Safety evaluation and risk reasoning of metro station based on IFPN

Wang Ke1*, Huang Ying1,2, Zhang Lili1

1 School of Civil Engineering, Xi'an University of Architecture & Technology, Xi'an, 710055, China
2 National Experimental Teaching Center for Civil Engineering Virtual Simulation (XAUAT), Xi'an, 710055, China
*Corresponding author’s e-mail: wei19591@163.com

Abstract. In order to realize the accurate evaluation of the safety status of metro station and the high-efficiency identification of the risk cause, an improved fuzzy petri net is introduced to describe the safety risk propagation process of the metro station. The normal gray cloud whitening weight model combined with whitening weight function in gray clustering system and cloud theory is introduced, and the uncertainty of the initial token of place is comprehensively described. The Apriori algorithm is used to extract the transition confidence and weight according to the strong association rules between places, and an IFPN analysis model to support the evolution of the safety state of metro station is established. Through the forward reasoning, the interpretation of the risk propagation path is realized, and the safety status of the metro station is solved. Through the reverse reasoning, the risk is identified and the risk place that has the greatest impact on the safety status of metro station is investigated. Finally, the model is reasoned with an example to verify the effectiveness of the evaluation method.

1. Introduction
As an important part of the metro system, metro station is an important unit to ensure the safety and orderly operation of metro. It is necessary to identify and check the safety risks of metro stations, improve the safety management level of metro stations and reduce the occurrence of safety accidents to ensure the stability of metro operation (Song et al. 2018).

At present, there are many methods to evaluate the safety state of metro, but there are few theoretical methods to study the risk propagation and safety state evolution of metro stations. Fuzzy petri net (FPN) is used as a mathematical model to describe the development and correlation of events (Meng et al. 2017). Because it can describe the spread of unsafe state of risk failure by means of graphical modeling, it has been widely used by many scholars in the field of risk failure management and safety state assessment. Zhou et al. (2019) proposed an emergency response action modeling and performance analysis method based on coloured time Petri net to ensure the efficiency and feasibility of industrial fire emergency response action. Chu et al. (2016) introduced the interlocking reaction process of FPN reasoning fire development, and used the dynamic weight concept to reflect the contributions of different elements to fire. Yao et al. (2018) adopted the fuzzy Petri net method in the process of evaluating the safety of air traffic control, and used the reverse search method to simplify the complex FPN. The study of FPN theory enriches the theory of metro station safety management from different angles, but there are still some common problems. Wang et al. (2017) used FPN theory
to analyze machine faults, and the determination of transition confidence in the model relied too much on manual experience, which affected the reliability of fault reasoning. Ni et al. (2019) built a hierarchical fuzzy petri net model for fault component diagnosis considering dynamic weight, however, for transitions with few input place, subjective and objective weight assignment will reduce the authenticity. Chu et al. (2016) dynamically improved the weight of key input places based on the transfer of token between places, but the initial token of places came from the average processing of expert weight assignment, and the reasoning algorithm was subjective. Gong et al. (2015) used BP neural network to learn samples to adjust the initial data in fuzzy reasoning rules. However, there were too many samples required, and the fuzzy reasoning was complex, which led to heavy iterative tasks.

In order to solve the above problems, gray cloud theory and data mining theory are combined to solve the above problems. Instead of the traditional method that the token in place is directly determined by experts or manual experience, the qualitative concept is further processed by the normal gray cloud model to achieve the initialization of token in place. The Apriori algorithm (Chen et al. 2018) in data mining is used to extract the association rules between risk parameters and different states as well as the association rules between states, and the key parameters are selected and analyzed according to the strong correlation. Based on the close connection with the big data of prior accidents, an efficient and reliable description of the reliability of accident incentives is realized.

2. Description of IFPN

2.1. Definition of IFPN

Definition 1. IFPN can be defined as an 11-tuple IFPN={P, T, D, I, O, α, ω, Th, μ, R, M}.

P={p1, p2, ..., pn} is a finite set of places; T={t1, t2, ..., tn} is a finite set of transitions; D={d1, d2, ..., dn} is a finite set of propositions; I : P×T → {0,1} is a n×m-dimensional transition input matrix, I = (aij). When there is a directed arc between pi and ti, aij=1, otherwise aij=0; O : T×P → {0,1} is a m×n-dimensional transition output matrix, O =(bij). When there is a directed arc between ti and pj, bij=1, otherwise bij=0; α=(α1, α2, ..., αm)T is the initial token of the place; ω : P×T → {0,1} is a m×n-dimensional weight matrix; Th=(λ1, λ2, ..., λn)T is the threshold of transition; μ = diag (μ1, μ2, ..., μn) is the transition confidence (CF); Rk = (r1, r2, ..., rn)T is the potential transition enabling matrix fired by the equivalent input place; M=(m1, m2, ..., mn)T is the marking vector, reflecting the risk propagation in the place. There are two basic rules of IFPN:

Rule 1: IF d1 and, ..., and dn THEN dk , transitions are fired when \( \sum_{i=1}^{n} \alpha_i \omega_i > \lambda_k \), CF = \( \sum_{i=1}^{n} \alpha_i \omega_i \mu_j \).

Rule 2: IF d1 or, ..., or dn THEN dk , transitions are fired when \( \forall (\alpha_i \omega_i > \lambda_k \), CF = max(\alpha_i \mu_j) .

2.2. Fuzzy reasoning algorithm

Set A, B,C to be m×n-dimensional matrices, E,F to be a m×q, q×n-dimensional matrix respectively.

The comparison operator \( \bowtie : C = A \bowtie B \), if \( a_i > b_i \), \( c_i = a_i \), if \( a_i < b_i \), \( c_i = 0 \).

The bigger operator \( \oplus : C = A \oplus B \), \( c_i = \max(a_i, b_i) \).

The smaller operator \( \ominus : C = A \ominus B \), \( c_i = \min(a_i, b_i) \).

The multiplication operator \( \odot : C = E \odot F \), \( c_i = \max(e_i, f_i) \).

3. Metro station safety risk IFPN reasoning algorithm

3.1. Forward reasoning and risk propagation path deduction

The forward reasoning of metro station safety state includes the reasoning of equivalent input credibility of transition, transition fired judgment and propagation of risk identification.
Let \( k \) be the updated times of token, the initial values of \( k \) is 0. According to IFPN production rules, transition fired judgment matrix \( U \) is expressed as:
\[
U = (\omega, \alpha) \cap Th
\]  
(1)

The token of the precursor place is passed to the subsequent places through fired transition.
\[
\alpha_{k+1} = \alpha_k \oplus [(O \mu \cap U)]
\]  
(2)

When \( \alpha_{k+1} = \alpha_k \), the reasoning is completed and the token values of all libraries are updated. Non-zero element in \( U \) is replaced by 1 to indicate transition is fired by equivalent input of places.
\[
R_k = R_0 \odot (IM_{k-1}) \quad k = 1
\]
\[
R_k = R_0 \odot [I(M_{k-1} - M_{k-2})] \quad k = 2, 3, \ldots
\]  
(3)

With the corresponding transitions fired by risk propagation, the marking vector is updated as:
\[
M_k = M_{k-1} \oplus [(O - I) \otimes R_k]
\]  
(4)

### 3.2 Reverse reasoning and risk identification
Risk identification refers to the inference of basic underlying risk when metro station is in an unsafe state. From the target unsafe state, the risk propagation path leading to this state can be deduced.

The input and output places of reverse reasoning are opposite to the forward reasoning.
\[
R_k^* = [(O^* M_{k+1}) \odot n] \cap R_0^*
\]  
(5)
\[
M_k^* = M_{k+1}^* \oplus (O^* \otimes R_k^*)
\]  
(6)

### 4. Data acquisition and model construction

#### 4.1 Determination of the initial token in the place
The token is described by uncertain concepts defined by human experience. Based on the normal gray weight model which combines the whiten weight function in the gray clustering system and cloud theory, the fuzzy and gray information of the qualitative concepts are comprehensively described, and the whiten value of the gray cloud has a certain randomness (Wang et al. 2019).

Let \( U = \{x\} \) be a discourse domain, and \( T \) is the qualitative language in \( U \). If \( x_i \) is a random realization with a stable tendency of the gray concept, the distribution of the bleaching weight on the discourse domain \( U \) is called the gray cloud bleaching weight function \( f(x) \), referred to as gray cloud digital characteristics of the gray cloud model are denoted as \( GC = (Cx; Lx; Rx; En; He) \), Represent peak value, left and right boundary, entropy and hyper-entropy respectively.

There are \( n \) samples that have been determined to belong to a certain class. The digital characteristics of the gray cloud model composed of sample set \( \{x_1, x_2, \ldots, x_n\} \) are calculated by the reverse cloud generator (Lui et al. 2018).
\[
(Cx, En, He) = (\frac{1}{n} \sum_{i=1}^n x_i, \sqrt{\frac{1}{2} \sum_{i=1}^n |x_i - Cx|} \left( \frac{1}{n-1} \sum_{i=1}^n (x_i - Cx)^2 - En^2 \right)^{1/2})
\]  
(7)

According to the distribution of cloud droplets, measure upper limit - normal gray cloud model is obtained:
\[
f(x) = \begin{cases} 
\exp[-(x-Cx)^2/(2En^2)], & x \in [Lx, Cx] \\
1, & x \in [Cx, Rx] \\
0, & x \notin [Lx, Rx]
\end{cases}
\]  
(8)

In the formula, \( En' \sim N(En, He) \), which obeys normal distribution.

#### 4.2 The mining of weight and transitional confidence
The risk factors affecting the safety of metro stations are disordered, complex and multi-dimensional. In fact, the weight of input places and confidence of transitions reflect the causal relationship between risk cause and safety state The main idea of Apriori algorithm is to find all subsets of frequently
occurring items in data set $S$ and their correlation (Li et al. 2018). It uses the idea of two-stage mining to realize the mining of frequent item sets by scanning data sets multiple times.

Definition 2: $X \Rightarrow Y$, $X \subseteq L_k, Y \subseteq L_k, X \cap Y \neq \emptyset$.

Stage 1: To find the maximum $k$-frequent item set: To calculate the ratio between frequency item set and data set, regard it as the support degree of each frequent item set, and eliminate the item set that do not exceed the preset minimum support. The $k$-frequent item set is used to find $(k+1)$-candidate item set $C_{k+1}$, and the $(k+1)$-frequent item set $L_{k+1}$ is obtained until the next frequent item set cannot be found.

$$V_{\text{supp}}(X \Rightarrow Y) = \frac{\text{count}(X \cup Y)}{|S|}$$

Definition 3: $V_{\text{con}}(X \Rightarrow Y) = \frac{V_{\text{supp}}(X \cup Y)}{V_{\text{supp}}(X)} = \frac{\text{count}(X \cup Y)}{\text{count}(X)}$

Stage 2: Association rules are generated by frequent sets: strong association rules are generated by using the maximum frequent item set and the preset minimum confidence, and the correlation degree is used to judge whether the strong association rules are accidental or inhibitory, so as to eliminate misleading rules (Wang et al. 2018).

4.3. Construction of IFPN

Through the analysis of the evolution mechanism of the safety state of metro stations, some key influencing factors that promote the change of safety state of metro stations are selected to establish the IFPN of safety state assessment of metro stations, as shown in figure 1. The specific meanings of places are shown in table 1. When the place is in a non-absolute security state, it may have an adverse impact on the safety state of metro stations. Therefore, the threshold is set as 0, indicating that any state of the key cause place will have an impact on the safety state of metro stations.

| place | Description                        | place | Description                        | place | Description                        | place | Description                        |
|-------|-----------------------------------|-------|-----------------------------------|-------|-----------------------------------|-------|-----------------------------------|
| $p_1$ | Reliability of evacuation facilities | $p_3$ | Fire classification and fire condition | $p_5$ | Ability of fire fighting system | $p_{13}$ | Reliability of fire fighting equipment |
| $p_2$ | Overall quality of passenger      | $p_4$ | Fire and smoke partition rationality | $p_6$ | Fire source control system reliability | $p_{14}$ | Fire safety status |
| $p_3$ | Overall quality of staff          | $p_7$ | Site layout                       | $p_8$ | Design on building fire protection |       |                     |
| $p_4$ | Daily safety management level     | $p_9$ | Evacuation of passengers           | $p_{12}$ | Evacuation environment           |       |                     |
5. Safety assessment and risk communication analysis of metro stations

5.1. Determination of the initial value of IFPN

5.1.1. Determine the token in the place. Determine the impact of the initial place state on the overall security system. Taking "reliability of evacuation facilities" as an example, when the safety system is in a non-safety state, some historical data show that the 100-point evaluation value of $P_1$ is $(75, 80, 66, 68, 71, 85, 55, 76, 92, 88)$ respectively. $GC=(75.600, 0, 100, 10.778, 2.996)$ can be obtained through equation (7), and then the normal gray cloud model is established, as shown in figure 2. When the evaluation state score of the corresponding proposition in place is 70, the corresponding measure is 0.85, which is obtained from the measure upper limit - normal gray cloud model. Similarly, the initial state of all places are obtained as $\alpha_0=(0.85, 0.68, 0.58, 0.73, 0.45, 0.38, 0.58, 0, 0, 0, 0, 0, 0, 0, 0)$.  

5.1.2. Determination of weight and transition confidence. The original safety state data of 40 groups of metro stations are collected as a data set $S$, to find $k$-frequent item set $L_k$, and calculate the support degree of each frequent item set by equation (9). According to the IFPN model, the required frequent item sets are screened out, and then the weights and the transition confidence are mined. According to equation (10), $\mu$ and $\omega$ of the model are calculated as follows.

\[
\begin{align*}
\mu &= \text{diag}(0.917, 0.8, 0.643, 0.5, 0.763, 1, 0.891, 0.956, 1), \\
\omega &= \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.360 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.274 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.366 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1.1 & 0.296 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.376 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.329 & 0.344 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.656 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.308 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.401 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.292 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}, \\
I &= \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}, \\
o &= \begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{align*}
\]
5.1.3. **Determination of topological relations.** Further, according to the topological relations in figure 1, the input matrix $I$ and output matrix $O$ of the model can be obtained.

5.2. **Forward reasoning and risk propagation path deduction**

The initial data of IFPN model are substituted into equation (1) - (2). Judging from the token in place to fire the potential transition, the transition fired judgment matrix $U$ is obtained. Through forward reasoning, the state of the next-level place is calculated, $\alpha = (0.85, 0.68, 0.58, 0.73, 0.45, 0.38, 0.58, 0.78, 0.29, 0.23, 0.36, 0, 0, 0)^T$; Until $\alpha = (0.85, 0.68, 0.58, 0.73, 0.45, 0.38, 0.58, 0.78, 0.29, 0.23, 0.36, 0.71, 0.26, 0.47)^T$, forward reasoning is completed, and all token of places are updated.

The final token of metro station safety state is 0.47, which is in “alert”. When part of initial places is in an unstable state, forward reasoning can be used to predict the risk propagation path. Take "reliability of emergency evacuation auxiliary facilities" and "daily safety management level" with high token in the initial place as an example, $p_1$ and $p_4$ as the initial marks, the forward reasoning initial marking vector is $M_0 = (1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0)^T$. The initial transition enabling matrix $R_0$ of risk propagation is obtained through transition fired judgment matrix, $R_0 = (1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)^T$. Put the original data into equation (3) - (4) to get the marking moving path. When $R = R_0$, the reasoning process is completed, $M_4 = (1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0)^T$ is calculated to indicate the activated risk marking, as shown in figure 3. It can be seen from the figure that $p_1$ is fired by risk, while $p_4$ is not fired. Manager can take corresponding measures against the risks on the basis of the marking moving path and corresponding token.

5.3. **Reverse reasoning and risk identification**

The forward reasoning of the security state is “alert”. It can be seen from the token of the superior database that the main security hidden dangers exist in the subsystem of "evacuated environment". Taking "evacuated environment" as an example, the subsystem with the highest risk is identified through reverse inference. It can be seen from the token value of the superior place that the main safety risks exist in the subsystem of "evacuation environment". Taking "evacuation environment" as an example, the initial place with the highest risk is identified through reverse reasoning.

The reverse reasoning initial marking vector is $M_0 = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0)^T$. The initial transition enabling matrix $R_0$ of risk propagation is obtained through transition fired judgment matrix, $R_0 = (1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1)^T$. Put the original data into equation (5)-(6) to get the reverse reasoning marking moving path. When $R = R_0$, the reasoning process is completed, $M_4 = (1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0)^T$ is calculated to indicate the major risk factors, as shown in figure 4. The key minimal cut sets to cause $p_{12}$ is $G_1 = \{p_1\}$, $G_2 = \{p_2, p_3, p_4\}$ and $G_3 = \{p_5, p_6\}$. 

![Figure 3](image3.png)  
Figure 3. These two figures have been placed side-by-side to save space. Forward reasoning marking moving path

![Figure 4](image4.png)  
Figure 4. These two figures have been placed side-by-side to save space. Reverse reasoning marking moving path

![Figure 3](image3.png)  
Figure 3. These two figures have been placed side-by-side to save space. Forward reasoning marking moving path

![Figure 4](image4.png)  
Figure 4. These two figures have been placed side-by-side to save space. Reverse reasoning marking moving path
Assuming the premise of the occurrence of a minimal cut set is true, the credibility of the risk minimal cut set is calculated. When the subsequent transition is fired, the next step of reasoning can be continued; If false, the premise of the occurrence of the minimal cut set is taken as the sub-target, and the causes of the occurrence of risks are found from other paths. The reliability of risk cut set is calculated as $A, S$ and $D$.

$$f(G_1) = 0.85, \quad f(G_2) = 0.67 \quad \text{and} \quad f(G_3) = 0.64$$

successively. The sequence of risk identification is $G_1, G_2$ and $G_3$.

6. Conclusion

By using the normal gray cloud model to describe the initial safety risk state of metro station, the qualitative concept carrying fuzzy and gray information is transformed into a qualitative measure with randomness. Based on the traditional FPN, weight and transition confidence are obtained through data mining, which provides data support for identifying the propagation of safety risks in the IFPN model.

Based on IFPN model, the development of metro station safety risk is presented as a multi-stage and multi-system dynamic decision-making fuzzy reasoning process. The final evaluation result of metro station safety state is obtained by forward and reverse reasoning. At the same time, it realizes the deduction of risk propagation path and risk identification, and effectively assists management to carry out targeted management design and scientific prevention.

Due to the limitations of relevant data, this method still has shortcomings in verifying the safety of some metro stations. In the next step, the IFPN model of metro station safety should be further optimized to consider the evolution relationship between risk factors and subsequent places in a more comprehensive way. Meanwhile, the influence of dynamic weight on risk propagation reasoning is further considered.

Acknowledgments

This study is supported by National Natural Science Foundation of China (Nos.51308448), Shaanxi Provincial Construction Science and Technology Plan Project (2016-RJ21), Xi'an Construction Science and Technology Project (SJW2017-02). we would like to thank the editors and reviewers for your time and we appreciate it very much.

References

[1] SONG, Z Z. SONG W B. LIN L. (2018) Fire risk assessment of metro station based on multi-level extension evaluation method. J. Manufacturing Automation, 40(12):26-30+41.

[2] MENG F X. LEI Y J. LEI Y, et al.(2017) Hybrid Reasoning Using Intuitionistic Fuzzy Petri Nets J. Acta Electronica Sinica, 45(08):1937-1946.

[3] ZHOU J F. LI Z C. (2019) Modeling and performance analysis for the emergency response actions to the industrial fire based on the colored time Petri net. J. Journal of Safety and Environment, 19(02):562-568.

[4] CHU P Y. LIU L. YIN J S. (2016) On the metro fire risk assessment based on the dynamically variable weight Petri net. J. Journal of Safety and Environment, 16(06):39-44.

[5] YAO D K. WANG Q H. GAN X S. (2018) Safety risk assessment on the air traffic control via the improved fuzzy Petri net J. Journal of Safety and Environment, 18(02):413-417.

[6] WANG G H. FAN P F. LI X R, et al. (2017) One Approach for Failure Analysis of Auto-loader Based on Cloud Model and Improved Fuzzy Fault Petri Net J. Journal of Gun Launch & Control, 38(03):85-91.

[7] Ni L H. Wen J U. Lu G Y, et al.(2019). Power grid fault diagnosis method of hierarchical fuzzy petri net based on comprehensive variable weight. J/OL. Electrical Measurement & Instrumentation. http://kns.cnki.net/kcms/detail/23. 1202. TH. 20190812. 1553. 006.html.

[8] GONG M F, ZHANG Y P, LIU Y N, et al.(2015). Fault diagnosis of power transformers based on back propagation algorithm evolving fuzzy Petri nets J. Power System Protection and Control, 43(03):113-117.
[9] CHEN B Y. DING J. CHEN S N. (2018) Selection of key incentives for power production safety accidents based on association rule mining. J. Electric Power Automation Equipment, 38:68-74.

[10] WANG S C. JIA X S. HU Q W, et al. (2019). Effectiveness evaluation for equipment maintenance support system based on normal gray cloud model. J. Systems Engineering and Electronics, 41(07):1576-1582.

[11] LIU D N. ZHANG Q. LI X T, et al. (2019). Identification of Potential Harmful Behaviors in Electricity Market Based on Cloud Model and Fuzzy Petri Net. J. Automation of Electric Power Systems, 43(02):25-37.

[12] LI P J. YANG B. LI H G. (2018) Association rules based conditional state fuzzy Petri nets with applications in fault diagnosis. J. CIESC Journal, 69(08):3517-3527.

[13] WANG Y Y. ZHOU L W. LIANG X H. (2018) Markov Forecasting Model of Power Transformer Fault Based on Association Rules Analysis. J. High Voltage Engineering, 44(04):1051-1058.