propagation of BP neural network to improve the adaptability of NFPN.
- The NFPN model of the motor was established. The fault relationship of the motor was obtained by combining FMEA with FPN. Meanwhile, forward reasoning was used to describe the propagation process of the fault, which effectively prevents the blindness of diagnosis.

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