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RELIABILITY ANALYSIS OF MULTI-STATE SYSTEM WITH COMMON CAUSE FAILURE BASED ON BAYESIAN NETWORKS

ANALIZA NIEZAWODNOŚCI SYSTEMU WIELOSTANOWEGO Z USZKODZENIEM SPOWODOWANYM WSPÓLNĄ PRZYCZYNĄ W OPARCIU O SIECI BAYESOWSKIE

Taking account of the influence of common cause failure (CCF) to system reliability and the widespread presence of multi-state system (MSS) in engineering practices, a method for reliability modeling and assessment of a multi-state system with common cause failure is proposed by taking the advantage of graphic representation and uncertainty reasoning of Bayesian Network (BN). The model is applied to a two-axis positioning mechanism transmission system to demonstrate its effectiveness and capability for directly calculating the system reliability on the basis of multi-state probabilities of components. Firstly, the reliability block diagram is built according to the hierarchy of structure and function of multi-state system. Then, the traditional Bayesian Networks model of the transmission system is constructed based on the reliability block diagram, failure logic between components and the failure probability distribution of them. In this paper, the β-factor model is used to analyze the CCF of the transmission system, and a new Bayesian network combining with CCF is established following by the implementation of reliability analysis. Finally, the comparison between the proposed method and the one without considering CCF is made to verify the efficiency and accuracy of the proposed method.

Keywords: *common cause failure (CCF), system reliability, multi-state system (MSS), Bayesian network (BN), β-factor model.*

Uwzględniając wpływ uszkodzeń spowodowanych wspólną przyczyną (CCF) na niezawodność systemów oraz powszechne występowanie w praktyce inżynierskiej systemów wielostanowych (MSS), zaproponowano metodę modelowania i oceny niezawodności systemu wielostanowego z uszkodzeniem spowodowanym wspólną przyczyną, która wykorzystuje reprezentację graficzną sieci Bayesa (BN) i oparte na nich wnioskowanie przybliżone. Model zastosowano do analizy układu przenoszenia napędu dwu-osiowego mechanizmu pozycjonowania. Zbadano w ten sposób skuteczność modelu oraz możliwość wykorzystania go do bezpośredniego obliczania niezawodności systemu na podstawie wielostanowych prawdopodobieństw elementów składowych. W pierwszej kolejności stworzono schemat blokowy niezawodności uwzględniający hierarchię struktury i funkcji badanego systemu wielostanowego. Następnie, w oparciu o schemat blokowy niezawodności, logikę uszkodzeń komponentów oraz rozkład prawdopodobieństwa uszkodzeń tych komponentów, skonstruowano tradycyjny model bayesowski układu przenoszenia napędu. W niniejszej pracy wykorzystano model współczynnika β do analizy CCF układu przenoszenia napędu oraz opracowano nową sieć Bayesa uwzględniającą CCF, po czym przeprowadzono na ich podstawie analizę niezawodności. Skuteczność i dokładność proponowanej metody sprawdzono poprzez porównanie jej z metodą nie wykorzystującą CCF.

Słowa kluczowe: *uszkodzenie spowodowane wspólną przyczyną (CCF), niezawodność systemu, system wielostanowy (MSS), sieci bayesowskie (BN), model współczynnika β.*

1. Introduction

Traditional reliability analysis is based on the assumption that events are binary, i.e., success and complete failure. However, different degrees of damage may have different effects on system performance. In this case, ignoring the partial failure of components and system may result in a huge error between the real system and the mathematical model used for system reliability analysis. Thus, Multi-State System (MSS) reliability analysis has received much attention over the past years [5, 10, 12, 14]. As a kind of complex system consisting of elements with different performance levels, multi-state system (MSS) widely exists in engineering practices, and Barlow and Wu et al. first introduced it in 1978 [5]. The basic concepts of MSS reliability were formulated and the system structure function was defined in Ref. [12]. Since the introduction of generalized multi-state k-out-of-n: G system in [9], many researches on multi-state k-out-of-n: G system modeling and optimization have been carried out [12, 13–16, 19, 21]. For instance, Liu and Kapur [19] established a reliability assessment model on dynamic multi-state non-repairable systems based on non-homogeneous Markov model, and determined a definition of two kinds of reliability measures for system performance. Ramirez-Marquez and Coit [21] presented and evaluated composite importance measures for MSS with multi-state components (MSMC), and a Monte Carlo simulation methodology was used to estimate the reliability of MSMC. An approach for the analysis of multi-state system with dependent elements was proposed by Levitin [14]. In order to analyze reliability of system having components with multiple failure modes, fault tree analysis method was incorporated into MSS by Huang [10]. The universal generating function (UGF) method for MSS reliability analysis was proposed by Ushakov [22], followed by an approach incorporating Markov model with UGF to calculate the reliability of MSS presented by Lisnianski and Levitin [12, 14, 15].

In the conventional system reliability analysis, it is often assumed that components and subsystems are independent. In reality, the common or shared fundamental cause, such as extreme environmental condition or design weaknesses may result in failure in multiple components, which is called Common Cause Failure (CCF). There are two fundamental methods to analyze the reliability of failure system with CCF: implicit method and explicit method [4]. Aiming at the CCF in power substation, the incorporated independent failure and the CCF was proposed in literature [6] by using the dynamic fault tree. Ref. [23] used an implicit method to incorporate CCF with a general procedure into system analysis to simplify the Boolean manipulation and quantification of fault trees. α-Factor model, multiple Greek letters model, and β-factor model etc. are used in the implicit method to estimate and evaluate the CCF in systems. A simplified α-factor model was implemented by Warren [24] to provide practical guidance for reducing complexity of the model, which needs to tailor to specific component failure criteria. BÖRCSÖK J gave details about the estimation and evaluation of common failures and used the β-factor model to assess a 1oo2 system in [4]. Levitin [15] utilized the universal generating function method to analyze system reliability by incorporating CCF into non-repairable MSS. An optimization model of MSS reliability in the presence of CCF was built and solved by Li et al. [13]. However, there is still lack of a general model that can be used to obtain reliability indexes of multi-state system with CCF [30].

Bayesian network (BN), which is based on a well-defined theory of probabilistic reasoning and the ability to express complex dependencies between random variables, has been applied to a variety of practical problems, especially in dependability assessment, risk analysis and maintenance [25]. Static BN was employed by Yin [28] and Zhou [30] to evaluate the reliability of MSS, after which many works have focused on the dynamic models by transforming the dynamic fault trees (DFT) into dynamic BN, the dynamic aspect had been integrated into system modeling and evaluating by Boudali and Dugan which can be referred to Ref. [1, 2]. To deal with the aforementioned issues in system reliability analysis, a multi-state system reliability analysis method is introduced in this paper by incorporating common cause failure into Bayesian network. The proposed method is applied to an engineering example of two-axis positioning mechanism of a satellite antenna.

The remainder of this paper is organized as follows: Section 2 briefly reviews the Bayesian network and introduces the procedure for system reliability CCF modeling. Bayesian network is applied to the multi-state transmission system in Section 3. Section 4 analyzes the reliability of MMS with CCF based on BN. It is demonstrated that BN is able to analyze the multi-state system reliability, and also deal with the common cause problems in multi-state systems.

2. Bayesian network and system reliability CCF modeling

2.1. Bayesian network

Bayesian network (BN), which was first proposed by Pearl [20], is a unique form of graphic description of probability relationships. A BN model typically includes a Directed Acyclic Graph (DAG) and a set of Conditional Probability Tables (CPT). In the directed acyclic graph, there are nodes representing random variables and directed arcs between pairs of nodes representing dependencies between them [7, 20].

Suppose A and B are two random events and the probability $P(B)>0$. Utilizing the Bayesian formula, the conditional probability of A given that B has happened is defined as follows:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

where $P(A)$ is the prior probability. Suppose that A has n possible states i.e. $a_1, a_2, \cdots, a_n$. Based on the total probability formula, $P(B)$ can be expressed as:

$$P(B) = \sum P(B|A = a_i)P(A = a_i) \tag{2}$$

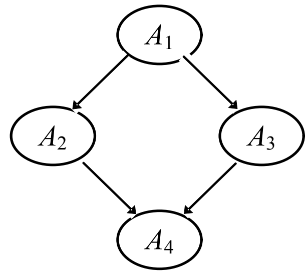

Fig. 1. A simple example of Bayesian network

A simple BN is shown in Figure 1. Here, A_i, i =1, 2, 3, 4 represents an event and the directed arc between any two nodes represents their causal relationships. A_1 does not have any incoming arcs and has no parents, thus it is a root node, which has marginal prior probability. A_2 and A_3 are intermediate nodes. Since A_4 is a node without outgoing arcs and having no children, it is called a leaf node. According to the chain rule of joint probability distribution, the joint probability of all the nodes in the aforementioned graph takes the following form [18],

$$P(A_1, A_2, A_3, A_4) = \prod_{i=1}^{4} P\{A_i | parent(A_i)\}$$
$$= P(A_1)P(A_2|A_1) \cdot P(A_3|A_1, A_2) \cdot P(A_4|A_1, A_2, A_3) \tag{3}$$

Due to the conditional dependence relationship of the events within the Bayesian network, it is convenient to derive the posterior probability from the prior probability as well as implementing reliability assessment of the system. The backward reasoning also makes it possible to evaluate the importance of components and carry out fault diagnosis. Because of the capability of describing the multi-state characteristics and the uncertainty of the logic relationship of events, Bayesian network is suitable for characterizing the random uncertainty and dependency of variables. Therefore, from its state description and inference mechanism, Bayesian network has been used in reliability analysis [7, 27, 28, 30, 31, 32].

2.2. Procedure for system reliability CCF modelling

The key to using BN to construct a CCF model for system reliability is to divide the failure rate λ_t of common cause component into an independent failure rate λ_I and CCF rate λ_c [8]. In this section, the procedure to construct a CCF model for system reliability based on BN will be shown by the modeling of several typical CCF systems. For components with m states, suppose state "1" means that the component is in good condition and state "0" means that the component fails. Between "0" and "1", there are m-2 states representing the different performance levels of the component.

(1) Series system

A series system with n components is the simplest and the most common model used in reliability analysis. Let $R_i(t)$ and $\lambda_i(t)$ denote the reliability and failure rate of component i, and $R_s(t)$ the reliability of the system. The mathematical model of the series system can be formulated as follows [26]:

$$R_s(t) = \prod_{i=1}^{n} R_i(t) = \prod_{i=1}^{n} e^{\int_0^t \lambda_i(t)dt} \tag{4}$$

The BN of a series system with two components (n = 2) considering CCF is shown in Figure 2. Here, X_i (i =1, 2) is a root node, D_1 and D_2 are intermediate nodes. X_i, C and D_1, D_2 are in two separate series.

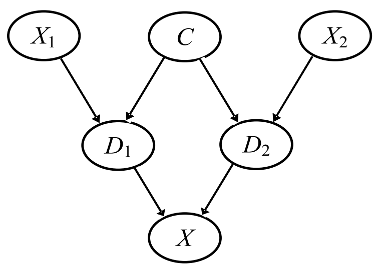

Fig. 2. The BN of series system considering CCF

In this paper, capital letters are used to express the events or the nodes of BN and small letters are variables representing the realization of the random events, so the mathematical expression of the reliability of the two-component series system is [27]

$$\begin{aligned} p(x=1) &= \sum_{x_1,x_2,c,d_1,d_2} p(x_1,c,x_2,d_1,d_2,x) \\ &= \sum_{d_1,d_2} \{p(x=1|d_1,d_2)\cdot \sum_{x_1,c}[p(d_1=1|x_1,c)p(x_1)p(c)] \\ &\cdot \sum_{x_2,c}[p(d_2=1|x_2,c)p(x_2)p(c)]\} \\ &= p(x_1=1)p(x_2=1)p(c=1) \end{aligned} \tag{5}$$

(2) Parallel system

The BN of a parallel system with two components is the same as that in a series system. The difference is that D_1 and D_2 shown in Figure 2 are now in parallel. The mathematical model of this two-component parallel system can be expressed as follows,

$$R_s(t) = 1 - \prod_{i=1}^{n}[1 - R_i(t)] \tag{6}$$

When $X_1 = X_2$, that is the two-components are identical, the expression of system reliability is,

$$\begin{aligned} p(x=1) &= \sum_{x_1,x_2,c,d_1,d_2} p(x_1,c,x_2,d_1,d_2,x) \\ &= \sum_{d_1,d_2}\{p(x=1|d_1,d_2)\cdot\sum_{x_1,c}[p(d_1=1|x_1,c)p(x_1)p(c)] \\ &\cdot\sum_{x_2,c}[p(d_2=1|x_2,c)p(x_2)p(c)]\} \\ &= 2p(x_1=1)p(c=1) - p^2(x_1=1)p(c=1) \end{aligned} \tag{7}$$

3. MSS reliability analysis based on BN

The requirements of high reliability and long lifetime for aerospace products are prevalent with the development of aerospace technology and have become the ultimate goal of the aerospace industry. As a commonly used satellite antenna control mechanism, the two-axis positioning mechanism has an important effect on the pointing accuracy of the antenna, to ensure the reliability of the launch and operation of the satellite [29]. This system has been widely used in military communications satellites, interplanetary exploration satellites, and earth observation satellites [11, 17, 29].

3.1. The two-axis positioning mechanism of the satellite antenna

As a key part for realizing a large range of satellite antenna rotation and high precision of positioning, the two-axis positioning mechanism is prone to failure, therefore, its reliability analysis is of great significance. According to its functions, the entire two-axis positioning mechanism can be divided into two subsystems: the transmission system and the control system. The transmission system achieves accurate positioning of the satellite antenna system through adjusting the direction of the pitch axis and the azimuth axis. Each axis is mainly composed of a motor, a reducer, and the shafts. According to the basic operating principle and the structure of the transmission system shown in Figure 3, the reliability block diagram can be expressed as a parallel-series structure. Each axis consists of stepper motor, drive shaft, and harmonic reducer that follow the series structure. In this paper, the pitch axis and the azimuth axis are simplified as parallel units, i.e. one axis failure does not cause the failure of the entire system.

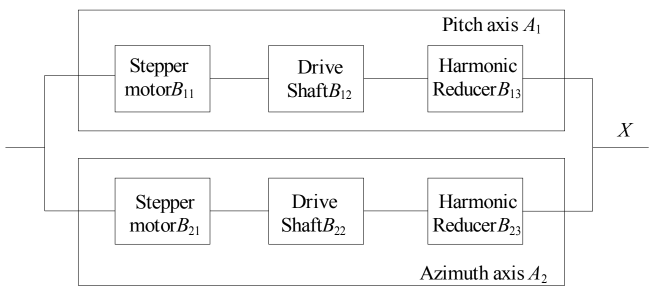

Fig. 3. The reliability block diagram of the transmission system

Since the pitch axis and the azimuth axis of the positioning mechanism are in a parallel structure, the relationship between the states of the two sets of components (A_1 is the state of the pitch axis, A_2 is the state of the azimuth axis) and the system state (X) is as follows: the failure of both sets of components will cause the failure of the whole transmission system. If one set of components is failed and the other is partially failed, the system is failed too. The system is working properly only when the two sets of components are working perfectly.

According to the descriptions above, we consider the two sets of components as two subsystems each with 3 states. Both the stepper motor and the harmonic reducer have 3 states: failure, partial failure, and working. The drive shaft has only 2 states: failure and working. We denote failure with X=0, partial failure with X=1, and working with X=2. The logic operator A_1, A_2 and X can be expressed as follows:

$$a_i = \min(b_{i1}, b_{i2}, b_{i3}) \quad (i=1,2) \tag{8}$$

$$x = \begin{cases} 0 & (a_1 a_2) \in ((00),(01),(10)) \\ 1 & others \\ 2 & (a_1 a_2) \in (22) \end{cases} \tag{9}$$

The Conversion of logic operators A_1, A_2 and X to conditional probability distributions can be obtained:

$$\begin{aligned} &P(a_i = 0 | b_{i1}, b_{i2}, b_{i3}) = 1 \quad b_{i1} \cdot b_{i2} \cdot b_{i3} = 0 \\ &P(a_i = 1 | b_{i1}, b_{i2}, b_{i3}) = 1 \quad others \quad i = 1,2 \\ &P(a_i = 2 | b_{i1}, b_{i2}, b_{i3}) = 1 \quad (b_{i1} b_{i2} b_{i3}) \in (222) \end{aligned} \tag{10}$$

$$\begin{aligned} &P(x = 0 | a_1, a_2) = 1 \quad (a_1 a_2) \in ((00),(01),(10)) \\ &P(x = 1 | a_1, a_2) = 1 \quad others \\ &P(x = 2 | a_1, a_2) = 1 \quad (a_1 a_2) \in (22) \end{aligned} \tag{11}$$

Since the azimuth axis has the same components as the pitch axis, each pitch axis is analyzed using the following multi-state reliability analysis approach.

3.2. Mapping reliability block diagram to Bayesian network

Because of the similarity between the principles of reliability block diagram and Bayesian network, the conversion algorithm of mapping reliability block diagram to Bayesian networks comprises the following steps: firstly, create a root node and assign its state space in the BN for each component of the system. Next, assign the prior probability to root nodes, and then create a corresponding node for each subsystem and assign its state space in the BN, and connect the nodes in the BN. Finally, assign the equivalent conditional probability distribution to the corresponding nodes according to its logic operator [30].

The mapping algorithm is performed on the example transmission system. The topology of the Bayesian network is shown in Figure 4. The conditional probability distribution of A_1 and A_2, which are converted from logic operator A_1 and A_2, are shown in the previous section 3.1.

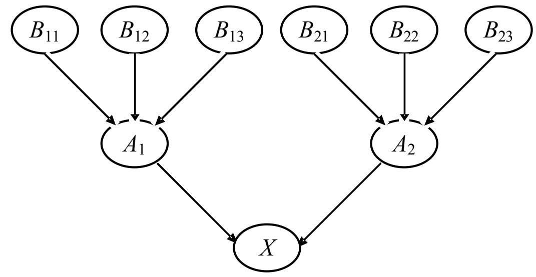

Fig. 4. Bayesian network of the transmission system

Due to the complexity of the two-axis positioning mechanism of satellite antenna and the shortage of data, the probability in each state of a root node are given based on experience [3, 4, 11]. For t = 3000h, the prior probability distribution of the root nodes of the Bayesian network is listed in Table 1 [11].

Table 1. Prior probability distribution of root nodes in Figure 4

Code	0	1	2
B_{i1}	3.0E_04	2.0E_04	9.995E_01
B_{i2}	7.0E_04	X	9.993 E_01
B_{i3}	6.0E_04	4.0 E_04	9.990E_01

3.3. Reliability analysis based on BN

The marginal probability distributions of an intermediate node and a leaf node that correspond to the probability distribution of the subsystems and the system can be obtained easily. In this section, according to equation (5) and (7), the probability of the system being in each state could be determined as follows:

$$p(X = j) = \sum p(b_{11}, b_{12}, b_{13}, a_1, b_{21}, b_{22}, b_{23}, a_2, x) \tag{12}$$

Where $b_{i1}, b_{i3}, a_1, a_2, x \in \{0,1,2\}$, $b_{i2} \in \{0,2\}$ and i=1,2; $j = 0,1,2$.

Combining the former equation with the BN in Figure 4, the detailed expression of system reliability is,

$$\begin{aligned} p(X=2) &= \sum p(b_{11}, b_{12}, b_{13}, a_1, b_{21}, b_{22}, b_{23}, a_2, x) \\ &= \sum_{a_1, a_2} \{ p(x=2 | a_1, a_2) \\ &\cdot \sum_{b_{11}, b_{12}, b_{13}} [p(a_1 | b_{11}, b_{12}, b_{13}) p(b_{11}) p(b_{12}) p(b_{13})] \\ &\cdot \sum_{b_{21}, b_{22}, b_{23}} [p(a_2 | b_{21}, b_{22}, b_{23}) p(b_{21}) p(b_{22}) p(b_{23})] \} \end{aligned} \tag{13}$$

Using the BNT and MATLAB to calculate the marginal probability distributions of A_1, A_2 and the probability of each state of the system X, the result is listed in Table 2 and Table 3.

Table 2. Marginal probability distributions of A_1 and A_2

The states of A_1 and A_2	0	1	2
Prob.	0.001599	0.000599	0.997802

Table 3. Probability of each state of transmission system

The states of *X*	0	1	2
Prob.	0.000004	0.004388	0.995608

4. Reliability analysis of multi-state system with CCF based on BN

When taking hardware redundancy measures, the stability of system could be greatly improved while the other parts of the system will not be changed. Common cause failure has been regarded as a kind of important form of interrelated failure that is present in many mechanical components and systems. Being a major source of the failure of redundant systems, common cause failure increases the joint failure probability of each failure mode of the system and then leads to the reduction of the redundant system reliability.

Interrelated failures may occur to the mechanical components of an aerospace system and a nuclear system with high reliability requirement. The assumption that the failures of different parts of a system are independent, or the correlation of system failure is ignored, always leads to errors when analyzing system reliability [3, 4, 11, 17, 29].

4.1. β-factor model

Since it is difficult to measure the probability of common cause event accurately, the parametric modeling to assign the failure rate of components, such as α-factor model, β-factor model, has become the commonly used quantitative method. These parameter values are based on engineering experience and the published statistics of common cause failures. In this paper, the β-factor model is used to analyze the CCF of the transmission system [3].

Assume that Q_t is the total probability of failure for each component, which can be expanded into an independent contribution Q_I, and a dependent contribution Q_c. The parameter β is defined as the fraction of the total failure probability attributable to dependent failures [4]:

$$\beta = \frac{Q_c}{Q_t} = \frac{Q_c}{Q_I + Q_c} = \frac{(1-\exp(-\lambda_c \cdot t))}{(1-\exp(-\lambda_t \cdot t))} = \frac{(1-\exp(-\lambda_c \cdot t))}{(1-\exp(-\lambda_I \cdot t))+(1-\exp(-\lambda_c \cdot t))} \quad (14)$$

The range of the β-factor is from 0 to 0.25 (0 means no common cause failure) and reflects expert opinions about the β-factor in the range of 0.1% to 10% for hardware failure. If the associated components are sensitive to environmental stressors, it will have a high β-factor [4].

Assuming that the lifetime of all components obeys the exponential distribution, the failure rate of A_1 and A_2 can be computed following section 3 under $\lambda_1 = \lambda_2 = 0.002146$. The operating environment of the two-axis positioning mechanism of satellite antenna is complicated, so it has a high β-factor about 10%. According to equation (14), the dependent failure rate of common cause is $\lambda_c = 3.9194\text{E\_}05$. Table 4 shows the probability of common cause failure.

Table 4. The probability of CCF occurs or not occurs

CCF	Occur (0)	Not occur (2)
Prob.	0.110932	0.889068

4.2. Reliability analysis of two-axis positioning mechanism transmission system with CCF based on BN

Using the proposed method in section 2 and section 3, we can generate the Bayesian network considering CCF, as shown in Figure 5.

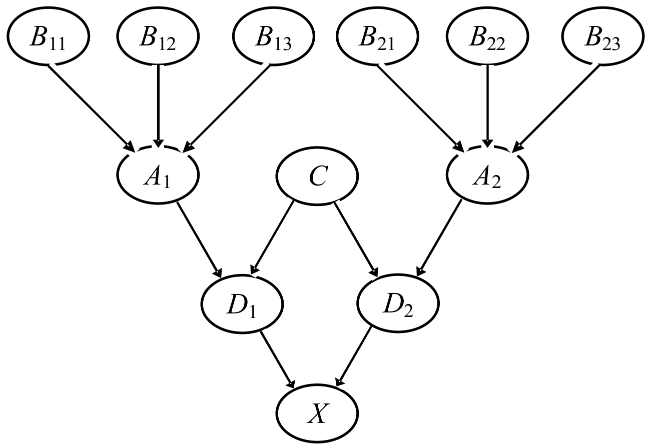

Fig. 5. The BN of transmission system considering CCF

The logic operator and the conditional probability distributions of D_1, D_2 and X are separately listed as the following equations,

$$d_i = \min(a_i, c) \quad (i=1,2) \quad (15)$$

$$x = \begin{cases} 0 & (d_1 d_2) \in ((00),(01),(10)) \\ 1 & others \\ 2 & (d_1 d_2) \in (22) \end{cases} \quad (16)$$

$$\begin{aligned} &P(d_i = 0 | a_i, c) = 1 \quad others \\ &P(d_i = 1 | a_i, c) = 1 \quad (a_i c) \in (12) \\ &P(d_i = 2 | a_i, c) = 1 \quad (a_i c) \in (22) \end{aligned} \quad (17)$$

$$\begin{aligned} &P(x = 0 | d_1, d_2) = 1 \quad (d_1 d_2) \in ((00),(01),(10)) \\ &P(x = 1 | d_1, d_2) = 1 \quad others \\ &P(x = 2 | d_1, d_2) = 1 \quad (d_1 d_2) \in (22) \end{aligned} \quad (18)$$

According to the equation (12) in section 3.3, the detailed expression of system reliability can be determined by equation (19). Finally, the probability of each state of system X considering CCF is listed in Table 5.

$$p(X=2)=\sum p(b_{11},b_{12},b_{13},a_1,d_1,b_{21},b_{22},b_{23},a_2,d_2,c,x)$$
$$=\sum_{d_1,d_2}\{p(x=2|d_1,d_2)$$
$$\cdot\sum_{a_1,c}\{p(d_1|a_1,c)\,p(c)\cdot\sum_{b_{11},b_{12},b_{13}}[p(a_1|b_{11},b_{12},b_{13})]p(b_{11})\,p(b_{12})\,p(b_{13})\}$$
$$\cdot\sum_{a_2,c}\{p(d_2|a_2,c)\,p(c)\cdot\sum_{b_{21},b_{22},b_{23}}[p(a_2|b_{21},b_{22},b_{23})]p(b_{21})\,p(b_{22})\,p(b_{23})\}\} \quad (19)$$

Table 5. Probability of each state of transmission system considering CCF

The states of *X*	0	1	2
Prob.	0.110934	0.003903	0.885163

From Table 5 we know that the probabilities for the transmission system to be in state 0, 1, 2 are $P(X{=}0)$=0.110934, $P(X{=}1)$=0.003803 and $P(X{=}2)$=0.885163. In addition, the reliability of the system is 0.885163 when t = 3000 h.

Comparing the data in Table 3 and Table 5, it is obviously that the probability for the transmission system in state 0 considering CCF in Table 5 is much greater than that in Table 3. That is, CCF has a remarkable effect on reliability of the transmission system in the two-axis positioning mechanism of the satellite antenna. So it is necessary to take measures to avoid or reduce the impact of common cause failure on the system.

5. Conclusion

In this paper, we proposed a Bayesian Network model to analyze the reliability of two-axis positioning mechanism transmission system used in the satellite antenna considering the CCF effects. The result shows that CCF has a considerable impact on the system reliability. This method can clearly express the influence of common cause failure on system reliability and does not require either the computation of minimal cut sets, or the determination of complicated algebraic expression of system unreliability.

In this paper, we only considered the cases where the component reliability states are three and the common cause failure only happened between the pitch axis and the azimuth axis. It should be pointed out that multi-state systems with more complex common cause failures and more states could still be handled using the proposed method. This is because the posterior probability distribution on each common cause and the importance of each component could be calculated conveniently under the Bayesian network framework. Furthermore, the proposed approach on qualitative analysis and quantitative assessment of multi-state system provided a reasonable guidance for system fault diagnosis and maintenance. How to avoid or reduce the impact caused by common cause failure will be investigated in our further work.

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