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Fault Diagnosis of Train Network Control Management System Based on Dynamic Fault Tree and Bayesian Network

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ABSTRACT Train network control management system (TCMS) is an important part of the High-speed rail train. Because of the TCMS's complex and redundant structure, long-term operation environment, etc., breakdowns inevitably in the long-time running. Based on the historical fault data of the TCMS accumulated during their online service, the working principles, failure modes, and effects analysis of TCMS are researched and the dynamic fault tree (DFT) model of TCMS failure is built. Then, the dynamic fault tree model is transformed into the Bayesian network (BN) model, which can model the reliability of such types of systems. Finally, combining DFT with BN is used for fault probability estimation and reliability assessment. The results present that increasing the reliability of key modules for the TCMS would be of great help to High-speed rail train engineers in the fault diagnosis field.

INDEX TERMS Train network control management system, dynamic Fault tree analysis, Bayesian network, fault diagnosis.

I. INTRODUCTION

With the fast development of China's Railway, the High-speed rail train, which is a large-scale intelligent system with sophisticated structures, has become a significant mode of transportation in China. However, the High-speed rail train breaks down inevitably in the long-time running. Fault diagnosis will play a very significant role in the safety and efficient operations. One crucial technical system of high-speed rail train is the Train network Control Management System, which is the core of ensuring safe and efficient train operation. The failure of TCMS will seriously threaten the safe running of the High-speed rail train. Therefore, the research of TCMS fault diagnosis has a great significance to the further development of the High-speed railway.

Complexity is defined in two forms: structural complexity and fault complexity. The High-speed rail train system is a complex system with redundancy, both in its structure and in its failure modes. Although the structure of the TCMS seems relatively simple, the working principles and failure modes of TCMS are particularly complex [11]. For instance, there are a lot of complex failure modes for the TCMS, which are related to training operation, mechanical structures, electrical facilities, network control, and many other aspects. The operation of the TCMS on a High-speed rail train is dominated by on-board equipment and microprocessors.

The TCMS involves mechanical structures and electrical equipment such as CCU, TCN Gateway, WTD, REP, RIOM, and HMI. The complex failure modes of the TCMS consists of power supply anomaly, equipment anomaly, circuit board failure, communication anomaly, and system failure. The relationship between different failures is complicated and uncertain.

Hence, the TCMS of High-speed rail trains is regarded as a complex system, which is designed to achieve high levels of reliability and redundancy. Failure of any such subsystems will have a heavy impact on the service itself, resulting in obvious deterioration of performance, reduction of perceived quality, and increment of costs. A beneficial approach combining dynamic fault tree analysis and Bayesian network is applied to resolving the TCMS's fault diagnosis with uncertainty reasoning, solving complex and polymorphism

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problems, which will be appropriate for the fault diagnosis and maintenance decision for High-speed Railways.

The traditional fault tree analysis is a graphical method that models how failures propagate through the system and how component failures lead to system failure. It provides methods and tools to compute a wide range of properties and measures [12]. FTA technique is widely used for both qualitative and quantitative assessment. However, with the development of modern engineering, the equipment is becoming more and more complex. Systems designed to achieve high levels of reliability frequently employ high levels of redundancy, dynamic redundancy management, and complex fault & error recovery techniques, Dugan *et al*. [6] presented dynamic fault tree modeling techniques for handling these difficulties. This method solves the reliability analysis of three advanced fault-tolerant computer systems.

Volk *et al.* [1] have presented a DFT modeling approach, which can serve to provide additional insights into the criticality of field elements, for infrastructure reliability analysis of railway station areas. Kabir *et al.* [2] have proposed a hybrid modularization scheme where independent sub-trees of a DFT are identified and quantified in a hierarchical order. This method could provide an approximate solution to DFTs without unacceptable loss of accuracy. Volk *et al.* [4] have presented a new state-space generation approach for dynamic fault trees (DFTs) that exploits several successful reduction techniques from the field of model checking. Ghadhab *et al*. [5] have proposed the approach of constructing dynamic fault trees, which can be used to evaluate various quantitative measures by model checking, to model a variety of safety concepts and E/E architectures for drive automation. The DFT model can reveal clear failure mechanisms and clear logical relationships between failures, however, as to the complex and redundancy system, they cannot compute the importance measure of basic event and have bidirectional inference. The Bayesian network takes advantage of probability theory and graph theory reasoning uncertainty relation of events, which is more clearly on the logic. Moreover, the Bayesian network has bidirectional inference and update related information according to the circumstance. From this point of view, the Bayesian network is better than DFTA.

Cai *et al.* [7] have proposed a novel real-time reliability evaluation methodology by combing the root cause diagnosis phase based on Bayesian networks, which can calculate the real-time reliability of the entire system by forwarding inference of BNs. Cai *et al*. [8] have proposed a dynamic Bayesian network-based fault diagnosis methodology, which can identify the faulty components and distinguish the fault types, in the presence of TF and IF for electronic systems. Cai *et al.* [9] have proposed using object-oriented Bayesian networks to reduce the overall complexities of BNs for diagnosis and the reporting of faults that immediately occur. Cai *et al.* [10] have presented a hybrid physics-model-based and data-driven remaining useful life estimation methodology of structure systems considering the influence of multiple causes by using dynamic Bayesian. A case study showed that the estimation methodology could calculate the RUL of structure systems with multiple influencing causes. Yang *et al.* [18] have presented the Bayesian network-based software reliability modeling method and task flow-oriented software reliability simulation prediction method, which can utilize the prior information of software architecture, history data, and software task flows to conduct the dynamic reliability prediction and find the reliability weaknesses. He *et al.* [19] have applied the dynamic fuzzy subset theory into the Bayesian network, in which the fault probability of the leaf node fault state and fuzzy dynamic fault probability was developed and calculated. Halabi *et al.* [22] have applied the Bayesian network and multivariate logistic regression to model the relationship between sources of information. Boudali and Dugan [23] have presented a novel reliability modeling and analysis framework based on the Bayesian network formalism.

However, there is another problem worth considering: it's not easy to build the Bayesian network model for complex engineering systems. The surprise is that transforming the dynamic fault tree model into the Bayesian model will resolve the problem well.

Hamza and Hacene [13] have discussed the advantages of the Bayesian network over the fault tree in reliability and safety analysis. Zheng *et al.* [16] have presented the transformation algorithm from the fault tree to the Bayesian network, aiming to develop a bridge crane spreader fault diagnosis system, which can effectively use historical fault data to support subsequent maintenance. Bobbio *et al.* [25] have introduced the basic inference techniques of FT mapped into a BN, which can obtain some additional power both at the modeling and at the analysis level. Kabir *et al.* [26] have applied the fault tree analysis and the dynamic Bayesian network to assess the reliability of flare systems. Khakzad *et al.* [27] have presented the application of BNs in safety analysis and introduced the similarity between FTs and BNs. Rahman *et al.* [28] have built up the fault tree model of marine logistics, then a Bayesian network approach is used to develop the risk model considering interdependencies and conditional relationships among the contributing factors. Zhang *et al.* [29] have introduced a fuzzy AHP index system of respective expert judgment ability and built up an event tree, then quantitative risk reasoning and sensitivity analysis of foundation pit collapse is achieved by using fuzzy Bayesian inference. Feng *et al.* [30] have established a fault tree model of gas pipelines and mapped this model to the Bayesian network. Qiao *et al.* [31] have presented an event tree of the analytic hierarchical process for the evaluation of expert capability, and then built up a Bayesian network model of maritime accident scenarios. Xiao *et al.* [32] have transformed a seaplane risk evaluation indicator system into an event tree, and then proposed a novel approach to modeling the risk of seaplane operation safety using a Bayesian network.

The rest of the paper is organized as follows: Section II describes the analysis of the Dynamic fault tree method. An overview of Bayesian network analysis is also provided in this section. The structural analysis of TCMS and DFT modeling of TCMS are described in section III. The description includes the structural analysis and working principle of TCMS, failure mode, and effects analysis of TCMS, and the dynamic fault tree modeling of TCMS. Section IV shows the fault diagnosis progress of TCMS. The process includes the method of mapping DFT into BN, the method verification and case study, the Bayesian network modeling of TCMS, the results of experimental analysis, and the comparison of other methods. Finally, Section V presents the concluding remarks.

II. METHODOLOGIES USED

The TCMS consists of many parts and complex structure, moreover, the logical relationship, and the operating environment is not clear. The lack of effective data in the field data is also a problem to be considered in TCMS's fault diagnosis. Meanwhile, to deal with the limitations of redundancy analysis, the static fault tree is extended to a dynamic fault tree by introducing a dynamic logic gate [6]. Dynamic fault tree refers to the fault tree that contains at least one dynamic logic gate so that it has can model and analyze the dynamic system.

Bayesian network is suitable for handling multi-state description of events. By setting different values of node variables to represent different states of the subsystem, and by setting the CPT of corresponding nodes to conveniently express the logical relationship between variables, the characteristics of multi-state systems can be clearly described.

The combination of Dynamic fault tree analysis and the Bayesian network method to achieve the reasonable expression of multi-source information will provide a new idea for fault uncertainty processing of TCMS.

A. DYNAMIC FAULT TREE ANALYSIS

In the static fault tree analysis method [16], OR gate and AND gate are the two most commonly used forms. The graphical notations are shown in Fig. 1 and Fig. 2.

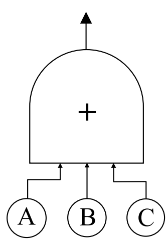

FIGURE 1. OR gate.

1) OR GATE

When at least one of the input events corresponding to the OR gate is in a failure state, the output event of the logical gate will fault occur.

2) AND GATE

When all input events corresponding to AND gate are in a failure state, the output event of the logical gate will fault occur.

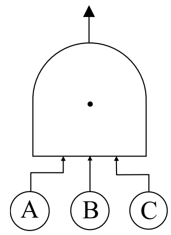

FIGURE 2. AND gate.

In the dynamic fault tree analysis method, Priority-AND (PAND) gate, and Functional Dependency (FDEP) gate are used to describe the timing of part failure. Spare gate (SP) is mainly used for reliability modeling and evaluation when some equipment has spare parts in some complex systems [6].

3) PAND GATE

The input events of the PAND gate can be either the basic event or the output event of another logic gate. The failure mechanism is as follows: when the input events of PAND break down from left to right and the output events of the logic gate will fault occurs.

Assume PAND has three input events, and its graphical notation is shown in Fig. 3. When B fails before A, C fails before A, or B and C fail simultaneously before a fails. Then the output event of the logic gate will break down.

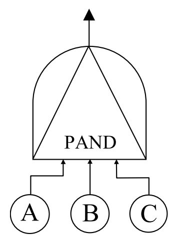

FIGURE 3. Priority-AND gate.

4) FDEP GATE

FDEP contains one triggering event and the related events can be one or more. The failure mechanism is that related events fail individually or triggering events failure leading to all related events fail, then the output events of the logic gate will fault occurs.

Assume FDEP has two related events A and B, and one triggering event Tr. Then its graphical notation is shown in Fig. 4. When A and B fail, or Tr failure leading to A and B fails, the output event of the logic gate will break down.

5) SP GATE

The SP Gate can be divided into Cold spare (CSP), Warm spare (WSP), and Hot spare (HSP). The graphical notations are shown in Fig. 5. Besides, the ratio of failure rate during the backup period to failure rate during the operation period is called Dormancy Factor β, and its graphical notation is shown in Figure 4. Among them, the dormancy factors of CSP, WSP, and HSP are $\beta = 0$, $0 < \beta < 1$, and $\beta = 1$ respectively.

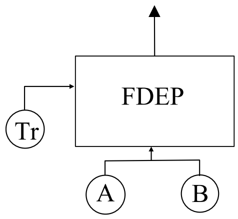

FIGURE 4. Functional Dependency gate.

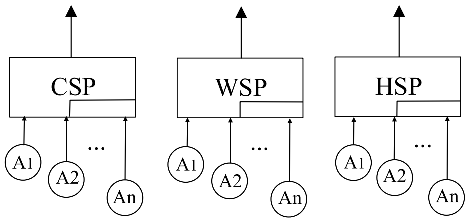

FIGURE 5. Spare gate.

Since all the devices in the TCMS are in the state of hot spare redundancy, we will mainly use the HSP as the dynamic fault tree logic gate.

In the HSP, both the host and back-up parts enter the working state at the same time. When the host part fails, any back-up part can be regarded as the host part to ensure the normal working state of the whole system. Therefore, the output event breaks down only when both the host and back-up components fail.

B. BAYESIAN NETWORK

BN is an organic set of Bayesian methods and graph theory. It is a directed acyclic graph (DAG), which contains a probability table and is composed of network structure and parameters. The network structure of BN includes two parts: node-set and directed edge set. Each node can be regarded as a variable with discrete or continuous values, and each directed edge represents the dependency between nodes. BN parameter refers to a set of conditional probability distributions of the Bayesian network model, which represents the conditional probability distribution (CPD) of a node under a certain value state of its parent node. In the case of discrete values of network nodes, CPD can be expressed as a conditional probability table (CPT).

Consider a two-state system with N components, each of which is represented by X_i. Because the Bayesian network has a strong conditional independent relationship, when given a parent node of one node, it is conditional independent from all other nodes except its descendants.

According to the conditional independence and the chain rule, BN represents the joint probability distribution P(X) of variables of any BNs as [13]:

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

BN can update the prior probability of any events given new information (posterior probability), called evidence M taking advantage of Bayes theorem:

$$P(X/M) = \frac{P(X, M)}{P(M)} = \frac{P(X, M)}{\sum_X P(X, M)} \tag{2}$$

A basic Bayesian network is shown in Fig. 6.

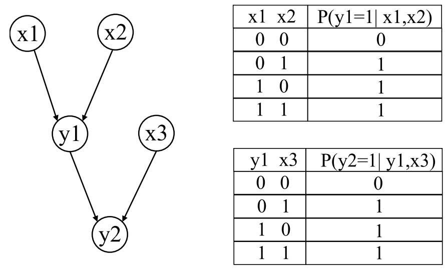

FIGURE 6. Basic Bayesian network.

III. STRUCTURAL ANALYSIS AND DYNAMIC FAULT TREE MODELING OF TCMS

In this section, we are going to introduce the TCMS system that belongs to the 200km/h intercity EMU train KDZ15, which is independently developed by *CRRC Corp*.

A. STRUCTURAL ANALYSIS AND WORKING PRINCIPLE OF TCMS

The 200km/h intercity EMU is a fixed grouping of 8 vehicles, in which a traction unit is defined for every 4 vehicles. And the names of train marshaling are Mc1-Tp2-M3-T4-Tb5-M6-Tp7-Mc8, Where M represents the bullet train, Mc represents the bullet train with a cab, which is located at the head of the train. T represents the trailer, and Tp represents the trailer with a pantograph.

Among them, TCMS is responsible for the transmission of instructions and braking control of EMUs and monitoring the main equipment's status on the train. What's more, TCMS can be capable of fault diagnosis and fault recording function. The network topology of the KDZ15 train is shown in Fig. 7.

By utilizing the train network, TCMS collects all kinds of information related to the running condition of vehicles, such as traction, braking, auxiliary power supply, air conditioning, and other subsystems, makes a comprehensive logical judgment on these data, and then sends the results back to each subsystem after processing to realize management of each subsystem.

The composition of TCMS consists of network topology lines and network devices, which are attached to High-speed rail trains via the WTB line and the MVB line. What's more, the main components of TCMS include Central Control Unit (CCU), Input / Output Module in Cab (IOM Cab), Remote Input / Output Module (RIOM), TCN Gateway (GW), Repeater (REP), Human Machine Interface (HMI) and Wireless Transmission Device (WTD). Besides, the main functions of each component are shown in Table 1.

At the beginning of TCMS's design, the reliability factor has been taken into account. For instance, the WTB line and the MVB line are designed with redundancy. Furthermore,

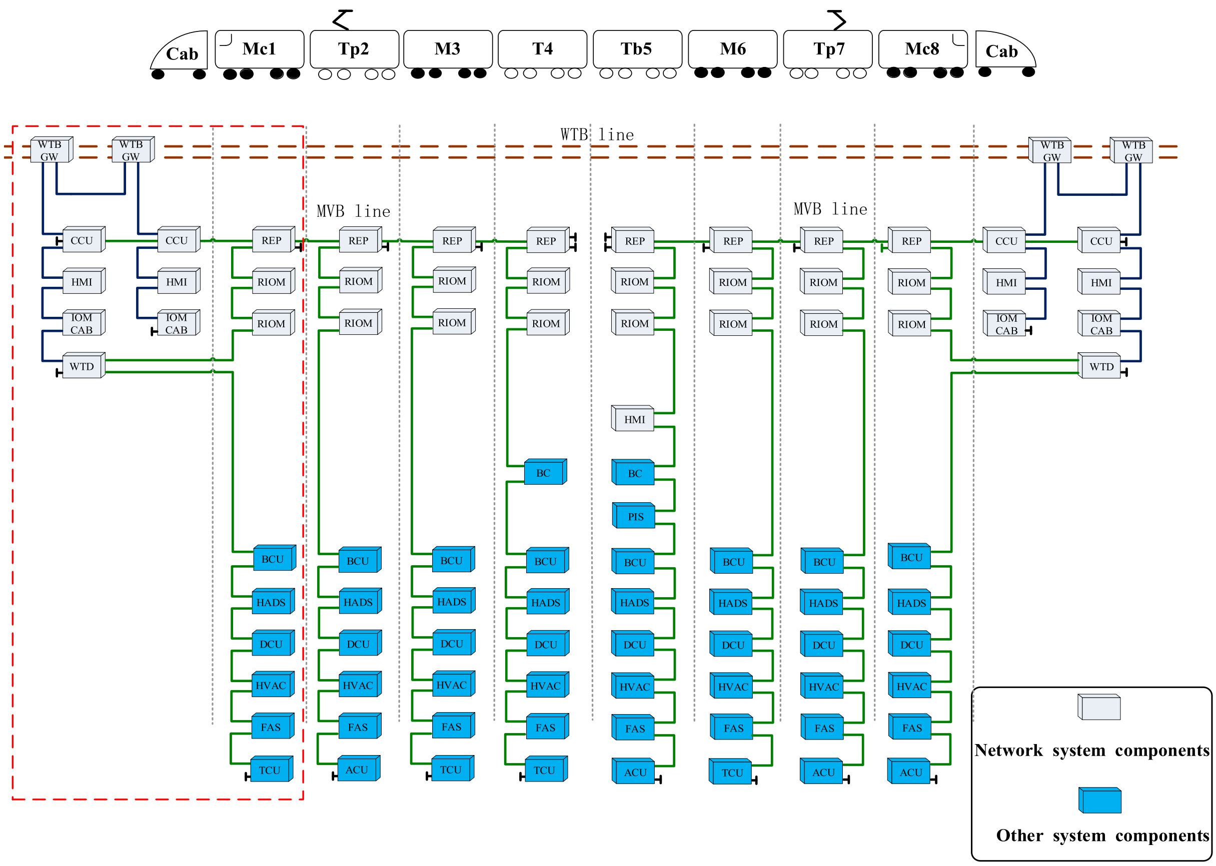

FIGURE 7. Train network topology.

hot standby redundant design has also been applied to the important network equipment, such as CCU, TCN GW, IOM CAB, RIOM, HMI, WTD, and REP. When they work properly, one is defined as the master device and the other as the slave device. The master and slave equipment will monitor the working state of each other in real-time. If the master equipment fails, the slave equipment will take over its work automatically. After the switch is completed, the system can continue to work.

B. FAILURE MODE AND EFFECTS ANALYSIS (FMEA) OF TCMS

If the TCMS is in normal working condition, each component must be in normal condition. While the technology of train control is so advanced, the TCMS's failure is inevitable. Hence, it is necessary to make research on fault diagnosis and reliability analysis of TCMS.

The TCMS of EMU train is a typical and complex system, its normal operation is done by the cooperation of hundreds of board cards. When the onboard equipment and its board cards in the system break down, it will lead to a fault alarm of TCMS.

Through the way of classifying and researching fault tracking records, the most frequent TCMS failure modes can be summarized as follows.

1) FAILURE MODE 1:

CCU failure, resulting in the CCU communication anomaly.

Probable causes:
(a) MVB equipment board card failure.
(b) Equipment power supply anomaly.
(c) CPU card fault.
(d) CCU system failure.

2) FAILURE MODE 2

TCN GW failure, resulting in the TCN Gateway communication anomaly.

Probable causes:
(a) MVB equipment board card failure.
(b) Equipment power supply anomaly.
(c) CPU card fault.
(d) CCU system failure.

3) FAILURE MODE 3

IOM CAB failure, resulting in the IOM CAB communication anomaly.

Probable causes:
(a) MVB equipment board card failure.
(b) Equipment power supply anomaly.
(c) CPU card fault.

TABLE 1. Main functions of the TCMS component.

Number	Component Name	Functions
1	CCU (Redundancy)	Responsible for MVB bus management, control, monitoring, and fault diagnosis
2	TCN GW (Redundancy)	Responsible for WTB bus management, WTB/MVB protocol conversion, and information transmission
3	IOM CAB (Redundancy)	Responsible for collecting IO signal, interacting with CCU, and outputting control instructions, located in driver's cab
4	RIOM (Redundancy)	Responsible for collecting IO signal, interacting with CCU, and outputting control instructions, located in train carriages
5	HMI (Redundancy)	Responsible for the display of train status and fault information, issue control instructions to the crew
6	WTD (Redundancy)	Responsible for receiving train status and fault information for local storage and delivery to ground servers
7	REP (Redundancy)	Responsible for regeneration and shaping of MVB signal

4) FAILURE MODE 4

RIOM failure, resulting in the RIOM communication anomaly.

Probable causes:

(a) MVB equipment board card failure.
(b) Equipment power supply anomaly.
(c) CPU card fault.

5) FAILURE MODE 5

HMI failure, resulting in the HMI communication anomaly.

Probable causes:

(a) MVB equipment board card failure.
(b) Equipment power supply anomaly.
(c) CPU card fault.
(d) CCU system failure.

6) FAILURE MODE 6

WTD failure, resulting in the wireless transmission devices communication anomaly.

Probable causes:

(a) MVB equipment board card failure.
(b) Equipment power supply anomaly.
(c) CPU card fault.
(d) CCU system failure.

7) FAILURE MODE 7

REP failure, resulting in the Repeater communication anomaly.

Probable causes:

(a) Equipment power supply anomaly.
(b) Hardware failure of Repeater.

C. DYNAMIC FAULT TREE MODELING OF TCMS

The core function of TCMS is to be able to run normally without failure. Moreover, TCMS adopts a modular structure, and the component units are designed with a redundant structure. For instance, the CCU, TCN GW, IOM CAB, RIOM, HMI, WTD, and REP have applied for the hot spare redundancy.

It is assumed that the failures of the components other than those with dynamic failure mechanisms are independent of each other, and the life distribution of the comment units conforms to an exponential law.

Based on the classification of the High-speed emu system and the cause of failure of all modules, a dynamic fault tree was established by taking the TCMS system fault of KDZ15 emu, as shown in Fig. 8.

The dynamic fault tree model is composed of two logic gates, one is the "OR" gate, and the other is the "HSP" gate.

The symbol "T" is on behalf of the top event, which means "TCMS fails to work".

The symbol "M*" is on behalf of the intermediate events, which consist of M1: CCU communication anomaly, M2: TCN GW communication anomaly, M3: IOM CAB communication anomaly, M4: RIOM communication anomaly, M5: HMI communication anomaly, M6: WTD communication anomaly, M7: Repeater communication anomaly.

The symbol "M**" represents the redundant events, which consist of M11: CCU host failure, M12: CCU back-up failure, M21: TCN GW host failure, M22: TCN GW back-up failure, M31: IOM CAB host failure, M32: IOM CAB back-up failure, M41: RIOM host failure, M42: RIOM back-up failure, M51: HMI host failure, M52: HMI back-up failure, M61: WTD host failure, M62: WTD back-up failure.

The symbol "X*" is on behalf of the basic events, which are made up of X1: Power supply board card no output, X2: MVB board card communication anomaly, X3: CPU board card failure, X4: DI acquisition boards anomaly, X5: DO acquisition boards anomaly, X6: Backboard failure, X7: Power supply board card no output, X8: MVB board card communication anomaly, X9: CPU board card failure, X10: WTB boards hardware failure, X11: Backboard failure, X12: Power supply board card failure, X13: CPU board card failure, X14: IOM Cab Backboard failure, X15: DI acquisition card failure, X16: DO output card anomaly, X17: Power supply board card failure, X18: CPU board card failure, X19: RIOM Backboard failure, X20: DI acquisition card failure, X21: DO output card anomaly, X22: Power supply anomaly, X23: MVB board card communication anomaly, X24: CPU board card failure, X25: LCD failure, X26: Power supply anomaly, X27: MVB board card communication failure, X28: CPU board card failure, X29: Communication interface card failure, X30: Backboard failure,X31: Communication function board card failure, X32: REP host failure, X33: REP back-up failure.

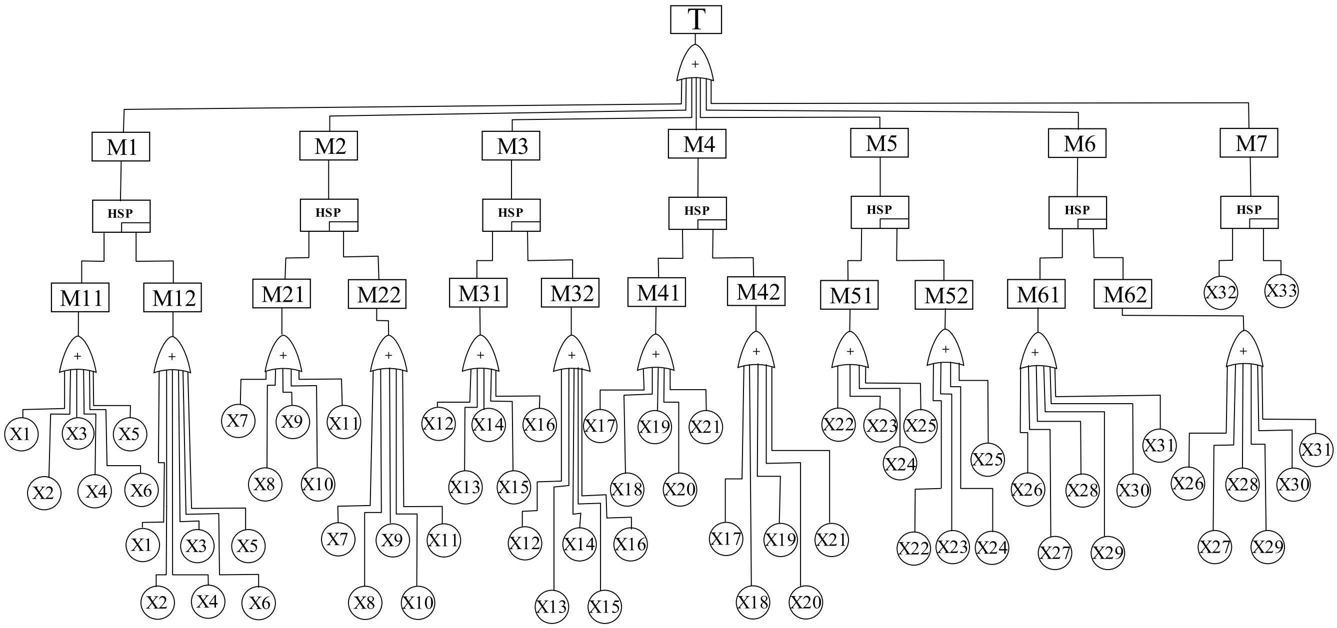

FIGURE 8. DFTA modeling of the TCMS.

By analyzing the structure-function and failure process of the object in detail, the dynamic fault tree model of the system is established according to the basic flow of fault tree modeling. This step is the foundation of the entire modeling and analysis process. It is necessary to accurately and reasonably select the top event and determine the failure logic relationship between various parts of the system, to ensure the correctness of the final analysis results. According to the established dynamic fault tree model, the events in the model are mapped to the nodes of the Bayesian network model layer by layer.

The components' hidden trouble incidence calculated by field historical data and the reliability parameters obtained by expert evaluation. Furthermore, we have a deep cooperative relationship with *CRRC Corp* thus their experts provide us with the practical FMECA data, which can be applied in the field of fault diagnosis and reliability analysis. As is shown in Table 2.

TABLE 2. Reliability parameters of basic events.

Event code	Failure rate (10^{-7}/h)	Meantim-e to repair (h)	Even-t code	Failure rate (10^{-7}/h)	Meantim-e to repair (h)
X1	1.10626	0.5	X18	3.42075	0.5
X2	6.34973	0.5	X19	0.0633471	0.5
X3	7.61967	0.5	X20	1.21627	0.5
X4	2.70922	0.5	X21	1.52033	0.5
X5	3.38652	0.5	X22	4.43355	0.5
X6	1.41105	0.5	X23	61.5771	0.5
X7	1.01984	0.5	X24	3.83146	0.5
X8	0.585366	0.5	X25	2.62729	0.5
X9	7.02439	0.5	X26	1.05194	0.5
X10	7.28455	0.5	X27	7.2455	0.5
X11	0.130081	0.5	X28	4.50831	0.5
X12	0.185877	0.5	X29	5.40998	0.5
X13	1.28027	0.5	X30	7.2455	0.5
X14	0.455208	0.5	X31	4.50831	0.5
X15	0.56901	0.5	X32	8.525004	0.5
X16	0.0237087	0.5	X33	8.525004	0.5
X17	0.496642	0.5			

IV. FAULT DIAGNOSIS OF TCMS

A. THE METHOD OF MAPPING DFT INTO BN

Before modeling, not only the scope and boundary of the model need to be determined, but also the important variables and states need to be defined. Dynamic fault tree makes use of the logic gate to express the relationship between the event and the Bayesian network is used to connect the edge nodes. A Bayesian network's parents' nodes represent the input events of the fault tree and the child nodes represent the output.

Furthermore, the transformation of dynamic fault tree and Bayesian network model consists of two parts, one is the transformation of structure between DFT and BN, the other is the establishment of CPT for non-root nodes. Concrete corresponding relationships between them and the simplified processes are as shown in Fig. 9.

Note that the dynamic fault tree shown in Figure 8 has applied static logic gate and HSP logic gate, hence the

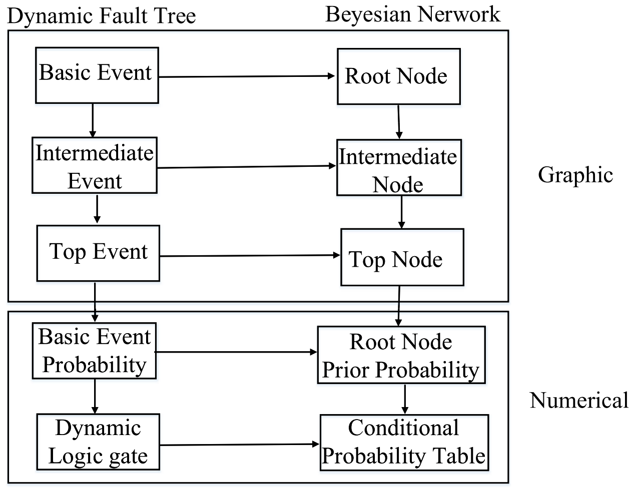

FIGURE 9. Simplified process of Bayesian network based on dynamic fault tree [26].

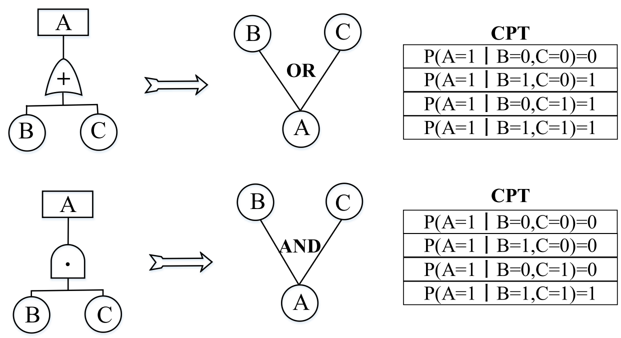

FIGURE 10. Transformation of static gate.

transformation of structure and the establishment of CPT on these two logic gates are presented respectively below.

1) TRANSFORMATION OF STATIC GATE

The transformation of structure for OR gate and AND gate is shown in the Fig. 10.

Make X1 $= [A_1, A_2, \ldots, A_m]$, m is the number of input events for OR gate, $A_i(i = 1, 2, \ldots, m)$ is the state variable of the input event. Make Y1 is the set of state variables for the output event. There is the conditional probability distribution of Y1:

$$P(Y1 = k|X1) = \begin{cases} 1 & k = j \\ 0 & k \neq j \end{cases} \tag{3}$$

where $j = min\ (A_1, A_2, \ldots, A_m)$.

Make X2 $= [A_1, A_2, \ldots, A_n]$, n is the number of input events for AND gate, $A_i(i = 1, 2, \ldots, n)$ is the state variable of the input event. Make Y2 is the set of state variables for the output event. There is the conditional probability distribution of Y2:

$$P(Y2 = k|X2) = \begin{cases} 1 & k = j \\ 0 & k \neq j \end{cases} \tag{4}$$

where $j = max\ (A_1, A_2, \ldots, A_n)$.

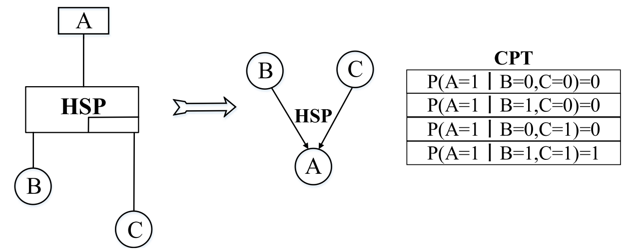

FIGURE 11. Transformation of HSP logic gate.

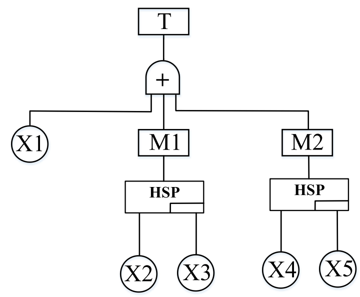

FIGURE 12. Case model of dynamic fault tree.

2) TRANSFORMATION OF HSP LOGIC GATE

The transformation of structure for the HSP logic gate is shown in the Fig. 11.

Make M $= [A_1, A_2, \ldots, A_g]$, g is the number of input events for HSP logic gate, $A_i(i = 1, 2, \ldots, g)$ is the state variable of the input event. Make N is the set of state variables for the output event. There is the conditional probability distribution of N:

$$P(N = k|M) = \begin{cases} 1 & k = j \\ 0 & k \neq j \end{cases} \tag{5}$$

where $j = max\ (A_1, A_2, \ldots, A_g)$.

B. METHOD VERIFICATION AND CASE ANALYSIS

Taking the dynamic fault tree shown in Fig. 12 as an example. To verify the accuracy of the above method, which is compared with the computation results of the Binary Decision Diagrams (BDD) method [33].

The dynamic fault tree model is composed of a static logic gate and dynamic logic gate, which are the OR gate and the HSP gate respectively.

Firstly, the topology of the dynamic fault tree model is transformed into the structure of the Bayesian network model. Then, according to the construction method of CPT according to Formula (1) – (3). The input of CPT and the construction of the BN model were carried out in GeNIe software. Furthermore, the fault diagnosis of the BN model and reliability analysis was accomplished by GeNIe software.

The transformed Bayesian network model is shown in Fig. 13. Moreover, the corresponding relationship between the nodes of each layer and the events in Fig. 12 is described as follows:

i) The First layer: Node 1, 2, 3, 4, and 5 corresponds to the basic event X2, X3, X4, X5, and X1.

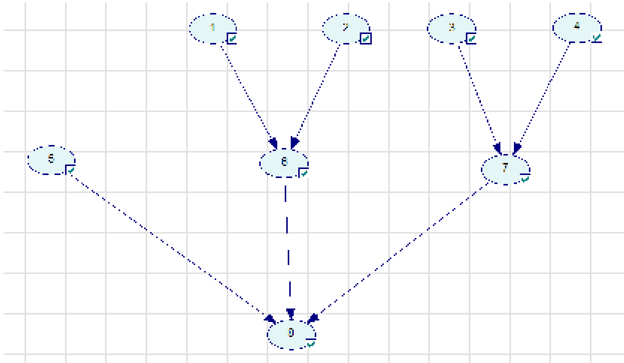

FIGURE 13. Case model of Bayesian network structure.

TABLE 3. Comparison of BN and BDD simulation results.

Probability of failure for top event T	BN (%)	BDD (%)
$P1[T=1\|(X_1=1, X_2=1, X_3=1, X_4=1, X_5=1)] = P1[T=1\|(0, 0, 0, 0, 0)]$	0	0
$P2[T=1\|(X_1=1, X_2=1, X_3=1, X_4=1, X_5=1)]=P2[T=1\|(0.1, 0.2, 0.3, 0.4, 0.5)]$	32.32	32.32
$P3[T=1\|(X_1=1, X_2=1, X_3=1, X_4=1, X_5=1)]= P3[T=1\|(0.9, 0.8, 0.7, 0.6, 0.5)]$	96.92	96.92
$P4[T=1\|(X_1=1, X_2=1, X_3=1, X_4=1, X_5=1)]= P4[T=1\|(0.1, 0.7, 0.5, 0.8, 0.2)]$	50.86	50.86
$P5[T=1\|(X_1=1, X_2=1, X_3=1, X_4=1, X_5=1)]= P5[T=1\|(0.6, 0.3, 0.7, 0.2, 0.9)]$	74.088	74.088
$P6[T=1\|(X_1=1, X_2=1, X_3=1, X_4=1, X_5=1)]= P6[T=1\|(0.5, 0.5, 0.5, 0.5, 0.5)]$	71.875	71.875
$P7[T=1\|(X_1=1, X_2=1, X_3=1, X_4=1, X_5=1)]= P7[T=1\|(1, 1, 1, 1, 1)]$	100	100

ii) The Second layer: Node 6 and 7 corresponds to the intermediate events M1 and M2.

iii) The Third layer: Node 8 corresponds to the top event T.

Assuming that the failure rate of each basic event in the dynamic fault tree respectively are $P1(X_1 = 1, X_2 = 1, X_3 = 1, X_4 = 1, X_5 = 1) = (0, 0, 0, 0, 0)$, $P2(X_1 = 1, X_2 = 1, X_3 = 1, X_4 = 1, X_5 = 1) = (0.1, 0.2, 0.3, 0.4, 0.5)$, $P3(X_1 = 1, X_2 = 1, X_3 = 1, X_4 = 1, X_5 = 1) = (0.9, 0.8, 0.7, 0.6, 0.5)$, $P4(X_1 = 1, X_2 = 1, X_3 = 1, X_4 = 1, X_5 = 1)= (0.1, 0.7, 0.5, 0.8, 0.2)$, $P5(X_1 = 1, X_2 = 1, X_3 = 1, X_4 = 1, X_5 = 1) = (0.6, 0.3, 0.7, 0.2, 0.9)$, $P6(X_1 = 1, X_2 = 1, X_3 = 1, X_4 = 1, X_5 = 1) = (0.5, 0.5, 0.5, 0.5, 0.5)$, $P7(X_1 = 1, X_2 = 1, X_3 = 1, X_4 = 1, X_5 = 1) = (1, 1, 1, 1, 1)$, among them the number "1" in parenthesis mark after the letter "P*" represents the corresponding event has failed. And the numbers in parenthesis mark after the equal sign represents the failure rate of each basic event. According to the hypothesis, the fault diagnosis simulation of the Bayesian network model is carried out, which is compared to the computation results based on the Binary Decision Diagrams method [34], as shown in Table 3.

It can be seen from the Table 3 that the results calculated by the two methods are extremely close, which verifies the effectiveness of the Bayesian network for the reliability assessment of the system.

TABLE 4. Node definition.

Number	Name of the event
T	Status of TCMS
M1	Status of CCU communication
M2	Status of TCN GW communication
M3	Status of IOM CAB communication
M4	Status of RIOM communication
M5	Status of HMI communication
M6	Status of WTD communication
M7	Status of REP GW communication
M11	Status of CCU host
M12	Status of CCU back-up
M21	Status of TCN GW host
M22	Status of TCN GW back-up
M31	Status of IOM CAB host
M32	Status of IOM CAB back-up
M41	Status of RIOM host
M42	Status of RIOM back-up
M51	Status of HMI host
M52	Status of HMI back-up
M61	Status of WTD host
M62	Status of WTD back-up
X1	Status of CCU's power supply board card
X2	Status of CCU's MVB board card
X3	Status of CCU's CPU board card

TABLE 5. The CPT of node M11.

X1	X2	X3	X4	X5	X6	P(M11=m11|X1,X2,X3,X4,X5,X6), m11=(0,1)	
						M11=0	M11=1
0	0	0	0	0	0	1	0
1	0	0	0	0	0	0	1
0	1	0	0	0	0	0	1
0	0	1	0	0	0	0	1
0	0	0	1	0	0	0	1
0	0	0	0	1	0	0	1
0	0	0	0	0	1	0	1
1	1	0	0	0	0	0	1
0	1	1	0	0	0	0	1
0	0	1	1	0	0	0	1
…	…	…	…	…	…	…	…
1	1	1	1	0	0	0	1
0	1	1	1	1	0	0	1
0	0	1	1	1	1	0	1
1	1	1	1	1	0	0	1
0	1	1	1	1	1	0	1
1	1	1	1	1	1	0	1

C. THE BAYESIAN NETWORK MODEL OF TCMS

The Bayesian network model has the function of bidirectional inference, which can express the association relation between

TABLE 6. The CPT of node M1.

M11	M12	P(M1=m1|M11,M12), m11=(0,1) M1=0	M1=1
0	0	1	0
0	1	1	0
1	0	1	0
1	1	0	1

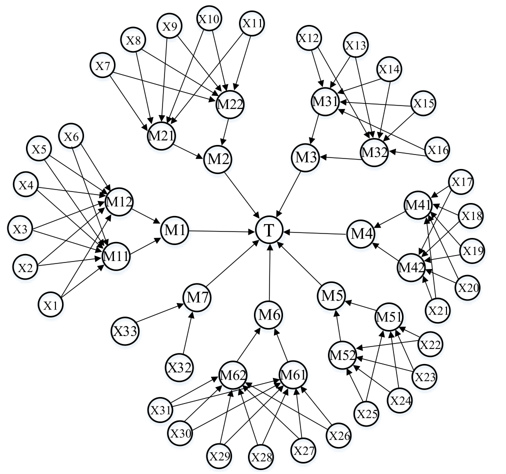

FIGURE 14. Bayesian network model of TCMS.

TABLE 7. The CPT of node T.

M1	M2	M3	M4	M5	M6	M7	P(T=t|M1,M2,M3, M4,M5,M6,M7), t=(0,1) T=0	T=1
0	0	0	0	0	0	0	1	0
1	0	0	0	0	0	0	0	1
0	1	0	0	0	0	0	0	1
0	0	1	0	0	0	0	0	1
0	0	0	1	0	0	0	0	1
0	0	0	0	1	0	0	0	1
0	0	0	0	0	1	0	0	1
0	0	0	0	0	0	1	0	1
1	1	0	0	0	0	0	0	1
0	1	1	0	0	0	0	0	1
0	0	1	1	0	0	0	0	1
…	…		…	…	…	…	…	…
1	1	1	1	1	0	0	0	1
0	1	1	1	1	1	0	0	1
0	0	1	1	1	1	1	0	1
1	1	1	1	1	1	0	0	1
0	1	1	1	1	1	1	0	1
1	1	1	1	1	1	1	0	1

elements more clearly and intuitively, providing a solid foundation for security modeling.

According to the corresponding relationship and transformation rules, the dynamic fault tree model in Fig. 8 is transformed into the Bayesian network model in Fig. 14.

TABLE 8. Posterior probability.

Node	Posterior probability	Node	Posterior probability
X1	0.010613597	X27	0.097749806
X2	0.060919866	X28	0.060822097
X3	0.073103843	X29	0.072986524
X4	0.025992473	X30	0.097749817
X5	0.032490599	X31	0.060822103
X6	0.001353775	X32	0.032716443
X7	0.009784409	X33	0.032716443
X8	0.056160509	M1	0.2044723
X9	0.067392609	M2	0.20447232
X10	0.069888627	M3	0.002845262
X11	0.001248011	M4	0.020312299
X12	0.000210381	M5	0.1308623
X13	0.001449054	M6	0.40431991
X14	0.000515219	M7	0.032715619
X15	0.000644024	M11	0.20447399
X16	0.000026834337	M12	0.20447399
X17	0.001501826	M21	0.20447401
X18	0.010344209	M22	0.20447401
X19	0.000191559	M31	0.002845513
X20	0.003677941	M32	0.002845513
X21	0.004597426	M41	0.020312957
X22	0.034028804	M42	0.020312957
X23	0.047262228	M51	0.13086378
X24	0.029407607	M52	0.13086378
X25	0.020165222	M61	0.40432169
X26	0.014191807	M62	0.40432169

The meanings of the nodes represented are shown in Fig. 14.

Due to the limited space, the CPT of leaf node T and intermediate node M1 and M11 were given in Table 5, 6, and 7. Moreover, the number "0" represents the normal state and the number "1" represents the failure state.

D. RESULTS OF THE EXPERIMENTAL ANALYSIS

We utilize the simulation software named GeNIe version 2.0 for the inference usage of the developed BN models. Cheng *et al.* [17] modeled the dynamic Bayesian network, which is based on the GeNIe software, to locate the fault of the train control system and deduce the system maintenance strategies. Yang *et al.* [18] modeled the integrated and sub-Bayesian network of TCMS, which is based on the GeNIe software, to utilize the prior information and find the reliability weaknesses. Halabi *et al.* [22] presented the BN of reliability and risk model, which is modeled in the GeNIe version 2.0. Kabir *et al.* [26] built the DBN of the FT model for the flare system, which is based on GeNIe software. Rahman *et al.* [28] built the modified BN model for marine offshore logistics operation, which is based on GeNIe software, to address the interdependencies and conditional relationships among the critical factors. Feng *et al.* [30] modeled the Bayesian network of pipe failure and risk diagnosis-based

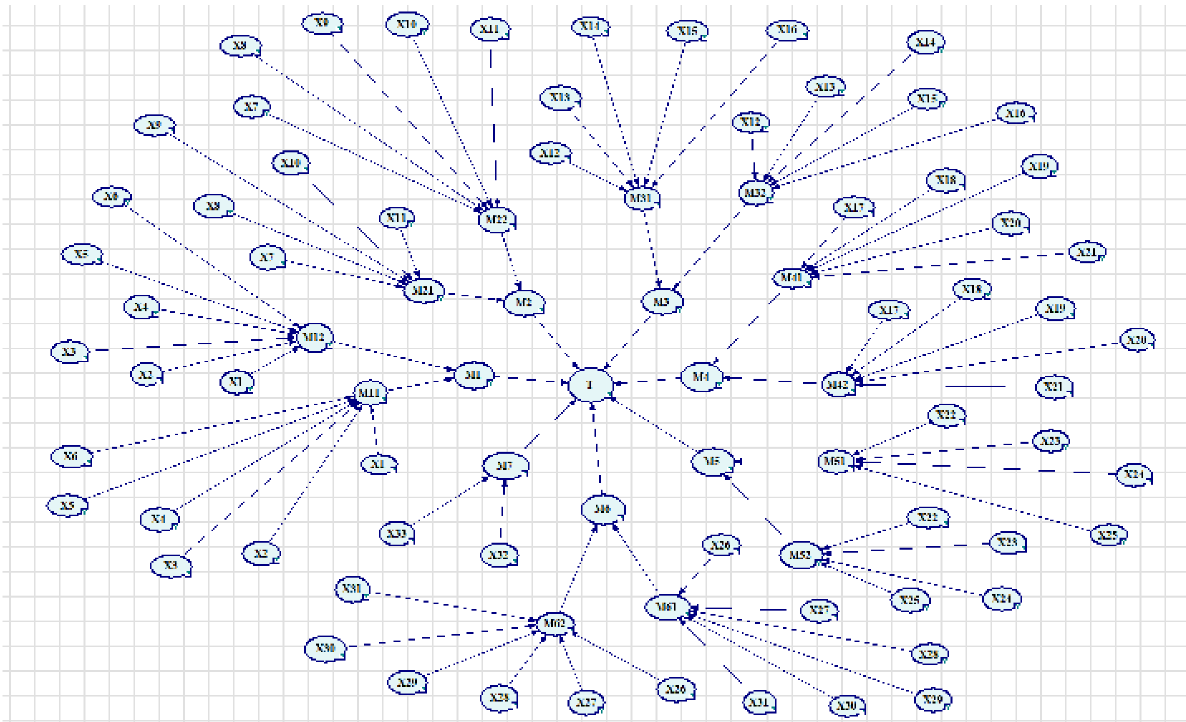

FIGURE 15. Simulation diagram of Bayesian network.

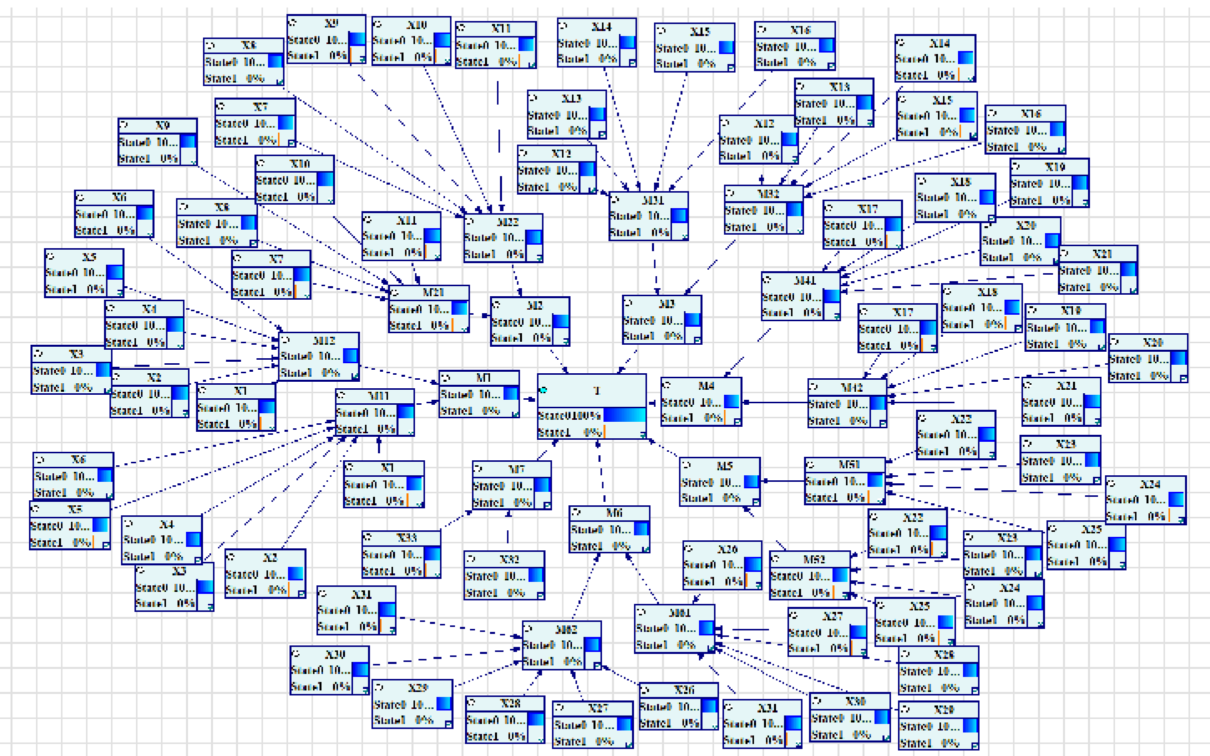

FIGURE 16. Bayesian network based on the prior failure rate.

BN of Noisy-OR gates, which is conducted on GeNIe software.

It is assumed that the states of parts and systems are only normal and failure and the failure of parts is subject to the exponential distribution. The failure efficiency of basic events is shown in Table 2. Furthermore, mapping each level of events and failure logic relationships of the dynamic fault tree into each level of nodes of the Bayesian network, as can be

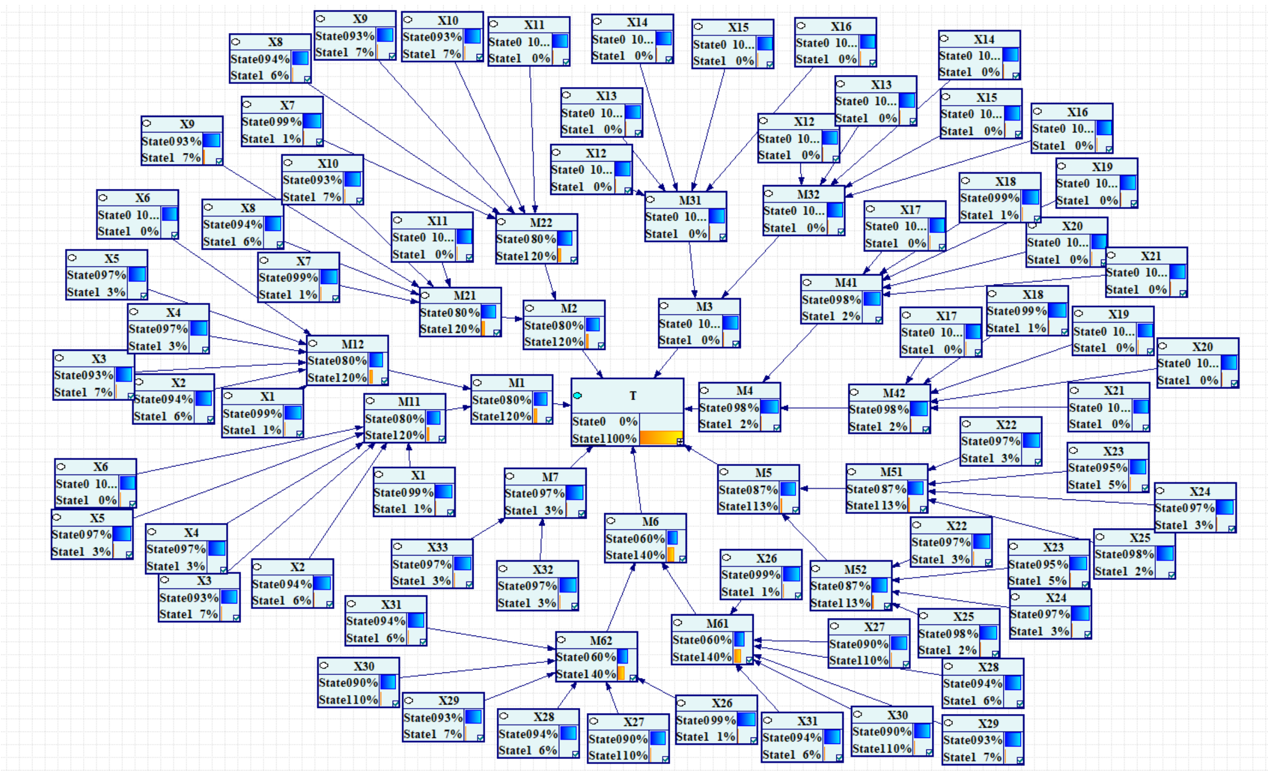

FIGURE 17. **The posterior probability of T node failure.**

seen in Fig. 15, the BN model has 1 leaf node, 19 intermediate nodes, and 33 root nodes.

After the BN model of TCMS is built, the GeNIe is used to conduct simulation analysis on it, which is shown in Fig. 16. When we insert the inputs of each root node into the BN model, we can get the occurrence probability of intermediate nodes and leaf node T. The result shows that the probability of the top event is $2.2214327e^{-11}$.

When the TCMS has fault occurs, the state of T is set to "1" in GeNIe. Therefore, the failure probability of each basic event is computed by using the reverse reasoning of the Bayesian network, as is shown in Table 8 and Fig. 17.

The variation trend of the posterior probability of each basic and intermediate event was illustrated in Fig. 18 and Fig. 19. The Fig. 20 shows the comparison of prior probability and posterior probability changes, which indicates that although the X23 has the maximum original failure rate when the top event is in the failure state, the X27 and X30 have the maximum occurrence probability instead.

Through data analysis, we can find that X16 (Status of IOM CAB's DO card) has the minimum probability of failure. Then, X27 (Status of WTD's MVB board card), X30 (Status of WTD's CPU board card), and M6 (Status of WTD communication) have the maximum probability of failure, the corresponding parts and components are the weak links of the TCMS reliability service. Therefore, the stability of WTD equipment is more sensitive to failure and system reliability.

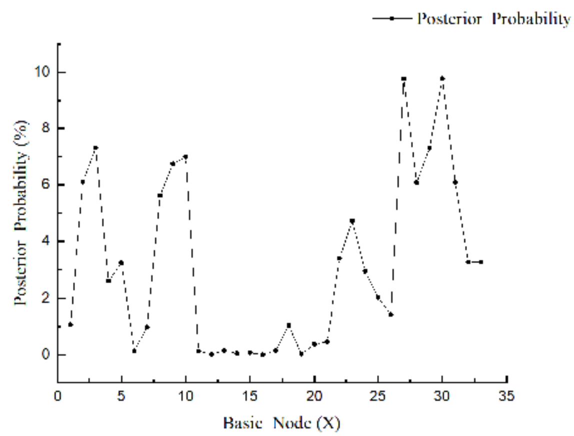

FIGURE 18. **The posterior probability of the basic event.**

The higher the module reliability is, the higher the TCMS reliability is, which makes sense. We can conclude that to ensure the reliability of TCMS, all events' reliability should be improved and the reliability of key modules such as WTD has a greater impact on the system reliability should be ensured at a high level.

E. COMPARISON OF METHODS

The experimental data in this paper, which has the features of long duration and incompleteness, is based on the field operation data and historical statistics of the High-speed rail train equipment. Moreover, the fault diagnosis and reliability

TABLE 9. Comparison between DFT-BN and other methods [16].

Methods	Characteristics	Time consumption	Accuracy
1. Fault Tree	1) Limited static structure 2) Be weak in coping with uncertainty inference 3) Be suitable for small systems	More (Traditional FT)	Lower than BN
2. Bayesian Network	1) Explicit representation of dependencies of events 2) Updating probabilities 3) Do well in dealing with uncertainties	Less than FT	Higher than FT
3. Support Vector Machine	1) Small data samples are taken to make decisions	Less than ANN	Medium
4. Artificial Neural Network	1) Suitable for complex non-linear problems 2) Need more data to avoid over fitting 3) Need more data to do preprocessing work	More than SVM	High (DNN) Low (SNN)
5. Monte Carlo Simulation	1) Need vast samples to get approximate results 2) Generate random sequences accompanied with formulas, need large and complex computation	More than BN	Close to BN
6. Dynamic Fault Tree + Bayesian Network	1) Combine the advantages of DFT and BN 2) Data quality requirements are less than networks 3) Be more suitable for reliability analysis of small sample data 4) Better use of prior information	Less than FT	Higher than FT

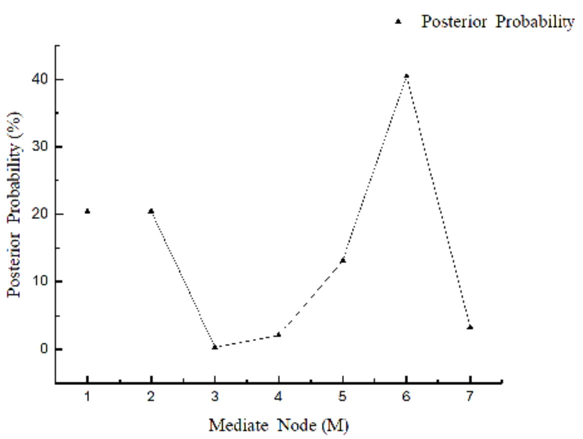

FIGURE 19. The posterior probability of the mediate event.

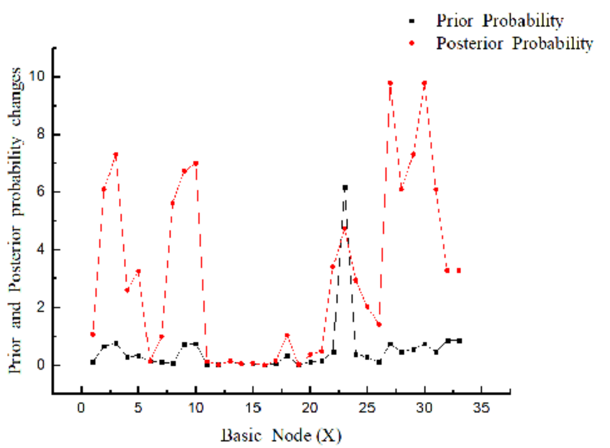

FIGURE 20. The comparison of prior probability and posterior probability changes.

analysis of the TCMS demands a precise inference approach, which can make full use of the prior information.

The comparison among diverse methods is shown in Table 9. And the presented method has combined the advantages of DFT and BN. The DFT model can be easily built from the FMEA analysis and previous data, and the DAG and CPT of BN can be acquired. Furthermore, BN is not only fit for dealing with the uncertainty problem according to the prior information, but also diagnosing faults and analyzing reliabilities of the complex systems. In general, this method has the best capability in this real instance compared to other methods.

V. CONCLUSION

In this paper, we have addressed the limitations of DFT and BN among their applications in Introduction section. Then we analyzed and summarized the critical basic events which contributed to the TCMS failure condition. Moreover, we systematically discussed the working principles and failure modes of TCMS. The dynamic fault tree was established by analyzing the logical relationship between the redundancy systems. Then, the dynamic fault tree model was transformed into the Bayesian network model. Hence, we explained the method of mapping DFT into BN and introduced the features of the two methods that help to contrast them. BN is one of the significant ways to resolve the problem for uncertain inference of the period. The experimental simulation and fault diagnosis of the BN model were conducted on GeNIe software.

This method can significantly increase fault analysis efficiency in engineering practice, and it can make full use of prior knowledge and historical fault data to improve the effectiveness of pursuant fault analysis. The major contribution of this article is to combine two approaches, which include dynamic fault tree and Bayesian network, to resolve a significant and actual case engineering problem and has a certain promotional value.

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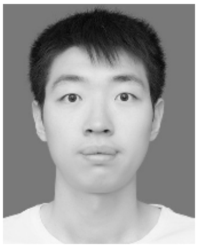

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