A failure probability assessment method for train derailments in railway yards based on IFFTA and NGBN

Jun Lai [a, b, c], Kai Wang [a, b], Jingmang Xu [a, b, *], Ping Wang [a, b], Rong Chen [a, b], Shuguo Wang [d], Michael Beer [c, e, f]

[a] *Key Laboratory of High-speed Railway Engineering Ministry of Education, Southwest Jiaotong University, Chengdu, 610031, China*

[b] *School of Civil Engineering, Southwest Jiaotong University, Chengdu, 610031, China*

[c] *Institute for Risk and Reliability, Leibniz Universität Hannover, Callinstr. 34, Hannover, 30167, Germany*

[d] *Railway Engineering Research Institute, China Academy of Railway Sciences Corporation Limited, Beijing 100089, China*

[e] *Institute for Risk and Uncertainty and School of Engineering, University of Liverpool, Peach Street, Liverpool L69 7ZF, UK*

[f] *International Joint Research Center for Resilient Infrastructure & International Joint Research Center for Engineering Reliability and Stochastic Mechanics, Tongji University, Shanghai 200092, PR China*

* *Corresponding author's email address: mang080887@163.com*

Abstract: Derailment is one of the main hazards during train passes through railway turnouts (RTs) in classification yards. The complexity of the train-turnout system (TTS) and unfavorable operating conditions frequently cause freight wagons to derail at RTs. Secondary damages such as hazardous material spillage and train collisions can result in loss of life and property. Therefore, the primary goal is to assess the derailment risk and identify the root causes when trains pass through RTs in classification yards. To address this problem, this paper proposes a failure probability assessment approach that integrates intuitionistic fuzzy fault tree analysis (IFFTA) and Noisy or gate Bayesian network (NGBN) for quantifying the derailment risk at RTs. This method can handle the fact that the available information on the components of the TTS is imprecise, incomplete, and vague. The proposed methodology was tested through data analysis at Taiyuan North classification yard in China. The results demonstrate that the method can efficiently evaluate the derailment risk and identify key risk factors. To reduce the derailment risk at RTs and prevent secondary damage and injuries, measures such as optimizing turnout alignment, controlling impact between wagons, lubricating the rails, and regularly inspecting the turnout geometries can be implemented. By developing a risk-based model, this study connects theory with practice and provides insights that can help railway authorities better understand the impact of poor TTS conditions on train safety in classification yards.

Keywords: Train derailment, railway turnout, failure probability, IFFTA, Bayesian network, preventive measures

1 Introduction

The transportation of goods across the world heavily relies on rail freight transport. A classification yard is used to separate railway vehicles onto one of several tracks. The railway turnout (RT) is a vital element in a classification yard that guides trains from one track to another. Ensuring train safety, especially at RTs in a classification yard, is currently facing significant challenges due to increased transport demand, and the long-term service of the equipment [1, 2]. The derailments related to infrastructure in the UK account for approximately 39% [3]. Over the past 15 years, maintenance costs have constituted half of the total. By investigating the impact of infrastructure on derailments, more than 50% of train derailments are caused by switch defects, as shown in Fig. 1 (a). In China, where more than 250,000 turnouts are in use, there have been over 100 derailments at low-speed turnouts in the past five years. Ensuring train safety and reducing secondary damage and injuries is the primary goal of railway authorities. Although operators strictly adhere to safety standards and weather conditions are not extreme, train derailments and corresponding damages can still occur at RTs due to other factors such as track defects, poor alignments, as well as vehicle conditions [4]. These incidents can lead to serious consequences, including disruptions to railway lines and the potential for loss of life and property.

As shown in Fig. 1 (b), train derailments can cause extensive secondary damage to infrastructure and the surrounding environment. For instance, when a train derails, it can damage the tracks [5], vehicles [6], and other equipment along the railway line [7], potentially disrupting train services for days or even weeks. In addition, a derailed train can spill hazardous materials, such as fuel, chemicals, or even radioactive materials, which can pose a serious threat to nearby communities and the environment [8].

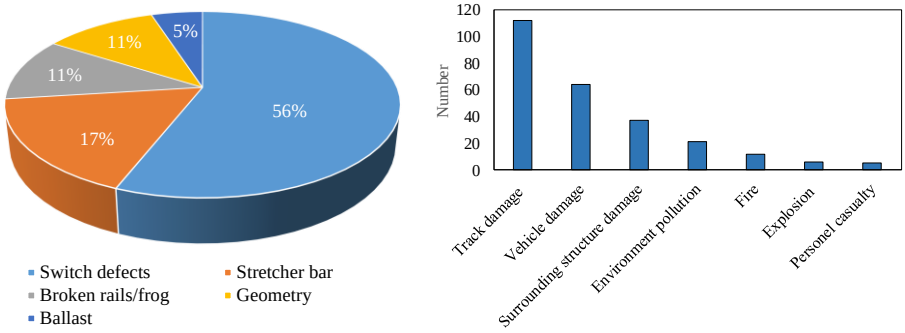

Fig. 1. (a) Distribution of train derailments caused by infrastructure in [3], and (b) statistics of secondary damage caused by derailed vehicles.

The TTS is a complex system comprising multiple sub-systems [9]. The risk of train derailment depends on the quality of both railway vehicles and turnouts [10, 11]. The wheels are constrained by the wheel flange, and typically derail in the form of wheel climbing or wheel jumping. To reduce the likelihood of derailment during its service life, wheel load reduction rate and derailment coefficient should be controlled [12]. Previous studies have individually assessed the derailment risk based on examining the effect of each parameter on passive safety. For example, Ge et al. [13] developed a dynamic simulation model for the TTS and revealed the effect of coupler forces and wheel-rail friction coefficients on dynamic derailment risk at RTs. Burgelman et al. [14] performed a multi-body dynamic simulation and examined the passive safety in a #1:9 turnout based on dynamic derailment coefficients. The results showed that the lateral contact force increases significantly when braking forces are applied to the front wheels, thereby increasing the risk of derailment. Lai et al. [15, 16] investigated the mechanism of wheel climbing derailment and wheel jumping derailment during a vehicle passes over a turnout. However, few studies have attempted to investigate the causal relationship between the conditions of the TTS and the risk of derailment at RTs. Therefore, for such high derailment risk areas as turnouts, there is an urgent need to quantitatively assess the derailment and develop safety enhancement measures to prevent secondary damage from hazardous materials and vehicle collisions.

To address this gap, the objective of this study is to propose a failure probability assessment method to systematically analyse derailment risk in classification yards with the uncertainty of the TTS. The approach can be used to evaluate the safety of trains passing through RTs and suggest preventive

measures to reduce derailment risk in classification yards. The development of the proposed model was based on IFFTA, and NGBN. Intuitionistic fuzzy sets (IFS) are employed to handle linguistic terms obtained from different experts, which cannot be accurately expressed using probability distribution functions. By utilizing the updated probabilities of input variables derived from current inspection data, the Bayesian inference is capable of producing probabilities that reflect the risk of derailment at RTs.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive review of the relevant literature. Section 3 introduces the TTS and freight train derailment mechanism at RTs. Section 4 presents the fundamentals of intuitionistic fuzzy Bayesian network (IFBN) and Noisy or gate model. The data analysis, model verification and preventive measures are presented in Section 5. Finally, conclusions, contributions, and future work are briefly summarized.

2 Literature review

2.1 Fault tree analysis

Various probabilistic risk assessment methods such as Fault tree analysis (FTA) [17], Event tree analysis (FTA) [18], failure mode and effects analysis (FMEA) [19], Markov chains [20], Bayesian network (BN) [21], and Petri nets [22] have been proposed. Among these methods, FTA is commonly used for root cause analysis in multiple industries [17]. The method involves converting a physical system into a structured logical graph where a sequence of basic events (BEs) leads to a specified top event [17]. FTA includes both qualitative and quantitative analysis [23]. It helps assess potential failure modes and causes for complex systems such as the electronics, transportation, nuclear industry, and chemical industry. FTA has found valuable applications in the field of rail safety. Nguyen et al. [24] employed the FTA method to assess the failure probabilities associated with potential accidents, including train collisions. Huang et al. [25] introduced a combined approach that incorporated FTA and fuzzy D-S evidential reasoning to investigate the risks associated with the transportation of hazardous goods by rail. Jafarian et al. [26] presents a comprehensive study on the evaluation of the railway safety risks using the fuzzy FTA. To assess adjacent-track accidents, Lin et al. [27] used an event tree and a fault tree to identify basic events that contribute to the accidents. Esmaeeli et al. [28] used FTA and event tree to evaluate the accident risk for railway transportation in Canada. Although FTA allows for the identification of risk factors in railway system, they still have limitations in expressing the uncertainty of event logical relations and probability updates since they are unable to capture the unpredictability of risk events. Relying solely on FTA for evaluating the risk of train derailment at the marshalling yard is inadequate.

2.2 Intuitionistic fuzzy set theory

When the necessary data, such as failure rates and probabilities, is available, the probability of the undesired event can be quantified. Obtaining accurate failure probability for large and complex systems is challenging because of inadequate observations and insufficient historical data. Fuzzy set theory was developed by Zadeh in 1965 to deal with imprecise information and uncertainty for system safety [29]. This theory is an extension of the classical set that only has two states. A combination of expert elicitation method and fuzzy set theory is able to be used to calculate the prior probability of BEs when historical data is not available [30]. For instance, Huang et al. [25] proposed a combined approach of FT and Fuzzy D-S evidential reasoning to analyse risk of railway dangerous goods transportation, which addresses the issues of uncertainty modeling and information fusion during accident analysis. Cheliyan et al. [31] used fuzzy FTA to analysis the failure probability of oil and gas leaks in subsea production system. However, in complex decision environments, traditional fuzzy sets that only rely on membership functions may result in a loss of information. In order to overcome the limitations, Atanassov [32] extended conventional fuzzy sets and proposed IFS in 1986. This theory can use the membership, non-membership, and degrees of hesitate to better express the uncertainty and fuzziness [33]. When compared with classical fuzzy set, IFS is more effective in dealing with realistic situations and modeling human thinking when compared to classical fuzzy sets [34]. The combination of the expert elicitation method and IFS has been effectively utilized in various industries for risk assessment [34-36].

2.3 *Bayesian network*

BN is one of the most efficient methods for dealing with uncertainty in complex systems. It allows for easy expression of variable relationships using graphics and conditional probability tables (CPTs). BN can also predict system safety with high accuracy from small data sets and update the dynamic risk with new information [37]. Previous studies have shown the applicability of BN model in various fields, such as chemical industry [38], ocean engineering [39], medical diagnosis [40], and civil engineering [41, 42]. BN models have also been applied to fault diagnosis and failure prediction in road and railway systems [43, 44]. However, there are so many risk factors for the TTS and the existing derailment databases at RTs are insufficient for the BN analysis. As a result, the failure data of root nodes and CPTs required for the BN parameter learning are difficult to be obtained. To overcome this shortcoming, the Delphi method and Noisy-or gate model were integrated into BN approach to assist identifying joint probability distribution (JPD) of a system [44, 45].

2.4 *Risk analysis in railway classification yards*

Cozzani et al. [46] examined three distinct types of accidents that can occur in railway yards: (i) "in-transit-accident-induced" releases; (ii) "shunting-accident-induced" spills; and (iii) "non-accident-induced" leaks. They developed a comprehensive risk assessment framework that combined Hazard and Operability analysis with Fault Tree Analysis (FTA). Zhang et al. [47] introduced a set of three control measures to enhance operational safety in classification yards. These measures encompass preventive control, process control, and result control perspectives. Ye et al. [48] developed an acoustic-based technology to detect the unreleased braking of freight wagons during the uncoupling operation at a railway yard. Lai et al. [49] assessed the dynamic derailment risk associated with vehicle retarders through numerical simulation and 3D quasi-static analysis. Chang et al. [50] observed that the risk of accidents in classification yards tends to be higher due to the intricate track layout and semi-automated traffic control systems. These studies have significantly contributed to enhancing safety within railway yards by analyzing and evaluating various accident risks. However, it is noteworthy that none of these studies have delved into the assessment of train derailments at railway turnouts (RTs) within classification yards, especially considering the uncertainties associated with the TTS. Therefore, there is a clear need to establish a comprehensive research framework dedicated to analyzing the risk of derailments as trains pass through RTs within railway yards.

2.5 *Application of BN and fuzzy sets in rail transportation system*

The failure analysis for the rail transport system has been a topic of interest for researchers who have tried to assess the safety of railroads from different perspectives. For instance, Liu et al. [51] investigated the causal relationship between the frequency of ultrasonic rail defect inspections and the risk associated with the transportation of hazardous materials on railroads. Wang et al. [52] studied the risk of broken rail in freight railroads using machine learning. Ishak et al. [53] proposed a maintenance strategy for turnout geometry based on risk analysis that takes into account various types of failures in order to reduce the risk of derailments. Dindar et al. [44] proposed a BN-based probabilistic risk analysis method for quantifying the derailment risk at RTs, particularly under extreme weather conditions. They employed Buckley's confidence interval-based method to derive both marginal and conditional probabilities for Bayesian Network inference. In addition, their study also provides new insights into human errors, which result in derailments at RTs [54]. Inspired by their work, we have developed an enhanced methodology. This approach effectively converts qualitative linguistic assessments provided by experts into more reliable estimates of failure probabilities when historical data is insufficient. It is designed to assess derailment risks within railway classification yards, further contributing to the enhancement of railway safety.

Table 1

Examples of the use of BN and fuzzy sets in the area of railroad transportation safety.

Authors	Area of focus	Approaches	Key findings/marks

Dindar et al. [44]	Train safety under extreme weather condition	Fuzzy set theory, BN	BN and Fuzzy Sets were employed to assess the risk of train derailment when faced with uncertain climate conditions.
Liu et al. [55]	High-speed railway accidents	IFS theory and FTA	An IFFTA model is proposed and used to quantify the risk of high-speed railway system due to the incompleteness of prior information.
Wang et al. [56]	Turnout failure prediction	Entropy Minimization, Causal noisy Max model, BN	A BN was established to forecast the weather-related failure of turnouts. The Causal Noisy Max model was utilized to handle the CPTs based on limited data sets.
Liang et al. [57]	Risk analysis on railway level crossings	BN	A new BN framework is proposed to quantify the risk associated with railway level crossings.
Castillo et al. [58]	Risk analysis of railway lines	Markovian-BN	A Markovian-BN model has been created to assess the likelihood of accidents occurring when trains pass over conventional or high-speed railway lines, considering the possibility of human error.
Huang et al. [59]	Hazardous goods transportation	BN, Interpretive Structural Modeling (ISM)	An approach based on ISM and BN was utilized to analyse the degree of interaction between various risk factors involved in the transportation of hazardous goods by railway.
Panrawee et al. [60]	Railway accidents	BN, decision tree, petri-net	A Bayesian approach has been adopted to cope with uncertainties of railway accident and the model is validated using petri-net and decision tree

Table 1 presents some typical examples of research results related to the application of BN and fuzzy sets in the field of railroad transportation safety. These studies have shown that BN model has good capability for the risk quantification in the field of railway transportation, such as track failure estimation, dangerous goods transportation and collision accident analysis. There are also some gaps need to be filled. In the process of expert judgement, uncertainties and hesitations can arise when determining the membership of classical fuzzy sets. Using IFS can better express the fuzziness and uncertainty from expert opinions. Furthermore, for a complex BN structure with too many nodes and directed arcs in this study, there may be inadequate accident data in railway yards for the CPT estimation. To address this limitation, we integrated BN with the Noisy-or gate model to reveal the causal relationship and derailment risk when railway vehicles run in railway yards under uncertainties.

3 Material and background

3.1 Brief introduction of TTS

The TTS is composed of several crucial sub-systems that work in conjunction to guarantee the secure operation of trains. The TTS comprises of three main sub-systems: the train sub-system, the turnout sub-system, and the wheel-rail contact module. The train sub-system primarily consists of multiple wagons, bogies, wheelsets, and couplers. The turnout sub-system, on the other hand, guides and supports vehicles. It is a complex system comprised of a variety of track components, including rails, fasteners, ballast, switches, crossings, and other related components. This paper has taken into account the switch section, closure section, and frog section in risk analysis. In addition, as the turnout is a combination of multiple rails, the wheel-rail relationship at RTs is complex and random. The vehicle retarders are installed in front of turnouts at classification yards in China as a measure to reduce train speed, as illustrated in Fig. 2. The presence of sharp curves and vehicle retarders before the turnout

can also decrease train running safety. The contact between the wheels and rails can significantly impact the safety [61]. For instance, when contact points shift to the wheel flange, wheels may climb up to railhead and cause a derailment [11]. Furthermore, intense impacts between the wheels and turnouts are very common due to the discontinuities of the track, which can result in the wheel jumping to the railhead.

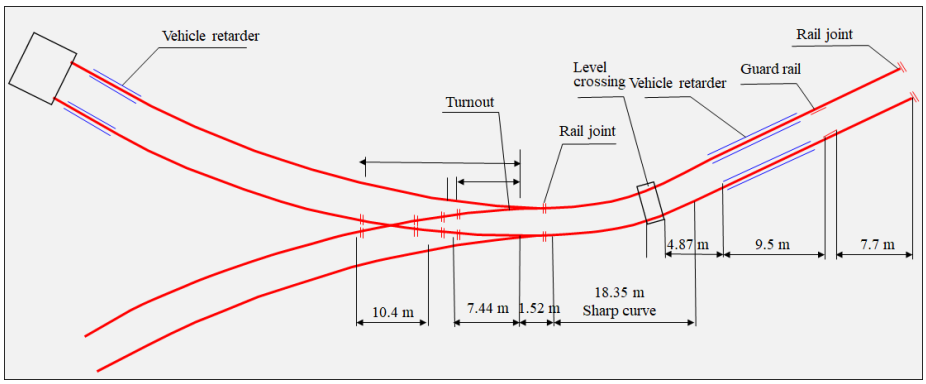

Fig. 2. Schematic diagram of the track alignment at classification yard in China.

3.2 *Derailment mechanism at RTs*

When a wheel passes over a RT, it needs to pass over a split rail in order to follow the correct track. However, if the relationship of the wheel-rail contact is abnormal, it can cause the wheel to derail. Fig. 3 illustrates a diagram of derailment processes when railway vehicles pass through the railway switch. The process of a wheel derailing on a switch typically involves the wheel climbing up the switch rail instead of following the intended path. This can cause the wheel to lose contact with the rail and potentially cause damage to the switch and surrounding tracks. As the wheel continues to move forward, it can then fall off the rail completely or get stuck in a position where it cannot move any further. This can cause a delay in train traffic as crews work to remove the derailed wheel and repair any damage caused. It is noted that when vehicles are traveling at high speeds, it may cause the carriage to overturn, leading to the spread of hazardous materials. Overall, derailments at turnouts can be caused by different factors, such as mechanical issues with the rail switch, poor maintenance of the track, or vehicle component failure. The occurrence of any abnormal states between them may cause the railway vehicle to derail at turnouts.

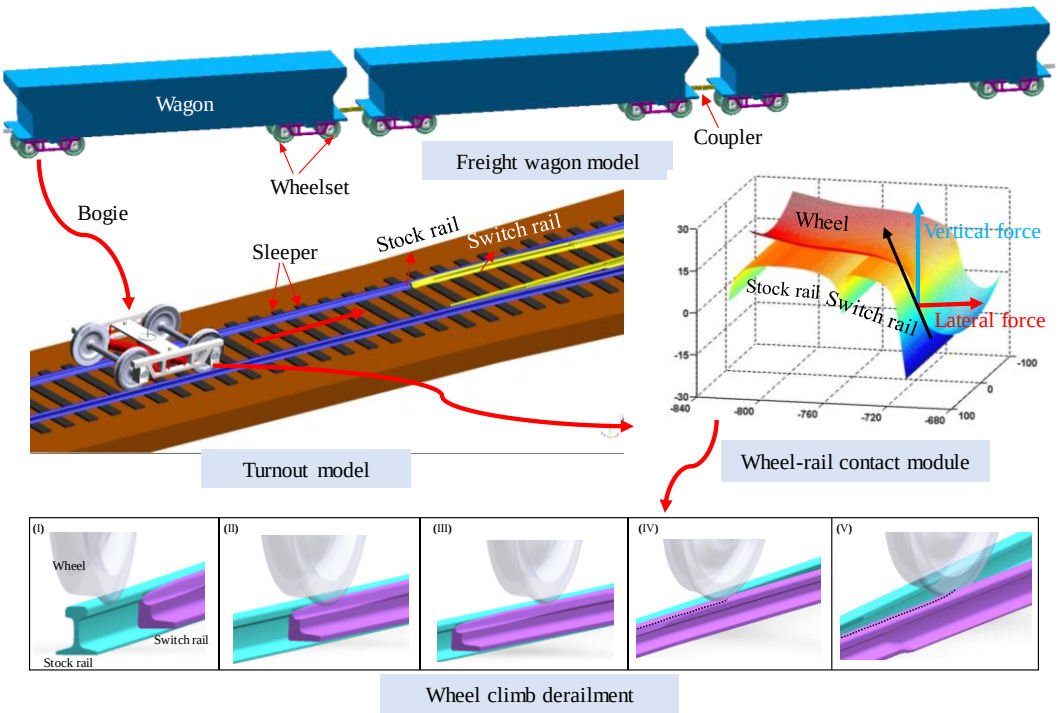

Fig. 3. A simplified diagram of wheel derailment processes at RTs.

4 Proposed IFFTA and NGBN methodology

The approach for derailment risk analysis is based on the IFFTA model, the Noisy or gate, and the BN model. Fig. 4 illustrates the research framework for the proposed methodology. Firstly, a fault tree is constructed. Secondly, opinions from different experts are collected and corresponding linguistic terms for BEs are quantified as TIFNs. An improved aggregation method is then introduced to aggregate the TIFNs, which has considered the effect of experts' weight degree of consensus. Thirdly, the fuzzy failure probability of BEs can be calculated and the fault tree is mapped into the BN structure. The Noisy-or gate modeling is then introduced and integrated into the naïve BN model to derive the CPTs. Finally, Bayesian inference, sensitivity analysis, model verification, and preventive measures are presented. The details are presented as follows.

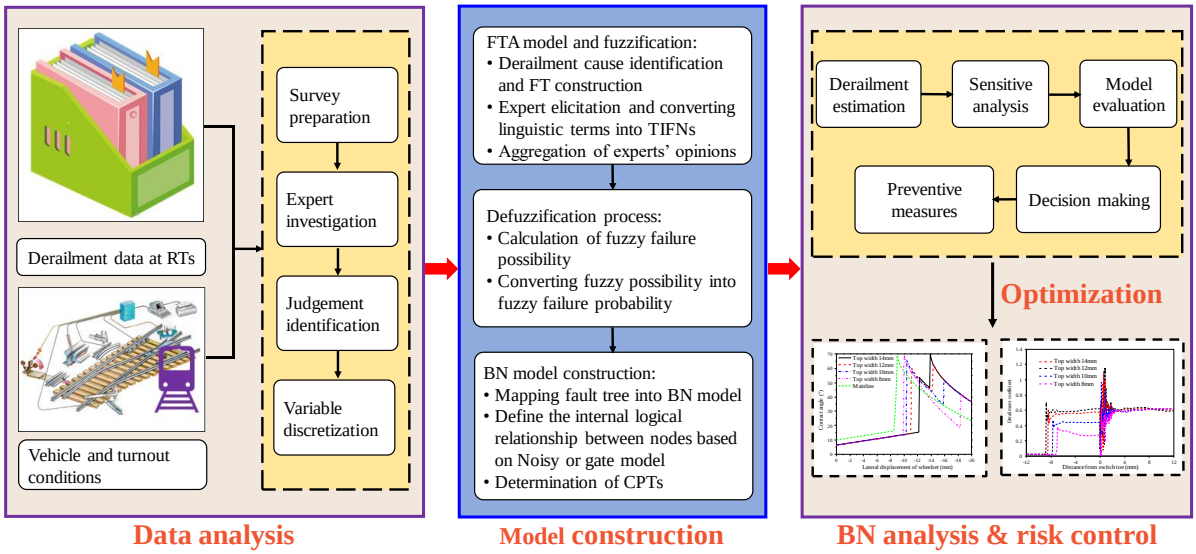

Fig. 4. Flowchart of proposed methodology.

4.1 *Derailment cause identification and FT construction*

Identifying risk factors for TTS is a critical step in analysing the risk of the train derailment at RTs. It represents the first step in conducting a reliability analysis. Typically, hazards and operability analysis [62] and FMEA [63] are two common methodologies used for identifying potential hazards in industrial processes and systems. In this paper, the risk factors are determined by analysing historical data from 27 derailment cases that occurred at RTs from 2014 and 2019. Besides, literature [3, 4, 64], and expert judgment are also utilized to identify the risk factors.

A fault tree for the train derailment at RTs is shown in Fig. 5. The diagram is divided into three levels: (1) BEs are at the lowest level, (2) intermediate events (IEs) are at the middle level, and (3) top-level event (TE) is at the top level. The connections between various events are represented by logical symbols. In this study, the derailment risk at RTs is designated as the top event for the risk analysis of derailment. The full name of each abbreviation in the fault tree is provided in Section 5.2.

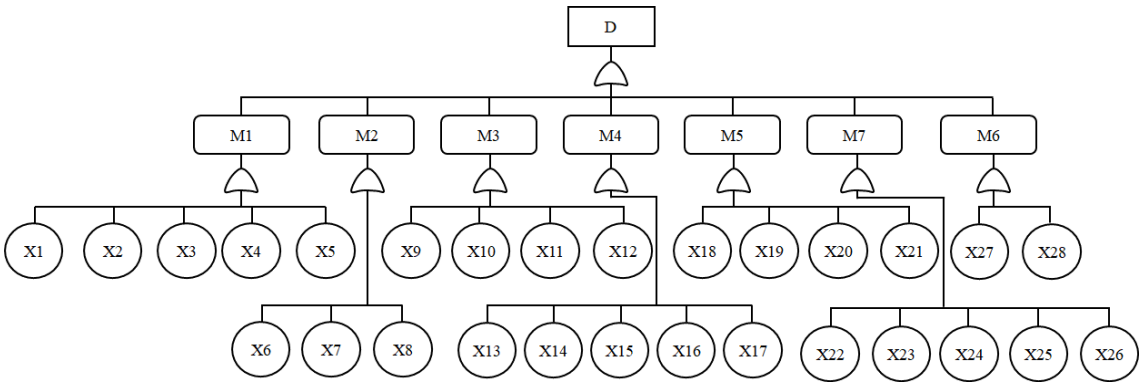

Fig. 5. The fault tree for the train derailment at RTs.

4.2 Introduce IFS to obtain probability of BEs

For the quantification analysis of derailment risk at RTs, the accurate prior probability of root nodes should be obtained. The probability of an event occurring can be determined using various methods such as statistical analysis, historical data, and expert elicitation. Note that accurate historical data for the TTS in this study is insufficient. Thus, the combined approach of expert elicitation and IFS is a good choice for identifying the failure probability of the BEs. The detailed procedures for determining the fuzzy failure probability of BEs are presented as follows.

4.2.1 Concept of IFS theory

Definition 1: Intuitionistic fuzzy set.

If X is a universe of discourse, the IFS $\tilde{A}$ in X can be expressed as [32]:

$$\tilde{A}=\left\{\left\langle x,u_{\tilde{A}}(x),v_{\tilde{A}}(x)\right\rangle \middle| x\in X\right\} \tag{1}$$

where: $u_{\tilde{A}}(x):X\to[0,1]$ and $v_{\tilde{A}}(x):X\to[0,1]$ represent the membership function and non-membership function of $\tilde{A}$. The functions satisfy the following two conditions:

$$u_{\tilde{A}}(x)+v_{\tilde{A}}(x)\in[0,1],\ \forall x\in X \tag{2}$$

$$\pi_{\tilde{A}}(x)=1-u_{\tilde{A}}(x)-v_{\tilde{A}}(x) \tag{3}$$

where $\pi_{\tilde{A}}(x)$ represents the IF index of $x\in\tilde{A}$, also referred to as the degree of uncertainty or level of hesitation.

Definition 2: Intuitionistic fuzzy number.

Convex intuitionistic fuzzy set [32]:
Membership functions of $u_{\tilde{A}}(x)$ of $\tilde{A}$ is fuzzy-convex i.e.

$$u_{\tilde{A}}(\lambda x_1+(1-\lambda)x_2)\geq\min\left\{u_{\tilde{A}}(x_1),\ u_{\tilde{A}}(x_2)\right\}\quad\forall\ x_1,x_2\in X,\ 0\leq\lambda\leq1 \tag{4}$$

Non-membership functions of $v_{\tilde{A}}(x)$ of $\tilde{A}$ is fuzzy-concave i.e.

$$v_{\tilde{A}}(\lambda x_1+(1-\lambda)x_2)\leq\max\left\{v_{\tilde{A}}(x_1),\ v_{\tilde{A}}(x_2)\right\}\quad\forall\ x_1,x_2\in X,\ 0\leq\lambda\leq1 \tag{5}$$

A triangular-shaped intuitionistic fuzzy number (TIFN) can be denoted as Eqs. (6) and (7). The shape of TIFN is shown in Fig. 6.

$$u_{\tilde{A}}(x)=\begin{cases}\dfrac{x-a}{b-a}, & a\le x\le b\\ \dfrac{c-x}{c-b}, & b\le x\le c\\ 0\quad , & otherwise\end{cases} \tag{6}$$

$$v_{\tilde{A}}(x)=\begin{cases}\dfrac{b-x}{b-a'}, & a'\le x\le b\\ \dfrac{x-b}{c'-b}, & b\le x\le c'\\ 1\quad , & otherwise\end{cases} \tag{7}$$

where the TIFN is expressed by $\tilde{A}=(a,\ b,\ c;\ a',\ b,\ c')$.

4.2.2 Expert elicitation and IF-fuzzification

Expert elicitation can be used as an alternative statistical method when data is not available or unreliable, and it relies on expert knowledge and judgment to estimate probabilities. It is also one of the efficient methods for supporting system reliability analysis. In this study, the knowledge from multi-experts is utilized to obtain fuzzy failure probabilities (FFP) of BEs. The expert judgment method describes the probability of BEs by dividing the probability range into *k* regions and matching the corresponding linguistic terms. In this work, it is divided into 7 levels of linguistic terms, which consist of very low (VL), low (L), reasonably low (RL), moderate (M), reasonably high (RH), high (H), and very high (VH). Besides, based on the historical derailment data in classification yards, we have categorized the derailment risk into seven levels based on the frequency of train derailments. The probability range is from 6.61e-6 to 1.10e-1, as shown in **Table 2**. The annual frequency is determined by the fuzzy possibility score and fuzzy failure probability in Eqs. (16-18). Fig. 6 illustrates the graphical representation of all the potential failure scenarios.

Table 2

Risk level for derailment at RTs in classification yards.

Risk level	Description	Annual frequency
Very high	≥1 derailment accident per month during operations	>1.10e-01
High	≥1 derailment accident per quarter of a year during operations	2.60e-02~1.10e-01
Reasonably high	≥1 derailment accident per half-year during operations	5.20e-03~2.60e-02
Moderate	≥1 derailment accident per year during operations	1.00e-03~5.20e-03
Reasonably low	≥1 derailment accident in 2 years during operations	1.92e-04~1.00e-03
Low	≥1 derailment accident in 5 years during operations	4.71e-05~1.92e-04
Very low	≥1 derailment accident in 10 years during operations	6.61e-06~4.71e-05

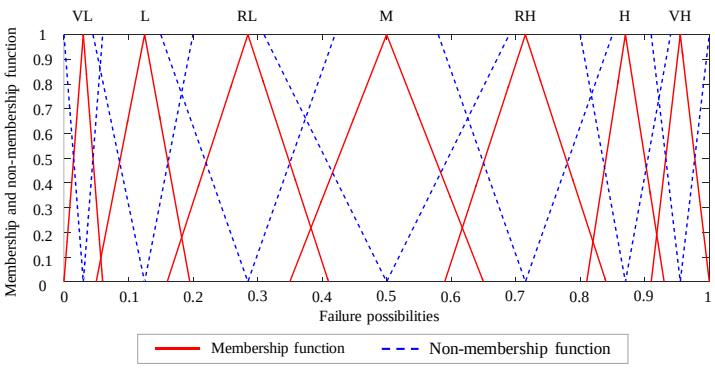

Fig. 6. TIFNs corresponding to linguistic terms.

4.2.3 Aggregation of expert opinions

Given that the selected experts possess diverse backgrounds, experiences, and levels of expertise, their judgments on the risk level of BEs may be different. In order to obtain a unique intuitionistic fuzzy failure possibility, their opinions should be aggregated. In this study, we utilize the Similarity Aggregation method (SAM) [65] to aggregate the linguistic terms of a group of experts. **Table 3** is used to determine the weighting scores (WS) of experts in this study. It should be noted that the term "worker" refers to a young employee who has just joined the railroad company and lacks sufficient work experience. The details for the aggregation method are presented as follows:

Step 1. The similar degree of opinions $\tilde{A}_i$ and $\tilde{A}_j$ from experts E_i and E_j can be expressed as $S(\tilde{A}_i, \tilde{A}_j)$, and it can be calculated by Eq. (8):

$$S(\tilde{A}_i, \tilde{A}_j) = \begin{cases} KW(A_i) / KW(A_j), & if \ \ KW(A_i) \le KW(A_j) \\ KW(A_j) / KW(A_i), & if \ \ KW(A_i) \ge KW(A_j) \end{cases} \tag{8}$$

$$KW(\tilde{A}_i) = \frac{(a_i + a_i^{'}) + 4b_i + (c_i + c_i^{'})}{8} \tag{9}$$

where $KW(A_i)$ and $KW(A_j)$ denote the expectancy evaluation for TIFNs $\tilde{A}_i$ and $\tilde{A}_j$ respectively.

The similarity matrix (SM) can be obtained in the following form when there are m experts:

$$SM = \begin{bmatrix} 1 & S_{12} & S_{13} & \cdots & S_{1m} \\ S_{21} & 1 & S_{23} & \cdots & S_{2m} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ S_{m1} & S_{m2} & S_{m3} & \cdots & 1 \end{bmatrix} \tag{10}$$

A larger value of S_{ij} represents a higher degree of consistency between the opinions of the experts. Conversely, if $S_{ij} = 0$, it means that there is no overlap or intersection between the opinions of the experts.

Step 2. The average agreement degree of each expert E_i is obtained as

$$AA(E_i) = \frac{1}{m-1} \sum_{\substack{j=1 \\ j \ne i}}^{m} s_{ij}, \ i = 1, 2, ..., m \tag{11}$$

Step 3. The relative agreement degree (RAD) for each expert E_i can be calculated as

$$RAD(E_i) = \frac{AA(E_i)}{\sum_{i=1}^{m} AA(E_i)}, \ i = 1, 2, ..., m \tag{12}$$

Step 4. Weighting factor (WF)

The WF for each expert is calculated based on four criteria, including professional position, years of work experience, educational level, and age. This approach improves the credibility of the data by assigning different weights to each expert, instead of treating all experts as equal. Thus, five experts are selected from the field of railway engineering, who come from universities, maintenance departments, safety management, each expert has a distinct WS. Firstly, entropy technology is utilized to determine the importance weights of the four criteria [66]. And then, the WF of expert E_i is calculated based on Eq. (13).

$$WF(E_i) = \frac{WS(E_i)}{\sum_{i=1}^{m} WS(E_i)}, \ i = 1, 2, ..., m \tag{13}$$

Step 5. Aggregated weight calculation.

The weight of the aggregated opinions is calculated by combining the $WF(E_i)$ and $RAD(E_i)$ of each expert E_i, as shown in Eq. (14).

$$CC(E_i) = \beta \cdot WF(E_i) + (1-\beta) \cdot RAD(E_i) \tag{14}$$

where β $(0 \le \beta \le 1)$ denotes the relaxation factor, which represents the importance expert weight and relative degree of agreement.

Step 6. Aggregated results.

The intuitionistic fuzzy aggregation results of expert opinions can be calculated by Eq. (15) [67].

$$\tilde{R}_{AG} = \sum_{i=1}^{m} (\oplus T_{\omega}) CC(E_i) \cdot \tilde{A}_i \tag{15}$$

Table 3

Weighting score for experts.

Attributes				Score
Professional position	Service time	Education level	Age	
Senior academic, Chief Engineer, Director	>20 years	PhD	>60	5
Junior academic, Manager	15-20	Master	50-60	4
Engineer	10-14	Bachelor	40-49	3
Technician	5-9	HND	30-39	2
Worker	<5	School-level	<30	1

4.2.4 IF-defuzzification

The aggregated TIFN $\tilde{A} = (a, b, c;\ a', b, c')$ of the BE can be defuzzied by the center of area method [68]. The processes of transforming TIFN into FFP through defuzzification are divided into two stages: converting the TIFN into a fuzzy possibility score (FPS), and then converting the FPS into FFP. It can be expressed as follows:

$$FPS = \frac{1}{3}\left[\frac{(c'-a')(b-2c'-2a') + (c-a)(a+b+c) + 3(c'^2 - a'^2)}{c'-a'+c-a}\right] \tag{16}$$

4.2.5 Converting FPS into FFP

In order to obtain the FFP, the IF-defuzzification procedure generates an FPS that signifies the likelihood of BEs taking place. Onisawa [69] proposed a conversion method, whereas it is not universally applicable across different industries. This work utilized an improved approach to compute the FFP using Eqs. (17) and (18), taking into account that the failure likelihood is segmented into seven distinct regions.

$$FFP = \begin{cases} 1/10^{K} & FPS \neq 0 \\ 0 & FPS = 0 \end{cases} \tag{17}$$

$$K = \begin{cases} -0.721 \ln FPS + 2.839, & 0 \le FPS < 0.2 \\ -1/3 \times (10FPS - 14), & 0.2 \le FPS \le 0.8 \\ [(1-FPS)/FPS]^{0.445} \times 3.705, & 0.8 < \mathrm{FPS} \le 1 \end{cases} \tag{18}$$

The derivation of the coefficient K can be found in Ref. [67]. This method was originally proposed and validated to deal with the probability of failure of human-machine systems. Inspired by the method [67], the modified coefficient is determined based on the seven-level probability regions provided in Table 2. The proposed method could avoid the subjective understanding deviation that arises when converting qualitative empirical knowledge from

domain experts into quantitative failure probability.

4.3 Bayesian modeling

4.3.1 Bayesian network

BN is a type of graphical model that utilizes a directed acyclic graph to depict a series of variables and their conditional dependencies. Each node in the graph represents a variable and the edges between the nodes represent the probabilistic relationships between the variables. BN can be used to represent causal relationships, represent uncertainty and perform probabilistic inference. It can be used to calculate the probability of a variable given the evidence provided by observed variables and the known relationships encoded in the network structure [70]. Besides, one can perform probabilistic inference to calculate the failure probability for the overall system. Additionally, sensitivity analysis can be conducted to understand how changes in component failure probabilities impact the system reliability. Overall, a BN model that combines IFFTA is a flexible approach for derailment risk analysis because it can handle complex systems with multiple interacting components and uncertainties in the failure probabilities. The JPD of a group of nodes can be defined as Eq. (19), taking into account the conditional dependencies and chain rules [70].

$$P(X) = P(X_1, X_2, \cdots X_n) = \prod_{i=1}^{n} P(X_i \left| Parent(X_i)\right.) \tag{19}$$

The conditional probability can be expressed as follows:

$$P(A\left|B_i\right.) = \frac{P(AB_i)}{P(B_i)} \tag{20}$$

The BN updates the occurrence probability (prior) of root nodes based on new evidence using Bayes' theorem. The updated probability (posterior) of the root nodes is expressed as:

$$\pi(B_i) = \frac{P(AB_i)}{P(A)} = \frac{P(B_i)P(A\left|B_i\right.)}{\sum_{i=1}^{n} P(B_i)P(A\left|B_i\right.)} \tag{21}$$

After obtaining the prior probability and posterior probability, the critical root nodes can be determined by ratio of variation (RoV), as shown in Eq. (22).

$$RoV(X_i) = \frac{\pi(X_i) - \theta(X_i)}{\theta(X_i)} \tag{22}$$

Where $\pi(X_i)$ represents posterior probability, and $\theta(X_i)$ is prior probability.

4.3.2 Mapping fuzzy fault tree model into BNs

The process of mapping FT into BN involves two stages, which are graphical mapping and numerical mapping, as shown in Fig. 7. The root nodes in BN are equivalent to the bottom events in FT, while the leaf node in BN is equivalent to the top event in FT. In numerical mapping, the fuzzy failure probability of each bottom event in FT is assigned as the prior probability of the corresponding root node in BN. The CPT is made for the intermediate nodes and leaf node, and it is determined according to the type of gate.

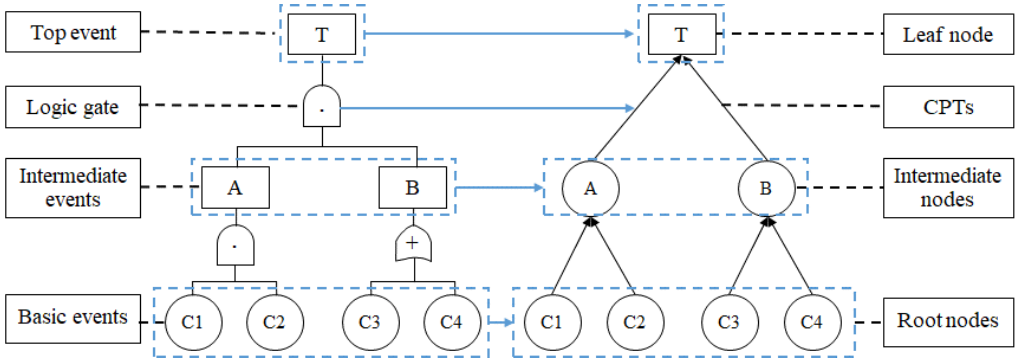

Fig. 7. Mapping process from FT into BN.

4.3.3 Noisy-or gate model

In the FTA model, logical 'OR' and 'AND' gates are used to derive the probability of occurrence. However, logic gate analysis describes the relationship between BE and IE in a very absolute way (0 or 1), in practice, it is not a simple binary. Besides, when assessing the risk of train derailment at RTs, many classification yards have not yet established a complete risk database. The use of the Noisy-or gate model allows for the derivation of CPTs with small data sets, enabling a more accurate assessment of system risk [71]. It is an interaction model used to describe the relationship between n parent nodes B_1, B_2, ..., B_n and child node T. The model must satisfy the two assumptions when applying Noisy-or gate model for BN inference. Then the conditional probability of node T can be calculated using Eq. (23).

$$P(T=Y|B_i)=1-\prod_{i:X_i\in X_T}(1-P_i) \tag{23}$$

In the actual analysis, besides the set B, there are other unknown factors that cannot be effectively identified in the risk factors that affect node T. It needs to use the extended Leaky Noisy-or gate model to attribute all risk factors that cannot be effectively identified to one factor B_L, and its connection probability is the Leaky probability, which is denoted as P_L.

The CPT of node T can be further expressed as Eq. (24).

$$P(T=Y|B_i)=1-(1-P_L)\prod_{i:X_i\in X_T}(1-P_i) \tag{24}$$

The Leaky Noisy-or gate model can also be used to determine the connection probability of the parent nodes. Assume that the network consists of two parent nodes, which could be expressed as variables C_i and C_{all}. The probabilities of occurrence of them are P_i and P_{all}, respectively. Eq. (25) can be obtained based on Eq. (23). Then, substitute Eq. (26) into Eq. (25), the connection probability is calculated by Eq. (27).

$$P(Y|C_i)=1-(1-P_i)(1-P_{all})=P_i+P_{all}-P_iP_{all} \tag{25}$$

$$P(Y|\overline{C_i})=P_{all} \tag{26}$$

$$P_i=\frac{P(Y|C_i)-P(Y|\overline{C_i})}{1-P(Y|\overline{C_i})} \tag{27}$$

5 Engineering application: A case study in China

5.1 Derailment scenario description

The appendix A provides examples of ten derailment incidents that occurred at low-speed RTs

from March 2014 to March 2019. Fig. 8 shows a freight wagon carrying hazardous materials derailed in the turnout area at Taiyuan North marshalling station. A derailment scenario depicted in Fig. 8 (IV) shows that when the rear freight wagon passes through the turnout, the leading wheelset of the wagon begins to climb the rail at the front of the switch rail and then drops down on the sleepers at the heel of the switch rail. Based on the field investigation, the leading wheel eventually fell off the top of the rail 6.2 m from the toe of the rail switch and the wagon stopped after traveling 12 m on the sleepers, as shown in Fig. 8 (IV). The turnout is located at the front of a sharp curve with a radius of 180 m. When inspecting the condition of the track, it was found that the workers did not maintain the geometry of the turnout in time. Besides, the combination of the new switch rail and the worn stock rail results in poor wheel-rail relationships between the wheel and the rail, which increases the risk of derailment. These indicate that the poor conditions of both the vehicles and the tracks can increase the risk of derailment. Based on this analysis, it is recommended to consider factors such as vehicle abnormal responses, track alignments, train formation types, turnout defects, inappropriate wheel-rail contact interface, and track maintenance in risk assessment of derailment.

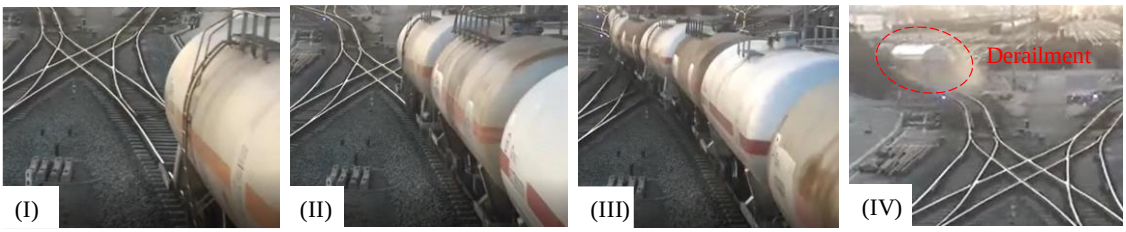

Fig. 8. A freight wagon carrying hazardous materials derailed in the turnout area.

5.2 *Construction of BN model*

The potential factors that contribute to derailment risk at RTs have been analysed through expert judgment, literature review and accident reports. The identified risk factors were grouped into seven categories, including poor vehicle conditions (M1), train formation risk (M2), abnormal wheel-rail contact (M3), turnout defects (M4), track alignment risk (M5), high rail stiffness at RT (M6), and lack of track maintenance (M7). To evaluate the derailment probability, a BN model was developed, with 28 root nodes, 7 intermediate nodes, and one target node. The complete BN model was constructed adopting GeNIe software, and is presented in Fig. 9. The details of each root node are listed in Appendix B.

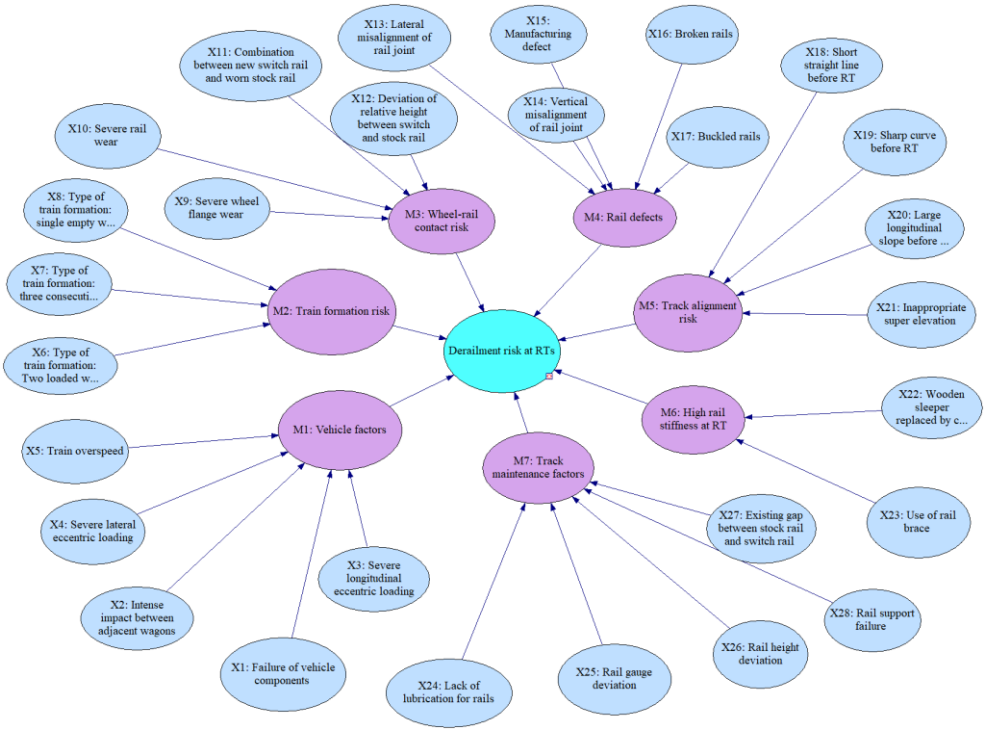

Fig. 9. BN model for derailment risk analysis based on IFFTA.

5.3 Parameters determination

Before beginning Bayesian analysis, it is necessary to determine the accurate prior probability of root nodes. Expert judgments for the BEs are provided in Appendix B. Based on the calculation procedure in section 4.2.3, the aggregation results from multi-experts and corresponding FFP of the BEs are presented in Appendix B. In addition, an example of calculation results for CPT of node M5 can be derived using Noisy or gate model, as shown in **Table 5**. If we define $P(\mathrm{M5}|\mathrm{X18}) = 0.92$, $P(\mathrm{M5}|\bar{\mathrm{X}}18) = 0.82$, $P(\mathrm{M5}|\mathrm{X19}) = 0.96$, $P(\mathrm{M5}|\bar{\mathrm{X}}18) = 0.70$, $P(\mathrm{M5}|\mathrm{X20}) = 0.95$, $P(\mathrm{M5}|\bar{\mathrm{X}}18) = 0.83$, $P(\mathrm{M5}|\mathrm{X21}) = 0.63$, $P(\mathrm{M5}|\bar{\mathrm{X}}18) = 0.30$. The connection probability between parent node M5 and child nodes X18, X19, X20, and X21 can be calculated by Eq. (27). The variable x_i, which is not known, follows a Gaussian probability distribution with a confidence level of 99%.

Table 4

Connection probability of M5.

Node	State			
X18	Y	N	N	N
X19	N	Y	N	N
X20	N	N	Y	N
X21	N	N	N	Y
P(M5=Y|X_i)	0.56	0.87	0.71	0.47

Table 5

The CPT of Node M5.

X18	X19	X20	X21	P(M5=Y|X_i)	P(M5=N|X_i)
Y	Y	Y	Y	0.99	0.01
Y	Y	Y	N	0.98	0.02
Y	Y	N	Y	0.97	0.03
Y	Y	N	N	0.94	0.06
Y	N	Y	Y	0.93	0.07
Y	N	Y	N	0.87	0.13
Y	N	N	Y	0.77	0.23
Y	N	N	N	0.56	0.44
N	Y	Y	Y	0.98	0.02
N	Y	Y	N	0.96	0.04
N	Y	N	Y	0.93	0.07
N	Y	N	N	0.87	0.13
N	N	Y	Y	0.85	0.15
N	N	Y	N	0.71	0.29
N	N	N	Y	0.48	0.52
N	N	N	N	0.01	0.99

5.4 Bayesian network inference

Once the IFBN structure and parameters were determined, the prediction of derailment risk at RTs was carried out using an academic version of GeNIe. The derailment probability is estimated to be 2.52%, as shown in Fig. 10. In other words, this indicates that the risk level at Taiyuan North yard is high risk. To obtain the posterior probabilities of the root nodes and identify key events, probability updates are performed by introducing evidence into the BN. When the occurrence probability of 'derailment risk at RTs' is set to 100%, the updated probabilities of root nodes could be calculated. Fig. 11 illustrates the comparison between the prior and posterior probability of the root nodes. It is

observed the posterior probabilities of some root nodes increase significantly, which represent the critical role in causing derailment risk.

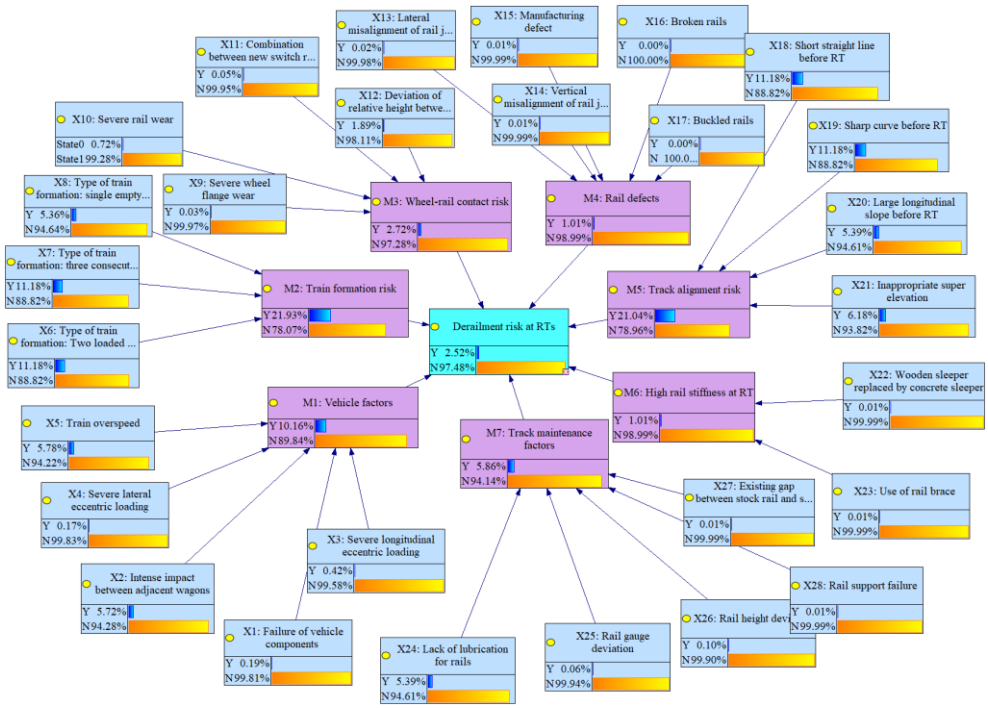

Fig. 10. The prediction result of derailment probability at RTs based on IFBN.

The RoV can be further calculated based on Eq. (22). As shown in Fig. 12, the critical basic events include node X2 (intense impact between adjacent wagons), node X10 (severe rail wear), node X11 (twist of track), node X5 (train overspeed), node X1 (failure of vehicle components), node X12 (deviation of relative height between switch and stock rail), and node X4 (lateral deviation of vehicle center of gravity). Thus, all of these factors need to be given more attention when trains pass through RTs.

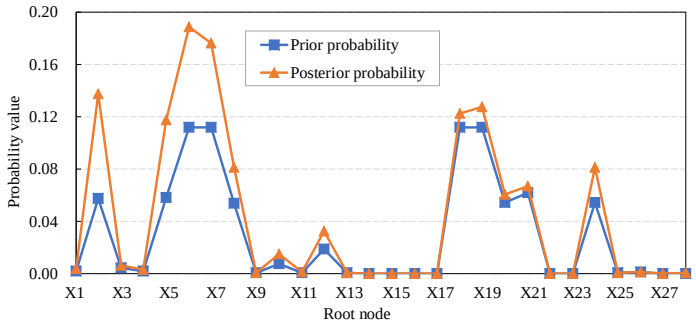

Fig. 11. Comparison of prior probability and posterior probability of root nodes.

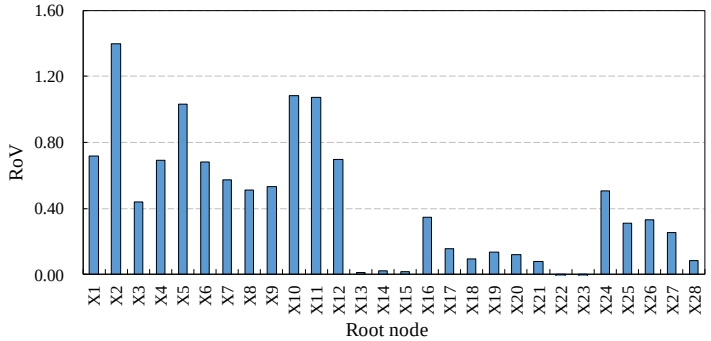

Fig. 12. RoV of root nodes.

5.5 *Sensitive analysis*

Sensitivity analysis measures the sensitivity, or responsiveness, of model results to changes in inputs. The nodes that have a significant effect on the derailment risk at RTs are shown in Fig. 12. By changing the probability of the nodes of X2, X10, X11, and X5, we obtained the sensitivity value of each node. Fig. 13 depicts the sensitivity of various variables to derailment risk at RTs. As seen in Fig. 13, a slight increase or decrease in the prior probability of the parent nodes, and intense longitudinal impact load between adjacent wagons, leads to a relative increase or decrease in the child node (derailment probability at RTs). Thus, the longitudinal impacts caused by the vehicle retarder should be controlled.

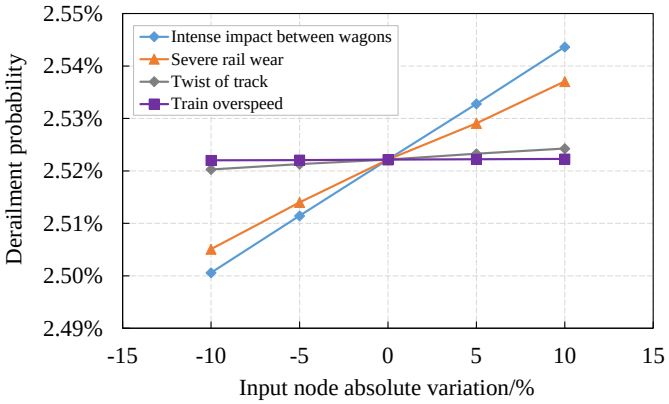

Fig. 13. Sensitivity for derailment probability at RTs against other variables.

To obtain the influence of the risk factors on derailment risk at RTs, we further utilized the GeNIe software to conduct a sensitivity analysis of the TTS by using backward reasoning for the IFBN model. Fig. 14 shows the tornado graph in GeNIe and the target node is set to ‘derailment risk at RTs’. The length of the bar indicates the extent of variation in the target state when the probabilities of all other nodes change by 100%. In addition, the green bar expresses the positive influence and the red bar reflects the negative impact. The longer the bar, the greater the influence of the cause on the result. The 20 most influential factors are presented. As illustrated in Fig. 14, it is observed that the state of ‘Derailment risk at RTs’ being Y can be changed from 0.0185 to 0.517. We can notice that P(Derailment=Y|M1=N, M2=N, M3=N, M4=N, M5=N, M6=N, M7=N) impacts P(Derailment=Y) most. Namely, P(Derailment=Y) decreases from 0.517 to 0.0185 as M1 to M7 are checked as N. The results indicate that node M1, node X2, node M3, node X5, node X10, node X11, and node X6 have a great influence on the derailment risk at RTs. This is in agreement with historical statistics in Taiyuan North marshalling station.

Railroad managers have responded to these critical events by taking targeted measures. These measures involve timely development of in-service inspections, preventive testing, and maintenance of vehicles and turnouts, as well as timely replacement of defective and degraded turnout components. Moreover, they have optimized the track parameters in the vicinity of turnouts to reduce the risk of derailment.

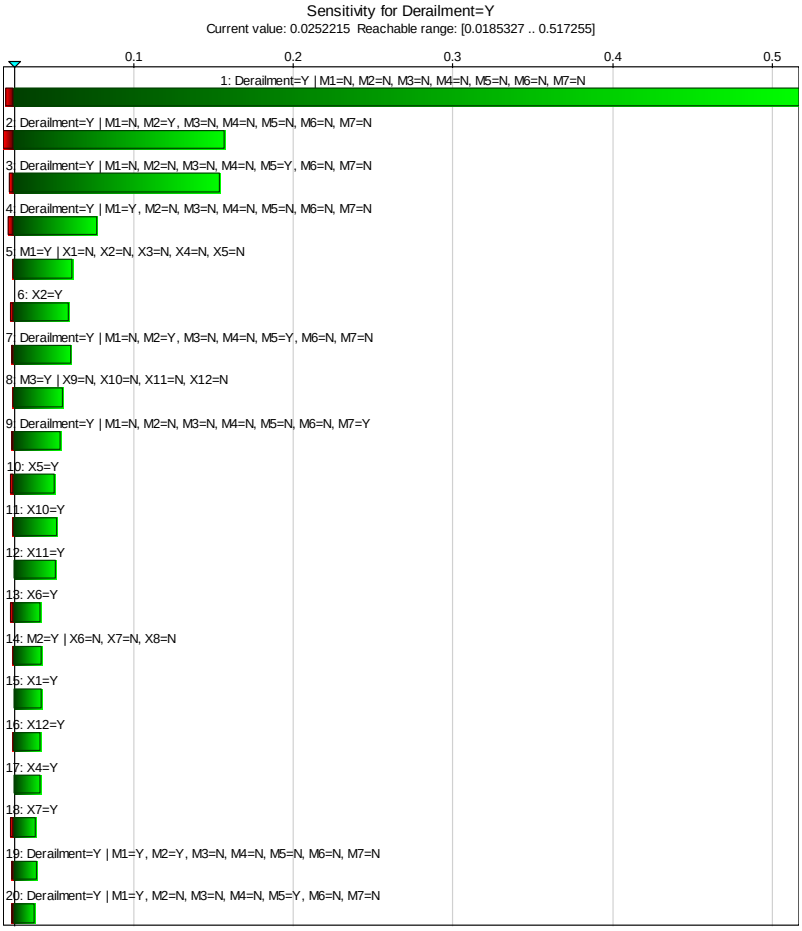

Fig. 14. Tornado diagram of sensitive analysis results.

5.6 *Model validation*

To verify the proposed model, the results of comparison of fuzzy failure probability between traditional FBN method and improved IFBN method are presented in Fig. 15. It is observed that the improved method generally produces smaller calculation results compared to the traditional method. This is because current approach divides the probability regions corresponding to TIFN into more reasonable intervals, leading to more accurate accident probability estimates for derailments at RTs. The traditional method was initially proposed and has been widely adopted for assessing the failure probability of human-machine systems. However, for other industries, the evaluation results are subject to inevitable objective errors. The proposed method in this study can help to mitigate the subjective understanding bias that arises when converting qualitative empirical knowledge into quantitative failure probability.

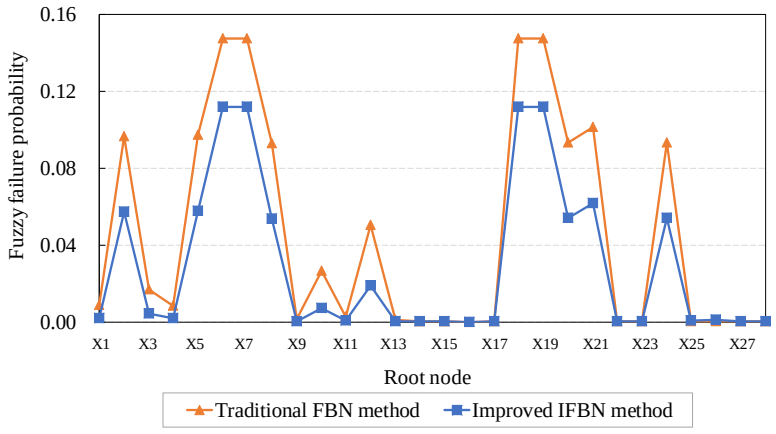

Fig. 15. Comparison of FFP of root nodes between improved IFBN and traditional method.

In addition, to confirm the efficacy of the Noisy or gate model, we examined the conditional probabilities of each node to validate the effectiveness of the proposed model. The results of a comparison between the IFFTA and Noisy or gate BN method and the IFTA and BN method are presented in Fig. 16. It can be observed that there is a minimal difference between the IFFTA and Noisy or gate BN model and the IFFTA and BN model. The proposed approach incorporating the Noisy or gate model can not only meet the accuracy requirements for practical analysis but also reduce the number of parameters necessary for BN analysis.

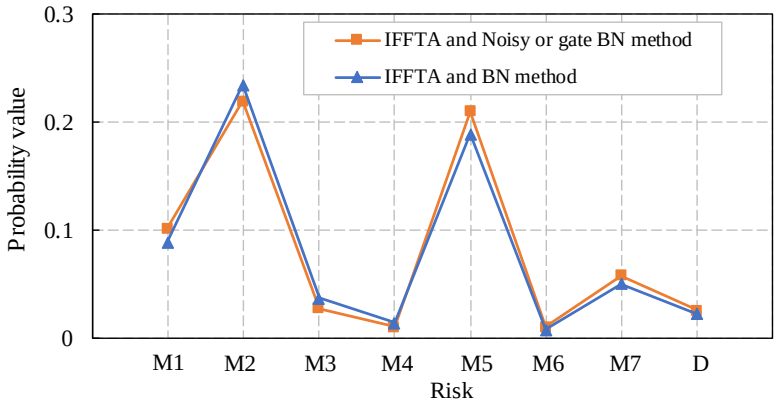

Fig. 16. Comparison of probability obtained by Noisy or gate IFBN method and IFBN method.

5.7 Preventive measures

By conducting a quantitative risk analysis of freight train passes through RTs, measures can be taken to mitigate the risk of derailment and reduce the secondary damages and injuries caused by derailed vehicles.

(1) When freight wagons pass over the vehicle retarder in front of the turnout, an intense longitudinal impact will occur between the adjacent wagons. It is recommended to adjust the position of the vehicle retarder in order to reduce the impact of the retarder on the operation of the vehicle in the turnout area.

(2) Regular inspections and maintenance should be carried out to detect and repair any damage or deviations in the geometry of turnouts in a timely manner. Due to high transportation demand, various defects are more likely to occur at turnouts during operation. Railroad operators should install track condition online monitoring and warning equipment in the turnout area to ensure train safety and prevent secondary damages.

(3) Proper lubrication of the switch rail needs to be carried out to reduce friction, rail wear and derailment coefficient. This can decease the lateral force between the wheel and switch rail and reduce the risk of wheel climb derailment.

(4) The track alignment and parameters before the turnout should be optimized. Small radius curves should be avoided as much as possible from being laid in front of the turnout.

5 Conclusions

The railway turnout area is a high-risk area for freight train derailment. It is significant to quantify the freight train derailment risk at turnouts and reduce the secondary damage to surrounding environment, buildings, and infrastructures. This paper presents a failure probability assessment method and demonstrates its application in quantifying the risk of derailment due to unfavourable operating conditions in railway vehicles and turnout systems. The approach utilized in this study is based on the IFFTA and NGBN model. The combination of expert elicitation, IFS, and improved SAM is employed to calculate the FFP of BEs due to its capability to handle incomplete information and hesitate decisions. The CPTs of the proposed IFBN model is derived using the Noisy-or gate technique to overcome the limitations of complex node computation and data dependency in this study.

The feasibility and efficacy of risk analysis method are demonstrated by analysing the empirical data from derailment incidents in the turnout area at Taiyuan North marshalling station in China. The derailment risk at RTs can be estimated using Bayesian forward analysis and the posterior probabilities and critical events can be identified by Bayesian backward analysis. The results indicate that the derailment probability at RTs is 2.52%. Additionally, intense impact between adjacent wagons, vehicle overspeed, twist of track and severe rail are assessed as the four most influential basic factors. When compared with traditional method, the results obtained from the IFFTA and Noisy or gate BN model with improved SAM method are more reasonable when considering proper division for the linguistic terms. In this paper, the IFBN model is applied to TTS, but the same method can be potentially used to other systems for failure prediction, especially for tasks involving multiple risk sources for which accurate data are difficult to obtain.

The main contributions of this study can be summarized as follows: (1) An IFBN-reliability method is proposed for quantitative assessment for derailment risk at RTs. This method is capable of efficiently handling the derailment probability at RTs when prior information of the system components is incomplete and the decision environment is complex and hesitating. (2) A case study at Taiyuan North marshalling yard is presented to verify the accuracy of the proposed IFFTA and NGBN method. The comparative analysis between current method and traditional method is also carried out. The analysis results illustrate that it can meet the requirements of derailment probability assessment at RTs. (3) The critical risk factors and sensitivity analysis of the TTS are discussed, and the derailment risk at RTs can be updated by monitoring the real-time conditions of the TTS. Preventive measures for risk-based design of TTS and reducing the secondary damage caused by derailed vehicles are provided.

Dynamic risk assessment in the turnout area is crucial for ensuring safe and reliable railway transportation. With the continuous development of monitoring technology, we can collect more and finer monitoring data to improve the accuracy and reliability of the BN model. Besides, machine learning techniques can help us uncover potential patterns and correlations in monitoring data, thus better assessing the dynamic risk in railway switch areas. Therefore, in future work, we will apply the method of combining monitoring data and the BN model to the real-time warning system, so that the dynamic risk of derailment can be detected in advance and targeted measures can be taken to prevent accidents.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

Acknowledgments

The work was supported by the Chinese Scholarship Council (Grant No. 202207000077), National Natural Science Foundation of China (Grant No. 52122810 and 52108418), and Natural Science Foundation of Sichuan Province (Grant No. 2023NSFSC0398). The authors also thank the anonymous reviewers for their valuable comments that have improved the quality of this paper.

Appendix A. Derailments occurred at RTs and conditions of TTS

No.	Track alignments before turnout	Distance between retarder and turnout	Use of guard rails	Lubricat measure	Climbing position	Falling location	Sleeper type	Loading condition	Track condition	Longitudinal slope before turnout
1	Curved line (R=200 m)	>14 m	No	Lack of lubricati on	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Poor track geometry	—
2	Curved line (R=200 m)	>14 m	No	Lack of lubricati on	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	poor track geometry	—
3	Straight line	<14 m	Yes	Lack of lubricati on	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry	-2.6‰

4	Straight line	<14 m	Yes	Lack of lubrication	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry	-2.6‰
5	Straight line	<14 m	Yes	Lack of lubrication	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry	-4.2‰
6	Straight line	>14 m	No	Lack of lubrication	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry	-3.5‰
7	Straight line	>14 m	No	Lack of lubrication	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry	-3.5‰
8	Curved line (R=180 m)	Without vehicle retarder	Yes	Lack of lubrication	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry Poor manufacturing	—
9	Curved line (R=180 m)	Without vehicle retarder	Yes	Lack of lubrication	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry Poor manufacturing	—
10	Curved line (R=150 m)	>14 m	Yes	Lack of lubrication	Front zone of switch	Heel of switch	Concrete sleeper with rail brace	Empty wagon	Good track geometry Poor manufacturing	—

Appendix B Details of BEs and fuzzy failure probability

BEs	Description	Aggregated intuitionistic fuzzy number	FPS	FFP
X1	Failure of vehicle components	0.5496, 0.5849, 0.6201; 0.5403, 0.5849, 0.6295	0.5849	0.0019
X2	Intense impact between adjacent wagons	0.9088, 0.9209, 0.9330; 0.9068, 0.9209, 0.9350	0.9209	0.0572
X3	Longitudinal deviation of vehicle center of gravity	0.6557, 0.6866, 0.7175; 0.6533, 0.6866, 0.7199	0.6866	0.0042
X4	Lateral deviation of vehicle center of gravity	0.5363, 0.5732, 0.6102; 0.5264, 0.5732, 0.6200	0.5732	0.0018
X5	Train overspeed	0.9072, 0.9216, 0.9359; 0.9048, 0.9216, 0.9383	0.9216	0.0578
X6	Type of train formation: two loaded wagons sandwiched between an empty wagon	0.9441, 0.9550, 0.9659; 0.9441, 0.9550, 0.9659	0.9550	0.1118
X7	Type of train formation: three consecutive empty wagons	0.9441, 0.9550, 0.9659; 0.9441, 0.9550, 0.9659	0.9550	0.1118
X8	Type of train formation: single empty wagon	0.9029, 0.9172, 0.9315; 0.9005, 0.9172, 0.9339	0.9172	0.0536
X9	Severe wheel flange wear	0.3043, 0.3363, 0.3684; 0.2984, 0.3363, 0.3743	0.3360	0.0003
X10	Severe rail wear	0.7305, 0.7575, 0.7845; 0.7284, 0.7575, 0.7866	0.7575	0.0072
X11	Combination between new switch rail and worn stock rail	0.3810, 0.4176, 0.4543; 0.3712, 0.4176, 0.4640	0.4176	0.0005
X12	Deviation of relative height between switch and stock rail	0.8303, 0.8480, 0.8657; 0.8288, 0.8480, 0.8672	0.8480	0.0189
X13	Lateral misalignment of rail joint	0.2740, 0.3073, 0.3405; 0.2651, 0.3073, 0.3494	0.3073	0.0002
X14	Vertical misalignment of rail joint	0.1629, 0.1868, 0.2106; 0.1610, 0.1868, 0.2125	0.1868	0.0001
X15	Manufacturing defects	0.1609, 0.1890, 0.2171; 0.1586, 0.1890, 0.2194	0.1890	0.0001
X16	Broken rails	0.0513, 0.0654, 0.0779; 0.0504, 0.0654, 0.0788	0.0649	0.0000
X17	Buckled rails	0.0928, 0.1096, 0.1244; 0.0917, 0.1096, 0.1255	0.1089	0.0000
X18	Short straight line before RT	0.9441, 0.9550, 0.9659; 0.9441, 0.9550, 0.9659	0.9550	0.1118

X19	Sharp curve line before RT	0.9441, 0.9550, 0.9659; 0.9441, 0.9550, 0.9659	0.9550	0.1118
X20	Large longitudinal slope before RT	0.9030, 0.9175, 0.9319; 0.9006, 0.9175, 0.9343	0.9175	0.0539
X21	Inappropriate super elevation	0.9135, 0.9253, 0.9371; 0.9115, 0.9253, 0.9390	0.9253	0.0618
X22	Wooden sleepers replaced by concrete sleepers	0.1246, 0.1440, 0.1612; 0.1233, 0.1440, 0.1625	0.1433	0.0001
X23	Use of rail brace	0.1545, 0.1764, 0.1983; 0.1528, 0.1764, 0.2000	0.1764	0.0001
X24	Lack of lubrication for rails	0.9030, 0.9175, 0.9319; 0.9006, 0.9175, 0.9343	0.9175	0.0539
X25	Rail gauge deviation	0.3916, 0.4267, 0.4618; 0.3822, 0.4267, 0.4712	0.4267	0.0006
X26	Rail height deviation	0.4638, 0.5000, 0.5362; 0.4541, 0.5000, 0.5459	0.5000	0.0010
X27	Existing gap between stock rail and switch rail	0.1548, 0.1772, 0.1996; 0.1530, 0.1772, 0.2013	0.1772	0.0001
X28	Rail support failure	0.1914, 0.2170, 0.2425; 0.1893, 0.2170, 0.2446	0.2170	0.0001

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