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A KNOWLEDGE-BASED REAL TIME MONITORING AND DIAGNOSTIC APPROACH FOR AIRCRAFT BRAKING SYSTEM

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Abstract

Taking advantage of advanced sensors and data processing techniques, certain states of complex systems in aircraft can be monitored in real-time. However, it still takes efforts in practical trouble shooting in order to locate the exact faulty component after some malfunction alerts. This often consumes great time and energy, sometimes may even cause flight delay. A new diagnostic approach is developed based on a hierarchical Bayesian network that can combine both Fault Mode and Effect Analysis (FMEA) and real-time monitoring information. An aircraft brake system, as one of the typical electromechanical systems, is selected and two different statistical models are proposed in case study. The intelligent fault diagnostic approach has the potential to improve the efficiency and accuracy of aircraft system diagnosis.

1 Introduction

Current aircraft maintenance follows two categories: scheduled maintenance and unscheduled maintenance [1]. The former one belongs to preventative behavior which is mostly time-based whereas the alternative addresses problems occurred unexpectedly, which may have a side effect on flight safety. During unscheduled maintenance, a fault diagnostic procedure is carried out relying on Built-In Test (BIT) and Fault Isolation Manual (FIM) after flight. For some systems, there is an exact corresponding relationship between fault symptom and faulty component, but for most complex systems, there are many possible fault causes and the trouble-shooting process is largely based on engineering experience. This consumes great time and manpower. Being the frequent fault area, the aircraft brake system often causes flight delays due to overtime maintenance.

Uncertainty widely exists in fault diagnosis, especially for large complex systems in aircraft. It is mainly embodied in three aspects: evidence uncertainty, knowledge uncertainty and inference uncertainty [2]. Specifically, the noise and the acquisition process could result in evidence uncertainty; blurred cognition of the object as well as randomness of the fault causal correlation could lead to knowledge uncertainty; insufficient knowledge propagation and incomplete evidence accumulation always causes inference uncertainty.

In order to reduce the uncertainty in fault diagnosis, an intelligent decision support system with the ability of self-evolution with new information is desired to facilitate maintenance engineers with minimum cost and fastest fault location and elimination. As one of the robust artificial tools, Bayesian Network (BN) is capable of addressing uncertainty expression and reasoning by integrating prior knowledge and new observations [3]. A comparison of multiple methodologies, e.g. Neural Network, Petri Net, etc. was conducted from a dozen of aspects and it is proved that BN is more fit for dealing with diagnostic and decision-making issues [4]. Early in 2001, a knowledge engineering framework called DAEDALUS was introduced by Lee [5] as a methodology for combining design and diagnosis models among modelling environments around common domain ontology. Later, Shi and Wang [6] developed a BN model based on Fault Mode and Effect Analysis (FMEA) for a complex engine system. automatic BN construction based on FMECA was presented making use of the hierarchical relationship of the product structure. [7]. Besides FMEA, Fault Tree Analysis (FTA) is also a common method for large safety critical system. Bobbio et.al [8] compared BN with FTA and developed a direct mapping method from FTA to BN where basic inference techniques in the latter could be used to obtain classical parameters calculated from the former. During the mapping procedure, Duan [9] focused on the calculation of diagnostic importance factor of components and minimal cut sets. Moreover, Bluvband et al. [10] treated FMEA and FTA together and introduced a BFA method, in which FTA was regarded as a complement of FMEA.

In aircraft maintenance, there is a lack of effective combination between design knowledge and operation practice. BN provides a promising approach to address this issue by incorporating system safety analysis results and real-time monitoring information. This study intends to construct a knowledge-based BN for an aircraft brake system and use operational information for inference update in order to provide more effective diagnosis.

2 Bayesian Network

Bayesian Network (BN) is a combination of graph representation and probabilistic theories. A standard BN includes a Directed Acyclic Graph (DAG) structure and a set of Condition Probability Tables (CPTs) [11]. The dependent and independent relationship among variables is expressed by directed graph and probabilities: 1) each variable is taken as a node; 2) a directed arc connects a parent node and a child node indicating a probabilistic dependency. The child node is associated with a conditional probability distribution dependent on the parents' states. Any node without parent node is defined as a root note and the probability associated is considered as prior knowledge.

Given a set of variable $X=(X_1,X_2,...,X_n)$, then the joint probability distribution (JDP) of the variables is a product of conditional probability distributions according to the chain rule [12]

$$P(X_1,...X_n)=P(X_1)P(X_2/X_1)...P(X_n/X_1,...,X_{n-1})$$
$$=\prod_{i=1}^{n}P(X_i/\pi(X_i))$$

where $\pi(X_i)$ denotes the parent node set of variable X_i.

Theoretically, once the JDP of the whole event is obtained, any state of the event can be determined. However, in most cases it is difficult to acquire JDP. BN solves this problem by decomposing JDP into the product of several local probability distributions in order to reduce computation complexity. This is one of the advantages of BN over most traditional methods.

The general formula of Bayes theorem is

$$P(X/Y)=\frac{P(XY)}{P(Y)}=\frac{P(Y/X)P(X)}{P(Y)} \quad (1)$$

According to the theory, once the evidence of certain event is obtained, the probability of other nodes can be updated through probability inference

$$P(X/evidence)=\frac{P(X,evidence)}{P(evidence)}=\frac{P(X,evidence)}{\sum_{X}P(X,evidence)} \quad (2)$$

In this study, the density function is used and expressed as

$$p(\theta/x)=\frac{p(x/\theta)\pi(\theta)}{m(x)} \quad (3)$$

where $\pi(\theta)$ is the prior distribution of the parameter θ, representing the historical information, $p(x/\theta)$ is the conditional distribution of x given the parameter θ. $m(x)$ is the marginal density function of x and equals to $\int_{\Theta}p(x/\theta)\pi(\theta)d(\theta)$.

In Eq. (3), $p(x/\theta)$ is regarded as the likelihood function $L(\theta)$, denoting the observed sample information, which is calculated as

$$L(\theta)=\prod_{i=1}^{n}p(x_i/\theta) \quad (4)$$

Since $m(x)$ is a regularization factor which does not rely on θ, the posterior distribution is proportional to the product of the likelihood function and prior distribution, the Bayesian fraction can be expressed as

$$\pi(\theta / x) \propto p(x / \theta)\pi(\theta) \quad (5)$$

where symbol $\propto$ means that the only difference between the left and right side is a constant factor independent of the distribution parameter θ. Conjugate distribution is introduced to facilitate the calculation and it will be discussed in Section 4.

3 Aircraft Brake System and FMEA

Aircraft brake system is a typical electromechanical system in aircraft with frequent fault occurrences. The schematic diagram of the selected brake system is shown in Fig. 1.

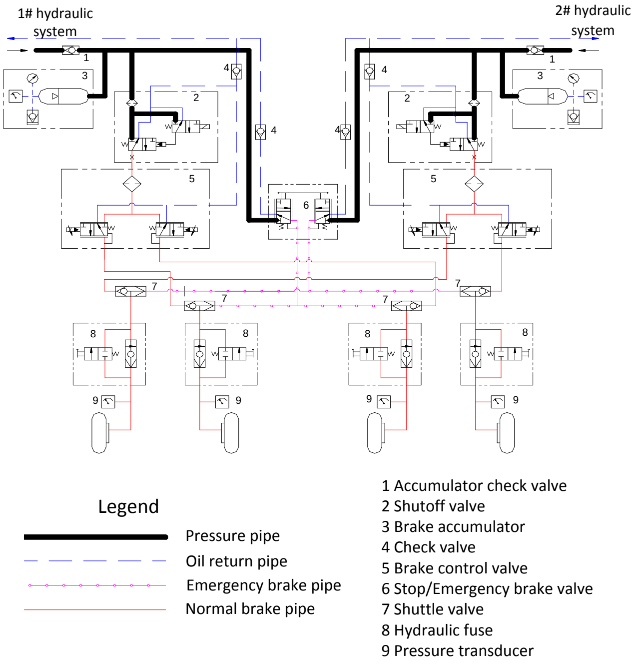

Fig. 1. Schematic Diagram of Aircraft Brake System

This parallel system has two subsystems, one is the normal brake system and the other is the emergency brake system. The brake function of the normal system is realized through pedal manipulation. The displacement transducer is installed in the pedal to obtain brake force from pilots and output proportional electrical signal to the brake control unit (BCU), a key component in the brake system. The BCU connects the shutoff valve first to turn on hydraulic path and then commands the control valve to output brake pressure. Meanwhile, the speed transducers feed back the rotation signals. Then the BCU adjusts the current magnitude through contrast operation to control brake pressure. The BCU also continuously monitors the internal channel, brake control valve and shutoff valve, etc. and transfer fault signal to Engine Indication and Crew Alerting System (EICAS) and Central Maintenance System (CMS). Once the normal brake system fails, the alternative brake system is used, which consists of a set of emergency mechanism and valves, and is manipulated by manpower.

Fault Mode and Effect Analysis (FMEA) is a bottom up approach outlining all possible faults and determining the effect of each fault as well as the severity level. It can be performed at different levels within the system such as part, component, function, etc.[13]. FMEA contains massive useful qualitative and quantitative information on both component and system faults. A typical FMEA table for the normal brake system is shown in Table 1.

Table 1. FMEA Example for Aircraft Normal Brake System

System: Brake system		Subsystem: Normal brake system				
FMEA No.	Component	Fault Mode/ Fault Cause	Fault Effect a. Local Effect b. higher Level Effect	Component Fault Rate (1E-6)	Fault Mode Rate (1E-6)	Detection Method
32-41-01-1.1	BCU	Channel fail/ Resistance shutdown	a. BCU loss control b. Impair normal brake function	81.02	26.17	System BIT
32-41-01-1.2	BCU	Brake manipulation fail/ U20 pin fail	a. BCU loss control b. Lose normal brake function	81.02	17.40	System BIT
…	…	…	…	…	…	…
32-41-03-1.1	Shut off valve	Response time increase / Clamping stagnation	a. Shutoff valve fault b. Impair normal brake function	29.50	12.94	System BIT
…	…	…	…	…	…	…

However, the cause, mode and effect are organized in a table sheet, which is insufficient for information transmission. Instead, the construction of BN based on FMEA can unify the fault mode, fault cause, fault effect as well as quantitative information such as fault probability into one framework and is capable of processing causal relationships in complex systems. Besides, BN can synthesize information from various sources, e.g. domain experts, experiment, operational data, etc. and update network configuration with knowledge accumulation. This would significantly enhance belief and make results closer to reality acknowledging the existence of uncertainty.

4 BN Construction and Inference

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4.1 Causal Interpretation

BN has the potential to map discrete FMEA knowledge into a systematic graph by integrating various fault modes, effects and probabilities, etc. of different components and fuse them with posteriori information such as in flight or post flight feedback. Generally, for a complex hierarchical system, a series of Bayesian networks mapping Cause-Mode-Effect is shown in Fig. 2. The arrows indicate that the fault cause in a higher level is the fault mode in a lower level.

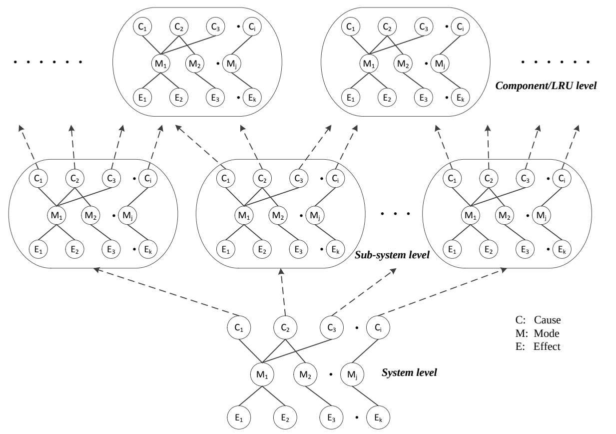

Fig. 2. BN-CME Hierarchy Model for Complex Systems

Although components in the brake system may contain various fault modes, in practical maintenance, it is those components that are identified as LRU are replaced directly. The fault location at LRU level is enough for this analysis. Besides, some components may have many modes, adding great complexity to the network. Therefore, considering the locating accuracy requirement and computing complexity, a single LRU is treated as a root node. A sub-sub system is defined to be the child node of the LRU at the next higher level. In other words, it can be interpreted that the fault mode is expressed implicitly by the responsible physical object. The simplified directed graph is shown in Fig. 3.

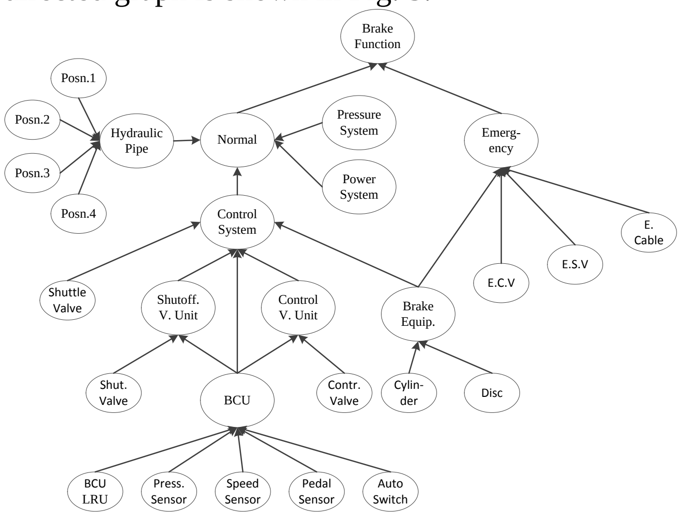

Fig. 3. Bayesian Network for Aircraft Brake System

Brake system belongs to landing gear system, at the top level Functional Hazard Analysis (FHA), wheel brake functional failure of the brake system is the main fault mode. Herein, the symmetrical wheel control system in terms of left and right, inner and external wheel is regarded as one system for simplification. Take the failure of the brake system as the final fault effect, a breakdown is conducted at the normal brake system and the emergency brake system respectively. The fault of the normal system may be caused by four sub-systems, including control system, hydraulic pipe, pressure system and power system. The faults of the latter two systems are caused by their subsystems outside of the brake system and they are considered as a whole. Further breakdown is performed aimed at the hydraulic pipe by giving four possible positions and the control system. Finally, main LRUs are selected to form the initial fault causes to complete the BN construction.

4.2 Prior Inference

The fault time of the components/LRUs in the aircraft brake system is assumed to follow exponential distribution as

$$f(t,\lambda)=\begin{cases}\lambda e^{-\lambda t}, & t\geq 0,\\ 0, & t<0.\end{cases} \qquad (6)$$

where λ is the fault rate, the reciprocal of λ is Mean Time Between Failure/Fault (MTBF). In this study, flight hour (FH) is used as unit time.

The probability of the fault occurring in a certain period t_0 is expressed as

$$P(X=Fault/\lambda)=P(T<t_0)=1-e^{-\lambda t_0} \qquad (7)$$

A series of LRUs' fault rates after roundness are listed in Table 2 together with the fault probability in 1000 flight hours according to FMEA.

Table 2. Fault Rate of Brake System LRUs

LRU	Fault rate λ	Probability (1000FH)
BCU LRU	8e-5	0.0769
Control Valve	6e-5	0.0582
Shuttle Valve	3e-6	0.0030
Shutoff Valve	3e-5	0.0296
Hydraulic Pipe (Position 1-4)	1e-5	0.0010
Pedal Transducer	2e-5	0.0198
Speed Transducer	2e-5	0.0198
Pressure Transducer	2e-5	0.0198
Auto Switch	3e-5	0.0296
Disc	1e-7	0.0001
Cylinder	2e-6	0.0020
Power System	5e-5	0.0488
Pressure System	5e-5	0.0488
Emergency Switch Valve	4e-6	0.0040
Emergency Control Valve	3e-6	0.0030
Emergency Cable	1e-6	0.0010

Compared with the prior probability of each component from FMEA, the conditional probability of the subsystem is comparatively difficult to obtain. Different from the deterministic "And" or "Or" gate in FTA, the conditional probability can be regarded as a kind of probabilistic gate. Engineering domain knowledge plays an important role in determination of these relationships. Take the node 'Control Valve Unit' as an example, the conditional probability of the control valve unit is given as below.

Table 3. Conditional Probability of Control Valve Unit

Parent Node (s)		Control Valve Unit		
BCU	Control Valve	Normal	Fault	Bar charts
Normal	Normal	1.0	0.0	
	Fault	0.0	1.0	
Fault	Normal	0.6	0.4	
	Fault	0.0	1.0	

The conditional probability assignment of the rest subsystems was determined in a similar way via consulting experienced trouble-shooting engineers.

Generally, the fault of the brake function is rare likely to occur since it has redundancy system. Herein, we focus on the normal brake system. Statistical inference was conducted based on prior knowledge. Suppose the fault of the normal brake function occurs, the most possible cause would be the control system, the fault probability of which is up to 95.56%. Further, the most likely fault component in the control system is the BCU, the ranking of the components from high to low is calculated based on predetermined CPT and is shown in Table 4.

Table 4. Faulty LRU Ranking with Probabilities

Faulty LRU ranking	Probability (1000FH)
BCU LRU	0.3404
Control Valve	0.2576
Shutoff Valve	0.1310
Pedal Sensor	0.0876
Pressure Sensor	0.0537
…	…

At this stage with design knowledge, this method is able to diagnose the fault of the brake system and determine the sequence of trouble-shooting according to the probability of occurrence. However, the actual probability of each LRU varies after the aircraft entering service when operational data is gradually accumulated. Moreover, the real-time monitoring system can help to locate the fault causes. Thus, the next effort is to take the operational information into consideration and update the BN inference.

4.3 Posterior Update with EICAS Information

In real operation, besides of post-flight inspection and scheduled maintenance, there is an Engine Indication and Crew Alerting System (EICAS) for real-time monitoring. It is an integrated electronic system used in modern aircraft indicating alert status and maintenance messages. EICAS receives inputs from hundreds of on-board system sensors and provides aircraft crew with aircraft engine and other systems instrumentation and crew annunciations [14]. Typical other systems include pneumatic, deicing, control surface and brake system for example. It is noted that in fault diagnosis, the crew-alerting system (CAS) for some systems is capable of locating the exact LRU while CAS for most systems can only reflect a rough area with a list of possible LRU faults. In this study, the CAS information for the selected aircraft brake system is categorized and corresponded to potential subsystems or LRUs as shown in Fig. 4.

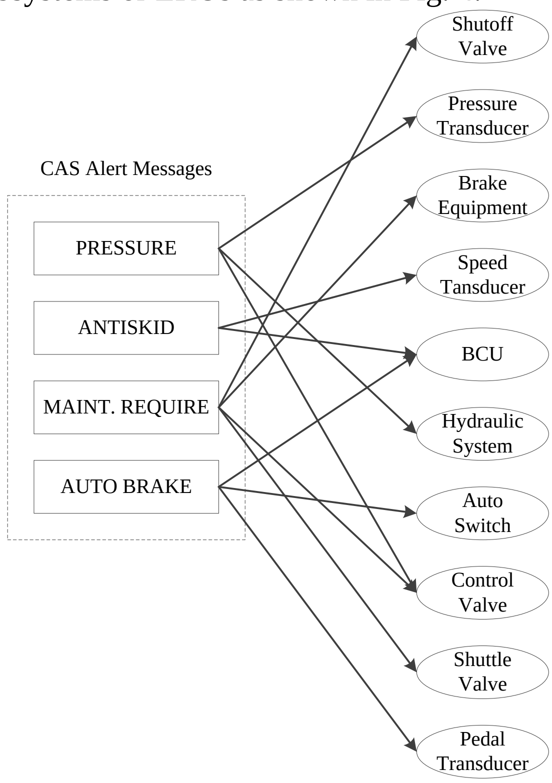

Fig. 4. CAS Information Correspondence

Two statistical models are presented to illustrate how observed information can be incorporated as posterior inference.

4.4 Basic theory of Gamma distribution

It is assumed that the fault rate/MTBF of all components in the brake system is constant according to Original Equipment Manufacturer (OEM). Therefore, the likelihood function $L(\theta)$ is set to follow exponential distribution. Then the calculation (integration of the denominator in Bayes' theorem Eq. (4)) difficulty relies on the different choices of the prior distribution of the parameter θ. For certain choices of the prior, the posterior would have the same algebraic form with different parameter values. The prior and posterior are called conjugate distributions. Thus, in order to facilitate the calculation, a Gamma prior of the means of the parameter λ is selected. The expression of the Gamma distribution is:

$$f(x) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}, \quad \alpha \ge 0, \beta \ge 0 \tag{8}$$

where α is the shape parameter and β is the scale parameter, $\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx, \quad x > 0$.

The mode of Gamma distribution, which can be regarded as the mean value of λ, is

$$\lambda = \frac{\alpha - 1}{\beta} \quad \text{for } \alpha \ge 1 \tag{9}$$

With the exponential distribution for the likelihood and Gamma distribution for the prior, the posterior in the proportional expression Eq. (6) becomes

$$\begin{aligned} \pi(\lambda / X) &\propto p(X / \lambda) \cdot \pi(\lambda) \\ &\propto \prod_{i=1}^{n} \lambda e^{-\lambda x_i} \cdot \frac{\beta^{\alpha}}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda} \\ &\propto \frac{\beta^{\alpha}}{\Gamma(\alpha)} \lambda^{\tilde{\alpha}} e^{-\tilde{\beta}\lambda} \end{aligned} \tag{10}$$

where $\tilde{\alpha} = \alpha - 1 + n, \quad \tilde{\beta} = \beta + \sum_{i=1}^{n} x_i$.

The updated mode is obtained as

$$\tilde{\lambda}' = \frac{\tilde{\alpha} - 1}{\tilde{\beta}} \tag{11}$$

4.5 Basic theory of Beta distribution

Alternatively, Beta distribution can also be employed to model the probability of the fault occurrence, since the state of the system is divided into two conditions, the normal state and the fault state. The expression of Beta distribution is

$$Beta(\theta / a,b) = \frac{1}{B(a,b)}\theta^{a-1}(1-\theta)^{b-1} \quad (12)$$

where a and b are hyper-parameters, which are the parameters of the distribution of θ,

$$B(a,b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}, \quad \Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt \quad (13)$$

The expectation and variance of the variable are

$$E(\theta) = \frac{a}{a+b} \quad (14)$$

$$Var(\theta) = \frac{ab}{(a+b)^2(a+b+1)} \quad (15)$$

According to Bayesian theorem $\pi(\theta / x) \propto p(x/\theta)\pi(\theta)$

Assume m faults occur during n observations, the prior information follows Beta distribution. The posterior distribution becomes

$$\begin{aligned}\pi(\theta / x) &\propto p(x/\theta)\pi(\theta)\\ &\propto \binom{n}{m}\theta^m(1-\theta)^{n-m}\frac{1}{B(a,b)}\theta^{a-1}(1-\theta)^{b-1} \quad (16)\\ &\propto \theta^{m+a-1}(1-\theta)^{n-m+b-1}\end{aligned}$$

where $\binom{n}{m} \equiv \frac{n!}{(n-m)!m!}$.

Substitute Eq. (12) into Eq. (16) and $\pi(\theta / x)$ becomes

$$\begin{aligned}\pi(\theta / x) &= \frac{\Gamma(n+a+b)}{\Gamma(m+a)\Gamma(n-m+b)}\theta^{m+a-1}(1-\theta)^{n-m+b-1}\\ &= \frac{1}{B(a+m,b+n-m)}\theta^{m+a-1}(1-\theta)^{n-m+b-1} \quad (17)\\ &= Beta(\theta / a+m, b+n-m)\end{aligned}$$

Then the updated expectation of parameter θ is expressed as

$$E(\theta) = \frac{a+m}{a+b+n} \quad (18)$$

5 Case Study

Take the BCU LRU as an illustration. The original fault rate $\lambda = 8\times10^{-5}$ from FMEA, for Gamma distribution, $\frac{\alpha-1}{\beta} = 8\times10^{-5}$, let $\alpha - 1 = 6$, $\beta = 7.5\times10^4$. The number of fault occurrence in BCU LRU from operational EICAS messages is 22 among the fleet of 33 airplanes during one year. The total flight hour of the selected aircraft is 3300 per year. Then the average MTBF=3300/(22/33)= 4950 flight hours based on the assumption that the fault rate is constant. Therefore, the hyper-parameters become

$$\tilde{\alpha} = \alpha - 1 + n = 28, \ \tilde{\beta} = \beta + \sum_{i=1}^{n} x_i = 184000$$

Substituting new values into Eq. (11):

$$\tilde{\lambda}' = \frac{\tilde{\alpha}-1}{\tilde{\beta}} = 1.52\times10^{-4}$$

For Beta distribution, the original fault rate is expressed as $\frac{a}{a+b} = 8\times10^{-5}$. Let $a = 6$, $b = 7.5\times10^4$. Assume that one flight hour represents one observation, the total observation time is the number of airplanes multiplies the flight hours. Therefore, the fault occurrence time $m = 22$ and the total observation time $n = 33\times3300 = 108900$. The updated fault rate according to Eq. (14) is calculated as $\frac{a+m}{a+b+n} = 1.52\times10^{-4}$, which is the same as the result from Gamma distribution.

Both prior and posterior distribution of the fault rate for BCU LRU is shown in Fig. 5. The value on x axis indicated by the vertical line is the expectation of parameter θ.

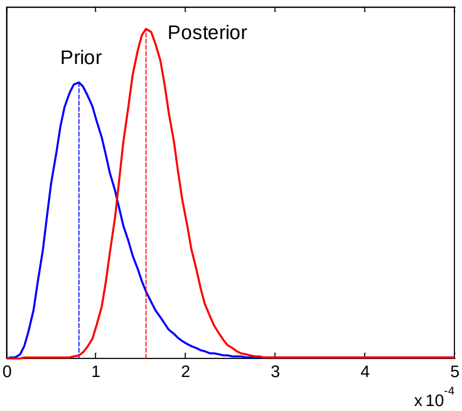

Fig. 5. Prior and Posterior Distribution of Parameter θ

The fault rate distributions of those LRUs with EICAS information update is computed in a similar manner and the result of posterior fault rates and probabilities are listed in Table 5.

Table 5. Fault Rate Update

LRU	Prior fault rate θ	Posterior fault rate θ	Probability (1000FH)
BCU	8e-5	1.52e-4	0.1412
Control Valve	6e-5	9.57e-5	0.0913
Shuttle Valve	3e-6	3.79e-6	0.0038
Shutoff Valve	3e-5	2.91e-5	0.0287
Hydraulic Pipe (Posn 1-4)	1e-5	9.87e-6	0.0098
Pedal Transducer	2e-5	2.69e-5	0.0265
Speed Transducer	2e-5	2.69e-5	0.0265
Pressure Transducer	2e-5	2.45e-5	0.0242
Auto Switch	3e-5	4.21e-5	0.0412

Although the introduction of EICAS can help the maintenance engineer identify a group of possible components, it cannot locate the exact faulty LRU. This BN model together with operational EICAS information has the potential to improve the trouble-shooting procedure by pinpointing the most possible LRU. A combination of EICAS messages and LRU probability ranking for the selected aircraft normal brake system is shown in Table 6.

Table 6. LRU Ranking Update with EICAS Information

EICAS message	Component/LRU ranking	Probability (1000FH)	Priority
PRESSURE	Control Valve	0.0913	1
	Pressure Transducer	0.0242	2
	Hydraulic Pipe (1-4)	0.0098	3
ANTISKID	BCU	0.1412	1
	Speed Transducer	0.0265	2
MAINT.REQUIRE	Control Valve	0.0913	1
	Shutoff Valve	0.0287	2
	Shuttle Valve	0.0038	3
	Brake Equipment	0.0021	4
AUTO BRAKE	BCU	0.1412	1
	Auto-Switch	0.0412	2
	Pedal Transducer	0.0265	3

6 Conclusion

This paper considers the application of Bayesian Network (BN) on aircraft brake system for diagnostic analysis. The contribution of this study is the development of a BN model that can fully make use of design knowledge and operational information, particularly from real-time monitoring. The qualitative part of the BN provides an explicit method to map the causal relationship from Fault Mode and Effect Analysis (FMEA) of a complex system into a hierarchical directed graph. In addition, the quantitative part of BN offers an effective tool for combining prior design knowledge and real-time monitoring information. With accumulative operational experience, this method can adjust the order of potential faulty LRUs dynamically and assist the trouble-shooting engineer to locate fault with less time. Further, by considering maintenance hours and resources, a decision-making system can be developed to realize system health management.

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