Fault Analysis for Flight Control System Using Weighted Fuzzy Petri Nets
Jiufu LIU, Kui CHEN, Zhisheng WANG
Institute of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing P.R.China,
{liujiufujs@sina.com, chenkui8693@163.com, wangzhisheng@nuaa.edu.cn}
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Abstract
The safety issue plays an important role for the reliability of flight control software of unmanned aerial vehicle (UAV), it is required to design a fault diagnosis expert system in flight control system. Our contribution to this work is in providing a weighted fuzzy Petri Nets approach for modeling the fault diagnosis of flight control system. The systematic rule-based knowledge is obtained from human expertise and the fault diagnosis is online, in which the reasoning rules can be updated and added anytime. The diagnosis result of the proposed fault diagnosis of flight control system without human expert is consistent with the real result. It is shown that the fault diagnosis of flight control system is very effective and efficient.

Keywords: Flight Control System, Fault Analysis, Weighted Fuzzy Petri Nets, Rule Based Reasoning

1. Introduction
The fault diagnosis expert system of flight control system of unmanned aerial vehicle (UAV) was ever developed, in which rule based reasoning approach was used and the rules come from many human experts and the rules can be updated added. Good effectiveness is obtained. However, the abnormality flight control components is uncertain and it is necessary to qualify the diverse abnormality. Thus the fault diagnosis expert system of flight control must be more efficient and adaptable to practice. This is the principle motivation behind this research work.

The Petri Nets (PN) [1][2] approach has the ability to concurrently represent and analyze in a simple way and with synchronization phenomena, and the approach can be easily combined with other techniques and theories such as fuzzy sets, neural networks, etc. These combined PN [3][11][12] are widely used in knowledge-based systems and process control, as well as other kinds of engineering applications. Fuzzy logical reasoning has its special ability to solve some difficult problems coupled with uncertain and fuzzy factors. So it could be a wonderful solution to formulate the fault diagnosis expert system of flight control.

The Fuzzy Petri Nets (FPN) is introduced in this paper to model the fault diagnosis expert system of flight control. In [6], Fuzzy Petri Nets is used as a modeling tool to build fault diagnosis models aimed to accurately diagnose faults for electric power systems when some incomplete and uncertain alarm information of protective relays and circuit breakers is detected. In [7], The fuzzy Petri Net approach is adopted to formulate the decision rules of train dispatchers in case of abnormality as the basis for future development of a dispatching decision support system.

An expert system mainly applies the "IF–THEN" to indicate knowledge rules. In [8], the approach makes use of a hypotheses generation and test technique to isolate and identify the responsible faulty component or subsystem in a system, the entire methodology consists mainly of a low level constraint evaluation process and a high level scheduling rule based reasoning process in which certain heuristic knowledge has been incorporated. In [9], the integrated flight control system, developed from the combination of a diagnosis with a flight control system, is able to correctly react on both external as well as internal disturbances. The knowledge-based monitoring, diagnosis and assessment system completes the developed flight control system by detecting the errors inside the system, evaluating and displaying them and initiating appropriate measures to avoid undesired inputs. An expert defines
features for each component of the flight control system which point to an error or a failure of the component. Tyan Ching-Yu and Wang Paul P. [10] proposes a rule-based expert system for aircraft flight control system using Bayesian probability theory and fuzzy logic approaches to deal with uncertainty. The fault diagnosis/detection monitor is governed by eigenstructure assignments of observer and flight dynamic system control is designed by state feedback controller.

In this paper, we present a new approach for formulating the fault diagnosis expert system of flight control system. The rest of this work is organized as follows. In section II, Petri Nets, Fuzzy Petri Nets and Fuzzy Reasoning are explicated. In section III, the fault diagnosis is modeled based on Weighted Fuzzy Petri Nets. In section IV, the fault reasoning of the fault diagnosis of flight control system is analysed. In section V, some conclusions and future works are presented.

2. Petri Net

2.1. Petri Nets approach

A Place/Transition net (P/T net) is a 4-tuple $N = (P,T,Pr,Post)$, where $P$ is a set of $m$ places (represented by circles), $T$ is a set of $n$ transitions (represented by empty boxes and each one associated to an event), $Pr : P \times T \mapsto N(\text{Post} : T \times P \mapsto N)$ is the pre-(post-) incidence matrix. $Pr(LT \times P = \omega(\text{Post}(L \times P \times \omega))$ means that there is an arc with weight $\omega$ from $p$ to $t$ (from $t$ to $p$); $C = \text{Post} - Pr \omega$ is the incidence matrix. The symbols $p(t)$ and $p(t)$ are used for the pre-set and post-set of a place $p \in P$ (transition $t \in T$), respectively. e.g., $t = \{p \in P|Pr \omega(t, p) \neq 0\}$.

A marking is a function $m : P \mapsto N$ that assigns to each place of a net a nonnegative integer number of tokens, draw as black dots. It is useful to represent the marking of a net with a vector $m \in N^m$. A net system $N = (N,m_0)$ is a net $N$ with an initial marking $m_0$. A transition $t$ is enabled at $m$ iff $m \geq Pr \omega(t, t)$ and this is denoted as $m[t]$. An enabled transition $t$ may fire, yielding the marking $m'[t] + C\omega(t)$ and this is denoted as $m[t]$. A firing sequence from $m$ is a sequence of transitions $\sigma = t_1 t_2 \ldots t_k$ such that $m[t_1] > m[t_2] > m[t_3] \ldots [t_k] > m[\sigma]$, and this is denoted as $m[\sigma] > m[\sigma]$, an enabled sequence $\sigma$ is denoted as $m[\sigma] > m[\sigma]$, while $t_i \in \sigma$ denotes that the transition $t_i$ belong to the sequence $\sigma$. The empty sequence is denoted as $\nu$.

A marking $m'$ is said to be reachable from $m_0$ iff there exists a sequence $\sigma$ such that $m_0 [\sigma] > m'$. $R(N,m_0)$ denotes the set of reachable markings of the net system $\{N,m_0\}$.

The function $\sigma : T \mapsto N$, where $\sigma(t)$ represents the number of occurrences of $t$ in $\sigma$, is called a firing count vector of the firing sequence $\sigma$. As it has been done for the marking of a net, the firing count vector is often denoted by a vector $\sigma \in N^m$. The notation $\sigma = \pi(\sigma)$ is used to denote that $\sigma$ is the firing count vector of $\sigma$. Note that, if a sequence is made by a single transition, i.e., $\sigma = t_i$, then the corresponding firing count vector is the $i$-th canonical basis vector denoted as $E_{t_i}$.

If $m_0[\sigma] > m$, then it is possible to write the vector equation

$$m = m_0 + C \cdot \sigma$$

(1)
Which is called the state equation of the net system.

2.2. Fuzzy Petri Nets

A generalized fuzzy Petri Nets structure can be defined as an 8-tuple \( [2]-[4] \):

\[
FPN = (P, T, D, I, O, f, \alpha, \beta)
\]  

\( P = \{p_1, p_2, \ldots, p_n\} \) is a finite set of places;
\( T = \{t_1, t_2, \ldots, t_m\} \) is a finite set of transitions;
\( D = \{d_1, d_2, \ldots, d_n\} \) is a finite set of propositions, and \( P \cap T \cap D = \Psi, |P| = |D| \)

\( I : T \rightarrow P^\alpha \) is an input function, a mapping from transitions to bags of places which determines the input places to a transition, and \( P^\alpha \) denotes bags of places;

\( O : T \rightarrow P^\beta \) is an output function, a mapping from transitions to bags of places which determines the output places from transitions;

\( f : T \rightarrow [0,1] \) is an association function, a mapping from transitions to real values between 0 and 1;

\( \alpha : P \rightarrow [0,1] \) is an association function, a mapping from places to real values between 0 and 1;

\( \beta : P \rightarrow D \) is an association function, a bijective mapping from places to propositions.

2.3. Weighted Fuzzy Petri Nets

The concept of Weight Fuzzy Petri Nets is derived from Petri Nets and Fuzzy Petri Nets. The definition of a generalized Weight Fuzzy Petri Nets structure (WFPN) is as follows:

\[
WFPN = (P, T, D, I, O, f, \alpha, \beta, W)
\]  

\( P = \{p_1, p_2, \ldots, p_n\} \) is a finite set of places;
\( T = \{t_1, t_2, \ldots, t_m\} \) is a finite set of transitions;
\( D = \{d_1, d_2, \ldots, d_n\} \) is a finite set of propositions, and \( P \cap T \cap D = \Psi, |P| = |D| \)

\( I : T \rightarrow P^\alpha \) is an input function, a mapping from transitions to bags of places which determines the input places to a transition, and \( P^\alpha \) denotes bags of places;

\( O : T \rightarrow P^\beta \) is an output function, a mapping from transitions to bags of places which determines the output places from transitions;

\( f : T \rightarrow [0,1] \) is an association function, a mapping from transitions to real values between 0 and 1;

\( \alpha : P \rightarrow [0,1] \) is an association function, a mapping from places to real values between 0 and 1;

\( \beta : P \rightarrow D \) is an association function, a bijective mapping from places to propositions;

\( W : P \rightarrow [0,1] \) is an association function, a mapping from places to fuzzy numbers between 0 and 1;

2.4. Fuzzy Reasoning

The fuzzy reasoning depends on the fuzzy rule set
\( R = \{R_1, R_2, \ldots, R_s\} \)
and

\[ R_i : \text{If } d_j \text{ Then } d_k \text{ (CF= } \mu_i) , \quad (i = 1,2,\ldots,n) \]

where, 1) \( d_j \) and \( d_k \) are propositions that include fuzzy variables, such as: “high”, “low” and “hot”, etc., the truth value of each proposition is a real value between 0 and 1. 2) \( \mu_i \) is the certainty factor (CF) of \( R_i \), which indicates the reliability of \( R_i \).

As a matter of fact, the fuzzy reasoning with FPN is carried out based on the certainty factor of fuzzy rules. Let \( \lambda \in [0,1] \) be the threshold, and if the truth value of proposition \( d_j \) is \( y_j \in [0,1] \), then:

Case 1) if \( y_j \geq \lambda \) then \( R_i \) can be fired, and the truth value of proposition.

Case 2) if \( y_j < \lambda \) then \( R_i \) cannot be fired.

For complex knowledge rules, some predicates, such as “and” and “or” are composed as follows.

Case 1) \( R_i : \text{If } d_{j_1} \text{ and } d_{j_2} \text{ and } \ldots \text{ and } d_{j_n}, \text{then } d_k \text{ (CF= } \mu_i) \).

Where \( d_{j_1}, d_{j_2}, \ldots, d_{j_n} \) and \( d_k \) are propositions, \( \mu_i \) is a fuzzy number indicating the certainty factor of rule \( R_i \).

Assume that the weights of the propositions \( d_{j_1}, d_{j_2}, \ldots, d_{j_n} \) are \( \omega_{j_1}, \omega_{j_2}, \ldots, \) and \( \omega_{j_n} \), respectively. And assume that the fuzzy truth values of the propositions \( d_{j_1}, d_{j_2}, \ldots, d_{j_n} \) and \( d_k \) are \( \alpha_{j_1}, \alpha_{j_2}, \ldots, \alpha_{j_n} \) and \( \alpha_k \), respectively. The fuzzy truth values of the proposition \( \alpha_k \) can be evaluated.

Let \( W^T = (\omega_{j_1}, \omega_{j_2}, \ldots, \omega_{j_n}) \) and \( A^T = (\alpha_{j_1}, \alpha_{j_2}, \ldots, \alpha_{j_n}) \), then

\[ \alpha_k = [W^T A] \mu_i \] \hspace{1cm} (4)

Case 2) \( R_i : \text{If } d_j \text{, then } d_{k_1} \text{ and } d_{k_2} \text{ and } \ldots \text{ and } d_{k_n} \text{ (CF= } \mu_i) \).

Where \( d_j, d_{k_1}, d_{k_2}, \ldots, d_{k_n} \) are propositions, \( \mu_i \) is a fuzzy number indicating the certainty factor of rule \( R_i \).

This type of rule can be equivalently decomposed into the following rules:

\[ R_{i_1} : \text{If } d_j \text{, then } d_{k_1} \text{ (CF= } \mu_i) \]

\[ R_{i_2} : \text{If } d_j \text{, then } d_{k_2} \text{ (CF= } \mu_i) \]

\[ \vdots \]

\[ R_{i_n} : \text{If } d_j \text{, then } d_{k_n} \text{ (CF= } \mu_i) \]

In these rules, the weight \( \omega_j \) of the propositions \( d_j \) is equal to 1.

Assume that the fuzzy truth value of the proposition \( d_j \) is \( \alpha_j \). The fuzzy truth value of the propositions \( d_{k_1}, d_{k_2}, \ldots, d_{k_n} \) are equal. Assume that the fuzzy truth value of the propositions \( d_{k_1}, d_{k_2}, \ldots, d_{k_n} \) is denoted as \( \alpha_k \). The fuzzy truth values of the proposition \( \alpha_k \) can be evaluated, then

\[ \alpha_k = \alpha_j \mu_i \] \hspace{1cm} (5)
Case 3) If $d_{j1}$ or $d_{j2}$ or ...and $d_{jn}$, then $d_{k}$ (CF = $\mu_i$).

Where $d_{j1}$, $d_{j2}$ ... $d_{jn}$ and $d_{k}$ are propositions, $\mu_i$ is a fuzzy number indicating the certainty factor of rule $R_i$.

This type of rule can be equivalently decomposed into the following rules:

$R_{j1}$: If $d_{j1}$, then $d_{k}$ (CF = $\mu_i$)

$R_{j2}$: If $d_{j2}$, then $d_{k}$ (CF = $\mu_i$)

... 

$R_{jn}$: If $d_{jn}$, then $d_{k}$ (CF = $\mu_i$)

Assume that the weights of the propositions $d_{j1}$, $d_{j2}$ ... $d_{jn}$ are $\omega_{j1}$, $\omega_{j2}$, ..., and $\omega_{jn}$, respectively. And assume that the fuzzy truth values of the propositions $d_{j1}$, $d_{j2}$ ..., $d_{jn}$ and $d_{k}$ are $\alpha_{j1}$, $\alpha_{j2}$, ..., $\alpha_{jn}$ and $\alpha_{k}$, respectively. The fuzzy truth values of the proposition $\alpha_{k}$ can be evaluated.

$$\alpha_k = \left[ \bigvee_{j=1}^{n} (\omega_j \alpha_j) \right] \mu_i$$  

(6)

Where $\bigvee$ is the OR operator of fuzzy numbers.

3. Modeling the Fault Diagnosis Based On WFPN

It is the Complexity of flight control and mission management of unmanned aerial vehicle(UAV) that make the requirements of flight control system higher and higher such as the function, the reliability, the adaptation and the cost. As the core of flight control system, flight controller(FC) is a typical intricate embedded real-time hybrid system. It covers diversified discrete control algorithm and continuous control algorithm which is used to implement the control and management function including data collection, control law, logic and scheduling judgment, equipment monitoring, autonomic navigation, automatic takeoff and landing, long distance communication, etc.

3.1. Flight control system with the fault diagnosis

In Figure 1 fault-tolerant control system is shown. Fault detection part send fault information to fault recognition part to fix the precise fault, then control law is readjusted to adapt the fault and not to degrade the flight control system performance.

The faults of unmanned aerial vehicle include left aileron failure, right aileron failure, rudder failure, angle gyroscope failure, angle acceleration gyroscope failure, and GPS failure etc.

The failure or abnormality degree can be measured by fuzzy mathematics. The failure values are between 0 and 1.

3.2. Fuzzy measurement

Since the degree for the abnormality of the components in UAV flight control system is uncertain and fuzzy, fuzzy measurement is introduced to qualify the degree for the abnormality. After all, membership functions for the individual abnormality degree are needed established.

Successfully establishing a membership function to express fuzzy concepts is not easy. Membership functions consist of discrete membership functions and continuous membership functions. Typically applied continuous membership functions are bell shaped, triangular shaped, trapezoid shaped, S function, Z function, and Pi function. The bell shaped and triangular shaped continuous membership functions have only one point with a membership grade value equal to 1. The trapezoid shaped continuous membership functions have a membership grade value of 1 between...
certain intervals. The S function is monotonically increasing. However, Z function is monotonically decreasing.

As Figure 2 shows, a S function F is characterized by two parameters, the location NP of the neutral point (F(NP) = 1/2) and the width 2w between nonmembership and membership. S function is adopted to qualify the degree of the components abnormality of UAV in this study.

\[
F(x, NP, w) = \begin{cases} 
0 & \text{if } x \in (0, NP-w), \\
(1/2w)(x-NP+w) & \text{if } x \in [NP-w, NP+w], \\
1 & \text{if } x \in (NP+w, \infty). 
\end{cases} 
\tag{7}
\]

3.3. The fault diagnosis model based on Weighted Fuzzy Petri Nets approach

In Figure 3, the fault diagnosis of the rudder failure of UAV is modeled using FPN. There are 15 places and 7 transitions. C1 denotes rudder feedback abnormality, C2 denotes AD sampling abnormality, C3 denotes AD loop circuit abnormality, C4 denotes AD transformation board abnormality, C5 denotes AD signal conditioning circuit abnormality, C6 denotes AD transformation board failure, C7 denotes AD signal conditioning circuit failure, C8 denotes DA sampling abnormality, C9 denotes DA loop circuit abnormality, C10 denotes DA transformation board abnormality, C11 denotes DA signal conditioning circuit abnormality, C12 denotes rudder abnormality, C13 denotes DA transformation board failure, C14 denotes DA signal conditioning circuit failure, C15 denotes rudder failure. R1, R2, R3, R4, R5, R6 and R7 denote the transitions. The model based on FPN comes from expert knowledge and skills. In long period practice, experts obtain the reasoning rules. The fault diagnosis of the rudder failure of UAV integrates these reasoning rules of human expert.

These reasoning rules are:
1) If rudder feedback abnormality (C1) and AD sampling abnormality (C2) Then AD loop circuit abnormality (C3).
2) If AD loop circuit abnormality (C3) and AD transformation board abnormality (C4) Then AD transformation board failure (C6).
3) If AD loop circuit abnormality (C3) and AD signal conditioning circuit abnormality (C5) Then AD signal conditioning circuit failure (C7).
4) If rudder feedback abnormality (C1) and DA sampling abnormality (C8) Then DA loop circuit abnormality (C9).
5) If DA loop circuit abnormality (C9) and DA transformation board abnormality (C10) Then DA transformation board failure (C13).
6) If DA loop circuit abnormality (C9) and DA signal conditioning circuit abnormality (C11) Then DA signal conditioning circuit failure (C14).
7) If DA loop circuit abnormality (C9) and rudder abnormality (C12) Then rudder failure (C15).
Note that R1 and R4 are the middle transition. While the transition reliability is 100%, R1, R9, C3 and C9 can be reduced. Therefore, above reasoning rules can reduce to 5 rules. Rule 1 and Rule 4 can be combined. The combined reasoning rules are presented as follows.

1) rudder feedback abnormality (C1) and AD sampling abnormality (C2) and AD transformation board abnormality (C4) then AD transformation board failure (C6).
2) If rudder feedback abnormality (C1) and AD sampling abnormality (C2) and AD signal conditioning circuit abnormality (C5) then AD signal conditioning circuit failure (C7).
3) If rudder feedback abnormality (C1) and DA sampling abnormality (C8) and DA transformation board abnormality (C10) then DA transformation board failure (C13).
4) If rudder feedback abnormality (C1) and DA sampling abnormality (C8) and DA signal conditioning circuit abnormality (C11) then DA signal conditioning circuit failure (C14).
5) If rudder feedback abnormality (C1) and DA sampling abnormality (C8) and rudder abnormality (C12) then rudder failure (C15).

Complex Petri nets can be analysed using reachable graph and reachable tree analysis approaches. Therefore many reasoning rules will be combined.

4. Case Analysis

After the fault diagnosis of UAV flight control system is modeled based on FPN, its reasoning mechanism of decision making can be analysed.

To simplify the reasoning process, it is assumed that the abnormality of individual UAV component has been qualified as a value by fuzzy measurement and the reliability of the fire transition of Petri Nets is 0.95.
The diagnosis results are shown as follows.

**Case 1.**
Rudder feedback abnormality (C1) is fuzzily qualified as 1, AD sampling abnormality (C2) is 0.95, DA sampling abnormality (C8) is 0, then R1 is fired. Let the weights of rudder feedback abnormality and AD sampling abnormality are both 0.5, AD loop circuit abnormality (C3) can be calculated out, that is \((1 \times 0.5 + 0.95 \times 0.5) \times 0.95 = 0.92625\). At this time, AD transformation board abnormality is 0.97 (C4) and AD signal conditioning circuit abnormality (C5) is 0, then R2 is fired. Let the weights of AD loop circuit abnormality and AD signal conditioning circuit abnormality are both 0.5, AD transformation board failure (C6) can be calculated out, that is \((0.92625 \times 0.5 + 0.97 \times 0.5) \times 0.95 = 0.90072\).

Diagnosis results:

**Figure 3.** Weighted Fuzzy Petri Nets approach for the fault diagnosis of UAV
AD transformation board is faulted ,and its abnormality value is 0.90072.

Case 2.
Rudder feedback abnormality (C1) is fuzzily qualified as 1, AD sampling abnormality(C2) is 0.95, DA sampling abnormality(C8) is 0, then R1 is fired. Let the weights of rudder feedback abnormality and AD sampling abnormality are both 0.5, AD loop circuit abnormality (C3) can be calculated out, that is 

$$ (1 \times 0.5 + 0.95 \times 0.5) \times 0.95 = 0.92625 $$

At this time, AD transformation board abnormality is 0(C4) and AD signal conditioning circuit abnormality(C5) is 098, then R3 is fired. Let the weights of AD loop circuit abnormality and AD signal conditioning circuit abnormality are both 0.5, AD signal conditioning circuit failure (C7) can be calculated out, that is 

$$ (0.92625 \times 0.5 + 0.98 \times 0.5) \times 0.95 = 0.90547 $$

Diagnosis results:
AD signal conditioning circuit is faulted ,and its abnormality value is 0.90547.

Case 3.
Rudder feedback abnormality (C1) is fuzzily qualified as 1, AD sampling abnormality(C2) is 0, DA sampling abnormality(C8) is 0.97, then R4 is fired. Let the weights of rudder feedback abnormality and DA sampling abnormality are both 0.5, DA loop circuit abnormality (C9) can be calculated out, that is 

$$ (1 \times 0.5 + 0.97 \times 0.5) \times 0.95 = 0.93575 $$

At this time, DA transformation board abnormality (C10) is 0.93 and DA signal conditioning circuit abnormality (C11) is 0 and rudder abnormality (C12) is 0, then R5 is fired. Let the weights of DA loop circuit abnormality and DA transformation board abnormality are both 0.5, DA transformation board failure (C13) can be calculated out, that is 

$$ (0.93575 \times 0.5 + 0.93 \times 0.5) \times 0.95 = 0.88623 $$

Diagnosis results:
DA transformation board is faulted ,and its abnormality value is 0.88623.

Case 4.
Rudder feedback abnormality (C1) is fuzzily qualified as 1, AD sampling abnormality(C2) is 0, DA sampling abnormality(C8) is 0.97, then R4 is fired. Let the weights of rudder feedback abnormality and DA sampling abnormality are both 0.5, DA loop circuit abnormality (C9) can be calculated out, that is 

$$ (1 \times 0.5 + 0.97 \times 0.5) \times 0.95 = 0.93575 $$

At this time, DA transformation board abnormality (C10) is 0 and DA signal conditioning circuit abnormality (C11) is 0.95 and rudder abnormality (C12) is 0, then R6 is fired. Let the weights of DA loop circuit abnormality and DA signal conditioning circuit abnormality are both 0.5, DA signal conditioning circuit failure (C14) can be calculated out, that is 

$$ (0.93575 \times 0.5 + 0.95 \times 0.5) \times 0.95 = 0.89573 $$

Diagnosis results:
DA signal conditioning circuit is faulted ,and its abnormality value is 0.89573.

Case 5.
Rudder feedback abnormality (C1) is fuzzily qualified as 1, AD sampling abnormality(C2) is 0, DA sampling abnormality(C8) is 0.97, then R4 is fired. Let the weights of rudder feedback abnormality and DA sampling abnormality are both 0.5, DA loop circuit abnormality (C9) can be calculated out, that is 

$$ (1 \times 0.5 + 0.97 \times 0.5) \times 0.95 = 0.93575 $$

At this time, DA transformation board abnormality (C10) is 0 and DA signal conditioning circuit abnormality (C11) is 0 and rudder abnormality (C12) is 0.97, then R7 is fired. Let the weights of DA loop circuit abnormality and rudder abnormality are both 0.5, rudder failure (C15) can be calculated out, that is 

$$ (0.93575 \times 0.5 + 0.97 \times 0.5) \times 0.95 = 0.90523 $$

Diagnosis results:
Rudder is faulted ,and its abnormality value is 0.90523.

The Diagnosis results are consistent with the real results, so the fault diagnosis system based on WFPN is satisfactory and feasible.

5. Conclusions
The Weighted Fuzzy Petri Nets approach is adopted to formulate the fault diagnosis of flight control system of unmanned aerial vehicle. The systematic rule-based knowledge is obtained from human
expertise and the fault diagnosis is opening, in which the reasoning rules can be updated and added anytime. The diagnosis result of the proposed fault diagnosis of flight control system is consistent with the real result without human expert.

In the future study, we will adopt an advanced Petri Nets (including Time Petri Nets and Colored Petri Nets, etc.) to formulate the flight control system and the fault diagnosis of flight control system of unmanned aerial vehicle.

6. References


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