



Reliability Analysis of Metro Door System Based on Fuzzy Multi-State Bayesian Network

Zhenliang Fu¹, Na Li¹, Xueyan Tian¹, Yonghua Li^{2,*} & Ziqiang Sheng³

¹Product R&D Center, CRRC Tangshan Co., LTD.,
No. 3 Changqian Road, Fengrun District, Tangshan 064000, China

²School of Locomotive and Rolling Stock Engineering, Dalian Jiaotong University,
No. 794 Huanghe Road, Shahekou District, Dalian 116028, China

³School of Mechanical Engineering, Dalian Jiaotong University,
No. 794 Huanghe Road, Shahekou District, Dalian 116028, China

*E-mail: yonghuali@163.com

Highlights:

- The prior probabilities of root nodes with missing data in BN can be obtained by using fuzzy theory.
- The main cause of door system faults were internal module faults of the electronic door control unit (EDCU) according to the bi-directional reasoning of BN.
- The method proposed in this paper provides a new way of diagnosing other machinal systems.

Abstract. Considering the shortcomings of the fault tree analysis (FTA) method in the reliability analysis of metro door systems, Bayesian network (BN) and fuzzy theory were introduced to establish the failure probability model of a metro door system. A fault tree of the metro door system was established based on the structure of the metro door, the operation data record and the practical experience of relevant engineers. The BN of the metro door system was constructed based on the fault tree. For the problem that the prior probabilities of root nodes with missing data were unavailable, fuzzy theory was introduced to convert the expert language values on these missing data nodes to corresponding prior probabilities, which were substituted into the BN along with the root nodes whose prior probabilities were obtained from the operation fault data to calculate the leaf node probability. Cause analysis of the metro door system was performed with bi-directional reasoning of BN, which provided a way to find the key factors that caused door faults and the metro door system fault probabilities.

Keywords: *Bayesian network; fault tree analysis; fuzzy theory; metro door; reliability analysis.*

1 Introduction

As one of the key systems of metro vehicles, the reliability of the metro door system has a solid connection with vehicle operation stability and passenger safety. Due to the large number of stops at platforms during the operation of metro vehicles, the metro doors are opened and closed with high frequency, which results in easy wearing or damaging of the components of the metro door system, which leads to high frequency of metro door faults. This seriously affects the quality of operation of the metro [1]. Therefore, it is necessary to perform a reliability analysis of metro door systems.

FTA is a commonly used method for system reliability analysis, which can clearly and intuitively show the cause of system faults. Besides that, it can also quantitatively measure system reliability and the influence of base events on top events [2]. At present, FTA is mainly used to evaluate system safety and reliability, which has been well applied in many fields [3-5]. However, because of the huge fault tree structure and complex logical relationships in the reliability analysis when FTA faces complex systems, the quantitative calculation is very complicated. Moreover, FTA cannot reflect the correlations between events and it assumes that events in the fault tree only have two states, because of which FTA cannot perform an uncertainty analysis [6]. Bayesian network (BN) can consider the uncertainty of events and describe multi-state events. Moreover, unlike FTA, BN has bi-directional reasoning ability. Due to these advantages of BN, it can effectively make up for the shortcomings of FTA, which make it widely used in reliability analysis [7-9]. Because of the similar structure between fault tree and BN, many scholars choose to convert fault tree to BN to use it for reliability and safety analysis of complex systems. Wang [10] proposed a diagnosis method for lubrication systems based on FTA and BN, which realized fault decoupling and diagnosis. Chiremsel [11] proposed a probabilistic fault diagnosis method based on FTA and BN. Fault diagnosis software for safety instrumented systems has been developed based on this method. Chen [12] evaluated the falling risk in the process of bridge construction by transforming the fault tree into BN and verified the effectiveness of the method with practical engineering cases.

However, the research results mentioned above were based on the prior probability of each root node in the BN, which was previously acquired. Fuzzy theory can be introduced when the prior probabilities of some root nodes are not available because of the incompleteness of the fault data record in engineering practice [13]. Triangular fuzzy numbers are used to convert expert language values into prior probabilities of these missing data nodes [14]. Prior probabilities obtained by expert language values and operation data records are both put into a multi-state BN that is constructed for a reliability analysis based on the FTA of

a metro door system. The reasoning ability of the BN can help the maintainer to quickly find out fault sources and provide a reference for improving the reliability of the metro door system.

2 The Basic Theory of Multi-State BNs

BNs are developed on the basis of the Bayesian theorem and consist of a directed acyclic graph (DAG) and a conditional probability table (CPT). The nodes in the DAG include root nodes, intermediate nodes and leaf nodes, which represent different variables respectively. The directed edge connecting different nodes qualitatively represents the relationship between nodes, while the CPT describes the relationship quantitatively.

The equation for calculating the posterior probability of a node in a BN can be expressed in Eq. (1) as follows:

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

where $P(A)$ is the prior probability of the node; $P(B|A)$ is the probability of event B under the occurrence of event A . If A is a variable with n states ($A=a_1, a_2, a_3, \dots, a_n$), $P(B)$ can be expressed in Eq. (2) as follows:

$$P(B) = \sum_{i=1}^n P(B|A=a_i)P(A=a_i) \quad (2)$$

In engineering practice, the states of components and systems often show multiple fault modes. These different states are interconnected and can be transformed into one another, which means that the boundary between two different states is blurred. This fuzziness brings difficulties to system reliability analysis. BN can consider both multi-state events and the logical uncertainty of events, which makes it closer to engineering practice. Moreover, BN cannot only calculate the posterior probabilities of events but also perform cause analysis based on existing fault data by bi-directional reasoning.

3 Treatment for Fuzzy Probability with Triangular Fuzzy Number

3.1 Triangular Fuzzy Number

The prior probabilities of some part nodes cannot be obtained because the metro operation data records are incomplete, because of which the reliability analysis based on BN cannot be performed. Therefore, triangular fuzzy numbers are

introduced to express the fuzzy probabilities of the root nodes. It is worth mentioning that the reason for choosing triangular fuzzy numbers rather than DS theory is that triangular fuzzy numbers are more general in terms of application and easier to implement. The fuzzy probabilities are transformed into prior probabilities of root nodes with defuzzification. The membership function of triangular fuzzy numbers can be expressed in Eq. (3) as follows:

$$\mu(x) = \begin{cases} (x-a)/(b-a) & a \leq x \leq b \\ (c-x)/(c-b) & b < x \leq c \\ 0 & \text{Others} \end{cases} \quad (3)$$

where a , b and c represent the three parameters of the triangular fuzzy number and the triangular fuzzy number is denoted as (a, b, c) ; x is an arbitrary element in the universe. The two triangular fuzzy numbers $\tilde{A}=(a_1, b_1, c_1)$ and $\tilde{B}=(a_2, b_2, c_2)$ have the following algorithms. The sum of \tilde{A} and \tilde{B} can be expressed in Eq. (4) as follows:

$$\tilde{A} \oplus \tilde{B} = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (4)$$

If there is a real number m , \tilde{A} / m can be expressed in Eq. (5) as follows:

$$\tilde{A} / m = (a_1 / m, b_1 / m, c_1 / m) \quad (5)$$

3.2 Detailed Steps for Dealing with Fuzzy Probabilities

The following steps are used to convert language values to accurate probabilities.

1. The language values are converted into triangular fuzzy probabilities. The evaluation results of the i -th root node x_i in state j are given by several experts. The evaluation results of the k -th expert are transformed into the triangular fuzzy probability of node x_i . The triangular fuzzy number of the i -th root node x_i in state j that is given by the k -th expert can be expressed in Eq. (6) as follows:

$$\tilde{P}_{ij}^k = (a_{ij}^k, b_{ij}^k, c_{ij}^k) \quad k=1, 2, \dots, q \quad (6)$$

where q is the number of experts participating in the evaluation.

2. The mean value of the obtained triangular fuzzy probabilities should be calculated. The average triangular fuzzy probability of the i -th node in state j is obtained by the arithmetic average method, considering the experts' evaluation synthetically, and it can be expressed Eq. (7) as follows:

$$\tilde{P}_{ij}^* = \frac{\tilde{P}_{ij}^1 \oplus \tilde{P}_{ij}^2 \oplus \cdots \oplus \tilde{P}_{ij}^q}{q} = (a_{ij}^*, b_{ij}^*, c_{ij}^*) \quad (7)$$

3. The average triangular fuzzy probability in step (2) should be clarified. The mean area method [15] is used to convert the fuzzy probability into an accurate probability value. The accurate probability of the i -th node in state j can be expressed Eq. (8) as follows:

$$P_{ij}^* = \frac{a_{ij}^* + 2b_{ij}^* + c_{ij}^*}{4} \quad (8)$$

4. To make the sum of the different node probabilities in different states 1, the probabilities of each node in different states need to be normalized. The normalization formula can be expressed Eq. (9) as follows:

$$P_{ij} = P_{ij}^* / \sum_{j=0}^r P_{ij}^* \quad (9)$$

where r represents the state number of the i -th node.

4 Practical Engineering Example

4.1 Calculation of Prior Probabilities from Language Values

In this study, the fault tree of a metro door system was established referring to a metro operation data record and the practical experience of metro vehicle designers. The fault tree structure is shown in Figure 1. The corresponding symbols for all events are shown in Table 1. Most of the events' prior probabilities in the fault tree could be obtained by statistical analysis of the operation data record of the metro line. However, the probabilities of motor bearing faults and motor circuit faults could not be directly obtained due to missing operation data records. Therefore, it was necessary to get the prior probabilities of the motor bearing faults and the motor circuit faults with the help of expert experience and triangular fuzzy numbers.

In engineering practice, the bear fault states of a motor can be divided into three states, i.e. *normal state*, noted as 0, *stuck state* that can still be operated, noted as 1, and *serious fault state*, noted as 2. The drive motor circuit states can be divided into *normal*, noted as 0, *short circuit*, noted as 1 and *open circuit*, noted as 2. In order to convert the expert language value into prior probabilities of events, seven language values are introduced: very high (VH), high (H), medium high (MH), medium (M), medium low (ML), low (L), very low (VL).

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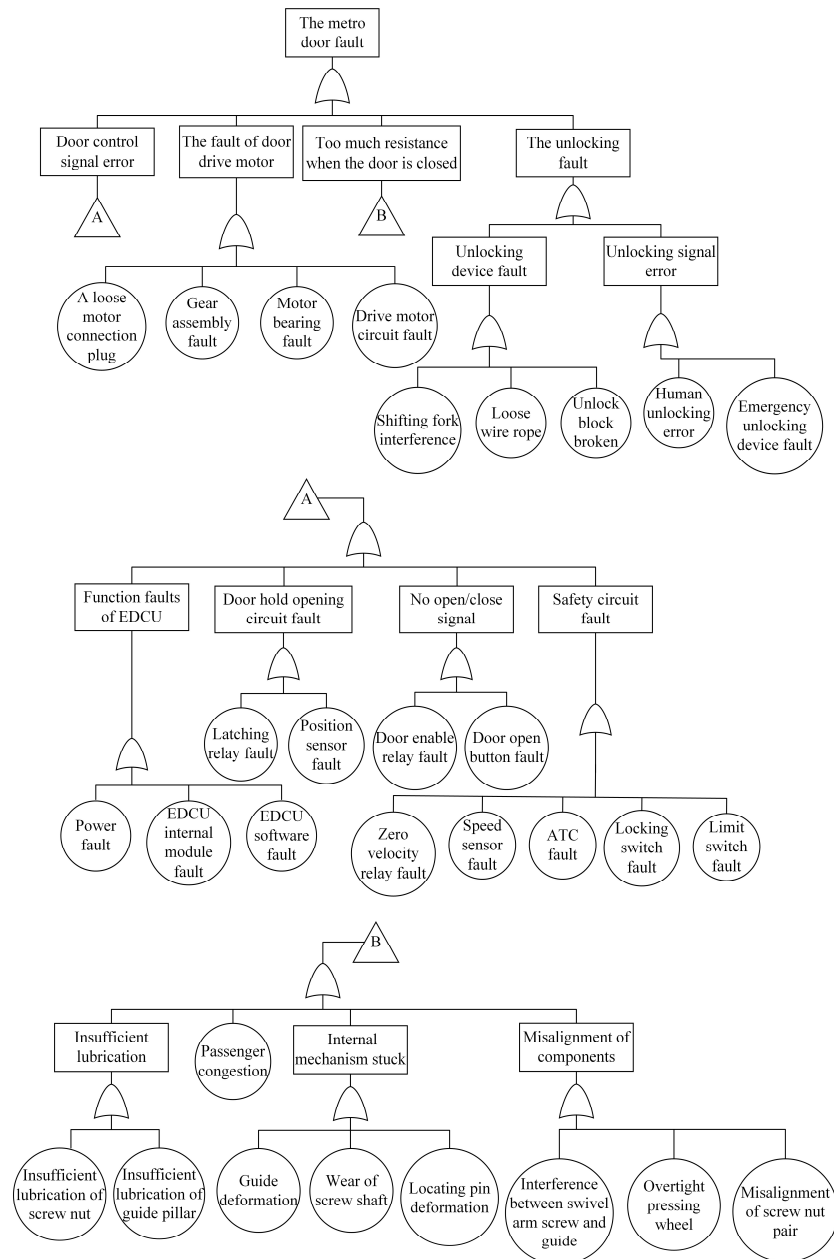


Figure 1 Fault tree of the metro door system.

Table 1 Symbols for all events.

Symbol	Event description	Symbol	Event description
T	Metro door fault	x_9	Speed sensor fault
y_1	Door control signal error	x_{10}	ATC fault
y_2	Door drive motor fault	x_{11}	Locking switch fault
y_3	Over resistance when the door is closed	x_{12}	Limit switch fault
y_4	Unlocking fault	x_{13}	A loose motor connection plug
y_5	Unlocking device fault	x_{14}	Gear assembly fault
y_6	Unlocking signal error	x_{15}	Motor bearing fault
y_7	Function faults of EDCU	x_{16}	Drive motor circuit fault
y_8	Door hold opening circuit fault	x_{17}	Insufficient lubrication of screw nut
y_9	No open/close signal	x_{18}	Insufficient lubrication of guide pillar
y_{10}	Safety circuit fault	x_{19}	Passenger congestion
y_{11}	Insufficient lubrication	x_{20}	Guide deformation
y_{12}	Stuck internal mechanism	x_{21}	Wear of screw shaft
y_{13}	Misalignment of components	x_{22}	Locating pin deformation
x_1	Power fault	x_{23}	Interference between swivel arm screw and guide
x_2	EDCU internal module fault	x_{24}	Over tight pressing wheel
x_3	EDCU software fault	x_{25}	Misalignment of screw nut pair
x_4	Latching relay fault	x_{26}	Shifting fork interference
x_5	Position sensor fault	x_{27}	Loose wire rope
x_6	Door enable relay fault	x_{28}	Unlock block broken
x_7	Door open button fault	x_{29}	Human unlocking error
x_8	Zero velocity relay fault	x_{30}	Emergency unlocking device fault

The corresponding triangular fuzzy numbers for the seven language values are defined in Table 2, which refers to relevant technical literature and the engineering practice experience of technical engineers who have been engaged in design work in related fields for many years [16]. The evaluation of the four

experts on different states of the *motor bearing fault* and *motor circuit fault* events are shown in Table 3.

Table 2 Language values of events and their triangular fuzzy numbers.

Language value	Triangular fuzzy number	Language value	Triangular fuzzy number
VH	(0.9, 1.0, 1.0)	ML	$(1 \times 10^{-4}, 2 \times 10^{-4}, 2.5 \times 10^{-4})$
H	(0.8, 0.9, 1.0)	L	$(0, 5 \times 10^{-5}, 8 \times 10^{-5})$
MH	(0.7, 0.8, 0.9)	VL	$(0, 0, 1 \times 10^{-7})$
M	(0.2, 0.3, 0.4)		

Table 3 Expert evaluation of the events states.

Symbol	States	Expert 1	Expert 2	Expert 3	Expert 4
x_{15}	0	H	MH	M	H
	1	ML	ML	L	ML
	2	L	VL	VL	L
x_{16}	0	H	MH	H	H
	1	ML	ML	L	VL
	2	L	L	L	L

According to Eq. (7), the mean value of the triangular fuzzy probabilities in each event state is calculated as follows:

$$\tilde{P}_{15\ 0}^* = (0.625000, 0.725000, 0.825000),$$

$$\tilde{P}_{15\ 1}^* = (0.000075, 0.000163, 0.000208),$$

$$\tilde{P}_{15\ 2}^* = (0.000050, 0.000125, 0.000165),$$

$$\tilde{P}_{16\ 0}^* = (0.850000, 0.950000, 0.975000),$$

$$\tilde{P}_{16\ 1}^* = (0.000050, 0.000113, 0.000145),$$

$$\tilde{P}_{16\ 2}^* = (0.000000, 0.000050, 0.000080);$$

The obtained average fuzzy probabilities are transformed into accurate probabilities according to Eq. (8). The accurate probability of events in each state is as follows:

$$P_{15\ 0}^* = 0.725000, P_{15\ 1}^* = 0.000152, P_{15\ 2}^* = 0.000116,$$

$$P_{16\ 0}^* = 0.931250, P_{16\ 1}^* = 0.000105, P_{16\ 2}^* = 0.000045;$$

The normalization result of the accurate probabilities is obtained based on Eq. (9), as follows:

$$P_{15\ 0} = 0.999630, P_{15\ 1} = 0.000209, P_{15\ 2} = 0.000160, \\ P_{16\ 0} = 0.999839, P_{16\ 1} = 0.000113, P_{16\ 2} = 0.000048;$$

The calculated prior probabilities of the two missing data events are shown in Table 4. In order to show the detailed calculation process, $P_{15\ 0}^*$ will be taken as an example. According to Table 3 and Eq. (7), we can get

$$\tilde{P}_{15\ 0}^* = (0.625000, 0.725000, 0.825000)$$

The accurate probability of $P_{15\ 0}^*$ can be gotten based on Eq. (8):

$$P_{15\ 0}^* = 0.725000$$

Table 4 Prior probabilities of motor bearing fault and motor circuit fault.

Event description	States		
	0	1	2
Motor bearing fault	0.999630	0.000209	0.000160
Motor circuit fault	0.999839	0.000113	0.000048

4.2 Establishment of Bayesian Network Based on Fault Tree

The main steps for transforming the fault tree into a BN are as follows:

1. Create a root node in the BN for each basic event in the fault tree. The repeated events in the fault tree should be reduced to one single root node in the BN.
2. Specify that the root node has the same probability as the basic event in the fault tree.
3. Create intermediate nodes for each intermediate event.
4. Connect the intermediate nodes with the node corresponding to the basic event that causes the intermediate events.
5. Determine the node CPT in the BN according to the corresponding logic gate in the fault tree.

The BN in Figure 2 was constructed based on the fault tree structure shown in Figure 1. Assuming that there are only two states, *normal* and *fault*, for the other nodes, except nodes x_{15} and x_{16} , which were recorded as 0 and 1, respectively, the prior probability of each root node is shown in Table 5. The CPT of intermediate nodes can be obtained according to the logical relationship in the fault tree.

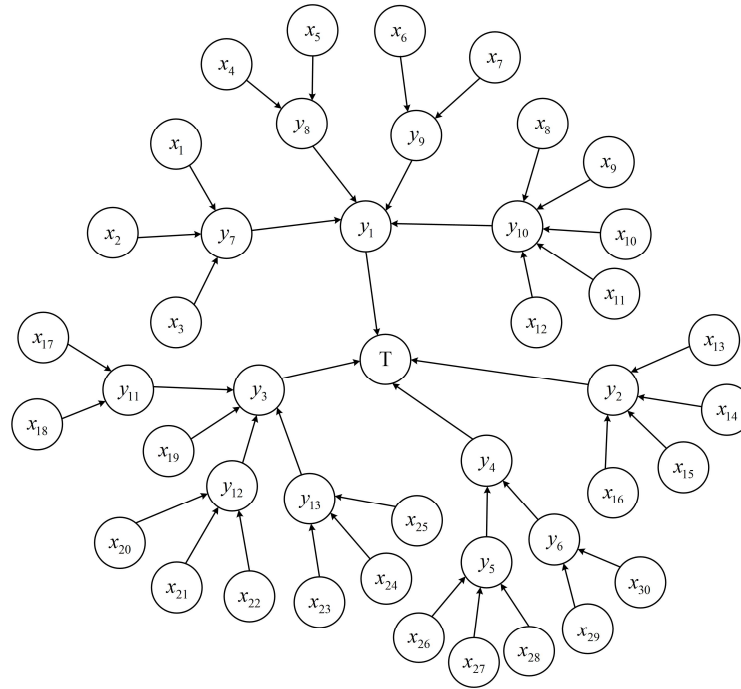


Figure 2 Topology of the Bayesian network.

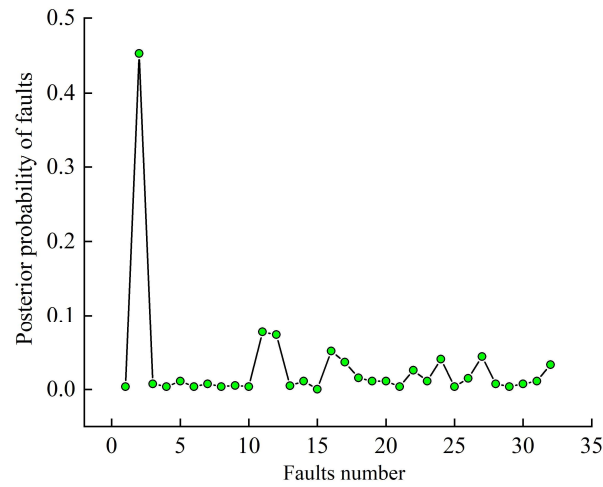
4.3 Bi-Directional Reasoning of Bayesian Network

A reliability analysis program for the metro door system was compiled based on BN, which took the junction tree algorithm (JTA) [17] as the reasoning algorithm for the BN. Causal reasoning of BN was performed. The prior probabilities of the root nodes and the CPT of intermediate nodes were imported into the BN program. The probability of door system faults was calculated to be 0.003096.

Assuming that a door system fault has occurred, the posterior probability of each root node was calculated by cause analysis of the BN. The posterior probability distribution of each fault is shown in Figure 3. The six faults with high posterior probability were: *EDCU internal module fault*, *locking switch fault*, *limit switch fault*, *bear serious fault*, *locating pin deformation* and *misalignment of screw nut pair*, according to the analysis in Figure 3, which is under the condition that a door system fault has occurred. The analysis results show that components relevant to the faults with high posterior probability were weak links that caused door system faults. Therefore, risk control should give priority to the relevant components of the above six fault modes to improve the door reliability during the door design and maintenance phases.

Table 5 Prior probabilities of root nodes.

Root nodes	States			Root nodes	States		
	0	1	2		0	1	2
x_1	0.999989	0.000011	—	x_{16}	0.999839	0.000113	0.000048
x_2	0.998598	0.001402	—	x_{17}	0.999966	0.000034	—
x_3	0.999977	0.000023	—	x_{18}	0.999966	0.000034	—
x_4	0.999989	0.000011	—	x_{19}	0.999989	0.000011	—
x_5	0.999966	0.000034	—	x_{20}	0.999920	0.000080	—
x_6	0.999989	0.000011	—	x_{21}	0.999966	0.000034	—
x_7	0.999977	0.000023	—	x_{22}	0.999875	0.000125	—
x_8	0.999989	0.000011	—	x_{23}	0.999989	0.000011	—
x_9	0.999983	0.000016	—	x_{24}	0.999954	0.000046	—
x_{10}	0.999989	0.000011	—	x_{25}	0.999863	0.000137	—
x_{11}	0.999761	0.000239	—	x_{26}	0.999977	0.000023	—
x_{12}	0.999772	0.000228	—	x_{27}	0.999989	0.000011	—
x_{13}	0.999984	0.000015	—	x_{28}	0.999977	0.000023	—
x_{14}	0.999966	0.000034	—	x_{29}	0.999966	0.000034	—
x_{15}	0.999630	0.000209	0.000160	x_{30}	0.999897	0.000103	—

**Figure 3** Posterior probability distribution of faults.

5 Conclusions

This work established a BN for metro door system faults based on fault tree analysis, which avoids many disjunction calculations in the quantitative analysis of FTA and improves the analysis efficiency. The analysis result was more in line with engineering practice due to the consideration of multi-state events and correlations. Triangular fuzzy numbers were introduced to transform the language values of experts into the prior probabilities of the root nodes in the BN for the problem that some prior probabilities cannot be obtained because of missing operation data records. The introduction of triangular fuzzy numbers improves the ability of BN to deal with uncertain multi-state problems, which expands the application field of BN. The posterior probability of each fault is calculated with the help of BN under the condition that a door system fault has occurred. The key components causing the door system faults are identified, which provides theoretical support and a reference for vehicle production and daily maintenance.

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