Wang *et al. Management System Engineering* (2022) 1:8
https://doi.org/10.1007/s44176-022-00008-x

Management System Engineering

RESEARCH ARTICLE **Open Access**

A dynamic failure mode and effects analysis for train systems failures risk assessment using FCM and prospect theory

Weizhong Wang*, Yi Wang and Xiao Han

Abstract

Improving the reliability of railway train systems and preventing potential failures in the train operation process is one of the most significant tasks. The failure mode and effects analysis (FMEA) is the most effective and widely applied technique for identification, evaluation, and prevention risk of potential failures in diverse fields. Nevertheless, current risk prioritization approaches for FMEA overlook the transfer of decision makers' risk preferences under different risk states of potential failures. In addition, little attrition has been paid to addressing the risk prioritization problems in FMEA under a dynamic environment. In order to bridge these research gaps, this paper proposes a dynamic prioritization approach for FMEA by integrating the Fuzzy Cognitive Map (FCM) and the prospect theory. First, improved weighted arithmetic averaging (WAA) operator based on the similarity measure is constructed to aggregate each decision maker's evaluation information. Then, the FCM is applied to obtain the risk matrix and interaction relationships among failures under different risk states. Next, the dynamic prospect theory is built to determine the risk priority of each failure by considering the risk preference of decision makers, in which the dynamic weight functions are derived based on the risk matrix under different risk states. Finally, the proposed dynamic risk prioritization approach for FMEA is tested by the failures risk analysis of the railway train bogie system in the railway train systems. The comparison study is conducted to demonstrate the reliability and rationality of the proposed risk prioritization approach.

Keywords: Railway train systems, Risk analysis, Failure mode and effects analysis (FMEA), Fuzzy Cognitive Map (FCM), Prospect theory

1 Introduction

High-speed rail in China has developed rapidly in recent years. By the end of 2019, the high-speed railway mileage had surpassed 3.5 million kilometers. Furthermore, maintaining reliability and safety in such a fast-moving process is difficult. To enhance the safety and reliability of train operations, dervise automatic techniques and systems have been adopted (Wang et al. 2018b). As a result, train systems are more likely to fail (Ding et al. 2018). In the absence of proactive risk analysis tools, these failures may cause various failure modes and unsafe railway operation statuses. Previous literature shows that many FMEA (failure mode and effects analysis)-based risk analysis models have been employed for identifying, evaluating and prioritizing risks and enhancing the reliability of complex systems (Zheng et al. 2021; He et al. 2022). There are, however, some limitations to using risk priority numbers (RPNs) for (FMEA). Following is a summary of the most criticized (Wu et al. 2021; Hassan et al. 2022): (i) there is no consideration for uncertainty in the process of RPN computing. (ii) The risk parameter's relative importance is not considered. (iii) There is no scientific evidence supporting conventional RPN calculations. There are several versions of uncertain risk rarting information modeling tools that have been extended into risk analysis to overcome the limitations of RPN methods in FMEA (Wang

*Correspondence: wzyu@ahnu.edu.com
School of Economics and Management, Anhui Normal University, Wuhu, Anhui, China

et al. 2019b, 2018a, 2018c; Huang et al. 2017). Furthermore, MCDM (multi-criteria decision-making) methods have also been applied to tackle the risk priority calculation problems in FMEA (Boral and Chakraborty 2021; He et al. 2022; Sayyadi Tooranloo and Saghafi 2021; Wang et al. 2020). Despite the improvements made by these extended calculation methods for risk priority in FMEA, there remain some limitations in this process.

(1) Most existing risk prioritization models for FMEA were proposed with MCDM approaches, which overlook the transfer of weight for each risk parameter under different failure states. These models include the TOPSIS (technique for order preference by similarity to ideal solution) based risk prioritization approach (Liu et al. 2019c), the VIKOR (VIse Kriterijumska Optimizacija I Kompromisno Resenje) based risk prioritization approach (Safari et al. 2014), the QUALIFLEX (qualitative flexible multiple criteria method) based risk prioritization model (Liu et al. 2016), the PT (prospect theory) based risk prioritization approach (Wang et al. 2018c, 2023), and the generalized TODIM (an acronym in Portuguese of Interactive and Multi-criteria Decision Making) based risk prioritization approach (Wang et al. 2018a), etc.

(2) The dynamic MCDM approaches can be adopted to address the risk analysis problem under a dynamic environment (Ding et al. 2019; Bali et al. 2015), however, these approaches have no capability to capture the patterns and trends of past decision making information. In addition, current dynamic MCDM approaches based risk prioritization approaches cannot simulate the interactions among risk factors under different periods.

(3) A few risk prioritization approaches for FMEA have taken into account the risk preference of decision makers (Wang et al. 2018c, 2018a, 2019a; Huang et al. 2017), however, none of them can model the risk priorities of train systems failures under different risk states. In addition, no research has developed risk prioritization approaches for FMEA by using PT and the Fuzzy Cognitive Map (FCM), especially, for train systems failures risk assessment.

In the light of these limitations summarized above, it is beneficial to develop a dynamic risk prioritization approach for failures risk analysis of railway train systems within the uncertain and dynamic context, in which the transfer of risk scores of failure modes is taken into account. Compared with the conventional dynamic MCDM techniques, the learning algorithm-based MCDM techniques can generate a multiple-period evaluation matrix. Thus, it is justifiable to incorporate the learning algorithm-based MCDM techniques into the risk prioritization approach for comping with the FMEA-based train system failures analysis problem. In addition, the PT is an effective and widely adopted MCDM technique for modeling the risk preference of each decision maker in the risk analysis process(Wang et al. 2018c), however, it is insufficient to simulate the transfer of risk scores of failure modes under different risk status. The FCM, introduced by Kosko (1986), is a useful tool to depict the system transitions through different states, especially in the dynamic decision-making environment. Furthermore, no research has been conducted on the FCM and PT to construct a risk prioritization approach for FMEA. Therefore, we develop a dynamic risk prioritization approach based FMEA model for risk analysis of railway train systems failures by integrating the FCM and the PT. In this hybrid approach, the Jaya algorithm based FCM learning is introduced to derive the future risk evaluation information of failure modes.

As discussion mentioned above, the novelties of this paper and the contributions to the literature on risk prioritization approaches for FMEA can be presented as follows:

(1) The proposed dynamic risk assessment framework is the first method incorporating the FCM and PT into the FMEA model for risk analysis of train systems failures. Compared with current FMEA-based risk assessment approaches, the proposed risk assessment framework not only can simulate the different weights of risk parameters but also can take the decision makers' risk preference information under different states into account.

(2) The FCM learning is incorporated into the risk prioritization approach, which can depict the interactions among the failure modes. This is the first paper that applies the intelligent algorithm to model interactions among risk factors. In addition, the proposed risk prioritization approach in this paper is the first time that the learning algorithm is applied to address the risk priority determining problem for the FMEA model.

(3) The risk priority ranking order of train systems failures can be determined under different states, namely, short-term, medium-term, and long-term. In this process, the different risk preferences can also be captured by using past, current, and future risk evaluation information. First time in FMEA-related literature, future risk evaluation information is derived by using an intelligent algorithm.

(4) The risk analysis result of the illustrative example indicates that the proposed dynamic risk assessment framework outperforms other FMEA-based risk assessments for coping with the train systems failures risk analysis problem. The proposed framework can calculate the future risk priorities of train systems failures that can provide a more flexible, reasonable, and valid risk assessment result for enhancing the safety and reliability of train systems.

The remainder part of this paper is organized as follows. The next section provides a brief literature review. In Sect. 3, the extended PT-based FMEA model is presented. In Sect. 4, a real risk analysis example is selected to demonstrate the application and feasibility of the developed FMEA framework. Sensitivity and comparison studies are subsequently led to illustrating the effectiveness of the proposed approach. Finally, the conclusions and future research directions are provided in Sect. 5.

2 Related literature

2.1 Improvement of FMEA

In current years, the FMEA has attracted considerable interest and also has been one of the most popular and widely adopted failures risk analysis tools in various fields (Liu et al. 2016, 2019b; Huang et al. 2019; Wang et al. 2019a, 2019c). In the utilization of this tool, one of the most significant problems is the calculation of risk priority for each failure mode. In order to address this problem, various kinds of risk prioritization approaches have been developed. Among these approaches, the MCDM techniques-based risk prioritization approaches are the most popular research trends (Li et al. 2019; Wang et al. 2019b; Liu et al. 2019b). The best–worst method (BWM) and TOPSIS are used by Lo et al. (2019) for RPN calculation in FMEA-based risk analysis issue. A MABAC (multi-attribute border approximation area comparison) method is proposed by Liu et al. (2019a) for risk prioritization under interval-valued intuitionistic fuzzy environments. Zhang et al. (2022) developed ANP approach to improve performance of the RPN calculation in FMEA. A synthesized GLDS (gained and lost dominance score) method is reported by Wang et al. (2019b) to implement the RNP calculation for FMEA. To explore the efficience of MCDM frameworks in RPN calculation, many other MCDM tools are also incorporated into RPN compution for strengthening its availability (see for instance, Wang et al. (2021), Akram et al. (2020), Boral and Chakraborty (2021), Wang et al. (2020), Li and Zhu (2020)).

Recently, the risk preference of each decision maker has been taken into the risk prioritization approach for the FMEA model. Liu et al. (2018) proposed a new risk prioritization approach for dealing with the large group FMEA-based risk analysis problem, in which the PT is adopted to model a large number of experts' risk preferences. In order to simulate the risk preference of each decision maker in the risk evaluation process, Wang et al. (2018c) introduced an extended PT to improve the performance of the risk prioritization approach. Fang et al. (2019)introduced a hybrid risk prioritization approach for the FMEA model, in which the risk preference of each decision maker is modeled by PT. Sagnak et al. (2020) combined PT with the TODIM method for risk priorities calculation procedure in FMEA by taking the risk preference of each decision maker into account.

2.2 Application of FCM

FCM is an effective graphical technique for simulating in which various kinds of cause-effect relationships are included (Jamshidi et al. 2017). Compared with other modeling approaches for interaction relationships among factors, such as DEMATEL, ANP (Analytic network process), and Choquet integral, the FCM can depict more detailed interactions among factors and also can simulate these interaction relationships within a dynamic context (Navas de Maya and Kurt 2020). It can provide an accurate prediction of systems' evolutionary behavior.

Owing to the simplicity and modeling capability of the dynamic system, the FCM has been used as a decision support technique in various fields such as the logistics industry (Jamshidi et al. 2017), energy (Alipour et al. 2017), healthcare (Bevilacqua et al. 2018), food industry (Jahangoshai Rezaee et al. 2018) (for a detailed review see: Papageorgiou and Salmeron (2013)). Recently, the FCM has been applied to address the risk analysis problem in an uncertain environment. For example, Lopez and Salmeron (2014) developed an FCM-based dynamic risk analysis approach to address. Dabbagh and Yousefi (2019) developed a hybrid FMEA-based risk analysis approach using FCM and MOORA (multi-objective optimization on the basis of Ration Analysis) approach. Bevilacqua et al. (2018) utilized the FCM method to identify and analyze the risk of the drug administration process. De Maio et al. (2016) introduced a 2-Tuple linguistic variables based FCM to analyze the risk in the software development process.

2.3 Application of PT

The PT, originally proposed by Kahneman (1979), is a widely utilized technique for modeling the characteristics of decision makers' bounded rational behavior under the risk and uncertain environment. Compared with other MCDM approaches, the PT determines the priorities of alternatives that can depict the bounded rational decision behaviors such as loss aversion, reference dependence, and risk aversion. It helps decision-makers to obtain a more reasonable priority ranking order of each alternative under the uncertain environment.

The PT has been extensively adopted to address priority ranking problems because of its modeling capability of decision makers' behavior characters under the uncertain environment. In order to address the optimal portfolio selection problem, Zhou et al. (2019) developed a priority ranking calculation approach by using PT. Liu et al. (2019d) introduced a PT-based priority determining method for emergency alternatives in an uncertain environment. Chen et al. (2020) introduced an optimal renewable energy source determining approach by using PT. In order to depict the influences of online reviews on customers' decisions about product ranking, Zhang et al. (2020) combined PT with VIKOR to prioritize customized products.

The literature review mentioned above shows that various MCDM approaches have been extended into the FMEA model for dealing with the risk prioritization problem. But little attention has been paid to developing a dynamic MCDM approach-based risk prioritization approach for the FMEA model. In addition, no evidence shows how to combine the FCM with PT for risk prioritization in FMEA, in which the dynamic risk preference of each decision maker is taken into account. On the other hand, there has been limited research on train system failures using FMEA based risk analysis framework by integrating FCM and PT. Consequently, this paper develops a dynamic risk prioritization approach for train system failures by using FCM and PT. The proposed risk prioritization approach also aims to improve a more effective and reliable risk prioritization approach for FMEA-based risk analysis problem under a dynamic environment.

3 A dynamic risk prioritization approach for failures risk analysis

IN this section, a dynamic risk prioritization approach-based FMEA framework is proposed for failures risk analysis, in which the FCM and PT are incorporated. The proposed risk prioritization approach based FMEA framework consists of three phases. The detailed steps of this framework are expressed as follows.

3.1 Description of the dynamic risk prioritization problem for FMEA

AS discussed above, let us consider a dynamic risk prioritization problem as a dynamic MCDM problem, in which includes m potential failure modes $FM_i(i = 1, 2, \ldots, m)$ in terms of n risk indicators $c_j(j = 1, 2, \ldots, n)$, which should be evaluated by q FMEA team members $d_k(k = 1, 2, \ldots, q)$. Let the matrix $W = \left(\omega_{ji}\right)_{m\times m}$ be the causal relationships among failure modes. Assume that the set of all risk states is denoted as $t = \left\{t_1, t_2, \ldots, t_p\right\}$. The weight vector of risk factors is expressed by $[w_1(t_\tau), w_2(t_\tau), \ldots, w_n(t_\tau)]^T(\tau = 1, 2, \ldots, p)$ in which $w_j(t_\tau) \geq 0$ and $\sum_{j=1}^{n} w_j(t_\tau) = 1$. The risk matrix at the risk state t_τ is denoted as $A(t_\tau) = \left(a_{ij}(t_\tau)\right)_{m\times n}$ where $a_{ij}(t_\tau)$ is the value of failure mode FM_i with respect to risk factor c_j at period t_τ.

In the application of FMEA based risk analysis problem, the first step of the risk prioritization approach is to gather the FMEA team members' information about rating scores of failure modes with respect to each risk factor. Every decision maker in the FMEA team d_k is asked to determine the rating score of failure mode FM_i with respect to risk indicator c_j by fuzzy linguistic variables which are provided in Tables 1, 2 and 3, respectively.

Table 1 Linguistic variable for Severity

Linguistic term	Rank	$\tilde{c}^l$	$\tilde{c}^m$	$\tilde{c}^u$
Very High (VH)	9,10	0.75	1.00	1.00
High (H)	7,8	0.50	0.75	1.00
Medium (M)	4,5,6	0.25	0.50	0.75
Low (L)	2,3	0.00	0.25	0.50
Very Low (VL)	1	0.00	0.00	0.25

3.2 Construction of group risk matrix

3.2.1 Compute the similarity degree

Let the element $x_{ij}^k = (x_{ij1}^k, x_{ij2}^k, x_{ij3}^k)$ be the risk scor offered by decision maker d_k, then the similarity measure and weights of decision makers is obtained as:

First, the mean value of decision makers' risk scores is computed as:

Table 2 Linguistic variable for Occurrence

Linguistic term	Predicted frequency	$\tilde{c}^l$	$\tilde{c}^m$	$\tilde{c}^u$
Very High (VH)	> 1 in 2, 1 in 8	0.75	1.00	1.00
High (H)	1 in 20, 1 in 40	0.50	0.75	1.00
Medium (M)	1 in 80, 1 in 400, 1 in 1000	0.25	0.50	0.75
Low (L)	1 in 4000, 1 in 20000	0.00	0.25	0.50
Very Low (VL)	< 1 in 10^6	0.00	0.00	0.25

Table 3 Linguistic variable for Detection

Linguistic term	Rank	$\tilde{c}^l$	$\tilde{c}^m$	$\tilde{c}^u$
None (N)	10	0.8	1.0	1.0
Very Low (VL)	9	0.6	0.8	1.0
Low (L)	7,8	0.4	0.6	0.8
Medium (M)	5,6	0.2	0.4	0.6
High (H)	3,4	0.0	0.2	0.4
Very High (VH)	1,2	0.0	0.0	0.2

The parameters $\tilde{c}^l$, $\tilde{c}^m$ and $\tilde{c}^u$ indicate the values of a triangular fuzzy number

$$\bar{x}_{ij} = \frac{1}{q}(x_{ij}^1 + x_{ij}^2 + \ldots + x_{ij}^q). \tag{1}$$

Then, the similarity measure is calculated as:

$$s_{ij}^k(x_{ij}^k, \bar{x}_{ij}) = 1 - \frac{\sum_{\rho=1}^{3}\left|x_{ij\rho}^k - \bar{x}_{ij\rho}\right|}{8} - \frac{d(x_{ij}^k, \bar{x}_{ij})}{2}. \tag{2}$$

In which, $d(x_{ij}^k, \bar{x}_{ij})$ is denoted as:

$$d\left(x_{ij}^k, \bar{x}_{ij}\right) = \sqrt{1/3\left[\sum_{l=1}^{3}(x_{ijl}^k - \bar{x}_{ijl})^2\right]}. \tag{3}$$

3.2.2 Form the group risk evaluation matrix

Based on Eq. (3), the decision maker's weights is computed as:

$$\varpi_{ij}^k = s_{ij}^k(x_{ij}^k, \bar{x}_{ij}) \Big/ \sum_{k=1}^{q} s_{ij}^k(x_{ij}^k, \bar{x}_{ij}). \tag{4}$$

The group risk evaluation matrix $G = \left[\tilde{g}_{ij}\right]_{m\times n}$ is generated as:

$$\begin{aligned}\tilde{g}_{ij} =&(g_{ij1}, g_{ij2}, g_{ij3})\\ =&WAA_{\varpi}(x_{ij}^1, x_{ij}^2, \ldots, x_{ij}^q) = \sum_{k=1}^{q}\varpi_{ij}^k x_{ij}^k\\ =&(\sum_{k=1}^{q}\varpi_{ij}^k x_{ij1}^k, \sum_{k=1}^{q}\varpi_{ij}^k x_{ij2}^k, \sum_{k=1}^{q}\varpi_{ij}^k x_{ij3}^k).\end{aligned} \tag{5}$$

3.3 Calculation of dynamic risk priority using PT and FCM

The risk priority of each failure mode is determined by the dynamic PT, in which both the dynamic risk preference of the decision maker and the dynamic weight function are taken into account. However, the traditional PT-based risk prioritization approach is unable to address the decision maker's risk preference and weight function under a dynamic environment. Consequently, FCM learning is introduced to construct dynamic risk matrix and weight functions, and then these risk matrices and weight functions are selected as the input of PT. In this sub-section, we develop a dynamic risk prioritization approach for FMEA by integrating FCM and PT.

3.3.1 Construction of FCM model for failure modes

In this step, the initial values of concepts $FM_i (i = 1, 2, \ldots, m)$ are denoted as $C_i(0)$ in the FCM model, and the consecutive rows of the aggregated risk matrix $G = \left[\tilde{g}_{ij}\right]_{m\times n}$ are adopted. The aggregated interaction matrix $W^{\text{init}} = \left(\omega_{ji}\right)_{m\times m}$ provided by decision-makers is used to derive the causal relationships among failure modes, in which $W^{\text{init}} = [\omega_{11}, \omega_{12}, \ldots, \omega_{1m}, \omega_{21}, \omega_{22}, \ldots, \omega_{2m}, \ldots, \omega_{m1}, \omega_{m2}, \ldots, \omega_{mm}]$ are calculated by using the WAA operator as the following form.

$$\begin{aligned}\omega_{ji} &= WAA_{\varpi}\left(\omega_{ji}^{(1)}, \omega_{ji}^{(2)}, \ldots, \omega_{ji}^{(q)}\right) = \bigoplus_{k=1}^{q}\varpi_{ji}^k\omega_{ji}^{(k)}\\ &= \left(\sum_{k=1}^{q}\varpi_{ji}^k\omega_{ji1}^{(k)}, \sum_{k=1}^{q}\varpi_{ji}^k\omega_{ji2}^{(k)}, \sum_{k=1}^{q}\varpi_{ji}^k\omega_{ji3}^{(k)}\right).\end{aligned} \tag{6}$$

where $\omega_{ji}^{(k)}$ is denoted as $\omega_{ji}^{(k)} = \left[\omega_{11}^{(k)}, \omega_{12}^{(k)}, \ldots, \omega_{1m}^{(k)}, \omega_{21}^{(k)}, \omega_{22}^{(k)}, \ldots, \omega_{2m}^{(k)}, \ldots, \omega_{m1}^{(k)}, \omega_{m2}^{(k)}, \ldots, \omega_{mm}^{(k)}\right]$.

Then, the ABC algorithm is adopted to optimize the interaction matrix $W^{\text{init}} = \left(\omega_{ji}\right)_{m\times m}$ because this algorithm is able to find optimal solutions with relatively modest computational requirements (Hajek and Froelich, 2019). In addition, the ABC algorithm requires fewer control parameters than the above-mentioned population-based algorithms. In consequence, using the ABC algorithm does not require rigorous tuning of parameters. Also, recent studies have demonstrated the high effectiveness of ABC in learning FCM(Hajek and Froelich 2019). The goal of the optimization is to detect a matrix W that leads the FCM model to a steady state. The steady states W of the failure modes are used in the objective function $f(W)$ for the ABC algorithm(Hajek and Froelich 2019):

$$\begin{aligned}f(W) =& \sum_{i=1}^{m}\sum_{j=1}^{out_m}H\left(C_{out_{ij}}^{\min} - C_{outij}\right)\left|C_{out_{ij}}^{\min} - C_{outij}\right|\\ &+ \sum_{i=1}^{m}\sum_{j=1}^{out_m}H\left(C_{outij} - C_{out_{ij}}^{\max}\right)\left|C_{out_{ij}}^{\max} - C_{outij}\right|.\end{aligned} \tag{7}$$

In which,C_{outij} is the steady-state value of the i-th output failure mode for the j-th risk factor, and the function H is the Heaviside function $H(x) = 0$ for $x > 0$ and $H(x) = 1$ for $x \leq 0$. And the function $f(W)$ is defined as follows.

$$f(W) = \frac{1}{1 + e^{-\lambda W}}. \tag{8}$$

Finally, the steady-state risk matrix of failure modes under each risk factor can be obtained as follows.

$$C_i^{j(\tau+1)} = f\left(C_i^{j(\tau)} + \sum_{\substack{i'=1\\ i'\neq i}}^{m} W_{i'i}C_{i'}^{j(\tau)}\right). \tag{9}$$

In which, the function $W_{i'i}$ is the steady state causal relationships between each two failure modes FM_i and

$FM_{i'}$. And $C_i^{j(\tau+1)}$ indicates that the risk value of failure mode FM_i under risk factor c_j in the risk state $t = \tau + 1$.

3.3.2 Development of dynamic PT for risk prioritization

According to the risk matrix $A(t_\tau) = \left(a_{ij}(t_\tau)\right)_{m\times n}$ and weight vector $[w_1(t_\tau), w_2(t_\tau), \ldots, w_n(t_\tau)]^T$ under different risk states, we can develop the dynamic prospect decision matrix $V_{ij}^{(t_\tau)}$ as follows.

$$V^{(t_\tau)}(FM_i, FM_l) = \pi\left(w_j(t_\tau)\right) v_j^{(t_\tau)}(FM_i, FM_l). \tag{10}$$

In which, the function $\pi\left(w_j(t_\tau)\right)$ and $v\left(a_{ij}(t_\tau)\right)$ can be calculated in the following form.

$$\pi\left(w_j(t_\tau)\right) = \begin{cases} \dfrac{\left[w_j(t_\tau)\right]^\gamma}{\left[\left(w_j(t_\tau)\right)^\gamma + \left(1 - w_j(t_\tau)\right)^\gamma\right]^{1/\gamma}}, \ a_{ij}(t_\tau) \succ a_{lj}(t_\tau) \\ \dfrac{\left[w_j(t_\tau)\right]^\delta}{\left[\left(w_j(t_\tau)\right)^\delta + \left(1 - w_j(t_\tau)\right)^\delta\right]^{1/\delta}}, \ a_{ij}(t_\tau) \prec a_{lj}(t_\tau) \end{cases}. \tag{11}$$

$$v_j^{(t_\tau)}(FM_i, FM_l) = \begin{cases} \left[a_{ij}(t_\tau) - a_{lj}(t_\tau)\right]^\alpha, \ a_{ij}(t_\tau) \succ a_{lj}(t_\tau) \\ -\theta\left[a_{lj}(t_\tau) - a_{ij}(t_\tau)\right]^\beta, \ a_{ij}(t_\tau) \prec a_{lj}(t_\tau) \end{cases}. \tag{12}$$

In which, the parameters γ and δ indicate the the degree of distortion in the probability assessmen. The values of the two parameters are set as $\gamma = 0.61$ and $\delta = 0.69$. The paprameters α and β are βare the risk attitude coefficient of each decision-maker. Further, the weight of each risk factor under risk states $w_j(t_\tau)$ is derived through the entropy method as follows.

$$E_j(t_\tau) = -K\sum_{i=1}^{m}\left[a_{ij}(t_\tau)\right]\ln\left[\left(a_{ij}(t_\tau)\right)\right]. \tag{13}$$

In which, the parameter $K = {}^{1}\!/_{\ln(n)}$.

$$G_j(t_\tau) = 1 - E_j(t_\tau). \tag{14}$$

$$w_j(t_\tau) = \frac{G_j(t_\tau)}{\sum\limits_{j=1}^{n} G_j(t_\tau)}. \tag{15}$$

Then, the risk priority of each failure mode can be obtained as follows.

$$\phi(a_i(t_\tau)) = \sum_{i=1}^{m}\sum_{j=1}^{n} V^{(t_\tau)}(FM_i, FM_l). \tag{16}$$

Which is equal to the sum of all the elements of the matrix $\phi(a_i(t_\tau))$, and the risk priority ranking order of each failure mode FM_i according to the value $\phi(a_i(t_\tau))$.

3.3.3 Procedures of the proposed method

According to the specific procedures mentioned above, the calculation schematic of the proposed dynamic risk prioritization approach for FMEA-based risk analysis is provided in Fig. 1, which includes the following steps.

Step1: Determine the risk score of each failure mode by using the linguistic terms, and then transform the linguistic risk matrix into a triangular fuzzy numbers-based risk matrix.

Step 2: Assign the causal relationships among failure modes using linguistic terms.

Step 3: Obtain the group risk matrix $G = \left[\tilde{g}_{ij}\right]_{m\times n}$ and weighted group causal relationships $W^{\text{init}} = \left(\omega_{ji}\right)_{m\times m}$ using Eqs. (1–6).

Step 4: Construct the FCM model for causal relationships $W_{i'i}$ and risk matrix $C_i^{j(\tau+1)}$ of failure modes by using Eqs. (7–9).

Step 5: Determine the weight functions for failure modes under risk states by using Eq. (11).

Step 6: Calculate the value function $v\left(a_{ij}^l(t_\tau)\right)$ for failure modes under each risk state by using Eq. (12).

Step 7: Obtain the prospect values of failure modes by using Eq. (10).

Step 8: Determine the final risk priority of each failure mode by using Eq. (16).

4 Illustrative example

In this section, a real case of failures risk analysis for the railway train bogie system in a railway train system (Kou et al. 2018) is selected to demonstrate the application of the proposed dynamic risk prioritization approach based FMEA framework. In addition, the comparison study is led to illustrating the effectiveness of the developed dynamic FMEA framework.

4.1 Problem description

In order to demonstrate the specific application procedures of the proposed framework, the bogie system is chosen as the case study. The Bogie system is one of the most major complex mechatronic parts of a railway train and can be easily prone to fail. The Bogie system can account for a substantial 21.1% based on the accumulation of failure data in a couple of years (Kou et al. 2018). In this paper, a specific railway train bogie system is applied to illustrate the dynamic risk prioritization approach for FMEA model-based risk analysis. In order to simplify the calculation process, we select the most important four components in the bogie system as an example. Then, we ask three decision makers $d_k(k = 1, 2, 3)$ from a certain train operation company

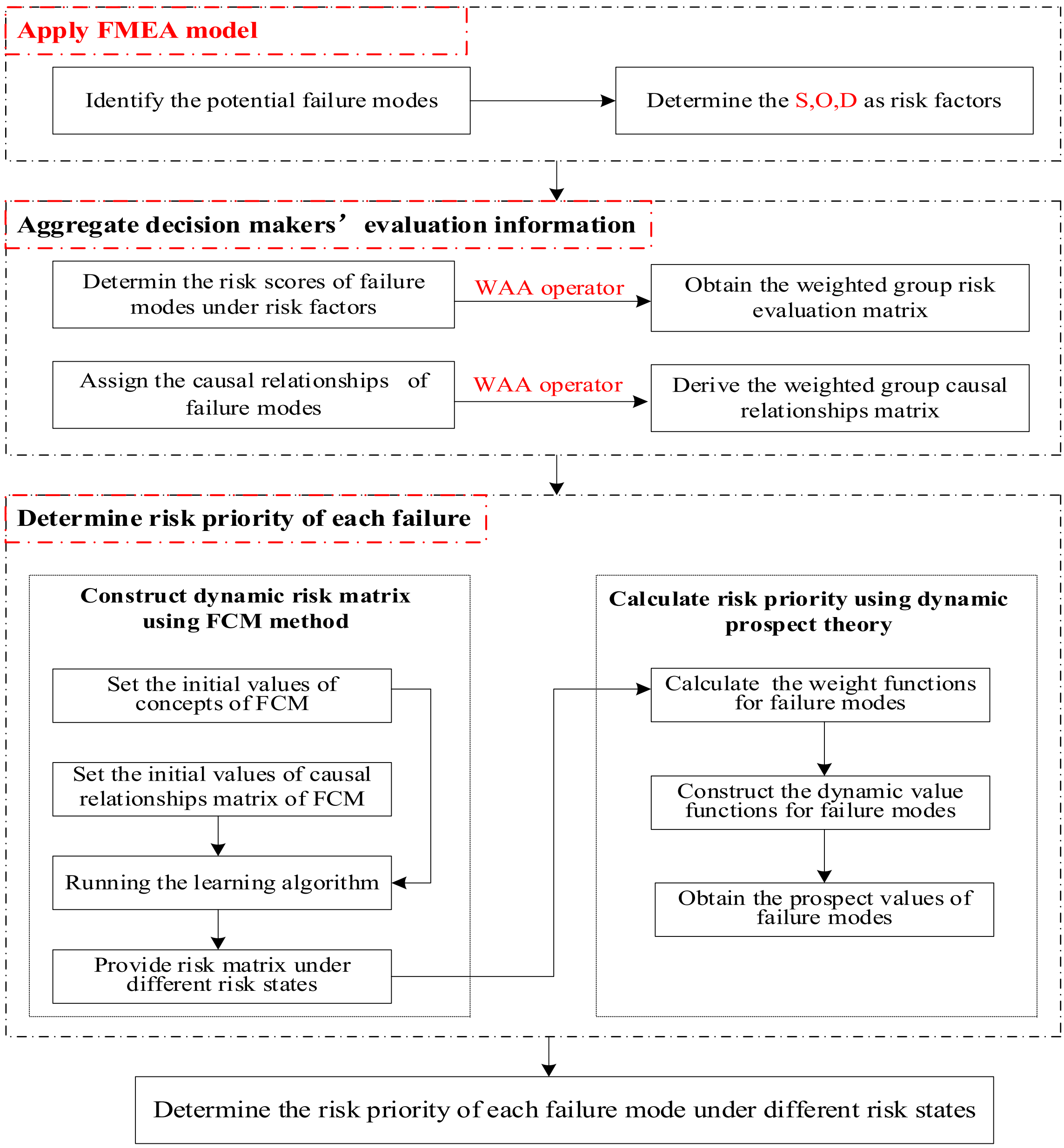

Fig. 1 The flowchart of the proposed method

Table 4 The failure modes of import components

Component	No	Failure modes	Component	No	Failure modes
Frame assembly	FM_1	Micro crack	Wheel	FM_8	Tread crack
	FM_2	Crack		FM_9	Wheel wear
Axle	FM_3	Micro crack	Axle box body	FM_{10}	Micro crack
	FM_4	Crack		FM_{11}	Wear
Wheel	FM_5	Crack		FM_{12}	Crack
	FM_6	Tread scratch		FM_{13}	Abnormal temperature
	FM_7	Tread peeling		FM_{14}	Scratch

to identify the potential failure modes in the five components. It should note that the three decision-makers include the manager, operator, and railway maintenance personnel. The result is shown in Table 4.

4.2 The application of the proposed approach

The proposed dynamic FMEA framework is employed to performe the identified train system failures risk analysis. The detailed failure modes are provided in Table 4. The application of this framework is described below.

It is necessary to conduct the first stage of the RPN calculation procedure, and the subsequent stages must be applied. To assess the risk scores, we use the three risk indicators: Severity (S), Occurrence (O), and Detection (D). Following the identification of failure modes, three decision makers are asked to provide the risk scores of the failures by describing it linguistically. Decision-makers use the five-point linguistic terms provided in Tables 1, 2 and 3 when expressing risk scors. Thus, the linguistic risk scors for the fourtheen failures given by decision makers are listed in Table 5.

In the second stage of this framework, group causal relationships and group risk matrices will be constructed. First, Eqs. (8–10) are used to determine the similarity of each element in the TrFNs-based risk matrix. Then, the decision makers' weights are determined using Eq. (11). Thus, the group risk matrix is generated using Eq. (12), shown in Table 6.

Then, the three decision-makers also are invited to determine the causal relationships among each pair of failure modes. Drawing the experience of literature (Jamshidi et al. 2017), the five-point linguistic terms are adopted to evaluate the causal relationships, as shown in Table 7. And then, the result is expressed by FCM, shown in Fig. 2.

The group causal relationships among failure modes can be calculated by using Eq. (13), shown in Table 8.

Table 6 The group risk matrix of system failures

Failure modes	Group risk matrix		
	$\tilde{c}^l$	$\tilde{c}^m$	$\tilde{c}^u$
FM_1	0.331	0.521	0.711
FM_2	0.431	0.646	0.798
FM_3	0.123	0.250	0.423
FM_4	0.531	0.771	0.903
FM_5	0.000	0.000	0.073
FM_6	0.056	0.133	0.261
FM_7	0.053	0.125	0.248
FM_8	0.114	0.229	0.389
FM_9	0.202	0.354	0.552
FM_{10}	0.361	0.521	0.623
FM_{11}	0.260	0.438	0.660
FM_{12}	0.318	0.521	0.703
FM_{13}	0.000	0.000	0.048
FM_{14}	0.381	0.583	0.741

In order to illustrate the specific procedures of the dynamic PT-based risk prioritization approach, the prospect values calculation process of all failure modes under risk parameter S is selected as an example. According to the FCM contribution process, the initial weight matrix $W^{\text{init}} = \left(\omega_{ji}\right)_{m\times m}$ (shown in Table 8) and the initial values of the concept $C^{\text{initial}} = [0.521, 0.630, 0.261, \ldots, 0.516, 0.012, 0.572]$ are selected as the input of the learning-based FCM model. Then, according to the Eqs. (14–16), the simulation process in all procedures of the dynamic PT is performed using Matlab R2018b. The result in 24 iterations scenarios of the simulation process is shown in Table 9 and Fig. 3.

Finally, the steady state of prospect value $\phi(a_i(t_\tau))$ for each failure mode FM_i can be derived as follows:

Table 5 The linguistic risk matrix of system failures

Failure modes		FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8	FM_9	FM_{10}	FM_{11}	FM_{12}	FM_{13}	FM_{14}
d_1	*S*	H	H	M	H	VL	L	VL	M	M	H	M	M	VL	H
	O	VH	H	M	H	H	M	L	H	M	H	H	VH	M	VH
	D	L	L	VL	L	N	N	N	VL	VL	L	VL	VL	N	L
d_2	*S*	H	VH	M	H	VL	L	L	L	H	VH	H	M	VL	VH
	O	H	VH	L	VH	VL	L	M	L	H	VH	M	VH	VL	H
	D	M	M	VL	L	N	N	N	N	L	M	L	VL	N	M
d_3	*S*	M	M	M	VH	L	M	M	M	M	L	H	H	VL	M
	O	M	H	H	VH	VL	M	M	M	M	VL	H	H	VL	M
	D	VL	VL	VL	M	N	VL	VL	VL	VL	N	L	L	N	VL

Table 7 The causal relationships among failure modes

Failure modes	Failure modes	Direction	Evaluation information from the decision maker		
			d_1	d_2	d_3
FM_1	FM_9	−	VL	L	L
FM_2	FM_{13}	+	H	H	VH
FM_3	FM_1	+	M	H	H
FM_4	FM_9	+	VH	VH	VH
FM_5	FM_2	+	VL	VL	M
FM_7	FM_5	+	M	H	M
FM_8	FM_7	+	L	M	M
FM_8	FM_{11}	+	VH	VH	H
FM_8	FM_{14}	+	VL	M	VL
FM_9	FM_{12}	+	M	M	M
FM_{10}	FM_{12}	+	H	VH	H
FM_{11}	FM_{12}	+	M	M	L
FM_{12}	FM_{13}	+	L	L	L
FM_{13}	FM_{11}	+	H	H	H
FM_{13}	FM_7	+	L	VL	L
FM_{13}	FM_2	+	H	H	M
FM_{14}	FM_3	+	VH	H	VH
FM_{14}	FM_4	+	M	M	M
FM_{14}	FM_6	+	VL	VL	L

$$\phi(a_i(t_\tau))=\begin{bmatrix} 0.899, 0.921, 0.850, 0.754, 0.884, 0.500, 0.872, \\ 0.175, 0.898, 0.227, 0.929, 0.963, 0.961, 0.453 \end{bmatrix}$$

Consequently, it can be seen that the risk priority ranking order of each failure mode of machine tools according to the $\phi(a_i(t_\tau))$ is FM_{12}, FM_{13}, FM_{11}, FM_2, FM_1, FM_9, FM_5, FM_7, FM_3, FM_4, FM_6, FM_{14}, FM_8, and FM_{10}.

4.3 The comparison analysis

In order to verify the efficiency of the developed FMEA approach, comparison research is performed with other approaches based on the example mentioned above. The risk priority of each failure mode obtained by the proposed risk prioritization approach is compared with other risk prioritization approaches including the traditional RPN method, and PT-based risk prioritization approach (Wang et al. 2018c). The calculation result of the three approaches is shown in Table 10.

From Table 10, we can derive the below findings:

Despite their differences, these three models produce some consistent results on the ranking orders of failure modes. This is similar to what is obtained by PT-based prioritization for failure modes FM_{12} and FM_{13}. Moreover, the proposed model and the PT-based model both indicate that the FM_{10} and FM_8 have the lowest risk priority. Based on this finding, the proposed FMEA approach and PT-based model are relatively homogeneous. Further,

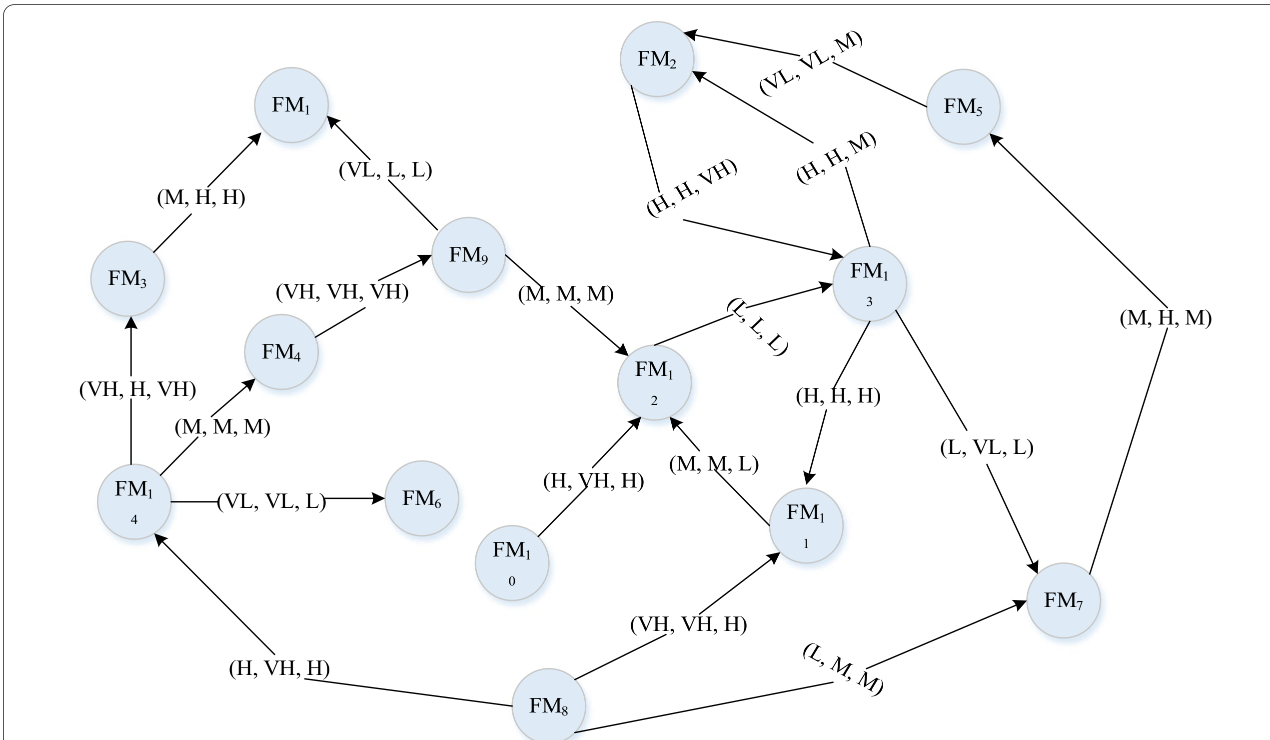

Fig. 2 The causal relationships among failure modes

Table 8 The group causal relationships among failure modes

Failure modes	Failure modes	Group causal relationships			Numeric impact
		$\tilde{c}^l$	$\tilde{c}^m$	$\tilde{c}^u$	
FM_1	FM_9	0.667	1.667	0.3167	− 0.179
FM_2	FM_{13}	6.833	8.333	9.333	0.821
FM_3	FM_1	5.167	6.667	8.167	0.667
FM_4	FM_9	8.500	10.00	10.00	0.963
FM_5	FM_2	0.000	0.000	1.500	0.038
FM_7	FM_5	4.333	5.833	7.333	0.583
FM_8	FM_7	2.667	4.167	5.667	0.417
FM_8	FM_{11}	7.667	9.167	9.667	0.892
FM_8	FM_{14}	1.167	1.667	3.167	0.192
FM_9	FM_{12}	3.500	5.000	6.500	0.500
FM_{10}	FM_{12}	6.833	8.333	9.333	0.821
FM_{11}	FM_{12}	2.667	4.167	5.667	0.417
FM_{12}	FM_{13}	1.000	2.500	4.000	0.250
FM_{13}	FM_{11}	6.000	7.500	9.000	0.750
FM_{13}	FM_7	3.500	5.000	6.000	0.488
FM_{13}	FM_2	5.167	6.667	8.167	0.667
FM_{14}	FM_3	7.667	9.167	9.667	0.892
FM_{14}	FM_4	3.500	5.000	6.500	0.500
FM_{14}	FM_6	0.333	0.833	2.333	0.108

duplication rate, however, is an important indicator to evaluate FMEA (Wang et al. 2019b). From Table 10, the duplication rate of the traditional RPN method is 35.7%, 28.6% for the PT-based method, and 0.0% for the proposed method. Since the railway train company has limited resources, the risk manager needs to rank failure modes accurately when taking preventative measures. Duplication rates should be as low as possible in such cases. Therefore, in conclusion, the dynamic PT method based FMEA framework provides a valid method for analyzing the rail systems failures.

A risk priority derived from traditional FMEA differs greatly from that obtained by the proposed FMEA framework. On one hand, traditional RPN methods calculate risk priorities with crisp numbers without considering the dynamic and uncertain nature of risks. However, this framework uses the TrFN to express randomness and uncertainty, which overcomes the limitations of traditional RPNs. Moreover, the FCM is used to construct the risk matrix by simulating the dynamic risk matrix. In contrast, the traditional RPN model considers expert to be equally important for risk evaluation aggregation. This assumption is not reasonable because some failure modes may be over- or underestimated. Using the traditional

Table 9 Outputs of failure modes in the iterations

iterations	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8	FM_9	FM_{10}	FM_{11}	FM_{12}	FM_{13}	FM_{14}
0	0.521	0.63	0.261	0.744	0.018	0.146	0.138	0.24	0.365	0.506	0.449	0.516	0.012	0.572
1	0.613	0.568	0.435	0.747	0.103	0.163	0.141	0.235	0.538	0.501	0.415	0.597	0.237	0.568
2	0.694	0.723	0.497	0.751	0.143	0.198	0.278	0.231	0.597	0.493	0.607	0.674	0.356	0.564
3	0.735	0.795	0.578	0.754	0.178	0.227	0.315	0.227	0.632	0.487	0.683	0.743	0.475	0.561
4	0.787	0.858	0.594	0.751	0.235	0.259	0.398	0.224	0.695	0.479	0.719	0.798	0.533	0.559
5	0.796	0.877	0.646	0.748	0.356	0.278	0.459	0.221	0.747	0.465	0.798	0.852	0.599	0.556
6	0.832	0.884	0.709	0.744	0.469	0.294	0.493	0.219	0.793	0.461	0.833	0.898	0.623	0.552
7	0.873	0.895	0.785	0.741	0.583	0.325	0.534	0.217	0.839	0.455	0.878	0.932	0.674	0.497
8	0.884	0.907	0.803	0.739	0.617	0.362	0.579	0.215	0.876	0.447	0.903	0.961	0.698	0.494
9	0.892	0.916	0.839	0.735	0.719	0.393	0.617	0.213	0.893	0.441	0.917	0.963	0.715	0.491
10	0.898	0.921	0.846	0.731	0.735	0.421	0.658	0.211	0.893	0.436	0.923	0.963	0.762	0.487
11	0.899	0.921	0.85	0.728	0.747	0.463	0.696	0.209	0.893	0.429	0.926	0.963	0.797	0.483
12	0.899	0.921	0.85	0.725	0.752	0.487	0.732	0.206	0.893	0.425	0.929	0.963	0.813	0.481
13	0.899	0.921	0.85	0.721	0.791	0.492	0.787	0.203	0.893	0.416	0.929	0.963	0.845	0.478
14	0.899	0.921	0.85	0.719	0.827	0.5	0.843	0.201	0.893	0.409	0.929	0.963	0.878	0.475
15	0.899	0.921	0.85	0.716	0.835	0.5	0.869	0.198	0.893	0.401	0.929	0.963	0.923	0.471
16	0.899	0.921	0.85	0.712	0.862	0.5	0.872	0.197	0.893	0.396	0.929	0.963	0.956	0.469
17	0.899	0.921	0.85	0.708	0.875	0.5	0.872	0.195	0.893	0.387	0.929	0.963	0.961	0.466
18	0.899	0.921	0.85	0.703	0.883	0.5	0.872	0.194	0.893	0.375	0.929	0.963	0.961	0.462
19	0.899	0.921	0.85	0.701	0.883	0.5	0.872	0.192	0.893	0.364	0.929	0.963	0.961	0.459
20	0.899	0.921	0.85	0.698	0.883	0.5	0.872	0.189	0.893	0.355	0.929	0.963	0.961	0.457
21	0.899	0.921	0.85	0.695	0.883	0.5	0.872	0.187	0.893	0.343	0.929	0.963	0.961	0.455
22	0.899	0.921	0.85	0.687	0.883	0.5	0.872	0.184	0.893	0.319	0.929	0.963	0.961	0.454
23	0.899	0.921	0.85	0.683	0.883	0.5	0.872	0.181	0.893	0.302	0.929	0.963	0.961	0.453

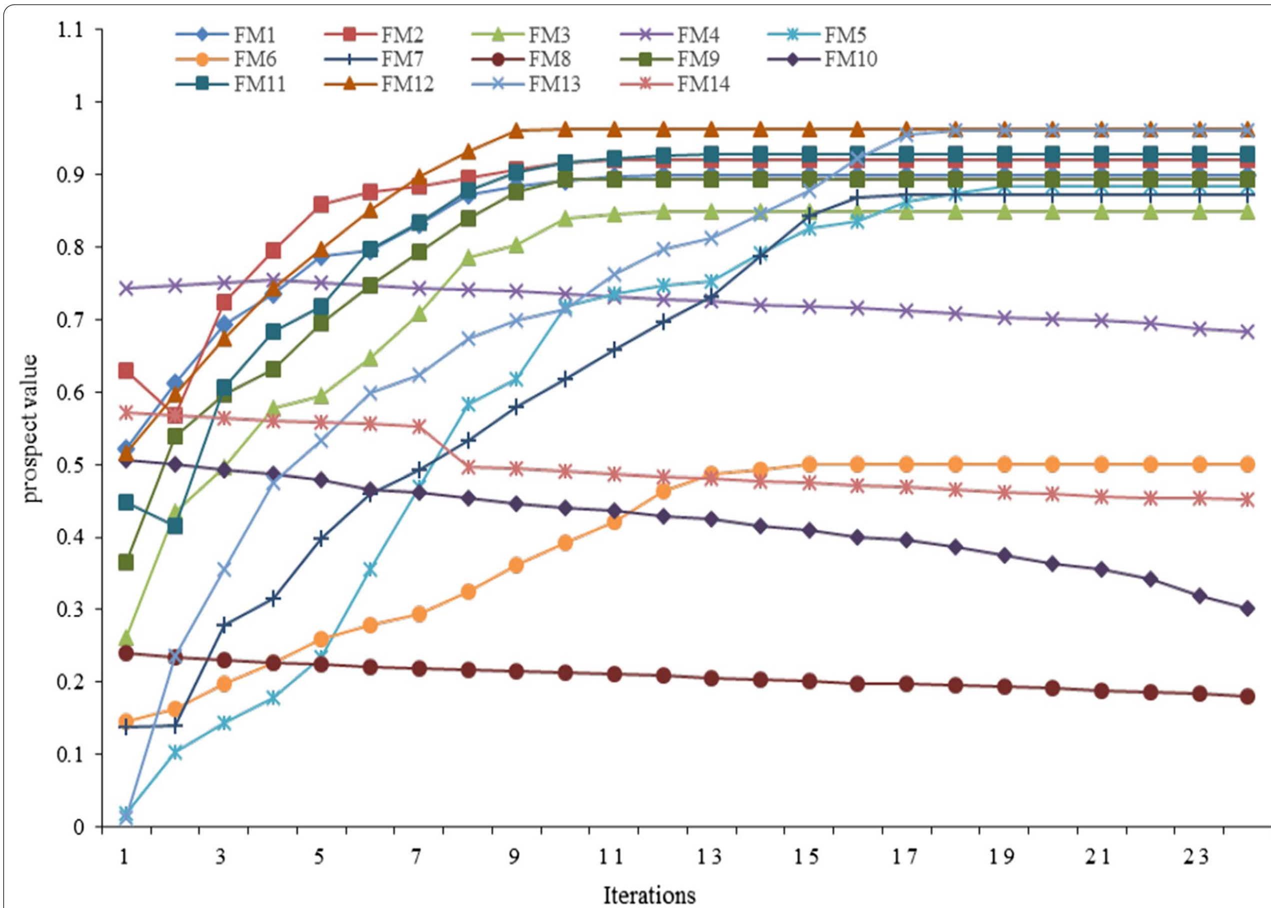

Fig. 3 The prospect values of failure modes under iterations

Table 10 The comparison analysis result of different approaches

Failure modes	Risk priority ranking order of each failure mode		
	Traditional RPN method	PT-based method	The proposed method
FM_1	3	5	5
FM_2	2	3	4
FM_3	8	8	9
FM_4	1	9	10
FM_5	11	7	7
FM_6	10	10	11
FM_7	11	7	8
FM_8	9	11	13
FM_9	7	6	6
FM_{10}	5	12	14
FM_{11}	6	4	3
FM_{12}	4	1	1
FM_{13}	11	2	2
FM_{14}	2	9	12

RPN model, each decision maker assigns a different risk score to FM_5 and FM_7. The risk priorities of both failure modes are the same, however, if experts are given equal weight. Nevertheless, FM_5 has a higher risk priority in the proposed model than FM_7 since the experts with different weigts. Since the neglect of expert's weight in the conventional RPN model, the ranking order of FM_{13} has also increased.

In contrast to the proposed model, the PT-based method has different risk priority ranking orders, which can be explained as follows: In addition to accounting for the risk preferences of each decision maker, the latter model considers the correlation between failure modes. From Table 10, PT-based methods reveal a decrease in the ranking orders of some failure modes. Compared with the proposed model, FM_{14} has been ranked lower from 9 to 12 in terms of priority. PT ranks failure modes with prospect values which considers risk preference. In contrast, in the traditional PT, the reference points stay static which may decrease the risk priority. The risk preferences of decision makers cannot be captured by this method since the influence of different risk states. Furthermore, the PT-based method neglects the interdependence among failures, which may result in an overestimated or underestimated risk evaluation result. It is possible that this unreasonable result in the risk analysis will cause misleading risk prevention measures.

In summary, compared with the traditional RPN model and its extended frameworks, the proposed dynamic FMEA framework has the following properties: first, in the dynamic FMEA model-based framework, the different risk preference of each decision maker is simulated in the risk prioritization process. Second, the dynamic weight functions in the PT are modeled in the risk priority determining procedure, which is obtained by using the learning algorithm and entropy method. Then, it is incorporated into PT to construct a comprehensive way to determine the ultimate risk priority of each failure mode of train failures. Moreover, the proposed framework takes into account the dynamic relationships among failure modes and overall reflects the potential correlations among these failure modes in the risk prioritization process.

5 Conclusions

An extended risk priority compution method based on dynaminc PT is reported in this work for enhancing the serviceability of FMEA framework for the train systems risk analysis. Further, the FCM is integrated with the conventional PT to tackle train system failures risk analysis under dynamic and uncertain situation. Then, this new FMEA framework is tested through a real case of train system. The results show the improved model has the following feayures. (1) This introduced model is able to hold the failure risk assessment problem considering the dynamic risk preference and interdepent failures. Besides, this method also reflects the impact of dynamic reference effects on final failures ranking. (2) In addition, the proposed risk prioritization approach for the FMEA model not only can effectively address risk evaluation and prioritization problems with dynamic and uncertain risk information but also can determine the risk priority of failure mode by considering the decision maker's dynamic risk preference and interactions among failure modes. In addition, the comparison analysis shows that the proposed FMEA framework can be adopted to actual risk analysis of train system failures, especially within the context where the risk preference of each decision maker is dynamic and uncertain.

Further research may focus on these directions, which are provided as follows. Firstly, the risk evaluation information is provided by decision makers using fuzzy numbers, which may lead to a subjective result. Thus, in future research, the data of failure modes from detection devices can be used. Secondly, there are only three experts in this paper, which cannot fully reflect the real risk states of failure modes. Hence, a large group decision-making method can be used in the risk prioritization procedure. Finally, the proposed dynamic risk prioritization approach can be extended to different risk analysis problems in various fields.

Abbreviations

FMEA: Failure mode and effect analysis; FCM: Fuzzy cognitive map; WAA: Weighted arithmetic averaging; RPN: Risk priority number; MCDM: Multi-criteria decision-making; TOPSIS: Technique for order preference by similarity to ideal solution; VIKOR: VIse Kriterijumska Optimizacija I Kompromisno Resenje; QUALIFLEX: Qualitative flexible multiple criteria method; TODIM: An acronym in Portuguese of Interactive and Multi-criteria Decision Making; GLDS: Gained and lost dominance score); DEMATEL: Decision-making trial and evaluation laboratory); MULTIMOORA: Multi-Objective Optimization by Ratio Analysis plus the Full Multiplicative Form; BWM: Best–worst method; MABAC: Multi-attributive border approximation area comparison.

Acknowledgements

We thank the Executive Editor-in-Chief, Prof. Jindong Qin and referees for their insightful and constructive comments and suggestions which have much improved the paper.

Author contributions

WW: Conceptualization, investigation, methodology, writing original draft and review. XH: Software, formal analysis, editing. All authors read and approved the final manuscript.

Funding

This work was supported in part by the Social Science Planning Project of Anhui province (AHSKQ2021D20).

Availability of data and materials

All data generated or analysed during this study are included in this published article.

Declarations

Ethics approval and consent to participate

This paper does not contain any studies with human participants or animals performed by any of the authors.

Competing interests

The authors declare that they have no competing interests.

Received: 27 July 2022 Revised: 24 August 2022 Accepted: 11 September 2022
Published online: 18 November 2022

References

Akram, M., A. Luqman, and J.C.R. Alcantud. 2020. Risk evaluation in failure modes and effects analysis: Hybrid TOPSIS and ELECTRE I solutions with Pythagorean fuzzy information. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-020-05350-3.

Alipour, M., R. Hafezi, M. Amer, and A.N. Akhavan. 2017. A new hybrid fuzzy cognitive map-based scenario planning approach for Iran's oil production pathways in the post–sanction period. *Energy* 135: 851–864. https://doi.org/10.1016/j.energy.2017.06.069.

Bali, O., M. Dagdeviren, and S. Gumus. 2015. An integrated dynamic intuitionistic fuzzy MADM approach for personnel promotion problem. *Kybernetes* 44 (10): 1422–1436. https://doi.org/10.1108/k-07-2014-0142.

Bevilacqua, M., F.E. Ciarapica, and G. Mazzuto. 2018. Fuzzy cognitive maps for adverse drug event risk management. *Safety Science* 102: 194–210. https://doi.org/10.1016/j.ssci.2017.10.022.

Boral, S., and S. Chakraborty. 2021. Failure analysis of CNC machines due to human errors: An integrated IT2F-MCDM-based FMEA approach. *Engineering Failure Analysis* 130: 105768. https://doi.org/10.1016/j.engfailanal.2021.105768.

Chen, T., Y.-T. Wang, J.-Q. Wang, L. Li, and P.-F. Cheng. 2020. Multistage decision framework for the selection of renewable energy sources based on prospect theory and PROMETHEE. *International Journal of Fuzzy Systems* 22 (5): 1535–1551. https://doi.org/10.1007/s40815-020-00858-1.

Dabbagh, R., and S. Yousefi. 2019. A hybrid decision-making approach based on FCM and MOORA for occupational health and safety risk analysis. *Journal of Safety Research* 71: 111–123. https://doi.org/10.1016/j.jsr.2019.09.021.

De Maio, C., G. Fenza, V. Loia, and F. Orciuoli. 2016. Linguistic fuzzy consensus model for collaborative development of fuzzy cognitive maps: A case study in software development risks. *Fuzzy Optimization and Decision Making* 16 (4): 463–479. https://doi.org/10.1007/s10700-016-9259-3.

Ding, Z., Y. Zhou, G. Pu, and M. Zhou. 2018. Online failure prediction for railway transportation systems based on fuzzy rules and data analysis. *IEEE Transactions on Reliability* 67 (3): 1143–1158.

Ding, X.-F., H.-C. Liu, and H. Shi. 2019. A dynamic approach for emergency decision making based on prospect theory with interval-valued Pythagorean fuzzy linguistic variables. *Computers & Industrial Engineering* 131: 57–65. https://doi.org/10.1016/j.cie.2019.03.037.

Fang, H., J. Li, and W. Song. 2019. Failure mode and effects analysis: An integrated approach based on rough set theory and prospect theory. *Soft Computing* 24 (9): 6673–6685. https://doi.org/10.1007/s00500-019-04305-8.

Hajek, P., and W. Froelich. 2019. Integrating TOPSIS with interval-valued intuitionistic fuzzy cognitive maps for effective group decision making. *Information Sciences* 485: 394–412. https://doi.org/10.1016/j.ins.2019.02.035.

Hassan, S., J. Wang, C. Kontovas, and M. Bashir. 2022. Modified FMEA hazard identification for cross-country petroleum pipeline using Fuzzy Rule Base and approximate reasoning. *Journal of Loss Prevention in the Process Industries* 74: 104616.

He, S.-S., Y.-T. Wang, J.-J. Peng, and J.-Q. Wang. 2022. Risk ranking of wind turbine systems through an improved FMEA based on probabilistic linguistic information and the TODIM method. *Journal of the Operational Research Society* 73 (3): 467–480. https://doi.org/10.1080/01605682.2020.1854629.

Huang, J., Z. Li, and H.-C. Liu. 2017. New approach for failure mode and effect analysis using linguistic distribution assessments and TODIM method. *Reliability Engineering & System Safety* 167: 302–309. https://doi.org/10.1016/j.ress.2017.06.014.

Huang, J., D. Xu, H. Liu, and M. Song. 2019. A new model for failure mode and effect analysis integrating linguistic Z-numbers and projection method. *IEEE Transactions on Fuzzy Systems*. https://doi.org/10.1109/TFUZZ.2019.2955916.

Jahangoshai Rezaee, M., S. Yousefi, M. Valipour, and M.M. Dehdar. 2018. Risk analysis of sequential processes in food industry integrating multi-stage fuzzy cognitive map and process failure mode and effects analysis. *Computers & Industrial Engineering* 123: 325–337. https://doi.org/10.1016/j.cie.2018.07.012.

Jamshidi, A., D. Ait-kadi, A. Ruiz, and M.L. Rebaiaia. 2017. Dynamic risk assessment of complex systems using FCM. *International Journal of Production Research* 56 (3): 1070–1088. https://doi.org/10.1080/00207543.2017.1370148.

Kahneman, D., and A. Tversky. 1979. Prospect theory—Analysis of decision under risk. *Econometrica* 47 (2): 263–291.

Kosko, B. 1986. Fuzzy cognitive maps. *International Journal of Man-Machine Studies* 24 (1): 65–75. https://doi.org/10.1016/S0020-7373(86)80040-2.

Kou, L., Y. Qin, X. Zhao, and Y. Fu. 2018. Integrating synthetic minority oversampling and gradient boosting decision tree for bogie fault diagnosis in rail vehicles. *Proceedings of the Institution of Mechanical Engineers, Part f: Journal of Rail and Rapid Transit* 233 (3): 312–325. https://doi.org/10.1177/0954409718795089.

Li, Y., and L. Zhu. 2020. Risk analysis of human error in interaction design by using a hybrid approach based on FMEA, SHERPA, and fuzzy TOPSIS. *Quality and Reliability Engineering International* 36 (5): 1657–1677. https://doi.org/10.1002/qre.2652.

Li, G.-F., Y. Li, C.-H. Chen, J.-L. He, T.-W. Hou, and J.-H. Chen. 2019. Advanced FMEA method based on interval 2-tuple linguistic variables and TOPSIS. *Quality Engineering*. https://doi.org/10.1080/08982112.2019.1677913.

Liu, H., J. You, P. Li, and Q. Su. 2016. Failure mode and effect analysis under uncertainty: An integrated multiple criteria decision making approach. *IEEE Transactions on Reliability* 65 (3): 1380–1392. https://doi.org/10.1109/TR.2016.2570567.

Liu, H.-C., X.-Y. You, F. Tsung, and P. Ji. 2018. An improved approach for failure mode and effect analysis involving large group of experts: An application to the healthcare field. *Quality Engineering* 30 (4): 762–775. https://doi.org/10.1080/08982112.2018.1448089.

Liu, H.-C., J.-X. You, and C.-Y. Duan. 2019a. An integrated approach for failure mode and effect analysis under interval-valued intuitionistic fuzzy environment. *International Journal of Production Economics* 207: 163–172. https://doi.org/10.1016/j.ijpe.2017.03.008.

Liu, H., Y. Hu, J. Wang, and M. Sun. 2019b. Failure mode and effects analysis using two-dimensional uncertain linguistic variables and alternative queuing method. *IEEE Transactions on Reliability* 68 (2): 554–565. https://doi.org/10.1109/TR.2018.2866029.

Liu, H., L. Wang, Z. Li, and Y. Hu. 2019c. Improving risk evaluation in FMEA with cloud model and hierarchical TOPSIS method. *IEEE Transactions on Fuzzy Systems* 27 (1): 84–95. https://doi.org/10.1109/TFUZZ.2018.2861719.

Liu, Y., Y. Wang, M. Xu, and G. Xu. 2019d. Emergency alternative evaluation using extended trapezoidal intuitionistic fuzzy thermodynamic approach with prospect theory. *International Journal of Fuzzy Systems* 21 (6): 1801–1817. https://doi.org/10.1007/s40815-019-00682-2.

Lo, H.-W., J.J.H. Liou, C.-N. Huang, and Y.-C. Chuang. 2019. A novel failure mode and effect analysis model for machine tool risk analysis. *Reliability Engineering & System Safety* 183: 173–183. https://doi.org/10.1016/j.ress.2018.11.018.

Lopez, C., and J.L. Salmeron. 2014. Dynamic risks modelling in ERP maintenance projects with FCM. *Information Sciences* 256: 25–45. https://doi.org/10.1016/j.ins.2012.05.026.

Navas de Maya, B., and R.E. Kurt. 2020. Marine accident learning with Fuzzy Cognitive Maps (MALFCMs): A case study on bulk carrier's accident contributors. *Ocean Engineering* 208: 107197. https://doi.org/10.1016/j.oceaneng.2020.107197.

Papageorgiou, E.I., and J.L. Salmeron. 2013. A review of Fuzzy Cognitive Maps research during the last decade. *IEEE Transactions on Fuzzy Systems* 21 (1): 66–79. https://doi.org/10.1109/TFUZZ.2012.2201727.

Safari, H., Z. Faraji, and S. Majidian. 2014. Identifying and evaluating enterprise architecture risks using FMEA and fuzzy VIKOR. *Journal of Intelligent Manufacturing* 27 (2): 475–486. https://doi.org/10.1007/s10845-014-0880-0.

Sagnak, M., Y. Kazancoglu, Y.D. Ozkan Ozen, and J.A. Garza-Reyes. 2020. Decision-making for risk evaluation: Integration of prospect theory with failure modes and effects analysis (FMEA). *International Journal of Quality & Reliability Management*. https://doi.org/10.1108/ijqrm-01-2020-0013.

Sayyadi Tooranloo, H., and S. Saghafi. 2021. Assessing the risk of hospital information system implementation using IVIF FMEA approach. *International Journal of Healthcare Management* 14 (3): 676–689. https://doi.org/10.1080/20479700.2019.1688504.

Wang, W., X. Liu, J. Qin, and liu, S. 2018a. An extended generalized TODIM for risk evaluation and prioritization of failure modes considering risk indicators interaction. *IISE Transactions* 51 (11): 1236–1250. https://doi.org/10.1080/24725854.2018.1539889.

Wang, W., X. Liu, and Y. Qin. 2018b. A modified HEART method with FANP for human error assessment in high-speed railway dispatching tasks. *International Journal of Industrial Ergonomics* 67: 242–258. https://doi.org/10.1016/j.ergon.2018.06.002.

Wang, W., X. Liu, Y. Qin, and Y. Fu. 2018c. A risk evaluation and prioritization method for FMEA with PT and Choquet integral. *Safety Science* 110: 152–163. https://doi.org/10.1016/j.ssci.2018.08.009.

Wang, W., X. Liu, X. Chen, and Y. Qin. 2019a. Risk assessment based on hybrid FMEA framework by considering decision maker's psychological behavior character. *Computers & Industrial Engineering* 136: 516–527. https://doi.org/10.1016/j.cie.2019.07.051.

Wang, W., X. Liu, and S. Liu. 2019. Failure mode and effect analysis for machine tool risk analysis using extended gained and lost dominance score method. *IEEE Transactions on Reliability*. https://doi.org/10.1109/TR.2019.2955500.

Wang, W., X. Liu, and J. Qin. 2019c. Risk priorization for failure modes with extended MULTIMOORA method under interval type-2 fuzzy environment. *Journal of Intelligent & Fuzzy Systems* 36 (2): 1417–1429. https://doi.org/10.3233/jifs-181007.
Wang, W., X. Liu, and S. Liu. 2020. Failure mode and effect analysis for machine tool risk analysis using extended gained and lost dominance score method. *IEEE Transactions on Reliability* 69 (3): 954–967. https://doi.org/10.1109/TR.2019.2955500.
Wang, L., F. Yan, F. Wang, and Z. Li. 2021. FMEA-CM based quantitative risk assessment for process industries—A case study of coal-to-methanol plant in China. *Process Safety Environmental Protection* 149: 299–311.
Wang, W., X. Han, W. Ding, Q. Wu, X. Chen, and M. Deveci. 2023. A Fermatean fuzzy Fine-Kinney for occupational risk evaluation using extensible MARCOS with prospect theory. *Engineering Applications of Artificial Intelligence* 117: 105518. https://doi.org/10.1016/j.engappai.2022.105518.
Wu, Z., W. Liu, and W. Nie. 2021. Literature review and prospect of the development and application of FMEA in manufacturing industry. *The International Journal of Advanced Manufacturing Technology* 112 (5): 1409–1436.
Zhang, C., Y.-X. Tian, L.-W. Fan, and Y.-H. Li. 2020. Customized ranking for products through online reviews: A method incorporating prospect theory with an improved VIKOR. *Applied Intelligence* 50 (6): 1725–1744. https://doi.org/10.1007/s10489-019-01577-3.
Zhang, Z.-X., L. Yang, Y.-N. Cao, and Y.-W. Xu. 2022. An Improved FMEA Method Based on ANP with Probabilistic Linguistic Term Sets. *International Journal of Fuzzy Systems* 24 (6): 2905–2930. https://doi.org/10.1007/s40815-022-01302-2.
Zheng, Q., X. Liu, and W. Wang. 2021. An extended interval type-2 fuzzy ORESTE method for risk analysis in FMEA. *International Journal of Fuzzy Systems* 23 (5): 1379–1395. https://doi.org/10.1007/s40815-020-01034-1.
Zhou, X., L. Wang, H. Liao, S. Wang, B. Lev, and H. Fujita. 2019. A prospect theory-based group decision approach considering consensus for portfolio selection with hesitant fuzzy information. *Knowledge-Based Systems* 168: 28–38. https://doi.org/10.1016/j.knosys.2018.12.029.

Publisher's Note