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An ELICIT information-based ORESTE method for failure mode and effect analysis considering risk correlation with GRA-DEMATEL

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ABSTRACT

Failure mode and effect analysis (FMEA) is one of the most powerful reliability analysis techniques for identifying and preventing potential risks across various fields. Current FMEA methods, while effective, still present several shortcomings. For example, using experts' subjective pairwise comparisons of risk factors to determine their weights reduces the stability of the result; different relationships among failure modes are often ignored. To improve the performance of FMEA, multi-criteria decision-making (MCDM) methods have been employed to support risk evaluation and prioritization in recent years. This paper proposes a novel FMEA method by exploring several MCDM techniques. First, the Extended Comparative Linguistic Expressions with Symbolic Translation (ELICIT) are utilized to generate group risk assessments under uncertainty. Then, grey relation analysis (GRA) is incorporated into the decision-making trial and evaluation laboratory (DEMATEL) method to objectively determine the weight of risk factors. Afterward, the traditional ORESTE (organísation, rangement et Synthèse de données relarionnelles (in French)) method is generalized to the ELICIT environment to prioritize the failure modes, in which the Besson's ranking is replaced by deviation measure for more accurate ranking results. Finally, a case study of FMEA for electro-mechanical actuators is presented to illustrate the effectiveness of the proposed method. The results indicate that our approach can express risk information more flexibly, determine the weight of risk factors more objectively, and prioritize failure modes more reasonably.

1. Introduction

Failure mode and effect analysis (FMEA) is a group-oriented reliability management tool for evaluating and eliminating possible failures to improve system performance [1,2]. If these potential failure modes are not well managed, they can cause severe damage to the equipment and body alike [3,4]. NASA initially utilized FMEA within the aerospace industry as a safety protocol [5]. Since then, FMEA has been extensively employed in various industrial categories, such as machine manufacturing [6], food manufacturing [7], and pharmaceutical manufacturing [8].

Traditionally, FMEA prioritizes failure modes by calculating risk priority numbers (RPNs), which are multiplied by three different risk parameters (i.e., Occurrence (O), Detection (D), Severity (S)) [9]. A larger RPN value means the corresponding failure mode has a higher risk. Even though the traditional FMEA is easy to understand and implement, its application is limited due to several inherent drawbacks [10,11]. For example, (i) risk factors are evaluated on a 1–10 scale with crisp numbers, which cannot reflect the uncertainty of human cognition, (ii) the risk factors are confined to O, S, and D; their weight is not considered, and (iii) the calculation of RPN is unreasonable, that is, different combinations of O, S, and D can produce the same RPN despite having different implications. Given these shortcomings, scholars have proposed different approaches to improve the traditional FMEA. Multi-criteria decision-making (MCDM) is the most widespread method to enhance the analysis capability of FMEA [12]. Determining the ranking of failure modes in FMEA can be regarded as a multifaceted challenge that requires MCDM analysis. In other words, FMEA can be viewed as MCDM problems due to the involvement of multiple risk factors in the assessment and prioritization of failure modes. As a well-known field in operations research, MCDM can provide helpful ideas for improving FMEA regarding expressing uncertain risk information, calculating risk factor weights, and ranking failure modes [13,14].

Various fuzzy set theories have been introduced to better express experts' risk assessment. For example, Yener et al. [15] utilized intuitionistic fuzzy numbers to evaluate the risk levels in an assembly line. Ghoushchi et al. [16] used Z-numbers to prioritize the failure

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modes in an automotive spare parts factory. Jin et al. [17] introduced interval-valued q-rung orthopair fuzzy numbers into the FMEA to enhance the risk assessment of tool-changing manipulators. Later, linguistic variables were introduced into the FMEA to capture the uncertainty of the evaluation to a greater extent [18]. For example, linguistic distribution assessments were used to collect the preference information of experts [19]. Considering different words have different meanings for different people, Zhang et al. [20] explored the personalized individual semantics (PISs) of experts in linguistic evaluation. Later, Gai et al. [21] developed a consensus-trust driven bidirectional feedback mechanism to improve the consensus level of experts' assessments. Ko [22] utilized 2-tuple linguistic variables to assist with semiconductor packaging risk evaluation. However, the 2-tuple linguistic representation model only uses single linguistic terms to assess risk factors, which cannot adequately reflect the hesitancy and ambiguity of FMEA experts. Recently, Labella proposed The Extended Comparative Linguistic Expressions with Symbolic Translation (ELICIT), which is a flexible linguistic structure that extends the representation of comparative linguistic expressions to a continuous domain to better model experts' preferences [23]. Compared with other linguistic expressions, the ELICIT is much closer to the human reasoning process and can enhance the interpretability and accuracy of the results [24]. Dutta et al. [25] employed ELICIT information to deal with uncertain expert opinions in a manufacturing plant location problem. However, ELICIT has not yet been utilized in FMEA problems. Therefore, it is used in this study to facilitate the expression and processing of uncertain risk information.

The weight of risk factors exerts a substantial impact on the final risk priority and therefore should be considered in the FMEA. Many strategies have been developed to determine the weight of risk factors, such as the maximum deviation method [7], data envelopment analysis [8], the consensus-based weighting method [26], and the entropy method [27]. However, these methods ignore the correlation between risk factors in the weighting process. Therefore, several techniques have been introduced into FMEA to overcome this deficiency, such as the decision-making trial and evaluation laboratory (DEMATEL) [28], the analytic hierarchy process (AHP) [29], and the analytical network process (ANP) [30].

Among these methods, DEMATEL stands out as a practical structural modeling approach with the advantage of visualizing the intensity of elements' relations and their importance using graph theories and matrix computations. It is worth noting that the causal diagrams in DEMATEL use bidirectional digraphs rather than directionless graphs to portray the critical contextual relationships and the influence strength among the involved elements. Therefore, DEMATEL has been widely used in multi-criteria decision-making problems to quantify the importance of criteria [31]. However, among these methods, the direct-relation matrix is constructed based on experts' subjective pairwise comparisons of factors. When the number of risk factors involved increases, comparing every two risk factors becomes a heavy workload. Additionally, the consistency of the pairwise comparison is difficult to guarantee. A relatively small change in the direct-relation matrix can cause a more significant difference in the total-relation matrix, which reduces the method's stability. Grey relation analysis (GRA) can remedy this shortcoming by replacing the subjective pairwise comparison with the grey relational coefficient. The major advantage of GRA is that it is not limited by the sample size and normally distributed data [32]. Additionally, the calculation process is simple and easy to understand. Therefore, we combine GRA and DEMATEL to take advantage of both to calculate the weight of risk factors based on objective risk information. In this way, the correlation between risk factors can be considered more impartially and efficiently.

FMEA aims to rank potential failure modes under multiple risk factors. Much research has applied MCDM techniques to facilitate risk prioritization. For instance, Zhang et al. [33,34] proposed several consensus-based FMEA methods to obtain the acceptable risk order for most experts. Huang et al. [35] developed a TOPSIS-based FMEA approach to perform risk analysis for steam systems. Liu et al. [7] improved the PROMETHEE method to evaluate risk levels of green logistics systems. Compared with these decision-making techniques, an outranking method ORESTE (organísation, rangement et Synthèse de données relarionnelles (in French)) has the following advantages: (i) It is simple to understand and easy to apply; and (ii) The process is straightforward and we can observe variations in the results when initial evaluations are changed or when different thresholds are defined [36,37]. Previous research has shown that conflict analysis in ORESTE is more effective in separating the preference, indifference, and incomparability relations between alternatives than other outranking methods, such as PROMETHEE and ELECTRE [38]. Also, Chatterjee et al. [39] illustrated the superiority of ORESTE regarding the reliability of results in a flexible manufacturing selection problem. However, the traditional ORESTE method cannot deal with uncertain evaluations. Additionally, Besson's ranks are utilized to represent the important degree of criteria and the performance of alternatives, which brings about information loss. To take advantage of the conflict analysis in ORESTE and enhance its accuracy in calculating preference scores, we improve the classical ORESTE method and generalize it into the ELICIT environment to address risk prioritization problems. In this way, we can obtain the risk priority number of failure modes and capture the relationship between them.

Based on the previous analysis, this paper proposes an ELICIT information-based ORESTE method for FMEA considering risk correlation with GRA-DEMATEL. The main contributions are summarized as follows.

(1) The ELICIT information is first applied to FMEA to determine group risk evaluation. Compared with other fuzzy information structures, ELICIT is closer to the human reasoning process and can preserve more information during computing with words processes, which can improve the accuracy of the final risk priority.
(2) Obtaining the weight of risk factors is an essential part of FMEA. We incorporate GRA into DEMATEL for weight calculation with objective risk information. Specifically, the elements in the direct-relation matrix are determined by calculating grey correlation coefficients. In this way, when many risk factors are involved, the inconsistency of pairwise comparisons caused by traditional DEMATEL can be avoided. Additionally, the correlation between risk factors can be analyzed more objectively and efficiently.
(3) FMEA aims to rank potential failure modes so that effective measures can be taken to prevent risks. We improve the classical ORESTE method and generalize it into the ELICIT environment for risk prioritization. In the original ORESTE, the global preference score is determined by Besson's ranking, which may result in information loss. To overcome this limitation, we utilize the deviation measure to replace Besson's ranking for a more accurate risk priority result. Besides, the relations between failure modes can be distinguished in terms of preference, indifference, and incomparability.
(4) This study applies the proposed method to address the risk prioritization problem of an electro-mechanical actuator, in which a two-level hierarchical structure of risk factors is constructed. Validity, reliability, and comparative analysis prove the effectiveness of our method in dealing with practical engineering problems.

The rest of this paper is organized as follows. Section 2 briefly reviews the basic concepts of ELICIT information and the ORESTE method. Section 3 develops the improved risk prioritization method. Section 4 validates the effectiveness of our method through the risk analysis of an electro-mechanical actuator. Discussions are given in Section 5 to demonstrate the superiority of our method. Finally, conclusions are provided in Section 6.

2. Preliminaries

In this section, some basic concepts of Hesitant Linguistic Term Sets (HFLTSs), Comparative Linguistic Expressions (CLEs), ELICIT information and the ORESTE method are reviewed in brief.

2.1. The Hesitant Linguistic Term Sets and Comparative Linguistic Expressions

Due the inherent ambiguity of human cognition, a single linguistic term is insufficient to model the preferences of experts. In practical situations, experts may hesitate among multiple linguistic terms to describe their judgments. To address this issue, Rodríguez et al. [40] introduced the concept of Hesitant Linguistic Term Sets, which enables experts to express their opinions flexibly.

Definition 1 (*[40]*)**.** Let $S = \{s_0, s_1, \dots, s_g\}$ be a linguistic term set, an HFLTS H_S is an ordered finite subset of the consecutive linguistic terms of S. Then, the empty HFLTS and full HFLTS for a linguistic variable ϑ can be defined as $H_S = \phi$ and $H_S = \{S\}$, respectively. Any other HFLTS is formed with at least one linguistic term in S.

Example 1. Let $S = \{s_0 : very\, low, s_1 : low, s_2 : medium, s_3 : high, s_4 : very\, high\}$ denotes a linguistic term set, an HFLTS might be $H_S(\vartheta) = \{s_1 : low, s_2 : medium\}$.

Although experts can utilize HFLTS directly to describe their evaluations, they are not close to the expressions used by human beings. Later, Rodríguez et al. [41] proposed the Comparative Linguistic Expressions (CLEs) based on HFLTS to better model the hesitancy of experts. CLEs are constructed with context-free grammars G_H. A basic context-free grammar for generating CLEs is shown as follows.

Definition 2 (*[41]*)**.** Let $S = \{s_0, s_1, \dots, s_g\}$ be a linguistic term set and G_H be a context-free grammar. The elements of $G_H = (V_N, V_T, I, P)$ are defined as follows.

$$V_N = \left\{ \begin{array}{l} (primary\ term), (composite\ term), \\ (unary\ relation), (binary\ relation), (conjunction) \end{array} \right\}$$

$$V_T = \{at\ least, at\ most, between, and, s_0, s_1, \dots, s_g\}$$

$$I \in V_N$$

The production rules defined in an extended Backus–Naur Form are shown as follows.

$$P = \left\{ \begin{array}{l} I ::= (primary\ term) \,|(composite\ term) \\ (composite\ term) ::= (unary\ relation)(primary\ term)| \\ (binary\ relation)(primary\ term) \\ (conjunction)(primary\ term) \\ (primary\ term) ::= s_0 \left| s_1 \right| \dots \left| s_g \right. \\ (unary\ relation) ::= at\ least\,|at\ most \\ (binary\ relation) ::= between \\ (conjunction) ::= and \end{array} \right\}$$

The CLEs can be transformed into HFLTS for computation, which is defined as follows.

Definition 3 (*[41]*)**.** Let E_{G_H} denotes the transformation from CLEs to HFLTS, i.e., $E_{G_H} : S_{ll} \to H_S$. S is the linguistic term set used by G_H and S_{ll} is the expression domain generated by G_H.

2.2. The ELICIT information

The ELICIT linguistic model is an extension of comparative linguistic expressions (CLEs), which can improve the interpretability and accuracy of the results in computing with words processes [23]. ELICIT extends the CLEs by utilizing the concept of symbolic translation used by the 2-tuple linguistic model. Given its flexible representation structures, ELICIT can retain more information during the computation process.

Definition 4 (*[23]*)**.** Let $S = \{s_0, s_1, \dots, s_g\}$ denotes a set of linguistic terms, and $g+1$ is the granularity of S. The possible ELICIT expressions can be denoted as: "*at least* $(s_i, \alpha)^\gamma$", "*at most* $(s_i, \alpha)^\gamma$", and "*between* $(s_i, \alpha_1)^{\gamma_1} \& (s_j, \alpha_2)^{\gamma_2}$", where α is the symbolic translation parameter with $\alpha \in [-0.5, 0.5)$, γ is the adjustment parameter with $\gamma \in \left(-\frac{1}{2g}, \frac{1}{2g}\right)$ for $i, j = 1, 2, \dots, g$. When $\alpha = \gamma = 0$, the ELICIT expression becomes CLE.

For ELICIT information, the approach of computing with words includes three stages: translation, manipulation, and re-translation. The specific process is as follows.

Definition 5 (*[23]*)**.** Let x_{el} be an ELICIT expression and $Tr(a, b, c, d)$ be a trapezoidal fuzzy number (TrFN). The function ξ^{-1} is defined as:

$$\xi^{-1} : x_{el} \to Tr(a, b, c, d) \tag{1}$$

The transformation function can be defined in different ways according to the specific ELICIT expression. Please refer to [23] for more information.

Definition 6 (*[23]*)**.** The manipulation stage involves fuzzy arithmetic computations of the TrFNs obtained in the transformation process. Let $Tr_A(a_1, b_1, c_1, d_1)$ and $Tr_B(a_2, b_2, c_2, d_2)$ be two fuzzy envelops modeled by two TrFNs. The addition of these two fuzzy envelops is defined by a shape function μ_{A+B} as:

$$\mu_{A+B} = \begin{cases} \frac{(x-(a_1+a_2))^n}{(b_1+b_2)-(a_1+a_2)} & a_1 + a_2 \le x \le b_1 + b_2 \\ 1 & b_1 + b_2 \le x \le c_1 + c_2 \\ \frac{((d_1+d_2)-x)^n}{(d_1+d_2)-(c_1+c_2)} & c_1 + c_2 \le x \le d_1 + d_2 \\ 0 & otherwise \end{cases} \tag{2}$$

It is worth noting that, in our method, the computational process deal with normal TrFNs. Therefore, $n = 1$.

Definition 7 (*[23]*)**.** The subtraction of the two fuzzy envelops by two TrFNs $Tr_A(a_1, b_1, c_1, d_1)$ and $Tr_B(a_2, b_2, c_2, d_2)$ is defined with a shape function μ_{A-B} as:

$$\mu_{A-B} = \begin{cases} \frac{(x-(a_1-d_2))^n}{(b_1-a_1)+(d_2-c_2)} & a_1 - d_2 \le x \le b_1 - c_2 \\ 1 & b_1 - c_2 \le x \le c_1 - b_2 \\ \frac{((d_1-a_2)-x)^n}{(d_1-c_1)+(b_2-a_2)} & c_1 - b_2 \le x \le d_1 - a_2 \\ 0 & otherwise \end{cases} \tag{3}$$

where $n = 1$.

Definition 8 (*[23]*)**.** In the re-translation process, the TrFN $\tilde{\beta}$ derived in the manipulation procedure is transformed into an equivalent ELICIT by inverse function ξ^{-1}. Therefore, the function $\xi : \tilde{\beta} \to \widetilde{x_{el}}$ is a mapping defined as follows:

(1) If $\tilde{\beta} = Tr(a, b, 1, 1)$, then $\xi(\tilde{\beta}) = at\ least(s_i, \alpha)^\gamma$.
(2) If $\tilde{\beta} = Tr(0, 0, c, d)$, then $\xi(\tilde{\beta}) = at\ most(s_i, \alpha)^\gamma$.
(3) If $\tilde{\beta} = Tr(a, b, c, d)$, then $\xi(\tilde{\beta}) = between(s_i, \alpha_1)^{\gamma_1} \& (s_j, \alpha_2)^{\gamma_2}$.

Definition 9 (*[23]*)**.** Let x_{el1} and x_{el2} be two ELICIT expressions, and let $\widetilde{\beta_1} = Tr_1(a_1, b_1, c_1, d_1)$ and $\widetilde{\beta_2} = Tr_2(a_2, b_2, c_2, d_2)$ be their equivalent fuzzy numbers obtained from $\xi^{-1}(x_{el1})$ and $\xi^{-1}(x_{el2})$, respectively. Then, the distance between x_{el1} and x_{el2} can be determined as:

$$d\left(x_{el1}, x_{el2}\right) = d\left(\widetilde{\beta}_1, \widetilde{\beta}_2\right) = \sqrt{\frac{\left(a_1 - a_2\right)^2 + \left(b_1 - b_2\right)^2 + \left(c_1 - c_2\right)^2 + \left(d_1 - d_2\right)^2}{4}} \tag{4}$$

Definition 10 (*[23]*). Let $\{x_{el1}, x_{el2}, \ldots, x_{elk}\}$ be a set of CLEs or ELICIT expressions. $\{\widetilde{\beta}_1, \widetilde{\beta}_2, \ldots, \widetilde{\beta}_k\}$ represents the set of equivalent TrFNs obtained from inverse functions $\{\xi^{-1}(x_{el1}), \xi^{-1}(x_{el2}), \ldots, \xi^{-1}(x_{elk})\}$. The weighted average of $\{x_{el1}, x_{el2}, \ldots, x_{elk}\}$ can be calculated as:

$$x_{el} = \xi\left(w_1\widetilde{\beta}_1 + w_2\widetilde{\beta}_2 + \cdots + w_k\widetilde{\beta}_k\right) \tag{5}$$

where $\xi(\bullet)$ is the mapping given in Definition 5. w_k denotes the weight of x_{elk}.

2.3. The ORESTE method

The ORESTE method, proposed by Roubens, is an effective ranking method for multi-criteria decision-making [36]. Compared with other methods, the ORESTE has the advantages of simple calculation and strong adaptability. Let $A = \{a_1, a_2, \ldots, a_m\}$ and $C = \{c_1, c_2, \ldots, c_n\}$ denote the sets of m alternatives and n criteria, respectively. The main steps of the classical ORESTE are given as follows.

Step 1: Calculate the global preference score.

$$G\left(z_{ij}\right) = \sqrt{\varphi\left(p_j\left(a_i\right)\right)^2 + (1-\varphi)\left(p_j\right)^2} \tag{6}$$

where $G\left(z_{ij}\right)$ denotes the global preference score of alternative $a_i(i = 1, 2, \ldots, m)$ under criterion $c_j(j = 1, 2, \ldots, n)$. p_j and $p_j\left(a_i\right)$ denote the Besson's rank of c_j and the performance of a_i over c_j, respectively. $\varphi\,(\varphi \in (0,1))$ is an adjustment parameter indicating the relative importance between p_j and $p_j\left(a_i\right)$.

Step 2: Determine the weak ranking of alternatives, which can be calculated as:

$$R\left(a_i\right) = \sum_{j=1}^{n} G\left(z_{ij}\right) \tag{7}$$

If $R\left(a_i\right) < R\left(a_l\right)$, then the relationship between a_i and a_l is preference relation (i.e., $a_i P a_l$); if $R\left(a_i\right) = R\left(a_l\right)$, then the relationship between a_i and a_l is indifference relation (i.e., $a_i I a_l$).

Step 3: Obtain the preference intensities. To derive a more reasonable ranking result, the conflict analysis should be performed according to preference intensities. The average preference intensity of a_i over a_l can be calculated as:

$$T\left(a_i, a_l\right) = \frac{\sum_{j=1}^{n} \max\left\{G\left(z_{lj}\right) - G\left(z_{ij}\right), 0\right\}}{n} \tag{8}$$

Afterwards, the net preference intensity of a_i over a_l can be computed as:

$$\Delta T\left(a_i, a_l\right) = T\left(a_i, a_l\right) - T\left(a_l, a_i\right) \tag{9}$$

Step 4: Establish the PIR structure and determine the strong ranking of alternatives. The preference (P), indifference (I), and incomparability (R) relationships between alternatives can determined by following principles.

$$If\left|\Delta T\left(a_i, a_l\right)\right| < \tau, then \begin{cases} a_i I a_l & if\ T\left(a_i, a_l\right) < \delta\ and\ T\left(a_l, a_i\right) < \delta \\ a_i R a_l & if\ T\left(a_i, a_l\right) \geq \delta\ or\ T\left(a_l, a_i\right) \geq \delta \end{cases} \tag{10}$$

$$If\left|\Delta T\left(a_i, a_l\right)\right| \geq \tau, then \begin{cases} a_i P a_l & \Delta T\left(a_i, a_l\right) > 0 \\ a_l P a_i & \Delta T\left(a_i, a_l\right) \leq 0 \end{cases} \tag{11}$$

where τ, δ, and ζ are three thresholds set according to practical situations.

Then, the strong ranking of alternatives can be determined based on the weak ranking and the PIR structure.

3. Risk prioritization for FMEA based on ORESTE dealing with ELICIT information

This section develops an improved risk prioritization method based on the extended ORESTE with ELICIT information. First, the flowchart and steps of the proposed method are presented in Section 3.1. Then, the risk assessment matrix is established in Section 3.2. In Section 3.3, the weight of risk factors is derived with the GRA-DEMATEL approach. Finally, failure modes are prioritized with the extended ORESTE in Section 3.4.

3.1. The flowchart and steps of the proposed method

A flowchart is shown in Fig. 1 to illustrate the proposed method more clearly. The specific steps are presented as follows and further detailed in the coming subsections.

Stage I: Establish the group risk assessment matrix with ELICIT information

Step 1.1: Identify the possible failure modes $FM = \{FM_1, FM_2, \ldots, FM_m\}$ and construct a hierarchical risk factor structure $RF = \{RF_1, RF_2, \ldots, RF_n\}$.

Step 1.2: Assemble a group of FMEA experts $E = \{E_1, E_2, \ldots, E_v\}$ to evaluate the risk factors with comparative linguistic expressions $X^k = (x_{ij}^k)_{m\times n}$.

Step 1.3: Establish the group risk assessment matrix with ELICIT information $X^g = (x_{ij}^g)_{m\times n}$ by Eq. (5).

Stage II: Calculate the weight of risk factors by GRA-DEMATEL

Step 2.1: Establish the direct-relation matrix $B = (b_{hj})_{n\times n}$ based on grey relation analysis by Eqs. (13)–(14).

Step 2.2: The direct-relation matrix $B = (b_{hj})_{n\times n}$ is normalized by Eq. (15).

Step 2.3: Compute the total-relation matrix $T = (t_{hj})_{n\times n}$ by Eq. (16).

Step 2.4: Analyze the influence relation between risk factors.

Step 2.5: Obtain the weight of risk factors w_{RF_j} $(j = 1, 2, \ldots, n)$ by Eq. (19).

Stage III: Prioritize the failure modes with the extended ORESTE

Step 3.1: Compute the global preference score $G\left(x_{ij}^g\right)$ of failure modes over risk factors via Eq. (20).

Step 3.2: Derive the weak ranking of failure modes by Eq. (21).

Step 3.3: Determine the average intensity $T\left(FM_i, FM_l\right)$ and net intensity $\Delta T\left(FM_i, FM_l\right)$ of failure modes by Eqs. (22)–(23).

Step 3.4: Construct the PIR structures and prioritize the failure modes by Eqs. (26)–(27).

3.2. Stage I : Establish the group risk assessment matrix with ELICIT information

Suppose a risk prioritization problem with m failure modes represented as $FM = \{FM_1, FM_2, \ldots, FM_m\}$ and n risk factors denoted as $RF = \{RF_1, RF_2, \ldots, RF_n\}$. Engineers with rich work experience and experts with specialized knowledge are invited to form a group of FMEA experts, which can be represented as $E = \{E_1, E_2, \ldots, E_v\}$. The weight of expert is denoted as w_{E_k} with $\sum_{k=1}^{v} w_{E_k} = 1$. Due to the uncertainty of risk assessment, CLEs are adopted to evaluate the risk level of failure modes. Since 7-point scale is shown to be more accurate, easier to use, and a better reflection of a respondent's true evaluation [42], the 7-scale linguistic term set $S = \{s_0 = \text{very low}, s_1 = \text{low}, s_2 = \text{reasonably low}, s_3 = \text{average}, s_4 = \text{reasonably high}, s_5 = \text{high}, s_6 = \text{very high}\}$ is used for risk evaluation. Let $X^k = (x_{ij}^k)_{m\times n}$ be the CLE from expert E_k, where x_{ij}^k denotes the risk level of FM_i

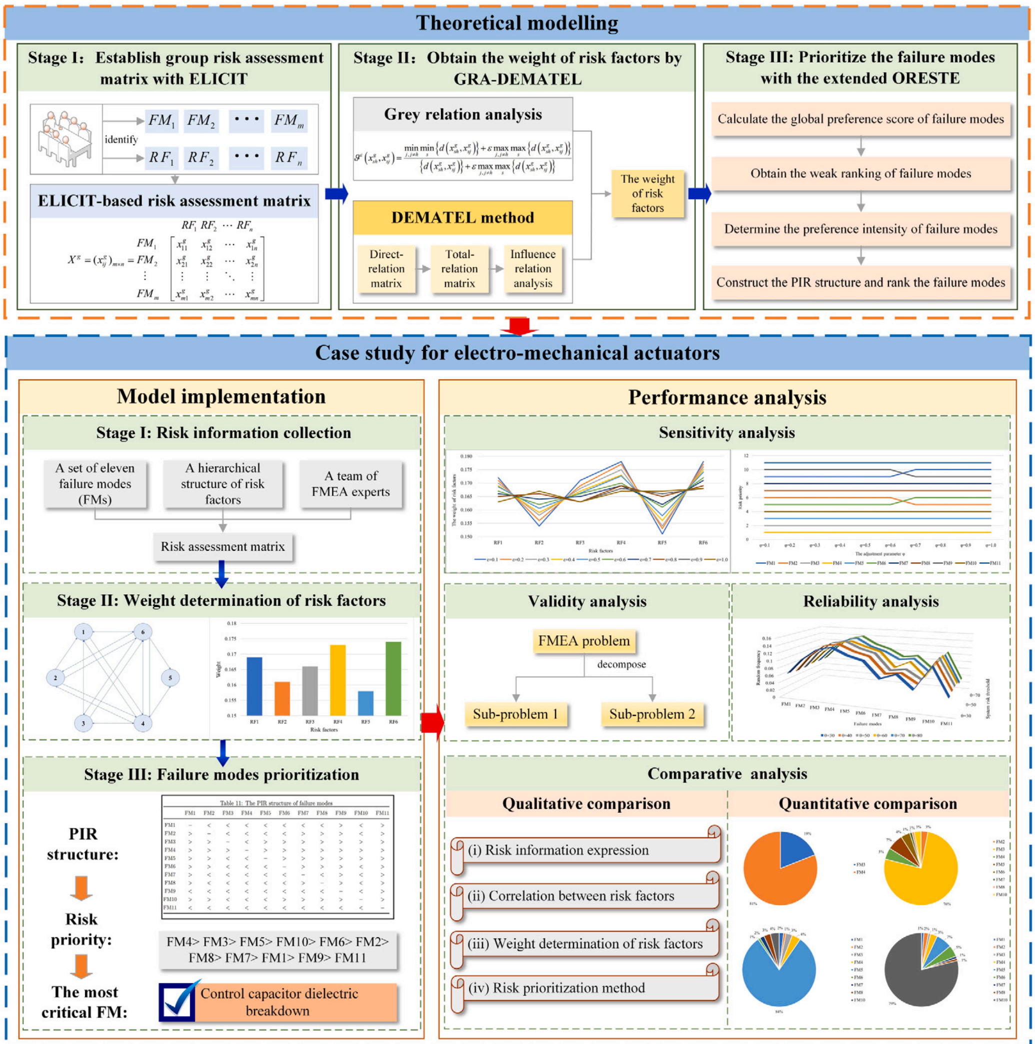


Fig. 1. The flowchart of the proposed risk prioritization method.

regarding RF_j. Then, the individual risk assessment matrices can be constructed as follows.

$$X^k = (x_{ij}^k)_{m\times n} = \begin{array}{c} \\ FM_1 \\ FM_2 \\ \vdots \\ FM_m \end{array} \begin{array}{c} RF_1\,RF_2 \cdots RF_n \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1}^k & x_{m2}^k & \cdots & x_{mn}^k \end{bmatrix} \end{array} (k = 1, 2, \dots, v) \tag{12}$$

In this study, experts' weight w_{E_k} is given in advance. Then, the group risk evaluation matrix $X^g = (x_{ij}^g)_{m\times n}$ can be calculated by aggregating the individual risk assessment by Eq. (5).

3.3. Stage II : Determine the weight of risk factors with GRA-DEMATEL

In the classical DEMATEL method, experts are required to make pairwise comparisons of risk factors to determine the direct-relation matrix. However, when the number of risk factors involved increases, such as 40, then each expert needs to perform 1560 pairwise comparisons, which is a considerable workload and very unrealistic. Also, the consistency of pairwise comparisons will be difficult to guarantee. Slight differences in the direct-relation matrix can cause significant changes in the total-relation matrix. Therefore, it is necessary to propose an objective and efficient weighting method that can simultaneously consider the correlation between risk factors.

In this section, we incorporate grey relation analysis into the DEMATEL method to derive the weight of risk factors based on objective risk information. Specifically, the grey correlation coefficient is used to derive the influence level between risk factors and further construct the asymmetric direct-relation matrix.

Step 1: The group risk assessment matrix obtained in Stage I can be rewritten as $X^g = (X_1^g, X_2^g, \dots, X_n^g)$ where $X_j^g = (x_{1j}^g, x_{2j}^g, \dots, x_{mj}^g)^T (j = 1, 2, \dots, n)$ is a column vector. In this way, the group risk assessment matrix can be regarded as a row vector with n sequences. Suppose $X_h^g = (x_{1h}^g, x_{2h}^g, \dots, x_{mh}^g)^T$ is the behavioral characteristic sequence of system in GRA, and $X_1^g = (x_{11}^g, x_{21}^g, \dots, x_{m1}^g)^T, \dots, X_{h-1}^g = (x_{1,h-1}^g, x_{2,h-1}^g, \dots, x_{m,h-1}^g)^T$, $X_{h+1}^g = (x_{1,h+1}^g, x_{2,h+1}^g, \dots, x_{m,h+1}^g)^T$, …, $X_n^g = (x_{1n}^g, x_{2n}^g, \dots, x_{mn}^g)^T$ are $n-1$ sequences of relevant factors. Based on GRA, the direct-relation matrix $B = (b_{hj})_{n\times n}$ can be derived as follows.

$$\vartheta^{\varepsilon}\left(x_{sh}^g, x_{sj}^g\right) = \frac{\min_{j,j\neq h}\min_s\left\{d\left(x_{sh}^g, x_{sj}^g\right)\right\} + \varepsilon \max_{j,j\neq h}\max_s\left\{d\left(x_{sh}^g, x_{sj}^g\right)\right\}}{\left\{d\left(x_{sh}^g, x_{sj}^g\right)\right\} + \varepsilon \max_{j,j\neq h}\max_s\left\{d\left(x_{sh}^g, x_{sj}^g\right)\right\}} \tag{13}$$

$$b_{hj} = \frac{\sum_{s=1}^m \vartheta^{\varepsilon}\left(x_{sh}^g, x_{sj}^g\right)}{m} \tag{14}$$

where $d\left(x_{sh}^{g}, x_{sj}^{g}\right)$ denotes the distance between ELICIT expressions x_{sh}^{g} and x_{sj}^{g}. ε is a distinguish coefficient with $\varepsilon \in [0,1]$.

Each column of the risk information matrix will be treated as the behavioral characteristic sequence once to derive the asymmetric direct-relation matrix $B = (b_{hj})_{n\times n}$.

Step 2: The normalized direct-relation matrix $\overline{B} = (\overline{b_{hj}})_{n\times n}$ can be computed as:

$$\overline{b_{hj}} = \frac{b_{hj}}{\max\left\{\max\left\{\sum_h b_{hj}\right\}, \max\left\{\sum_j b_{hj}\right\}\right\}} \tag{15}$$

Step 3: Based on Eq. (15), the total-relation matrix $T = (t_{hj})_{n\times n}$ can be calculated as:

$$T = \lim_{N\to\infty}(\overline{B} + \overline{B}^2 + \cdots + \overline{B}^N) = \overline{B}(I - \overline{B})^{-1} \tag{16}$$

where I is the identity matrix, and $\overline{B}$ denotes the normalized direct relation matrix.

The diagram of influence relation between risk factors can be drawn by the threshold $\chi(T) = \frac{\sum_{h=1}^{n}\sum_{j=1}^{n} t_{hj}}{n^2}$.

Step 4: The sums of the rows and columns of $T = (t_{hj})_{n\times n}$ can be obtained as:

$$\mu_h = \sum_{j=1}^{n} t_{hj} \tag{17}$$

$$\upsilon_j = \sum_{h=1}^{n} t_{hj} \tag{18}$$

$\mu_j - \upsilon_j$ denotes the net effect of risk factor c_j. If $\mu_j - \upsilon_j > 0$, c_j is a cause factor, otherwise c_j is a result factor.

Step 5: Based on Eqs. (17)–(18), the weight of risk factors w_{RF_j} $(j = 1,2,\dots,n)$ can be computed as:

$$w_{RF_j} = \frac{\mu_j + \upsilon_j}{\sum_{j=1}^{n}(\mu_j + \upsilon_j)} \tag{19}$$

3.4. Stage III : Prioritize the failure modes with the extended ORESTE

The traditional ORESTE method utilizes Besson's ranking to determine the global preference score, which may lead to information loss and inaccurate results. Additionally, the traditional ORESTE method cannot address risk priority problems under uncertainty. Therefore, in this section, we improve the ORESTE method by replacing Besson's ranking with deviation measures and extending it into the ELICIT environment for better risk prioritization results. The specific process is as follows.

Step 1: In the original ORESTE method, the importance degree of risk factor $RF_j (j = 1,2,\dots,n)$ and the performance of failure mode $FM_i (i = 1,2,\dots,m)$ regarding RF_j are represented by Besson's ranks rather than crisp values, which may result in information loss. An example is shown as follows.

Example 2. Let $S = \{s_0 = \text{very low}, s_1 = \text{low}, s_2 = \text{reasonably low}, s_3 = \text{average}, s_4 = \text{reasonably high}, s_5 = \text{high}, s_6 = \text{very high}\}$ be a linguistic term set. Suppose the evaluations on three failure modes FM_1, FM_2, and FM_3 regarding RF_1 are $x_{11}^{g} = \{at\ least\ s_5\}$, $x_{21}^{g} = \{bet\ s_4\ \&\ s_5\}$, and $x_{31}^{g} = \{s_0\}$, respectively. Therefore, we can get $x_{11}^{g} > x_{21}^{g} > x_{31}^{g}$. Based on the original ORESTE method, the Besson's ranks of these three evaluations are $p_1(FM_1) = 1$, $p_1(FM_2) = 2$, and $p_1(FM_3) = 3$. From the evaluations we can observe that x_{21}^{g} is obviously closer to x_{11}^{g} than x_{31}^{g}. However, the Besson's ranks reflect that the difference between x_{11}^{g} and x_{21}^{g} is the same as x_{31}^{g} and x_{21}^{g}, which leads to information loss.

According to Eq. (6), we utilize the deviation measure between the ELICIT expression and the positive ideal solutions $d\left(x_{ij}^{g}, x_j^{+}\right)$ to replace the ranking value $p_j(a_i)$, and the deviation between the risk factor weight and the maximum value of risk factor weight $d\left(w_{RF_j}, w_j^{+}\right)$ to replace the ranking value p_j. Compared with the original method, measuring the deviation between each evaluation and the positive ideal solution can better reflect the differences in the performance of each failure mode. In this way, the global preference score of $FM_i (i = 1,2,\dots,m)$ over $RF_j (j = 1,2,\dots,n)$ can be calculated as:

$$G\left(x_{ij}^{g}\right) = \sqrt{\varphi d\left(x_{ij}^{g}, x_j^{+}\right)^2 + (1-\varphi)\, d\left(w_{RF_j}, w_j^{+}\right)^2} \tag{20}$$

where $x_j^{+} = \begin{cases} \max_i\left\{x_{ij}^{g}\right\} & RF_j \text{ is a positive risk factor} \\ \min_i\left\{x_{ij}^{g}\right\} & RF_j \text{ is a negative risk factor} \end{cases}$, $w_j^{+} = \max_j\left\{w_{RF_j}\right\}$, and $\varphi\,(\varphi \in (0,1))$ is an adjustment parameter denoting the relative importance between $d\left(x_{ij}^{g}, x_j^{+}\right)^2$ and $d\left(w_{RF_j}, w_j^{+}\right)^2$.

Step 2: The weak ranking of failure modes can be determined as:

$$R\left(FM_i\right) = \sum_{j=1}^{n} G\left(x_{ij}^{g}\right) \tag{21}$$

If $R(FM_i) > R(FM_l)$, then $FM_i P FM_l (l = 1,2,\dots,m)$; if $R(FM_i) = R(FM_l)$, then $FM_i I FM_l (l = 1,2,\dots,m)$.

Step 3: The average preference intensity of failure mode FM_i over FM_l can be derived as:

$$T\left(FM_i, FM_l\right) = \frac{\sum_{j=1}^{n}\max\left\{G\left(x_{lj}^{g}\right) - G\left(x_{ij}^{g}\right), 0\right\}}{n} \tag{22}$$

where $G\left(x_{ij}^{g}\right)$ and $G\left(x_{lj}^{g}\right)$ denote the global preference score of FM_i and FM_l over risk factor RF_j, respectively.

Afterwards, the net preference intensity of FM_i over FM_l can be derived as:

$$\Delta T\left(FM_i, FM_l\right) = T\left(FM_i, FM_l\right) - T\left(FM_l, FM_i\right) \tag{23}$$

Step 4: The PIR structures of failure modes contain three relationships, i.e., preference (P) relationship, indifference (I) relationship, and incomparability (R) relationship. Therefore, three parameters should be determined to construct the PIR structures: preference threshold τ, indifference threshold ζ, and the incomparability threshold δ. According to [36], the thresholds can be calculated as follows.

$$\tau = \frac{\zeta}{n} \tag{24}$$

$$\delta = \begin{cases} \frac{(n+2)\zeta}{2n} & if\ n\ is\ odd \\ \frac{\zeta}{2} & if\ n\ is\ even \end{cases} \tag{25}$$

where $\zeta \in \left[0, \sqrt{\varphi}\kappa\right]$, $\varphi\,(\varphi \in (0,1))$ is the adjustment parameter in Eq. (20), and $\kappa\,(\kappa \in (0,1))$ is determined by the experts based on the practical circumstances.

According to the above analysis, the PIR structures of FM_i can be established as follows.

$$If \left|\Delta T\left(FM_i, FM_l\right)\right| < \tau,$$
$$then \begin{cases} FM_i I FM_l & if\ T\left(FM_i, FM_l\right) < \delta\ and\ T\left(FM_l, FM_i\right) < \delta \\ FM_i R FM_l & if\ T\left(FM_i, FM_l\right) \geq \delta\ or\ T\left(FM_l, FM_i\right) \geq \delta \end{cases} \tag{26}$$

$$If \left|\Delta T\left(FM_i, FM_l\right)\right| \geq \tau,$$
$$then \begin{cases} FM_i P FM_l & \Delta T\left(FM_i, FM_l\right) > 0 \\ FM_l P FM_i & \Delta T\left(FM_i, FM_l\right) \leq 0 \end{cases} \tag{27}$$

4. Risk prioritization for an electro-mechanical actuator

The electro-mechanic actuator (EMA), one of the most critical components in the next generation of aircraft, is utilized to manipulate the location of the vehicles and deploy the equipment, especially the

Table 1
The causes and effects of failure modes.

Component	Item	Failure mode	Failure cause	Failure effect
Motor	FM1	Stator winding insulation aging	Over-current or over-voltage	Unstable power supply
	FM2	Rotor magnet chemical bond aging	Motor overload or short circuit	Damage to the motor
	FM3	Rotor eccentric	Support bearing damage	Damage to the motor
Power electronics	FM4	Control capacitor dielectric breakdown	Short circuit, or open circuit of power device	Power electronics incapacity
	FM5	Inverter dielectric breakdown	Short circuit, or open circuit of power device	Damage to the inverter
	FM6	Wire overheating	Insulation damage, thermal switch failure, cooling fan damage	Affect the operation of the device
Mechanical structures	FM7	Screw broken	Strong vibration of mechanical structure	Degrade motor output performance
	FM8	Excessive wear on the screw	Rust, connection key fault	Loss of motion accuracy
	FM9	Nut broken	Strong vibration of mechanical structure	Damage to the mechanical structures
	FM10	Bearing fracture	Stress concentration is not eliminated in the manufacturing process	Mechanical disintegration
	FM11	Bearing corrosion	Ambient temperature and humidity	Damage to the EMA functions

Table 2
The hierarchical structure of risk factors.

First-level factors	Symbol	Second-level factors	Symbol
Occurrence	O	Frequency Repeatability	RF_1 RF_2
Detection	D	Visibility Inspection	RF_3 RF_4
Severity	S	Equipment damage Economic loss	RF_5 RF_6

embedded optic apparatus (e.g., telescopes and cameras). With the continuous development of aerospace systems, EMAs are becoming increasingly crucial to the safety of aerospace vehicles. The failure of EMAs can seriously affect the operation of vehicles, leading to enormous economic loss. Therefore, conducting failure analysis on EMAs is of great significance. However, to our knowledge, there are few studies on risk prioritization for EMAs. Thus, it is necessary to implement our FMEA method to address this issue and allocate limited resources to prevent failure modes from occurring.

4.1. Stage I : Establish the risk assessment matrix with ELICIT

Step 1.1: Identify the failure modes and construct a hierarchical risk factor system.

Based on literature analysis and experience of FMEA team members, eleven failure modes are sorted out. The detailed information is presented in Table 1.

In traditional FMEA, risk factors are confined to Occurrence (O), Detection (D), and Severity (S), which are inadequate for a comprehensive risk assessment. In this study, we establish a two-layer risk factor structure, which includes three dimensions and six sub-level factors. The details are shown in Table 2.

Step 1.2: Three FMEA experts with profound expertise and rich working experience are invited to give their opinions on the risk level of failure modes. Due to the uncertainty of the FMEA problem and the hesitancy of expert evaluation, CLEs are used to evaluate the six risk factors with a 7-scale linguistic term set $S = \{s_0 = \text{very low}, s_1 = \text{low}, s_2 = \text{reasonably low}, s_3 = \text{average}, s_4 = \text{reasonably high}, s_5 = \text{high}, s_6 = \text{very high}\}$. The original risk information is presented in Tables 3–5.

Step 1.3: The experts' weight is given in advance as: $w_{E_1} = 0.3$, $w_{E_2} = 0.3$, and $w_{E_3} = 0.4$. Then, the ELICIT information-based group risk evaluation can be derived, and the results are shown in Tables 6 and 7.

4.2. Stage II : Obtain the weight of risk factors by GRA-DEMATEL

Step 2.1: The direct-relation matrix $B = (b_{hj})_{6\times6}$ of risk factors can be constructed based on grey correlation coefficient via Eqs. (13)–(14) with $\varepsilon = 0.5$.

$$B = (b_{hj})_{6\times6} = \begin{bmatrix} 0 & 0.683 & 0.634 & 0.645 & 0.542 & 0.662 \\ 0.712 & 0 & 0.509 & 0.679 & 0.569 & 0.602 \\ 0.690 & 0.527 & 0 & 0.662 & 0.625 & 0.786 \\ 0.657 & 0.671 & 0.622 & 0 & 0.656 & 0.702 \\ 0.546 & 0.551 & 0.579 & 0.648 & 0 & 0.621 \\ 0.691 & 0.592 & 0.707 & 0.711 & 0.639 & 0 \end{bmatrix}$$

Step 2.2: Then, the direct-relation matrix can be normalized to obtain $\overline{B} = (\overline{b_{hj}})_{6\times6}$ by Eq. (15) as:

$$\overline{B} = (\overline{b_{hj}})_{6\times6} = \begin{bmatrix} 0 & 0.202 & 0.188 & 0.191 & 0.161 & 0.196 \\ 0.211 & 0 & 0.151 & 0.201 & 0.167 & 0.178 \\ 0.205 & 0.156 & 0 & 0.196 & 0.185 & 0.233 \\ 0.195 & 0.199 & 0.184 & 0 & 0.194 & 0.208 \\ 0.162 & 0.163 & 0.172 & 0.192 & 0 & 0.184 \\ 0.205 & 0.176 & 0.210 & 0.211 & 0.189 & 0 \end{bmatrix}$$

Step 2.3: According to Eq. (16), we can obtain the total-relation matrix as:

$$T = (t_{hj})_{6\times6} = \begin{bmatrix} 2.844 & 2.817 & 2.828 & 3.038 & 2.788 & 3.062 \\ 2.942 & 2.579 & 2.731 & 2.969 & 2.723 & 2.972 \\ 3.110 & 2.875 & 2.762 & 3.140 & 2.896 & 3.187 \\ 3.109 & 2.910 & 2.922 & 2.982 & 2.908 & 3.174 \\ 2.813 & 2.631 & 2.657 & 2.867 & 2.491 & 2.880 \\ 3.144 & 2.920 & 2.967 & 3.184 & 2.930 & 3.032 \end{bmatrix}$$

Step 2.4: With threshold $\chi(T) = 2.9$, the influence relation between risk factors is given in Fig. 2.

Step 2.5: According to Eqs. (17)–(18), the sums of the rows and columns of $T = (t_{hj})_{6\times6}$ can be obtained as: $\mu_1 = 17.377$, $\upsilon_1 = 17.960$, $\mu_2 = 16.915$, $\upsilon_2 = 16.732$, $\mu_3 = 17.970$, $\upsilon_3 = 16.868$, $\mu_4 = 18.005$, $\upsilon_4 = 18.179$, $\mu_5 = 16.339$, $\upsilon_5 = 16.736$, $\mu_6 = 18.176$, $\upsilon_6 = 18.307$. Then, the weight of risk factors can be calculated as: $w_{RF_1} = 0.169$, $w_{RF_2} = 0.161$, $w_{RF_3} = 0.166$, $w_{RF_4} = 0.173$, $w_{RF_5} = 0.158$, $w_{RF_6} = 0.174$.

Table 3
The risk evaluation of failure modes $FM_i(i = 1, 2, \dots, 11)$ over risk factors $RF_j(j = 1, 2, \dots, 6)$ from E_1.

	$RF1$	$RF2$	$RF3$	$RF4$	$RF5$	$RF6$
$FM1$	s_3	bet s_1 & s_2	bet s_3 & s_5	bet s_1 & s_2	at most s_2	bet s_2 & s_3
$FM2$	at most s_2	bet s_2 & s_3	s_3	at most s_2	bet s_2 & s_3	s_3
$FM3$	bet s_2 & s_3	bet s_2 & s_3	s_3	at least s_4	bet s_3 & s_5	s_3
$FM4$	bet s_1 & s_2	at most s_2	at least s_4	bet s_4 & s_5	s_3	bet s_4 & s_5
$FM5$	at most s_2	at most s_2	at least s_5	bet s_4 & s_5	bet s_4 & s_5	at most s_5
$FM6$	bet s_2 & s_3	at least s_4	bet s_1 & s_2	at most s_2	at least s_4	at most s_2
$FM7$	s_3	bet s_1 & s_2	at most s_2	at most s_2	at least s_4	bet s_2 & s_3
$FM8$	at least s_5	at least s_4	bet s_2 & s_3	s_3	s_3	s_3
$FM9$	at least s_4	bet s_3 & s_4	at most s_2	bet s_1 & s_2	at most s_2	bet s_1 & s_2
$FM10$	at most s_2	bet s_3 & s_4	s_3	bet s_2 & s_3	bet s_4 & s_5	at least s_4
$FM11$	bet s_2 & s_3	s_3	at most s_2	bet s_2 & s_3	bet s_3 & s_4	bet s_2 & s_3

Table 4
The risk evaluation of failure modes $FM_i(i = 1, 2, \dots, 11)$ over risk factors $RF_j(j = 1, 2, \dots, 6)$ from E_2.

	$RF1$	$RF2$	$RF3$	$RF4$	$RF5$	$RF6$
$FM1$	bet s_2 & s_3	at most s_2	s_3	at most s_2	bet s_1 & s_2	bet s_2 & s_3
$FM2$	s_3	bet s_1 & s_2	s_3	at most s_2	bet s_1 & s_2	bet s_2 & s_3
$FM3$	s_3	bet s_2 & s_3	at most s_2	bet s_3 & s_5	at least s_4	s_3
$FM4$	at most s_2	at most s_2	at least s_4	s_3	at least s_5	at least s_4
$FM5$	bet s_1 & s_2	at most s_2	s_3	bet s_4 & s_5	bet s_3 & s_5	bet s_2 & s_3
$FM6$	s_3	at least s_4	bet s_2 & s_3	bet s_2 & s_3	s_3	bet s_1 & s_2
$FM7$	bet s_1 & s_2	s_3	bet s_2 & s_3	at most s_2	at most s_2	bet s_2 & s_3
$FM8$	at least s_5	at least s_4	bet s_2 & s_3	s_3	s_3	s_3
$FM9$	bet s_2 & s_3	bet s_3 & s_5	at most s_2	bet s_2 & s_3	bet s_2 & s_3	at most s_2
$FM10$	bet s_1 & s_2	bet s_2 & s_3	bet s_1 & s_2	s_3	at least s_4	s_3
$FM11$	at most s_2	at most s_2	s_3	at most s_2	bet s_4 & s_5	bet s_2 & s_3

Table 5
The risk evaluation of failure modes $FM_i(i = 1, 2, \dots, 11)$ over risk factors $RF_j(j = 1, 2, \dots, 6)$ from E_3.

	$RF1$	$RF2$	$RF3$	$RF4$	$RF5$	$RF6$
$FM1$	at most s_2	bet s_2 & s_3	bet s_3 & s_4	bet s_2 & s_3	bet s_1 & s_2	s_3
$FM2$	bet s_2 & s_3	at most s_2	at least s_4	bet s_2 & s_3	bet s_2 & s_3	bet s_2 & s_3
$FM3$	bet s_1 & s_2	bet s_3 & s_5	s_3	s_3	s_3 & s_3	bet s_2 & s_3
$FM4$	bet s_2 & s_3	bet s_3 & s_4	bet s_4 & s_5	bet s_3 & s_5	at least s_2	at least s_4
$FM5$	s_3	at most s_2	s_3	at least s_4	bet s_4 & s_5	s_3
$FM6$	at most s_2	at least s_4	bet s_2 & s_3	bet s_2 & s_3	bet s_2 & s_3	bet s_1 & s_2
$FM7$	bet s_1 & s_2	s_3	bet s_1 & s_2	at most s_2	bet s_3 & s_4	bet s_2 & s_3
$FM8$	at most s_2	at least s_5	bet s_2 & s_3	at least s_4	bet s_1 & s_2	at least s_4
$FM9$	bet s_3 & s_4	bet s_3 & s_4	bet s_1 & s_2	bet s_2 & s_3	at most s_2	bet s_3 & s_4
$FM10$	bet s_1 & s_2	s_3	at most s_2	s_3	bet s_4 & s_5	bet s_2 & s_3
$FM11$	bet s_2 & s_3	at most s_2	s_3	at most s_2	bet s_3 & s_5	s_3

Table 6
The group risk evaluation of failure modes $FM_i(i = 1, 2, \dots, 11)$ over risk factors $RF_j(j = 1, 2, 3)$.

	$RF1$	$RF2$	$RF3$
$FM1$	bet $\left(s_1, 0.492\right)^{0.150}$ & $\left(s_2, 0.162\right)^{0.100}$	bet $\left(s_1, 0.096\right)^{0.067}$ & $\left(s_2, 0.072\right)^{0.067}$	bet $\left(s_3, 0.252\right)^{0.003}$ & $\left(s_4, 0.240\right)^{0.003}$
$FM2$	bet $\left(s_2, 0.300\right)^{-0.003}$ & $\left(s_3, 0.372\right)^{-0.053}$	bet $\left(s_1, 0.102\right)^{0.050}$ & $\left(s_2, 0.138\right)^{0.050}$	bet $\left(s_4, 0.162\right)^{-0.100}$ & $\left(s_5, 0.498\right)^{-0.150}$
$FM3$	bet $\left(s_2, 0.096\right)^{-0.020}$ & $\left(s_3, 0.402\right)^{-0.070}$	bet $\left(s_3, 0.264\right)^{-0.267}$ & $\left(s_4, 0.522\right)^{-0.200}$	bet $\left(s_2, 0.102\right)^{0.063}$ & $\left(s_3, 0.630\right)^{-0.053}$
$FM4$	bet $\left(s_1, 0.096\right)^{0.067}$ & $\left(s_2, 0.072\right)^{0.067}$	bet $\left(s_1, 0.198\right)^{0.133}$ & $\left(s_2, 0.144\right)^{0.133}$	bet $\left(s_5, 0.336\right)^{-0.170}$ & $\left(s_6, 0.402\right)^{0.000}$
$FM5$	bet $\left(s_1, 0.498\right)^{0.133}$ & $\left(s_2, 0.072\right)^{0.067}$	at most $\left(s_1, 0.102\right)^{0.435}$	bet $\left(s_3, 0.846\right)^{-0.067}$ & $\left(s_4, 0.102\right)^{-0.233}$
$FM6$	bet $\left(s_1, 0.498\right)^{0.150}$ & $\left(s_2, 0.162\right)^{0.100}$	at least $\left(s_5, 0.102\right)^{-0.269}$	bet $\left(s_2, 0.300\right)^{-0.053}$ & $\left(s_3, 0.300\right)^{-0.053}$
$FM7$	bet $\left(s_1, 0.300\right)^{0.100}$ & $\left(s_2, 0.300\right)^{0.050}$	bet $\left(s_2, 0.402\right)^{0.063}$ & $\left(s_3, 0.300\right)^{-0.053}$	bet $\left(s_1, 0.000\right)^{0.050}$ & $\left(s_2, 0.030\right)^{0.050}$
$FM8$	bet $\left(s_3, 0.276\right)^{-0.150}$ & $\left(s_4, 0.042\right)^{-0.200}$	at least $\left(s_5, 0.606\right)^{0.153}$	bet $\left(s_2, 0.600\right)^{-0.053}$ & $\left(s_3, 0.630\right)^{-0.053}$
$FM9$	bet $\left(s_3, 0.330\right)^{-0.170}$ & $\left(s_4, 0.300\right)^{-0.167}$	bet $\left(s_3, 0.724\right)^{0.283}$ & $\left(s_4, 0.645\right)^{0.124}$	bet $\left(s_1, 0.312\right)^{-0.174}$ & $\left(s_2, 0.495\right)^{-0.152}$
$FM10$	bet $\left(s_1, 0.458\right)^{0.141}$ & $\left(s_2, 0.614\right)^{0.167}$	bet $\left(s_3, 0.756\right)^{-0.063}$ & $\left(s_4, 0.417\right)^{-0.105}$	bet $\left(s_2, 0.189\right)^{0.143}$ & $\left(s_3, 0.292\right)^{0.172}$
$FM11$	bet $\left(s_2, 0.142\right)^{0.538}$ & $\left(s_3, 0.395\right)^{0.476}$	bet $\left(s_1, 0.823\right)^{0.154}$ & $\left(s_2, 0.733\right)^{0.204}$	bet $\left(s_2, 0.634\right)^{0.300}$ & $\left(s_3, 0.598\right)^{0.330}$

4.3. Stage III : Prioritize the failure modes with the extended ORESTE

Step 3.1: The global preference score of failure modes over risk factors can be computed via Eq. (20) with $\varphi = 0.5$, and the results are presented in Table 8.

Step 3.2: The weak ranking of FM_i can be derived via Eq. (21), which is shown in Table 9.

Step 3.3: The average intensity and net intensity of failure modes can be calculated by Eqs. (22)–(23), which are given in Tables 10 and 11, respectively.

Step 3.4: According to Eqs. (24)–(25), the threshold values can be set as: $\zeta = 0.03$, $\tau = 0.01$, $\varepsilon = 0.025$. Then, the PIR structure of failure modes can be constructed, which is shown in Table 12.

Therefore, the strong ranking of failure modes is obtained as: FM4 > FM3 > FM5 > FM10 > FM6 > FM2 > FM8 > FM7 > FM1 >

Table 7
The group risk evaluation of failure modes $FM_i (i = 1, 2, \dots, 11)$ over risk factors $RF_j (j = 4, 5, 6)$.

	$RF4$	$RF5$	$RF6$
$FM1$	bet $(s_1, 0.096)^{0.067}$ & $(s_2, 0.072)^{0.067}$	bet $(s_0, 0.702)^{0.000}$ & $(s_2, 0.330)^{0.000}$	bet $(s_2, 0.042)^{0.063}$ & $(s_3, 0)^{-0.003}$
$FM2$	bet $(s_1, 0.069)^{0.067}$ & $(s_2, 0.458)^{0.137}$	bet $(s_2, 0.512)^{0.063}$ & $(s_3, 0.437)^{0.049}$	bet $(s_1, 0.014)^{0.167}$ & $(s_3, 0.325)^{0.203}$
$FM3$	bet $(s_4, 0.354)^{0.167}$ & $(s_5, 0.289)^{0.033}$	bet $(s_3, 0.156)^{-0.327}$ & $(s_5, 0.276)^{-0.257}$	bet $(s_2, 0.012)^{-0.167}$ & $(s_3, 0.031)^{-0.033}$
$FM4$	bet $(s_3, 0.632)^{0.153}$ & $(s_5, 0.524)^{0.167}$	bet $(s_4, 0.379)^{0.412}$ & $(s_6, 0.435)^{0.241}$	at least $(s_5, 0.174)^{0.268}$
$FM5$	bet $(s_4, 0.096)^{0.033}$ & $(s_5, 0.503)^{0.062}$	bet $(s_3, 0.314)^{0.520}$ & $(s_5, 0.368)^{0.428}$	bet $(s_2, 0.498)^{0.151}$ & $(s_3, 0.137)^{0.124}$
$FM6$	bet $(s_1, 0.396)^{0.117}$ & $(s_2, 0.372)^{0.117}$	bet $(s_3, 0.228)^{-0.183}$ & $(s_4, 0.102)^{-0.233}$	bet $(s_1, 0.300)^{0.000}$ & $(s_2, 0.330)^{0.000}$
$FM7$	at most $(s_1, 0.102)^{0.184}$	bet $(s_3, 0.270)^{-0.217}$ & $(s_4, 0.330)^{-0.217}$	bet $(s_2, 0.000)^{-0.003}$ & $(s_3, 0.000)^{-0.003}$
$FM8$	bet $(s_4, 0.162)^{-0.010}$ & $(s_5, 0.498)^{-0.150}$	bet $(s_2, 0.204)^{0.030}$ & $(s_3, 0.402)^{-0.070}$	bet $(s_3, 0.240)^{-0.200}$ & $(s_4, 0.102)^{-0.250}$
$FM9$	bet $(s_2, 0.300)^{-0.053}$ & $(s_3, 0.300)^{-0.053}$	bet $(s_1, 0.402)^{0.050}$ & $(s_2, 0.468)^{0.050}$	bet $(s_1, 0.498)^{0.133}$ & $(s_2, 0.474)^{0.133}$
$FM10$	bet $(s_2, 0.702)^{0.113}$ & $(s_3, 0.000)^{-0.003}$	bet $(s_4, 0.330)^{0.000}$ & $(s_5, 0.300)^{0.000}$	bet $(s_3, 0.228)^{-0.183}$ & $(s_4, 0.102)^{-0.233}$
$FM11$	bet $(s_1, 0.402)^{0.050}$ & $(s_2, 0.468)^{0.050}$	bet $(s_4, 0.366)^{-0.117}$ & $(s_5, 0.103)^{-0.050}$	bet $(s_2, 0.067)^{0.063}$ & $(s_3, 0.000)^{-0.003}$

Table 8
The global preference scores of failure modes over risk factors.

	$RF1$	$RF2$	$RF3$	$RF4$	$RF5$	$RF6$
$FM1$	0.591	0.622	0.354	0.661	0.791	0.674
$FM2$	0.573	0.640	0.506	0.661	0.454	0.534
$FM3$	0.366	0.462	0.485	0.214	0.289	0.439
$FM4$	0.426	0.494	0.301	0.330	0.404	0.000
$FM5$	0.402	0.713	0.239	0.464	0.438	0.396
$FM6$	0.691	0.437	0.407	0.406	0.548	0.734
$FM7$	0.601	0.527	0.573	0.651	0.672	0.598
$FM8$	0.621	0.509	0.626	0.501	0.566	0.696
$FM9$	0.504	0.497	0.727	0.667	0.680	0.740
$FM10$	0.573	0.474	0.462	0.531	0.511	0.491
$FM11$	0.690	0.741	0.685	0.598	0.678	0.674

Table 9
The weak ranking of failure modes.

	$FM1$	$FM2$	$FM3$	$FM4$	$FM5$	$FM6$	$FM7$	$FM8$	$FM9$	$FM10$	$FM11$
$R(FM_i)$	0.616	0.561	0.376	0.326	0.442	0.537	0.604	0.587	0.636	0.507	0.678
Weak ranking	9	6	2	1	3	5	8	7	10	4	11

Table 10
The average preference intensity between failure modes.

	$FM1$	$FM2$	$FM3$	$FM4$	$FM5$	$FM6$	$FM7$	$FM8$	$FM9$	$FM10$	$FM11$
$FM1$	0.000	0.028	0.022	0.000	0.015	0.036	0.038	0.054	0.074	0.018	0.090
$FM2$	0.083	0.000	0.000	0.000	0.012	0.069	0.063	0.074	0.110	0.010	0.127
$FM3$	0.262	0.186	0.000	0.054	0.114	0.178	0.228	0.211	0.260	0.135	0.302
$FM4$	0.290	0.236	0.104	0.000	0.130	0.221	0.278	0.261	0.310	0.184	0.352
$FM5$	0.189	0.132	0.048	0.014	0.000	0.151	0.193	0.179	0.230	0.105	0.236
$FM6$	0.114	0.093	0.017	0.010	0.056	0.000	0.104	0.068	0.130	0.036	0.151
$FM7$	0.049	0.020	0.000	0.000	0.031	0.038	0.000	0.029	0.053	0.000	0.083
$FM8$	0.083	0.049	0.000	0.000	0.034	0.018	0.046	0.000	0.071	0.005	0.095
$FM9$	0.054	0.035	0.000	0.000	0.036	0.031	0.021	0.021	0.000	0.012	0.072
$FM10$	0.127	0.064	0.000	0.000	0.040	0.066	0.097	0.085	0.141	0.000	0.171
$FM11$	0.029	0.011	0.000	0.000	0.000	0.010	0.009	0.004	0.030	0.000	0.000

Table 11
The net preference intensity between failure modes.

	$FM1$	$FM2$	$FM3$	$FM4$	$FM5$	$FM6$	$FM7$	$FM8$	$FM9$	$FM10$	$FM11$
$FM1$	0.000	−0.055	−0.240	−0.290	−0.174	−0.078	−0.011	−0.029	0.020	−0.109	0.061
$FM2$	0.055	0.000	−0.186	−0.236	−0.120	−0.024	0.043	0.025	0.075	−0.054	0.116
$FM3$	0.240	0.186	0.000	−0.050	0.066	0.161	0.228	0.211	0.260	0.135	0.302
$FM4$	0.290	0.236	0.050	0.000	0.116	0.211	0.278	0.261	0.310	0.184	0.352
$FM5$	0.174	0.120	−0.066	−0.116	0.000	0.095	0.162	0.145	0.194	0.065	0.236
$FM6$	0.078	0.024	−0.161	−0.211	−0.095	0.000	0.066	0.050	0.099	−0.030	0.141
$FM7$	0.011	−0.043	−0.228	−0.278	−0.162	−0.066	0.000	−0.017	0.032	−0.097	0.074
$FM8$	0.029	−0.025	−0.211	−0.261	−0.145	−0.050	0.017	0.000	0.050	−0.080	0.091
$FM9$	−0.020	−0.075	−0.260	−0.310	−0.194	−0.099	−0.032	−0.050	0.000	−0.129	0.042
$FM10$	0.109	0.054	−0.135	−0.184	−0.065	0.030	0.097	0.080	0.129	0.000	0.171
$FM11$	−0.061	−0.116	−0.302	−0.352	−0.236	−0.141	−0.074	−0.091	−0.042	−0.171	0.000

Table 12
The PIR structure of failure modes.

	$FM1$	$FM2$	$FM3$	$FM4$	$FM5$	$FM6$	$FM7$	$FM8$	$FM9$	$FM10$	$FM11$
$FM1$	–	<	<	<	<	<	<	<	>	<	>
$FM2$	>	–	<	<	<	<	>	>	>	<	>
$FM3$	>	>	–	<	>	>	>	>	>	>	>
$FM4$	>	>	>	–	>	>	>	>	>	>	>
$FM5$	>	>	<	<	–	>	>	>	>	>	>
$FM6$	>	>	<	<	<	–	>	>	>	<	>
$FM7$	>	<	<	<	<	<	–	<	>	<	>
$FM8$	>	<	<	<	<	<	>	–	>	<	>
$FM9$	<	<	<	<	<	<	<	<	–	<	>
$FM10$	>	>	<	<	<	>	>	>	>	–	>
$FM11$	<	<	<	<	<	<	<	<	<	<	–

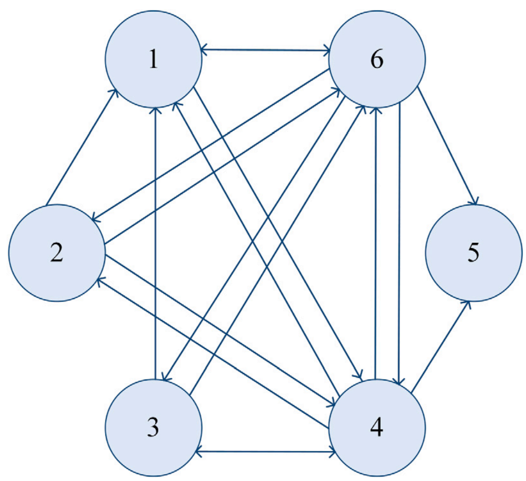


Fig. 2. The influence relation between risk factors.

FM9 > FM11. In other words, FM4 (i.e., control capacitor dielectric breakdown) is the most critical failure mode. Therefore, corresponding measures should be taken first for failure modes with higher risk priority to avoid potential accidents.

5. Discussions

5.1. Sensitivity analysis

In this subsection, we conduct sensitivity analyses to discuss the effect of distinguish coefficient on the weight of risk factors and the impact of adjustment parameter on the final risk priority.

5.1.1. Analyze the effect of distinguish coefficient ε on the weight of risk factors

While calculating the weight of risk factors, grey relation analysis is utilized to determine the direct-relation matrix. There exists a distinguish coefficient ε in Eq. (13) reflecting the degree of differentiation between grey correlation coefficients. Therefore, it is necessary to analyze the effect of this distinguish coefficient on the weight of risk factors. Fig. 3 illustrates the variation of risk factor weights as the distinguish coefficient ε changes from 0.1 to 1.

From Fig. 3, we can observe that the weight of RF1, RF3, RF4, and RF6 decreases as ε increases from 0.1 to 1, while the weight of RF2 and RF5 increases as ε increases. The weight of RF1 is least affected by the change in ε, while the weight of RF5 is most affected by the change in ε. The smaller the ε, the larger the discrimination among the weight of risk factors. Therefore, the value of distinguish coefficient ε has an impact on the weight of risk factors, and an appropriate value should be selected according to the actual situation.

5.1.2. Discuss the impact of adjustment parameter φ on risk prioritization

The first step in risk prioritization is determining the global preference score for failure modes regarding each risk factor. According to Eq. (20), φ is an adjustment parameter reflecting the relative importance between two deviation measures. The first is the deviation between risk assessments and the positive ideal solution; the second is the deviation between the weight of risk factors and the largest weight. Therefore, it is worth discussing the influence of φ on the final risk priority. Fig. 4 shows the change in risk priority as φ increases from 0.1 to 1 with a step size of 0.1.

Fig. 4 shows that $\varphi = 0.7$ is a key point at which the ranking of failure modes changes. Specifically, when φ changes from 0.1 to 0.6, the risk priority remains FM4 > FM3 > FM5 > FM10 > FM6 > FM2 > FM8 > FM7 > FM1 > FM9 > FM11; when φ varies from 0.7 to 1, the risk priority changes to FM4 > FM3 > FM5 > FM10 > FM2 > FM6 > FM8 > FM7 > FM9 > FM1 > FM11. On one hand, a balance between the two deviations should be considered to determine a more reasonable result. On the other hand, the top four failure modes in the risk priority remain the same despite the variation of φ, which indicates the stability of our method.

5.2. Validity analysis

In this subsection, we will verify the validity of our risk prioritization approach from the following three aspects. First, when a failure mode with non-highest risk priority is replaced by a failure mode with a lower risk level, the failure mode with the highest risk priority obtained by the proposed method should be unchanged. Second, an effective risk ranking method should satisfy the transitive property. Third, suppose a risk prioritization problem is deconstructed into several sub-problems and the same FMEA approach is utilized to solve these sub-problems. In that case, the failure modes should be prioritized in an order consistent with the original problem.

Regarding the first aspect, we modify the original risk assessment information of FM10, which is shown in Table 13. The original risk evaluation of the remaining failure modes other than FM10 remains unchanged. By employing the proposed method, the new risk priority can be obtained as: FM4 > FM5 > FM3 > FM6 > FM8 > FM2 > FM9 > FM7 > FM1 > FM11 > FM10. Compared with the original risk priority derived in Section 4.3, the failure mode with the highest risk priority remains the same, i.e., FM4, which illustrates the validity of the proposed method from the first aspect.

To verify from the second and third aspects, we divided the original set of failure modes into the following two subsets: $\Theta_1 = \{FM_1, FM_3, FM_5, FM_8, FM_{10}, FM_{11}\}$, and $\Theta_2 = \{FM_2, FM_4, FM_6, FM_7, FM_9\}$. According to our method, the risk priority of FM_i in Θ_1 is derived as: FM3 > FM5 > FM10 > FM8 > FM1 > FM11. The risk priority in Θ_2 is calculated as: FM4 > FM6 > FM2 > FM7 > FM9. The risk prioritization in these two subsets is consistent with the ranking in the original set of failure modes, which further verifies the validity of the proposed method.

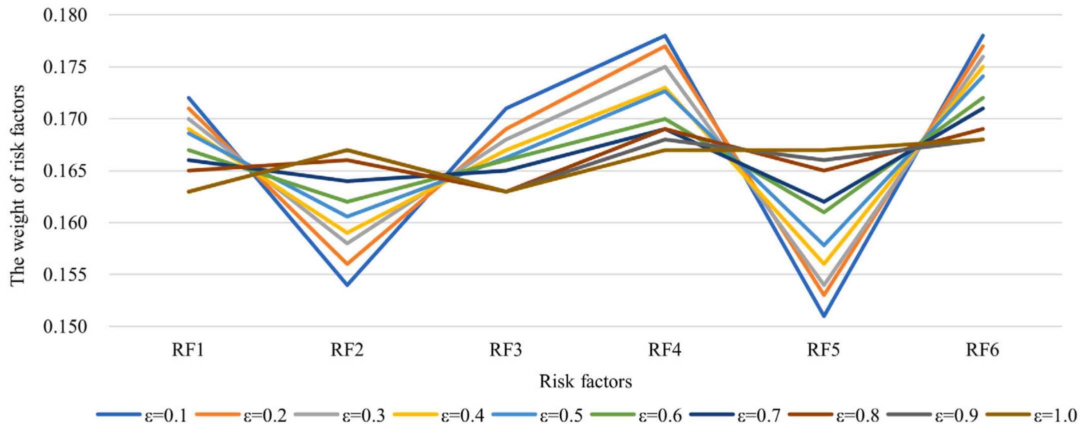


Fig. 3. The weight of risk factors under different ε.

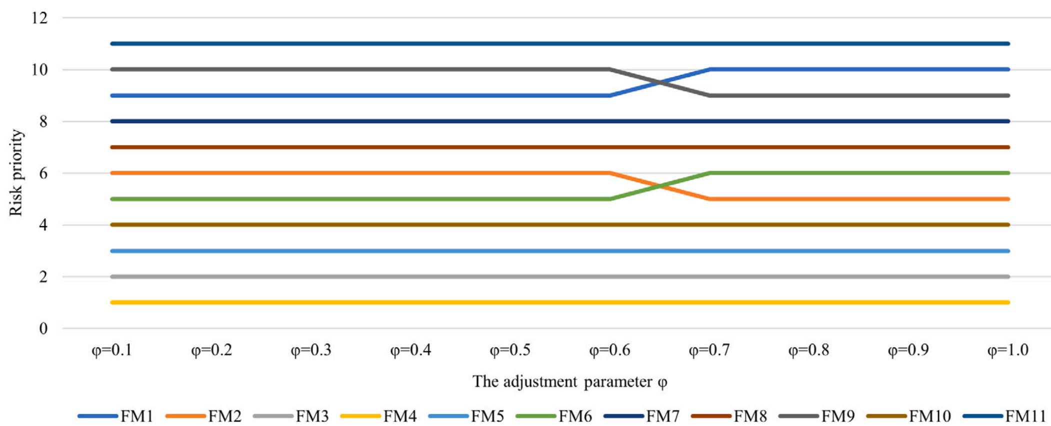


Fig. 4. The risk priority of failure modes under different φ.

Table 13
The original and modified risk assessment of FM10.

	$RF1$	$RF2$	$RF3$	$RF4$	$RF5$	$RF6$
The original $FM10$	at most s_2	bet s_3 & s_4	s_3	bet s_2 & s_3	bet s_4 & s_5	at least s_4
The modified $FM10$	s_1	s_1	bet s_1 & s_2	s_1	s_1	bet s_1&s_2

5.3. Reliability analysis

In this subsection, we utilize Monte Carlo simulation to illustrate the reliability of the proposed approach. To begin with, we randomly construct sequences that simulate the order in which failure modes emerge. Then, for electro-mechanical actuator systems, the level of risk increases as failure modes occur in order. Once the risk level reaches the system risk threshold θ, the system will crash. The threshold θ reflects the failure tolerance ability of the system. The larger the θ, the greater the risk the system can bear. The occurrence of failure modes during this process will be recorded. In this simulation, we set θ to vary between 30 and 80 to explore the effect of the system risk threshold on the priority of failure modes.

According to the above analysis, we conduct 100 000 simulation experiments and obtained statistically significant data. Fig. 5 shows the random frequency of failure modes with various system risk threshold θ.

From Fig. 5, we can observe that the risk priority of FM_i obtained by random frequency is consistent with those obtained by the proposed method in Section 4.3, which proves the reliability of our method.

5.4. Comparative analysis

In this subsection, qualitative and quantitative comparisons are conducted with some typical methods to further illustrate the advantages of our method.

5.4.1. Qualitative comparative analysis

To begin with, qualitative comparisons are carried out from the following four aspects: (i) the expression structure of risk information, (ii) the correlation between risk factors are considered or not, (iii) weight determination method of risk factor, and (iv) risk prioritization method. The specific information is shown in Table 14.

For the expression of risk information, most existing methods utilize crisp numbers [43–45] or fuzzy numbers [15,17,46,47] to evaluate the risk level of failure modes under different risk factors. Nevertheless, fuzzy numbers are inadequate to reflect the uncertainty in human thinking. While [7,48,49] use linguistic variables to describe risk assessment, the hesitancy of expert evaluation cannot be reflected because each linguistic variable contains only one linguistic term. In our method, the risk information is expressed with CLEs and the group evaluation is generated in the form of ELICIT information, which extends the representation of CLEs to a continuous domain to better

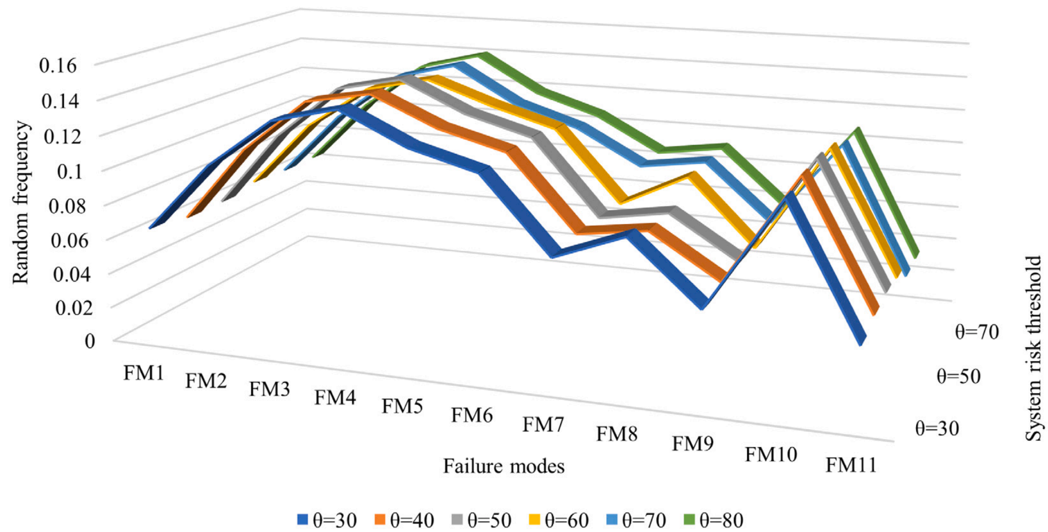


Fig. 5. The random frequency of failure modes with various system risk threshold θ.

Table 14
Qualitative comparisons of various risk prioritization methods.

Method	Risk information expression	Correlation between risk factors	Weight determination of risk factors	Risk prioritization method
[43]	Crisp number	Not considered	Assumed to be equal	Traditional RPN method
[44]	Crisp number	Considered	AHP method	Weighted RPN method
[45]	Crisp number	Not considered	Assumed to be equal	Classification-based consensus method
[46]	Triangular fuzzy number	Not considered	Determined by experts	Fuzzy QFD
[15]	Intuitionistic fuzzy number	Considered	DEMATEL method	MABAC method
[47]	Z-number	Considered	Z-FUCOM	Z-CoCoSo method
[17]	IVq-ROFN	Not considered	Maximum deviation method	The extended ARAS method
[7]	Linguistic variable	Not considered	Maximum deviation method	RT-PROMETHEE method
[48]	Linguistic variable	Not considered	Given in advance	FIS-RPN method
[49]	Linguistic variable	Not considered	Entropy method	The extended VIKOR method
[6]	LDA	Not considered	Assumed to be equal	Social network-based consensus model
[11]	LDA	Not considered	Assumed to be equal	Bounded confidence-based consensus model
This paper	ELICIT	Considered	GRA-DEMATEL	The extended ORESTE method

† RPN: Risk priority number; AHP: Analytic hierarchy process; QFD: Quality function deployment; DEMATEL: Decision-making trial and evaluation laboratory; MABAC: Multi attribute border approximation area comparison; Z-FUCOM: Z-Full consistency method; Z-COCOSO: Z-Combined compromise solution; IVq-ROFN: interval-valued q-rung orthopair number; ARAS: additive ratio assessment; RT-PROMETHEE: Regret theory-preference ranking organization method for enrichment evaluations; FIS-RPN: fuzzy inference system-risk priority number; VIKOR: vlsekriterijumska optimizacija i kompromisno resenje; LDA: Linguistic Distribution Assessment; ELICIT: Extended comparative linguistic expressions with symbolic translation; GRA-DEMATEL: Grey relation analysis-decision-making trial and evaluation laboratory; ORESTE: Organísation, rangement et Synthèse de données relarionnelles.

model experts' preferences. ELICIT is closer to human thinking and can improve the interpretability and precision in the process of computing with words.

Regarding the weight determination of risk factors, many methods fail to capture the correlation between different risk factors [6,7,11,17,43,46,48,49]. The methods that consider this interaction (e.g., AHP [44], DEMATEL [15], and Z-FUCOM [47]) are based on subjective pairwise comparisons of risk factors given by the experts. However, when many risk factors are involved in FMEA, the workload of pairwise comparison is too large, and consistency is difficult to guarantee. In our study, we incorporate the grey correlation coefficient into the DEMATEL method to capture the correlation between risk factors based on objective risk information, which can enhance the efficiency and accuracy of risk priority results.

Finally, to overcome the deficiencies in the traditional RPN approach, multiple MCDM techniques have been extended into FMEA to prioritize the failure modes, such as weighted RPN [44], MABAC [15], the extended VIKOR [49], and consensus-based methods [6,11,45]. Compared with these methods, the extended ORESTE proposed in our method can not only determine the utility value of failure modes, but also establish their PIR structures. Therefore, with the weak ranking and the PIR structure, the risk priority derived with our method is more reasonable.

5.4.2. Quantitative comparative analysis

After qualitative comparisons, we select the weighted RPN method [44], the extended ARAS method [17], and the extended VIKOR method [49] for quantitative comparisons. Because different methods utilize different risk information expressions, we uniformly use crisp numbers for risk evaluation, and use the same example to compute the risk priority obtained by each method. The results are shown in Fig. 6.

Fig. 6 shows that the risk priority varies by method, but FM4 is the highest risk-prioritized failure mode of all methods, and FM11 is the lowest. However, it is not convincing enough to illustrate the effectiveness of our approach through a single calculation. Therefore, the following simulation experiment is conducted based on the risk prioritization case given in Section 4. We utilize MATLAB to randomly generate 10 000 sets of weight of risk factors. Then, these four methods are applied to calculate the risk priority. Subsequently, we record the proportion of each failure mode in the top four positions of risk priority under four methods, which is shown in Figs. 7–10.

In Figs. 7–10, we can observe that the largest proportion of failure modes with the highest risk priority derived by each method is FM4, which further demonstrates the effectiveness of our method. Additionally, we found that in the proposed method, among the top four failure modes in the risk priority order, the failure mode with the largest percentage has an absolute advantage. For example, the percentage of FM4 in the highest risk priority position in our method is 81%, which is

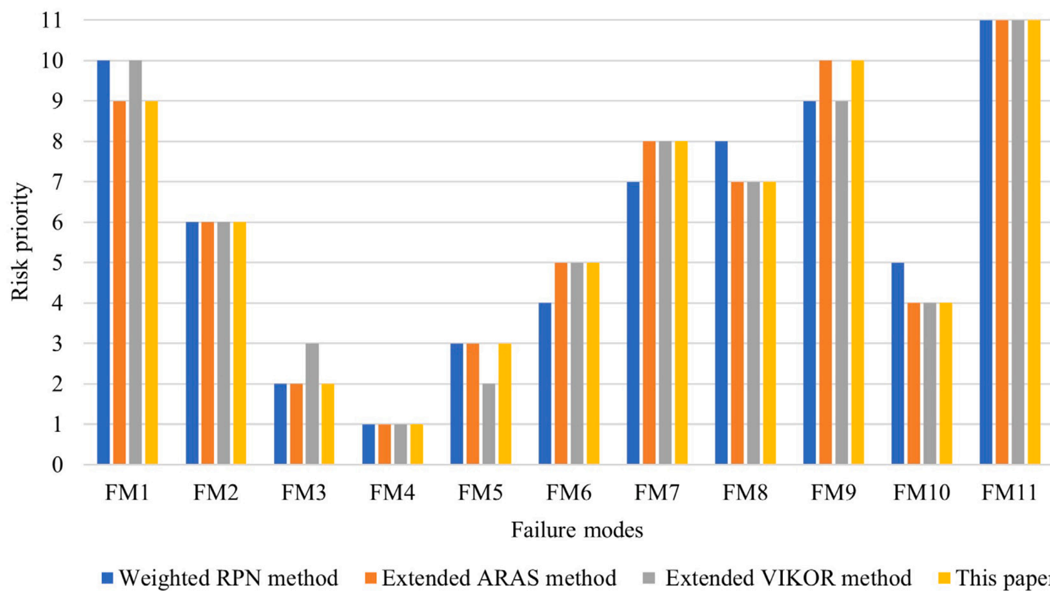


Fig. 6. The risk priority of failure modes under different methods.

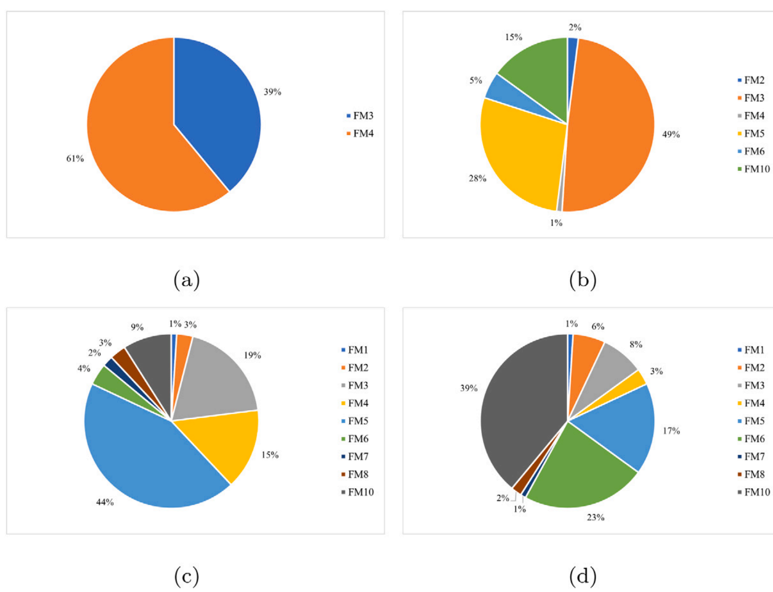


Fig. 7. (a), (b), (c), and (d) represent the proportion of each failure mode in the highest risk priority position, the second position, the third position, and the fourth position in the weighted RPN method, respectively.

significantly better than the 61% from [17,43] and the 58% from [48]. Therefore, compared with other approaches, our method has better convergence and can distinguish the risk priority to a greater extent.

5.5. The theoretical and practical implications

From the theoretical perspective, a novel FMEA framework that can deal with uncertain risk information and correlative risk factors is constructed. In this study, ELICIT information is utilized to elicit the group risk evaluation, which can improve the interpretability of the generated results. Considering the correlation between risk factors, GRA is combined with DEMATEL to calculate their weights more objectively. In risk prioritization, the ORESTE method is improved and generalized into ELICIT environment to capture the preference, indifference, and incomparability relations of failure modes through conflict analysis.

From the practical point of view, in the risk prioritization problem of an electro-mechanical actuator problem, our method can take advantage of the empirical knowledge of FMEA experts in the form of ELICIT. Other practical issues, such as the relationship between risk factors, are also considered. Discussions show that our method has better convergence and can distinguish the risk priority to a greater extent. Additionally, the proposed framework is well-structured and easy to implement. As a result, this method can be extended to solve risk prioritization in other fields, such as green logistic risk assessment.

6. Conclusion

Both the timely detection and elimination of failure modes are critical to system operation. In light of the limitations of existing FMEA methods, this paper proposes an improved risk prioritization method based on the extended ORESTE with ELICIT information. From our

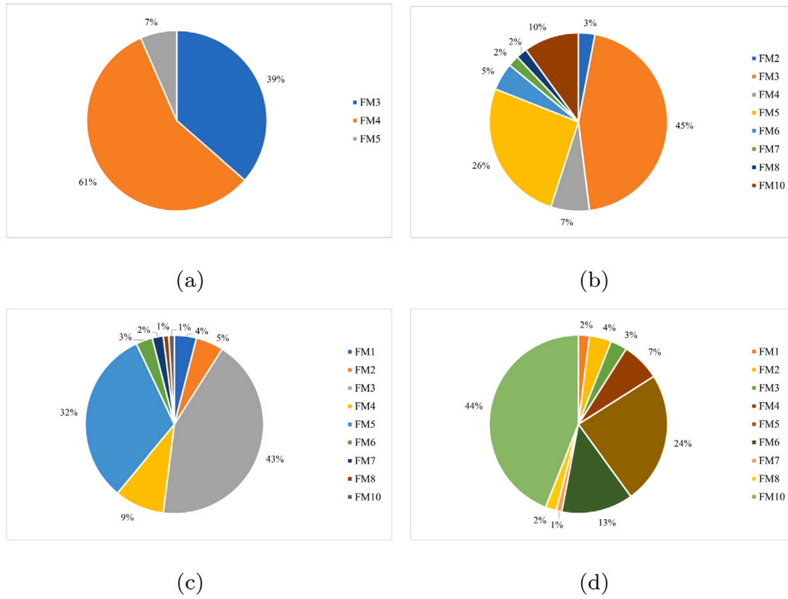


Fig. 8. (a), (b), (c), and (d) represent the proportion of each failure mode in the highest risk priority position, the second position, the third position, and the fourth position in the extended ARAS method, respectively.

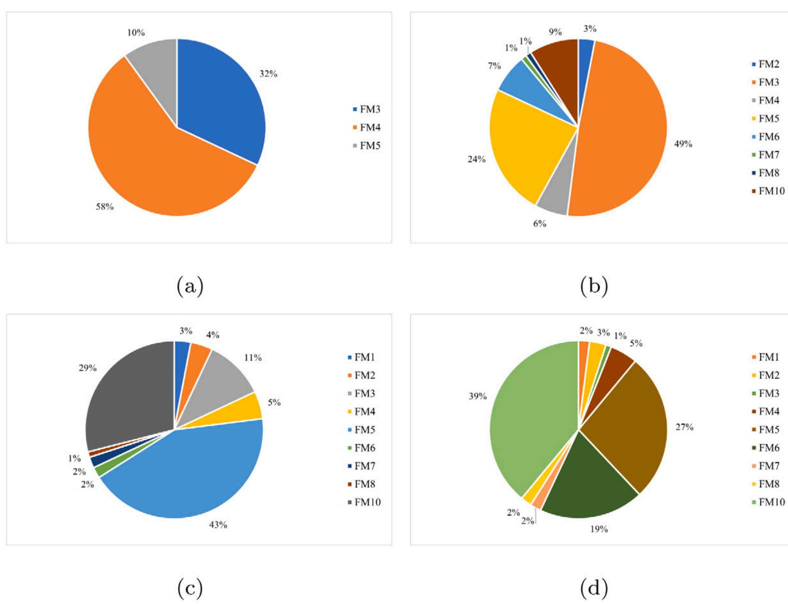
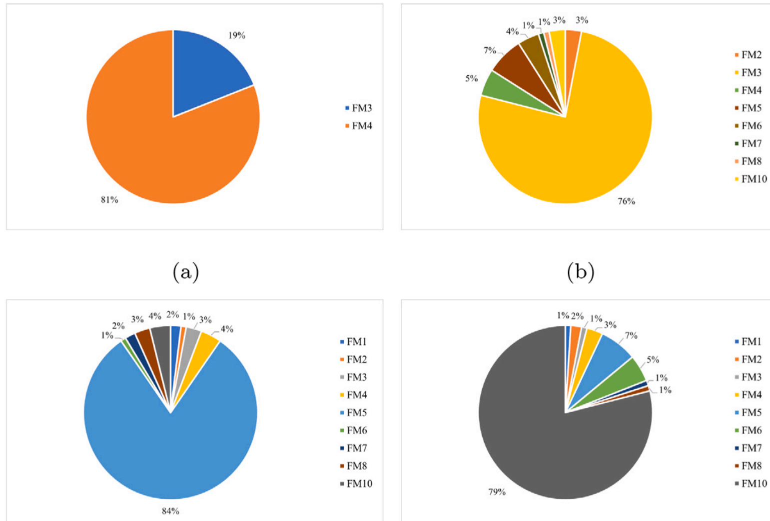


Fig. 9. (a), (b), (c), and (d) represent the proportion of each failure mode in the highest risk priority position, the second position, the third position, and the fourth position in the extended VIKOR method, respectively.

theoretical analysis and the case study for verification, we can draw the following conclusions:

(1) FMEA experts can utilize ELICIT information to flexibly assess the degree of risk of failure modes, which reduces information loss and enhances the method's practicality.
(2) The weight of risk factors is more objectively determined by introducing grey relation analysis into the traditional DEMATEL, improving risk prioritization efficiency.
(3) We advance the ORESTE method by replacing Besson's ranking with deviation measures and extend it into the ELICIT context, which improves the accuracy of the risk priority result.
(4) By applying our method to the risk analysis problem of electromechanical actuators, the validity, effectiveness, and advantages of our method are comprehensively verified.

In future research, classifying failure modes into several predefined and risk-ordered categories can improve efficiency in risk management [26,50,51]. Therefore, how to cluster failure modes more effectively deserves further study. Second, arriving at a consensual decision among FMEA experts is important since a highly accepted solution to the FMEA problem can facilitate the implementation of corrective measures [6,11]. Thus, we plan to incorporate feedback mechanisms into the FMEA framework to assist group members in reaching a consensus. Third, artificial intelligence methods can be introduced into FMEA to facilitate risk analysis. Nowadays, data availability from past activities enables new possibilities for advanced data analytics. Using historical and operational data as another source of knowledge, data analytic tools can predict specific failure probabilities. These results can be integrated into the FMEA to achieve dynamic risk evaluation. Therefore, developing data-driven FMEA methodologies with deep learning



(a) (b)

(c) (d)

Fig. 10. (a), (b), (c), and (d) represent the proportion of each failure mode in the highest risk priority position, the second position, the third position, and the fourth position in the proposed method, respectively.

models on historical data to support risk analysis is another direction worth exploring.

CRediT authorship contribution statement

Zhen Hua: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Xiaochuan Jing:** Validation, Formal analysis, Investigation, Writing – review & editing. **Luis Martínez:** Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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