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DIAGNOSIS STRATEGY FOR MICRO-COMPUTER CONTROLLED STRAIGHT ELECTRO-PNEUMATIC BRAKING SYSTEM USING FUZZY SET AND DYNAMIC FAULT TREE

WYKORZYSTANIE ZBIORÓW ROZMYTYCH I DYNAMICZNEGO DRZEWA USZKODZEŃ W STRATEGII DIAGNOSTYKI ELEKTRO-PNEUMATYCZNEGO UKŁADU HAMULCOWEGO STEROWANEGO ZA POMOCĄ MIKROKOMPUTERA

In this paper, a new diagnosis strategy for micro-computer controlled straight electro pneumatic braking system is developed to improve the diagnostic efficiency, which makes full use of some reliability theories and fuzzy set techniques. Specifically, it adopts expert elicitation and fuzzy set theory to evaluate the failure rate of the basic events for the braking system, and uses a dynamic fault tree model to capture the dynamic failure mechanisms and calculates some reliability results by mapping a dynamic fault tree into an equivalent Bayesian network (BN). Furthermore, the schemes are proposed to update the diagnostic importance factor (DIF) and the cut sets according to the sensors data. Finally, an efficient diagnostic algorithm is developed based on these reliability results to guide the maintenance crew to diagnose the braking system. The experimental results demonstrate that the proposed method can locate the fault of the braking system with less diagnosis cost.

***Keywords**: Diagnosis strategy, Fuzzy set, Dynamic fault tree, Expected diagnosis cost.*

W niniejszej pracy, opracowano nową strategię diagnostyki elektro-pneumatycznego układu hamulcowego sterowanego za pomocą mikrokomputera Celem badań była poprawa efektywności diagnostycznej. Strategię oparto na wybranych teoriach niezawodności oraz technikach zbiorów rozmytych. W szczególności, strategia wykorzystuje ocenę ekspercką oraz teorię zbiorów rozmytych do określania intensywności uszkodzeń dla podstawowych zdarzeń zachodzących w układzie hamulcowym oraz posługuje się modelem dynamicznego drzewa uszkodzeń aby uchwycić dynamiczne mechanizmy uszkodzeń. Za pomocą przedstawionej strategii oblicza się także wyniki analiz niezawodnościowych poprzez mapowanie dynamicznego drzewa błędów do równoważnej sieci bayesowskiej (BN). Ponadto w artykule zaproponowano schematy służące do aktualizacji czynnika ważności diagnostycznej (DIF) oraz przekrojów niezdatności zgodnie z danymi z czujników. Wreszcie, w oparciu o uzyskane wyniki analiz niezawodnościowych, opracowano wydajny algorytm diagnostyczny, który zawiadamia załogę konserwatorką o konieczności przeprowadzenia diagnostyki układu hamulcowego. Wyniki doświadczeń pokazują, że proponowana metoda pozwala na zlokalizowanie usterki układu hamulcowego przy mniejszych kosztach diagnozy.

***Słowa kluczowe**: Strategia diagnostyki, zbiór rozmyty, dynamiczne drzewo błędów, przewidywany koszt diagnozowania*

1. Introduction

The micro-computer controlled straight electro-pneumatic braking system is a key system to ensure the safe operation of urban rail transit. Its performance has been greatly improved with wide application of high technology. On the other hand, its complexity of technology and structure increasing significantly raise challenges in system diagnosis and maintenance. These challenges are displayed as follows: (1) lack of sufficient fault data. Fault data integrity has significant influence on the system diagnosis efficiency. However, it is very difficult to obtain mass fault samples which need lots of case studies in practice due to some reasons. One reason is imprecise knowledge in early stage of new product design. The other reason is the changes of the environmental conditions which may cause that the historical fault data can not represent the future failure behaviours. (2) Failure dependency of components. The micro-computer controlled straight electro-pneumatic braking system adopts many redundancy units and fault tolerance techniques to improve its reliability. So the behaviours of components in the system and their interactions, such as failure priority, sequentially dependent failures, functional dependent failures, and dynamic redundancy management, should be taken into consideration. (3) High level of uncertainty. The micro-computer controlled straight electropneumatic braking system is usually operated in a dynamic environment and is greatly affected by the technical, human and operational malfunctions that may lead to hazardous incidents. Aiming at these issues, many efficient diagnosis methods have been proposed. Assaf et al. proposed a fault tree based approach to determine the diagnosis order of components using DIF, which can, to some extent alleviate fault data acquisition bottleneck [1, 17]. However, this method determines the diagnostic sequence only by components' DIF, and usually causes minimal cut sets with a smaller DIF to be checked first, thereby influencing the diagnosis result. Tao et al. presented an improved method for system fault diagnosis which makes the overall consideration of components' DIF and minimal cut sets' DIF [22]. However, these diagnosis methods are based the static fault tree which cannot model dynamic fault behaviours. For this purpose, Duan et al. proposed a hybrid diagnosis method using dynamic fault tree and discrete-time BN [15]. In many cases, when a system fails, additional evidence is observed too, which may be collected from sensors. Hence, Assaf et al. put forward a method to incorporate evidence data from sensors into the diagnostic process to further improve the diagnosis efficiency [2]. But, the solution for dynamic fault tree was based on Markov model which is ineffective in handing larger dynamic fault tree and modelling power capabilities. What's more, it cannot incorporate the evidence information into the reasoning and can't update the components' posterior failure probability based on the evidence data from sensors, which affects the diagnostic accuracy. In the application of fault tree analysis mentioned above, the failure probability of basic events must be known. In addition, the failure rates of the system components are considered as crisp values. However, in practice, the failure rates of the system components are imprecise, deficient or vague in the system modelling. To overcome these difficulties and limitations in fault tree analysis, Fuzzy fault tree has been proposed, which employs fuzzy set and possibility theory, and deals with ambiguous, qualitatively incomplete, ill-defined and inaccurate information [3, 5, 12]. However, these approaches use the static fault tree to model the system fault behaviours and can not handle the challenge (2).So fuzzy dynamic fault tree (FDFT) analysis has been introduced [10], which takes into account not only the combination of failure events but also the order in which they occur. But the solution for FDFT is Markov chains (MC) based approach, which has the infamous state space explosion problem and can not incorporate sensors data into diagnosis process. Usually, BN is one of the most efficient models in the uncertain knowledge and reasoning field. It has been used to locate the system fault in many fields [4, 13]. However, the construction of BN model usually needs lots of fault data, which are very difficulty to obtain in reality. Motivated by the problems mentioned above, this paper presents a diagnosis strategy for micro-computer controlled straight electro-pneumatic braking system based on fuzzy set and dynamic fault tree. It pays special attention to meeting above three challenges. We adopt expert elicitation and fuzzy set theory to deal with insufficient fault data and uncertainty problem by treating failure rate as fuzzy numbers. Furthermore, we use a dynamic fault tree model to capture the dynamic behaviours of the braking system failure mechanisms and calculate some reliability results by mapping a dynamic fault tree into an equivalent BN in order to avoid the infamous state space explosion problem. In addition, we present a new method to incorporate sensors data into the system diagnosis to optimize the diagnosis process. The objective of this paper is to present an efficient diagnosis strategy for micro-computer controlled straight electro-pneumatic braking system using fuzzy set and dynamic fault tree. The rest sections of this paper are organized as follows: Section 2 provides a brief introduction on the braking system and its dynamic fault tree model. In section 3 describes estimation of failure rate for the basic events. Section 4 presents a novel diagnosis strategy which makes use of the qualitative structure, quantitative information and sensors data. The outcomes of the research and future research recommendations are presented in the final section.

2. Dynamic fault tree of braking system

The micro-computer controlled straight electro-pneumatic braking system has been the first choice braking system for urban rail transit, which has the advantages of the swift response, flexible operation, combined application with electric braking and anti-slip control. It is an electro-mechanic control system, and achieves its function by the coordination of electrical circuit part and air circuit part. Specifically, it includes power unit for braking system, service braking instruction processing unit, service braking control unit, emergency braking instruction processing unit, air supply unit and braking execution unit. The service braking instruction processing unit includes braking controller, logic controller and braking instruction line, which generates the service braking signals and transmits them into the braking control unit of every vehicle; service braking control unit receives service braking signals, calculates service braking force and detects braking system state. It consists of microcomputer brake control unit (MBCU) and several valves; Four modules (empty weight valves, under compaction switch, emergency braking button and emergency braking switch) form the emergency braking instruction processing unit which generates the emergency braking signals and transmits them into the emergency braking control unit; air supply unit offers air for braking system and thus a train is actuated to brake by braking execution unit. High coupling degree together with complicated logic relationships exists in these modules. Lots of current research about the micro-computer controlled straight electro-pneumatic braking system has focused on its reliability analysis using a reliability block diagram [14] or static fault tree [21]. It attempts to find out the weakest part of the system and then presents some reasonable solutions to improve its reliability. Fig. 1 shows a dynamic fault tree for service braking failure of a micro-computer controlled straight electro-pneumatic braking system. Any one of braking control failure, air supply unit failure, braking control output failure and braking execution unit failure will result in service braking failure. The failure events and different components of the braking system are represented by different symbols which are presented in Table 1.

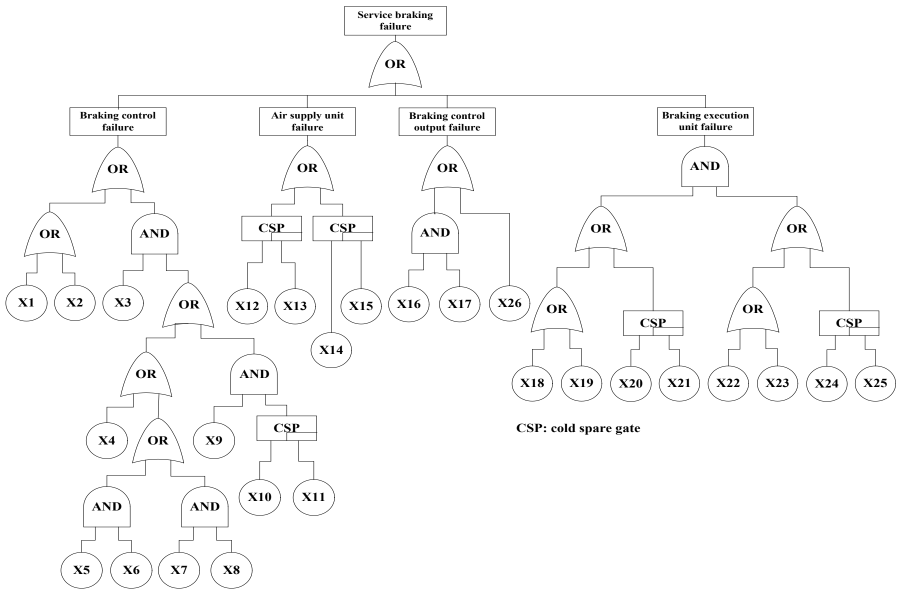

Fig. 1. A dynamic fault tree for service braking failure of braking system

3. Estimation of failure rates for braking system

In order to evaluate the reliability result for the braking system, failure rates of the basic events must be known. However, it is very difficult to estimate a precise failure rate due to insufficient data, or vague characteristic of the events, especially for the new equipments. In this study, the expert elicitation through several interviews and questionnaires and fuzzy set theory are used to determine the failure rates of the basic events.

3.1. Experts evaluation

Experts are selected from different fields, such as design, installation, operation, maintenance and management of the braking system, to judge failure rates of the basic events. They evaluate them in quali-

Table 1. The basic events of the braking system

Node symbol	Description	Node symbol	Description
X1	Microcomputer brake control unit	X14	Air cylinder 1
X2	EP brake valve	X15	Air cylinder 2
X3	Brake line failure	X16	Large membrane
X4	Power board of pulse width modulation	X17	Small membrane
X5	Digital input board	X18	High pressure oil seal ring 1
X6	Input/output board	X19	Low pressure oil seal ring 1
X7	Modulation board	X20	Left clamp 1
X8	Digital output board	X21	Left clamp 2
X9	Pulse width modulation line	X22	High pressure oil seal ring 1
X10	Multifunction Vehicle Bus 1 failure	X23	Low pressure oil seal ring 2
X11	Multifunction Vehicle Bus 2 failure	X24	Right clamp 1
X12	Compactor 1 failure	X25	Right clamp 2
X13	Compactor 2 failure	X26	Relay valve

tative natural languages based on their experiences and knowledge about the braking system. The granularity of the set of linguistic values usually used in engineering fields is from four to seven terms. In the paper, the component failure rates are defined by seven linguistic values, i.e. very high, high, reasonably high, medium, reasonably low, low and very low.

3.2. Converting linguistic terms to fuzzy numbers

After experts' evaluation, a numerical approximation method is used to systematically map linguistic terms into triangular fuzzy numbers. Each predefined linguistic value has a corresponding mathematical representation. The shapes of the membership functions to mathematically represent linguistic variables in engineering systems are shown in Fig. 2. To eliminate the bias coming from an expert, eleven experts are asked to justify how likely a basic event will fail in the system under investigation. So, it is necessary to aggregate their opinions into a single one. There are many methods to combine fuzzy numbers. A popular approach is the linear opinion pool [7]:

$$M_i = \sum_{j=1}^{n} \omega_j A_{ij}, \quad i = 1,2,3,\ldots,m \tag{1}$$

where m is the number of basic events; A_{ij} is the linguistic expression of a basic event i given by expert j; n is the number of the experts; ω_{ij} is a weighting factor of the expert j and M_i represents combined fuzzy number of the basic event i.

Usually, an α-cut addition followed by the arithmetic averaging operation is used for aggregating more membership functions of fuzzy numbers of different types. The membership function of the total fuzzy numbers from n experts' opinion can be computed as follows:

$$f(z) = \max_{z=x_1+x_2+,\ldots,+x_n} \left[\omega_1 f_1(x) \wedge \omega_2 f_2(x) \wedge \ldots \wedge \omega_n f_n(x))\right] \tag{2}$$

where $f_n(x)$ is the membership function of a fuzzy number from expert n and $f(z)$ is the membership function of the total fuzzy numbers.

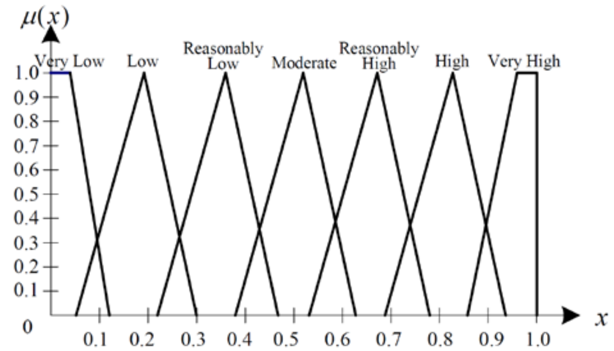

Fig. 2. Fuzzy numbers used for representing liguistic value

3.3. Calculating fuzzy fault rates of the basic events

Obviously, the final ratings of the basic events are also fuzzy numbers and cannot be used for fault tree analysis because they are not crisp values. So, fuzzy number must be converted to a crisp score, named as fuzzy possibility score (*FPS*) which represents the most possibility that an expert believes occurring of a basic event. This step is usually called defuzzification. There are several defuzzification techniques [8]: area defuzzification technique, the left and right fuzzy ranking defuzzification technique, the centroid defuzzification technique, the area between the centroid point and the original point defuzzification technique, and the centroid based Euclidean distance defuzzification technique. In this paper, an area defuzzification technique is used to map the fuzzy numbers into *FPS*. If (a, b, c; 1) is a normal triangular-fuzzy number, then its area defuzzification technique is as follows:

$$FPS = \frac{(2a+2b)^2 + (b+c)(2b-3a-c) - 2b(3b+c) - 4ab}{18(\mathrm{a}-c)} \tag{3}$$

The event fuzzy possibility score is then converted into the corresponding fuzzy failure rate (*FFR*), which is similar to the failure rate. Based on the logarithmic function proposed by Onisawa [18], which utilizes the concept of error possibility and likely fault rate, the fuzzy failure rate can be obtained by the following equation (4).

Table 2. The FPS and FFR of basic events

Basic events	Fuzzy numbers			FPS	FFR
	a	b	c		
X1	0.1498	0.2499	0.4094	6.98e-2	3.5e-6
X2	0.1991	0.2201	0.3584	5.88e-2	1.6e-6
X3,X9, X10,X11	0.1101	0.2099	0.2572	5.04e-2	7.6e-7
X4	0.0996	0.2005	0.1999	4.44e-2	4.1e-7
X5	0.1802	0.3403	0.9097	9.61e-2	1.4e-5
X6	0.1151	0.2148	0.2844	5.33e-2	1.0e-6
X7	0.1397	0.2301	0.8426	9.07e-2	1.1e-5
X8	0.1698	0.3204	0.5534	8.63e-2	8.9e-6
X12,X13	0.1651	0.3103	0.5744	8.58e-2	8.7e-6
X14,X15	0.1549	0.2801	0.5688	8.16e-2	7.1e-6
X16,X17	0.1131	0.2128	0.2224	4.93e-2	6.8e-7
X18,X19,X22,X23	0.1851	0.6502	0.9716	1.31e-1	4.8e-5
X20,X21,X24,X25	0.1801	0.5499	0.9526	1.24e-1	3.8e-5
X26	0.1599	0.3002	0.5666	8.37e-2	7.8e-6

Table 2 shows the fuzzy failure rates of the basic events for the braking system.

$$FFR = \begin{cases} \dfrac{1}{10^{\left[\frac{1-FPS}{FPS}\right]^{\frac{1}{3}} \times 2.301}}, & FPS \neq 0 \\ 0, & FPS = 0 \end{cases} \tag{4}$$

4. Diagnosis strategy

4.1. Calculating reliability data

After the dynamic fault tree is constructed and all basic events have their corresponding fault rates, reliability results of the braking system can be calculated. We use the zero-suppressed binary decision diagram (ZBDD) to generate all minimal cut sets (*MCS*) [19]. Firstly, it converts the dynamic fault tree into the static fault tree by separating logic constraints and timing constraints. Secondly, this algorithm generates the minimal cut sets of the resulting static fault tree using some set operations as follows:

$$\begin{aligned} &S_c = S_1 \cap S_2, D_1 = S_1 - S_c, D_2 = S_2 - S_c \\ &U = D_1 \cup D_2, P = D_1 * D_2, D_3 = U - P \end{aligned} \tag{5}$$

where $S_1$and S_2 are the input of *MCS-AND* and *MCS-OR*. S_c, D, U, and P respectively represent set intersection, set difference, set union, and set product.

The *MCS* generation algorithm is executed recursively during the depth-first left-most traversal of a fault tree. It first generates the *MCS* of the inputs of a connection gate, and then performs a serial of set operations to combine the *MCS* of the inputs into the *MCS* of the output of the connection gate. Finally, it expands each minimal cut set to minimal cut sequences by considering the timing constraints. For convenience, we define the sum of all minimal cut sets as the characteristic function of the system. The characteristic function of the braking system is

$$\begin{aligned} F = {} & X1 + X26 + X2 + X12X13 + X18X23 + X19X24X25 \\ & + X18X24X25 + X19X23 + X19X22 + X23X20X21 \\ & + X14X15 + X3X5X6 + X3X4 + X3X7X8 + X22X20X21 \\ & + X18X22 + X16X17 + X3X9X10X11 + X24X20X21X25 \end{aligned} \tag{6}$$

Quantitative analysis for dynamic fault tree is used to calculate the importance parameters. DIF is the corner stone of our methodology and provides an accurate measure of components' relevance from a diagnosis perspective. The DIF is defined conceptually as the probability that an event has occurred given the top event has also occurred.

$$DIF_{MCS_n} = P(MCS_n | S), DIF_C = P(C | S) \tag{7}$$

MCS_n: n^{th} minimal cut sets, C: a component in system S

In order to avoid infamous state space explosion problem we calculate the DIF by mapping a fault tree into an equivalent discrete-time BN (DTBN). In addition, DTBN can deal with the evidence data and update the DIF after receiving them. We divide the mission time into n+1intervals. Each node variable has a finite number n+1 of states. The n first states divide the time interval [0, T] (T is the mission time) into n equal intervals, and the last state n+1 represents the time interval [T,∞]. Random variables X is in state n+1 means that the corresponding basic component or gate output did not fail during the mission time [6]. In the paper, we use n=2 to balance the accuracy and computational complexity. Assume mission time 2000, we convert the dynamic fault tree in Fig. 1 to the BN using the approach in [6,11] and enter the evidence that the braking system has failed:

$$\begin{aligned} &P(Top = state2) = 0 \\ &P(Top = state1) = 0.5 \\ &P(Top = state0) = 0.5 \end{aligned} \tag{8}$$

Solving the BN using the inference algorithm gives the results of some importance factors in Table 3 and Table 4.

Table 3. DIF of components for the braking system

Components	Components' DIF	Components	Components' DIF
X18,X19	3.24e-1	X6,X7	7.01e-3
X22,X23	3.24e-1	X21,X25	4.79e-3
X26	2.87e-1	X6	2.01e-3
X1	1.25e-1	X3	1.55e-3
X20,X24	7.64e-2	X9,X10	1.52e-3
X2	5.74e-2	X16,X17	1.39e-3
X5	2.71e-2	X13	1.34e-3
X7	2.17e-2	X15	8.74e-4
X8	1.77e-2	X4	8.19e-4
X14	1.47e-2	X11	5.78e-7

4.2. Updating reliability data according to sensors information

When the braking system fails, sometimes additional evidence from diagnostic sensors is observed too, and this may be used to optimize the system diagnosis. However, the performance of a diagnostic system highly depends upon the number and location of sensors. According to the optimal sensors placement in [16] and Table 3, X18 and X19 will be the best location of sensors. If sensors detect the failure of X18 and X19, we can adopt the evidence to reduce the number of the diagnosed minimal cut sets using algorithm 1. The cut sets under evidence (*CUE*) is the set of all essential minimal cut sets obtained after evidence eliminates some cut sets. The following *CUE* function is generated:

$$\begin{aligned} F_{CUE} = {} & X1 + X2 + X22 + X23 + X26 + X24X25 \\ & + X14X15 + X16X17 + X12X13 + X3X4 \\ & + X3X7X8 + X3X5X6 + X3X9X10X11 \end{aligned} \tag{9}$$

Since a failure sensor can lead to a faulty diagnosis progress, we introduce the DIF of sensor to take this situation into account. The DIF for a sensor with respect to the system is measured by the same way the DIF of the components:

$$DIF_{Sensor} = P(Sensor | S) = q_{Sensor} / Q_S \tag{10}$$

where q_{Sensor} and Q_S represent the unreliability of sensor and the system, respectively.

Assume sensors have a fixed probability of failure of 10^{-6}; the DIF of the sensor is 1.79×10^{-5}. The updated *CUE* function is as follows:

Table 4. DIF of minmal cut sets for the braking system

MCS	MCS' DIF	*MCS*	*MCS' DIF*
X26	2.78e-1	X19 X24 X25	2.25e-3
X18 X22	1.50e-1	X12 X13	1.34e-3
X18 X23	1.50e-1	X14 X15	8.74e-4
X19 X22	1.50e-1	X3 X4	1.17e-4
X19 X23	1.50e-1	X20 X21 X24 X25	3.37e-5
X1	1.25e-1	X16 X17	3.32e-5
X2	5.74e-2	X3 X4	2.17e-5
X23 X20 X21	2.25e-3	X7 X8 X3	1.32e-5
X18 X24 X25	2.25e-3	X3 X5 X6	1.50e-6
X22 X20 X21	2.25e-3	X3 X9 X10 X11	2.40e-11

$$\begin{aligned} F'_{CUE} &= X1 + X2 + X22 + X23 + X26 + X24X25 \\ &+ X14X15 + X16X17 + X12X13 + X3X4 \\ &+ X3X7X8 + X3X5X6 + X3X9X10X11 + Sensor \end{aligned} \tag{11}$$

In addition, we add the sensors evidence nodes to the BN from the dynamic fault tree and set the conditional probability, which can be used to update the DIF of the components and *CUE*. The DIF of the *CUE* can be calculated using equation (12).

$$DIF_{CUE} = \frac{P(CUE, E, S)}{P(S) DIF_E} \tag{12}$$

S: system, *E*: variables with given evidence.

Now we input the evidence defined as equation (13) to the BN and update the DIF of components and CUE using the inference algorithm. Table 5 and 6 shows the diagnostic data with sensors data.

$$\begin{aligned} &P(X18 = state2) = 0 \\ &P(X18 = state1) = P(X18 = state0) = 0.5 \\ &P(X19 = state2) = 0 \\ &P(X19 = state1) = P(X19 = state0) = 0.5 \end{aligned} \tag{13}$$

Algorithm 1 GetCUE(*F*, *E*, *v*)

Input:

F: *the characteristic function*

E: *evidence information function*

v: *if occurred,* *v*=1*, otherwise v*=0

Output: ***CUE***

F_{CUE}=*0*

if (*v*=0) {*E*=*ITE*(*E*,0,1)}

for ($\forall product \in E$)

{ *tempF*=*F*

for ($\forall component \in product$) {

if ($(\exists product \in F) = component$)

{ *tempF*=$F_{component=0}$ }

else { *tempF*=$F_{component=1}$ }

}

F_{CUE}=*ITE*(F_{CUE}, 0, *tempF*)

}

return (F_{CUE})

Table 5. The updated DIF of components for the braking system

Components	Components' *DIF*	Components	Components' *DIF*
X22,X23	4.65e-1	X14	1.41e-2
X26	7.86e-2	X25	6.93e-3
X24	7.84e-2	X6	1.99e-3
X20	7.32e-2	X3	1.55e-3
X1	3.54e-2	X9,X10	1.52e-3
X5	2.76e-2	X16,X17,X21	1.37e-3
X7	2.17e-2	X4	8.01e-4
X8	1.76e-2	X13	3.81e-4
X12	1.75e-2	X15	2.47e-4
X2	1.62e-2	X11	5.78e-7

Table 6. The updated DIF of CUE for the braking system

CUE	*CUE's DIF*	*CUE*	*CUE's DIF*
X22	4.65e-1	X14 X15	2.47e-3
X23	4.65e-1	Sensor	1.79e-5
X26	7.86e-2	X16 X17	9.33e-6
X1	3.54e-2	X3 X4	6.11e-6
X2	1.62e-2	X3 X7 X8	1.54e-6
X24 X25	6.93e-3	X3 X5 X6	2.22e-7
X12 X13	3.78e-4	X3 X9 X10 X11	3.53e-12

4.3. Diagnosis strategy

As *CUE* represents minimal sets of component failures under evidence that can cause a system failure, we should diagnose it one by one to find the root reason of the braking system failure. Only when we finish diagnosing a *CUE* can we do next. The order by which *CUE* are checked depends on its DIF ordering, while the order of components in the same *CUE* is determined by their DIF. The *CUE* with larger DIF is checked first. Accordingly, components with larger DIF in a *CUE* are checked first. This assures a reduced number of system checks while fixing the braking system. Based on quantitative and qualitative data obtained from reliability analysis after incorporating evidence, the diagnostic strategy is as follows:

Step1. Sort all *CUE* and select the *CUE* with highest DIF value.

Step2. Check the component *C* with highest DIF in the *CUE*.

Step3. Split the *CUE* into those with *C* and those without.

a) If *C* failed test we take the set of *CUE* that include *C*

- Select the *CUE* untested with highest DIF value.
- And recursively repeat Step2 - Step3.

b) If C has not failed test we take the other set of *CUE*

- Select the *CUE* untested with highest DIF value.
- And recursively repeat Step2 - Step3.

The diagnosis strategy can easily be described in the graphical diagnostic decision tree (DDT). It provides us with a map that allows us to recognize the failing components. It is a directed acyclic graph composed of circular nodes and arcs linking parent nodes to child nodes. A node represents a component being tested. Arcs point to the next component to be tested; right arcs point to components within the same cutest as the parent node, and left arcs point to components which are not in the same cutest as the parent node. Moreover, when diagnostician reaches a node and tests the component at the node, the test either fails or passes. If the test fails then the right arc is traversed indicating the need to repair the tested component in the parent node. If a test passes then the left arc is traversed indicating that the cut sets which include the tested component in the parent node have not failed. Once the order of components is determined, we can generate the DDT of the braking system shown in Fig.3.

Average diagnostic cost is often used to evaluate the fault diagnosis method. The diagnostic cost is lower; the method is better. As we all know, the output of fault diagnosis method is the DDT, we can evaluate it with the help of several decision tree evaluation measures. Traditional evaluation measures have the mean depth of the tree [20], which calculates the expected number of tests needed to isolate a fault, and the expected cost function [9], which takes into account the testing cost of a path as a weighting factor. But these measures only consider the test cost and the failure probability of components, and neglect system qualitative structure and the importance factors of each component. Also, they only diagnose one fault at a time and are not capable of detecting multiple faults by a single tree traversal. Based on these evaluation mechanisms, we introduce expected diagnostic cost (EDC) which incorporates the qualitative (structure) and quantitative (reliability analysis) into one measure for predicting diagnosis cost [16]. This evaluation index takes both diagnosis accuracy and diagnosis cost into consideration, also considers the relationship between component failure and system failure, and can evaluate the diagnosis algorithm objectively. EDC can be computed by:

$$EDC = \frac{\sum_{i=1}^{n} qcutset_i cp_i}{Q_S} \qquad (14)$$

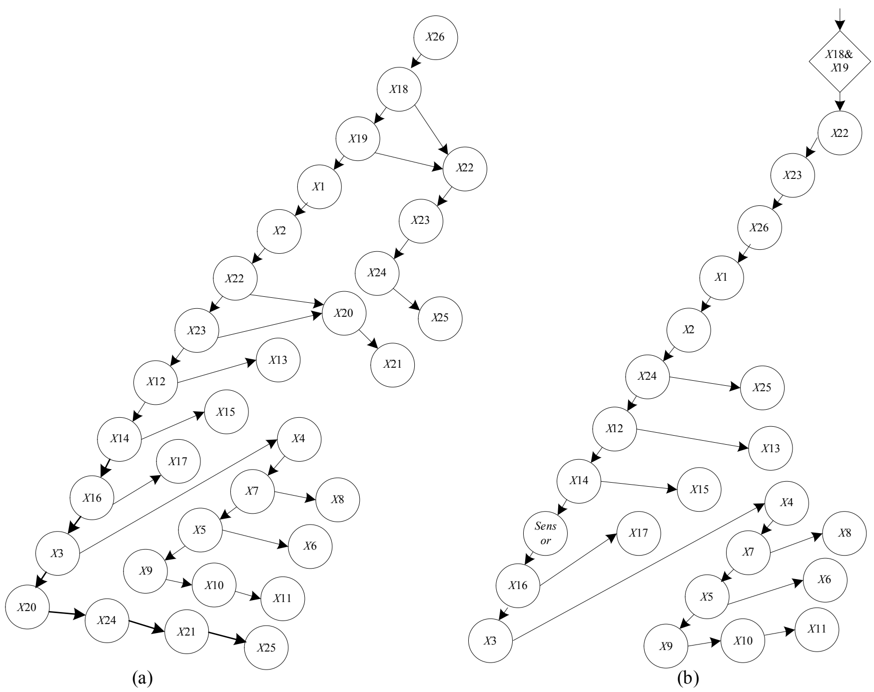

Fig. 3. DDT for service braking failure of braking system, (a) DDT without evidence from sensors; (b) DDT with evidence from sensors

where Q_s is the unreliability of the system, cp_i is the sum of all test costs from the top node to the cutset's leaf node, qcutseti is the unreliability of cut sequences.

For convenience, assuming all components have a unit test cost and their test cost is independent, the diagnostic cost of different algorithms using equation (14) is shown in Table 7, which indicates

Table 7. The comparison among three diagnosis methods

Diagnosis methods	*EDC*
Diagnosis method without sensors	3.562
Diagnosis method with sensors data by Assaf and Dugan [2]	2.586
Diagnosis method in the paper	1.918

the proposed approach is more efficient than others. Furthermore, the curve in Fig. 4 depicts the effect of sensors' reliability on EDC of the braking system. So we should choose the sensors with higher reliability to detect the components in order to decrease the diagnosis cost of the braking system.

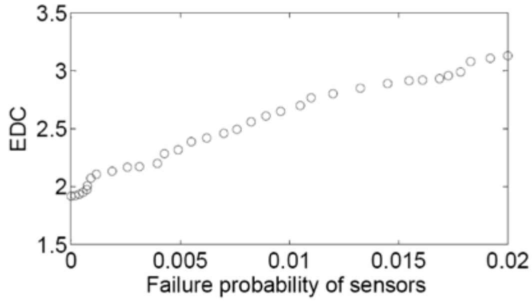

Fig. 4. The relation curves of EDC and failure probability of sensors

5. Conclusion

In this work, we have discussed the use of fuzzy set theory, dynamic fault tree and BN to diagnose the micro-computer controlled straight electro-pneumatic braking system. Specifically, it has emphasized three important issues that arise in engineering diagnostic applications, namely the challenges of insufficient fault data, uncertainty and failure dependency of components. In terms of the challenge of insufficient fault data and uncertainty, we adopt expert elicitation and fuzzy set theory to evaluate the failure rates of the basic events for the braking system; In terms of the challenge of failure dependency, we use a dynamic fault tree to model the dynamic behavior of system failure mechanisms and calculate some reliability results by mapping a dynamic fault tree into an equivalent BN in order to avoid the state space explosion problem. Furthermore, we incorporate sensors data into fault diagnosis, cope with the sensors reliability and propose the schemes on how to update DIF and the cut sets. In addition, an efficient diagnostic decision algorithm is developed based on these results to optimize system diagnosis. The experimental results demonstrate its efficiency. The proposed method makes use of the advantages of the dynamic fault tree for modeling, fuzzy set theory for handling the uncertainty and BN for inference ability, which is especially suitable for the complex system diagnosis.

In the future work, we will focus on the dynamic fault tree model optimization and take the test cost, sensitive analysis and other attributes into the diagnosis strategy.

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