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Risk Analysis for the Wireless Communication of the High-Speed Maglev under the Cognitive Uncertainties

Wenyi Zheng, Stanley Chien

Abstract— **The wireless communication between a train and the ground in 38GHz band is an important subsystem in operation and control system (OCS) which is the artificial neural network of the whole high-speed maglev transportation system. The risk analysis of wireless communication reliability is a critical issue related to operation safety. However, the fault parameters especially under cognitive uncertainties cannot always be properly estimated, not only because of the large number of redundancy design being applied in wireless communication system for the sake of reliability enhancement, but also the lack of status data collected by distributed sensors of the maintenance and management subsystem(MMS) displayed in wireless communication equipment due to the limited operation life. In this paper, based on the status data acquired by the distributed sensors from MMS, a risk analysis method is proposed using Continuous Time Bayesian Network with its key condition parameters expressed by Triangular Fuzzy Numbers. Moreover, with an expert confidence index, the credibility of the fuzzy probability evaluation for basic risk factors can be ensured, which means the limitation in risk analysis caused by cognitive uncertainties can be eliminated. The method proposed in this paper integrates together a risk analysis process with deductive reasoning, sensitivity analysis and abductive inference. Compared with traditional fault tree analysis, the proposed method is more flexible and adaptive in fault diagnosis and dynamic reliability estimation of wireless communication for high-speed maglev train.**

I. INTRODUCTION

Maglev system is attracting more and more attention nowadays for its advantages in low energy consumption, low noise, small turning radius, et al. The wireless communication between a train and the ground in 38GHz band is an important subsystem in operation and control system (OCS) which is the neural network of the whole high-speed maglev transportation system. It is of no doubt that the risk analysis of wireless communication reliability is a critical issue since it is closely related to operation safety. As the operation environment around the high-speed maglev system can be quite complex, the structure of wireless communication between a train and the ground is also complex as the design needs enhance the environment adaptability. Moreover, the relationship between signal sources and equipment inside the wireless communication subsystem is complicated, resulting in close coupling between modules and functions, and the complexity of fault propagation in the overall subsystem [1]. Thus, it is necessary and important to make credible evaluation of the reliability of such subsystem.

In high-speed maglev, various types of sensors are deployed in central control room, along the track or in trackside, and on the maglev trains. These sensors form a distributed network, which serves as the physical layer of the maintenance and management subsystem (MMS). Such distributed network can collect status data of almost all key equipment in high-speed maglev so as to help MMS monitor the operation of each subsystem, and to detect abnormal situations. As different key equipment may have different ways to describe their working status, different types of sensors are chosen separately to realize sensing of the most suitable working status of those key equipment as well as subsystems. Therefore, all kinds of sensors for collecting physical parameters are distributed in high-speed maglev, and of course, in wireless communication subsystem.

Even if the status data can be collected by MMS via the sensing network, the amount available status data is not large enough due to limited operation history. The MMS equipped maglev line has only operated in recent years in Shanghai, which means that there is a lack of sample status data of all types of failure modes collected by distributed sensors [2]. As there still might be uncertain factors in interpretation of those sensed status data, relying on this data for wireless communication subsystem may cause imprecise, fuzzy, incomplete description of system fault [3]. It is important and necessary to develop a novel risk-analysis method to make credible evaluation of the reliability for the wireless communication subsystem. This method should help make the best of sensed data from MMS and thus to ensure the operation safety of OCS. In this paper, based on the status data acquired by the distributed sensing network from MMS, a risk analysis method based on Continuous Time Bayesian Network with its key condition parameters expressed by Triangular Fuzzy Numbers is proposed. In the proposed method, the limitation in risk analysis caused by cognitive uncertainties is eliminated by utilizing expert confidence index, which ensures the credibility of fuzzy probability evaluation for basic risk factors based on sensed status data. The method proposed has an integrated risk analysis process that includes deductive reasoning, sensitivity analysis and abductive inference. Hence, compared with traditional fault tree analysis of wireless communication for high-speed maglev train, this method is more flexible and adaptive in fault diagnosis and dynamic reliability estimation.

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II. RELATED WORK

In the field of risk analysis and reliability evaluation, the dynamic fault tree, which can properly describe dynamic characteristics of status changes and redundancy of safe-critical systems, is always recognized as the most suitable model [4]. According to the dynamic fault behavior of system components, Dugan et al. (1992) have defined a complete set of dynamic logic gates to describe the dynamic fault characteristics with not only time correlation, but also function correlation [5]. However, reliability model based on dynamic fault tree is complex in finding accurate model solving algorithm, especially in model convergence calculation. Compared with dynamic fault tree, graph theory-based methods such as Petri net, Markov Chain, Continuous Time Bayesian Network, and probability theory has stronger ability in distinguishing uncertain information, describing system polymorphism, and realizing bidirectional-reasoning mechanism [6]. Thus, it is not surprising that related research has focused on employing dynamic Bayesian Network for solving system reliability modeling and evaluation problem recently. Popov (2013) proposed an approach for simplifying the complexity in solving dynamic fault tree based on Bayesian Network [7]. Montani et al. (2008) presented a method to convert the main logic gates into Bayesian network and introduced the calculation formulas for reliability parameters in it [8]. Boudali et al. (2006) presented a reliability evaluation method, which can convert the dynamic fault tree of a complex system into a Continuous Time Bayesian Network model and realize multiple analysis of system reliability and sensitivity [9].

It should be pointed out that in most cases of risk evaluation in practice, the status data of system components acquired via sensing network may not always be quite clear due to some unexpected reasons [10]. Therefore, one direction for solving this problem by researchers is to find novel data acquiring method [11], and the other direction is to adopt fuzzy uncertainty theory into risk evaluation methodologies. Jafarian et al. (2012) have redefined the status of top event in fault tree by employing subordinate function and proposed a method based on fuzzy integral to calculate the importance of basic event [12]. Y. Li et al. (2012) have employed Triangular Fuzzy Numbers to describe the occurring probability of basic event in fault tree and made comprehensive calculation on the cut sets of system failure and thus have made the description of random distribution range of system failure rate in quantity [13]. Considering the cognitive uncertainty, J. Tu et al. (2015) proposed a method of failure rate estimation, which described the uncertainty of failure rate of basic event as fuzzy number at first, and then converted it into an accurate real number [14].

It can be seen that the method of Continuous Time Bayesian Network has its own advantages in risk analysis of safety-critical systems with redundancy built-in the design. However, the method itself does not consider cognitive uncertainty problems, which may be pervasive in practical cases. It also should be pointed out that, in a system like wireless communication between train and ground in high-speed maglev system, fault characteristics are far more than one. It is of great importance to establish correctly a risk analysis model, which can reflect the dynamic fault mechanism and fault characteristics in make accurate risk evaluation.

III. DYNAMIC FAULT TREE OF THE WIRELESS COMMUNICATION SUBSYSTEM

As discussed above, wireless communication between train and ground in 38GHz band is an important subsystem in operation and control system (OCS) for high-speed maglev system. The bidirectional, nonstop information transmission realized by wireless communication is the basis in ensuring safe train operation. The wireless communication subsystem is a complex system comprised by many key components [2], including train positioning unit (usually called as PRW for short in German language), central radio control unit (CRCU), distributed radio control unit (DRCU) and move radio control unit (MRCU). All these components have modular design separately and are comprised together via BUS system with redundancy in the design, which ensures that the fault in each single component only affect its own output and the whole subsystem will not be affected by the fault module [15].

PRW is responsible for providing real-time train position for OCS. CRCU is responsible for ensuring the availability of all information for OCS function including traction control, operation control, operation voice communication, diagnosis and other added services. DRCU is responsible for ensuring the information access including data for operation control, diagnosis, train positioning, passenger information and other added services by each distributed operation control zones. DRCU is also in charge of the hand over process for wireless communication and help to realize the corresponding function. MRCU is responsible for ensuring the information access mentioned above into each maglev train in operation. It can be seen that the coupling degrees between those key components are high, and logic relationships between those key components are complicated. Thus, in risk analysis of wireless communication subsystem, the coupling relationship between functional modules in those key components, and the interaction between them should all be considered, including fault priority, sequential dependency, functional dependency and dynamic redundancy management.

The wireless communication subsystem can be modeled via a dynamic fault tree (DFT) to capture various dynamic behaviors of system fault mechanisms. The DFT of wireless communication subsystem of high-speed maglev is shown in Fig.1.

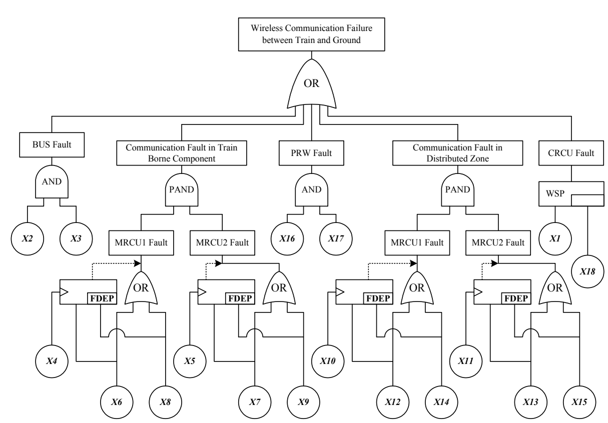

Figure 1. DFT of wireless communication subsystem

The communication failure between a train and the ground is defined as the top event. The cross relationships between communication subsystem and other subsystems apart from OCS have not been considered in this paper. It can be seen from Fig.1 that the DFT is suitable to model the system characterized by time dependent logics since DFT has a strong ability in dealing with stochastic events happened in complex system. Dependent events of certain components with redundant design, which typically exist in a system like wireless communication between a train and the ground in high-speed maglev system, can be properly taken into account by DTF.

IV. Fuzzy Fault Probability Evaluation for Basic Events

In this section, the acquisition of failure rate of basic events in DFT will be discussed in detail, such as how to realize the acquisition is under the limited condition, that is, the probability distribution data of basic failure events might be lacking, and status data of these events sensed by MMS cannot be used directly for risk evaluation. Besides based on probability distribution of basic events, non-probabilistic based fuzzy reliability algorithm can also be used for calculating the failure probability. As described in this section, the algorithm can get probability estimation of root nodes from human experts' investigation in three steps, (1) set certain rules to avoid cognitive uncertainty problem, (2) transform the linguistic and fuzzy expressions into fuzzy numbers, and (3) calculate the fuzzy probability of root nodes. This algorithm follows the process described in literature [16] to fuzzify the basic events in DFT.

A. Evaluation of Expert Confidence Index

The expert confidence index reflects the reliability of the data acquired from the distributed sensing network of MMS in wireless communication subsystem. To avoid cognitive uncertainty, the judgment ability should be taken into consideration at first, since the reliability of evaluation given by experts will raise deviation due to the individual cognition of fault in components or modules. Therefore, it is necessary to make a reliability evaluation for the sensed status data, with both the ability and subjectivity of experts being considered. In order to select the evaluation conclusions from experts reasonably, it is also necessary to quantify the authority of each expert. The technical title, work experience, academic level of each expert should all been considered and weighted in the authority quantification process. According to the analytic hierarchy process (AHP), the weight r_i of technical title, work experience, academic level can be calculated as 0.4, 0.3 and 0.3, respectively [17]. In fact, the selection of experts in risk evaluation for wireless communication subsystem is targeted so non-expert will not be selected. Therefore, the expert confidence index value is normalized set around 0.7 to 1, as shown in Table I.

It is of no doubt that an expert with richer experience has a better understanding of the components and modules of the wireless communication subsystem, thus, the credibility and weight in risk evaluation from the very expert will be higher than others. According to Table I, the authority ζ of an expert can be calculated by making a compulsory comparison of his background in technical title, work experience, academic level with others by employing equation (1):

$$\zeta = \sum_{i=1}^{3} r_i s_i \Big/ \sum_{i=1}^{3} r_i \tag{1}$$

where r_i is the weight of the i^{th} aspect of attribute in evaluating the background of the expert, and s_i is the corresponding score in such attribute of the expert.

TABLE I. EXPERT CONFIDENCE INDEX LEVELS

Attribute i	**Weight r_i**	**Hierarchy Descriptions**	**Score s_i**
Technical title	0.4	Professorate senior engineer	1
		Senior technician	0.9
		Engineer	0.8
		Assistant Engineer	0.7
Work experience	0.3	[20, +∞)	1
		[10, 20)	0.9
		[5, 10)	0.8
		(0, 5)	0.7
Academic level	0.3	Postgraduate	1
		Bachelor Degree	0.9
		Vocational degree	0.8
		Other	0.7

It should be pointed out that in the process of investigating the background of experts, their individual information related to their subjectivities in judging the status of components and modules from the data sensed by MMS should be collected. Such subjectivities of experts can be expressed by subjectivity reliability parameter ψ, which is divided into 5 levels: 0.6, 0.7, 0.8, 0.9 and 1. The higher the value ψ is, the more reliable the judgment should be. By taking both the authority level ζ and the subjectivity reliability level ψ into consideration, the expert confidence index can then be calculated by equation (2):

$$\theta = \zeta \cdot \psi \tag{2}$$

B. Division of Probability Interval

It is obvious that the probability interval represents the reliability parameter ψ of evaluation, short interval indicates that the evaluation result is more precise, while wide one indicates that the evaluation is more uncertain [16]. It is certain that a group of risk evaluation results with shorter intervals would be better to give a more precise risk analysis result of the top events shown in Fig. 2.

According to the failure probability of a system component, namely a root node in its DFT, random variable ak will randomly falls within the interval $[a_k^L, a_k^U]$. From the basic concept in probability theory, normal Gaussian distribution is the most common probability distribution in describing random events that happen in nature. Since the failure probability of a system component is most likely to fall in the midpoint of the interval $[a_k^L, a_k^U]$, and the probability falling near the endpoints of the interval decreases to a relatively lower value, it can be inferred that the failure probability a_k of a system component obeys normal Gaussian distribution $N(\mu_k, \sigma_k^2)$ with mean values at the midpoint $(a_k^L + a_k^U)/2$ of the interval. According to the 3σ criterion [20], equation (3) is true for a_k:

$$P(|a_k - \mu_k| \le 3\sigma_k) \approx 0.9973 \tag{3}$$

The failure probability a_k of a system component will just fall into the interval $[\mu_k - 3\sigma_k, \mu_k + 3\sigma_k]$. In this paper, the occurrence probability of root nodes is divided into 11 intervals, which are represented by interval "1" to "11" as shown in Table II. The k^{th} interval is defined as $a_k = [a_k^L, a_k^U]$ and $c_k = (a_k^L + a_k^U)/2$ $(1 \le k \le 11)$. In the process of expert evaluation, two types of key information must be collected, the occurrence probability interval $[a_k^L, a_k^U]$ for failure probability a_k, and the subjectivity reliability parameter ψ.

TABLE II. DIVISION OF OCCURRENCE PROBABILITY INTERVALS FOR BASIC EVENTS

Interval k	Lower boundary a_k^L	Average value C_K	Upper boundary a_k^U
1	0	0.025	0.05
2	0.05	0.1	0.15
3	0.15	0.2	0.25
4	0.25	0.3	0.35
5	0.35	0.4	0.45
6	0.45	0.5	0.55
7	0.55	0.6	0.65
8	0.65	0.7	0.75
9	0.75	0.8	0.85
10	0.85	0.9	0.95
11	0.95	0.975	1

Suppose that an expert thinks that the occurrence probability of certain root node is in the k^{th} interval of a subjectivity reliability ψ, the expert confidence index θ can be calculated from equation (2). The value of θ is lower than 1 in general and will never be greater than 1, which means that the root node still has a residual probability $1 - \theta$ in other intervals. According to the distribution patterns of random variables in normal Gaussian distribution, the occurrence probability tends to fluctuate around its expected value and decrease gradually as it goes far away from the expectation. Thus, a simplified formula, which concerns the distribution of residual probability in intervals other than interval $[\mu_k - 3\sigma_k, \mu_k + 3\sigma_k]$, can be written as:

$$P_i = \begin{cases} \dfrac{a_k^L - a_{k-i}^L}{\sum_{j=1}^{k-1}(a_k^L - a_j^L)} \times \dfrac{1-\theta}{2}, & 1 \le i \le k-1 \\ \theta, & i = k \\ \dfrac{a_{12+k-i}^L - a_k^L}{\sum_{j=k+1}^{11}(a_j^L - a_k^L)} \times \dfrac{1-\theta}{2}, & K+1 \le i \le 11 \end{cases} \tag{4}$$

An example is the process of evaluating the occurrence probability of basic event *X14*, namely the event "Fault of DRCU de-multiplexing board". It is assumed that (1) the authority ζ of the expert is 0.9 as calculated from equation (1), (2) subjectivity reliability parameter ψ is 0.6, and (3) the expert thinks that the probability is within the 5^{th} interval (as shown in Table II. According to equation (2), the most likely occurrence probability for *X14* is between 35% and 45% with a completely reliable confidence $\theta = 0.54$. Therefore, the residual reliable confidence $1 - \theta = 0.46$ is distributed among the other 10 intervals, as shown in Fig.2.

C. Fuzzy Failure Probability of Basic events

In a case study of risk analysis of wireless communication between a train and the ground for high-speed maglev system the number of experts, S, were invited to do the evaluation.

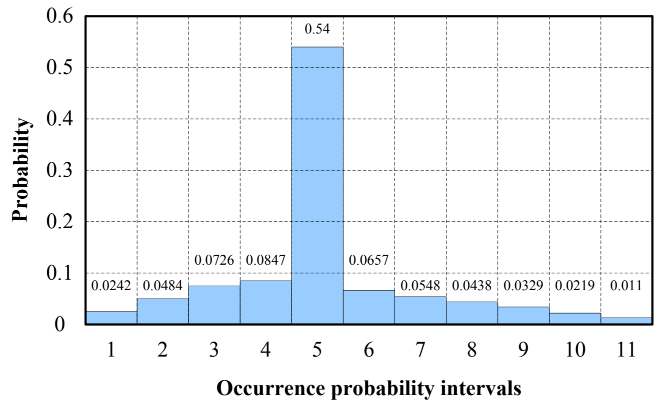

Figure 2. Occurrence probability distributions among all intervals for root node X14 obtained from an example expert

For the sake of data normalization processing, the average occurrence probability P_i $(1 \le i \le 11)$ of a certain basic event within the i^{th} interval can be calculated by equation (5):

$$P_i = \sum_{i=1}^{S} \frac{p_i}{S} \tag{5}$$

As the "3σ criterion" has been adopted in the probability fuzzification process, the failure occurrence probability for all the basic events in DFT shown in Fig.1 can be described by Triangular Fuzzy Numbers (a, m, b) by employing equation (6), (7) and (8).

$$m = E(P) = \sum_{i=1}^{11}(c_i \times P_i) \tag{6}$$

$$\sigma = \sqrt{D(P)} = \sqrt{\sum_{i=1}^{11}\left[[c_i - E(P)]^2 \times p_i\right]} \tag{7}$$

$$a = m - 3\sigma \,;\, b = m + 3\sigma \tag{8}$$

where c_i is the mean value of the i^{th} probability interval, the Triangular Fuzzy Numbers which describe the failure occurrence probability of each basic event in DFT of wireless communication subsystem is acquired as shown in Table III.

V. RISK ANALYSIS BASED ON CONTINUOUS TIME BAYESIAN NETWORK

A. Continuous Time Bayesian Network Based Reasoning

As mentioned in INTRODUCTION, Continuous Time Bayesian Network has stronger ability in dealing with uncertain information distinguishing, system polymorphism description, calculation than DFT [6], and DFT can be converted into Continuous Time Bayesian Network for analysis. In such conversion process, conditional probability table or conditional probability density functions should be built. Those density functions give the conditional probability distribution of output events for dynamic logic gates. In order to reflect the impacts of different input events for logic gates on the output event status, Boudali et al. (2006) have proposed a method to build the output distribution for logic gate by employing a unit step function. This function can describe the failure time of input event and express the

TABLE III. FUZZY OCCURRENCE PROBABILITY OF BASIC EVENTS IN DFT SHOWN IN FIG. 1

Basic event	Event description	Triangular Fuzzy Number
1	Fault of main CRCU communication module	(0.1654, 0.2550,0.5342)
2	Fault of main BUS	(0.18, 0.21, 0.23)
3	Fault of secondary BUS	(0.22, 0.24, 0.27)
4	Fault of main MRCU power supply board	(0.2501, 0.4261, 0.8577)
5	Fault of backup MRCU power supply board	(0.2501, 0.4261, 0.8577)
6	Fault of main MRCU multiplexing board	(0.2701, 0.5902, 0.9628)
7	Fault of backup MRCU multiplexing board	(0.2701, 0.5902, 0.9628)
8	Fault of main MRCU de-multiplexing board	(0.1604, 0.2498,0.5324)
9	Fault of backup MRCU de-multiplexing board	(0.1604, 0.2498,0.5324)
10	Fault of main DRCU power supply board	(0.2381, 0.4201, 0.8037)
11	Fault of backup DRCU power supply board	(0.2381, 0.4201, 0.8037)
12	Fault of main DRCU multiplexing board	(0.2688, 0.5799, 0.9351)
13	Fault of backup DRCU multiplexing board	(0.2688, 0.5799, 0.9351)
14	Fault of main DRCU de-multiplexing board	(0.2583, 0.4998, 0.9276)
15	Fault of backup DRCU de-multiplexing board	(0.2583, 0.4998, 0.9276)
16	Fault of main PRW positioning board	(0.1602, 0.2381, 0.4693)
17	Fault of backup PRW positioning board	(0.1602, 0.2381, 0.4693)
18	Fault of backup CRCU communication module	(0.2589, 0.5835, 0.8199)

relation between output distribution and each input distribution accurately [9]. Consider that Bayesian Network (BN) is a directed acyclic graph (DAG), it is an information representation framework combining causal knowledge and probability theory together. Moreover, BN is comprised by nodes and directed edges connecting those nodes, each node represents a variable, namely an event. Therefore, the directed edges can represent the causal relationship between events, and the quantitative information can be described by the joint probability density of nodes. It can be seen that the complexity of BN depends highly on the number of nodes as well as the network structure. More nodes and more directed edges will cause a more complicated BN algorithm [1].

Consider that the Continuous Time BN model is converted form DFT, here in this section, the way of building conditional probability density function for all non-root nodes in Fig.1 will be discussed in detail based on the definition of logic gates in DFT.

Without specific instruction, suppose that A and B are two input events, and T is an output event in a BN, both A and B are root nodes which can be treated as continuous time variables. Following part shows how to get Fuzzy probability distribution of output event for five gates contained in DFT model.

- AND Gate

The DFT model and its corresponding Continuous Time BN model for an AND gate is shown in Fig.3(left). Consider about the influence of fuzzy uncertainty, Triangular Fuzzy Numbers λ_A and λ_B are used to express the fault rate of input event. Suppose that the basic event obeys exponential distribution, the prior fuzzy marginal probability density functions $f_A(a)$ and $f_B(b)$ of input event A and B can be calculated as:

$$f_A(a) = \lambda_A \exp(-\lambda_A a) \tag{9}$$

$$f_B(b) = \lambda_B \exp(-\lambda_B b) \tag{10}$$

Respectively. According to the fault mechanism of AND gate, the conditional probability density function of the output event T can be built based on the unit step function and impulse function:

$$f_{T|A,B}(x|a,b) = u(b-a)\delta(t-b) + u(a-b)\delta(t-a) \tag{11}$$

where $u(b-a)\delta(t-b)$ means T and B will fall into fault status simultaneously if A fails before B; while $u(a-b)\delta(t-a)$ means T and A will fall into fault status simultaneously if B fails before A.

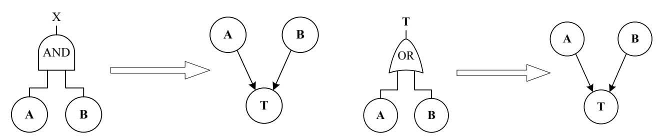

Figure 3. The structure of DFT and Continuous Time BN for an AND gate(left) and OR gate (right)

Thus, the fuzzy joint probability density function of Continuous Time BN shown in Fig. 3(left) can be calculated as:

$$f_{A,B,T}(a,b,t) = f_{T|A,B}(t|a,b) f_B(b) f_A(a) \tag{12}$$

The fuzzy marginal probability density function of output event T can be calculated by equation (13) which contains variables a and b:

$$\begin{aligned} f_T(t) &= \int_0^\infty \int_0^\infty u(b-a)\delta(t-b) f_B(b) f_A(a) \mathrm{d}b\mathrm{d}a + \int_0^\infty \int_0^\infty u(a-b)\delta(t-a) f_B(b) f_A(a) \mathrm{d}b\mathrm{d}a \\ &= \int_0^\infty \delta(t-b) f_B(b)\mathrm{d}b \int_b^\infty u(b-a) f_A(a)\mathrm{d}a + \int_0^\infty \delta(t-a) f_A(a)\mathrm{d}a \int_a^\infty u(a-b) f_B(b)\mathrm{d}b \\ &= \int_0^\infty f_B(b)\delta(t-b)\mathrm{d}b \int_0^b f_A(a)\mathrm{d}a + \int_0^\infty f_A(a)\delta(t-a)\mathrm{d}a \int_0^a f_B(b)\mathrm{d}b \\ &= [F_B(t)F_A(t)]' \end{aligned} \tag{13}$$

Then similarly, the fuzzy failure probability density distribution function of an AND gate in DFT with n input basic events can be calculated as:

$$f_T(t) = \left[\sum_{i=1}^{n} F_i(t) \right]' \tag{14}$$

Then the fuzzy failure probability distribution function of top event T in Continuous Time BN in time period [0, t] can be calculated as:

$$f_T(t) = P(T \le t) = \int_0^t f_T(\tau)\mathrm{d}\tau = F_B(t)F_A(t) \tag{15}$$

- OR Gate

The DFT model and its corresponding Continuous Time BN model for an OR gate can be shown in Fig.3(right).

The conditional density function and probability density distribution function of OR gate are similar to those of AND gate. Moreover, the AND gate and OR gate have the same Continuous Time BN structure. According to the fault mechanism of OR gate, the conditional probability density function of the output event T can be built based on the unit step function and impulse function:

$$f_{T|A,B}(t|a,b) = u(b-a)\delta(t-a) + u(a-b)\delta(t-b) \tag{16}$$

where $u(b-a)\delta(t-a)$ means T and B will fall into fault status simultaneously if B fails before A, and $u(a-b)\delta(t-b)$ means T and A will fall into fault status simultaneously if A fails before B. Thus, the fuzzy joint probability density function of Continuous Time BN shown in Fig.3(right) can be calculated via the same equation as (12), and the fuzzy marginal probability density function of output event T can be calculated by equation (17):

$$\begin{aligned} f_T(t) &= \int_0^\infty\int_0^\infty u(b-a)\delta(t-a)f_B(b)f_A(a)\mathrm{d}b\mathrm{d}a + \int_0^\infty\int_0^\infty u(a-b)\delta(t-b)f_B(b)f_A(a)\mathrm{d}b\mathrm{d}a \\ &= \int_0^\infty \delta(t-a)f_A(a)\mathrm{d}a\int_0^a f_B(b)\mathrm{d}b + \int_0^\infty \delta(t-b)f_B(b)\mathrm{d}b\int_0^b f_A(a)\mathrm{d}a \\ &= \int_0^\infty f_A(a)\delta(t-a)[1-F_B(a)]\mathrm{d}a + \int_0^\infty f_B(b)\delta(t-b)[1-F_A(a)]\mathrm{d}b \\ &= f_A(a) + f_B(b) - [F_B(t)F_A(t)]' \end{aligned} \tag{17}$$

Similarly, the fuzzy failure probability density distribution function of an OR gate in DFT with *n* input basic events can be calculated as:

$$f_T(t) = \left[\sum_{i=1}^{n}(-1)^{i+1}\binom{i}{n}\big(F_1(t), F_2(t), ..., F_n(t)\big)\right]' \tag{18}$$

Then the fuzzy failure probability distribution function of top event T in Continuous Time BN in time period [0, t] in can be calculated as:

$$f_T(t) = P(T \le t) = \int_0^t f_T(\tau)\mathrm{d}\tau = F_A(t) + F_B(t) - F_B(t)F_A(t) \tag{19}$$

- Priorty-AND Gate

The priority-AND gate(PAND) is an AND gate plus the condition that the input events must occur in a specific order [5]. The output of the gate is true if both A and B have occurred and A occurred before B. Specifically, if A fails before B, then T and B will fail at the same time. Otherwise, T will fail at an infinity time. The DFT model and its corresponding Continuous Time BN model for a PAND gate can be shown in Fig.4.

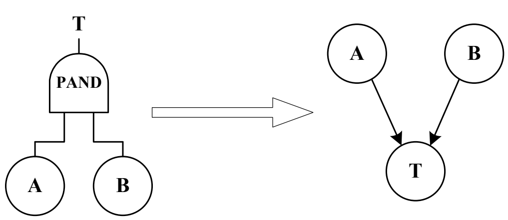

Figure 4. The structure of DFT and Continuous Time BN for an AND gate

The conditional density function and probability density distribution function of PAND gate are similar to those of AND gate. Moreover, the AND gate and PAND gate have the same Continuous Time BN structure. According to the fault mechanism of PAND gate, the conditional probability density function of the output event T can be built based on the unit step function and impulse function:

$$f_{T|A,B}(t|a,b) = u(b-a)\delta(t-b) + u(a-b)\delta(t-\infty) \tag{20}$$

where $u(b-a)\delta(t-b)$ means T and B will fall into fault status simultaneously if A fails before B, and $u(a-b)\delta(t-\infty)$ means T will fail at an infinite time if B fails before A. Thus, the fuzzy marginal probability density function of output event T can be calculated by equation (21):

$$\begin{aligned} f_T(t) &= \int_0^\infty\int_0^\infty u(b-a)\delta(t-b)f_B(b)f_A(a)\mathrm{d}b\mathrm{d}a + \int_0^\infty\int_0^\infty u(a-b)\delta(t-\infty)f_B(b)f_A(a)\mathrm{d}b\mathrm{d}a \\ &= \int_0^\infty \delta(t-b)f_B(b)\mathrm{d}b\int_0^b f_A(a)\mathrm{d}a + \delta(t-\infty)\int_0^\infty f_A(a)\mathrm{d}a\int_0^a f_B(b)\mathrm{d}b \\ &= f_B(t)F_A(t) + \delta(t-\infty)\int_0^\infty f_A(a)F_B(a)\mathrm{d}a \end{aligned} \tag{21}$$

Due to $t < \infty$ and $\delta(t-\infty) = 0$, the fuzzy failure probability distribution function of top event in Continuous Time BN T in time period [0, t] can be calculated as:

$$f_T(t) = P(T \le t) = \int_0^t f_T(\tau)\mathrm{d}\tau = \int_0^t f_B(\tau)f_A(\tau)\mathrm{d}\tau \tag{22}$$

- Functional Dependency Gate

Function Dependency (FDEP) gate has a single trigger input event and one or more dependent basic output events. The dependent basic events are functionally dependent on the trigger event. FDEP is to model the functional dependency between different components [5, 19]. When the trigger event T occurs, the dependent basic events are forced to occur. In order to explain the probability of FDEF, two new nodes are introduced in the Continuous Time BN model. Node B is a Bernoulli test with a success probability at P, where P is a fuzzy number. Since the outputs of event A depends on other events including T, all the events relied on A are linked to another new node A’.

The DFT model and its corresponding Continuous Time BN model for a FDEP gate can be shown in Fig.5.

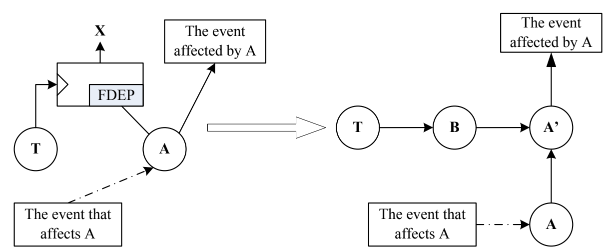

Figure 5. The structure of DFT and Continuous Time BN for an FDEP gate

The conditional probability density function of node B and A’ in Continuous Time BN can be built based on the unit step function and impulse function:

$$f_{B|T}(b|t) = P\cdot\delta(t-b) + (1-P)\delta(b-\infty) \tag{23}$$

$$f_{A'|B,A}(a'|b,a) = u(b-a)\delta(a'-a) + u(a-b)\delta(a'-b) \tag{24}$$

Then the fuzzy marginal probability density function of event A’ relies on trigger event T can be calculated by equation (25):

$$
\begin{aligned}
f_{A'}(a') &= \int_0^\infty \int_0^\infty \int_0^\infty f_{A'|B,A}(a'|b,a) f_{B|T}(b|t) f_T(t) f_A(a)\mathrm{d}b\mathrm{d}t\mathrm{d}a \\
&= \int_0^\infty \int_0^\infty \int_0^\infty [u(b-a)\delta(a'-a)+u(a-b)\delta(a'-b)] \\
&\quad \cdot [P\delta(b-t)+(1-P)\delta(b-\infty)] f_T(t) f_A(a)\mathrm{d}b\mathrm{d}t\mathrm{d}a \\
&= f_A(a')+Pf_T(a')-P[F_A(a')f_T(a')]+(1-P)[1-F_A(a')]\delta(a'-\infty)
\end{aligned} \tag{25}
$$

It is obvious that if P = 1, equation (25) will be the same as equation (17), which is the marginal probability density function of output event for OR gate. Therefore, the probability distribution function of a FDEP gate can be deduced based on OR probability distribution.

- Spare Gate

An Spare gate (SP) has a primitive input A, a backup input B and an output T. The DFT model and its corresponding Continuous Time BN model for an SP gate can be shown in Fig. 6.

The fuzzy failure rate of A and B can be given by Fuzzy Numbers λ_{Ai} and λ_{Bi} respectively. According to different types of backup status, an SP gate can describe hot standby, cold standby, and warm standby separately by setting different value of back up parameter α. To be specific, $\alpha = 1$ means a hot standby, whereas $\alpha = 0$ means a cold standby, $0 < \alpha < 1$ means warm standby. Product $\alpha\lambda_{Bi}$ describes the fuzzy failure rate of spare status.

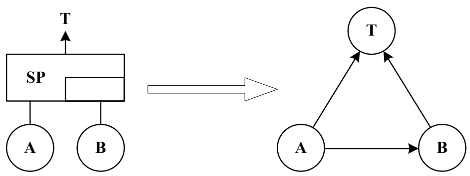

Figure 6. The structure of DFT and Continuous Time BN for an SP gate

Warm standby is the most representative situation of SP gate. Suppose that the primitive input A fails at time a, then the conditional failure probability of backup B at time b can be built based on the unit step function:

$$
\lambda_{B|A}(b|a) = u(a-b)\cdot\alpha\cdot\lambda_{Bi}(b)+u(b-a)\cdot\lambda_{Bi}(b) \tag{26}
$$

The fuzzy conditional probability density function $f_{B|A}(b|a)$ of B can be calculated using equation (27), and its fuzzy marginal probability density function $f_B(b)$ can be calculated using equation (28).

$$
\begin{aligned}
f_{B|A}(b|a) &= \lambda_{B|A}(b|a)\exp\left[-\int_0^b \lambda_{B|A}(t|a)\mathrm{d}t\right] \\
&= [u(a-b)\cdot\alpha\lambda_{Bi}(b)+u(b-a)\lambda_{Bi}(b)]\exp\left[-\int_0^b [u(a-t)\alpha\lambda_{Bi}(t)+u(t-a)\lambda_{Bi}(t)]\mathrm{d}t\right] \\
&= u(a-b)\cdot\alpha\lambda_{Bi}(b)\left[\exp\left[-\int_0^b \lambda_{Bi}(t)\mathrm{d}t\right]\right]^\alpha + u(b-a)\lambda_{Bi}(b)\cdot[F_{Bi}(a)]^\alpha \times \frac{\exp\left[-\int_0^b \lambda_{Bi}(t)\mathrm{d}t\right]}{\exp\left[-\int_0^a \lambda_{Bi}(t)\mathrm{d}t\right]} \\
&= u(a-b)\cdot\alpha f_{Bi}(b)\cdot[1-F_{Bi}(b)]^{\alpha-1}+u(b-a)f_{Bi}(b)\cdot[1-F_{Bi}(a)]^{\alpha-1}
\end{aligned} \tag{27}
$$

$$
\begin{aligned}
f_B(b) &= \int_0^\infty f_{B|A}(b|a)f_A(a)\mathrm{d}a \\
&= \alpha f_{Bi}(b)[1-F_{Bi}(b)]^{\alpha-1}[1-F_A(b)]+\int_0^b f_{Bi}(b)[1-F_{Bi}(b)][1-F_{Bi}(a)]^{\alpha-1}f_A(a)\mathrm{d}a
\end{aligned} \tag{28}
$$

Till now, the Continuous Time BN representation of necessary logic gates shown in the DFT of wireless communication subsystem for high-speed maglev (as shown in Fig.1) have been discussed. Such presentation can help build a formalized reasoning process based on parameter learning. By employing the closed form formula discussed above, the relevant parameters of continuous time BN can be calculated. Therefore, the risk analysis and reliability evaluation can be done as shown in next section.

B. Risk Analysis of Wireless Communication Subsystem

The DFT model of wireless communication subsystem as shown in Fig.1 contains OR gates, AND gates, PAND gates, FDEP gates and SP gates. According to the mapping method, each gate can be converted into its corresponding Continuous Time BN model and eventually, the entire dynamic Continuous Time BN model can be constructed as shown in Fig.7.

The introductory probability evaluation on the basic events of DFT can be firstly acquired by referencing both historical fault data and the expert investigation on the status data sensed by the sensor network of MMS. Considering the effect of uncertainty to the system reliability, triangular fuzzy numbers are used to describe the fuzzy uncertainties of all the basic events (an example is shown in Table III).

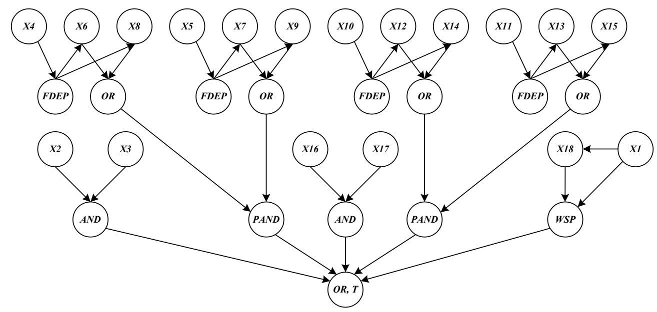

Figure 7. The Continuous Time BN model for wireless communication subsystem

Function (29) and (30) can be used to present the fuzzy marginal probability density function and fuzzy marginal distribution function of each basic event, respectively.

$$
f_{E_i}(e_i)(i=1,2,...,18) \tag{29}
$$

$$
F_{E_i}(e_i)(i=1,2,...,18) \tag{30}
$$

According to the inference algorithm of dynamic BN, the fuzzy marginal failure probability $F_T(t)$ of top event T can be gotten by employing hierarchical solution of BN model [20], which means that the fuzzy failure probability of system corresponding to the dynamic fault tree at a given time t can be calculated. Thus, the relationship between the system fuzzy probability and time can be acquired.

Fig.8 shows the member function $\mu(t)$ of the fuzzy failure probability at the system time t = 1000h. It can be seen from the figure that the minimum value of the system failure probability is 0.6748, while the maximum value is 0.8764 and the maximum potential failure probability is 0.8146. Fig.9 shows the fuzzy failure probability curve in the whole range of system time t from 0 to 1000h under the condition of member function $\mu(t)$ = 0 and 1 separately. It can be seen that the reliability of system decreases gradually over time. Moreover, due to the increments of the fault probability of components, the uncertainty of system becomes greater.

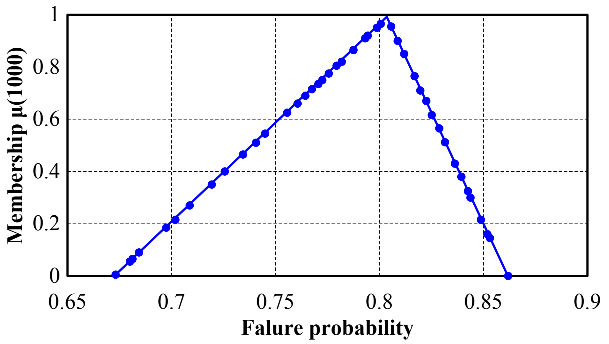

Figure 8. Fuzzy failure probability at t = 1000h

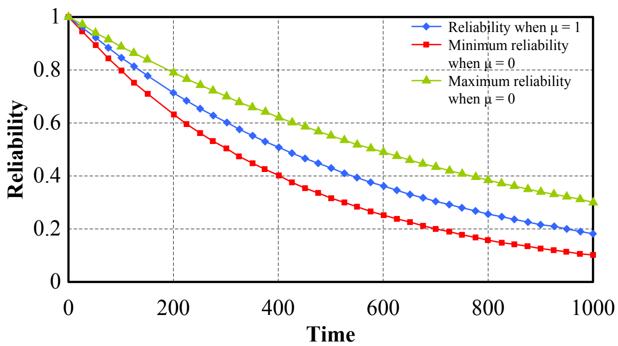

Figure 9. Fuzzy failure probability from t = 0 to 1000h

VI. CONCLUSION

Wireless communication subsystem which realizes the information exchange of OCS in high speed maglev system, is a highly complicated system with a wide range of types of risks. Risk analysis for wireless communication subsystem is important, as it is close related to operation safety in such safety-critical transportation system. Usually, it is difficult to make an exact estimation of the failure rate of the occurrence probability of undesired events, due to a lack of sufficient fault data, and the cognitive uncertainty factors from different people or experts on the data sensed by sensing network of MMS.

The risk analysis method proposed in this paper provides a better way of doing risk analysis. It reasonably utilizes the status data collected by distributed sensors under cognitive uncertainty situation. The proposed method can take a full consideration of fuzzy uncertainty of failure information of components, including various kinds of uncertainties, complex correlation between faults of components and their corresponding dynamic characteristics. Based on DFT, this method performs the modeling process and dynamic reliability evaluation system based on Continuous Time BN under fuzzy uncertainty conditions. It describes the dynamic behaviors and the interaction between main function modules of wireless communication subsystem, and effectively improves the credibility of evaluation results by integrating the experience from different experts, historical status data collected by distributed sensors, and incomplete and uncertain information during the analysis process.

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