Fault Isolation Based on Subjective Bayes' Reasoning for Redundant Actuation System

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***Abstract*—Directing to the difficulties of fault isolation based on mathematical model, this paper presents a new fault isolation method that utilizes the limit apriori knowledge of expert, infers the failure process recursively and realizes the fault isolation with Bayes' reasoning. Through dividing the system into several levels hierarchically according to their information flow, the system failure process can be reasoned from bottom to up with Bayes' sufficient factor LS and Bayes' necessary factor LN, and find the fault place with likelihood rate by the Bayes' reasoning.. Because the subjective Bayes reasoning can strength the fault information and eliminate specious information, this method is suitable to determine the failure location for complicated system. Application of tri-redundant actuation system indicates that the subjective Bayes' reasoning can accomplish the fault isolation effectively.**

***Keywords*—Subjective Bayes' reasoning, fault isolation, likelihood rate, tri-redudnat actuation system**

I. INTRODUCTION

Model-based fault diagnosis method is widely used in control system state monitoring and management through comparing the residual error and designed threshold, in which the residual error is generated by difference between actual system output and model output [1]. However, it is difficult to find the fault place because most of the failures can lead to the output variance. In order to improve the system maintainability, it is required to determine the exact fault location in fault diagnosis system design.

In the beginning of fault diagnosis research, many academicians focused on the fault observer design such as Tae Kyeong Yue provided a sliding mode observer to detect the known fault model [2], F. W. Poon adopted Luenberger observer to detect the failure of hydraulic system [3] and Gaddouna B. O. utilized the unknown input observer to extract the failure information [4]. The above methods can detect the failure existing in system, but it is difficult to find the fault place accurately. Then many fault diagnosis methods based on intelligent techniques came forth such as multimode neural networks and rough sets techniques [5]. Although the fault diagnosis methods aforementioned can determine the fault unit, it needed lots of training samples to obtain their regulation. As a matter of fact, we only know limit knowledge when we design the fault diagnosis system. So it is urgent to find an effective method that not only can detect the failure but also can isolate it with limit information.

Based on the Bayes principle, this paper presents a subjective Bayes' reasoning method, in which the data fusion and likelihood rate reasoning are integrated hierarchically. With the limit apriori knowledge, we can get the likelihood rate of every sub-model, and then infer the failure probability of key component with Bayes' reasoning. Application results indicate that the subjective Bayes' reasoning method can strengthen the failure characteristics and eliminate the amphibolous information, so that it can be used in fault isolation effectively.

The rest of this paper is organized as follows. Section II gives the notation of hydraulic actuation system (HAS). In section III, the hierarchical model of hydraulic actuation system is provided for fault diagnosis. In section IV, we present the subjective Bayes' reasoning method and provide the reasoning process. Section V gives an application of tri-redundant actuation system. Section VI concludes the paper.

II. NOTATION

u—input voltage (V)
K_a—I/V transform coefficient (A/V)
x_v—core displacement of servo valve (m)
K_v—gain of servo valve (m^3/s•A)
T_v—time constant of servo valve (s)
P_f—load pressure (N/m^2)
P_s—power pressure (N/ m^2)
W—orifice width of servo valve (m)
C—flow coefficient
ρ—oil density (N•s^2/m^4)
Q_f—load flow (m^3/s)
A_t—effective area of piston (m^2)
x_t—piston displacement (m)
C_l—leakage coefficient (cm^5/N•s)
V_t—effective volume (m^3)
E_y—plastic module of oil (N/m^2)

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M —equivalent mass of piston output (N)
M_t —mass of load (N)
B_t —damping coefficient of load (N•m•s)
x_p —rudder displacement (m)
K_b —feedback coefficient
K_s —stiffness coefficient
x_p —displacement of transform mechanism (m)
F —load force (N)
B_m —damping coefficient of transform mechanism (N•m•s)
K_e —plastic coefficient of transform mechanism

III. HIERARCHICAL MODEL OF ACTUATION SYSTEM

A. *Mathematical Model of Hydraulic Actuator*

Fig.1 shows the structural diagram of tri-redundant actuation system, in which the single hydraulic actuator consists of controller (PID), amplifier, servo valve, cylinder and LVDT. The output of different channel of actuator is colligated in the output rod to drive the rudder of airplane through switching mechanism. Due to tri-redundant design, the actuation system has good performance with high reliability.

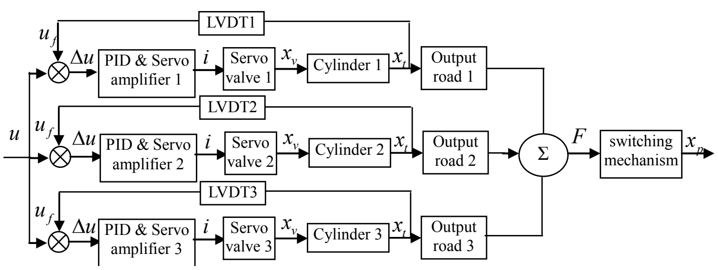

Figure 1. Structural diagram of tri-redundant actuation system

According to the operation principle of HAS, we can establish the mathematical model of hydraulic actuator as follows.

- PID and amplifier

$$i = PID \bullet K_a \Delta u = PID \bullet K_a (u - u_f) \quad (1)$$

- Servo valve

$$x_v(s) = \frac{K_v}{T_v + 1} i(s) \quad (2)$$

With high frequency width (⩾100Hz), servo valve can be considered as inertia unit.

- Flow equation of servo valve

$$Q_f = CWx_v \sqrt{\frac{P_s - P_f}{\rho}} \quad (3)$$

It is a nonlinear relationship between servo valve flow and load pressure.

- Flow continous equation

$$Q_f(s) = A_t S x_t(s) + C_t P_f(s) + \frac{V_t}{4E_y} S P_f(s) \quad (4)$$

- Force balance equation

$$A_t P_f(s) = MS^2 x_t(s) + B_t S x_t(s) + F(s) \quad (5)$$

$$\begin{aligned} F(s) &= [x_t(s) - x_p(s)] K_s \\ F(s) &= Ms^2 x_p(s) + B_m s x_p(s) + K_e x_p(s) \end{aligned} \quad (6)$$

- Feedback equation

$$u_f = K_b x_t(s) \quad (7)$$

In Fig.1, it is obvious that there exists strong information coupling among components and channels, i.e. the output of component not only depends on its input but also relies on the coupling factors come from other component; the output of tri-redundant actuation system is affected both by command and coupling from other channels. Considering the information flow relation of hydraulic actuator, we can establish the hierarchical model shown in Fig.2, in which the fault information can be strengthened from basic level to system level. With the stepwise reasoning with probability, we can find a method to carry out fault isolation for HAS.

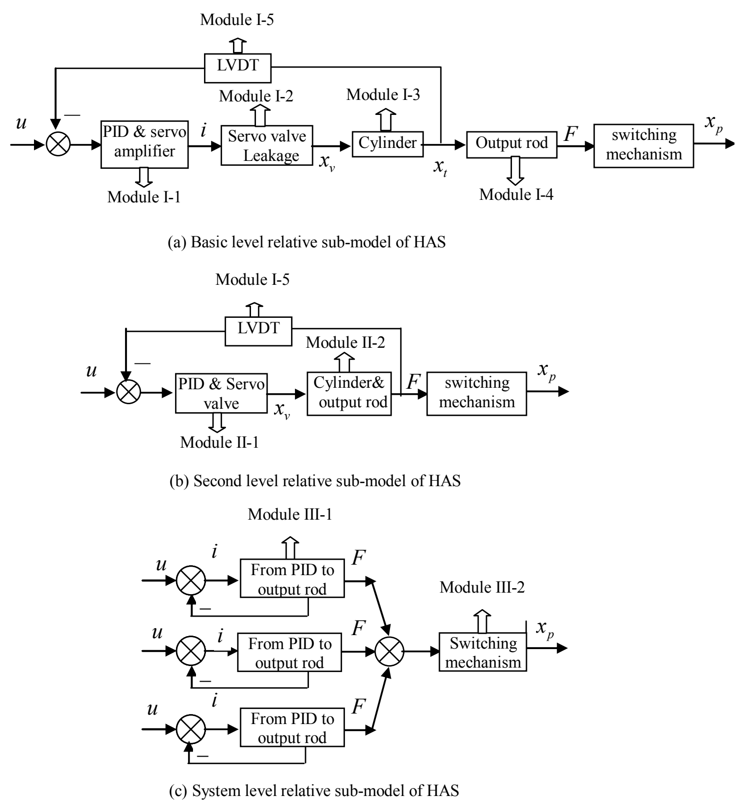

Figure 2. Basic level sub-model of hydraulic actuator

In order to realize the hierarchical fault reasoning, this paper establishes three level sub-models as follows:

(1) Basic level sub-model

Focusing on the single hydraulic actuator, we establish the five key component sub-models, in which module I-1 is PID & amplifier, module I-2 is servo valve, module I-3 is cylinder, module I-4 is output rod and module I-5 is LVDT shown in Fig.2.

(2) Second level sub-model

Combine module I-1 and module I-2 as module II-1, and integrate module I-3 and module I-4 as module II-2, then obtain the second level sub-model that can reduce the coupling among components.

(3) System level sub-model

Directing to the tri-redundant actuation system, consider the single actuator as module III-1 and the switching mechanism as module III-2 to describe the coupling among channels.

Based on the hierarchy information flow model, we can reason the fault place from basic level to system level if the probability between bottom level and up level is known. We can define the relative probability with Bayes formula and push the recursion reasoning from component to system to realize the fault isolation.

IV. SUBJECTIVE BAYES' REASONING PRINCIPLE

Supposing that "B" expresses "phenomenon" and "C" denotes "reason", its uncertainty of "B→C" can be described with conditional probability $p(C|B)$. If the probability of "B" is known, the probability of "C" under B can be described with Bayes theory:

$$p(C \mid B) = \frac{p(B \mid C) \times p(C)}{p(B)} \tag{8}$$

Where $p(B)$ and $p(C)$ express the apriori probability of B and C separately, which is independent to of the rule "B→C"; $p(B|C)$ is the posterior probability of "B" under "C".

Generally, there are a lot of reasons "C" that can lead to phenomenon "B", so it is more difficult to get the apriori probability of B than that of C. In order to overcome the difficulties, we make some modification on the Bayes' formula as follows.

A. Likelihood Rate of Rule Intensity

In order to avoid the utilization of $p(B)$, we can calaulate the $p(\bar{C} \mid B)$ firstly as follows.

$$\begin{aligned} p(\bar{C} \mid B) &= 1 - p(C \mid B) = 1 - \frac{p(B \mid C) p(C)}{p(B)} = \frac{p(B) - p(B,C)}{p(B)} \\ &= \frac{p(B,\bar{C}) + p(B,C) - p(B,C)}{p(B)} = \frac{p(B,\bar{C})}{p(B)} \\ &= \frac{p(B \mid \bar{C}) \times p(\bar{C})}{p(B)} \end{aligned} \tag{9}$$

With (8) and (9), we can get the following relation:

$$\frac{p(C \mid B)}{p(\bar{C} \mid B)} = \frac{p(B \mid C) \times p(C)}{p(B \mid \bar{C}) \times p(\bar{C})} \tag{10}$$

Define the apriori likelihood rate $O(C)$ and conditional likelihood rate $O(C \mid B)$ as:

$$\begin{aligned} O(C) &= \frac{p(C)}{p(\bar{C})} = \frac{p(C)}{1 - p(C)} \\ O(C \mid B) &= \frac{p(C \mid B)}{p(\bar{C} \mid B)} = \frac{p(B \mid C)}{p(B \mid \bar{C})} \times O(C) \end{aligned} \tag{11}$$

Where $O(C)$ means the ratio of probability of C to the probability of $\bar{C}$. It is obvious that $O(C)$ increases with $p(C)$. $O(C \mid B)$ is the ratio of probability of C to the probability of $\bar{C}$ under condition B.

Define the likelihood rate of rule intensity as:

$$LS = \frac{p(B \mid C)}{p(B \mid \bar{C})} \tag{12}$$

Where LS expresses the influence degree of B to C, then

$$O(C \mid B) = LS \times O(C) \tag{13}$$

(12) is named as Bayes' sufficient factor of "B→C" that makes it easy to calculate the conditional likelihood ratio of C with its apriori probability and likelihood rate. Then

$$p(C \mid B) = \frac{O(C \mid B)}{1 + O(C \mid B)} \tag{14}$$

The value of LS consists of three conditions:

$$LS = \begin{cases} 1 & O(C \mid B) = O(C), B \text{ doesn't affect } C \\ >1 & O(C \mid B) > O(C), B \text{ support } C \text{ partly} \\ <1 & O(C \mid B) < O(C), B \text{ doesn't support } C \text{ partly} \end{cases}$$

B. Non-likelihood Rate of Rule Intensity

Similarity, define the likelihood rate under condition $\bar{B}$ as:

$$LN = \frac{p(\bar{B} \mid C)}{p(\bar{B} \mid \bar{C})} \tag{15}$$

Where LN denotes the influence degree of $\bar{B}$ to C, then

$$O(C \mid \bar{B}) = LN \times O(C) \tag{16}$$

LN is called as necessary factor of "B→C". The scaling scope of LN includes following relation:

$$LN = \begin{cases} 1 & O(C \mid \bar{B}) = O(C), \bar{B} \text{ doesn't affect } C \\ >1 & O(C \mid \bar{B}) > O(C), \bar{B} \text{ support } C \text{ a certain extent} \\ <1 & O(C \mid \bar{B}) < O(C), \bar{B} \text{ doesn't suport } C \text{ a certain extent} \end{cases}$$

It is noted that LS and LN can improve the application of Bayes' reasoning. Even if there is not enough statistical data, we also can get the LS and LN based on expert knowledge. Herein, we call $p(C|B)$ as subjective probability because it is calculated by expert subjective evaluation. At the same time, the reasoning method of subjective probability is called as subjective Bayes' reasoning.

C. Transmission of Uncertainty

Assume the uncertainty of B is related to another phenomenon $B^{'}$, that is $B^{'} \Rightarrow B \Rightarrow C$, the probability of C under $B^{'}$ can be described as

$$\begin{aligned} p(C|B^{'}) &= \frac{p(C,B^{'})}{p(B^{'})} = \frac{P(C,B,B^{'}) + p(C,\bar{B},B^{'})}{p(B^{'})} \\ &= \frac{p(C,B,B^{'}) \times p(B,B^{'})}{p(B^{'}) \times p(B,B^{'})} + \frac{p(C,\bar{B},B^{'}) \times p(\bar{B},B^{'})}{p(B^{'}) \times p(\bar{B},B^{'})} \\ &= p(C|B,B^{'}) \times p(B|B^{'}) + p(C|\bar{B},B^{'}) \times p(\bar{B},B^{'}) \end{aligned} \quad (17)$$

Where $p(C|B,B^{'})$ is the probability of C under B and $B^{'}$; $p(C|\bar{B},B^{'})$ is the probability of C under $\bar{B}$ and B', in which B' affect C through B while B and $\bar{B}$ have determined. So

$$p(C|B^{'}) = p(C|B) \times p(B|B^{'}) + p(C|\bar{B}) \times p(\bar{B}|B^{'})$$

Where $p(C|\bar{B})$ and $p(C|B)$ can be calculated by (14). Similarity, only $p(B)$ is known, we can get the $p(B|B^{'})$, then get the $p(\bar{B}|B^{'}) = 1 - p(B|B^{'})$, next we can obtain the $p(B|B^{'})$, finally we can get the $p(C|B^{'})$, that is the probability of C under $B^{'}$.

Here, (15) is called uncertainty transmission formula that has a characteristics that is $p(C|B) = p(C)$ when $p(B|B^{'}) = p(B)$. With the transmission formula, the uncertainty can transfer for a long distance, for example, if $B^{'} \Rightarrow B \Rightarrow C \Rightarrow W$, then:

$$p(W|B^{'}) = p(W|C) \times p(C|B^{'}) + p(W|\bar{C}) \times p(\bar{C}|B^{'})$$

D. Combination of Uncertainty

If there are two preconditions support same result, that is:

$$\begin{aligned} B_1^{'} \Rightarrow B_1 \Rightarrow C \\ B_2^{'} \Rightarrow B_2 \Rightarrow C \end{aligned} \quad (18)$$

Suppose $B_i^{'}(i = 1,2)$ is independent, then we can get the probability of C under $B_1^{'}, B_2'$ as:

$$\begin{aligned} p(C|B_1^{'},B_2^{'}) &= p(C|B_2,B_1^{'},B_2^{'}) \times p(B_2|B_1^{'},B_2^{'}) \\ &+ p(C|\bar{B}_2,B_1^{'},B_2^{'}) \times p(\bar{B}_2|B_1^{'},B_2^{'}) \end{aligned} \quad (19)$$

It is obvious that B_2 is independent of B_1', so the influence of B_2' can be ignored when B_2 is absolutely true or false. Then (19) can be transferred as:

$$\begin{aligned} p(Q|P_1^{'},P_2^{'}) &= p(C|B_2,B_1^{'}) \times p(B_2|B_2^{'}) \\ &+ p(C|\bar{B}_2,\bar{B}_1^{'}) \times p(\bar{B}_2|\bar{B}_2^{'}) \end{aligned}$$

Then we can get:

$$O(C|B_2,B_1^{'}) = \frac{p(C|B_2,B_1^{'})}{p(\bar{C}|B_2,B_1^{'})} = \frac{p(B_2|C)}{p(B_2,\bar{C})} \times O(C|\bar{B}_1^{'}) = LS2 \times O(C|B_1^{'}) \quad (20)$$

Similarly, we also can get the following relation:

$$O(C|\bar{B}_2,B_1^{'}) = \frac{p(\bar{B}_2|C)}{p(\bar{B}_2|\bar{C})} \times O(C|B_1^{'}) = LN2 \times O(C\big|B_1') \quad (21)$$

It is obvious that we can calculate the $O(C|B_2,B_1^{'})$ and $O(C|\bar{B}_2,B_1^{'})$ if $LS2$ and $LN2$ are known, then achieve the $p(C|B_2,B_1^{'})$ and $p(C|\bar{B}_2,B_1^{'})$. In addition, we can get $p(C|B_1^{'},B_2^{'})$ if we know $p(B_2|B_2^{'})$.

V. Fault Isolation with Subjective Bayes' Reasoning for Redundant Actuation System

To the tri-redudnant actuation system shown in Fig.1, we can get the fault reasoning hiberarchy shown in Fig.3.

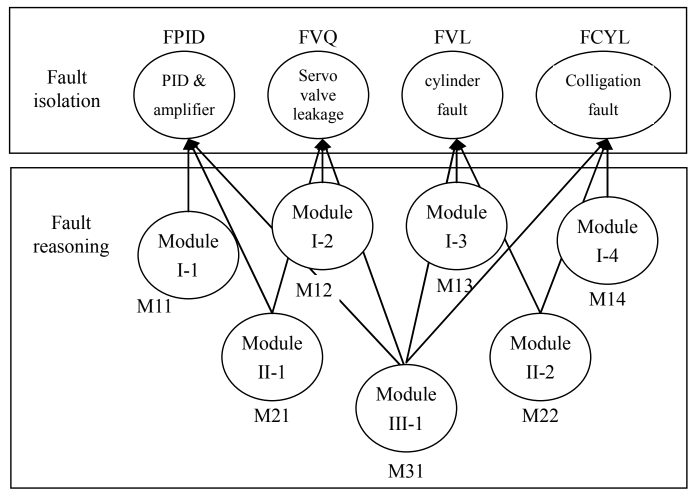

Figure 3. Fault reasoning relation of tr-redundant actuation system

Define the content of sub-model as Table I.

TABLE I. SYMBOL AND ITS CONTENT OF ACTUATION SYSTEM

Symbol	Content
FPID	Controller and I/V failure
FVQ	Servo valve leakage failure
FVL	Cylinder block failure
FCYL	Colligation failure
M11（F11）	Module I-1 detect failure
M12（F12）	Module I-2 detect failure
M13（F13）	Module I-3 detect failure
M14（F14）	Module I-4 detect failure
M21（F21）	Module II-1 detect failure
M22（F22）	Module II-2 detect failure
M31（F31）	Module III-1 detect failure

Using the modified Bayes' reasoning formula, we can get the failure probability depending on the measurement of sub-models. For example, M11 means the detection based on module I-1. If PID fails, its probability submits to following relation:

$$
\begin{cases}
p(FPID) = p(FPID \mid F11) \quad \text{or} \quad p(FPID \mid \overline{F11}) \\
p(\overline{FPID}) = p(\overline{FPID} \mid F11) \quad or \quad p(\overline{FPID} \mid \overline{F11}) \\
p(FPID \mid F11) + p(\overline{FPID} \mid F11) = 1 \\
p(FPID \mid \overline{F11}) + p(\overline{FPID} \mid \overline{F11}) = 1
\end{cases}
$$

The failure probability of PID is:

$$
\begin{aligned}
p(FPID) = r_1[p(FPID \mid F11) \quad &\text{or} \quad p(FPID \mid \overline{F11})] \\
+ s_1[p(FPID \mid F21) \quad &\text{or} \quad p(FPID \mid \overline{F21})] \\
+ t_1[p(FPID \mid F31) \quad &\text{or} \quad p(FPID \mid \overline{F31})]
\end{aligned}
$$

Where:

$p(FPID)$ —failure probability of PID in detection;

$p(FPID|F11)$ —probability of PID when M11 detect failure;

$p(FPID \mid \overline{F11})$ —probability of PID when M11 detect normal;

$p(FPID|F21)$ —probability of PID when M21 detect failure;

$p(FPID \mid \overline{F21})$ —probability of PID when M11 detect normal;

$p(FPID|F31)$ —probability of PID when M31 detect failure;

$p(FPID \mid \overline{F31})$ —probability of PID when M31 detect normal;

r_1 —the contribution rate of M11 detection to $p(FPID)$;

s_1 —the contribution rate of M21 detection to $p(FPID)$;

t_1 —the contribution rate of M31 detection to $p(FPID)$.

Where $r_1 + s_1 + t_1 = 1$.

Similarity, we can get the following relation when servo valve leakage occurs:

$$
\begin{aligned}
p(FVQ) = r_2[p(FVQ \mid F12) \quad &\text{or} \quad p(FVQ \mid \overline{F12})] \\
+ s_2[p(FVQ \mid F21) \quad &\text{or} \quad p(FVQ \mid \overline{F21})] \\
+ t_2[p(FVQ \mid F31) \quad &\text{or} \quad p(FVQ \mid \overline{F31})]
\end{aligned}
$$

Where $r_2 + s_2 + t_2 = 1$.

The failure probability of cylinder block can be described as:

$$
\begin{aligned}
p(FVL) = r_3[p(FVL \mid F13) \quad &\text{or} \quad p(FVL \mid \overline{F13})] \\
+ s_3[p(FVL \mid F22) \quad &\text{or} \quad p(FVL \mid \overline{F22})] \\
+ t_3[p(FVL \mid F31) \quad &\text{or} \quad p(FVL \mid \overline{F31})]
\end{aligned}
$$

Where $r_3 + s_3 + t_3 = 1$.

The failure probability of colligation failure is expressed as:

$$
\begin{aligned}
p(FCYL) = r_4[p(FCYL \mid F14) \quad &\text{or} \quad p(FCYL \mid \overline{F14})] \\
+ s_4[p(FCYL \mid F22) \quad &\text{or} \quad p(FCYL \mid \overline{F22})] \\
+ t_4[p(FCYL \mid F31) \quad &\text{or} \quad p(FCYL \mid \overline{F31})]
\end{aligned}
$$

Where $r_4 + s_4 + t_4 = 1$.

Adopt modified subjective Bayes' method to calculate the conditional probability as follows:

$$
\begin{cases}
p(FPID \mid F11) = \dfrac{LS_{1P} \times O(FPID)}{1 + LS_{1P} \times O(FPID)} \\
p(FPID \mid \overline{F11}) = \dfrac{LN_{1P} \times O(FPID)}{1 + LN_{1P} \times O(FPID)} \\
p(FPID \mid F21) = \dfrac{LS_{2P} \times O(FPID)}{1 + LS_{2P} \times O(FPID)} \\
p(FPID \mid \overline{F21}) = \dfrac{LN_{1P} \times O(FPID)}{1 + LN_{2P} \times O(FPID)} \\
p(FPID \mid F31) = \dfrac{LS_{3P} \times O(FPID)}{1 + LS_{3P} \times O(FPID)} \\
p(FPID \mid \overline{F31}) = \dfrac{LN_{3P} \times O(FPID)}{1 + LN_{3P} \times O(FPID)}
\end{cases}
\tag{21}
$$

Where the subscript "p" denotes "PID", the subscript number expresses the number of sub-model. The rest may be deduced by analogy to obtain the relation of $p(FVQ), p(FVL)$ and $p(FCYL)$.

Here we provide the apriori probability and likelihood rate of every component according to the expert experience shown in Table II.

TABLE II. APRIORI PROBABILITY AND LIKELIHOOD RATE OF COMPONENTS FOR HYDRAULIC ACTUATOR

para	value	para	value	Para	value	para	value
r_1	0.7	r_2	0.6	r_3	0.7	r_4	0.8
s_1	0.2	s_2	0,25	s_3	0.2	s_4	0.15
t_1	0.1	t_2	0.15	t_3	0.1	t_4	0.05
LS_{1P}	200	LS_{1Q}	150	LS_{1L}	200	LS_{1C}	400
LN_{1P}	0.2	LN_{1Q}	0.5	LN_{1L}	0.2	LN_{1C}	0.1
LS_{2P}	100	LS_{2Q}	100	LS_{2L}	100	LS_{2C}	100
LN_{2P}	0.4	LN_{2Q}	0.4	LN_{2L}	0.4	LN_{2C}	0.5
LS_{3P}	50	LS_{3Q}	50	LS_{3L}	50	LS_{3C}	50
LN_{3P}	0.6	LN_{3Q}	0.6	LN_{3L}	0.6	LN_{3C}	0.2
p_{FPID}	0.001	p_{FVQ}	0.005	p_{FVL}	0.003	p_{FCYL}	0.01

Where "para" is the abbreviation of parameter.

In Table II, all the parameters are determined by subject experience of expert. p_{FPID}, p_{FVQ}, p_{FVL}, p_{FCYL} denote apriori probability of PID, servo valve, cylinder and colligation separately. The value of LS and LV indicate the support degree of sub-module to failures. If LS and LN are greater than 1, the module supports the failures a certain extent. The greater the value is, the more support the module will. If LS and LN equal to 1or be less than 1, the module is independent to the failure. Suppose PID fails, we can get the result based on basic level shown in Table III.

TABLE III. PID FAILURE DETECTION RESULTS WITH SUB-MODEL

model	M11	M12	M13	M14	M21	M22	M31
Detect result	F	N	N	N	F	N	N (fail to report)

In Table III, F means "failure" and N means "normal".

According to the Fig.3, M11, M21 and M31 can detect the fault PID if there is not coupling and disturbance. But in fact, only M11 and M21 detect the failure while M31 fails to report PID failure because the traditional fault detection is easy to be confused by amphibolous information under limit data, which always makes the failure isolation rate low.

With the appiori probability and likelihood rate in Table II and Bayes' reasoning, we can reason the fault process and find the exact fault place with high fault isolation rate from bottom to up shown in Table IV, in which "—" express "no item".

TABLE IV. PID FAULT ISOLUTION WITH SUBJECTIVE BAYES' REASONING

$p(FPID \mid F11)$	0.167	$p(FVQ \mid F12)$	——	$p(FVL \mid F13)$	——	$p(FCYL \mid F14)$	——
$p(FPID \mid \overline{F11})$	——	$p(FVQ \mid \overline{F12})$	0.0025	$p(FVL \mid \overline{F13})$	0.0006	$p(FCYL \mid \overline{F14})$	0.001
$p(FPID \mid F21)$	0.09	$p(FVQ \mid F21)$	0.333	$p(FVL \mid F22)$	——	$p(FCYL \mid F22)$	——
$p(FPID \mid \overline{F21})$	——	$p(FVQ \mid \overline{F21})$	——	$p(FVL \mid \overline{F22})$	0.0012	$p(FCYL \mid \overline{F22})$	0.005
$p(FPID \mid F31)$	——	$p(FVQ \mid F31)$	——	$p(FVL \mid F31)$	——	$p(FCYL \mid F31)$	——
$p(FPID \mid \overline{F31})$	0.001	$p(FVQ \mid \overline{F31})$	0.003	$p(FVL \mid \overline{F31})$	0.0018	$p(FCYL \mid \overline{F31})$	0.002
Detection results							
$p(FPID)$	0.135	$p(FVQ)$	0.0005	$p(FVL)$	0.0008	$p(FCYL)$	0.0017

It is obvious that the value of $p(FPID)$ (0.135) is larger than any other item, so it is easy to detect and isolate the PID failure even there exists failing to report.

If the servo valve fails, we can get the detection results in Table V. It is obvious that M21 fails to report the servo valve failure and M22 gives the false alarm only depending on the sub-model detection. If we utilize the subjective Bayes' reasoning, we can find the exact fault place shown in Table VI.

TABLE V. SERVO VALVE FAILURE DETECTION WITH SUB-MODEL

model	**M11**	**M12**	**M13**	**M14**	**M21**	**M22**	**M31**
Detect result	N	F	N	N	N (fail to report)	F (false alarm)	F

TABLE VI. SERVO VALVE FAULT ISOLUTION WITH SUBJECTIVE BAYES' REASONING

$p(FPID \mid F11)$	——	$p(FVQ \mid F12)$	0.4286	$p(FVL \mid F13)$	——	$p(FCYL \mid F14)$	——
$p(FPID \mid \overline{F11})$	0.0002	$p(FVQ \mid \overline{F12})$	——	$p(FVL \mid \overline{F13})$	0.0006	$p(FCYL \mid \overline{F14})$	0.001
$p(FPID \mid F21)$	0.01	$p(FVQ \mid F21)$	——	$p(FVL \mid F22)$	0.2308	$p(FCYL \mid F22)$	0.01
$p(FPID \mid \overline{F21})$	——	$p(FVQ \mid \overline{F21})$	0.002	$p(FVL \mid \overline{F22})$	——	$p(FCYL \mid \overline{F22})$	——
$p(FPID \mid F31)$	0.048	$p(FVQ \mid F31)$	0.2	$p(FVL \mid F31)$	0.13	$p(FCYL \mid F31)$	0.33
$p(FPID \mid \overline{F31})$	——	$p(FVQ \mid \overline{F31})$	——	$p(FVL \mid \overline{F31})$	——	$p(FCYL \mid \overline{F31})$	——
Detection results							
$p(FPID)$	0.007	$p(FVQ)$	0.2877	$p(FVL)$	0.0596	$p(FCYL)$	0.0188

In Table VI, the $p(FVQ)$ (0.2877) shows that the subjective Bayes' reasoning can gain satisfied fault isolation result under failing to report and false alarm. So it is content in fault isolation of complex system.

CONCLUSIONS

This paper presents the subjective Bayes' reasoning method based on hierarchy that can strengthen the failure characteristics with likelihood rate of rule intensity and eliminate the amphibolous information existed in measurable point. Application of tri-redundant actuation system indicates that the subjective Bayes' reasoning can determine that fault location with high probability even the sub-model can not detect the failure correctly or gives false alarm. So the subjective Bayes' reasoning can realize fault isolation effectively with good robustness.

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REFERENCES

[1] Chung W.H., Speyer J.L., "A decentralized fault detection filter", Proceedings of the American Control Conference, Piladelphia, Pennsylvania, Vol.4, 1998, 2017-2021

[2] Tae Kyeong Yue, Shigeyasu KAWAJI, "Fault detection and isolation for descriptor system using sliding mode observer", proceedings of the 40th IEEE Conference on Decision and Control, Vol.1, 2001, 596-597

[3] F.W. Poon, D.W. Gu, "Fault detection using Luberger like observers", Proceedings of the 38th Conference on decision & Control Phoeniz, Arizona, USA, Vol.3, 1999, 3116-3121

[4] Gaddouna B.O., Quladsine M., "Fault diagnosis in a hydraulic process using unknown input observer", Proceedings of the 1997 IEEE International Conference on Control Application, 1997, 490-495

[5] Peng J.T., Chien C.F., Tseng T.L.B., "Rough set theory for data mining for fault diagnosis on distrbution feeder", IEE Proceedings on Generation, Transmission and Distribution, 2004, Vol.151, 689-697