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Risk assessment of crane operation hazards using modified FMEA approach with Z-number and set pair analysis

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ABSTRACT

In view of two key deficiencies of failure mode and effects analysis (FMEA) in crane operation hazard risk assessment—information loss and hazard grade lack, a crane operation hazard risk assessment model based on the Z-number and set pair analysis (Z-SPA) is proposed. In this research, the Z-number is used to address the information uncertainty. To reduce the risk losing evaluation information in the conversion of the Z-number into a crisp number, it is translated into an interval number. In this assessment model, the grades of crane operation hazards are determined using grade discrimination rules and a score function of a connection number based on set pair analysis. Two case studies are presented to exemplify the effectiveness of the approach. The first case validates the proposed method, and the second case illustrates the application of the modified FMEA to crane operation hazard risk analysis. Furthermore, the assessment results are analyzed and compared with previous studies to highlight the superiority of the proposed model.

1. Introduction

Cranes are crucial and widely employed in various fields, such as industrial and mining enterprises, ports, railway transportation, and real estate [1]. They have essential functions in these industries but should be acknowledged as high-risk apparatuses. Despite their usefulness, the operation of cranes presents significant safety concerns, as cranes pose formidable threats to the safety of individuals and properties [2–4]. The proper utilization of lifting machinery plays a significant role in the safety production of enterprises. Therefore, it is necessary to comprehensively analyze and predict the potential dangers and consequences of lifting machinery. The safety of lifting machinery is evaluated by analyzing the risk factors and accident consequences of lifting machinery, predicting the degree of accident risk, and proposing corresponding safety response measures, which provide an important guarantee for achieving safety production and strong support for administrative departments to supervise the safety of special equipment [5]. The risk assessment of crane operation hazards involves detailed analysis of collected and organized risk information, identification of uncertain factors, analysis of potential losses and probabilities of related events, and evaluation of the risk level of each hazard [6].

FMEA is a highly effective and widely used technique to prevent accident and analyze risk [7–9]. Its primary purpose is to identify, assess, and eliminate existing or potential failure modes (FMs) within complex systems for enhancing their reliability and safety. Through careful examination and evaluation of each FM, FMEA allows proactive decision-making for risk management. It provides crucial information that helps organizations make informed decisions on how to mitigate risks and enhance overall system performance. It serves as an important method for elevating the quality and safety of various industries and plays a key role in continuously enhancing the design, manufacturing, and operation processes of complex systems. Although it offers simplicity and clarity, there has

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been increasing focus on the shortcomings and deficiencies of traditional FMEA methods, prompting extensive discussions [10]. The many drawbacks can be summarized as follows: (1) The accuracy of the risk priority number (RPN) multiplication factor is debatable and is susceptible to fluctuations in risk assessment calculations [11]. (2) Various combinations of O, S, and D can yield identical RPN values, ultimately proving ineffective in practical risk management scenarios [12]. (3) Precisely determining evaluation information of O, S, and D poses challenges in numerous real-world situations [11,12]. (4) The conventional FMEA approach tends to overlook the weights of O, S, and D [13]. (5) Some cases lack adequate information for a thorough evaluation of risk priority numbers, injecting uncertainty into the risk assessment process [14]. (6) In specific systems, failure modes may be interconnected, making it challenging to allocate intervention actions [15]. (7) Conventional FMEA, along with many other risk management approaches, tends to evaluate system risk in a static manner and often disregards the temporal dimension within the system profile, overlooking dynamic aspects [16]. (8) The RPN calculation is highly sensitive to risk variations [17].

1.1. Literature review on FMEA with consensus reaching process

In their research on the consensus issue in FMEA, Zhang et al. [18] incorporated the consensus model into the traditional FMEA framework and addressed the weighting of risk assessment factors by optimizing the consensus model, thereby significantly accelerating the achievement of the final consensus. Fan et al. [19] considered the limited rationality of decision makers and incorporated prospect theory to develop an innovation feedback mechanism that simultaneously adjusts the original evaluation opinions and reference points, guiding experts to effectively reach consensus results. From a fairness perspective, Tang and Liao [20] improved the FMEA consensus-reaching process by examining social network structures in large-group environments. Xiao et al. [21] developed a multiphase consensus optimization model incorporating limited confidence to facilitate consensus-reaching for the FMEA team. Li et al. [22] introduced a consensus model to correct extreme or inaccurate risk assessments in the FMEA. Shi et al. [23] introduced a novel FMEA method that incorporated hesitant linguistic preference relations (HLPRs) and an extended dynamic consensus model. Li et al. [24] proposed an enhanced FMEA approach that considered risk attitudes and asymmetric cost consensus.

1.2. FMEA-MCDM literature review

As mentioned previously, there is an urgent requirement to enhance the conventional FMEA approach. Several scholarly articles have regarded risk prioritization as a problem in multi-criteria decision making (MCDM) [12]. As a result, the MCDM model has gained substantial popularity in resolving the limitations of FMEA. To address the research gap in submarine pipeline risk analysis and potential issues with the traditional TODIM (an acronym in Portuguese for interactive multi-criteria decision making) method, Yu et al. [25]. Introduced a new FMEA model based on an interval-valued intuitionistic fuzzy rough number (IVIFRN) and exponential TODIM-preference ranking organization method for enrichment evaluation II (ExpTODIM-PROMETHEE-II). Altubaishe and Desai [26] proposed a combinatorial method to evaluate potential risks in supplier selection by integrating FMEA with the preference ranking organization method for enrichment evaluation (PROMETHEE) and a hybrid analytical hierarchy process (AHP). To address the uncertainties arising from FMEA experts. Wu et al. [27] developed a novel approach for managing uncertainty in the evaluations provided by experts. This approach employs belief entropy and negation information within the framework of the Dempster–Shafer evidence theory (D-S). Du et al. [28] introduced an innovative method for identifying influential airports in airline networks based on failure risk factors using technique for order preference by similarity to ideal solution (TOPSIS). To address the limitations of existing FMEA, Fu et al. [12] proposed an innovative approach for prioritizing risks by utilizing the type-2 intuitionistic fuzzy VlseKriterijuska Optimizacija I Komoromisno Resenje (VIKOR) and cumulative prospect theory. In addition to the aforementioned methods, numerous alternative and innovative techniques have been extensively utilized in FMEA, such as data envelopment analysis (DEA) and cloud model combination technology [29], compromise solution (CoCoSo) [30], best-worst method-complex proportional assessment (BWM-COPRAS) [31], and the grey relational projection method (GRPM) [32].

1.3. Literature review on crane risk assessment

Traditional FMEA is also utilized in crane risk assessment and serves as the most prevalent approach for evaluating potential risks [33–37]. Additionally, researchers have considered crane risk assessment as a MCDM problem. For instance, Li et al. [38] integrated the fuzzy confidence theory and grey theory to rank the risk priority of the main lifting mechanism of an overhead crane in metallurgical plants. Additionally, Mandal et al. [39] proposed an FMEA framework incorporating a TrFN and fuzzy VIKOR to identify and prioritize risks in overhead crane operations. Das et al. [40] identified and ranked the potential failures of crane operations using the Z number in conjunction with the fuzzy VIKOR. To reflect the risk attitudes of experts and integrate subjective and objective weights, Li [41] proposed an improved FMEA method for human errors in crane operations by using cumulative prospect theory and improved combination weighting model of game theory. Although numerous studies have been conducted on FMEA using various approaches that integrate decision support techniques, there is a scarcity of research on the assessment of crane risks through the integration of MCDM with FMEA. Hence, it is necessary to enhance traditional FMEA for crane risk assessment.

1.4. Motivation and originality of this study

The motivation of this research is to better handle experts' subjective evaluation information for the risk assessment of crane operation hazards and to facilitate safety management. Considering the intricacies of reality, decision-making inherently involves imprecise and uncertain information. Thus, fuzzy set theories have been used, such as type-2 fuzzy sets [42,43], spherical fuzzy sets [44,45], intuitionistic fuzzy sets [46], triangular fuzzy numbers (TFNs) [47], trapezoidal fuzzy numbers [39], Z-numbers [48], pythagorean fuzzy sets [49], and probabilistic linguistic term sets [50], interval-valued probabilistic uncertain linguistic term sets [51]. In addition, probabilistic language preference relationships [52] have also been introduced into group decision-making. Various applications have been proposed with the development of this research. The Z-number possesses the capacity to effectively describe the imprecision and uncertainty inherent in information [53]. In numerous studies, Z-numbers have been utilized to resolve a multitude of decision-making conundrums, such as healthcare waste management [54], green supplier selection [55], smart product service system analysis [56], and oil project assessment [57]. Although TrFNs and TFNs are commonly used, the Z-number is recommended as a more suitable linguistic variable for describing real-world information [58]. Hence, the Z-number was adopted to express the experts' evaluation information for crane operation hazards. Generally, the majority of applications that utilize Z-numbers concentrate on incorporating Z-numbers into the existing MCDM models. The Z-numbers are then converted into regular fuzzy numbers to address common fuzzy MCDM problems. The integration of Z-numbers into MCDM methods has significantly contributed to traditional FMEA; however, two crucial issues have not yet been fully addressed. (1) Fuzzy numbers are always transformed into crisp numbers to become common fuzzy MCDM issues, which typically results in a loss of information [59–61]. (2) For crane risk assessment with FMEA, in most previous studies, only the risk ranking was provided, and the hazard grade was not classified. Although Zhao et al. [47] determined the FM hazard grades for quay crane heightening according to an equal division of the grey correlation degree, they may not reflect the actual scenario. Given the above analysis, it is necessary to develop a prioritization method for Z-numbers from a new perspective to achieve a reasonable ranking of them.

The set pair analysis (SPA) method is a method that combines certainty and uncertainty, and its theoretical advantages allow it to address issues in uncertain systems. In this method, the connection number (CN) serves as a fundamental mathematical tool. It uses the levels of "identity," "discrepancy," and "contradiction" to represent certainty, hesitancy, and uncertainty within a system, respectively. Since its proposal, the SPA theory has garnered significant attention from researchers who have conducted extensive investigations into its theoretical underpinnings and practical applications. Lin et al. [62] used a credible degree recognition criterion and the SPA to evaluate the growth potential of underground spaces in a city. Shi and Cai [63] comprehensively explored the safety evaluation and system development of tunnel linings using SPA. Wang et al. [64] developed an airport bird-strike risk assessment model based on SPA. To perform an impartial assessment of how hesitant fuzziness affects the prioritization of alternatives in multi-attribute decision making involving probabilistic hesitant fuzzy information, Shen et al. [65] employed the binary connection number from SPA to address the issue of hesitant fuzzy multi-attribute decision making. Li et al. [66] developed a fuzzy multicriteria decision-making model that utilized the Choquet integral and an improved CN score function in an interval-valued Pythagorean fuzzy environment. Ye [67] proposed an SPA approach to prioritize interval numbers. By converting the interval numbers into connection numbers, the arrangement of the interval numbers was ascertained using a score function. However, despite extensive research and analysis, there has been no practical application of the SPA theory within the Z-number fuzzy environment.

Motivated by the above analysis, the aim of this study was to establish a crane operation hazard risk assessment model based on the Z-SPA. As mentioned previously, the Z-number was selected in this research because it can better describe the imprecise and uncertain experts' opinions than the TrFN and TFN. Most related applications utilizing Z-numbers primarily concentrate on integrating the concept of Z-numbers into the existing MCDM method. These applications typically involve transforming the Z-numbers into crisp numbers, converting them into conventional fuzzy MCDM problems. However, converting Z-numbers into crisp numbers leads to a loss of assessment information. To resolve this issue, a modified FMEA method was developed based on the Z-number and SPA. To reduce information loss, the Z-number is first transformed into a connection number (CN) via SPA by converting it into an interval number. Then, the prioritization of the FM can be determined through the score function of the CN. In most related studies, only the risk ranking of FMs in the risk analysis process was obtained, rather than the hazard grade. This is inconvenient for crane safety management because the risk ranking does not indicate the risk level. In view of this issue, grade discrimination rules and the score function of the CN are employed to evaluate the grades of crane operation hazards.

The rest of this paper is structured as follows. In Section 2, the Z-number and SPA are introduced. The proposed model for hazard assessment in crane operation is described in Section 3. In Section 4, two case studies are used to demonstrate the implementation and evaluate the efficiency of the proposed model. Section 5 presents conclusions.

2. Methodology

2.1. Z-number

The Z-number, which was developed by Zadeh [48], provided a groundbreaking approach for handling uncertainty and imprecision in mathematical models and decision-making processes. The advantage of using the Z-number is that the confidence level is used to evaluate the values of the relevant variables [68]. A Z-number is described as an ordered pair $Z = (A, B)$. The first element A is a restriction of the domain X. Let A be a TrFN expressed as $A = (a_1, a_2, a_3, a_4)$. Then, the membership function $\mu_{A(x)}$ can be expressed as follows [59]:

$$\mu_A(x) = \begin{cases} 0 & x \le a_1 \\ \dfrac{x-a_1}{a_2-a_1} & a_1 \le x \le a_2 \\ 1 & a_2 \le x \le a_3 \\ \dfrac{a_4-x}{a_4-a_3} & a_3 \le x \le a_4 \\ 0 & x \ge a_4 \end{cases} \tag{1}$$

The second component B serves as an assessment of the dependability or trustworthiness of component A. Whereas component A implies a constraint on the magnitude or range of the variable, component B signifies the likelihood of its occurrence. In other words, B provides a measure of the probability associated with the reliability of component A. Let B be a TFN denoted as $B = (b_1, b_2, b_3)$. The membership function $\mu_{B(x)}$ [69] is expressed as

$$\mu_B(x) = \begin{cases} 0 & x \le b_1 \\ \dfrac{x-b_1}{b_2-b_1} & b_1 \le x \le b_2 \\ \dfrac{b_3-x}{b_3-b_2} & b_2 \le x \le b_3 \\ 0 & x \ge b_3 \end{cases} \tag{2}$$

Typically, the second element B of the Z-number is combined with the first element A to make the Z-number a regular fuzzy number, such as a TrFN or TFN. The process of transforming the Z-number into a regular fuzzy number is presented below.

First, the element B is defuzzified using Eq. (3), and the weighted Z-number (Z^{α}) is determined [70].

$$\alpha = \frac{\int x\mu_B(x)dx}{\int \mu_B(x)dx} = \frac{1}{3}[(b_3-b_1)+(b_2-b_1)]+b_1 \tag{3}$$

$$Z^{\alpha} = (x, \mu_{Z^{\alpha}}(x) | \mu_{Z^{\alpha}}(x) = \alpha\mu_A(x), x \in X) \tag{4}$$

here, α is the confidence coefficient.

Then, Z_{α} is converted into a regular fuzzy number $\widetilde{Z}$ as follows [70]:

$$\widetilde{Z} = \left(x, \mu_{Z^{\alpha}}(x) | x \in X\right) = (x, \mu_{\widetilde{Z}}(x) | \mu_{\widetilde{Z}}(x) = \mu_{Z^{\alpha}}\left(x / \sqrt{\alpha}\right) = \sqrt{\alpha}\mu_A(x), x \in X). \tag{5}$$

2.2. Set pair analysis and connection number

Zhao [71] proposed SPA for handling the uncertainty by defining the connection degree between the features of a set pair. SPA theory is widely used in economics [62], decision analysis [72], security assessment [73,74], and other fields. The core idea of this theory is that uncertainty is an inherent attribute of things, and it regards certainty and uncertainty as a whole. SPA divides certainty into two aspects: identity and opposition, which represent consistency and competition, respectively, within things. Meanwhile, uncertainty is called difference, and it includes the changes and diversity of things in different aspects. In SPA, systems are analyzed from the perspectives of identity, opposition, and difference, revealing the development and change patterns of things. Through such analysis of systems, corresponding contradictions and conflicts are better understood, thereby leading to a deeper understanding and effective management of the system.

Let $\Theta(\Psi, \Omega)$ be a set pair that contains two sets Ψ and Ω for a given problem G. Suppose that there are a total of N features in problem G. These features can be categorized into three groups: S identical features, P contrary features, and F = N − S − P discrepancy features. The CN μ of the set pair $\Theta(\Psi, \Omega)$ for problem G is defined as [67].

$$\mu = a + b\mathrm{I} + c\mathrm{J}, \tag{6}$$

where $a = \mathrm{S/N}$, $b = (\mathrm{N-S-P})/\mathrm{N}$, and $c = \mathrm{P/N}$ denote the “identity,” “discrepancy,” and “contrary” degrees, respectively, between Ψ and Ω. Clearly, $a \in [0,1]$, $b \in [0,1]$, $c \in [0,1]$, and $a + b + c = 1$. Generally, I represents the discrepancy coefficient, and J represents the contrary coefficient.

For an interval number $\mathrm{P} = [a^L, a^U]$ with $0 \le a^L \le a^U \le 1$, the CN μ of P can be obtained by using Eq. (6).

$$\mu = a + b\mathrm{I} + c\mathrm{J}, \tag{7}$$

where $a = a^L$, $b = a^R - a^L$, $c = 1 - a^R$, $\mathrm{I} \in [0,1]$, and $\mathrm{J} = 1$, in this study, I and J are only marking symbols.

For the CN $\mu = a + b\mathrm{I} + c\mathrm{J}$ obtained via Eq. (7), the score function [67] $S(\mu)$ of μ is given as

$$S(\mu) = a/c, \tag{8}$$

In addition, the order between μ_1 and μ_2 is as follows:

(i) $S(\mu_1) > S(\mu_2) \Rightarrow \mu 1 > \mu 2$;

(ii) $S(\mu_1) < S(\mu_2) \Rightarrow \mu 1 \prec \mu 2$;

(iii) $S(\mu_1) = S(\mu_2) \Rightarrow \mu 1 = \mu 2$.

3. Proposed modified FMEA approach for crane operation hazard evaluation

In this study, a modified FMEA approach was used for crane operation hazard assessment based on the Z-number and SPA, treating hazard assessment as an MCDM problem. The model considers the risk factors of each hazard as evaluation indices and ranks the

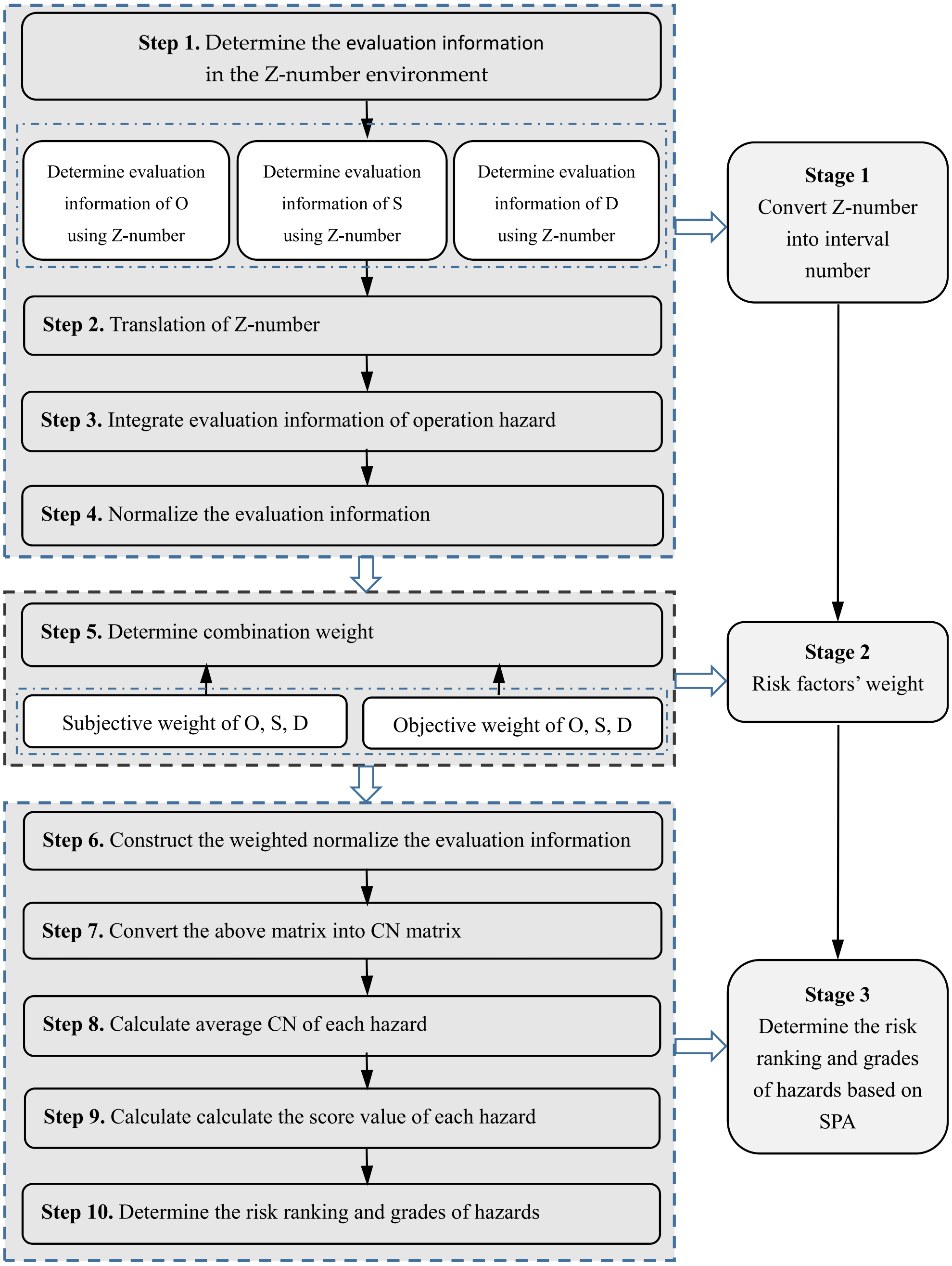


Fig. 1. Execution steps of the proposed model.

hazards in crane operation according to the scores of the hazards. The execution steps of the proposed model are illustrated in Fig. 1 and described below.

Step 1. Determine the evaluation information in the Z-number environment.

Suppose that there are n hazards (H_1, H_2, …, Hi, …, H_n) to be evaluated, each having three risk factors (O, S, and D) expressed by C_j ($j = 1, 2, 3$), and the kth expert is denoted as E_k ($k = 1, \ldots, K$). Let be the Z-number from E_k for the C_j value of the ith hazard. According to Eqs. (1)–(5), it can be expressed as

$$Z_{ij}^{k} = \left(A_{ij}^{k}, B_{ij}^{k}\right). \tag{9}$$

Step 2. Transform the Z-number.

In classical risk assessment studies utilizing MCDM models with fuzzy numbers, researchers tended to convert fuzzy numbers into crisp numbers, which were then treated as evaluation values to rank the hazards. However, this conversion process can result in the loss of critical information, affecting the accuracy of the evaluation outcome. Let $Z_{ij}^{k} = (A_{ij}^{k}, B_{ij}^{k})$ be the evaluation value for the Hi of the index C_j for Hi associated with E_k, and let $A_{ij}^{k} = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)_{ij}^{k}$ be a TrFN. $Z_{ij}^{k} = (A_{ij}^{k}, B_{ij}^{k})$ described in Eq. (9) is transformed into an interval number using the following formulas [60]. A TFN is a special case of a TrFN when $\alpha_2 = \alpha_3$.

$$\begin{aligned} Z_{ij}^{k} &= \left(A_{ij}^{k}, B_{ij}^{k}\right) \\ &= \left[\sqrt{\alpha}\,\alpha_1 + \sqrt{\alpha}\,\alpha(\alpha_2 - \alpha_1), \sqrt{\alpha}\,\alpha_4 - \sqrt{\alpha}\,\alpha(\alpha_4 - \alpha_3)\right]^{(k)} \\ &= \left[e_{ij}^{-}, e_{ij}^{+}\right]^{(k)} = \left(e_{ij}\right)^{(k)} \end{aligned} \tag{10}$$

Step 3. Integrate the evaluation information of the operation hazards.

The integrated risk score of each risk factor is given as follows [40]:

$$\begin{aligned} Agg\left(e_{ij}\right) &= Agg\left(e_{ij}^{(1)}, e_{ij}^{(2)}, \cdots, e_{ij}^{(k)}\right) \\ &= \text{average}\left[\left[e_{ij}^{-}, e_{ij}^{+}\right]^{(1)}, \left[e_{ij}^{-}, e_{ij}^{+}\right]^{(2)}, \cdots, \left[e_{ij}^{-}, e_{ij}^{+}\right]^{(k)}\right] \\ &= \frac{1}{K}\sum_{k=1}^{K} e_{ij}^{(k)}, \end{aligned} \tag{11}$$

where Agg (.) denotes the aggregation function.

Step 4. Normalize the evaluation information.

$$R = \begin{bmatrix} \left[e_{11}^{'-}, e_{11}^{'+}\right] & \left[e_{12}^{'-}, e_{12}^{'+}\right] & \cdots & \left[e_{1j}^{'-}, e_{1j}^{'+}\right] \\ \left[e_{21}^{'-}, e_{21}^{'+}\right] & \left[e_{22}^{'-}, e_{22}^{'+}\right] & \cdots & \left[e_{2j}^{'-}, e_{2j}^{'+}\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[e_{i1}^{'-}, e_{i1}^{'+}\right] & \left[e_{i2}^{'-}, e_{i2}^{'+}\right] & \cdots & \left[e_{ij}^{'-}, e_{ij}^{'+}\right] \end{bmatrix} \tag{12}$$

The normalized values for each interval number in the decision matrix $\boldsymbol{R}$ are calculated using the following formulas [75,76].

$$\begin{cases} e_{ij}^{'-} = \left(1/e_{ij}^{+}\right) \Big/ \sum_{i=1}^{m}\left(1/e_{ij}^{-}\right) \\ e_{ij}^{'+} = \left(1/e_{ij}^{-}\right) \Big/ \sum_{i=1}^{m}\left(1/e_{ij}^{+}\right) \end{cases} \quad j \in C \tag{13}$$

$$\begin{cases} e_{ij}^{'-} = e_{ij}^{-} \Big/ \sum_{i=1}^{m} e_{ij}^{+} \\ e_{ij}^{'+} = e_{ij}^{+} \Big/ \sum_{i=1}^{m} e_{ij}^{-} \end{cases} \quad j \in B \tag{14}$$

Step 5. Determine the combined weight.

Let $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ denote the subjective and objective weight vectors, respectively, for the risk factors (O, S, and D). The combined weight is calculated using Eq. (15) [40].

$$\mathrm{w} = \xi\,\mathrm{w}_1 + (1-\xi)\mathrm{w}_2 \ \ ; \ \xi \in [0,1] \tag{15}$$

here, ξ is a combination coefficient for the subjective and objective weights.

Step 6. Obtain the weighted normalized evaluation information.

$$\mathrm{v} = \left[v_{ij}\right]_{m\times n}, \quad i = 1,2,\cdots,m, \text{and } j = 1,2,\cdots,n. \tag{16}$$

here, $v_{ij} = e_{ij} \times w_j$.

Step 7. Convert the above matrix into the CN matrix via Eq. (17) [67]. This yields

$$\mathrm{u} = \left[u_{ij}\right]_{m\times n} = \left[v_{ij}^- + \left(v_{ij}^+ - v_{ij}^-\right)\mathrm{I} + \left(1 - v_{ij}^+\right)\mathrm{J}\right]_{m\times n}, \quad i = 1,2,\cdots,m, \text{and } j = 1,2,\cdots,n. \tag{17}$$

Step 8. Calculate the average CN [67] of each hazard.

$$\mu_i = \frac{1}{n}\left(\sum_{j=1}^{n} v_{ij}^- + \sum_{j=1}^{n}\left(v_{ij}^+ - v_{ij}^-\right)\mathrm{I} + \sum_{j=1}^{n}\left(1 - v_{ij}^+\right)\mathrm{J}\right), \quad i = 1,2,\cdots,m, \text{and } j = 1,2,\cdots,n. \tag{18}$$

Step 9. Calculate the score [67] of each hazard via Eq. (8).

$$S(\mu_i) = \frac{\sum_{j=1}^{n} v_{ij}^-}{\sum_{j=1}^{n}\left(1 - v_{ij}^+\right)}, \quad i = 1,2,\cdots,m, \text{and } j = 1,2,\cdots,n. \tag{19}$$

Step 10. Determine the risk ranking and grades of hazards.

Using Eq. (19), $S(\mu_i)$ for each hazard Hi is determined. The hazard prioritization is provided by ranking the $S(\mu_i)$ values. According to $S(\mu_i)$, the grade discrimination range of each hazard can be established. Thus, the grades of hazards for crane operation can be determined.

4. Case study

Two numerical cases were examined by the proposed modified FMEA. The first case was applied to validate the proposed approach. Toward this goal, according to the assessment data and Z-FUCOM-CoCoSo model of Yousefi et al. [77], the proposed Z-SPA was compared with other evaluation methods. In the second case, Z-SPA was applied to crane operation hazard risk assessment. According to the same assessment information from the study addressed in Das et al. [40], and the proposed Z-SPA method was compared with Z-VIKOR. Finally, the evaluation results were analyzed and compared to confirm the superiority of Z-SPA.

4.1. Case 1

In the first case, the evaluation data were selected from the literature [77]. To verify the results and assess the applicability of Z-SPA, 11 FMs of the automotive parts industry were selected, and the evaluation information of S, O, and D for each FM were given with Z-numbers, as shown in Table 1 [77].

The decision matrix with the Z-number (see Table 1) is transformed into an interval number (listed in Table 2) using Eq. (10). Then, the decision matrix is normalized using Eqs. (13) and (14). In this case, the weights of S, O, and D are obtained from the literature [77]. Because the weight values are TFNs, fuzzy values are defuzzified using the equation $w_j = (w_j^l + w_j^m + w_j^n)/3$. The weights of S, O, and D are presented in Table 1. The weighted normalized decision matrix can be obtained. Using Eqs. (16)–(19), the score value $S(\mu_i)$ of each hazard is determined. The results for the prioritized order of 11 failures are presented in Table 3.

As shown in Tables 3 and 4 and Figs. 2 and 3, the ranking orders of the different methods are not entirely the same. Additionally, a comparison of different methods is presented in Fig. 3. Clearly, the risk priority of our approach was the most similar to that of Z-FUCOM-CoCoSo. Because the Z-FUCOM-CoCoSo can provide administrators with more effective and trustworthy results than Fuzzy-FUCOM-CoCoSo and Fuzzy-FMEA [77], these findings suggest that the proposed Z-SPA approach is reliable.

4.2. Case 2

Hazard recognition and assessment are fundamental to safety management. However, onsite hazard identification in real-world scenarios is difficult, expensive, and hazardous. To address this issue, Das et al. [40] devised a virtual reality (VR)-based simulator for EOT cranes to facilitate hazard identification and collect assessment data pertaining to crane operation hazards. This study considered data from the literature [40] for comparative purposes to ensure the validity of the proposed methods. To illustrate the practical implementation of the Z-SPA method, an illustrative hazard prioritization case study involving crane operations [40] was conducted. This application example is described below.

Cranes are widely used in construction, dockyards, railway transportation, and other production fields for hoisting and conveying heavy loads. They are important to industrial enterprises but can cause accidents. Identification of hazards in crane operations is a vital procedure for the proposed framework. In this study, an expert team consisting of three members, i.e., DM_k ($k = 1, 2, 3$), was established to perform the risk evaluation of each operation hazard. Thirteen operation hazards were identified by the experts and denoted as Hi ($i = 1, 2, \ldots, 13$). The following hazards [40] were identified: “Worker may become injured when they are working in close proximity to the Scheuerle car” (H1), “During the preliminary processing of the ladle on the pre-processing stand, there is a possibility of workers falling” (H2), “Worker may stumble while walking near the railway track” (H3), “When working in close vicinity to the steel car, workers run the risk of being struck by the mast inside the car, which can cause them to fall” (H4), “Operator may be electrocuted by the live panel and MCB inside the cabin while performing activities in the cabin” (H5), “A potential hazard exists as operators have to jump to enter the cabin from the gantry path near it, which can lead to injuries or even fatalities” (H6), “The ladle may collide with the nozzle pipe as it travels through the bay, potentially causing an imbalance in its movement” (H7), “There is a risk of the ladle being misplaced and falling while the operator is placing it on the caster” (H8), “During the transfer of the ladle from one place to another, there is a possibility of it falling from the hook and injuring a ground worker” (H9), “The hoist rope may break while the ladle is being lifted with a hook, causing the ladle to fall on the ground and harm a worker” (H10), “When the operator tilts the full ladle, there is a possibility of molten metal spilling onto the ground and causing burns to ground workers” (H11), “Workers who are working near molten metal may be at risk of becoming ill due to excessive smoke exposure” (H12), and “The ladle may fall and injure a ground worker if the hook is not properly engaged while the operator is lifting or tilting it with the hook or back hook” (H13).

Table 1
[77] Values of risk factors of identified FMs in the form of the Z-number.

Failure	S		O		D	
	A	B	A	B	A	B
F01	(0.7,0.8,0.9)	(0.5,0.7,0.9)	(0.1,0.2,0.3)	(0.5,0.7,0.9)	(0.1,0.2,0.3)	(0.5,0.7,0.9)
F02	(0.8,0.9,1)	(0.7,1,1)	(0.2,0.3,0.4)	(0.7,1,1)	(0.1,0.2,0.3)	(0.7,1,1)
F03	(0.8,0.9,1)	(0.5,0.7,0.9)	(0.1,0.2,0.3)	(0.5,0.7,0.9)	(0.2,0.3,0.4)	(0.5,0.7,0.9)
F04	(0.8,0.9,1)	(0.5,0.7,0.9)	(0.3,0.4,0.5)	(0.5,0.7,0.9)	(0.2,0.3,0.4)	(0.5,0.7,0.9)
F05	(0.9,1,1)	(0.5,0.7,0.9)	(0.2,0.3,0.4)	(0.5,0.7,0.9)	(0.1,0.2,0.3)	(0.5,0.7,0.9)
F06	(0.9,1,1)	(0.7,1,1)	(0.2,0.3,0.4)	(0.7,1,1)	(0.1,0.2,0.3)	(0.7,1,1)
F07	(0.9,1,1)	(0.5,0.7,0.9)	(0.2,0.3,0.4)	(0.5,0.7,0.9)	(0.2,0.3,0.4)	(0.5,0.7,0.9)
F08	(0.8,0.9,1)	(0.7,1,1)	(0.2,0.3,0.4)	(0.7,1,1)	(0.3,0.4,0.5)	(0.7,1,1)
F09	(0.9,1,1)	(0.7,1,1)	(0.1,0.2,0.3)	(0.7,1,1)	(0.1,0.2,0.3)	(0.7,1,1)
F10	(0.9,1,1)	(0.7,1,1)	(0.1,0.2,0.3)	(0.7,1,1)	(0.2,0.3,0.4)	(0.7,1,1)
F11	(0.6,0.7,0.8)	(0.7,1,1)	(0.2,0.3,0.4)	(0.7,1,1)	(0.1,0.2,0.3)	(0.7,1,1)
Weight	(0.32,0.39,0.47)		(0.27,0.35,0.44)		(0.20,0.27,0.36)	

Table 2
Values of risk factors after converting to the interval number.

Failure	S	O	D
F01	[0.6442,0.6944]	[0.2845,0.3849]	[0.2845,0.3849]
F02	[0.8443,0.8633]	[0.5502,0.5882]	[0.3605,0.3984]
F03	[0.7279,0.7781]	[0.2845,0.3849]	[0.4518,0.5522]
F04	[0.7279,0.7781]	[0.6191,0.7195]	[0.4518,0.5522]
F05	[0.8116,0.8367]	[0.4518,0.5522]	[0.2845,0.3849]
F06	[0.9392,0.9487]	[0.5502,0.5882]	[0.3605,0.3984]
F07	[0.8116,0.8367]	[0.4518,0.5522]	[0.4518,0.5522]
F08	[0.8443,0.8633]	[0.5502,0.5882]	[0.74,0.7779]
F09	[0.9392,0.9487]	[0.3605,0.3984]	[0.3605,0.3984]
F10	[0.9392,0.9487]	[0.3605,0.3984]	[0.5502,0.5882]
F11	[0.6546,0.6736]	[0.5502,0.5882]	[0.3605,0.3984]

Table 3
Results of the implementation of Z-SPA.

Failure	$\sum_{j=1}^{n} v_{ij}^{-}$	$\sum_{j=1}^{n} (1 - v_{ij}^{+})$	$S(\mu_i)$	Priority
FM1	0.0597	2.9193	0.0205	11
FM2	0.0886	2.8967	0.0306	5
FM3	0.0719	2.9056	0.0248	10
FM4	0.0925	2.8820	0.0321	2
FM5	0.0772	2.9012	0.0266	9
FM6	0.0927	2.8929	0.0320	3
FM7	0.0858	2.8912	0.0297	6
FM8	0.1081	2.8741	0.0376	1
FM9	0.0810	2.9062	0.0279	7
FM10	0.0907	2.8950	0.0313	4
FM11	0.0804	2.9051	0.0277	8

Table 4
Comparison of the results with those of other methods.

	Z-SPA	Z-FUCOM-CoCoSo [77]	Fuzzy-FUCOM-CoCoSo [77]	Fuzzy-FMEA [77]
FM1	11	11	10	7
FM2	5	5	6	4
FM3	10	8	7	4
FM4	2	2	1	1
FM5	9	10	4	3
FM6	3	3	4	3
FM7	6	7	3	2
FM8	1	1	2	1
FM9	7	6	8	6
FM10	4	4	5	3
FM11	8	9	9	5

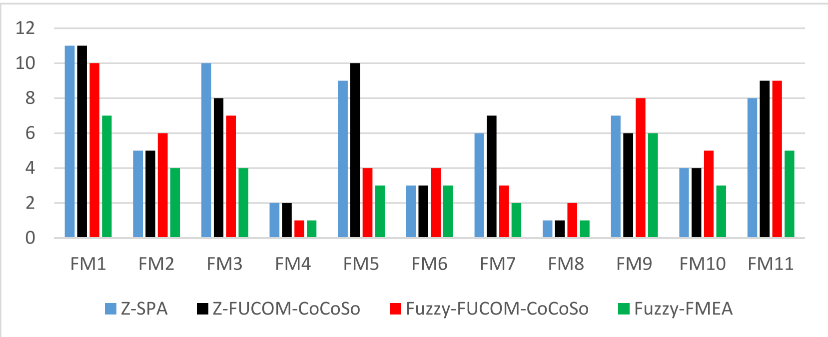
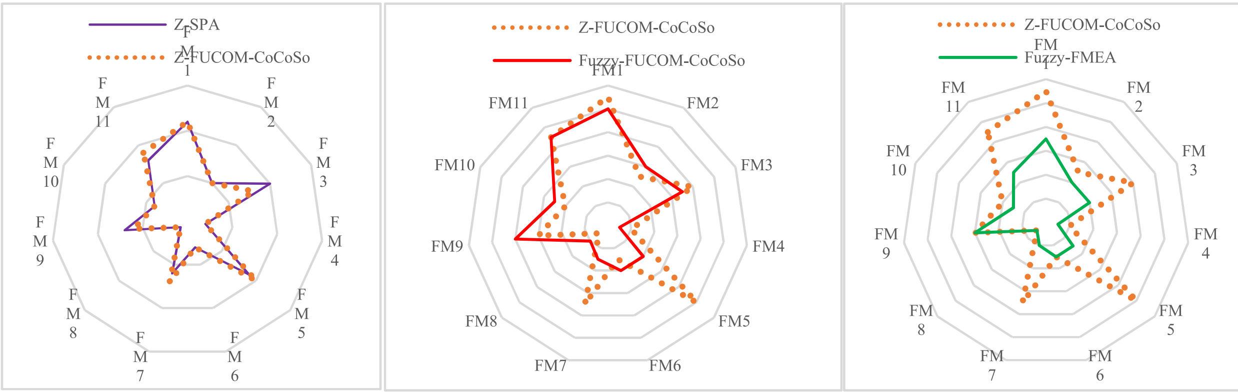


Fig. 2. Final ranking of the FMs with different methods for case study 1. (a) Z-SPC (b) Fuzzy-FUCOM-CoCoSo (c) Fuzzy-FMEA.



(a) Z-SPC (b) Fuzzy-FUCOM-CoCoSo (c) Fuzzy-FMEA

Fig. 3. The comparison with the Z-FUCOM-CoCoSo method, respectively: (a) Z-SPC. (b) Fuzzy-FUCOM-CoCoSo. (c) Fuzzy-FMEA.

Table 5
Values of risk factors after converting to the interval number.

	Hazard	S	O	D
DM1	H1	[7.3235,7.5717]	[6.4423,6.9443]	[5.3033,6.0104]
	H2	[3.182,3.8891]	[3.182,3.8891]	[3.182,3.8891]
	H3	[8.2544,9.3095]	[7.3235,7.5717]	[7.3235,7.5717]
	H4	[3.182,3.8891]	[3.182,3.8891]	[3.182,3.8891]
	H5	[4.769,6.1076]	[3.9323,4.4343]	[3.9323,4.4343]
	H6	[1.2598,2.5743]	[1.2598,2.5743]	[1.2598,2.5743]
	H7	[7.3235,7.5717]	[5.4616,6.6408]	[5.4616,6.6408]
	H8	[8.2544,9.3095]	[7.3235,7.5717]	[7.3235,7.5717]
	H9	[7.8328,7.8983]	[7.8328,7.8983]	[7.8328,7.8983]
	H10	[1.2598,2.5743]	[4.769,6.1076]	[4.769,6.1076]
	H11	[8.816,9.8319]	[8.816,9.8319]	[8.816,9.8319]
	H12	[8.816,9.8319]	[8.816,9.8319]	[8.816,9.8319]
	H13	[8.816,9.8319]	[1.2598,2.5743]	[3.182,3.8891]
DM2	H1	[0,0.6816]	[1.7378,1.986]	[8.2544,9.3095]
	H2	[0,0.6816]	[1.0607,1.7678]	[7.3235,7.5717]
	H3	[5.3033,6.0104]	[5.3033,6.0104]	[8.2544,9.3095]
	H4	[0,0.9311]	[1.7378,1.986]	[8.2544,9.3095]
	H5	[2.3552,3.122]	[4.769,6.1076]	[7.3235,7.5717]
	H6	[6.4423,6.9443]	[5.4616,6.6408]	[4.769,6.1076]
	H7	[1.7378,1.986]	[2.6687,3.8479]	[7.3235,7.5717]
	H8	[5.4616,6.6408]	[5.4616,6.6408]	[8.2544,9.3095]
	H9	[2.6687,3.8479]	[1.7378,1.986]	[7.3235,7.5717]
	H10	[8.2544,9.3095]	[2.5136,3.8479]	[7.3235,7.5717]
	H11	[7.3235,7.5717]	[8.2544,9.3095]	[8.2544,9.3095]
	H12	[7.3235,7.5717]	[5.4616,6.6408]	[7.8328,7.8983]
	H13	[7.3235,7.5717]	[7.3235,7.5717]	[7.3235,7.5717]
DM3	H1	[7.3235,7.5717]	[4.5306,4.7789]	[7.3235,7.5717]
	H2	[5.4616,6.6408]	[2.6687,3.8479]	[7.3235,7.5717]
	H3	[7.3235,7.5717]	[1.7378,1.986]	[7.3235,7.5717]
	H4	[8.816,9.8319]	[1.7378,1.986]	[7.3235,7.5717]
	H5	[8.2544,9.3095]	[1.7378,1.986]	[7.3235,7.5717]
	H6	[8.2544,9.3095]	[1.7378,1.986]	[7.3235,7.5717]
	H7	[7.3235,7.5717]	[2.6687,3.8479]	[7.3235,7.5717]
	H8	[7.3235,7.5717]	[5.4616,6.6408]	[7.3235,7.5717]
	H9	[8.2544,9.3095]	[4.5306,4.7789]	[7.3235,7.5717]
	H10	[8.2544,9.3095]	[1.7378,1.986]	[4.5306,4.7789]
	H11	[8.816,9.8319]	[2.6687,3.8479]	[7.3235,7.5717]
	H12	[2.6687,3.8479]	[4.5306,4.7789]	[7.3235,7.5717]
	H13	[1.7378,1.986]	[7.3235,7.5717]	[7.3235,7.5717]

Step 1. Determine the evaluation information in the Z-number environment.

The linguistic variables of O, S, and D are presented in Table A1 (see Appendix) [78] by Z-number. The descriptions of the Z-numbers for S, O, and D with respect to the 13 hazards are presented in Table A2 [40] (see Appendix).

Step 2. Transform the Z-number.

Using Eq. (10) and Tables A1 and A2, Z-numbers are transformed into interval numbers, as shown in Table 5.

Steps 3 and 4. Integrate and normalize the evaluation information of the operation hazards.

The integrated and normalized evaluation information are obtained by using Eqs. (11)–(14) and Table 5, as shown in Table 6.

Step 5. Determine the combined weights.

To compare the assessment results of the different methods, the subjective weights, objective weights and combined weights for the risk factors were examined, as shown in Table 7 [40].

Step 6. Obtain the weighted normalized evaluation information.

According to Tables 6 and 7, the weighted normalized fuzzy decision matrix was obtained as follows:

$$
R = \begin{array}{c} \\ \left[\begin{array}{ccc}
[0.0173, 0.0213] & [0.0199, 0.0259] & [0.0216, 0.0258] \\
[0.0244, 0.036] & [0.0287, 0.0477] & [0.0259, 0.0302] \\
[0.012, 0.0149] & [0.0175, 0.0229] & [0.0202, 0.0235] \\
[0.0187, 0.0259] & [0.0347, 0.0495] & [0.0238, 0.0287] \\
[0.0148, 0.0202] & [0.0218, 0.0316] & [0.0252, 0.0289] \\
[0.0145, 0.0195] & [0.0244, 0.0389] & [0.0304, 0.0403] \\
[0.016, 0.019] & [0.019, 0.0305] & [0.0227, 0.0267] \\
[0.0116, 0.0148] & [0.0131, 0.0181] & [0.0202, 0.0235] \\
[0.013, 0.0166] & [0.0186, 0.0234] & [0.0214, 0.0239] \\
[0.0129, 0.0175] & [0.0229, 0.0365] & [0.0267, 0.0323] \\
[0.01, 0.0125] & [0.0119, 0.0167] & [0.0185, 0.022] \\
[0.0129, 0.0166] & [0.0128, 0.0175] & [0.0195, 0.0224] \\
[0.0141, 0.0174] & [0.0154, 0.0207] & [0.0259, 0.0302] \\
[0.0456, 0.0537] & [0.0455, 0.0568] & [0.0823, 0.0927] \\
[0.023, 0.0356] & [0.0229, 0.0376] & [0.0415, 0.0615] \\
[0.0184, 0.0213] & [0.0184, 0.0225] & [0.0332, 0.0367] \\
[0.0132, 0.0177] & [0.0132, 0.0187] & [0.0238, 0.0306] \\
[0.0115, 0.0132] & [0.0115, 0.014] & [0.0208, 0.0229] \\
[0.0093, 0.0118] & [0.0093, 0.0125] & [0.0167, 0.0203]
\end{array}\right] \end{array}
\begin{array}{c}
\text{Hazard} \\
\text{H1} \\ \text{H2} \\ \text{H3} \\ \text{H4} \\ \text{H5} \\ \text{H6} \\ \text{H7} \\ \text{H8} \\ \text{H9} \\ \text{H10} \\ \text{H11} \\ \text{H12} \\ \text{H13} \\
\text{H} - \text{P} - \text{VH} \\ \text{H} - \text{MP} - \text{VH} \\ \text{H} - \text{M} - \text{VH} \\ \text{H} - \text{MG} - \text{VH} \\ \text{H} - \text{G} - \text{VH} \\ \text{H} - \text{VG} - \text{VH}
\end{array}
$$

Step 7. Convert the above matrix into the CN matrix via Eq. (17).

Table 6
Results for integration and normalization.

Hazard	S		O		D	
	Integration	Normalization	Integration	Normalization	Integration	Normalization
H1	[0.2048,0.1896]	[0.0485,0.0596]	[0.236,0.2188]	[0.0633,0.0824]	[0.1437,0.1311]	[0.0655,0.0783]
H2	[0.3471,0.2676]	[0.0685,0.1011]	[0.4341,0.3156]	[0.0912,0.1515]	[0.1683,0.1576]	[0.0788,0.0917]
H3	[0.1437,0.1311]	[0.0335,0.0418]	[0.2088,0.1927]	[0.0557,0.0729]	[0.131,0.1227]	[0.0614,0.0714]
H4	[0.25,0.2047]	[0.0524,0.0728]	[0.4506,0.3816]	[0.1103,0.1572]	[0.1599,0.1444]	[0.0722,0.0871]
H5	[0.1951,0.1618]	[0.0414,0.0568]	[0.2874,0.2395]	[0.0692,0.1003]	[0.1615,0.1532]	[0.0766,0.088]
H6	[0.188,0.1593]	[0.0408,0.0547]	[0.3546,0.2678]	[0.0774,0.1237]	[0.2247,0.1846]	[0.0923,0.1224]
H7	[0.1831,0.1751]	[0.0448,0.0533]	[0.2778,0.2093]	[0.0605,0.0969]	[0.1492,0.1377]	[0.0689,0.0813]
H8	[0.1426,0.1275]	[0.0326,0.0415]	[0.1644,0.1439]	[0.0416,0.0574]	[0.131,0.1227]	[0.0614,0.0714]
H9	[0.1599,0.1425]	[0.0365,0.0466]	[0.2127,0.2046]	[0.0591,0.0742]	[0.1335,0.1302]	[0.0651,0.0727]
H10	[0.1688,0.1416]	[0.0362,0.0492]	[0.3326,0.2512]	[0.0726,0.116]	[0.1805,0.1625]	[0.0813,0.0983]
H11	[0.1202,0.1102]	[0.0282,0.035]	[0.152,0.1305]	[0.0377,0.053]	[0.123,0.1123]	[0.0562,0.067]
H12	[0.1595,0.1412]	[0.0361,0.0464]	[0.1595,0.1412]	[0.0408,0.0557]	[0.1251,0.1186]	[0.0593,0.0682]
H13	[0.1678,0.1547]	[0.0396,0.0489]	[0.1886,0.1693]	[0.0489,0.0658]	[0.1683,0.1576]	[0.0788,0.0917]
H-P-VH	[0.5172,0.5002]	[0.128,0.1506]	[0.5172,0.5002]	[0.1446,0.1804]	[0.5172,0.5002]	[0.2502,0.2818]
H-MP-VH	[0.3428,0.2522]	[0.0645,0.0998]	[0.3428,0.2522]	[0.0729,0.1196]	[0.3428,0.2522]	[0.1261,0.1868]
H-M-VH	[0.2048,0.2021]	[0.0517,0.0596]	[0.2048,0.2021]	[0.0584,0.0715]	[0.2048,0.2021]	[0.1011,0.1116]
H-MG-VH	[0.1705,0.1446]	[0.037,0.0496]	[0.1705,0.1446]	[0.0418,0.0595]	[0.1705,0.1446]	[0.0723,0.0929]
H-G-VH	[0.1277,0.1266]	[0.0324,0.0372]	[0.1277,0.1266]	[0.0366,0.0445]	[0.1277,0.1266]	[0.0633,0.0696]
H-VG-VH	[0.1134,0.1017]	[0.026,0.033]	[0.1134,0.1017]	[0.0294,0.0396]	[0.1134,0.1017]	[0.0509,0.0618]

$$
R = \begin{bmatrix}
0.0173+0.004I+0.9787J & 0.0199+0.006I+0.9741J & 0.0216+0.0042I+0.9742J \\
0.0244+0.0116I+0.964J & 0.0287+0.0189I+0.9523J & 0.0259+0.0042I+0.9698J \\
0.012+0.003I+0.9851J & 0.0175+0.0054I+0.9771J & 0.0202+0.0033I+0.9765J \\
0.0187+0.0073I+0.9741J & 0.0347+0.0148I+0.9505J & 0.0238+0.0049I+0.9713J \\
0.0148+0.0055I+0.9798J & 0.0218+0.0098I+0.9684J & 0.0252+0.0037I+0.9711J \\
0.0145+0.005I+0.9805J & 0.0244+0.0146I+0.9611J & 0.0304+0.0099I+0.9597J \\
0.016+0.003I+0.981J & 0.019+0.0115I+0.9695J & 0.0227+0.0041I+0.9733J \\
0.0116+0.0032I+0.9852J & 0.0131+0.005I+0.9819J & 0.0202+0.0033I+0.9765J \\
0.013+0.0036I+0.9834J & 0.0186+0.0047I+0.9766J & 0.0214+0.0025I+0.9761J \\
0.0129+0.0046I+0.9825J & 0.0229+0.0137I+0.9635J & 0.0267+0.0056I+0.9677J \\
0.01+0.0024I+0.9875J & 0.0119+0.0048I+0.9833J & 0.0185+0.0036I+0.978J \\
0.0129+0.0037I+0.9834J & 0.0128+0.0047I+0.9825J & 0.0195+0.0029I+0.9776J \\
0.0141+0.0033I+0.9826J & 0.0154+0.0053I+0.9793J & 0.0259+0.0042I+0.9698J \\
0.0456+0.008I+0.9463J & 0.0455+0.0113I+0.9432J & 0.0823+0.0104I+0.9073J \\
0.023+0.0126I+0.9644J & 0.0229+0.0147I+0.9624J & 0.0415+0.02I+0.9385J \\
0.0184+0.0028I+0.9787J & 0.0184+0.0041I+0.9775J & 0.0332+0.0035I+0.9633J \\
0.0132+0.0045I+0.9823J & 0.0132+0.0056I+0.9813J & 0.0238+0.0068I+0.9694J \\
0.0115+0.0017I+0.9868J & 0.0115+0.0025I+0.986J & 0.0208+0.0021I+0.9771J \\
0.0093+0.0025I+0.9882J & 0.0093+0.0032I+0.9875J & 0.0167+0.0036I+0.9797J
\end{bmatrix}
\begin{array}{c}
\text{Hazard} \\
H1 \\ H2 \\ H3 \\ H4 \\ H5 \\ H6 \\ H7 \\ H8 \\ H9 \\ H10 \\ H11 \\ H12 \\ H13 \\ H-P-VH \\ H-MP-VH \\ H-M-VH \\ H-MG-VH \\ H-G-VH \\ H-VG-VH
\end{array}
$$

Step 8. Calculate the average CN of each hazard.

Using Eq. (18), the average CN of each hazard is obtained as follows:

Table 7
Weights of risk factors.

	S	O	D
Subjective weight	0.375288	0.304296	0.320416
Objective weight	0.337461	0.325038	0.337501
Combined weight	0.356375	0.314667	0.328959

$$\mu(\mathrm{H})=\frac{1}{3}\times\begin{array}{c}\\ \left[\begin{array}{c}0.0588+0.0142\mathrm{I}+2.9271\mathrm{J}\\0.0791+0.0348\mathrm{I}+2.8862\mathrm{J}\\0.0497+0.0117\mathrm{I}+2.9387\mathrm{J}\\0.0772+0.0269\mathrm{I}+2.8959\mathrm{J}\\0.0618+0.019\mathrm{I}+2.9193\mathrm{J}\\0.0693+0.0295\mathrm{I}+2.9013\mathrm{J}\\0.0577+0.0186\mathrm{I}+2.9238\mathrm{J}\\0.0449+0.0114\mathrm{I}+2.9437\mathrm{J}\\0.053+0.0109\mathrm{I}+2.9361\mathrm{J}\\0.0625+0.0239\mathrm{I}+2.9136\mathrm{J}\\0.0404+0.0108\mathrm{I}+2.9488\mathrm{J}\\0.0452+0.0113\mathrm{I}+2.9435\mathrm{J}\\0.0554+0.0128\mathrm{I}+2.9317\mathrm{J}\\0.1734+0.0297\mathrm{I}+2.7969\mathrm{J}\\0.0874+0.0472\mathrm{I}+2.8653\mathrm{J}\\0.0701+0.0104\mathrm{I}+2.9196\mathrm{J}\\0.0501+0.0168\mathrm{I}+2.933\mathrm{J}\\0.0439+0.0063\mathrm{I}+2.9499\mathrm{J}\\0.0353+0.0093\mathrm{I}+2.9554\mathrm{J}\end{array}\right]\end{array}\begin{array}{c}\mathrm{Hazard}\\ \mathrm{H1}\\ \mathrm{H2}\\ \mathrm{H3}\\ \mathrm{H4}\\ \mathrm{H5}\\ \mathrm{H6}\\ \mathrm{H7}\\ \mathrm{H8}\\ \mathrm{H9}\\ \mathrm{H10}\\ \mathrm{H11}\\ \mathrm{H12}\\ \mathrm{H13}\\ \mathrm{H-P-VH}\\ \mathrm{H-MP-VH}\\ \mathrm{H-M-VH}\\ \mathrm{H-MG-VH}\\ \mathrm{H-G-VH}\\ \mathrm{H-VG-VH}\end{array}$$

Step 9. Calculate the score of each hazard.

Using Eq. (19), the score $S(\mu_i)$ of each hazard was calculated, as shown in Table 8.

Step 10. Determine the risk ranking and grades of hazards.

Comparing the score values ($S(\mu_i)$; Table 8) of the hazards yielded the following risk priority ranking: H11 > H8 > H12 > H3 > H9 > H13 > H7 > H1 > H5 > H10 > H6 > H4 > H2. According to $S(\mu_i)$, the grade discrimination range of each hazard was established as follows:

$$\begin{cases}\mathrm{S(H-VG-VH)}=0.0119\le \mathrm{S(FM_i)}<\ \mathrm{S(H-G-VH)}=0.0149.\ \text{It belongs to grade I };\\ \mathrm{S(H-G-VH)}=0.0149\le \mathrm{S(FM_i)}\ <\ \mathrm{S(H-MG-VH)}=0.0171.\ \text{It belongs to grade II };\\ \mathrm{S(H-MG-VH)}=0.0171\le \mathrm{S(FM_i)}<\ \mathrm{S(H-M-VH)}=0.0240.\ \text{It belongs to grade III };\\ \mathrm{S(H-M-VH)}=0.0240\le \mathrm{S(FM_i)}\ <\ \mathrm{S(H-MP-VH)}=0.0305.\ \text{It belongs to grade IV};\\ \mathrm{S(H-MP-VH)}=0.0305\le \mathrm{S(FM_i)}<\ \mathrm{S(H-P-VH)}=0.0620.\quad \text{It belongs to grade V };\\ \mathrm{S(H-P-VH)}=0.0620\le \mathrm{S(FM_i)}.\ \text{It belongs to grade VI}.\end{cases}$$

According to Fig. 4, Table 9, and grade discrimination range, the grade of each hazard was determined. For example, the $S(\mu_1)$ for H1 was 0.0201, which was between 0.0171 (S(H-MG-VH)) and 0.024 (S(H-M-VH)). This indicates that the risk for H1 belongs to grade III. All the grades for the crane operation hazards are presented in the rightmost column of Table 9. Furthermore, apart from the risk-ranking region shown in Fig. 4, the bold lines in the figure serve as indicators of the level of danger associated with each region. The color scheme used further emphasizes this, with red representing the highest level of danger and green the least. This visual representation allows for a quick understanding of the comparative danger levels among regions. Notably, H11 is the most dangerous region, while H2 and H4 are relatively safe. The clear distinction between danger levels in Fig. 4 provides valuable insights and aids risk management.

5. Comparative analysis

To confirm the effectiveness of the proposed Z-SPA method, this study compared it with the method of Das et al., which combines the Z-number and VIKOR techniques (Z-VIKOR). The risk ranking outcomes of the different methods are presented in Fig. 4 and Table 9. As indicated by Table 9, the risk ranking for the method of Das et al. [40] was H11 > H12 > H8 > H3 > H9 > H1 > H13 > H7 > H5 > H6 > H10 > H4 > H2. Comparing the $S(\mu_i)$ values of the hazards yielded the following risk priority ranking: H11 > H8 > H12 > H3 > H9 > H13 > H7 > H1 > H5 > H10 > H6 > H4 > H2. The ranking orders of the different methods were not entirely the same. However, as shown in Fig. 5, they were similar.

Table 8
Results of the implementation of the proposed approach.

Hazard	$\sum_{j=1}^{n} v_{ij}^{-}$	$\sum_{j=1}^{n}(1 - v_{ij}^{+})$	$S(\mu_i)$	Priority
H1	0.0588	2.9271	0.0201	8
H2	0.0791	2.8862	0.0274	13
H3	0.0497	2.9387	0.0169	4
H4	0.0772	2.8959	0.0266	12
H5	0.0618	2.9193	0.0212	9
H6	0.0693	2.9013	0.0239	11
H7	0.0577	2.9238	0.0197	7
H8	0.0449	2.9437	0.0153	2
H9	0.0530	2.9361	0.0181	5
H10	0.0625	2.9136	0.0215	10
H11	0.0404	2.9488	0.0137	1
H12	0.0452	2.9435	0.0154	3
H13	0.0554	2.9317	0.0189	6
H-P-VH	0.1734	2.7969	0.0620	
H-MP-VH	0.0874	2.8653	0.0305	
H-M-VH	0.0701	2.9196	0.0240	
H-MG-VH	0.0501	2.9330	0.0171	
H-G-VH	0.0439	2.9499	0.0149	
H-VG-VH	0.0353	2.9554	0.0119	

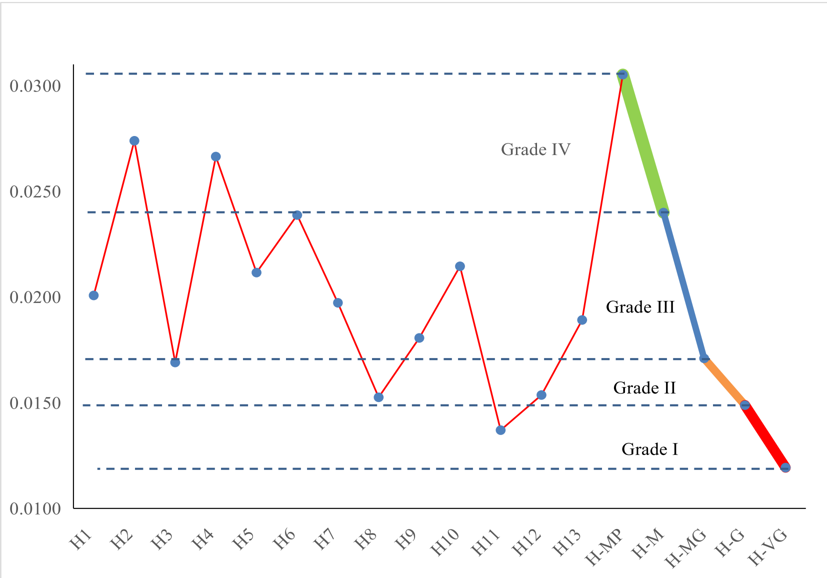


Fig. 4. Hazard grade discrimination range.

In Table 10, the crane operation hazard H11 located in grade I (in Z-SPA) is ranked first for Z-VIKOR. Hazards H12, H8, and H3 located in grade II (in Z-SPA) are ranked second, third, and fourth, respectively, in Z-VIKOR. Hazards H4 and H2 belonging to grade IV (in Z-SPA) have the two lowest rankings in Z-VIKOR. Meanwhile, hazards H9, H13, H7, H1, H5, H10, and H6 belonging to grade III (in Z-CPT) occupy the middle positions of the ranking. These results indicate the practicability and effectiveness of the Z-SPA method. Moreover, from Table 10, it can be finded that Z-VIKOR method only provides the ranking of the crane operation hazards, whereas the Z-SPA method can classify the crane operation hazards. Therefore, the Z-SPA method is superior to the Z-VIKOR method and can provide theoretical support for taking risk precaution measures.

6. Discussion and recommendations

6.1. Discussion

This study proposed a hybrid model that combines the Z-number and SPA to assess and prioritize the risk of crane operation hazards. This paper demonstrated the effectiveness of our model using two practical cases. The advantages of the proposed model are

Table 9
Ranking results based on different methods.

Hazard	Z-number & VIKOR [40] VIKOR (Value of Q)	Z-number & VIKOR [40] Risk rank	Proposed method (Z-SPA) Score $S(\mu_i)$	Proposed method (Z-SPA) Risk rank	Proposed method (Z-SPA) Risk grade
H1	0.466881	6	0.0201	8	Grade III
H2	-1.7×10^{-7}	13	0.0274	13	Grade IV
H3	0.669598	4	0.0169	4	Grade II
H4	0.160197	12	0.0266	12	Grade IV
H5	0.313432	9	0.0212	9	Grade III
H6	0.272032	10	0.0239	11	Grade III
H7	0.364556	8	0.0197	7	Grade III
H8	0.835503	3	0.0153	2	Grade II
H9	0.66818	5	0.0181	5	Grade III
H10	0.269407	11	0.0215	10	Grade III
H11	1	1	0.0137	1	Grade I
H12	0.890222	2	0.0154	3	Grade II
H13	0.403529	7	0.0189	6	Grade III
H-P-VH			0.0620		
H-MP-VH			0.0305		
H-M-VH			0.0240		
H-MG-VH			0.0171		
H-G-VH			0.0149		
H-VG-VH			0.0119		

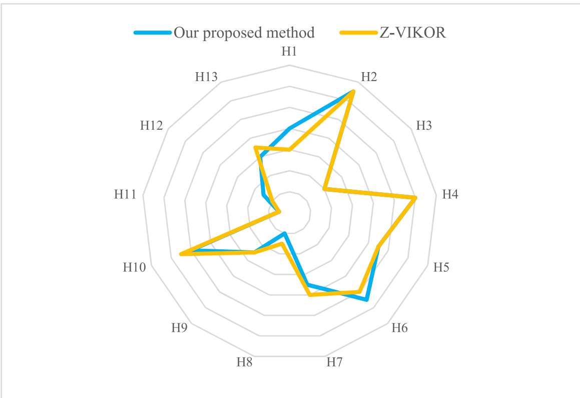


Fig. 5. Outcomes based on different methods.

Table 10
Ranking results based on Z-VIKOR and the proposed method.

Method	Ranking			
Z-VIKOR [40]	H11 ≻	**H12 ≻ H8 ≻ H3 ≻**	H9 ≻ H1 ≻ H13 ≻ H7 ≻ H5 ≻ H6 ≻ H10 ≻	**H4 ≻ H2**
	Grade I	**Grade II**	**Grade III**	**Grade IV**
Proposed method (Z-SPA)	H11 ≻	**H8 ≻ H12 ≻ H3 ≻**	H9 ≻ H13 ≻ H7 ≻ H1 ≻ H5 ≻ H10 ≻ H6 ≻	**H4 ≻ H2**

discussed in detail below.

(1) The model introduces the concept of the Z-number into the risk assessment of hazards. This concept helps to explain the reliability of information precisely. Moreover, in contrast to previous approaches that use crisp values, our method transforms Z-numbers into interval numbers. This preserves more information and reduces the loss of vital data compared with the Z-VIKOR [40].
(2) Our model not only ranks crane operations hazards but also provides a hazard grade that aids decision-making in risk management. Reducing classification errors minimizes losses and damages. This feature significantly enhances the overall risk management level.
(3) SPA is employed to address risk analysis problems. By utilizing connecting numbers, SPA employs "identity," "discrepancy," and "contrary" to represent a system's assurance, hesitancy, and uncertainty without the need for complex calculations. Consequently, the integration of the Z-number and SPA ensures an effective and stable risk-ranking method that significantly reduces the uncertainties, inaccuracies, and complexity in human thinking.

In summary, our proposed model offers an explicit description and quantification of risk factors for hazard prioritization. To validate its applicability and effectiveness, this study presented another case study involving the automotive parts industry in Section 4.

6.2. Recommendations

To prevent crane operation accidents and enhance the safety of crane operations, the following suggestions are proposed.

(1) Improve operator qualifications: When employing cranes, operators should be selected according to their qualifications and professional skills. Only employees with high levels of operational skill can ensure the correct and standardized use of metallurgical cranes, thereby avoiding accidents such as collisions and high-temperature injuries.
(2) Enhancing maintenance and repair skills: The crane maintenance and repair processes are complex and require a high level of technical expertise. It is necessary to learn and utilize modern technological methods for detection and proactive maintenance to ensure smooth progress in maintenance and repair work.
(3) Improve risk prediction ability: Predicting risks according to the operating characteristics of cranes, operating time, lubrication conditions, maintenance history, usage records, and performance data is crucial for minimizing the impact on production. Whenever possible, advanced monitoring tools should be appropriately utilized for early warnings, thereby enhancing the ability to prevent risks.

7. Conclusions

7.1. Conclusions

Crane operation hazard identification and ranking are fundamental for safety management. It is essential to establish an effective model to discuss the risk prioritization and grade determining problem of crane operation hazards under uncertain linguistic evaluation information. In this study, a modified FMEA model based on the Z-number and SPA was developed and applied to crane operation hazard risk assessment. The following conclusions are drawn.

(1) The Z-number was employed to capture the fuzzy information for three risk factors, and the evaluation information for each hazard was then obtained. In Z-SPA, the Z-number is used to deal with the information uncertainty, and a combined weighting approach is adopted to integrate subjective and objective weights.
(2) Aiming at the loss of evaluation information in the conversion of the Z-number into a crisp number, the Z-number is transformed into an interval number to reduce information loss. Through SPA, the risk ranking and grades of hazards can be determined according to the score $S(\mu_i)$.
(3) Two case studies were conducted to verify the efficiency of the proposed model. In case 1, Z-SPA was applied to rank 11 FMs of the automotive parts industry. The results indicated that risk priority of the proposed approach was the most similar to that of Z-FUCOM-CoCoSo. This suggests that the Z-SPA model is reliable. For case 2, the comparison results for crane operation hazard risk assessment confirmed that the proposed Z-SPA model not only provides the risk ranking of crane operation hazards but also can classify grades of crane operation hazards.
(4) The enhanced FMEA approach can provide theoretical support for controlling potential hazards, and the outcomes of the risk assessment will help to minimize the costs of incorrect judgment. Moreover, the proposed method can be implemented in other areas with potential FMs.

7.2. Limitations of study

The proposed model incorporating the Z-number and SPA for crane operation hazard risk assessment has limitations. First, the psychological factors of experts and their personal risk attitudes were not considered in the risk assessment of crane operations. Additionally, the expert evaluation information integrated in this study did not consider a dynamic consensus-reaching process.

Moreover, the I and J values in CN functioned merely as indicators in this study. In reality, specific numerical values depend on various conditions. Therefore, further investigations are essential for determining their values. Furthermore, the data collected in this study were limited, and the effectiveness of the proposed model was confirmed only through references [40,77]. To ensure the effectiveness of the proposed approach, it is necessary to validate it further using a broader range of real-world cases and different approaches.

7.3. Proposed further research

Future research in these directions can be conducted. Owing to the complexity and randomness of assessment information, it is feasible to apply other evaluation methods such as VFS and grey relational analysis and integrate them with other theories such as the cloud model. Additionally, to better reduce information loss, fuzzy-structured elements can be employed in future Z-MCDM research. Furthermore, in future studies, different fuzzy sets (such as spherical fuzzy sets, Pythagorean fuzzy sets, intuitionistic fuzzy sets, hesitant fuzzy sets, probabilistic linguistic term sets, and interval-valued probabilistic uncertain linguistic term sets) and probabilistic language preference relationships could be applied to the risk assessment of crane operation hazards.

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Data availability statement

All relevant data are within the paper.

CRediT authorship contribution statement

Aihua Li: Writing – original draft, Methodology.

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.

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Appendix A

Table A1
[78]. Linguistic variables of O, S, and D.

Restriction component)		Reliability component)	
A	TrFN	B	TFN
Very Poor (VP)	(0, 0, 1, 2)	Very Low (VL)	(0, 0, 0.1)
Poor (P)	(1, 2, 2, 3)	Low (L)	(0, 0.1, 0.3)
Medium Poor (MP)	(2, 3, 4, 5)	Medium Low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(4, 5, 5, 6)	Medium (M)	(0.3, 0.5, 0.7)
Medium Good (MG)	(5, 6, 7, 8)	Medium High (MH)	(0.5, 0.7, 0.9)
Good (G)	(7, 8, 8, 9)	High (H)	(0.7, 0.9, 1)
Very Good (VG)	(8, 9, 10, 10)	Very High (VH)	(0.9, 1, 1)

Table A2
[40]. Experts' assessment of each hazard.

	S						O						D					
	DM1		DM2		DM3		DM1		DM2		DM3		DM1		DM2		DM3	
	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R	A	R
H1	G	H	VP	L	G	H	G	MH	P	H	M	H	G	M	VG	H	G	H
H2	M	M	VP	L	MG	H	M	M	P	M	MP	H	M	M	G	H	G	H
H3	VG	H	G	M	G	H	G	H	G	M	P	H	G	H	VG	H	G	H

(continued on next page)

Table A2 (*continued*)

	S						O						D					
	DM1		DM2		DM3		DM1		DM2		DM3		DM1		DM2		DM3	
H4	M	M	VP	ML	VG	VH	M	M	P	H	P	H	M	M	VG	H	G	H
H5	MG	MH	M	ML	VG	H	M	MH	MG	MH	P	H	M	MH	G	H	G	H
H6	MP	ML	G	MH	VG	H	MP	ML	MG	H	P	H	MP	ML	MG	MH	G	H
H7	G	H	P	H	G	H	MG	H	MP	H	MP	H	MG	H	G	H	G	H
H8	VG	H	MG	H	G	H	G	H	MG	H	MG	H	G	H	VG	H	G	H
H9	G	VH	MP	H	VG	H	G	VH	P	H	M	H	G	VH	G	H	G	H
H10	MP	ML	VG	H	VG	H	MG	MH	MP	H	P	H	MG	MH	G	H	M	H
H11	VG	VH	G	H	VG	VH	VG	VH	VG	H	MP	H	VG	VH	VG	H	G	H
H12	VG	VH	G	H	MP	H	VG	VH	MG	H	M	H	VG	VH	G	VH	G	H
H13	VG	VH	G	H	P	H	MP	ML	G	H	G	H	M	M	G	H	G	H

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