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The Reliability Analysis of Horizontal Vibration of Elevator Based on Multi-State Fuzzy Bayesian Network

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Abstract

Reliability analysis is one of the important constituent parts of elevator safety evaluation. In order to obtain the exact value of fault probability of components in elevator system, by combining fuzzy theory with Bayesian network approach, we proposed a reliability analysis method of multi-state system based on fuzzy Bayesian networks. By expanding the traditional two-state Bayesian network to multi-state system, multi-state Bayesian network model of horizontal vibration of elevator is established. The language variable of the root probability is transformed into triangular fuzzy numbers under different states. After equalization, defuzzification and normalization, the precision probabilities can be gotten and then introduced to the multi-state Bayesian network model. The posterior probability and the probability importance degree of various root nodes are calculated with multi-state Bayesian network algorithm. The result can provide quantitative evaluation for the reliability of multi-state horizontal vibration of the elevator. Compared with the fuzzy fault analysis method based on T-S, the method we proposed is valid.

***Keywords**: Reliability Analysis; Fuzzy Theory; Bayesian Network; Horizontal Vibration*

1. Introduction

The elevator's vibration is one of the important indicators of measuring the quality of the elevator [1]. With the increase of high-rise buildings and the speed of elevators, elevator vibration will exacerbate [2]. Studies have shown that the horizontal vibration of the elevator has a linear relationship with its running speed [3]. Lots of factors can cause horizontal vibration of the elevator, mainly including manufacturing and fixing errors of rail, the guide wheel shape of the rolling guide shoes, the static equilibrium of the car and the change of passenger load, hoist way overall and hoist way airflow, the car speed [4].

Currently, the elevator fault diagnosis methods mainly include fault diagnosis method based on fault tree, fault diagnosis method based on expert system, fault diagnosis method based on artificial neural networks, fault diagnosis method based on information fusion, and so on. Zong et al. [5] proposed a fault diagnosis method of elevator based on fault tree expert system and established the fault diagnosis model of the elevator system and expert knowledge, thus solving the problem of obtaining expert system knowledge and poor integrity of knowledge. The literature [6] used the method of combining fault tree and expert system to improve the diagnosis accuracy in the elevator fault diagnosis. Zong et al. [7] applied BP neural network to solve the problem of traditional expert systems and achieved good results in the failure of the elevator. Li et al. [8] applied the information fusion technology to equipment fault diagnosis according to the multi-information characteristics of electrical fault diagnosis, improving the accuracy and reliability of fault diagnosis. Although these methods have a very good application prospects in the elevator system fault diagnosis and reliability analysis, their applications are limited because of the complicated calculation process.

In recent years, many methods of system reliability have been proposed and applied with the development of reliability theory, such as reliability block diagram analytical method [9], fault tree analysis method [10], binary decision diagram analytical method [11], importance analysis method of fuzzy fault tree based on T-S model [12], and Bayesian network analysis methods [13-14]. Bayesian network, proposed by Pearl in 1988, can express and analyze the uncertainty of information well and bi-directional reasoning of reliability of the system can be achieved. BN can describe polymorphism of events and non-deterministic logical relation, so it has a very good application in reliability, fault diagnosis and other fields [15-16]. Meanwhile, Bayesian network based on probability theory and graph theory has both solid mathematical foundation and intuitive semantics, which is an effective model to express the knowledge of uncertainty and the theory of reasoning [17]. Bayesian network not only has strong modeling capabilities, but also has a strong inference mechanism. With the complex of Bayesian network model, inference algorithms [18] tends to be perfect and simple and can solve well the probability problem of each node in Bayesian network model.

The multi-state fuzzy Bayesian network is applied to the elevator system. Because it is difficult to obtain the exact probability of each factor causing horizontal

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vibration of the elevator, it is obtained through the method of group decision-making with the help of the expertise. Then the expertise is transferred into triangular fuzzy function to obtain precise priori probabilities of BN nodes. At last, the important factors are gotten, causing the car horizontal vibration.

2. Multi-State Bayesian Network Overview

Bayesian network, BN for short, is a graphical network based on probabilistic inference. BN is composed of a DAG (directed acyclic graph) and certain CPT (conditional probability tables). The directed graph is called DAG (directed acyclic graph) if the directed graph cannot be from one point to the original point after a number of edges. DAG consists of representative variable node and directed edges connecting these nodes, in which nodes present variables and directed edges represent the relationship between variables. DAG describes the network structure of BN, which is the qualitative part. CPT is a table indicating the number dependence relationships of probability between the variable and its parent node, which describes network parameters of the BN, so it is quantitative section. According to the Bayesian formula, the definition of the conditional probability is given:

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

Where P(A) is priori probability; P(A/B) is posterior probability; P(B/A) is likelihood ratio.

If A is a multi-state variable having the states of ($a_1, a_2, \cdots, a_n$), the definition of the total probability formula is:

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

An obvious advantage of Bayesian network is bidirectional inference , i.e. causal reasoning and diagnostic reasoning. Causal reasoning is deduced from the priori probability to posterior probability that means that results are deduced by the reason. The process of diagnostic reasoning is contrary to that of causal reasoning. The probability of the working network can be calculated through bidirectional reasoning when any one or more of the variable nodes are given because the node variable of Bayesian network is independent. Then the probability of any one or more fault nodes can be calculated through the reverse inference when the network is fault, which can diagnose the weak link of the network. Bayesian network uses bucket elimination algorithm [19] to conduct the causal inference of network and uses Bayesian formula to conduct diagnostic reasoning, thus achieving bidirectional inference of Bayesian network.

According to the chain rule, when BN has many nodes $X_1, X_2, \cdots, X_n$, the joint distribution is:

$$P(X_1, X_2, \cdots, X_n)=\prod_{i=1}^{n}P(X_i/Pa_i) \tag{3}$$

Therefore, the complex BN can be simplified and disassembled with the help of conditional independence among variables nodes.

3. Multi-State Bayesian Network Model of Horizontal Vibration of the Elevator

Multi-state system is divided into discrete multi-state system and continuous multi-state system. This thesis mainly discusses discrete multi-state system. For example, a system has normal operating state, degraded working condition and completely failed state. Usually 0, 1, 2 are used to represent the three states.

3.1. Modeling Steps

Bayesian networks analyze various causes of fault (network nodes) from part to whole, from bottom to top, which are dendrites. First, we determine the network nodes, the root node of the network represents the basic event of the system and the leaf node represents the system. Then we identify discrete systems and multi-states of system components. Finally, the probability of each state of component is given. Since the probability of each state of component is difficult to obtain, it is obtained through a language variable given by the expertise. The directed arc of Bayesian network represents the dependency relationship between variables, and probability distribution table shows the dependence degree between variables. Then priori probability information and sample knowledge are combined.

3.2. Modeling Construction

Many factors can affect the horizontal vibration of the elevator, but the present article considers and analyzes the factors from the aspects of guidance system and car system. Guidance system consists of guide shoes, guide rails and rack components.

3.2.1. Each Node of the Model

Various factors affecting the horizontal vibration are mainly analyzed from the following two aspects: (1) Guidance system: the guide wheel shape of rolling guide shoe, surface profile of elevator guide rail, the installation quality of elevator guide rail, and (2) Car system: static equilibrium of the car and the load size of the passenger. Each influence factor can be seen as the root node of the Bayesian network. The surface profile and installation quality of elevator guide rail are quality problem of the guide, which can be seen as an intermediate node. The horizontal vibration of the elevator can be seen as the leaf node of the network.

3.2.2. Logical Relationships between Nodes

Logical “and” relationships are between surface profile of elevator guide rail and quality of the installation of the elevator guide rail and between static equilibrium of the car and the load size of the passenger. Each factor will lead to the occurrence of the above event. Logical “or” relationships are between the guide wheel shape of rolling guide shoe and the problem of guide quality and between guidance system and the car system. Each factor has three states. For example, the surface profile of the guide has three different states: the ideal state with small roughness, the normal state with the roughness within a reasonable range and large roughness having a serious impact on horizontal vibration.

3.2.3. The Model of Horizontal Vibration of Elevator under the Influence of Guidance System and Car System

The Bayesian network model of elevator horizontal vibration is established based on the logical relationship between the factors.

The root nodes X_1, X_2, X_3, X_4 and X_5, respectively, represent the surface profile of the elevator guide rail, the installation quality of the elevator guide rail, the guide wheel shape of the rolling guide shoe, the static equilibrium of the car, and the load size of passenger. A_1, A_2 and A_3 are used respectively to signify guidance system, car system and the quality of guide rail. T represents the leaf node. Each node has three states that are shown by using state space $\{0,1,2\}$. 0 represents the normal state, 1 represents semi-fault state, and 2 represents completely failed state. According to the dependencies between nodes, directed arcs are used to connect root node with leaf node to indicate the relationship between parent and offspring. Then the status space of all nodes and the conditional probability of the intermediate node are determined. Bayesian network model of horizontal vibration elevator is shown in Figure 1. The conditional probability tables of the node are omitted due to the limited space.

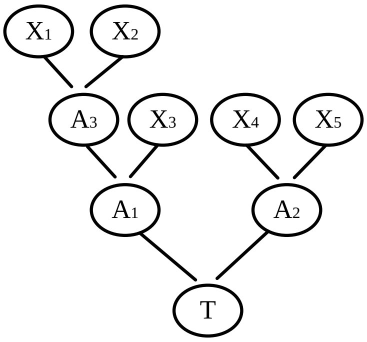

Figure 1. The Bayesian network model of horizontal vibration of elevator

4. The Analysis of Multi-State Bayesian Network Model of Horizontal Vibration of Elevator

4.1. Fuzzy Approach

The horizontal vibration factors are often in a variety of fault conditions in the elevator. The different fault conditions are interrelated and mutually transformed in the process of fault change. Fault state is often manifested as “this and that” state. In other words, it is fuzzy. The presence of ambiguity makes it difficult to obtain an exact probability value of each state. For example, the installation quality of the elevator guide rail may change when the surface profile of elevator guide rail changes. Thus, it is difficult to determine the installation quality of the elevator guide rail. Here, a fuzzy number is used to process this condition. The forms of fuzzy numbers are various, such as a triangular fuzzy number, a trapezoidal fuzzy number, a rectangular fuzzy number and an irregular shaped fuzzy number. The triangular fuzzy number is used to represent the probability of occurrence because the reference function of the triangular fuzzy is more convenient to handle and algebra is relatively easy. A form of membership function of the triangular fuzzy number is the following:

$$\mu(x) = \begin{cases} \max(0, \dfrac{x-a}{m-a}), x \le m \\ \max(0, \dfrac{b-x}{b-m}), x > m \end{cases} \qquad (4)$$

Therefore, the triangular fuzzy number can be represented by three parameters: “ a ”, “m” and “b” denoted by (a,m,b). For two triangular fuzzy numbers $A=(a_1,m_1,b_1)$ and $B=(a_2,m_2,b_2)$, the algorithm [20] is the following:

The sum of two numbers:

$$A \oplus B = (a_1+a_2, m_1+m_2, b_1+b_2) \qquad (5)$$

A precise number K exists, then:

$$\frac{A}{k} = (\frac{a_1}{k}, \frac{m_1}{k}, \frac{b_1}{k}) \qquad (6)$$

If

The result is gotten through group decision-making approach with the help of expertise under the condition of not being able to obtain exactly the state probability of event. In order to connect judging result of event probability given by expert with fuzzy number, we introduce seven language variables [21] of “very high”, “high”, “on the high side”, “secondary”, “on the low side”, “low”, “very low”. Table 1 is the corresponding relation between language variable and fuzzy number. Figure 2 is the membership function of triangular fuzzy numbers.

Table 1. Semantics value of event occurring probability and corresponding triangular fuzzy

Sequence number	Semantics value	triangular fuzzy number
1	very high	（0.9，1.0，1.0）
2	high	（0.7，0.9，1.0）
3	on the high side	（0.5，0.7，0.9）
4	secondary	（0.3，0.5，0.7）
5	on the low side	（0.1，0.3，0.5）
6	low	（0，0.1，0.3）
7	very low	（0，0，0.1）

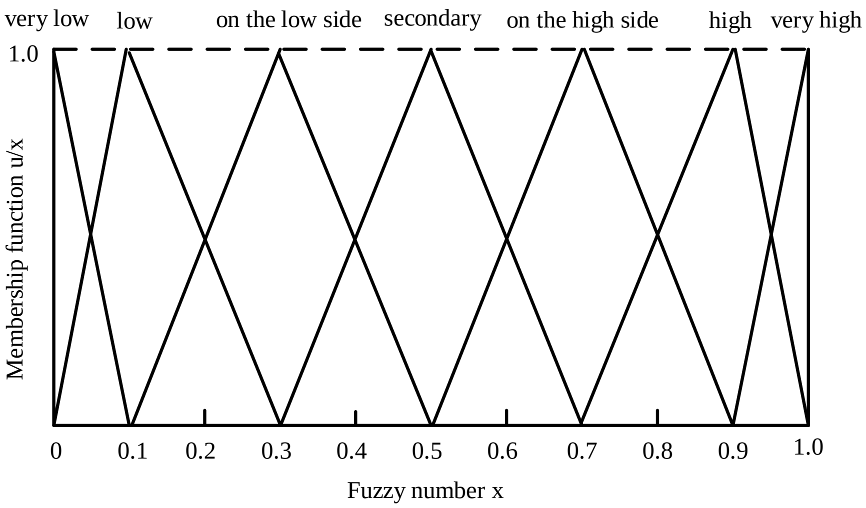

Figure 2. Membership function of triangular fuzzy number

The information of expertise is transformed into a fuzzy number expressed by a triangular fuzzy number through the above method.

4.2. The Probability Importance of Multi-State Bayesian Network:

Four experts estimate occurring probability of each root node in each state in horizontal vibration of elevator. They have been working in the elevator industry for many years and know the affecting factor of the horizontal vibration of elevator well. Language variable is gotten by the experts independently. In the evaluation process, the experts should consider comprehensively the using environment, production quality and frequency of failures in recent years of the various components. And the language variable of the same node given by different expert is different because every expert has a different opinion considering their familiarity, the extent grasping or human factors. Then the language variable is transformed into a fuzzy probability. The language variables of the expert and the corresponding fuzzy number are shown in Table 2.

Table 2.Experts' opinion of root nodes in different states

Root node		**Expert 1**	**Expert 2**	**Expert 3**	**Expert 4**
X_1	0	high (0.7,0.9,1.0)	very high (0.9,1.0,1.0)	high (0.7,0.9,1.0)	high (0.7,0.9,1.0)
	1	low (0,0.1,0.3)	very low (0,0,0.1)	low (0,0.1,0.3)	very low (0,0,0.1)
	2	very low (0,0,0.1)	low (0,0.1,0.3)	on the low side (0.1,0.3,0.5)	low (0,0.1,0.3)
X_2	0	high (0.7,0.9,1.0)	on the high side (0.5,0.7,0.9)	on the high side (0.5,0.7,0.9)	secondary (0.3,0.5,0.7)
	1	on the low side (0.1,0.3,0.5)	on the low side (0.1,0.3,0.5)	low (0,0.1,0.3)	low (0,0.1,0.3)
	2	low (0,0.1,0.3)	low (0,0.1,0.3)	on the low side (0.1,0.3,0.5)	very low (0,0,0.1)
X_3	0	very high (0.9,1.0,1.0)	very high (0.9,1.0,1.0)	very high (0.9,1.0,1.0)	high (0.7,0.9,1.0)
	1	very low (0,0,0.1)	very low (0,0,0.1)	low (0,0.1,0.3)	very low (0,0,0.1)
	2	very low (0,0,0.1)	low (0,0.1,0.3)	low (0,0.1,0.3)	low (0,0.1,0.3)
X_4	0	high (0.7,0.9,1.0)	on the high side (0.5,0.7,0.9)	high (0.7,0.9,1.0)	secondary (0.3,0.5,0.7)
	1	on the low side (0.1,0.3,0.5)	low (0,0.1,0.3)	low (0,0.1,0.3)	very low (0,0,0.1)
	2	low (0,0.1,0.3)	very low (0,0,0.1)	on the low side (0.1,0.3,0.5)	on the low side (0.1,0.3,0.5)
X_5	0	on the high side (0.5,0.7,0.9)	very high (0.9,1.0,1.0)	secondary (0.3,0.5,0.7)	on the high side (0.5,0.7,0.9)
	1	low (0,0.1,0.3)	on the low side (0.1,0.3,0.5)	very low (0,0,0.1)	very low (0,0,0.1)
	2	very low (0,0,0.1)	low (0,0.1,0.3)	on the low side (0.1,0.3,0.5)	low (0,0.1,0.3)

According to Table 2, the language variable of root node X_2, which is the probability of the state of 0 given by the first expert, is transformed into fuzzy probability $\tilde{P}_{20}^1 = (0.7,0.9,1.0)$.

In order to transform the experts' opinion into a relatively reasonable fuzzy probability, four experts' evaluation results are synthesized by using arithmetic average method. Average formula of fuzzy probability of the root node X_i （$i=1$, 2, 3） in the state of j is:

$$\tilde{P}_{ij}' = \frac{P_{ij}^1 \oplus P_{ij}^2 \oplus \cdots \oplus P_{ij}^4}{4} = (a_{ij}', m_{ij}', b_{ij}') \tag{7}$$

According to formula (7), the fuzzy probability mean of the root node in each state is shown in Table 3.

Table 3.: Fuzzy probability of the root node in different states

Fuzzy probability	**State j**		
	0	**1**	**2**
$\tilde{P}_{1j}'$	（0.75,0.925,1）	（0,0.05,0.2）	（0.025,0.125,0.3）
$\tilde{P}_{2j}'$	（0.5,0.7,0.875）	（0.05,0.2,0.4）	（0.025,0.125,0.3）
$\tilde{P}_{3j}'$	（0.85,0.975,1）	（0,0.025,0.15）	（0,0.075,0.25）
$\tilde{P}_{4j}'$	(0.55,0.75,0.9)	(0.025,0.125,0.3)	(0.05,0.175,0.35)
$\tilde{P}_{5j}'$	(0.55,0.725,0.875)	(0.025,0.1,0.25)	(0.025,0.125,0.3)

In order to transform fuzzy probability into exact probability, we use "mean area method" [22] to resolve the ambiguity of fuzzy probability. The exact probability of the root node X_i in the state of j is

$$P_{ij}' = \frac{a_{ij}' + 2m_{ij}' + b_{ij}'}{4} \tag{8}$$

According to formula (8), the exact probability mean of each root node in different states is shown in the Table 4.

Table 4. The exact probability of each root node in different states

Fuzzy probability	**State j**		
	0	**1**	**2**
P_{1j}'	0.9	0.0750	0.14375
P_{2j}'	0.69375	0.2125	0.14375
P_{3j}'	0.95	0.0500	0.1
P_{4j}'	0.7375	0.14375	0.1875
P_{5j}'	0.71875	0.11875	0.14375

In order to make the sum of the probability of the root node in various states be one, we conduct "normalization" on exact probability of the root node in various states. After the normalization, the exact probability of root node X_i in the state of j is:

$$P_{ij} = \frac{P_{ij}'}{\sum_{j=0}^{2} P_{ij}'} \tag{9}$$

According to the above formula, the exact probability mean of each root node in different states is shown in Table 5.

Table 5. After the normalization, the exact probability of each root node in different states

Fuzzy probability	State j		
	0	1	2
P_{1j}	0.804469	0.067039	0.128492
P_{2j}	0.660714	0.202381	0.136905
P_{3j}	0.863636	0.045455	0.090909
P_{4j}	0.690058	0.134503	0.175439
P_{5j}	0.732484	0.121019	0.146497

The probability of intermediate nodes and leaf nodes in different states can be calculated through priori probabilities of the root node in various states obtained by the above method and the known conditional probability. According to Bayesian formula, we use the bucket elimination method to calculate the posterior probability of the root node in various states.

The probabilities of leaf node in different states are gotten by algorithms of multi-state BN. $P_{T0}=0.739$, $P_{T1}=0.131$, $P_{T2}=0.130$. And then the probability of the root node in various states is obtained when the leaf node T is in different states, which is shown in Table 6.

Table 6.The posterior probability of different root nodes

T		0	1	2
X_1	0	0.862	0.577	0.708
	1	0.047	0.186	0.059
	2	0.091	0.237	0.233
X_2	0	0.708	0.474	0.581
	1	0.174	0.385	0.178
	2	0.118	0.141	0.241
X_3	0	1	0.667	0.285
	1	0	0.333	0.015
	2	0	0	0.700
X_4	0	0.753	0.458	0.568
	1	0.107	0.311	0.111
	2	0.140	0.231	0.321
X_5	0	0.799	0.486	0.603
	1	0.091	0.312	0.100
	2	0.110	0.202	0.297

Importance degree is a quantitative index of reflecting the influence of each component on the top event in the reaction system. According to different conditions, the importance degree has many definitions. Structural importance degree, probability importance degree and key importance degree are applied widely in practical production. In addition, importance degree can make the quantitative analysis of the safety and reliability of the system, which is important in systematic reliability.

Among them, probability importance degree reflects the role of basic event to the top event. And it can compare the importance of various events in the system [23]. When the state of multi-state system is ε , probability importance degree formula of the component j is:

$$I_{\varepsilon}^{\Pr}(X_j)=\frac{\sum_{\tau=1}^{M_j} I_{\varepsilon}^{\Pr}(X_j^{\tau})}{M_j} \tag{10}$$

Where M_j represents the non-zero state total number of the component j , $I_{\varepsilon}^{\Pr}(X_j)$ represents the evaluation of probability importance degree under the system state of ε when the component j is in different state.

The value of probability importance degree can be calculated by the above formula (10).

$I_1^{\Pr}(X_1)=0.303$, $I_1^{\Pr}(X_2)=0.192$, $I_1^{\Pr}(X_3)=0.480$, $I_1^{\Pr}(X_4)=0.238$, $I_1^{\Pr}(X_5)=0.259$

5. The Comparison with the Fuzzy Fault Analysis Based on T-S

T-S probability importance degree is calculated on the basis of T-S importance degree calculation method proposed by the literature [12] when the state of the top event is 1. It is shown in the Table 7.

Table 7. T-S probability importance degree of fuzzy probability when the fault states of the essential event are 1 and 2

Probability importance	**Fault state**	
	1	**2**
$I_1^{\Pr}(X_1)$	0.362422	0.241162
$I_1^{\Pr}(X_2)$	0.248564	0.134755
$I_1^{\Pr}(X_3)$	0.957160	0
$I_1^{\Pr}(X_4)$	0.302467	0.171630
$I_1^{\Pr}(X_5)$	0.336677	0.179992

The formula $I_{T_q}^{\Pr}(X_j)=\dfrac{\sum_{i_j=1}^{k'_j} I_{T_q}^{\Pr}(X_j^{(i_j)})}{k'_j}$ is used, where k'_j means the number when the part j is in the fault degree of 1 and 2. k'_j is two because the fault degree is described by fuzzy 0,1,2.

The probability importance that is the basic event X_1 to top event T is gotten by generally considering T-S probability importance of the basic event X_1 in the fault condition 1 and 2.

$$I_1^{\Pr}(X_1)=[I_1^{\Pr}(X_1^1)+I_1^{\Pr}(X_1^2)]/2=0.302$$

Similarly, T-S probability importance of each basic event is available.

$I_1^{\Pr}(X_1)=0.302$, $I_1^{\Pr}(X_2)=0.192$, $I_1^{\Pr}(X_3)=0.479$, $I_1^{\Pr}(X_4)=0.237$, $I_1^{\Pr}(X_5)=0.258$

The comparison of results calculated by two different methods is shown in Table 8.

Table 8. Comparison between the probability importance degree calculated by this method and T-S probability importance degree calculated by the fuzzy fault analysis method

The results	**Classification**	
	probability importance degree calculated by this method	T-S probability importance degree calculated by the fuzzy fault analysis method
$I_1^{\Pr}(X_1)$	0.303	0.302
$I_1^{\Pr}(X_2)$	0.192	0.192
$I_1^{\Pr}(X_3)$	0.480	0.479
$I_1^{\Pr}(X_4)$	0.238	0.237
$I_1^{\Pr}(X_5)$	0.259	0.258

The following conclusion can be gotten.

1. The calculation results obtained through T-S fuzzy fault tree analysis are similar to that with the method proposed by the author, which verifies the correctness of the result that is calculated by the above method. The important order of each basic event is $R_3 > R_1 > R_5 > R_4 > R_2$.
2. When we use T-S fault tree analysis to calculate we can only calculate the probability in accordance with the structure of T-S fuzzy fault tree one by one from the bottom event to the higher event until the top event. This approach will generate a lot of calculations and can not be bidirectional inference, while the Bayesian network is not only simple operation and analysis but also can be bidirectional inference. Therefore, the Bayesian network is more suitable for engineering application.

6. Conclusion

The triangular fuzzy number instead of language variable is used to describe the component fault probability, which solves the problem that the exact value of fault probability is difficult to obtain. Defuzzification of the fuzzy probability is conducted by using "mean area method", so the fuzzy information contained in operation is removed. The quantitative analysis and calculations of the system is realized, and the analytical results obtained are more clearly.

Currently Bayesian network in the elevator system reliability analysis is relatively limited. The application of Bayesian networks is expanded by combining fuzzy theory with Bayesian network. The importance degree of many factors affecting the elevator horizontal vibration is obtained by the importance analysis, and then the elevator is maintained and checked according to the importance degree. This can not only improve the reliability of the normal operation of the elevator, but also improve the maintenance efficiency.

Failure logical relational among components is determined. How to consider the ambiguity of failure probability and the uncertainty of failure logical relational among components will be the further research focus when failure logical relational is uncertainty.

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