

Research Article

Reliability Analysis of Special Vehicle Critical System Using Discrete-Time Bayesian Network

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The reliability assessment of special vehicles has become very important. However, due to the special structure of special vehicles, it is difficult to collect a large amount of experimental data. The use of traditional fault tree analysis cannot accurately assess product reliability. In this paper, dynamic fault trees are used to model the critical systems of special vehicles, and discrete Bayesian networks are used to evaluate the reliability of critical systems of special vehicles, which solved the problems of difficulty in accurately describing complex systems in the process of system reliability analysis and difficulty in obtaining accurate data in the process of analysis. Finally, through the combination of expert experience and the evaluation of the calculation results, the rationality of the method used in this paper in the reliability evaluation of special vehicles is verified.

1. Introduction

In recent years, the dynamic characteristics of the heavy Ammonium Nitrate/Fuel Oil (ANFO) vehicle are more obvious with the increase of parts or subsystems with dynamic characteristics. The conventional reliability analysis methods such as static fault tree are applied to calculate the reliability of ANFO. These methods usually do not consider dynamic correlation of parts in the system, such as sequence enforcing relationship, functional dependency, and spare relationship. It is widely used in various engineering fields, and the analysis accuracy can meet the engineering requirements as discussed by Mi et al. [1]. However, modern equipment such as the heavy ANFO vehicle has complex systems and cannot use the conventional fault tree to describe dynamic correlation [2]. Therefore, the reliability analysis of the subsystem with dynamic characteristics is the emphasis and difficulty of reliability analysis for the heavy ANFO vehicle.

Fault tree analysis is a risk assessment method to improve the traditional fault tree analysis, mainly for the study of uncertainty in qualitative and quantitative risk assessment procedures [3, 4]. The reliability analysis of the dynamic fault

tree can be carried out by Markov chain, cut sequence, extended cut sequence, module method, and Bayesian network as discussed by Fang et al. [2, 5]. In the initial stage of dynamic fault tree research, the minimum cut sequence is solved by the mixed integral formula, and then, the dynamic fault tree can be analyzed. Many scholars have extended the dynamic fault tree analysis method. Tremyasov and Tremyasov [6] established the dynamic fault tree model of the wind turbine generator and used Markov to calculate their operational reliability. Because the state explosion problem of Markov chain limits its application, Boudali and Dugan [3] proposed using the Bayesian network to solve dynamic fault tree, and a method of transforming dynamic fault tree logic gates into the Bayesian network was developed. Li et al. [2, 7] estimated the reliability of floating offshore wind turbines and their crucial systems by Bayesian networks. Li et al. [4] abandoned the global state modeling method and used the continuous time Bayesian network to analyze the dynamic fault tree. Meanwhile, the fuzzy number was applied to describe the parameter uncertainty caused by insufficient failure data. In the initial study of the dynamic fault tree, the distribution of spare parts' nodes can only be

exponential distribution. Li et al. [8] solved this limitation through an in-depth study. Ge et al. [9, 10] developed Sequential Binary Decision Diagrams (SBDDs) based on the BDD method and used the improved ITE (if-then-else) algorithm to avoid generating invalid nodes when building SBDDs. Some scholars divided the dynamic fault tree model into the parental Markov condition and other condition using the modular method. The former was analyzed by establishing the Markov model, while the latter was reasoned by building the Bayesian network model as discussed by Yuge et al. [11]. Although many scholars had studied SBDDs to optimize its state space explosion, computational efficiency, and application scope, there were still some limitations compared with the Bayesian network method as discussed by Mi et al. [1], Zhang et al. [12], and Zhang et al. [13]. Because of the disadvantages of the discrete-time Bayesian network, many scholars had further improved it. The accuracy and efficiency of the Bayesian network was greatly improved by the error compensation. The failure probability can be accurately calculated even in a short time interval as discussed by Lan et al. [14]. The collection of reliability data, as in [15–18], improved the accuracy of evaluation using multisource information fusion. Due to the complex state of nodes, the dynamic fault tree cannot be solved and reasoned manually and software was needed. Dugan [19] proposed Galileo, which is a prototype software tool for dynamic fault tree reliability analysis. It is mainly used to construct and analyze the dynamic fault tree containing the sequential failure mode. Firstly, it divides the dynamic fault tree into several subsystems. Then, a subsystem is transformed into a submodel based on BDD and Markov chain. Finally, the reliability of these submodels is analyzed as discussed by Dugan et al. [19, 20]. In recent years, RAATSS and Matlab tools are widely used in the reliability analysis of dynamic fault tree models because of their high accuracy and simple modeling. The dynamic fault tree analysis method had been used in the reliability analysis for different systems in various fields. It had obtained fruitful research results and had great significance for improving the reliability of the system. The advantage of the discrete-time Bayesian network is more obvious with the development. Therefore, this paper will apply it to analyze the reliability of the heavy ANFO vehicle.

2. Dynamic Fault Tree

The static fault tree is a graphical expression, which is widely used in reliability analysis of complex engineering. The static fault tree model can intuitively describe the combined failure form of parts that cause system failure. However, complex engineering equipment is not only affected by the external environment but also the relationship between internal parts. The reliability modeling of the system is facing great difficulties because of the correlation between parts. To solve such problems, Dugan et al. [20] proposed some dynamic logic gates to describe the relevance of parts. The method can well describe the temporary characteristic and dynamic failure behavior of the system (see [21]). In addition to using the logic gates of the static fault tree, this method added four

dynamic logic gates: priority-AND (PAND) gate, function dependency (FDEP) gate, sequence enforcing (SQE) gate, and spare gate.

2.1. Priority-AND. The input events of PAND are base events or the output event of the logical gate. The failure mechanism of PAND is that the output event occurs if the input events occur in the order from left to right. Assuming that a PAND has three input events, its graphical symbols are shown in Figure 1. When B fails before A , C fails before A or B and C fail before A at the same time; the output event of the PAND fails.

2.2. Function Dependency. The input events of FDEP contain a trigger event and one or more related events. Basic events or other logic gates can be used as trigger events. Input events of other logic gates can be used as output events. Assuming that an FDEP has two related events A and B and a trigger event Tr , the dynamic logic gates are shown in Figure 1. When A or B fails or Tr fails to cause A and B failures, the output event fails.

2.3. Sequence Enforcing. Although both SQE and PAND describe the temporary characteristic of the system, they differ from each other in input event and failure mechanisms. There are multiple basic events in the input event of SEQ. The failure mechanism of SEQ is that all the base events occur in a certain order. Assuming that SQE has n basic event inputs, its graphical symbol is shown in Figure 1. The output event will fail only if input events fail in the order of 1 to n .

2.4. Spare. The spare gate consists of a set of spare parts and a main part. When the main part fails, the transfer switch starts to make the spare part run. The condition for the failure of the spare parts' door is that all spare parts fail. In the spare gate, there is a dormancy factor. According to the size of the dormancy factor, the spare gate has the following states: cold spare (CSP), warm spare (WSP), and hot spare (HSP). The graphical symbols are shown in Figure 2. The dormancy factor of the three logic gates is $\alpha = 0, 0 < \alpha < 1$, and $\alpha = 1$, respectively.

In CSP gate, the base event enters the working state when the system begins to work, while the spare parts are in a nonworking state. After the failure of the base event, the spare event begins to work until all spare events fail.

The input of WSP is same as CSP. CSP do not fail before they are used. But WSP may have failed before they are used. It has two kinds of failure processes. The first is that the spare parts do not fail and can continue to work after the failure of the main part. The second is that the warm parts have failed before the failure of the main part.

The inputs of the warm spare part are same as WSP. The base event and spare parts of HSP operate at the same time. If a base event fails, the spare part becomes a base event. If all spare parts fail, the system fails.

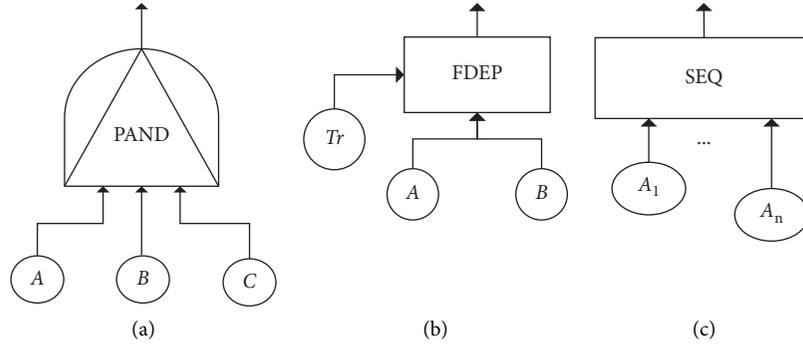


FIGURE 1: Dynamic logic gates. (a) Priority-AND. (b) Functional dependency. (c) Sequence enforcing.

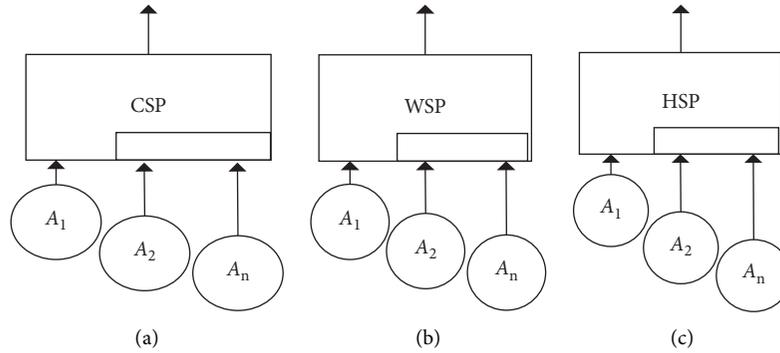


FIGURE 2: Spare gate.

3. Bayesian Network

3.1. *The Principle of Bayesian Network.* The direction of the directed line of the Bayesian network can be regarded as the causality of random variables. For a two-state system with n components, variables are defined as $Y_i, i = 1, 2, \dots, n$. The Bayesian network aggregates multiple random variables, which can represent the logical relationship between

random variables. The direction of the directed line can be regarded as the causality of random variables, when there are n components in the system. Assuming that all variables are not independent, variables are defined as $Y_i, i = 1, 2, \dots, n$. The chain rule can be used to describe the joint probability distribution, as shown in

$$P(Y_1, Y_2, \dots, Y_n) = P(Y_1)P(Y_2|Y_1) \dots P(Y_n|Y_1, Y_2, \dots, Y_{n-1}) = \prod_{i=1}^n P(Y_i|Y_1, Y_2, \dots, Y_{i-1}). \quad (1)$$

When the Bayesian network is established, the relationship between nodes is determined first. In addition to input nodes and output node, the node is conditionally independent from other remaining nodes. If $pa(Y_i) \subseteq \{Y_1, Y_2, \dots, Y_{i-1}\}$, Y_i is independent in $\{Y_1, Y_2, \dots, Y_{i-1}\}$. Its joint probability distribution is shown in

$$P(Y_1, Y_2, \dots, Y_n) = \prod_{i=1}^n P(Y_i|\delta pa(Y_i)), \quad (2)$$

where $pa(Y_i)$ is the set of input nodes for node Y_i .

3.2. *Discrete-Time Bayesian Network.* The discrete-time Bayesian network is a modeling and evaluation method for

nonrepairable systems, and it is an event-based Bayesian network. In discrete-time Bayesian networks, it is assumed that each event in the system can only occur once in the timeline.

The discrete Bayesian network divides the assumed task time interval $[0, t]$ into n equal parts. The length of each interval is defined as $\Delta = t/n$. Finally, it contains nondiscrete intervals $[t, +\infty]$, which are divided into $n+1$ subintervals. Time interval is defined as when a node fails in time interval $[(i-1)\Delta, i\Delta]$. If $i \leq n$, it indicates that the node failed during the task time. When a node fails in time interval $[n\Delta, +\infty]$, the state of the node is marked as $n+1$. Therefore, the time intervals corresponding to the state space of all nodes are defined as $[0, \Delta], [\Delta, 2\Delta], \dots, [(n-1)\Delta, n\Delta], [n\Delta, +\infty]$. The state is marked as $\{1, 2, \dots, n, n+1\}$. The unreliability of the

system at task time t is the sum of the probabilities of the first n states. The reliability of the system at time t is the probability of state $n+1$. Each state represents the behavior of the node in the corresponding time interval. If the node indicates a system failure, the division of the node indicates that the default system fails in the node. If the node indicates the gate, then the node is in this state, which means the gate output in the corresponding time interval.

3.3. Transform of Dynamic Fault Tree and Bayesian Network.

The transformation between the dynamic fault tree and Bayesian network includes two parts: one is the transformation of the structure between the dynamic fault tree and Bayesian network; the other is the establishment of the conditional probability table for nonroot nodes as discussed by Jiang and Gao [8].

3.3.1. Static Logic Gate. Static logic gates contain AND gate and OR gate. If $A = [A_1, A_2, \dots, A_m]$, where m is the number of input events for static logic gates, $A_i, i = 1, 2, \dots, m$, are input events. Assuming that B is the state variable of the output variable for the static logic gate and its state space is $\{1, 2, \dots, n+1\}$. If it is AND gate, then $j = \max(A_1, A_2, \dots, A_m)$. If it is OR gate, then $j = \min(A_1, A_2, \dots, A_m)$. The probability distribution of output event B is shown in

$$P(B = k|A) = \begin{cases} 1, & k = j, \\ 0, & k \neq j. \end{cases} \quad (3)$$

The AND/OR gate of the Bayesian network transformation is shown in Figure 3.

3.3.2. Function Dependency. An FDEP of Bayesian network transformation is shown in Figure 4. An FDEP contains a trigger event Tr and two input events A and B . The conditional probability t is shown as

$$P\{A = j|Tr = i\} = \begin{cases} F(j\Delta) - F((j-1)\Delta), & 0 < j < i, \\ 1 - F((i-1)\Delta), & j = i, \\ 0, & \text{other.} \end{cases} \quad (4)$$

3.3.3. Spare. WSP and HSP have the same way for building the Bayesian network, but their conditional probability tables are different (see Figure 5); A represents the main part; B represents the spare part. Assuming that the distribution function of the main component is $F(t)$. The distribution function of the spare part in the reserve period is $F_\alpha(t)$. After the warm spare parts are converted from the warm reserve state to the working state, the previous working process is ignored. In other words, after entering the working state, the failure probability of the component at time t is $F(t - t_0)$, where t_0 is the time when the reserve component starts to work normally.

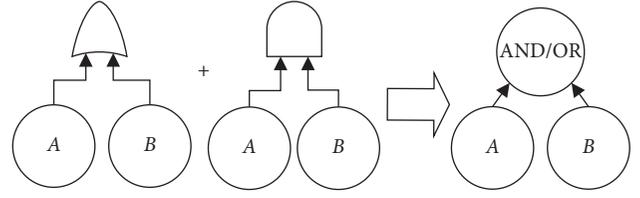


FIGURE 3: Bayesian network model of AND gate and OR gate.

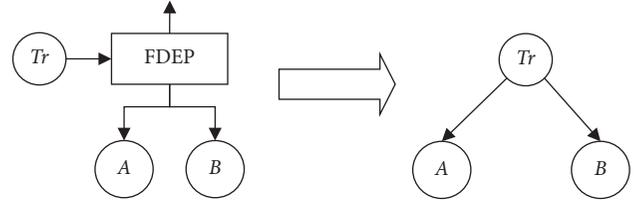


FIGURE 4: Bayesian network model of FDEP.

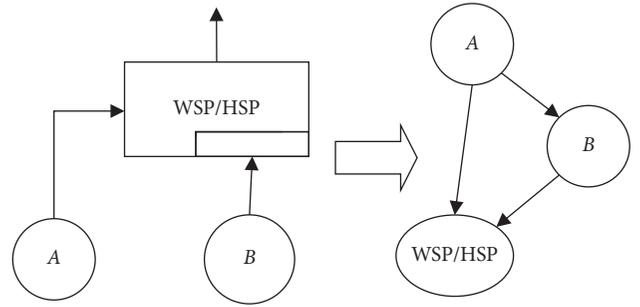


FIGURE 5: Bayesian network model of WSP and HSP.

Assume that t_0 when the reserve component starts to work is exactly an integer multiple of Δ . Since the component failure distribution can satisfy the human failure form, the conditional probability of failure of the reserve component in a certain time interval cannot be given analytically. When A fails in time interval i and B fails in time interval j ($i < j \leq n$), the failure probability is shown in

$$\Pr\{B = j|A = i\} = F((j-i)\Delta) - F((j-i-1)\Delta). \quad (5)$$

The conditional probability table of node B is shown in

$$\Pr\{B = j|A = i\} = \begin{cases} F_\alpha(j\Delta) - F_\alpha((j-1)\Delta), & 0 < j \leq i, \\ F((j-i)\Delta) - F((j-i-1)\Delta), & i < j \leq n, \\ 1 - \sum_{p=1}^n \Pr\{B = p|A = i\}, & h = n+1. \end{cases} \quad (6)$$

For CSP, the main part cannot directly cause output event failure, so there is no direct relationship between the main part and output event. Its Bayesian network takes on a chain shape. Its conditional probability table only needs dormancy factor $\alpha = 0$ in WSP.

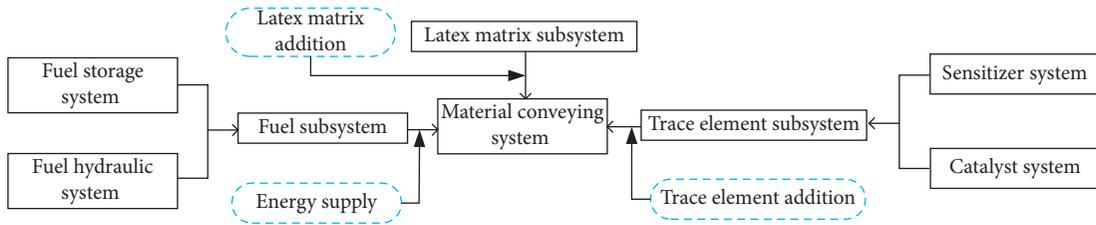


FIGURE 6: Material conveying system schematic.

TABLE 1: The table of event coding.

Event	Encoding
Material conveying system failure	T
Fuel filter failure	Tr1
Sensitizer filter failure	Tr2
Catalyst filter failure	Tr3
Fuel subsystem failure	A1
Latex matrix subsystem failure	A2
Trace element subsystem failure	A3
Fuel pipeline failure	B1
Hydraulic subsystem failure	B2
Fuel storage subsystem failure	B3
Latex matrix storage subsystem failure	B4
Latex matrix pump subsystem failure	B5
Latex matrix pipeline failure	B6
Sensitizer system failure	B7
Catalyst system failure	B8
Hydraulic joint failure	C1
Hydraulic control valve I failure	C2
Hydraulic control valve II failure	C3
Storage subsystem I failure	C4
Storage subsystem II failure	C5
Sensitizer hydraulic subsystem failure	C6
Sensitizer storage subsystem failure	C7
Sensitizer pipeline failure	C8
Catalyst hydraulic subsystem failure	C10
Catalyst storage subsystem failure	C11
Catalyst pipeline failure	C12
Catalyst pump subsystem failure	C13
Washer of float flowmeter failure	X1
Fuel pump failure	X2
Fuel pipe sealing ring failure	X3
Fuel pipe joint failure	X4
Fuel pipe failure	X5
Fuel inlet joint failure	X6
Hydraulic joint of fuel pipe failure	X7
Washer of fuel return pipe failure	X8
Fuel throttle valve failure	X9
Two-position four-way electro-hydraulic valve failure	X10
Fuel pipe of liquid level meter failure	X11
Fuel liquid level meter failure	X12

TABLE 1: Continued.

Event	Encoding
Fuel tank failure	X13
Latex matrix tank failure	X14
Latex matrix tank thermometer failure	X15
Latex matrix pump failure	X16
Flange sealing washer failure	X17
Rubber washer failure	X18
Latex matrix pump joint failure	X19
Latex matrix pump hose failure	X20
Sealing washer failure	X21
Butterfly valve failure	X22
Latex matrix pump rubber pipe failure	X23
Joint failure	X24
Clip failure	X25
Hose reel failure	X26
Two-position four-way solenoid valve failure	X27
Sensitizer pipe failure	X28
Sensitizer tank failure	X29
Liquid level display tube failure	X30
Sensitizer tank screw failure	X31
Sensitizer flowmeter failure	X32
Sensitizer hose failure	X33
Sensitizer hose joint failure	X34
Sensitizer hose jaw failure	X35
Sensitizer pump failure	X36
Sensitizer pump hose failure	X37
Fuel throttle valve failure	X38
Two-position four-way electro-hydraulic valve failure	X39
Latex matrix tank failure	X40
Latex matrix tank thermometer failure	X41
Catalyst flowmeter failure	X42
Two-position four-way solenoid valve failure	X43
Catalyst pipe failure	X44
Catalyst tank failure	X45
Liquid level display tube failure	X46
Catalyst box screw failure	X47
Catalyst rubber tube failure	X48
Catalyst hose joint failure	X49
Catalyst pump failure	X51
Catalyst pump rubber tube failure	X52

4. Reliability Modeling and Analysis of Material Conveying System

4.1. *Dynamic Fault Tree.* In order to ensure the accuracy of the establishment of the model, it is necessary to fully understand the main subcomponents contained in the research object system and the logical relationship between the

various components before modeling. FMEA technology can sort out the logical relationships between the components in the system as well as failure modes [22, 23]. The ANFO vehicle material conveying system consists of three main systems. They are a fuel subsystem composed of a fuel storage system and a fuel hydraulic control system and a trace element subsystem composed of a sensitizer subsystem and a catalyst subsystem. The third is the latex matrix subsystem, which works, as shown in Figure 6.

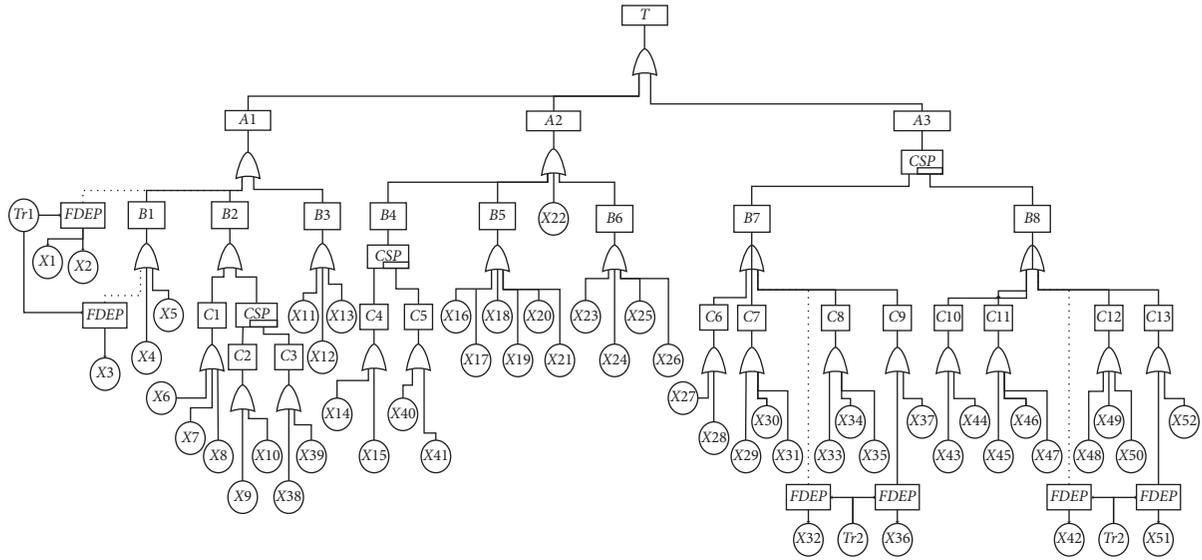


FIGURE 7: The diagram of the dynamic fault tree of the material conveying system.

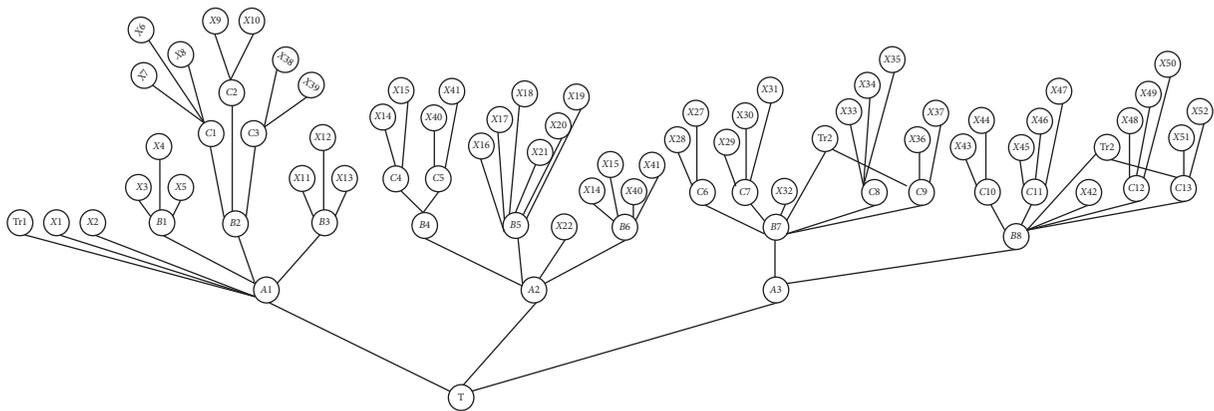


FIGURE 8: Bayesian network of the material conveying subsystem.

The material conveying system is the most important subsystem of the ANFO vehicle. The system is divided into the fuel conveying subsystem, latex matrix conveying subsystem, and trace element conveying subsystem through an in-depth study on the structure and principle of the system. The fuel conveying subsystem consists of two FDEP dynamic logic gates and one CSP dynamic logic gate. The latex matrix conveying subsystem contains one CSP dynamic logic gate. The trace element subsystem includes the sensitizer subsystem and catalyst subsystem. And, each of them contains one CSP dynamic logic gate. The events in the dynamic fault tree are shown in Table 1.

Except for dynamic components, the failure relationships of other components are independent of each other. Combined with the failure cause analysis of all modules, the dynamic fault tree model of the material conveying system is shown in Figure 7.

4.2. Bayesian Network Model. The Bayesian network model of dynamic fault tree conversion is shown in Figure 7. The

probability distribution of the spare part is the same as the main part. Therefore, the spare parts of C2, C4, and B7 are no longer displayed. Tr1, Tr2, X1, . . . , X37 are basic events of the dynamic fault tree corresponding to the root nodes of the Bayesian network. C1, C2, . . . , C9, B1, B2, . . . , B8 are intermediate events of the dynamic fault tree corresponding to intermediate nodes of the Bayesian network. T is the top event of the dynamic fault tree corresponding to the leaf node of the Bayesian network. The Bayesian network model is shown in Figure 8.

Because of the difficulty of collecting the operation data for this system, we will analyze the operation data of ten equipment for 2.5 years. The data source mainly comes from the maintenance records of the material transfer system of the ANFO vehicle. It is determined that all basic events obey exponential distribution, and their parameters are shown in Table 2.

All relevant subsystems involving dynamic logic gates can be defined in conditional probability according to their special meaning, which is not shown in the Bayesian network diagram.

TABLE 2: Summary table of failure probabilities for base events ($10^{-4}h^{-1}$).

Event	Parameter
Tr1	0.59
Tr2	0.71
X1	0.51
X2	0.89
X3	0.25
X4	0.11
X5	0.28
X6	0.38
X7	0.51
X8	0.13
X9	0.63
X10	0.76
X11	0.76
X12	0.76
X13	0.11
X14	0.25
X15	0.13
X16	0.51
X17	0.38
X18	0.13
X19	0.24
X20	0.34
X21	0.13
X22	0.76
X23	0.42
X24	0.18
X25	0.13
X26	0.15
X27	0.17
X28	0.13
X29	0.51
X30	0.25
X31	0.13
X32	0.38
X33	0.19
X34	0.25
X35	0.13
X36	0.63
X37	0.38
X25	0.13
X26	0.15
X27	0.17
X28	0.13
X29	0.51

The following data sources are from the maintenance records of the BZ15 heavy-duty oil ammonia explosive vehicle and related experimental data in the factory.

4.3. Reliability Analysis Based on Discrete Bayesian Network. Assuming that the task time is 240 h, when the discrete number n is 4, 5, and 6, the calculation time intervals are 48 h, 40 h, and 34.3 h. The reliability of the material conveying system is shown in Figure 9. The reliability under different discrete numbers was analyzed. At each time node, the maximum deviation of reliability under adjacent discrete numbers was calculated. The maximum deviation of reliability was 0.16% when the discrete numbers were 4 and 5.

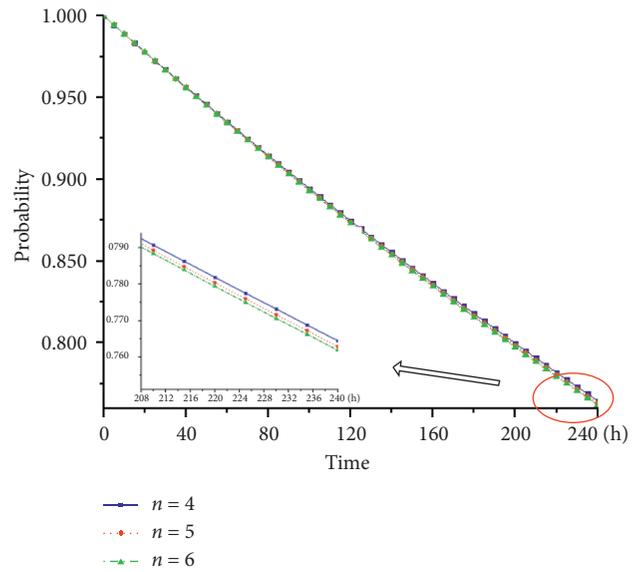


FIGURE 9: Reliability curves under different discrete numbers.

TABLE 3: The probability distribution table of the top event.

$T=i$	1	2	3	4	5	6	7
$P(T=i)$	0.0382	0.0386	0.0391	0.0399	0.0407	0.0416	0.7619

The maximum deviation of reliability was 0.1% when the discrete numbers were 5 and 6. The results of reliability calculation for discrete numbers 4, 5, and 6 had little deviation. Considering other uncertain factors, when the discrete number was 6, it can fully meet the accuracy requirements of the system evaluation. When the task time is 240 h and the discrete number is 6, the probability distribution of the top event in seven intervals is shown in Table 3.

Therefore, the failure probability of the material conveying system during the task time is $P = \sum_{i=1}^6 P(T=i) = 0.2381$, and the reliability is $R = P(T=7) = 0.7619$. When the state value of leaf nodes is 6, the joint tree reasoning algorithm can be used to calculate the failure probability of each basic event. The results are listed in Table 4. It can be seen that the failure probability of the fuel inlet joint and hydraulic joint of the fuel pipe is very small. They are reliable parts of the material conveying system. Sensitizer filter, sensitizer pump, sensitizer flowmeter, latex matrix tank, two-position four-way electro-hydraulic valve, fuel throttle valve, latex matrix tank thermometer, latex matrix pump rubber pipe, and sensitizer pump hose have high failure probability, which have a great impact on system reliability. Through the two-way reasoning algorithm, if the state value of each root node is 6 in turn, the failure probability of the leaf node is shown in Table 5.

From above Table 4, it can be seen that when the system fails, the sensitizer filter, sensitizer flowmeter, and sensitizer pump are more likely to fail. Therefore, this group of components can be considered as the weak link in the system. Improving its reliability may improve the overall reliability of the system and will have a significant impact.

TABLE 4: The failure probability of the top event when the basic event fails.

Event	Probability
Tr1	0.0461
Tr2	0.8680
X1	0.0460
X2	0.0460
X3	0.0461
X4	0.0085
X5	0.0216
X6	0.0004
X7	0.0006
X8	0.0001
X9	0.4574
X10	0.5509
X11	0.0586
X12	0.0586
X13	0.0085
X14	0.6589
X15	0.3431
X16	0.0393
X17	0.0293
X18	0.0100
X19	0.0185
X20	0.0262
X21	0.0100
X22	0.0586
X23	0.3209
X24	0.0100
X25	0.0100
X26	0.0116
X27	0.0031
X28	0.0024
X29	0.0094
X30	0.0046
X31	0.0024
X32	0.8676
X33	0.0035
X34	0.0046
X35	0.0024
X36	0.8680
X37	0.1388

TABLE 5: The failure probability of basic events when the top event fails.

Event	Probability
Tr1	1.0000
Tr2	0.2223
X1	1.0000
X2	1.0000
X3	1.0000
X4	1.0000
X5	1.0000
X6	0.8081
X7	0.8081
X8	0.8082
X9	0.2274
X10	0.2274
X11	1.0000
X12	1.0000
X13	1.0000
X14	0.2352
X15	0.2352
X16	0.5100
X17	1.0000
X18	1.0000
X19	1.0000
X20	1.0000
X21	1.0000
X22	1.0000
X23	1.0000
X24	1.0000
X25	1.0000
X26	1.0000
X27	0.2391
X28	0.2391
X29	0.2391
X30	0.2391
X31	0.2391
X32	0.2223
X33	0.2391
X34	0.2391
X35	0.2391
X36	0.2223
X37	0.2231

5. Discussion

Due to the obvious dynamic characteristics of the material conveying system, the traditional static fault tree analysis method cannot evaluate the system very well. In this paper, the dynamic fault tree is analyzed using the discrete Bayesian network. The results have shown that the reliability of the equipment was only 0.7619 in 240 h. The accuracy can meet the evaluation requirements of the equipment, when the discrete number was 6. Sensitizer filter, sensitizer pump, sensitizer flowmeter, and other parts are the weak links of the system. It is shown that the reliability of the system needs to be improved urgently. The improvement of sensitizer filter, sensitizer pump, sensitizer flowmeter, and other parts is an effective way to enhance the reliability of the system. In this article, the empirical method and statistical method were used to determine the failure distribution of parts. It is difficult to determine the exact failure distribution of parts

because the acquisition period of equipment operation data is very long. In the future, fuzzy theory and multidata synthesis method may be used to study data uncertainty.

6. Conclusion

The traditional static fault tree cannot accurately analyze the reliability of the system, where the dynamic characteristics of the system are ignored. In this paper, the method of combining dynamic fault tree analysis and Bayesian network is used to analyze the reliability of the material conveying system. The discrete Bayesian network was applied to improve the accuracy of reliability analysis results.

The discrete-time Bayesian network calculates the possible time periods of the research object on the basis of the original Bayesian network. When the specific aging time of the product cannot be determined, it provides more calculation results, so as to realize the reliability of the product.

More comprehensive analysis can be performed through the above information obtained. The continual improvement of the system can be carried out according to the results.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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