Railway Dangerous Goods Transportation System Risk Assessment: An Approach Combining FMEA With Pessimistic–Optimistic Fuzzy Information Axiom Considering Acceptable Risk Coefficient

Wencheng Huang and Yue Zhang

***Abstract*—In this article, a new systemic risk assessment approach, which combines failure mode and effect analysis (FMEA) and pessimistic–optimistic fuzzy information axiom (POFIA) considering acceptable risk coefficient (ARC), is proposed to evaluate the risk of railway dangerous goods transportation system (RDNGTS). This approach transforms the system risk assessment problem into the rank problem of severity of risk factors affecting system security. The triangular fuzzy numbers (TFNs) are applied to score the severity of failures (*S*), portability of occurrence (*O*), and possibility of detection (*D*) for each RDNGTS risk subindicator. The information contents of *S*, *O*, and *D* are calculated for each risk subindicator, two models are applied to calculate the information contents: POFIA, and POFIA considering ARC (POFIA-ARC). The product of information contents of *S*, *O*, and *D* is used to replace the risk priority number of FMEA. entropy weight method is used to calculate the weight of each risk subindicator. The comparison among the FMEA-POFIA-ARC, FMEA-POFIA, FMEA, FMEA with TFNs is conducted based on the historical data of Chinese RDNGTS accidents from 1986 to 2017. Results show that the potential human risk should be paid more attention. Compared with the analysis results of statistical accident number, the results of the approaches proposed in this article (especially the FMEA-POFIA-ARC) are more reliable than the results of FMEA and FMEA TFNs combined approach.**

***Index Terms*—Acceptable risk coefficient (ARC), failure mode and effect analysis (FMEA), pessimistic–optimistic fuzzy information axiom (POFIA), railway dangerous goods transportation system (RDNGTS), risk assessment.**

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I. Introduction

COMPARED with the road, air, or water transportation, the railway goods transportation has some obvious advantages, such as larger traffic volume, faster transportation speed, lower transportation costs, longer transport distance, lesser influence from weather, etc. [21], [22], [40], [54]. Recently, with the rapid economic development in China, the demand of the dangerous goods (e.g., petroleum, pulverized coal, natural gas, radioactive materials, and flammable and explosive materials) has increased continuously. The statistical data of National Bureau of Statistics of China shows the total railway dangerous goods transport volume increased from 0.2046 billion tons in 2007 to 0.3025 billion tons in 2017, increased by 47.8% [25], [41]; the average loading capacity of dangerous goods transported by the railway has already reached 8000 vehicles per day, the annual transportation volume has already reached 180 million tons, accounting for more than 36% of the total dangerous goods volume [7], [25], it is estimated that by 2020, the loaded vehicles will reach 35 000 vehicles per day and the total dangerous goods volume transported by railway will reach nearly 600 million tons per year [7], [25]. In conclusion, the railway dangerous goods transportation system (RDNGTS) is becoming a core component in Chinese dangerous goods transportation service system.

At the same time, the accidents in the RDNGTS also occurred frequently in China, caused serious casualties and property and environmental damage [18], [21]–[23]. In order to manage the RDNGTS successfully, an effective risk management approach is necessary. Generally, there are three processes of the RDNGTS risk management, including risk identification, assessment, and control. Risk assessment focuses on determining what could cause a potential loss and gaining insight into how and why the loss might happen. The key issues of the risk assessment process are to determine risk events and the factors that cause such events, calculate the importance (weight) of risk factors, and analyze the mutual relationship among these risk factors [23].

Usually, the risk factors, that influence the RDNGTS can be classified into five different categories, including risk factors of human (H), risk factors of machine (M_1), risk factors of materials (M_2), risk factors of environment (E), and risk factors

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of management (M_3) [18], [22], [23]. As there are dynamic and nonlinear interactions among these risk factors, the simple linear risk assessment approaches (e.g., safety checklist analysis, fault tree analysis, and event tree analysis, etc.) or complex linear risk assessment approaches (e.g., hazard and operability analysis and preliminary hazard analysis, etc.) are not able to handle the complexity. A systemic approach, e.g., the failure mode and effect analysis (FMEA), should be applied [48].

Risk assessment can be converted to a sorting problem by applying the fuzzy axiomatic design (FAD) theory. FAD aims at adding the capacity to the axiomatic design (AD) for solving various fuzzy decision-making problems, which was first introduced by Kulak and Kahraman [31]. In such problems, various uncertainties may occur, such as the lack of expert knowledge and the lack of executive or failure records about the RDNGTS, these uncertainties can be regarded as a risky environment [12], hence, it is necessary to reach a correct and realistic decision in various uncertainties situations. If the uncertainties are considered in FAD, the FAD can be called risk-based fuzzy axiomatic design (RFAD) [12], which employs the risk directly into the assessments instead of taking it as a criterion. The uncertainly may cause the evaluated values to deviate from the real ones, as in most cases, the evaluated values belong to the future events that have not yet happened, therefore, each criterion and evaluation need to be considered in the model. In this article, a pessimistic and optimistic fuzzy information axiom (POFIA) design model is proposed with the consideration of such uncertainties.

A further improvement of POFIA is that an acceptable risk coefficient (ARC) is considered. The RFAD model does not consider the risk attitudes of experts (or researchers, or analysts) who carry on the risk assessment work [12]. Assuming there is a standard that has the lowest priority in the view of experts, the corresponding experts assign the fuzzy values with some risk to assess the risk of an option related to the standard. If the experts can consider some of the risks as a risk factor in their calculations, then the percentage of risk can also be accepted; If the experts do not accept any risk for a standard, then the experts are called risk-averse decision makers. Hence, in this article an ARC is introduced to improve the POFIA design model. ARC presents the degree of risk acceptance during the evaluation of the alternatives related to a standard. In this study, we aim at combining FMEA with POFIA considering ARC (FMEA-POFIA-ARC), and try to solve the Chinese RDNGTS risk assessment problem.

The rest of this article is structured as follows: Section II is devoted to the literature review about the previous risk assessment approaches. In Section III, the RDNGTS risk factors are analyzed. Section IV is devoted to the description of the information axiom (IA), FAD, and RFAD. Section V is devoted to the risk assessment approach based on FMEA-POFIA and FMEA-POFIA-ARC. In Section VI, a case study is conducted by taking the RDNGTS accident data in China as a background. In order to test the performance of the approach presented in this article, the calculation results among FMEA, FMEA with TFNs and the approach presented in this article are compared. Finally, Section VII concludes this article.

II. Literature Review

Recently, considerable research works have been devoted to solve the system risk assessment problem. In general, these methods can be classified into the following three categories:
1) simple linear;
2) complex linear;
3) systemic.

Simple linear and complex linear methods are appropriate for the safety analyses of tractable systems. Systemic methods are suitable for intractable systems due to their ability to account for the following: emergent system behaviors, functional interdependence, performance variability, and nonlinearity [25], [48]. Next, these methods will be introduced, and their advantages and disadvantages will be presented.

A. Simple Linear Risk Assessment Methods

Simple linear methods aim at evaluating the individual factors in a linear relationship [25]. For example, safety checklist analysis (SCA) [39], SCA has some obvious advantages such as its simple and easy operation and application, but when there is a high demand of risk assessment objects, the workload and uncertainty caused by the different knowledge levels and experiences of the researchers will increase; Brainstorming and Delphi sessions [9], when the risk assessment tasks are simple and goal-oriented, Brainstorming is suitable; when the researchers need to split the work into smaller parts and discuss in sequence, the process involves heavy mental work and is time consuming by using Brainstorming. The Delphi method may entail hundreds of researchers when carrying out a risk assessment project, the limitation is that, there is no exact requirement for the number of researchers, and whether such researchers' opinions converge to objective reality is difficult to judge; fault tree analysis (FTA) [35] and event tree analysis (ETA) [16], these two approaches are the most widely used method by researchers for evaluating the main reason for incidents and calculating the probability of the top event when considering FTA and ETA's advantage of graphic intuition in determining the causal factors of incidents. However, some experienced experts are asked to build a tree, and with the arising complexity of a system (e.g., the RDNGTS), the difficulty of the modeling process also increases. Furthermore, the states of risk factors can only be defined by a binary relation, which involves an obvious subjectivity and some differences from practice. In conclusion, the abovementioned methods rely overly on the background and experience of researchers, and cannot practically address the complex and multistate risk factors [25].

B. Complex Linear Risk Assessment Methods

Complex linear risk assessment methods consider the state of system (e.g., unsupportive environment, latent conditions) and aim at evaluating the safety barriers and corresponding deficiencies [25]. For example, hazard and operability analysis (HAZOP) [8], [28], which is the most effective method to solve process flows problem, it is easy to perform for simple issues through straightforward risk analysis procedures, however, the

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limitations are obvious when the HAZOP is applied to a complex system with multistate risk factors; preliminary hazard analysis (PHA) [5], PHA is generally applied in the initial risk assessment during the early stage of an object, or as a complete risk analysis for a simple system to evaluate all potential dangerous events that may lead to an accident. Nevertheless, dangerous events must be foreseen by researchers, and the effects of interactions among dangerous events are not easily recognized; analytic hierarchy process (AHP) or fuzzy AHP, Hsu *et al*. [27] proposed a revised risk matrix based on fuzzy AHP to assess the risks of the risk factors in operational safety. AHP or fuzzy AHP also needs researchers to score the effects of interactions among the risk factors, and some of the effects of interactions are not easy to be recognized, which increase the workload and uncertainty caused by the different knowledge levels and experiences of the researchers; regression model (RM), an RM approach aims at evaluating the relations between risk and some other impact factors, e.g., Yip [53] used a negative binomial regression model to analyze the port traffic risks based on the record of dataset; Bendul and Skorna [2] applied a regression analysis to illustrate the relations between risk and quality-related impact factors and the shippers' ability to implement risk prevention activities. However, the RM approach needs a large amount of historical data on accidents and related risks, when the RM is applied to a complex system with multistate risk factors, the limitations are obvious.

C. Systemic Risk Assessment Methods

Systemic risk assessment methods consider the functions and interactions of the whole system, as well as the performance variability or control levels of the system [25]. For example, scenario analysis (SA) [32], which is a visualized qualitative prediction method that describes future states by evaluating key risk factors that influence the normal operations of the system. Usually, SA must be adopted along with other methods, e.g., Alam *et al*. [1] proposed an evolutionary multiobjective scenario-based methodology for the systemic identification of airspace collision risk tipping points; decision making trial and evaluation laboratory method (DEMATEL) [13], [34], which shows a superiority to handle the internal relations among standard. There are two limitations of DEMATEL method when it is applied to analyze the relationships of risk factors: one is that it cannot reduce the subjectivity of researchers evaluation; the other is that it cannot deal with the fuzziness of linguistic information; Bayesian Network (BN) [3] or BN-based approaches [52], compared with the methods mentioned above, the BN is more flexible and powerful for knowledge representation and reasoning under conditions of uncertainty. Considering real-time updated knowledge, the BN can also be adopted for dynamic risk assessment [14], [15], [45], [52]. Other methods, e.g., Powell *et al*. [43] applied a dynamic threat analysis approach to deal with the dynamic behavior of the system under threat during risk assessment process, acted as a procedure for mobilizing quantitative and qualitative dynamic system knowledge; Huang *et al*. [23] presented an improved work breakdown structure (WBS) and risk based supervision (RBS) method to evaluate the risk of RDNGTS. The interval-number coupled judgment matrix of expert scoring was used to replace the previous 0–1 coupling WBS-RBS matrix. The whole system interval number was identified and sorted by using the midpoint value of the interval number and the half-width of the interval, the whole system was sorted by the risk assessment and sorting according to the probabilities ordering vectors.

Another wildly used approach is FMEA [10], [49], which was originally developed as a reliability analysis tool by the U.S. military in the 1940s, and used by the NASA in the 1960s for safety and quality enhancement in the projects [37]. FMEA focuses on finding, prioritizing, and minimizing the failures before accidents happen [10], [25], [49]. FMEA procedure commences with reviewing design details, illustrating equipment block diagram, and recognizing all potential failures, respectively. Following recognition, all possible causes and effects should be classified into the related failure modes. When applied FMEA, some traditional methods have been devoted, e.g., risk priority number (RPN), hazard scoring matrix, simplified scoring method, portfolio matrix method [38]. Majority of the selected studies adopted the classical RPN method to determine the risk priority order of failure modes. RPN is the multiplication of severity of failures (S), portability of occurrence (O), and the possibility of detection (D) [25]. Usually, real numbers 1–10 are used to score the S, O, and D. Based on the RPNs, researchers will be allowed to focus on high RPNs immediately rather than all failure modes due to the highest priority. Moreover, they can prevent the disaster to assess the improvements for priority items. FMEA has the following three limitations [4], [25], [42]:

1) failure mode assessment information is usually uncertain and incomplete, it is difficult to directly represent by real numbers 1–10;
2) different combinations of O, S, and D may lead to an identical RPN value, failure modes with an identical RPN may correspond to different risk factors, hence the failure mode risk sequence is difficult to judge, and the unreasonable information fusion process will result in the loss of information;
3) ignores the risk factor weight information, which is inconsistent with the actual situation.

For previous FMEA, O, S, and D are assumed to be of the same weight. However, in reality, the degree of their importance may vary. In order to overcome the limitations mentioned above, some methods have been applied to improve RPN, such as fuzzy RPN method, revised RPN [37]. In addition, some improved methods have also been devoted to FMEA, such as fuzzy inference method, data envelopment analysis, fuzzy VIsekriterijumska optimizacija i KOm-promisno Resenje, fuzzy multiobjective optimization by ratio analysis, and the full multiplicative from MULTIMOORA [37], [38]. These approaches introduce the fuzzy information into the FMEA evaluation process, which is helpful to improve the accuracy of evaluation results. But these improved FMEA did not employ the risk directly into the assessments, and did not consider the risk attitudes of experts.

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TABLE I
THREE TYPES OF RISK ASSESSMENT MODELS

Model	Description	Example
Simple linear	Evaluating the individual factors in a linear relationship	1) SCA [39]; 2) Brainstorming and Delphi sessions [9]; 3) FTA [35]; 4) ETA [16]
Complex linear	1) Considering the state of system; 2) Evaluating the safety barriers and corresponding deficiencies	1) HAZOP [8], [28]; 2) PHA [5]; 3) AHP [27]; 4) RM [2], [53]
Systemic	1) Considering the functions and interactions of the whole system; 2) Considering the performance variability or levels of control of the system	1) SA [1]. [32] 2) DEMATEL [13]. [34]; 3) BN [3], [14], [15], [45], [52]; 4) Dynamic threat analysis approach [43]; 5) WBS- RBS [23]; 6) FMEA [10], [49]

The following Table I provides an overview of the three kinds of risk assessment models. Taking into account the advantages and disadvantages of the system risk assessment approaches mentioned above, an approach combining FMEA with POFIA considering acceptable risk coefficient will be used to evaluate the RDNGTS risk in this article, the RPN will be used to transform the system risk assessment problem into the rank problem of severity of risk factors affecting system security. In order to improve the limitations of RPN, the following is considered:

1) the TFNs are applied to score the *S*, *O*, and *D* for each RDNGTS risk subindicator;
2) the information contents of *S*, *O*, and *D* are calculated for each risk subindicator, two models are applied to calculate the information contents: POFIA without ARC, and POFIA with ARC;
3) the product of information contents of *S*, *O*, and *D* is used to replace the previous RPN and entropy weight method (EWM) is used to calculate the weight of each risk subindicator.

III. RDNGTS RISK FACTORS

RDNGTS belongs to a complex system [21]–[23], [25], the normal operation of the system is influenced by the dynamic and nonlinear interactions among multiple risk factors. Researchers usually classified the whole factors that influenced the RDNGTS into several categories for the potential risk assessment, for example, Gheorghe *et al.* [11] classified the risk factors that influence the RDNGTS into four categories including technical infrastructure, rolling stock, human actions, and regulation and management procedures; Huang *et al*. [18], [21]–[23] classified the risk factors that influenced the normal operation of RDNGTS into five categories, including risk factors of Human (H), risk factors of Machine (M_1), risk factors of Materials (M_2), risk factors of Environment (E), and risk factors of Management (M_3). In this article, the five kinds of risk factors will also be applied, see Table II for detailed information.

IV. INTRODUCTION OF IA, FAD, AND RFAD

A. Information Axiom

IA, first introduced by Suh [47], belongs to the second axiom of the AD [46]. IA aims at minimizing the information content of the design in order to determine the best alternative satisfying the required independent functional requirements (FRs), the most appropriate alternative is one that has the lowest information content [47]. For RDNGTS risk assessment problem, the most dangerous risk factor or subindicator is one that has the highest information content, hence, the severity rank of risk factors can be obtained according to the values of information content. For the k AD, the information content I_k is defined as the entropy that measures uncertainty, which can be formulated as follows:

$$I_k = \log_2 (1/p_k) \tag{1}$$

where p_k is the probability of success for a given functional requirement; p_k is calculated by the intersection area of system range and design range (dr), usually called the intersection area as common range or common area. Fig. 1(a) shows the relationship among the design range, common range, and the system range. Then, the p_k can be calculated as follows:

$$p_k = \int_{dr} p_s (\mathrm{FR}_k) d\mathrm{FR}_k. \tag{2}$$

B. Fuzzy Axiomatic Design

The advantage of IA is to enable the decision makers to define the desired characteristics for the considered standard. If the information of system range and design range is inaccurate, the fuzzy information axiom provides a reasonable tool for measuring uncertain overlapping regions [26]. System range and design range can be formulated by a value, above it or between the two values. The values can be formulated by using interval number, triangular fuzzy number, or trapezoidal fuzzy number [18], [22], [23], in this article we choose triangular fuzzy

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TABLE II
RISK FACTORS OF RDNGTS [21]–[23]

Risk factor	Sub-indicator	Explanation	Examples
H	u_{11}	physical discomfort and poor working environment of the staffs	e.g., sudden illness or discomfort
	u_{12}	inaccurate work attitude and operation of the staffs	e.g., prone and unpleasant psychology during the work
	u_{13}	staffs are lack of technical and knowledge during all aspects of transportation processes	e.g., mishandling of loading and unloading operations
	u_{14}	the staffs of dangerous goods manufacturer illegally overload or entrain the goods	e.g., illegal entrainment of goods that are not allowed
	u_{15}	non-railway personnel's illegal dangerous goods stealing	e.g., residents alone the railway lines illegally stealing coal
M_1	u_{21}	failure of transportation equipment	e.g., failure of vehicle's monitoring system
	u_{22}	failure of dangerous goods storage equipment	e.g., goods loading tank defects, parts aging and loose of the tanks
	u_{23}	failure of loading and unloading equipment in the handling stations	e.g., failure of technical performance of loading and unloading equipment,
M_2	u_{31}	the dangerous nature of the loaded and transported goods	e.g., flammable, explosive, corrosive, toxic, infectious and radioactive.
	u_{32}	the packaging of dangerous goods	e.g., mismatched packaging materials for the dangerous goods
	u_{33}	the volume of the dangerous goods	the more volume of the dangerous goods, the greater risk of the transportation system.
E	u_{41}	the extreme weather condition	e.g., gale, thunder, extreme temperatures, heavy rain
	u_{42}	the railway lines condition	e.g., electric spark between the power grid and railway vehicle pantograph
	u_{43}	the sudden natural disaster	e.g., the debris flow, avalanche, landslide, earthquake etc. along the railway lines.
M_3	u_{51}	failure of transportation laws and safety management	e.g., relevant laws, regulations and regulations are lacking or have omissions
	u_{52}	failure of safety education management	e.g., defects in staff safety education management system
	u_{53}	failure of Corporate Qualification Management	e.g., defects in illegal transportation management, defects in scheduling orders

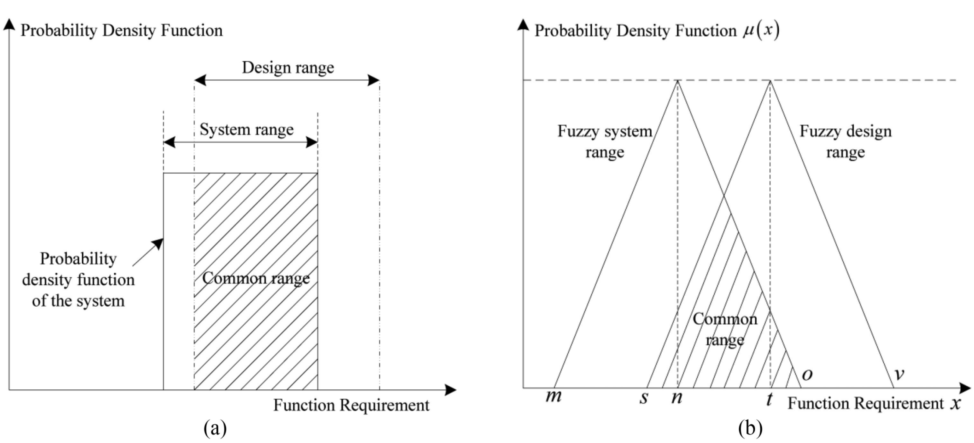

Fig. 1. Relationships among (fuzzy) design range, (fuzzy) system range and common range.

numbers (TFNs) to calculate the FAD, see Fig. 1(b). The fuzzy information content I_f can be calculated as follows:

$$I_f = \log_2 (\mathrm{FSR}/\mathrm{CR}). \tag{3}$$

Two characteristics are defined to calculate the I_f : 1) Fussy design range, intended by the designer, within that an option acts to meet the relevant criterion. Fuzzy design range gives the upper and lower values of the design goal and the system probability

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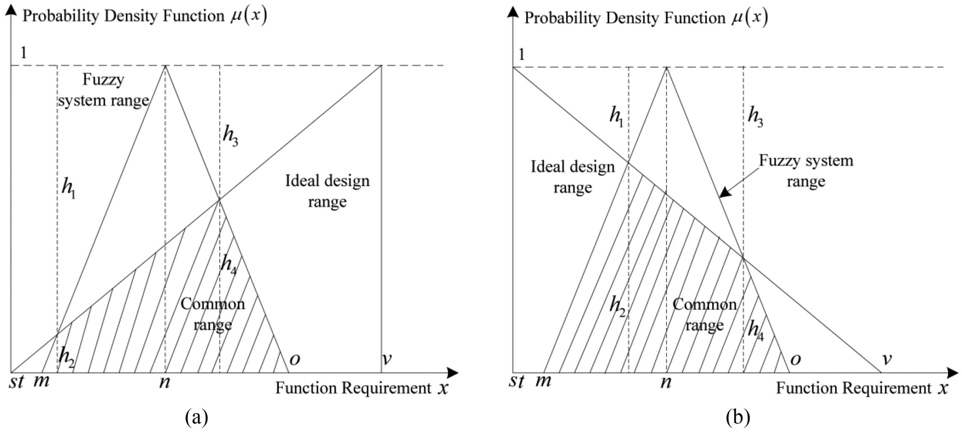

Fig. 2. Ideal design range and system range for (a) a benefit criterion and (b) a nonbeneficial criterion.

density function; 2) fuzzy system range, the evaluation number of the alternative associated with a criterion. In (3), FSR represents the area of fuzzy system range, CR represents the area of overlapped region between fuzzy design range and fuzzy system range, usually called common range, which is the region where the acceptable solution exists. When the probability $(\mathrm{FSR}/\mathrm{CR})$ equals to 1, then $I_f = 0$, means the amount of information is 0; conversely, when FSR/CR is close to 0, the I_f will be infinite.

In general, FAD can be divided into three kinds of problems [29]: the problems related to the desired design range; the problems related to reference design range; the problems related to rank. This article aims at evaluating the RDNGTS risk, so it is a rank problem, which is much like the TOPSIS approach in rank [22], [24]. Compared with the TOPSIS, the FAD has some advantages: 1) FAD does not need normalization; 2) FAD needs fewer calculation processes. To rank the risk problem, two ideal design ranges are considered: the benefit criterion (benefit attributes), and the nonbeneficial criterion (cost attributes). For the beneficial design range [see Fig. 2(a)], in particular, for a triangular fuzzy number (TFN) [shown in Fig. 1(b)] with $s = t = 0, \mu(s) = \mu(t) = 0$, and upper limit as $v = x_{\max}, \mu(v) = 1$, $x_{\max}$ is the maximum upper function requirement value of the alternative in the problem. For the nonbeneficial design range [see Fig. 2(b)], with $s = t = 0$, $\mu(s) = \mu(t) = 1$, and upper limit as $v = x_{\max}$, $\mu(v) = 0$.

Then, the information content of the benefit criterion I_b can be calculated as follows [use Fig. 2(a)]:

$$I_b = \log_2 \left\{ (o-m) / \left[o^2 / (v-n+o) - m^2 / (v-n+m) \right] \right\}. \tag{4}$$

Proof: To calculate the fuzzy system range and the common range in Fig. 2(a), the similar triangles will be applied to obtain the h_2 and h_4

$$\begin{aligned} h_2/h_1 &= m/(v-n) \Rightarrow h_2/(h_1+h_2) = m/(v-n+m) \\ &\Rightarrow h_2 = m/(v-n+m) \end{aligned} \tag{5}$$

$$\begin{aligned} h_4/h_3 &= o/(v-n) \Rightarrow h_4/(h_3+h_4) = o/(v-n+o) \\ &\Rightarrow h_4 = o/(v-n+o). \end{aligned} \tag{6}$$

Combine (5) and (6), the common range CR can be obtained as follows:

$$\mathrm{CR} = \left[o^2/(v-n+o) - m^2/(v-n+m) \right]/2. \tag{7}$$

The area of fuzzy system range is as follows:

$$\mathrm{FSR} = (o-m)/2. \tag{8}$$

Combining (3), (7), and (8), (4) can be obtained. The information content of the nonbenefit criterion I_{nb} can be calculated as follows [use Fig. 2(b)]:

$$\begin{aligned} I_{nb} = \log_2 \{ &(o-m) / \left[(v-m)^2 / (v+n-m) \right. \\ &\left. - (v-o)^2 / (v+n-o) \right] \}. \end{aligned} \tag{9}$$

Proof: To calculate the fuzzy system range and the common range in Fig. 2(b), the similar triangles will also be applied to obtain the h_2 and h_4

$$\begin{aligned} h_2/h_1 &= (v-m)/n \Rightarrow h_2/(h_1+h_2) \\ &= (v-m)/(n+v-m) \Rightarrow h_2 = (v-m)/(n+v-m) \end{aligned} \tag{10}$$

$$\begin{aligned} h_4/h_3 &= (v-o)/n \Rightarrow h_4/(h_3+h_4) \\ &= (v-o)/(n+v-o) \Rightarrow h_4 = (v-o)/(n+v-o). \end{aligned} \tag{11}$$

Combining (10) and (11), the common range CR can be obtained as follows:

$$\mathrm{CR} = \left[(v-m)^2/(v+n-m) - (v-o)^2/(v+n-o) \right]/2. \tag{12}$$

Combining (3), (7), and (12), (9) can be obtained.

C. Risk-Based FAD

Almost all assessments are affected by risk, when an alternative has a risk r, $0 < r < 1$ with respect to a criterion while assessing, the fuzzy information content can be obtained by the pessimistic assumption. Because the common area is the region where the acceptable solution exists, so the risk r will be used to calculate the common area by multiplying $(1-r)$, and obtained

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a new approach called the RFAD [12]

$$I_{fc} = \log_2 [\mathrm{FSR}/\mathrm{CR}(1-r)]. \tag{13}$$

After analyzing (13), it can be found that the amount of common area will be reduced, the fuzzy information content will be increased, and the best alternative will be obtained more easily and precisely. RFAD can be improved by considering the optimistic model and accepting the risk factor [12], so the RFAD can be formulated by using two models: POFIA, and POFIA-ARC.

1) First Model. POFIA: If the evaluated TFN is $\tilde{a}$ and risk of the evaluation is r. For beneficial criteria, assume the values $(1-r)$ as the pessimistic value and the value $(1+r)$ as the optimistic value. Obviously, in case of obtaining nonbeneficial criteria, these two values are opposite: $(1-r)$ is the optimistic value and $(1+r)$ is the pessimistic value. Define a new TFN $\tilde{A}_b$ for beneficial criteria

$$\tilde{A}_b = (tildea\,(1-r), \tilde{a}, \tilde{a}\,(1+r)). \tag{14}$$

Let $\tilde{a} = (m, n, o)$, $\tilde{A}_{ob}$ is an optimistic fuzzy value for a beneficial criterion, $\tilde{A}_{pb}$ is a pessimistic fuzzy value for a beneficial criterion, I_{ob} is the information content in the optimistic mode for a beneficial criterion, I_{pb} is the information content in the optimistic mode for a beneficial criterion. Insert (15) and (16) in (4), then the I_{ob} and I_{pb} will be obtained, respectively, as follows:

$$\tilde{A}_{ob} = \tilde{a}\,(1+r) = (a\,(1+r), b\,(1+r), c\,(1+r)) \tag{15}$$

$$\tilde{A}_{pb} = \tilde{a}\,(1-r) = (a\,(1-r), b\,(1-r), c\,(1-r)) \tag{16}$$

$$\begin{aligned} I_{ob} = \log_2\{(o-m)/[o^2/(v/(1+r)-n+o) \\ - m^2/(v/(1+r)-n+m)]\} \end{aligned} \tag{17}$$

$$\begin{aligned} I_{pb} = \log_2\{(o-m)/[o^2/(v/(1-r)-n+o) \\ - m^2/(v/(1-r)-n+m)]\}. \end{aligned} \tag{18}$$

The information content of $\tilde{a}$ can be obtained by (4), so the information content $I(\tilde{A}_b)$ of $\tilde{A}_b$ is shown as follows:

$$I\left(\tilde{A}_b\right) = (I_{ob}, I_b, I_{pb}). \tag{19}$$

Now define a new TFN $\tilde{A}_{nb}$ for a nonbeneficial criterion

$$\tilde{A}_{nb} = (tildea\,(1-r), \tilde{a}, \tilde{a}\,(1+r)). \tag{20}$$

Let $\tilde{a} = (m, n, o)$, $\tilde{A}_{onb}$ is an optimistic fuzzy value for a nonbeneficial criterion, $\tilde{A}_{pnb}$ is a pessimistic fuzzy value for a nonbeneficial criterion, I_{onb} is the information content in the optimistic mode for a nonbeneficial criterion, I_{pnb} is the information content in the optimistic mode for a nonbeneficial criterion. Insert (22) and (23) in (9), then the I_{onb} and I_{pnb} will be obtained, respectively, as follows:

$$\tilde{A}_{onb} = \tilde{a}\,(1-r) = (a\,(1-r), b\,(1-r), c\,(1-r)) \tag{21}$$

$$\tilde{A}_{pnb} = \tilde{a}\,(1+r) = (a\,(1+r), b\,(1+r), c\,(1+r)) \tag{22}$$

$$\begin{aligned} I_{onb} = \log_2\big\{(o-m)/\big[(v/(1-r)-m)^2/(v/(1-r) \\ +n-m)-(v/(1-r)-o)^2/(v/(1-r)+n-o)\big]\big\} \end{aligned} \tag{23}$$

$$\begin{aligned} I_{pnb} = \log_2\big\{(o-m)/\big[(v/(1+r)-m)^2/(v/(1+r) \\ +n-m)-(v/(1+r)-o)^2/(v/(1+r)+n-o)\big]\big\}. \end{aligned} \tag{24}$$

The information content of $\tilde{a}$ can be obtained by (9), so the information content $I(\tilde{A}_{nb})$ of $\tilde{A}_{nb}$ is shown as follows:

$$I(\tilde{A}_{nb}) = (I_{onb}, I_{nb}, I_{pnb}). \tag{25}$$

Now the problem becomes a typical fuzzy multicriteria decision-making problem, such that all criteria are of a nonbeneficial type, because the lower information content is favorable in the AD. As for RDNGTS risk assessment problem, the higher the information of the risk factor, the more serious the risk factor is.

2) Second Model. POFIA-ARC: The first model mentioned above is lack of decision maker's optimum percentage or his/her willingness to take the risk. In order to make the first model more precise, the factor, decision maker's optimum percentage or his/her willingness, can be added into the first model. Assuming that an ARC is AR, $0 < AR < 1$, then the AR optimism and $1 - AR$ pessimism would existed in the first model for each assessed criterion. The TFN for the beneficial criterion and for the nonbeneficial criterion will be presented as follows:

$$\tilde{A}'_b = (tildea\,(1-r\,(1-AR)), \tilde{a}, \tilde{a}\,(1+rAR)) \tag{26}$$

$$\tilde{A}'_{nb} = (tildea\,(1-rAR), \tilde{a}, \tilde{a}\,(1+r\,(1-AR))). \tag{27}$$

$\tilde{A}'_{ob}$ is an optimistic fuzzy value for a beneficial criterion considering AR, $\tilde{A}'_{pb}$ is a pessimistic fuzzy value for a beneficial criterion considering AR, I'_{ob} is the information content in the optimistic mode for a beneficial criterion considering AR, I'_{pb} is the information content in the optimistic mode for a beneficial criterion considering AR. Insert (28) and (29) in (4), then the I'_{ob} and I'_{pb} will be obtained, respectively, as follows:

$$\begin{aligned} \tilde{A}'_{ob} &= \tilde{a}\,(1+rAR) \\ &= (a\,(1+rAR), b\,(1+rAR), c\,(1+rAR)) \end{aligned} \tag{28}$$

$$\begin{aligned} \tilde{A}'_{pb} = \tilde{a}\,(1-r\,(1-AR)) = \big(a\,(1-r\,(1-AR)), \\ b\,(1-r\,(1-AR)), c\,(1-r\,(1-AR))\big) \end{aligned} \tag{29}$$

$$\begin{aligned} I'_{ob} = \log_2\big\{(o-m)/\big[o^2/(v/(1+rAR)-n+o) \\ - m^2/v/(1+rAR)-n+m\big]\big\} \end{aligned} \tag{30}$$

$$\begin{aligned} I'_{pb} = \log_2\big\{(o-m)/\big[o^2/(v/(1-r\,(1-AR))-n+o) \\ - m^2/(v/(1-r\,(1-AR))-n+m)\big]\big\}. \end{aligned} \tag{31}$$

The information content of $\tilde{a}$ can be obtained by (4), so the information content $I(\tilde{A}'_b)$ of $\tilde{A}'_b$ is shown as follows:

$$I\left(\tilde{A}'_b\right) = (I'_{ob}, I_b, I'_{pb}). \tag{32}$$

Define a new TFN $\tilde{A}'_{nb}$ for a nonbeneficial criterion considering AR, $\tilde{A}'_{onb}$ is an optimistic fuzzy value for a nonbeneficialcriterion considering AR, $\tilde{A}'_{pnb}$ is a pessimistic fuzzy value for a nonbeneficial criterion considering AR, I'_{onb} is the information content in the optimistic mode for a nonbeneficial

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criterion considering AR, I'_{pnb} is the information content in the optimistic mode for a nonbeneficial criterion considering AR. Insert (33) and (34) in (9), then the I'_{onb} and I'_{pnb} will be obtained, respectively, as follows:

$$\begin{aligned}\tilde{A}'_{onb} &= \tilde{a}(1-rAR)\\ &= (a(1-rAR), b(1-rAR), c(1-rAR))\end{aligned} \tag{33}$$

$$\begin{aligned}\tilde{A}'_{pnb} &= \tilde{a}(1+r(1-AR))\\ &= (a(1+r(1-AR)), b(1+r(1-AR)),\\ &\qquad c(1+r(1-AR)))\end{aligned} \tag{34}$$

$$I'_{onb} = \log_2 \left\{ (o-m) \Big/ \left[\left(\frac{v}{1-rAR} - m\right)^2 \Big/ \left(\left(\frac{v}{1-rAR}\right) + n - m\right) - \left(\frac{v}{1-rAR} - o\right)^2 \Big/ \left(\left(\frac{v}{1-rAR}\right) + n - o\right) \right] \right\} \tag{35}$$

$$I'_{pnb} = \log_2 \left\{ (o-m) \Big/ \left[\left(\frac{v}{1+r(1-AR)} - m\right)^2 \Big/ \left(\left(\frac{v}{1+r(1-AR)}\right) + n - m\right) - \left(\frac{v}{1+r(1-AR)} - o\right)^2 \Big/ \left(\left(\frac{v}{1+r(1-AR)}\right) + n - o\right) \right] \right\} \tag{36}$$

The information content of $\tilde{a}$ can be obtained by (9), so the information content $I(\tilde{A}'_{nb})$ of $\tilde{A}'_{nb}$ is shown as follows:

$$I\left(\tilde{A}'_{nb}\right) = \left(I'_{onb}, I_{nb}, I'_{pnb}\right). \tag{37}$$

Now the problem becomes a typical fuzzy multicriteria decision-making problem considering ARC, such that all criteria are of a beneficial type. As for RDNGTS risk assessment problem, the higher the information of the risk factor, the more serious the risk factor is.

V. FMEA and POFIA Approach

In order to evaluate RDNGTS risk, a new approach FMEA-POFIA-ARC is proposed in this article. The following methods are applied to improve the three limitations of FMEA.

1) The TFNs [33], [36] are applied to score the *S*, *O*, and *D* for each RDNGTS risk subindicator, replacing the real numbers 1–10 of FMEA.
2) The information contents [47] of the *S*, *O*, and *D* are calculated for each risk subindicator, the product of the information contents of *S*, *O*, and *D* are used to replace the previous RPN. There are two models applied to calculate the information contents, POFIA and POFIA-ARC, which are presented in Section IV.
3) EWM [22], [24] is used to calculate the weight of each risk subindicator, the initial input data for the weight are the historical data of Chinese RDNGTS accidents from 1986 to 2017.

The steps of the FMEA-POFIA-ARC approach to evaluate the RDNGTS risk are described as follows.

Step 1: Identify potential failure modes of RDNGTS. After analyzing the historical accidents, there are 5 kinds of risk factors and 17 subindicators that influence the safety of RDNGTS. The detailed information of the risk factors and subindicators is presented in Section III.

Step 2: Define the failure criterion of *S, O*, and *D* of FMEA. Invited three experts to transfer the failure criterion into TFNs, the results are presented in Table III. The TFNs of failure criterion can be regarded as the design range in Fig. 2.

Step 3: For each subindicator u_{ij} (presented in Section III), the three experts score the IFNs of *S, O, D* according to Table III, respectively. For the k expert, the IFNs matrix $\tilde{M}_k$ of *S, O, D* can be formulated as follows:

$$\tilde{M}_k = \begin{pmatrix} \tilde{A}^S_{11k} & \tilde{A}^O_{11k} & \tilde{A}^D_{11k} \\ \vdots & \vdots & \vdots \\ \tilde{A}^S_{ijk} & \tilde{A}^O_{ijk} & \tilde{A}^D_{ijk} \\ \vdots & \vdots & \vdots \\ \tilde{A}^S_{53k} & \tilde{A}^O_{53k} & \tilde{A}^D_{53k} \end{pmatrix}, \forall k. \tag{38}$$

Step 4: Aggregate the three matrix $\tilde{M}_k$ by averaging the scores of the three experts. The aggregated TFNs matrix $\tilde{M}$ can be formulated as the following equation (39). The aggregated TFNs in matrix $\tilde{M}$ are the fuzzy system range in Fig. 2, or more specifically, the evaluated TFN $\tilde{a}$

$$\tilde{M} = \begin{pmatrix} \tilde{A}^S_{11} & \tilde{A}^O_{11} & \tilde{A}^D_{11} \\ \vdots & \vdots & \vdots \\ \tilde{A}^S_{ij} & \tilde{A}^O_{ij} & \tilde{A}^D_{ij} \\ \vdots & \vdots & \vdots \\ \tilde{A}^S_{53} & \tilde{A}^O_{53} & \tilde{A}^D_{53} \end{pmatrix}. \tag{39}$$

Step 5: For each subindicator u_{ij}, the three experts discuss and score the evaluation risk r of S, O, D, respectively. The risk matrix R_{SOD} of S, O, D can be

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TABLE III
FAILURE CRITERION AND ITS CORRESPONDING TRIANGULAR INTUITIONISTIC FUZZY NUMBERS

Risk level	Severity (S)	Occurrence (O)	Detection (D)	TFNs
1	Almost no	Rarely happen	Extremely detectable	(1,1,3)
2	Nothing serious	Less happen	Easily detectable	(1,3,5)
3	General serious	Happen occasionally	Attention	(3,5,7)
4	Serious	Happen very often	Hard to detect	(5,7,9)
5	Extremely serious	Prone to happen	Extremely hard to detect	(7,9,9)

formulated as follows:

$$R_{SOD} = \begin{pmatrix} r_{11}^S & r_{11}^O & r_{11}^D \\ \vdots & \vdots & \vdots \\ r_{ij}^S & r_{ij}^O & r_{ij}^D \\ \vdots & \vdots & \vdots \\ r_{53}^S & r_{53}^O & r_{53}^D \end{pmatrix}. \tag{40}$$

Step 6: In the second model, the AR of ARC need to be calculated. For each subindicator u_{ij}, the three experts discuss and score the evaluation risk AR of S, O, D, respectively. The risk matrix AR_{SOD} of S, O, D can be formulated as follows:

$$AR_{SOD} = \begin{pmatrix} AR_{11}^S & AR_{11}^O & AR_{11}^D \\ \vdots & \vdots & \vdots \\ AR_{ij}^S & AR_{ij}^O & AR_{ij}^D \\ \vdots & \vdots & \vdots \\ AR_{53}^S & AR_{53}^O & AR_{53}^D \end{pmatrix}. \tag{41}$$

Step 7: Obtain a new TFNs matrix of S, O, D for each subindicator u_{ij}. There are two RFAD approaches proposed in Section IV-C. As for RDNGTS risk assessment problem, all criteria are nonbeneficial type in the first model, all criteria are beneficial type in the second model. According to (9), (23)–(25), (39), and (40), the new TFNs matrix $\tilde{U}_{SOD}$ of the first model can be formulated as follows:

$$\tilde{U}_{SOD} = \begin{pmatrix} \tilde{U}_{11}^S & \tilde{U}_{11}^O & \tilde{U}_{11}^D \\ \vdots & \vdots & \vdots \\ \tilde{U}_{ij}^S & \tilde{U}_{ij}^O & \tilde{U}_{ij}^D \\ \vdots & \vdots & \vdots \\ \tilde{U}_{53}^S & \tilde{U}_{53}^O & \tilde{U}_{53}^D \end{pmatrix}. \tag{42}$$

According to (4), (30)–(32), and (39)–(41), the new TFNs matrix $\tilde{U}'_{SOD}$ of the second model can be formulated as follows:

$$\tilde{U}'_{SOD} = \begin{pmatrix} \tilde{U}_{11}'^S & \tilde{U}_{11}'^O & \tilde{U}_{11}'^D \\ \vdots & \vdots & \vdots \\ \tilde{U}_{ij}'^S & \tilde{U}_{ij}'^O & \tilde{U}_{ij}'^D \\ \vdots & \vdots & \vdots \\ \tilde{U}_{53}'^S & \tilde{U}_{53}'^O & \tilde{U}_{53}'^D \end{pmatrix}. \tag{43}$$

Step 8: Obtain the information content of S, O, D for each subindicator u_{ij}. All criteria are nonbeneficial type in the first model, according to (9) and (42), the information content matrix I_{SOD} of the first model can be formulated as follows:

$$I_{SOD} = \begin{pmatrix} I_{11}^S & I_{11}^O & I_{11}^D \\ \vdots & \vdots & \vdots \\ I_{ij}^S & I_{ij}^O & I_{ij}^D \\ \vdots & \vdots & \vdots \\ I_{53}^S & I_{53}^O & I_{53}^D \end{pmatrix}. \tag{44}$$

All criteria are nonbeneficial type in the second model, according to (9) and (43), the information content matrix I'_{SOD} of the second model can be formulated as follows:

$$I_{SOD}{}' = \begin{pmatrix} I_{11}'^S & I_{11}'^O & I_{11}'^D \\ \vdots & \vdots & \vdots \\ I_{ij}'^S & I_{ij}'^O & I_{ij}'^D \\ \vdots & \vdots & \vdots \\ I_{53}'^S & I_{53}'^O & I_{53}'^D \end{pmatrix}. \tag{45}$$

Step 9: Based on I_{SOD} and I'_{SOD}, calculate the total information content I_{RPN}^{ij} and $I_{\mathrm{RPN}}'^{ij}$ for each subindicator u_{ij}

$$I_{\mathrm{RPN}}^{ij} = \varpi_{ij}^S \cdot I_{ij}^S + \varpi_{ij}^O \cdot I_{ij}^O + \varpi_{ij}^D \cdot I_{ij}^D \tag{46}$$

$$I_{\mathrm{RPN}}'^{ij} = \varpi_{ij}^S \cdot I_{ij}'^S + \varpi_{ij}^O \cdot I_{ij}'^O + \varpi_{ij}^D \cdot I_{ij}'^D \tag{47}$$

where ϖ_{ij}^S, ϖ_{ij}^O, ϖ_{ij}^D are the weights of S, O, D for each subindicator u_{ij} by using AHP (scored by the three experts mentioned above). Each subindicator j of risk factor i share the weight of S, O, D,

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e.g., $\varpi_{51}^{S}=\varpi_{52}^{S}=\varpi_{53}^{S}, \varpi_{51}^{O}=\varpi_{52}^{O}=\varpi_{53}^{O}, \varpi_{51}^{D}=\varpi_{52}^{D}=\varpi_{53}^{D}$.

Step 10: Based on I_{RPN}^{ij} and $I_{\mathrm{RPN}}^{\prime ij}$, calculate the total information content I_{RPN}^{i} and $I_{\mathrm{RPN}}^{\prime i}$ for each risk factor i (*H, M_1, M_2, E,* and M_3). Rank the risk factor i according to the final calculation results of I_{RPN}^{i} and $I_{\mathrm{RPN}}^{\prime i}$

$$I_{\mathrm{RPN}}^{i}=\sum_{j} w_{ij}\cdot I_{\mathrm{RPN}}^{ij}, \forall i \tag{48}$$

$$I_{\mathrm{RPN}}^{\prime i}=\sum_{j} w_{ij}\cdot I_{\mathrm{RPN}}^{\prime ij}, \forall i \tag{49}$$

where w_{ij} is the weight of each subindicator u_{ij}. EWM is applied to calculate the weight, details referring to [22] and [24]. EWM will work to calculate the weights as follows.

The historical accidents number of each subindicator is n_{ij}^{t}, t is the time series. For each risk factor i, the historical accidents number of each subindicator can be formulated as an information decision matrix $\mathrm{A}_i=[n_{ij}^{t}]_{(sumj)\times(sumt)}$, calculate the initial decision matrix as standardized decision matrix $\bar{\mathrm{A}}_i=[r_{ij}^{t}]_{(sumj)\times(sumt)}$. There are two types of standardized methods: when the subindicators are benefit-type, the calculation for normalization can be expressed as (50); when the indices are cost-type, the calculation for normalization can be formulated as (51). In this article, all subindicators are cost-type, so (51) should be applied

$$r_{ij}^{t}=\left[n_{ij}^{t}-\left(n_{ij}^{t}\right)_{\min}\right]\Big/\left[\left(n_{ij}^{t}\right)_{\max}-\left(n_{ij}^{t}\right)_{\min}\right], \forall i,j,t \tag{50}$$

$$r_{ij}^{t}=\left[\left(n_{ij}^{t}\right)_{\max}-n_{ij}^{t}\right]\Big/\left[\left(n_{ij}^{t}\right)_{\max}-\left(n_{ij}^{t}\right)_{\min}\right], \forall i,j,t \tag{51}$$

where r_{ij}^{t} is the decision number of subindicator which becomes n_{ij}^{t} after normalization, $(r_{ij}^{t})_{\max}$ is the maximum value of r_{ij}^{t}, $(r_{ij}^{t})_{\min}$ is the minimum value of r_{ij}^{t}, $(r_{ij}^{t})_{\max}\neq(r_{ij}^{t})_{\min}$. The probability p_{ij}^{t} of each r_{ij}^{t} is then calculated as follows:

$$p_{ij}^{t}=r_{ij}^{t}\Big/\sum_{t} r_{ij}^{t}, \forall i,j,t. \tag{52}$$

The information entropy for each index is defined as follows:

$$e_{ij}=-\left[\sum_{t}\left(p_{ij}^{t}\cdot\ln p_{ij}^{t}\right)\right]\Bigg/\ln\sum j, \forall i,j. \tag{53}$$

And the weight obtained from information entropy is expressed as follows:

$$w_{ij}=\left(1-e_{ij}\right)\Bigg/\left(sumj-\sum_{j} e_{ij}\right), \forall i,j \tag{54}$$

where $0\leq w_{ij}\leq 1$, and $\sum_j w_{ij}=1, \forall i$.

VI. Case Study and Results Discussions

In this section, a case study based on the FMEA-POFIA-ARC and FMEA-POFIA is conducted. First, the Chinese RDNGTS risk assessment results by using the approach proposed in this article are presented, followed by the comparison with FMEA and FMEA with TFNs, and finally a comprehensive discussion is carried out.

A. Calculation Results Based on FMEA-POFIA-ARC and FMEA-POFIA

We invited three experts (including one Professor from School of Transportation and Logistics, Southwest Jiaotong University, and two railway dangerous goods transportation management staffs in Chengdu Railway Bureau; all experts' specialization is railway dangerous goods transportation management and planning) to score the TFNs (38) of failure criterion of severity (S), occurrence (O), and detection (D) for each subindicator presented in Section III, the results are presented in Table IV. Then aggregated the three TFNs into one TFN (39) for each S, O, and D for each subindicator, the results (the bold TFNs) are presented in Table IV.

For each subindicator u_{ij} in the first model, the scoring results of risk r of S, O, D are shown in Table V. According to the (9), (23)–(25), (39), and (40), the calculation results of TFNs matrix $\tilde{U}_{SOD}$ are also presented in Table V.

For each subindicator u_{ij} in the second model, the scoring results of AR of S, O, D are shown in Table VI. According to (9), (23)–(25), (39), and (40), the calculation results of TFNs matrix $\tilde{U}_{SOD}$ are also presented in Table VI.

Based on the aggregated TFNs in Table IV, the information content of I_{ij}^{S}, I_{ij}^{O}, I_{ij}^{D} for each subindicator of the first model can be calculated (44), the results are presented in Table VII. The weights ϖ_{ij}^{S}, ϖ_{ij}^{O}, ϖ_{ij}^{D} of S, O, D for each subindicator are obtained by using AHP (scored by the three experts mentioned above), the results are presented in Table VII. Finally, the total information content I_{RPN}^{ij} for each subindicator u_{ij} (46) calculation results and rank are presented in Table VII.

For the first model, the final ranking results show that the following.

1) For risk factor of human, the most dangerous subindicator is u_{13}; the least dangerous subindicator is u_{11}.
2) For risk factors of machine, the most dangerous subindicator is u_{21}; the least dangerous subindicator is u_{22}.
3) For risk factors of materials, the most dangerous subindicator is u_{31}; the least dangerous subindicator is u_{32}.
4) For risk factors of environment, the most dangerous subindicator is u_{42}; the least dangerous subindicator is u_{41}.
5) For risk factors of management, the most dangerous subindicator is u_{53}; the least dangerous subindicator is u_{52}.

Related government departments and railway dangerous goods transport companies should pay more attention to the dangerous risk subindicators mentioned above.

Based on the aggregated TFNs in Table IV, the information content of $I_{ij}^{\prime S}$, $I_{ij}^{\prime O}$, $I_{ij}^{\prime D}$ for each subindicator of the second model can be calculated (45), the results are presented in Table VIII. The weights ϖ_{ij}^{S}, ϖ_{ij}^{O}, ϖ_{ij}^{D} of S, O, D for each subindicator are obtained by using AHP (scored by the three experts mentioned above), the results are presented in Table VIII.

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TABLE IV
TFNs OF S, O, D BY THE THREE EXPERTS (38) AND AGGREGATED $\tilde{M}_k$ (39) (BOLD TFN)

Risk factor	Sub-indicator	TFNs of S	TFNs of O	TFNs of D
(H)	u_{11}	(5,7,9) (5,7,9) (3,5,7) **(4.333,6.333,8.333)**	(7,9,9) (5,7,9) (3,5,7) **(5.000,7.000,8.333)**	(3,5,7) (3,5,7) (5,7,9) **(3.667,5.667,7.667)**
	u_{12}	(5,7,9) (7,9,9) (5,7,9) **(5.667,7.667,9.000)**	(5,7,9) (5,7,9) (3,5,7) **(4.333,6.333,8.333)**	(5,7,9) (3,5,7) (5,7,9) **(4.333,6.333,8.333)**
	u_{13}	(5,7,9) (5,7,9) (5,7,9) **(5.000,7.000,9.000)**	(7,9,9) (5,7,9) (5,7,9) **(5.667,7.667,9.000)**	(5,7,9) (7,9,9) (7,9,9) **(6.333,8.333,9.000)**
	u_{14}	(7,9,9) (5,7,9) (7,9,9) **(6.333,8.333,9.000)**	(7,9,9) (7,9,9) (5,7,9) **(6.333,8.333,9.000)**	(3,5,7) (3,5,7) (3,5,7) **(3.000,5.000,7.000)**
	u_{15}	(7,9,9) (5,7,9) (3,5,7) **(5.000,7.000,8.333)**	(5,7,9) (5,7,9) (5,7,9) **(5.000,7.000,9.000)**	(5,7,9) (5,7,9) (5,7,9) **(5.000,7.000,9.000)**
(M_1)	u_{21}	(5,7,9) (5,7,9) (3,5,7) **(4.333,6.333,8.333)**	(5,7,9) (3,5,7) (5,7,9) **(4.333,6.333,8.333)**	(3,5,7) (5,7,9) (5,7,9) **(4.333,6.333,8.333)**
	u_{22}	(5,7,9) (3,5,7) (5,7,9) **(4.333,6.333,8.333)**	(7,9,9) (3,5,7) (7,9,9) **(5.667,7.667,8.333)**	(3,5,7) (3,5,7) (3,5,7) **(3.000,5.000,7.000)**
	u_{23}	(3,5,7) (5,7,9) (5,7,9) **(4.333,6.333,8.333)**	(7,9,9) (5,7,9) (3,5,7) **(4.333,6.333,7.667)**	(3,5,7) (3,5,7) (5,7,9) **(3.667,5.667,7.667)**
(M_2)	u_{31}	(7,9,9) (5,7,9) (5,7,9) **(5.667,7.667,9.000)**	(5,7,9) (3,5,7) (7,9,9) **(5.000,7.000,8.333)**	(3,5,7) (1,3,5) (3,5,7) **(2.333,4.333,6.333)**
	u_{32}	(7,9,9) (7,9,9) (5,7,9) **(6.333,8.333,9.000)**	(3,5,7) (7,9,9) (3,5,7) **(4.333,6.333,7.667)**	(1,3,5) (7,9,9) (3,5,7) **(1.667,3.667,5.667)**
	u_{33}	(7,9,9) (7,9,9) (3,5,7) **(5.667,7.667,8.333)**	(3,5,7) (3,5,7) (3,5,7) **(3.000,5.000,7.000)**	(3,5,7) (5,7,9) (1,3,5) **(3.000,5.000,7.000)**
(E)	u_{41}	(1,3,5) (3,5,7) (3,5,7) **(2.333,4.333,6.333)**	(1,3,5) (1,3,5) (1,1,3) **(1.000,2.333,4.333)**	(1,3,5) (1,3,5) (1,3,5) **(1.000,3.000,5.000)**
	u_{42}	(3,5,7) (1,3,5) (3,5,7) **(2.333,3.667,5.667)**	(3,5,7) (3,5,7) (3,5,7) **(3.000,5.000,7.000)**	(3,5,7) (3,5,7) (3,5,7) **(3.000,5.000,7.000)**
	u_{43}	(5,7,9) (5,7,9) (5,7,9) **(5.000,7.000,9.000)**	(3,5,7) (1,1,3) (1,3,5) **(1.667,3.000,5.000)**	(1,3,5) (3,5,7) (1,3,5) **(1.667,3.667,5.667)**
(M_3)	u_{51}	(1,3,5) (1,3,5) (1,3,5) **(1.000,3.000,5.000)**	(3,5,7) (1,3,5) (1,3,5) **(1.667,3.667,5.667)**	(5,7,9) (1,3,5) (5,7,9) **(3.667,5.667,7.667)**
	u_{52}	(3,5,7) (3,5,7) (1,3,5) **(2.333,4.333,6.333)**	(1,3,5) (1,3,5) (3,5,7) **(2.333,4.333,6.333)**	(3,5,7) (3,5,7) (5,7,9) **(3.000,5.000,7.000)**
	u_{53}	(5,7,9) (5,7,9) (5,7,9) **(5.000,7.000,9.000)**	(5,7,9) (5,7,9) (5,7,9) **(5.000,7.000,9.000)**	(3,5,7) (3,5,7) (3,5,7) **(3.000,5.000,7.000)**

Finally, the total information content I'^{ij}_{RPN} for each subindicator u_{ij} (47) calculation results and rankings are presented in Table VIII.

For the second model, the final rank results show that the following.

1) For risk factor of human, the most dangerous subindicator is u_{13}; the least dangerous subindicator is u_{11}.
2) For risk factors of machine, the most dangerous subindicator is u_{21}; the least dangerous subindicator is u_{22}.
3) For risk factors of materials, the most dangerous subindicator is u_{31}; the least dangerous subindicator is u_{32}.
4) For risk factors of environment, the most dangerous subindicator is u_{42}; the least dangerous subindicator is u_{41}.
5) For risk factors of management, the most dangerous subindicator is u_{53}; the least dangerous subindicator is u_{52}.

Related government departments and railway dangerous goods transport companies should pay more attention to the dangerous risk subindicators mentioned above.

EWM is applied to calculate the weight w_{ij} of each subindicator u_{ij}, the initial data are the RDNGTS risk accidents in China from 1985 to 2017, which is presented in Table IX [22], [23]. The final weight of each subindicator is also showed in Table IX.

The greater the uncertainty of the information, the bigger the weight obtained by EWM is, the subindicator is more important and has more contribution to the risk assessment. The calculation results of weight for each sub-indicator show the following.

1) For the risk factors of human, the most important subindicator is u_{11}; the most not important subindicator is u_{12}.
2) For the risk factors of machine, the most important subindicator is u_{21}; the most not important subindicator is u_{23}.
3) For the risk factors of materials, the most important subindicator is u_{31}; the most not important subindicator is u_{32}.
4) For the risk factors of environment, the most important subindicator is u_{42}; the most not important subindicator is u_{41}.

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TABLE V
R_{SOD} (40) AND $\tilde{U}_{SOD}$ (42)

Risk factor	Sub-indicator	r of S	r of O	r of D	TFNs of S	TFNs of O	TFNs of D
(H)	u_{11}	0.45	0.5	0.4	(0.045,0.155,0.350)	(0.044,0.183,0.447)	(0.043,0.122,0.252)
	u_{12}	0.6	0.45	0.45	(0.034,0.223,0.651)	(0.045,0.154,0.350)	(0.0446,0.154,0.350)
	u_{13}	0.4	0.5	0.55	(0.065,0.191,0.405)	(0.053,0.223,0.555)	(0.0501,0.257,0.692)
	u_{14}	0.7	0.65	0.45	(0.022,0.257,0.875)	(0.003,0.227,0.779)	(0.028,0.094,0.208)
	u_{15}	0.55	0.4	0.5	(0.114,0.261, 0.560)	(0.065,0.191,0.405)	(0.045,0.191,0.478)
(M_1)	u_{21}	0.5	0.25	0.4	(0.037,0.154,0.379)	(0.084,0.154,0.250)	(0.053,0.154,0.323)
	u_{22}	0.4	0.3	0.3	(0.053,0.154,0.323)	(0.005,0.117,0.279)	(0.045,0.094,0.164)
	u_{23}	0.35	0.3	0.35	(0.063,0.154,0.297)	(0.071,0.148,0.259)	(0.050,0.122,0.233)
(M_2)	u_{31}	0.3	0.3	0.3	(0.106,0.223,0.397)	(0.087,0.183,0.323)	(0.034,0.070,0.121)
	u_{32}	0.2	0.3	0.3	(0.024,0.120,0.244)	(0.071,0.148,0.259)	(0.024,0.050,0.086)
	u_{33}	0.4	0.25	0.4	(0.075,0.215,0.444)	(0.052,0.094,0.151)	(0.033,0.094,0.193)
(E)	u_{41}	0.3	0.15	0.4	(0.034,0.070,0.121)	(0.015,0.021,0.028)	(0.012,0.033,0.066)
	u_{42}	0.4	0.2	0.2	(0.154,0.187,0.241)	(0.059,0.094,0.138)	(0.059,0.094,0.138)
	u_{43}	0.7	0.1	0.1	(0.016,0.191,0.654)	(0.028,0.034,0.042)	(0.040,0.050,0.061)
(M_3)	u_{51}	0.2	0.25	0.4	(0.021,0.033,0.048)	(0.028,0.050,0.079)	(0.042,0.122,0.252)
	u_{52}	0.3	0.2	0.1	(0.034,0.070,0.121)	(0.044,0.070,0.103)	(0.076,0.094,0.115)
	u_{53}	0.4	0.35	0.3	(0.065,0.191,0.405)	(0.077,0.191,0.372)	(0.045,0.094,0.164)

TABLE VI
AR (41) AND $\tilde{U}'_{SOD}$ (43)

Risk factor	Sub-indicator	AR_{ij}^{S}	AR_{ij}^{O}	AR_{ij}^{D}	TFNs of S	TFNs of O	TFNs of D
(H)	u_{11}	0.25	0.3	0.25	(0.798,0.920,1.423)	(0.677,0.837,1.365)	(0.697,0.810,1.253)
	u_{12}	0.15	0.3	0.2	(0.632,0.728,1.607)	(0.775,0.920,1.381)	(0.821,0.920,1.467)
	u_{13}	0.3	0.1	0.1	(0.677,0.803,1.192)	(1.188,1.242,1.971)	(0.598,0.657,1.497)
	u_{14}	0.15	0.15	0.3	(0.547,0.657,1.789)	(0.555,0.657,1.656)	(1.058,1.212,1.690)
	u_{15}	0.1	0.3	0.15	(0.775,0.837,1.692)	(0.677,0.803,1.192)	(0.842,0.923,1.595)
(M_1)	u_{21}	0.5	0.45	0.45	(0.668,0.920,1.268)	(0.798,0.920,1.096)	(0.732,0.920,1.219)
	u_{22}	0.55	0.4	0.6	(0.695,0.920,1.158)	(0.629,0.759,0.996)	(0.012,0.212,0.370)
	u_{23}	0.4	0.55	0.45	(0.531,0.682,0.965)	(0.782,0.961,1.138)	(0.883,1.055,1.317)
(M_2)	u_{31}	0.5	0.5	0.5	(0.574,0.728,0.916)	(0.677,0.837,1.030)	(1.222,1.400,1.601)
	u_{32}	0.45	0.5	0.45	(0.562,0.657,0.791)	(0.797,0.961,1.160)	(0.970,1.130,1.363)
	u_{33}	0.5	0.5	0.5	(0.553,0.665,0.801)	(0.794,0.936,1.102)	(0.992,1.212,1.491)
(E)	u_{41}	0.7	0.9	0.8	(0.022,0.323,0.487)	(0.008,0.171,0.191)	(0.534,0.888,0.996)
	u_{42}	0.85	0.9	0.85	(0.682,1.112 ,1.211)	(1.012,1.212,1.236)	(0.022,0.212,0.249)
	u_{43}	0.6	0.9	0.9	(0.431,0.803,1.192)	(1.646,1.755,1.768)	(0.021,0.130,0.143)
(M_3)	u_{51}	0.65	0.75	0.7	(0.730,0.888,0.982)	(0.399,0.616,0.698)	(0.768,1.055,1.211)
	u_{52}	0.65	0.8	0.75	(0.175,0.395,0.535)	(0.211,0.395,0.447)	(0.123,0.212,0.243)
	u_{53}	0.7	0.6	0.75	(0.535,0.803,0.951)	(0.594,0.803,0.978)	(0.968,1.212,1.308)

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TABLE VII
CALCULATION RESULTS OF I_{ij}^{S}, I_{ij}^{O}, I_{ij}^{D}, ϖ_{ij}^{S}, ϖ_{ij}^{O}, ϖ_{ij}^{D}, AND I_{RPN}^{ij} [(44) AND (46)]

Risk factor	Sub-indicator	I_{ij}^{S}	I_{ij}^{O}	I_{ij}^{D}	ϖ_{ij}^{S}	ϖ_{ij}^{O}	ϖ_{ij}^{D}	I_{RPN}^{ij}	Rank
	u_{11}	0.0022	0.0031	0.0014				0.002285797	5
	u_{12}	0.0048	0.0022	0.0022				0.003233796	4
(H)	u_{13}	0.0034	0.0047	0.0064	0.4	0.333	0.267	0.004607686	1
	u_{14}	0.0067	0.0051	0.0008				0.004592082	3
	u_{15}	0.0064	0.0034	0.0034				0.004597307	2
	u_{21}	0.0022	0.0022	0.0022				0.00217991	1
(M_1)	u_{22}	0.0022	0.0013	0.0008	0.333	0.383	0.284	0.001434126	3
	u_{23}	0.0022	0.0020	0.0014				0.001875653	2
	u_{31}	0.0046	0.0031	0.0004				0.003512085	1
(M_2)	u_{32}	0.0013	0.0020	0.0002	0.533	0.334	0.133	0.001391567	3
	u_{33}	0.0043	0.0008	0.0008				0.002647742	2
	u_{41}	0.0004	3.83E-05	9.95E-05				0.000236184	3
(E)	u_{42}	0.0032	0.0008	0.0008	0.417	0.117	0.466	0.001795563	1
	u_{43}	0.0036	0.0001	0.0002				0.001597359	2
	u_{51}	9.93E-05	0.0002	0.0014				0.000582537	2
(M_3)	u_{52}	0.0004	0.0004	0.0008	0.317	0.333	0.35	0.000568314	3
	u_{53}	0.0034	0.0033	0.0008				0.002457768	1

TABLE VIII
CALCULATION RESULTS OF $I_{ij}'^{S}$, $I_{ij}'^{O}$, $I_{ij}'^{D}$, ϖ_{ij}^{S}, ϖ_{ij}^{O}, ϖ_{ij}^{D} AND $I_{RPN}'^{ij}$ [(45) AND (47)]

Risk factor	Sub-indicator	$I_{ij}'^{S}$	$I_{ij}'^{O}$	$I_{ij}'^{D}$	ϖ_{ij}^{S}	ϖ_{ij}^{O}	ϖ_{ij}^{D}	$I_{RPN}'^{ij}$	Rank
	u_{11}	0.0874	0.0717	0.0662				0.076518017	5
	u_{12}	0.0610	0.0858	0.0890				0.076763667	4
(H)	u_{13}	0.0638	0.1785	0.0494	0.4	0.333	0.267	0.098187718	1
	u_{14}	0.0538	0.0515	0.1526				0.079392139	2
	u_{15}	0.0813	0.0638	0.0935				0.078726077	3
	u_{21}	0.0809	0.0797	0.0811				0.080497644	1
(M_1)	u_{22}	0.0790	0.0544	0.0040	0.333	0.383	0.284	0.048338074	3
	u_{23}	0.0441	0.0859	0.1069				0.077933172	2
	u_{31}	0.0491	0.0653	0.1893				0.073160862	1
(M_2)	u_{32}	0.0399	0.0868	0.1227	0.533	0.334	0.133	0.066555532	3
	u_{33}	0.0407	0.0819	0.1416				0.067912595	2
	u_{41}	0.0092	0.0026	0.0687				0.036227676	3
(E)	u_{42}	0.1072	0.1328	0.0039	0.417	0.117	0.466	0.061960539	1
	u_{43}	0.0601	0.3004	0.0015				0.060807054	2
	u_{51}	0.0718	0.0335	0.1009				0.069711568	2
(M_3)	u_{52}	0.0139	0.0137	0.0040	0.317	0.333	0.35	0.010198659	3
	u_{53}	0.0577	0.0589	0.1338				0.086027159	1

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TABLE IX
RDNGTS RISK ACCIDENTS IN CHINA FROM 1985 TO 2017 AND w_{ij}

Year	u_{11}	u_{12}	u_{13}	u_{14}	u_{15}	u_{21}	u_{22}	u_{23}	u_{31}	u_{32}	u_{33}	u_{41}	u_{42}	u_{43}	u_{51}	u_{52}	u_{53}
1985	6	2	4	5	2	3	1	2	3	2	3	4	3	4	4	2	2
1986	5	8	13	10	7	4	8	8	8	6	4	4	1	1	2	2	3
1987	7	9	21	11	9	13	4	9	5	5	9	2	1	4	1	3	4
1988	4	9	24	15	12	6	9	3	5	6	9	3	0	3	3	1	4
1989	2	6	15	9	6	6	2	2	3	4	7	2	0	4	3	4	6
1990	6	6	18	16	11	7	6	5	9	6	4	4	2	5	3	3	3
1991	1	3	6	5	3	8	6	4	10	6	2	3	1	1	4	4	5
1992	8	8	16	12	8	6	8	8	4	1	1	3	2	5	6	0	3
1993	2	11	28	9	12	9	5	9	7	3	3	2	4	1	5	0	3
1994	5	7	16	14	8	7	6	2	4	5	9	1	3	6	2	3	9
1995	6	8	26	12	12	5	4	1	8	4	4	3	3	3	6	2	7
1996	11	7	13	9	6	7	4	5	3	5	9	3	3	2	5	7	5
1997	3	1	2	2	5	6	2	2	5	7	2	4	4	2	4	2	4
1998	6	8	11	10	7	3	2	7	5	1	4	2	6	5	1	4	3
1999	9	4	8	9	9	6	10	2	5	3	1	5	6	4	9	9	2
2000	5	4	9	7	6	3	7	5	9	1	9	2	4	2	1	0	5
2001	9	11	20	10	11	4	4	9	9	3	9	1	7	3	3	2	3
2002	2	5	13	5	6	7	5	2	8	7	5	1	4	4	3	1	4
2003	5	7	12	7	9	6	7	10	12	4	8	4	8	1	4	3	9
2005	7	5	13	9	15	10	3	3	9	1	3	2	4	3	4	2	9
2006	9	11	20	11	11	12	2	9	7	5	2	1	4	3	4	1	2
2007	5	7	15	8	6	3	5	5	5	3	8	3	3	1	1	2	9
2008	7	10	19	12	10	10	7	7	3	1	2	1	7	2	2	1	5
2009	9	7	15	9	7	4	6	2	3	3	2	2	3	2	1	1	9
2010	6	3	5	7	8	4	1	4	4	7	7	2	2	2	1	2	9
2011	4	2	3	6	2	6	3	3	4	5	4	2	4	1	0	3	9
2012	4	8	3	4	5	3	3	2	4	3	2	3	3	2	0	0	4
2012	6	2	5	7	2	2	3	5	6	4	3	2	4	1	0	1	2
2013	5	3	4	6	3	6	1	0	7	1	6	1	2	3	1	2	1
2014	6	2	5	5	2	2	1	2	5	3	2	3	1	1	0	0	2
2015	3	3	2	4	2	6	1	3	1	1	1	0	0	1	0	1	3
2016	1	2	1	2	1	5	0	2	1	1	2	0	0	1	1	2	1
2017	1	1	1	2	0	3	1	4	0	0	3	0	1	0	2	1	2
w_{ij}	**0.38**	**0.08**	**0.12**	**0.23**	**0.19**	**0.70**	**0.20**	**0.10**	**0.86**	**0.06**	**0.08**	**0.14**	**0.56**	**0.30**	**0.17**	**0.27**	**0.56**

TABLE X
TOTAL INFORMATION CONTENT I^i_{RPN}, I'^i_{RPN} AND RANKING FOR EACH RISK FACTOR i

Risk factor	H	M_1	M_2	E	M_3
I^i_{RPN}	0.003613962	0.002002335	0.003314121	0.00152103	0.001623448
Ranking	1	3	2	5	4
I'^i_{RPN}	0.080216781	0.073932191	0.072331848	0.058078987	0.062586231
Ranking	1	2	3	5	4

5) For the risk factors of management, the most important subindicator is u_{53}; the most not important subindicator is u_{51}.

According to (48), the total information content I^i_{RPN} for each risk factor i in the first model can be obtained, which is presented in Table X. According to (49), the total information content I'^i_{RPN} for each risk factor i in the second model can be obtained, which is presented in Table X.

The higher the rank of I^i_{RPN} and I'^i_{RPN} is (or are), the more dangerous the risk factor is. The results in Table X show that for the first model, the human factor is the most dangerous risk factor, followed by risk factor of materials, risk factor of machine, and risk factor of management. The least dangerous risk factor is environment; for the second model, the human factor is the most dangerous risk factor, followed by risk factor of machine, risk factor of materials, and risk factor of management. The least dangerous risk factor is environment. The government departments and railway dangerous goods transport companies should pay more attention to the human risk during the daily management processes.

B. Calculation Results Based on FMEA and FMEA With TFNs

In order to test the approaches proposed in this article, two comparative case studies of RDNGTS risk assessment by using FMEA and FMEA with TFNs are given. For the first

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TABLE XI
FAILURE CRITERION AND ITS CORRESPONDING REAL NUMBERS

Risk level	Severity (S)	Occurrence (O)	Detection (D)	Real numbers
1	Almost no	Rarely happen	Extremely detectable	1
2	Nothing serious	Less happen	Easily detectable	3
3	General serious	Happen occasionally	Attention	5
4	Serious	Happen very often	Hard to detect	7
5	Extremely serious	Prone to happen	Extremely hard to detect	10

TABLE XII
CALCULATION RESULTS OF FMEA

Risk factor	Sub-indicator	S and $\bar{S}$	O and $\bar{O}$	D and $\bar{D}$	RPN_{ij}	Rank	RPN_i	Rank
(H)	u_{11}	8/8/6/**7.33**	10/8/6/**8.00**	6/6/8/**6.67**	391.111	5	483.195	1
	u_{12}	8/10/8/**8.67**	8/8/6/**7.33**	8/6/8/**7.33**	466.074	4		
	u_{13}	8/8/8/**8.00**	10/8/8/**8.67**	8/10/10/**9.33**	647.111	1		
	u_{14}	10/8/10/**9.33**	10/10/8/**9.33**	6/6/6/**6.00**	522.667	2=3		
	u_{15}	10/10/8/**9.33**	5/7/6/**6.00**	9/10/9/**9.33**	522.667	2=3		
(M$_1$)	u_{21}	7/8/6/**7.00**	8/8/8/**8.00**	6/8/8/**7.33**	410.667	1	355.864	4
	u_{22}	8/6/6/**6.67**	5/6/5/**5.33**	6/5/6/**5.67**	201.481	3		
	u_{23}	5/6/6/**5.67**	8/8/6/**7.33**	6/6/8/**6.67**	277.037	2		
(M$_2$)	u_{31}	10/8/8/**8.67**	8/6/10/**8.00**	6/5/6/**5.67**	392.889	1	377.602	2
	u_{32}	8/8/8/**8.00**	6/8/6/**6.67**	4/4/6/**4.67**	248.889	3		
	u_{33}	10/10/6/**8.67**	6/6/6/**6.00**	6/8/4/**6.00**	312.000	2		
(E)	u_{41}	6/8/8/**7.33**	6/6/4/**5.33**	8/6/6/**6.67**	260.741	3	351.447	5
	u_{42}	8/6/6/**6.67**	8/8/8/**8.00**	8/6/8/**7.33**	391.111	1		
	u_{43}	8/8/8/**8.00**	8/4/6/**6.00**	6/6/8/**6.67**	320.000	2		
(M$_3$)	u_{51}	6/6/6/**6.00**	8/6/6/**6.67**	8/6/8/**7.33**	293.333	3	360.733	3
	u_{52}	8/8/6/**7.33**	6/6/8/**6.67**	8/8/9/**8.33**	407.407	1		
	u_{53}	6/8/8/**7.33**	8/8/6/**7.33**	6/6/8/**6.67**	358.519	2		

comparative case study, for each subindicator u_{ij}, use real numbers 1-1-0 to score the S, O, and D, the failure criterions and its corresponding evaluation numbers are shown in Table XI. Also, the three experts were invited to score the S, O, and D for each u_{ij}, and calculate the average value $\bar{S}, \bar{O}$, and $\bar{D}$. The results are presented in Table XII. Next $\mathrm{RPN}_{ij} = \bar{S}_{ij} \times \bar{O}_{ij} \times \bar{D}_{ij}$ is applied to calculate the RPN and rank each u_{ij}, the results are shown in Table XII. Finally, use the weight w_{ij} (presented in Table IX) to multiply the RPN_{ij} and obtain the RPN_i for each risk factor i, the results are presented in Table XII.

The calculation results in Table XII show the following.

1) For risk factors of human, the most dangerous subindicator is u_{13}, the least dangerous subindicator is u_{11}. The rank of u_{14} equals to the rank of u_{15} because the $\mathrm{RPN}_{14} = \mathrm{RPN}_{15}$.
2) For risk factors of machine, the most dangerous subindicator is u_{21}, the least dangerous subindicator is u_{22}.
3) For risk factors of materials, the most dangerous subindicator is u_{31}, the least dangerous subindicator is u_{32}.
4) For risk factors of environment, the most dangerous subindicator is u_{42}, the least dangerous subindicator is u_{41}.
5) For risk factors of management, the most dangerous subindicator is u_{52}, the least dangerous subindicator is u_{51}.

The rank of RPN_i shows that the human factor is the most dangerous risk factor, followed by risk factor of materials, risk factor of management, and risk factor of machine. The least dangerous risk factor is environment.

For the second comparative case study, the FMEA with TFNs based on (9) and (39) is applied, and the aggregated results $\tilde{M}_k$ are presented in Table IV. The calculation results include I''^{S}_{ij}, I''^{O}_{ij}, I''^{D}_{ij}, the weights ϖ^{S}_{ij}, ϖ^{O}_{ij}, ϖ^{D}_{ij} of S, O, D for each subindicator u_{ij} (the same value in Tables VII and VIII), and the total information content I''^{i}_{RPN}. Results of the comparative case study are presented in Table XIII. Finally, the weight w_{ij} (presented in Table IX) multiplies the I''^{i}_{RPN} and obtain the I''^{i}_{RPN} for each risk factor i, and results are shown in Table XIII.

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TABLE XIII
CALCULATION RESULTS OF I''^{S}_{ij}, I''^{O}_{ij}, I''^{D}_{ij}, ϖ^{S}_{ij}, ϖ^{O}_{ij}, ϖ^{D}_{ij}, I''^{i}_{RPN}, AND I''^{i}_{RPN}

Risk factor	Sub-indicator	I^{S}_{ij}	I^{O}_{ij}	I^{D}_{ij}	ϖ^{S}_{ij}	ϖ^{O}_{ij}	ϖ^{D}_{ij}	I^{ij}_{RPN}	Rank	I''^{i}_{RPN}	Rank
(H)	u_{11}	0.218	0.151	0.314	0.4	0.333	0.267	0.221	2	0.1893	1
	u_{12}	0.089	0.218	0.218				0.166	3		
	u_{13}	0.142	0.089	0.048				0.099	5		
	u_{14}	0.048	0.048	0.435				0.151	4		
	u_{15}	0.048	0.587	0.089				0.239	1		
(M_1)	u_{21}	0.218	0.089	0.218	0.333	0.383	0.284	0.168	2	0.1836	2
	u_{22}	0.218	0.314	0.142				0.233	1		
	u_{23}	0.142	0.218	0.218				0.192	3		
(M_2)	u_{31}	0.089	0.151	0.435	0.533	0.334	0.133	0.156	2	0.1634	4
	u_{32}	0.048	0.232	0.314				0.145	1		
	u_{33}	0.095	0.435	0.435				0.254	3		
(E)	u_{41}	0.218	0.218	0.314	0.417	0.117	0.466	0.263	3	0.1599	5
	u_{42}	0.089	0.142	0.142				0.120	2		
	u_{43}	0.142	0.218	0.218				0.186	1		
(M_3)	u_{51}	0.314	0.218	0.218	0.317	0.333	0.35	0.248	2	0.1768	3
	u_{52}	0.218	0.089	0.142				0.148	3		
	u_{53}	0.218	0.151	0.142				0.169	1		

TABLE XIV
COMPARISON AMONG STATISTICAL ACCIDENT NUMBER, RANK OF SUBINDICATOR AND RISK FACTORS

	u_{11}	u_{12}	u_{13}	u_{14}	u_{15}	u_{21}	u_{22}	u_{23}	u_{31}	u_{32}	u_{33}	u_{41}	u_{42}	u_{43}	u_{51}	u_{52}	u_{53}
N	175	190	386	269	223	192	137	146	181	117	149	75	100	83	86	71	151
FR_1	5	4	1	3	2	1	3	2	1	3	2	3	1	2	2	3	1
FR_2	5	4	1	2	3	1	3	2	1	3	2	3	1	2	2	3	1
FR	5	4	1	2=3	2=3	1	3	2	1	3	2	3	1	2	3	1	2
FT	2	3	5	4	1	2	1	3	2	1	3	3	2	1	2	3	1

	(H)	**(M_1)**	**(M_2)**	**(E)**	**(M_3)**
TN	1243	475	447	258	308
FR_1	1	3	2	5	4
FR_2	1	2	3	5	4
FR	1	4	2	5	3
FT	1	2	4	5	3

Note: *N* represents the statistical accident number for each subindicator of RDNGTS in China from 1985 to 2017 (in Table IX); TN is the total statistical accident number for each risk factor; FR_1 is the rank results of FMEA-POFIA; FR_2 shows the rank results of FMEA-POFIA-ARC; FR shows the rank of FMEA. FT shows the rank of approach which combines FMEA and TFNs.

The calculation results in Table XIII show the following.

1) For risk factor of human, the most dangerous subindicator is u_{15}, the least dangerous subindicator is u_{13}.
2) For risk factors of machine, the most dangerous subindicator is u_{22}, the least dangerous subindicator is u_{23}.
3) For risk factors of materials, the most dangerous subindicator is u_{32}, the least dangerous subindicator is u_{33}.
4) For risk factors of environment, the most dangerous subindicator is u_{43}, the least dangerous subindicator is u_{41}.
5) For risk factors of management, the most dangerous subindicator is u_{53}, the least dangerous subindicator is u_{52}.

Related government departments and railway dangerous goods transport companies should pay more attention to the dangerous risk subindicators mentioned above.

The rank of RPN_i shows that the human factor is the most dangerous risk factor, followed by risk factor of materials, risk factor of management, and risk factor of machine. The least dangerous risk factor is environment.

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C. Discussion

In order to compare the RDNGTS risk assessment results among the FMEA, FMEA with TFNs as well as the approach proposed in this article, the rank of each subindicator, and rank of risk factor based on these approaches are shown in Table XIV.

For each subindicator, the FR_1, FR_2, FR, and FT are totally different in risk factors of human; the FR_1, FR_2, and FR are the same in risk factors of machine, risk factor of materials, risk factors of environment; the FR_1 and FR_2 are the same in risk factors of management. For risk factors of human, the FR of u_{14} and u_{15} is identical, this is an inherent defect of FMEA, different combinations of *O*, *S*, and *D* may lead to an identical RPN value, but the failure modes with an identical RPN may correspond to different risk factors. The statistical accident number of u_{14} and u_{15} shows that u_{14} is more frequent to have accident than u_{15}.

For each risk factor, the rank of the four models have no difference in risk factors of human and risk factors of environment, but the rank of the four models are totally different in risk factors of machine, risk factor of materials as well as the risk factors of management. Compared with the analysis results of statistical accident number, the results of the approaches proposed in this article (especially the FMEA-POFIA-ARC) are more reliable than the results of FMEA and FMEA TFNs combined approach.

VII. Conclusion

RDNGTS accidents occur frequently in China, which result in serious casualties, property damage, and environmental damage. In order to manage the RDNGTS successfully, it is of great importance to have an effective risk assessment approach. In this article, a systemic risk assessment approach which combines FMEA and POFIA considering acceptable risk was proposed to evaluate RDNGTS risk. The TFNs were applied to score the *S, O*, and *D* for each RDNGTS risk subindicator, replacing the real numbers 1–10 of FMEA. The information contents of the *S*, *O*, and *D* were calculated for each risk subindicator, the product of the information contents of *S*, *O*, and *D* replace the previous RPN. There are two models applied to calculate the information contents, POFIA and POFIA-ARC. EWM was used to calculate the weight of each risk subindicator, the initial input data for the weight is the historical data of Chinese RDNGTS accidents from 1986 to 2017.

The calculation results showed that, for the FMEA-POFIA, the staffs of dangerous goods manufacturer illegally overload or entrain the goods, failure of dangerous goods storage equipment, packaging of dangerous goods, the sudden natural disaster, as well as the failure of Corporate Qualification Management, are the most dangerous risk subindicator. For the FMEA-POFIA-ARC, physical discomfort and poor working environment of the staffs, failure of loading and unloading equipment in the dangerous goods handling stations, the volume of the dangerous goods, extreme weather condition, failure of transportation laws and safety management are the most dangerous risk subindicator. Related government departments and railway dangerous goods transport companies should pay more attention to the dangerous risk subindicators mentioned above.

In order to test and verify the validity of the approach applied in this article, two comparing calculation results based on FMEA approach and FMEA with TFNs are given, and the statistical accident number for each subindicator of RDNGTS in China from 1985 to 2017 is applied as a standard. Compared with the analysis results of statistical accident number, the approaches proposed in this article, especially the FMEA-POFIA-ARC, are more reliable than the results of FMEA approach and FMEA with TFNs.

The outlines of the future research works include the following.

1) Weights of the subindicators are important in this approach, when the initial data of the subindicator has small fluctuation amplitude, or the data remain unchanged during the operation periods, the weights of these subindicators are 0 [17], [20]. In order to overcome the limitation, the translation-corrected distance entropy [17], [20], improved group-G1 method [6], improved group-G2 method [51], etc., may be applied.
2) The TFNs are applied in this article, the intuitionistic fuzzy numbers, e.g., trapezoidal intuitionistic fuzzy numbers [33], [36], triangular intuitionistic fuzzy numbers [44], can also be used to improve the FMEA approach.
3) Interpretive structural modeling (ISM), which is a powerful qualitative tool and is a suitable modeling technique for analyzing the influence of one element and developing insights into a collective understanding of these relationships and their levels [50], so the ISM and ISM-based approaches [50] can be used as a systemic method, to solve the risk assessment problem of RDNGTS.

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