Fault Diagnosis Method for Avionics System based on Conditional Fuzzy Petri Nets

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Abstract: In order to analyse the fault of avionics system effectively, the conditional places are added on the basis of traditional fuzzy Petri nets. Firstly, by analysing the functional structure of the system and combining with the maintenance data, the forward reasoning model is established by using conditional fuzzy Petri nets for fault propagation analysis. Based on the forward reasoning model, the probability formula is combined to construct the backward reasoning model, and the certainty factor (CF) of partial reverse transitions is timely updated according to the state of the conditional places for fault diagnosis. Then, given the initial belief of the places, the forward and reverse reasoning model are quantitatively calculated by using the iterative algorithm based on maximal algebra, and the calculated result of each place in the next state is deduced to analyse the possibility of failure. Finally, an example is given to verify the effectiveness of the method.

Keywords: Avionics system; Petri nets; Fault diagnosis; Certainty factor.

1. INTRODUCTION

Avionics system mainly includes navigation, communication and other functions. With the development of technology, avionics system has gone through the stages of separation, combination and integrated modularization (De-Cai Yang, 2015). The integration modularization of avionics system brings convenience as well as high coupling between functions, which brings challenges to fault diagnosis and analysis (Zhi-Gang Li et al., 2005). For the fault of avionic system, due to the interconnection among the various functional units that make up the avionics system, the same fault symptom often corresponds to several fault causes, and the same fault causes can lead to multiple fault symptoms (Jie Li et al., 2007). When a fault occurs at a certain level of avionic system, the state of its related components will change, sometimes the uncertainty of environmental factors and its own characteristics always lead to the uncertainty of the fault.

Many experts are using fuzzy Petri nets to carry out forward reasoning (Peng Wu et al., 2019), and establishing expert system through fuzzy regularization (P. V. S. Reddy, 2016). For system fault diagnosis (Jie Li et al., 2007), not only tends to infer the possibility of failure phenomenon from the causes of the failure through forward reasoning way, but also tends to infer the possibility of failure causes from the failure phenomenon in a backward reasoning way (Liu Hu-Chen, 2013).

In order to analyse the fault of avionics system effectively, an avionics multi-fault diagnosis method based on probabilistic causal network is proposed by (Zhu Ya-Guang et al., 2010), use the probabilistic causal network and minimalistic coverage theory to solve avionics system faults, and gives the multi-fault diagnosis ICGS algorithm and relative likelihood evaluation algorithm. (Jie Yuan et al., 2008) proposed a reverse reasoning method based on fuzzy Petri nets (FPN), which made full use of the structure and behavior characteristics of FPN, identified the middle position through vector calculation, improved reasoning efficiency, and reduced the complexity and scale of FPN. (Hu, H. S., Li, Z. W., & Al-Ahmari, A, 2011) propose a model construction method, use fuzzy Petri nets to construct reverse reasoning model based on forward reasoning model, and the certainty factor(CF) of reverse transitions are set as the reciprocal of CF of forward transitions, and the iterative formula of maximal algebra method was used to calculate backward reasoning. Fuzzy Petri net can well represent the fuzziness, transitivity and uncertainty of the fault of complex system, for the fault of avionics system, fuzzy Petri net is also applicable. Therefore, an conditional fuzzy Petri net is proposed in this paper to effectively analyse and quantitatively calculate the fault of avionics system.

The organization of this paper is as follow: Section 2 introduces basic definition of conditional fuzzy Petri nets and presents a formal forward and backward reasoning algorithm. An example analysis is carried out to construct the model of forward and backward reasoning in Section 3. Section 4 introduces the calculation and verification of CFPN in forward reasoning and backward reasoning. Conclusion remarks are given in Section5.

2. CONDITIONAL FUZZY PETRI NETS

Petri nets was invented by C.A. Petri in the 1960s. It has both a strict mathematical expression and an intuitive graphical expression (Jie Yuan et al., 2008), which can well describe the concurrent and asynchronous dynamic behavior of complex systems (Hung-Pin Chen et al., 2000; Tao Hu et al.,2019), and has been gradually expanded into random Petri nets, color Petri nets, fuzzy Petri nets and so on (Jing-Yu Sheng et al., 2019).

2.1 Fuzzy Production Rules and Representation of Fuzzy Petri Nets

Fuzzy production rules describe the fuzzy relations of multiple propositions (X. Liu et al., 2009), the type of fuzzy production rules and corresponding representation of fuzzy Petri nets are as follow (Y. Liang et al., 2010; H. Guo et al., 2012):

Type 1: fuzzy production rule: if d_i then $d_k\left(CF=u_i\right)$

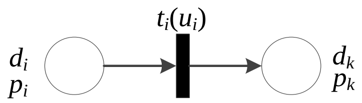

Fig 1. Fuzzy Petri nets representation of type 1

Mathematical expression: $CF(d_k)=\theta_{di}*\mu_i$

Type 2: fuzzy production rule: if d_1 and … and d_n then $d_k\left(CF=u_i\right)$

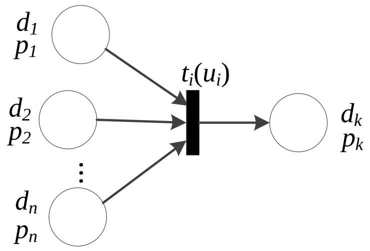

Fig 2. Fuzzy Petri nets representation of type 2

Mathematical expression: $CF\left(d_k\right)=\min\left(\theta_{d1},\theta_{d2}\cdots\theta_{dn}\right)*\mu_i$

Type 3: fuzzy production rule: if d_1 or d_2 …or d_n then $d_k\left(CF=u_i\right)$

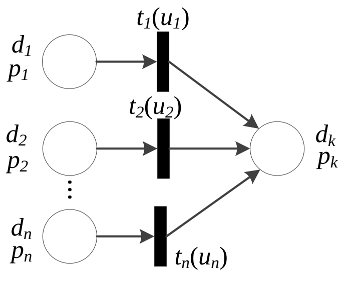

Fig 3. Fuzzy Petri nets representation of type 3

Mathematical expression: $CF(d_k)=\max(\theta_{d1},\theta_{d2}\cdots\theta_{dn})*\mu_i$

Where, $d_1\cdots d_n$ 、 d_k are propositions containing some fuzzy variables, corresponding to the places of fuzzy Petri nets, $d_1\cdots d_n$ represents the antecedent propositions or causes, d_k represents the consequence propositions or conclusions, and $u_i\in[0,1]$ is the certainty factor(CF) of the rules.

2.2 Definition of CFPN

Conditional fuzzy Petri nets is defined as an 8-tuple:

$$CFPN=(P,P_c,T,D,I,O,\theta,\phi)$$

(1) $P=\{p_1,p_2\cdots p_m\}$: represents a limited set of places, including failure symptoms and causes;

(2) $P_c=\{p_{c1},p_{c2}p_{c3}\cdots\}$:represents the conditional places, which does not participate in the forward and backward reasoning process, but will affect the CF of corresponding transitions in the backward reasoning;

(3) $T=\{t_1,t_2\cdots t_n\}$: represents the set of finite transitions, represents the state change of the places;

(4) $D=\{d_1,d_2\cdots d_m\}$: represents a set of propositions, corresponding to the places;

(5) $I=\{I_{ij}\}$: represents the input matrix, representing the relationship between P and T (excluding P_c), when the direction of P to T have arrows, I_{ij} is 1, otherwise is 0;

(6) $O=\{O_{ij}\}$: represents the output matrix, representing the relationship between T and P (excluding P_c), when the direction of T to P have arrows, O_{ij} is 1, otherwise is 0;

(7) θ : Each place corresponds to a belief, expressed as θ_i ,corresponding to the number of tokens, $CF(P)=\theta=\{\theta_1,\theta_2\cdots\theta_m\}$, $\theta_i\in\left[0,1\right]$;

(8) ϕ : Each transition corresponds to a certainty factor (CF), expressed as μ_i , $CF(P)=\theta=\{\theta_1,\theta_2\cdots\theta_m\}$, $\mu_i\in\left[0,1\right]$.

2.3 Forward reasoning and backward reasoning of CFPN

Forward reasoning model and backward reasoning model of CFPN are defined as follows:

Definition1:Let $CFPN1=(P_1,P_c,T_1,I_1,O_1,\theta_1,\phi_1)$ and $CFPN2=(P_2,P_c,T_2,I_2,O_2,\theta_2,\phi_2)$ be two conditional fuzzy Petri nets respectively, if $P_1=P_2,T_1=T_2,I_1=O_2,O_1=I_2$, Then we can conclude that, $CFPN1$ is the reverse fuzzy Petri nets of $CFPN2$, represented as $CFPN1=CFPN2^{-1}$

The forward reasoning model of CFPN is shown in Fig 4, and the backward reasoning model is shown in Fig 5.

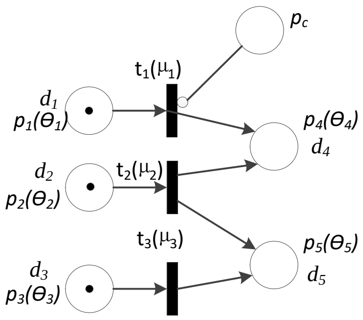

Fig 4. Forward reasoning model of CFPN

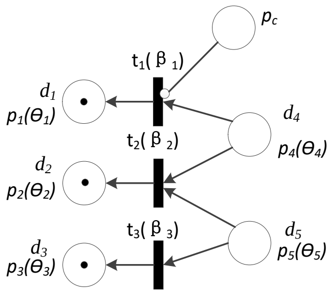

Fig 5. Backward reasoning model of CFPN

Where, $u_i \in [0,1]$ is the certainty factor(CF) of the rules, corresponding to the CF of forward transitions, $\beta_i \in [0,1]$ is the CF of reverse transitions, $d_1 \cdots d_n$ represents the antecedent propositions or premise place, d_k represents the consequence propositions or conclusion places, P_c is the conditional places.

The forward reasoning of CFPN means that under the condition that the belief of each premise place is not zero, the transitions could be triggered to obtain the belief of the conclusion places. At this point, the P_c do not participate in the forward reasoning process, nor do not affect the CF of the corresponding transitions.

The backward reasoning of CFPN is to obtain the belief of each premise place by means of transitions triggering under the condition that the belief of the conclusion places is not zero, so as to complete the process of backward reasoning. Based on the traditional fuzzy Petri nets, the P_c is added, and the inhibitor arc and transitions of Petri nets are connected. the inhibitor arc of traditional Petri nets is to inhibit the transitions triggering, which means the CF of corresponding transition is became 0, under the condition that the belief of the connected place is not zero. the following improvements are made on the original basis:

(1) the belief of P_c is between 0 and 1, indicating the degree of constraint on the CF of reverse transitions;
(2) modify CF of the connected reverse transitions, but do not completely make it 0.

P_c does not participate in backward reasoning process, while when the state of P_c is known, will update the CF of the corresponding reverse transitions.
Probability formula: $P(B|A) = P(B)P(A|B)/P(A)$

After deformation: $P(A|B) = P(A)P(B|A)/P(B)$
$P(A|B) = \beta_i, P(B|A) = \mu_i (i = 1, 2, \cdots)$, A is the premise place and B is the conclusion place.
Definition 2: $\phi_i = (\mu_1, \mu_2 \cdots \mu_n)$ represents the CF of forward transitions, and $\phi_2 = (\beta_1, \beta_2 \cdots \beta_n)$ represents the CF of reverse transitions, then could conclude that : $\beta_i = P(A)\mu_i / P(B)$.

Two symbols of maximal algebra are introduced to carry out the quantitative calculation of CFPN reasoning (Mei-Mei Gao et al., 2004).

(1) $\oplus: A \oplus B = C$, where, $A = (a_{ij}), B = (b_{ij}), C = (c_{ij})$, all of them are $m \times n$ dimensional matrices, and $c_{ij} = \max(a_{ij}, b_{ij})$, $i = \{1, 2 \cdots m\}$, $j = \{1, 2 \cdots n\}$
(2) $\otimes: A \otimes B = C$, where, $A = (a_{ij}), B = (b_{ji}), C = (c_{ii})$, all of them are $m \times n$ -dimensional matrices, and $C_{ij} = \max(a_{ik} \times b_{kj})$, $i = \{1, 2 \cdots m\}$, $j = \{1, 2 \cdots n\}$, $k = \{1, 2 \cdots n\}$

The iterative formula of forward reasoning is formally defined as follow (Hu, H. S., Li, Z. W., & Al-Ahmari, A. 2011):

$$\begin{cases} \theta_1^{k+1} = \theta_1^k \oplus \left[(O \times U_1) \otimes \rho(k) \right] \\ neg\left[\theta_1^k \right] = 1_m - \theta_1^k \\ \rho(k) = neg\{ I^T neg\left[\theta_1^k \right] \} \end{cases} \quad (1)$$

Do the iterative calculation until $\theta_1^{k+1} = \theta_1^k$. where, m stands for the number of places (P) (excluding P_c), n stands for the number of transitions, 1_m is the m-dimensional vector with all elements being 1, I is the $m \times n$ input matrix, O is the $n \times m$ output matrix, and U is the $n \times n$ matrix with the confidence ϕ of transitions as a diagonal.

Therefore, the iterative calculation formula of backward reasoning could be concluded that as follow:

$$\begin{cases} \theta_2^{k+1} = \theta_2^k \oplus \left[(I \times U_2) \otimes \rho(k) \right] \\ neg\left[\theta_2^k \right] = 1_m - \theta_2^k \\ \rho(k) = neg\{ O^T neg\left[\theta_2^k \right] \} \end{cases} \quad (2)$$

Where, I、O are the input and output matrix of the forward reasoning model.

2.4 Realization of Reasoning Algorithm of Conditional Fuzzy Petri Nets

The forward reasoning steps of CFPN are as follows:

(1) Complete the construction of fuzzy Petri nets forward reasoning model by analysing common fault information of maintenance data and according to the functional structure of the system;
(2) According to the model, input matrix I, output matrix O and the matrix of transitions *U1* are obtained, and under the situation of giving the initial state θ_1^0, substituting them into the iterative algorithm of forward reasoning;
(3) Calculate the next state after the transitions trigger until the belief of each place no longer changes.

The reasoning steps of CFPN's reverse fault diagnosis are as follows:

(1) Based on the forward reasoning model, according to the fault statistics of maintenance data, the backward reasoning model is established according to definition 1, and the matrix of transitions (*U2*) of the backward reasoning model is calculated according to definition 2;
(2) Input matrix I and Output matrix O belongs to the forward reasoning model, and under the situation of giving the initial state θ_2^0, substituting them into the iterative algorithm of backward reasoning;
(3) Calculate the next state after the transitions trigger until the belief of each place no longer changes.

3. MODELING ANALYSIS OF CFPN ON AVIONICS SYSTEM

3.1 VHF Communication System

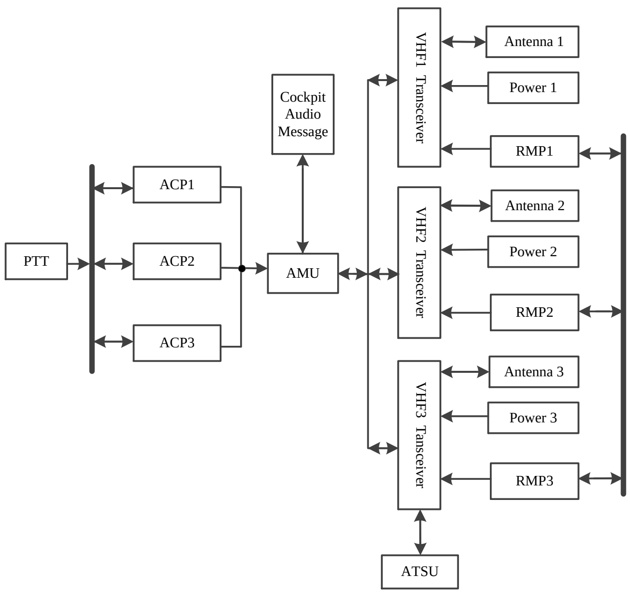

Fig.6. Function connection of VHF communication system

The following is the very high frequency communication system as an example to introduce the use of CFPN in avionics system. VHF communication system (VHF) is a kind of communication system between aircraft and aircraft and between aircraft and ground station at close range. The communication system consists of radio management panel (RMP), VHF transceiver, antenna, etc., and is connected with audio control panel (ACP) and audio management module (AMU). Most aircraft are equipped with three completely independent VHF systems that can be exchanged. There are three RMPs and three ACPs in the whole aircraft. Any RMP can be tuned to the VHF1, VHF2, and VHF3 system. Similarly, each ACP can control each transceiver selectively. The VHF functional connection is shown in Fig 6.

3.2 Construction of Forward Reasoning and Backward Reasoning Models

According to the failure maintenance data of the VHF communication of airline A in the past three years, and the experience of consulting maintenance personnel, the common fault types of VHF communication system are summarized, including data link fault, audio information fault, transceiver tuning fault and other main fault types. The causes of failure mainly include: antenna fault, transceiver fault, ACP fault, RMP fault, ATSU fault, AMU fault, etc. The statistical results of maintenance data of airline A in the past three years are shown in Table 1:

Table 1. Fault statistics of maintenance data of airline A

fault	Times	fault	Times
Transceiver Power failure	4	AMU failure	7
Transceiver hardware failure	275	Environmental interference	10
Transceiver software failure	81	Transceiver tuning failure	7
RMP button failure	8	Antenna fault warning	8
RMP software failure	1	Antenna crack corrosion	108
Screw loose on Antenna base	2	Transceiver fault warning	310
ACP failure	66	Audio message fault	330
PTT failure	4		

In the daily maintenance work, when the maintenance crew check the fault of the VHF communication system, the functional structure of the transceivers or RMPs always be configured or adjusted to diagnose the position of fault in the field, which exactly corresponds to the state of the conditional places(P_c) described in this paper. According to the functional connection of VHF and probability statistics of each fault, the forward reasoning model for fault propagation of CFPN is established based on the audio fault of VHF3 system as the final fault symptom, as shown in Fig 7, and the backward reasoning model for fault diagnosis is established based on the forward reasoning model, as shown in Fig 8.

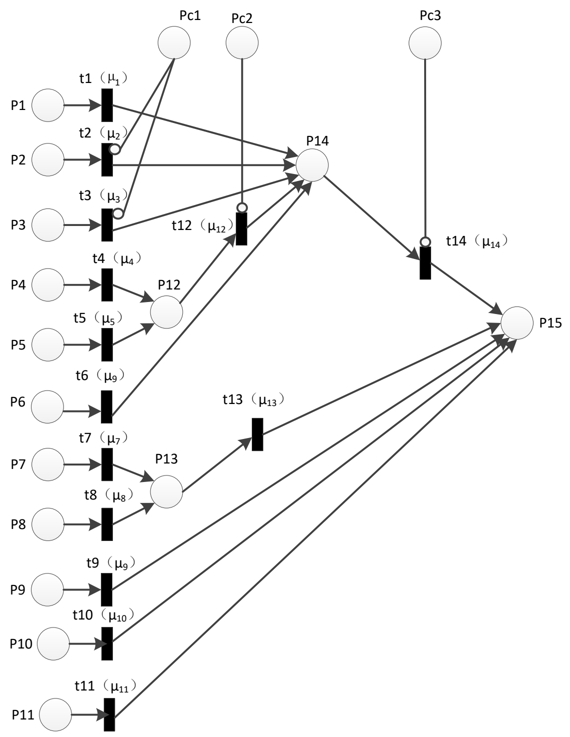

Fig.7. Forward reasoning model for fault propagation of VHF System

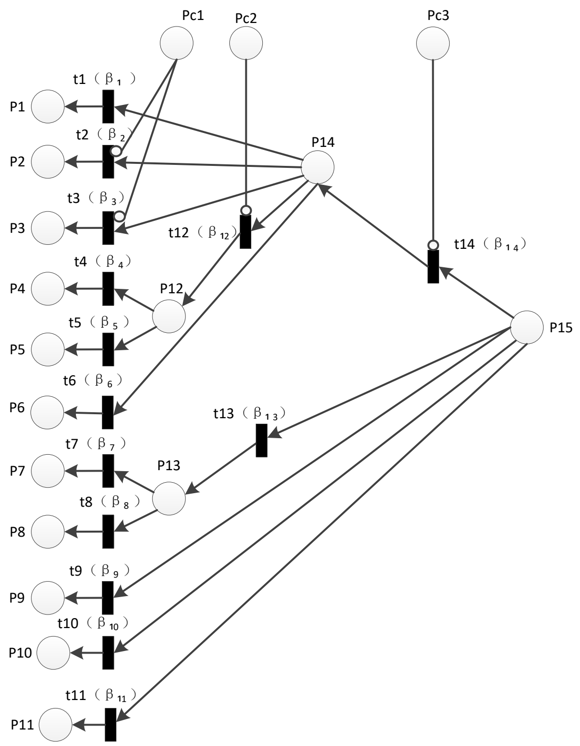

Fig.8. Backward reasoning model for fault diagnosis of VHF system

In the forward reasoning model, the arrow direction indicates the direction of fault transmission, the CF of forward transitions represents the degree of correlation between fault causes and fault symptoms, and the belief of places P (including conditional places P_c) represent the possibility of fault causes or fault symptoms. As can be seen from the Fig 7, P_{c1}, P_{c2} and P_{c3} are the conditional places, where P_{c1} is the audio state when other transceivers are switched, P_{c2} is the state of VHF transceivers when other RMPs are switched, and P_{c3} is the state of communication data chain. The arrow direction of the backward reasoning model is the direction of fault diagnosis, and the CF of reverse transitions represent the probability of each fault cause when the fault symptom occurs.

Table 2 shows the meanings of each place, Table 3 shows the meanings of forward transitions, Table 4 shows the CF of forward transitions in the forward reasoning model, which is scored according to expert experience and maintenance data, and Table 5 shows meaning of reverse reasoning transitions in the backward reasoning model.

Table 2. Meanings of each place

P	meaning	P	meaning
P1	Transceiver power failure	P10	AMU failure
P2	Transceiver hardware failure	P11	Environmental interference
P3	Transceiver software failure	P12	Transceiver tuning failure
P4	RMP buttons are not sensitive	P13	Antenna fault warning
P5	RMP software failure	P14	Transceiver fault warning
P6	PTT failure	P15	Audio message fault
P7	Antenna is corroded and cracked	Pc1	status of switching other Transceivers
P8	Screw loose on Antenna base	Pc2	status of switching other RMPs
P9	ACP failure	Pc3	Data link communication status

Table 3. Meaning of forward reasoning transitions

T	Fuzzy regularized description
T1	If the Power supply failure, then the Transceiver fails
T2	If Transceiver hardware failure, then Transceiver fails
T3	If the Transceiver software fails, then the Transceiver fails
T4	If RMP button fails, then Transceiver tuning fails
T5	If RMP software fails, then Transceiver tuning fails
T6	If PTT signal fails, then Transceiver fails
T7	If Antenna cracks corrode, then Antenna fails
T8	If the Antenna screw is unstable, then the Antenna fails
T9	If ACP fails, then Audio Message fails
T10	If AMU fails, then Audio Message fails
T11	If Environment interference, then Audio Message fails
T12	If Transceiver tuning fails, then Audio Message fails
T13	If the Antenna fails, then the Audio Message fails
T14	If Transceiver fails, then Audio Message fails

Table 4. The CF of forward reasoning transitions

μ_i	$CF(\mu_1)$	μ_i	$CF(\mu_1)$	μ_i	$CF(\mu_1)$
μ_1	0.9	μ_6	0.8	μ_{11}	0.6
μ_2	0.95	μ_7	0.05	μ_{12}	0.9
μ_3	0.95	μ_8	0.4	μ_{13}	0.9
μ_4	0.8	μ_9	0.8	μ_{14}	0.95
μ_5	0.8	μ_{10}	0.9		

Table 5. Meaning of reverse reasoning transitions

T	Fuzzy regularized description
T1	If Transceiver fails, then Power is unstable
T2	If Transceiver fails, then Transceiver hardware fails
T3	If Transceiver fails, then Transceiver system fails
T4	If Transceiver tuning fails, then RMP button fails
T5	If Transceiver tuning fails, then RMP software fails
T6	If the Transceiver fails, then the PTT signal fails
T7	If Antenna fails, then Antenna cracks and corrosion
T8	If Antenna fails, then Antenna screw is not fixed securely
T9	If Audio Message fails, then ACP fails
T10	If Audio Message fails, then AMU fails
T11	If Audio Message failure, then Environment interference
T12	If Audio Message fails, then transceiver tuning fails
T13	If the Audio Message fails, then the Antenna fails
T14	If Audio Message fails, then Transceiver fails

4. CALCULATION AND VERIFICATION OF CFPN IN FORWARD REASONING AND BACKWARD REASONING

4.1 Forward Fault Propagation Reasoning

The forward reasoning model of fault propagation represents the probability of fault symptoms caused by fault causes. The reasoning of fault symptoms at the next level is carried out according to the initial belief of the places of fault causes, and the final belief of the places of fault symptom is quantitatively calculated according to the forward reasoning iterative formula (1) (conditional places(P_c) do not participate in forward reasoning process).

(1) I、O input/output matrix

$$I = \begin{bmatrix} 1&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

$$O = \begin{bmatrix} 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&1&1&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&1&1&0&0&0&0&0&0 \\ 1&1&1&0&0&1&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&1&1&1&0&1&1 \end{bmatrix}$$

(2) The initial belief of the places is:
θ^0 = [0.1 0.85 0.2 0.1 0.15 0.2 0.4 0.1 0.1 0.1 0.2 0 0 0 0] ^{T}
(3) The matrix about the CF of the forward transitions:
U= diag (0.9 0.95 0.95 0.8 0.8 0.8 0.05 0.4 0.8 0.9 0.6 0.9 0.9 0.95)
(4) By resubstituting them into the iterative formula (1) of forward reasoning, we can obtain:
θ^1 = [0.1 0.85 0.2 0.1 0.15 0.2 0.4 0.1 0.1 0.1 0.2 0.12 0.04 0.8075 0.12] ^{T}
θ^2 = [0.1 0.85 0.2 0.1 0.15 0.2 0.4 0.1 0.1 0.1 0.2 0.12 0.04 0.8075 0.7671] ^{T};
θ^3 = [0.1 0.85 0.2 0.1 0.15 0.2 0.4 0.1 0.1 0.1 0.2 0.12 0.04 0.8075 0.7671] ^{T}.

Until $\theta^3 = \theta^2$, the iteration is done. The final iterative calculation results show that the final CF(P15) = 0.7671, that is, the probability of audio information failure is 0.7671 in the case of a given initial belief of cause places.

4.2 Calculation of Reverse Fault Diagnosis with the Conditional Places Unknown

The CF of reverse transitions calculated by combining definition 2 with maintenance data of airline A is shown in Table 6.

Table 6. The CF of reverse transitions

β_i	*CF*	β_i	*CF*	β_i	*CF*
β_1	0.0116	β_6	0.01032	β_{11}	0.0182
β_2	0.8427	β_7	0.6750	β_{12}	0.0203
β_3	0.2482	β_8	0.1	β_{13}	0.0218
β_4	0.9143	β_9	0.16	β_{14}	0.8924
β_5	0.1143	β_{10}	0.0191		

The matrix about the CF of the backward transitions:

U= diag (0.0116 0.8427 0.2482 0.9143 0.1143 0.01032 0.6750 0.1 0.16 0.0191 0.0182 0.0203 0.0218 0.8924)
Assume the initial belief of the places is:
θ^0 = [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.8] T
By resubstituting them into the iterative formula (2) of backward reasoning, we can obtain:
θ^1 = [0 0 0 0 0 0 0 0 0.1280 0.0153 0.0146 0 0.0174 0.7139 0.8] T
θ^2 = [0.0083 0.6016 0.1772 0 0 0.0074 0.0117 0.0017 0.128 0.0153 0.0146 0.0145 0.0174 0.7139 0.8] T
θ^3 = [0.0083 0.6016 0.1772 0.0133 0.00165 0.0074 0.0117 0.0017 0.128 0.0153 0.0146 0.0145 0.0174 0.7139 0.8] T
θ^4 = [0.0083 0.6016 0.1772 0.0133 0.00165 0.0074 0.0117 0.0017 0.128 0.0153 0.0146 0.0145 0.0174 0.7139 0.8] T

Until $\theta^4 = \theta^3$, the iteration is done. The iterative calculation results show that the belief of P1 to P11 is as follows: CF(P1)=0.0083 CF(P2) = 0.6016 CF(P3) = 0.1772 CF(P4) =0.0133 CF(P5) = 0.00165 CF(P6) =0.0074 CF(P7) =0.0117 CF(P8) =0.0017 CF(P9) =0.128 CF(P10) =0.0153 CF(P11) =0.0145. The higher the belief of P, the more likely the failure causes will occur. The posibility sort is P2, P3, P9, P10, P11, P4, P7, P1, P6, P8, P5, so as to guide the order of maintenance activities, which can save a lot of troubleshooting time to some extent.

4.3 Calculation of Reverse Fault Diagnosis with Conditional Places Known

Assuming that P_{c1}, P_{c2} and P_{c3} have normal and fault state, i.e. "0" and "1", Table 7 shows the corresponding relationship between the conditional places(P_c) state and the confidence of corresponding reverse transitions.

Table 7. Relationship between P_c state and the CF of corresponding reverse transitions

P_c	normal	fault
P_{c1}	$\beta_2 = 0.99, \beta_3 = 0.8$	$\beta_2 = 0.01, \beta_3 = 0.01$
P_{c2}	$\beta_{12} = 0.99$	$\beta_{12} = 0.01$
P_{c3}	$\beta_{14} = 0.99$	$\beta_{14} = 0.01$

For example, when RMP3 and RMP1 are switched, the communication audio state returns to normal, which means P_{c2} is in the normal state, it can be modified as $\beta_{12} = 0.99$, and then the matrix of reverse transitions can be updated as:

U= diag (0.0116 0.8427 0.2482 0.9143 0.1143 0.01032 0.6750 0.1 0.16 0.0191 0.0182 0.99 0.0218 0.8924)
Assume the initial belief of the places is:
θ^0 = [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.8] T
By resubstituting them into the iterative formula (2) of backward reasoning, we can obtain:
θ^1 = [0 0 0 0 0 0 0 0 0.128 0.0153 0.0146 0 0.0174 0.7139 0.8] T;
θ^2 = [0.0083 0.6016 0.1772 0 0 0.0074 0.0117 0.0017 0.128 0.0153 0.0146 0.7068 0.0174 0.7139 0.8] T;
θ^3 = [0.0083 0.6016 0.1772 0.6462 0.0808 0.0074 0.0117 0.0017 0.128 0.0153 0.0146 0.7068 0.0174 0.7139 0.8] T;
θ^4 = [0.0083 0.6016 0.1772 0.6462 0.0808 0.0074 0.0117 0.0017 0.128 0.0153 0.0146 0.7068 0.0174 0.7139 0.8] T.

Until $\theta^4 = \theta^3$, the iteration is done. The belief of P1 to P11 is as follows: CF(P1) = 0.0083 CF(P2) = 0.6016 CF(P3)=0.1772 CF(P4)=0.6462 CF(P5)=0.0808 CF(P6)=0.0074 CF(P7)=0.0117 CF(P8)=0.0017 CF(P9)=0.1280 CF(P10)=0.0153 CF(P11)=0.0146. At this time, the belief sort of places is updated as: P4, P2, P3, P9, P5, P10, P11, P7, P1, P6, P8. Therefore, under the P_{c2} is known, the CF of partial reverse transitions is updated according to the state of the P_c , which will eventually affect the belief of places and enhance the flexibility and accuracy of fault diagnosis, which has certain practical significance in the maintenance process.

4.4 Verification and Analysis of Results

In order to verify the effectiveness of the iterative results in backward reasoning for fault diagnosis, this paper also obtained the maintenance data of similar aircraft in the past three years from airline B for statistics, so as to make a comparative analysis of the results. The failure times in Table 8 are analyzed with the audio information failure as the final failure symptom, the statistical results are as follows:

Table 8. Statistical results of airline B

Fault	Times	Fault	Times
Audio message fault	74	RMP hardware failure	4
Transceiver hardware failure	27	RMP software failure	2
Transceiver software failure	17	Antenna failure	3

ACP failure	6	PTT faliure	3
Environmental interference	4	AMU failure	5
Peripheral Device	2	Transceiver power	1

(1) For the fuzzy Petri nets with the P_c which are unknown, the sort of the belief calculated quantitatively is P2, P3, P9, P10, P11, P4, P7, P1, P6, P8 P5, indicating that the hardware failure of the transceiver is the most likely to occur, followed by the transceiver software failure. The calculated results are basically consistent with the statistical results in Table 8.

(2) During the maintenance process of VHF communication system, troubleshooting is usually done through field configuration. Generally, a fault of a component is positioned by means of intermodulation transceivers or intermodulation RMPs, etc. When switching RMP, if the VHF audio is back to normal, the possibility of RMP fault will be greatly increased. Under the condition that P_c are known, the sort of the belief calculated quantitatively is P4, P2, P3, P9, P5, P10, P11, P7, P1, P6, P8. At this point, the belief of the RMP place is the highest. The qualitative analysis is consistent with the quantitative calculation results to verify the validity of the CFPN model.

5. CONCLUSIONS

In this paper, CFPN is used to construct a forward reasoning model for fault propagation about VHF communication system, and the qualitative analysis and quantitative calculation of fault propagation are realized. The backward reasoning model for fault diagnosis is established on the basis of forward reasoning model, the CF of reverse transitions could be calculated by combining with probability formula and maintenance data, so as to realize qualitative description and quantitative calculation from the fault symptoms to the fault causes. According to the status of P_c updates the CF of the partial reverse transitions, results of iterative calculation, which could be used to guide the maintenance crew troubleshoot, make fault diagnosis more flexible. The results show that CFPN can well take into account the fuzziness and transitivity of avionics system fault, which has certain guiding significance for avionics maintenance, and can save a lot of manpower and resource allocation.

At the same time, there are still some deficiencies in this paper, which are mainly manifested in the following aspects: First, fault probability based on the three-year maintenance data of an airline, which is subjective to some extent. More data will be used to make the results more objective; secondly, there is a certain subjectivity in fault correlation, and some correlation degrees need to be scored by experts. In the future, we will consider combining big data technology to fully mine fault data information.

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