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Failure Mode and Effects Analysis (FMEA) for Traffic Risk Assessment Based on Unbalanced Double Hierarchy Linguistic Term Set

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Abstract As an important technique in safety and reliability analysis, failure mode and effects analysis (FMEA) has been widely utilized to identify and eliminate existing and potential failure. When evaluating the failure modes (FMs), the weights of different FMs are always incompletely known, and different information forms are used to describe the risk assessment issues. The objective of the paper is developing a new approach to solve risk assessment problems faced by four transportation forms in fuzzy and complex environment. In the process of the assessment, the unbalanced double hierarchy linguistic term set (UDHLTS) is used as a linguistic technique to describe the information reasonably and practically. The contributions of this paper are reflected in the following four aspects. Firstly, three linguistic scale functions (LSFs) of the UDHLTS are improved and a semantic model with distinct linguistic cognitive bias parameters is constructed and unified. Secondly, multi-attribute decision-making (MADM) method is applied to FMEA, and an FMEA-MACBETH model is presented to address the risk assessment problems under UDHLTS environment. Meanwhile, weight determination method is built based on the CRITIC method under the situation of completely unknown weights. Finally, a case study of risk assessment in different transportation forms is used to explain the feasibility and rationality of the presented method. Comparison and discussion are conducted to further demonstrate the advantages of the proposed method.

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Keywords Transportation means selection · Unbalanced double hierarchy linguistic term set · Extended fuzzy MACBETH method · The CRITIC method · Multi-attribute decision-making

1 Introduction

As the diversification of transportation methods increases, the transport types are increasing and the transportation network is constantly improving, and the traffic safety has become an important research topic. In order to evaluate the traffic safety and formulate more realistic strategy of road traffic safety scientifically, scholars have carried out a series of studies [1]. Failure mode and effects analysis (FMEA) method [2–4] is regarded as an efficient mean in evaluating the risks, which can evaluate the causes of failure modes (FMs) from different problems. Furthermore, different potential FMs can be identified by the FMEA method. In traditional FMEA approach, Severity (*S*), Occurrence (*O*), and Detection (*D*) are three important factors, and the risk priority number (RPN) is the multiplication of the *O*, *S*, and *D*. Now the FMEA model has been extended to different fields because it is easy to use and understand [5–7]. However, the traditional FMEA method has some disadvantages in practical application. For example, the uncertainty of risk is not considered, especially, in practice, crisp numbers cannot completely describe the risk of FMs. Therefore, the FMEA model is extended to fuzzy environment [8–10]. In addition, the risk assessment is not efficient when the same RPN value represents different combination of risks. To address this drawback, some multiple-attribute decision-making (MADM) methods [11–14] are utilized to process the FMEA model [15–17]. By combing MADM methods, the disadvantages of classical FMEA method can be overcome. Furthermore, due to the increasing complexity of MADM problems, FMEA method was further extended to deal with the fuzzy problems. However, the classical FMEA method does not consider the weights of different risks, and the weight of each risk mode is equal. Obviously, it is inconsistent with the actual situation. In most studies using the FMEA, identification and prioritization of risks is carried out based on the traditional RPN score. RPN score focuses the improvement efforts on the failure mode that may have less severity with a higher score compared to other failure modes with the lower score [18, 19]. In addition, due to the proactive and teamwork nature of FMEA, the RPN determinant factors (S, O and D factors) can often not be regarded as definitive in most cases. In order to achieve more robust results against the opinions of different people, it is necessary to prioritize the failures with regard to the uncertainty in these factors. Also, the concept of reliability and uncertainty of the S, O and D factors could be used to determine the validity of failure prioritizations. Moreover, lack of full prioritization (the distinction between various failure priorities) and the assumption of same importance of the S, O, and D factors are other shortcomings of the conventional FMEA [20]. Therefore, considering the shortcomings of this score, it is necessary to develop a new score for prioritization of failures.

To address the malpractice of crisp numbers under fuzzy and complex environment, the fuzzy set (FS) [21] is proposed. To better express the qualitative evaluation information, linguistic term set (LTS) [22] is introduced. Then, some LTSs are presented, such as hesitant fuzzy LTSs, unbalanced LTSs (ULTSs) and so on. Among them, ULTS can describe the unbalanced distribution of linguistic information. With the increased diversity of decision-making problems, the uncertainty of the data becomes more apparent, and more detail of the rich information needs to be expressed. Based on this situation, Gou et al. [23] presented the double hierarchy LTSs (DHLTSs). Two hierarchy LTSs of DHLTSs can supply more details of the evaluation information. For example, when decision makers (DMs) use LTS S_1 or a double hierarchy linguistic term set (DHLTS) $S_{1\langle O_2^1\rangle}$ to express the evaluation information, the LTS only reflects a single aspect of the information, and the DHLTS can provide more details of the evaluation information. Then, Gou et al. [23, 24] extended the DHLTS to double hierarchy hesitant fuzzy LTS (DHHFLTS) and the DHHFLTS is applied in multi-attribute group decision-making (MAGDM) [12]. Further, Gou et al. [24] developed the distance and similarity measures of DHHFLTS, and Gou and Xu [25] proposed some extensions of DHHFLTS. Further, Gou et al. [26] and Krishankumar et al. [27] proposed some MAGDM methods based on preference information of DHHFLTS, Montserrat-Adell [28] extended the DHLTS to free DHLTS and FDHHFLTS. To represent complex and rich linguistic expressions more precisely and accurately, these forms of linguistic information are uniformly and symmetrically distributed. Nevertheless, some linguistic information is not uniformly distributed. Therefore, the unbalanced LTSs (ULTSs) are proposed to express the information which is not uniformly distributed. Under the ULTS context, the scale functions or transformation functions are the transformation of quantitative description of the LTS. Scale functions are the bridges between unevenly distributed linguistic terms and their semantics. For example, Zhou and Xu [29] contracted a function to express the asymmetric LTS; however, this function ignores the granularities of two linguistic terms. Wang et al. [30] used some linguistic scale functions (LSFs) to express the linguistic terms into crisp numbers. But the scale functions have some limitations. Liao et al. [31] proposed a score function to compare unbalanced hesitant fuzzy linguistic elements based on hesitant degrees and LSFs. To represent unbalanced linguistic information, Fu and Liao [32] proposed the unbalanced double hierarchy LTS (UDHLTS) based on DHLTS and ULTSs to describe the complex and unbalanced information, where, the second hierarchy LTS can give more details of evaluation information. Obviously, the UDHLTS can represent complex linguistic information elaborately and accurately. Furthermore, Fu and Liao [32] constructed different functions of the first and second hierarchy in unbalanced fuzzy environment. To this end, we unify the functions of two hierarchy LTSs and provide a semantic model with distinct linguistic cognitive bias parameters.

The presentation of UDHLTS increases the granularity of LTS, and by the second hierarchy LTS $O = \{o_{-3} =$ far from, $o_{-2} =$ only a little, $o_{-1} =$ a little, $o_0 =$ just right, $o_1 =$ much, $o_2 =$ very much, $o_3 =$ entirely$\}$, the UDHLTS makes the linguistic information expression more detailed than the signal hierarchy LTS $S = \{s_{-3} =$ none, $s_{-2} =$ very low, $s_{-1} =$ low, $s_0 =$ medium, $s_1 =$ high, $s_2 =$ very high, $s_3 =$ perfect$\}$. Therefore, compared with single hierarchy LTS, the UDHLTS can reflect more evaluation information of DMs. For example, when experts give the evaluation information "a little high," according to the semantics forms of UDHLTS, the first hierarchy linguistic term is "$s_1 =$ good," and the second hierarchy linguistic term is "$o_{-1} =$ a little." So, we can get the initial evaluation information by UDHLTS $s_{1\langle o_{-1}\rangle} =$ "a little high." Thus, UDHLTS can provide richer semantic expression by more granularity.

The Measuring Attractiveness by a Categorical Based Evaluation TecHnique (MACBETH) method is proposed to examine the alternatives with multi-attributes and conflicting objectives [33], and its consistency is improved. To address the disadvantages of traditional FMEA, the MACBETH method is utilized to classical FMEA model to avoid the simplicity and irrationality of RPN values. Liu et al. [34] and Huang et al. [35] conducted summary studies on FMEA method and its extensions. The FMEA is an effective tool to address the risk evaluation problems. In the risk assessment, weight determination is a significant work because it can influence the ranking results. Many methods are used to get the attribute weights, including subjective weight methods [36–38] and objective weight methods [12, 39]. Objective weight method can give the attribute weights by the objective evaluation information, and it is more in line with the actual evaluation information. The CRITIC (The CRiteria Importance Through Intercriteria Correlation, CRITIC) method, proposed by Diakoulaki, Mavrotas and Papayannakisin [40], is an effective and reasonable method to calculate the objective weights. In this method, the standard deviation and correlation coefficient are used to measure the contrast and correlation of the criteria. Subsequently, scholars modified the CRITIC method. Krishnan et al. [41] improved the method to Distance Correlation-based CRITIC method. Among other weighting methods, Shannon entropy method determines the objective weight according to the variability of the index. If the change of index value is very small or suddenly becomes larger and smaller, the entropy weight method [42] has limitations. The Integrated Determination of Objective CRIteria Weights (IDOCRIW) method is proposed based on Entropy and Criterion Impact LOSs (CILOS) methods [43]. Compared with these methods, CRITIC method not only considers the influence of attribute variation on weight, but also considers the conflict between attributes. So, the advantages of the CRITIC method are shown as follows: (1) It can identify different evaluation information and then determine objective weights of different attributes; (2) It is an objective method according to the relationship of the original data, so it does not increase the burden of DMs; and (3) the conflict is reflected by standard deviation and correlation coefficient. The larger the coefficient, the greater the conflict and the more information provided. Based on the above analysis, this paper conducts a study and comparison on the different weight determination method.

On the whole, the objective of the paper is to develop a new approach based on FMEA and MACBETH method to solve risk assessment problems faced by four transportation forms in unbalanced double hierarchy linguistic environment. The gaps and motivations are as below. A crisp number is hard to describe the complex and fuzzy information under the complex environment. To express information in more detail, the UDHLTS is presented as a better means to describe the complex evaluation information and describe the distinct linguistic cognitive bias. In addition, the traditional FMEA approach has some drawbacks in obtaining the ranking results according to the RPN scores. Besides, it ignores the significance of FMs and the weights of different risks. Based on these factors, we combine the FMEA and MACBETH method to overcome these shortcomings in the process of assessment. The FMEA method can evaluate different risk problems from O, S, and D. These three aspects can describe the risk factors more completely. Then according to the theory and method of multi-attribute decision-making, we can evaluate and rank different failure modes and alternatives. Therefore, based on the presented method, the risk evaluation problems can be better solved. Furthermore, the proposed framework contains the weight determination method. The weight determination method can evaluate the risk modes and determine the importance of each FM based on CRITIC method. Therefore, the proposed framework is complete and reasonable. The contributions can be highlighted as below. First, the UDHLTSs are utilized to describe complex and fuzzy evaluation information. Three non-uniform distributions of the first and second hierarchy LTS are analyzed, and two different LSFs are used to characterize the semantics of these distributions involving both balanced and unbalanced situations. Moreover, a semantic model with distinct linguistic cognitive bias parameters is constructed. Then, the FMEA and MACBETH approach is combined to deal with the risk assessment problems. The FMEA method can assess the risk factors from three aspect, namely *O*, *S* and *D*. The proposed method avoids the incompleteness of the MACBETH method in evaluating risk factors. Besides, a weight determination approach based on CRITIC method is constructed for risk assessment with completely unknown weight. This approach avoids the subjectiveness when obtaining the weights and makes the weight more realistic. The advantage of CRITIC method based on UDHLTSs is that it can reflect the relationship between information. By weight information, the drawback of FMEA in ignoring the attribute weight of FMs is overcome. Finally, to reflect the rationality of the presented framework, a case about of risk assessment in different transportation means is developed. The presented method and the case provide decision-making basis and reference for solving risk management problems.

The paper is completed as below. Section 2 overviews DHLTS, UDHLTS and their scale functions; three scale functions of two hierarchy LTSs are proved. Section 3 develops the FMEA-MACBETH model under UDHLTS context. Section 4 gives a case to show the feasibility and superiority of the presented framework. Section 5 gives the comparison and discussion of the proposed method and case study. The conclusions are covered in Sect. 6.

2 Preliminaries

In this section, we first reviewed two LSFs of the first hierarchy LTS discussed by Fu and Liao [32]. Section 2.1 shows three different balanced situations, Sect. 2.2 constructs a semantic model with distinct linguistic cognitive bias parameters, and Sect. 2.3 gives the scale functions of UDHLTS consisting of two hierarchies.

2.1 Two LSFs of the First Hierarchy LTS

In this subsection, two kinds of scale functions are used to reflect the semantic model of the first hierarchy LTS, and a mapping between different linguistic terms and their numerical scales based on a function with experts' cognitive bias parameters is given. Figures 1–3 show three different semantic models.

The above scenarios are the three most common linguistic distributions in real linguistic decision-making problems, and they represent three types of linguistic cognition: neutral (Fig. 1), radical (Fig. 2), and conservative (Fig. 3). Obviously, these different LSFs can provide us a mathematical avenue to capture uncertain linguistic information precisely, especially the unbalanced semantics.

The corresponding functions of the linguistic terms are shown in Fig. 4. From Fig. 4, we can see that $f_1(\eta = 1)$ expresses the neutrality cognitive bias of a decision-maker. When $0 < \eta < 1$, the risk attitude of the DMs decreases with the increasing performance of the object. When $\eta > 1$, the risk attitude of the DMs increases with the increasing performance of the object.

Definition 1 [32] Let $S = \{s_\kappa | \kappa = -t, \cdots, -1, 0, 1, \cdots, t;\}$ be the first hierarchy LTS,$s_\kappa \in S$.The linguistic scale function (LSF)f transforms the linguistic term s_κ into a numerical scale in [0,1], where f is an increasing function with respect to the subscript k, and $2t + 1$ is an integer, denoting the granularity of the first hierarchy LTS S. The LSF is selected according to the semantic forms of the LTS. According to the distribution of the first hierarchy LTS, there are two kinds of LSFs (see Figs. 1–3 for t = 3).

(1) For the balanced situation (Fig. 1), the LSF can be given as:

$$f_1(s_\kappa) = \frac{\kappa + t}{2t} \tag{1}$$

(2) For the unbalanced situation (Figs. 2 and 3), the LSF can be established as:

$$f_2(s_\kappa) = 0.5 - 0.5\,t^{-\eta}(-\kappa)^{\eta} \times 1_{\{\kappa<0\}} + 0.5 + 0.5\,t^{-\eta}\kappa^{\eta} \times 1_{\{\kappa \geq 0\}} \tag{2}$$

where $\eta \geq 0$ is the risk appetite parameters of "negative" and "positive," respectively, assigned by experts. $2t + 1$ is the granularity of the first hierarchy LTS. Note that $\eta \geq 0$, and when $\eta = 0$, the $o_v = \frac{1}{2}$.

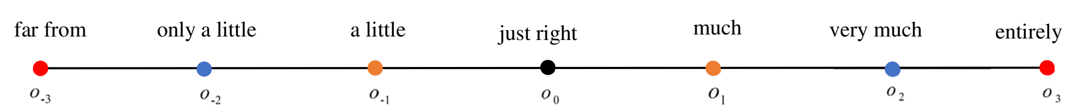

Fig. 1 The uniformly distributed LTS with equal deviation

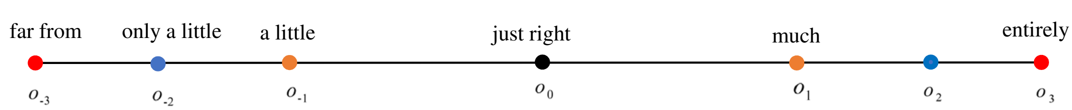

Fig. 2 The unbalanced distributed LTS with increasing deviation

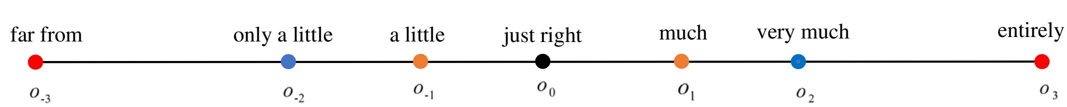

Fig. 3 The unbalanced distributed LTS with decreasing deviation

When the unbalanced situation is increasing deviation (Fig. 2), $\eta \in (0, 1)$ or when the unbalanced situation is decreasing deviation (Fig. 3), $\eta > 1$, the LSF can be established in Fig. 4.

2.2 The Unbalanced Semantics of the Second Hierarchy Linguistic Terms

This subsection shows three different situations of the second hierarchy LTS. The second hierarchy of UDHLTS is more accurate and detailed because of increasing the granularity of evaluation LTS, in the following, three different distributions are shown in Figs. 5–7.

In the second hierarchy linguistic term, the semantics vary with the first hierarchy. When $s_\kappa \geq s_0$, $O = \{o_{-3} =$ far from, $o_{-2} =$ only a little, $o_{-1} =$ a little, $o_0 =$ just right, $o_1 =$ much, $o_2 =$ very much, $o_3 =$ entirely$\}$; when $s_\kappa < s_0$, $O = \{o_{-3} =$ entirely, $o_{-2} =$ very much, $o_{-1} =$ much,$o_0 =$ just right, $o_1 =$ a little, $o_2 =$ only a little, $o_3 =$ far from$\}$.

Definition 2 [32] Let $S = \{s_\kappa | \kappa = -t, \cdots, -1, 0, 1, \cdots, t;\}$ be the first hierarchy LTS, $s_\kappa \in S$; $O = \{o_v | v = -\alpha, \cdots, -1, 0, 1, \cdots, \alpha\}$ be the second hierarchy LTS, $o_v \in O$. The LSF is g, where α is an integer and $2\alpha + 1$ is the granularity of the second hierarchy LTS. When the linguistic terms in O are uniformly distributed, the LSF can be expressed as follows (see Fig. 5).

$$g_1(o_v) = \frac{v}{2\alpha t} \tag{3}$$

When the semantics of O are unbalanced, the LSF of the second hierarchy LTS can be defined as

$$g_2(o_v) = \left(-0.5\alpha^{-\sigma}(-v)^{\sigma}\right) \times \frac{\min(v, 0)}{v} + \left(+0.5\alpha^{-\sigma}v^{\sigma}\right) \times \frac{\max(v, 0)}{|v|} \tag{4}$$

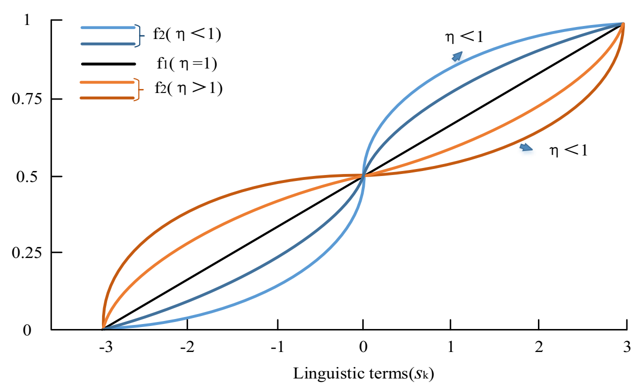

Fig. 4 Three LSFs of the first LTS

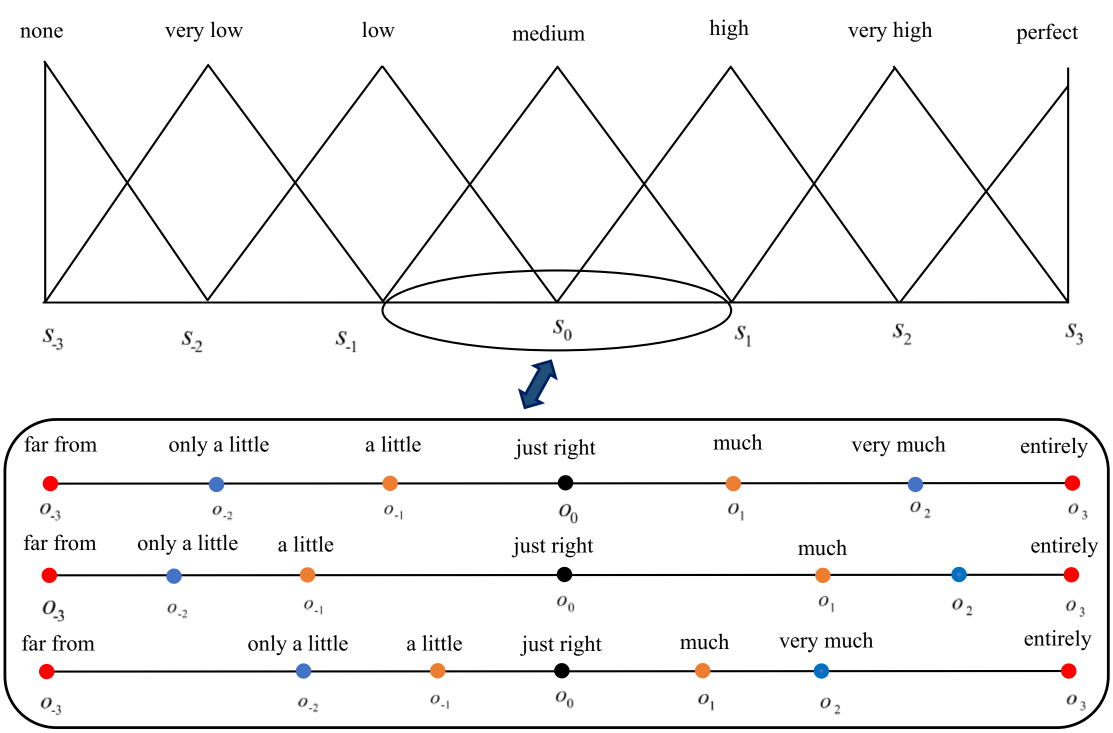

Fig. 5 The unbalanced distributed LTS with decreasing deviation

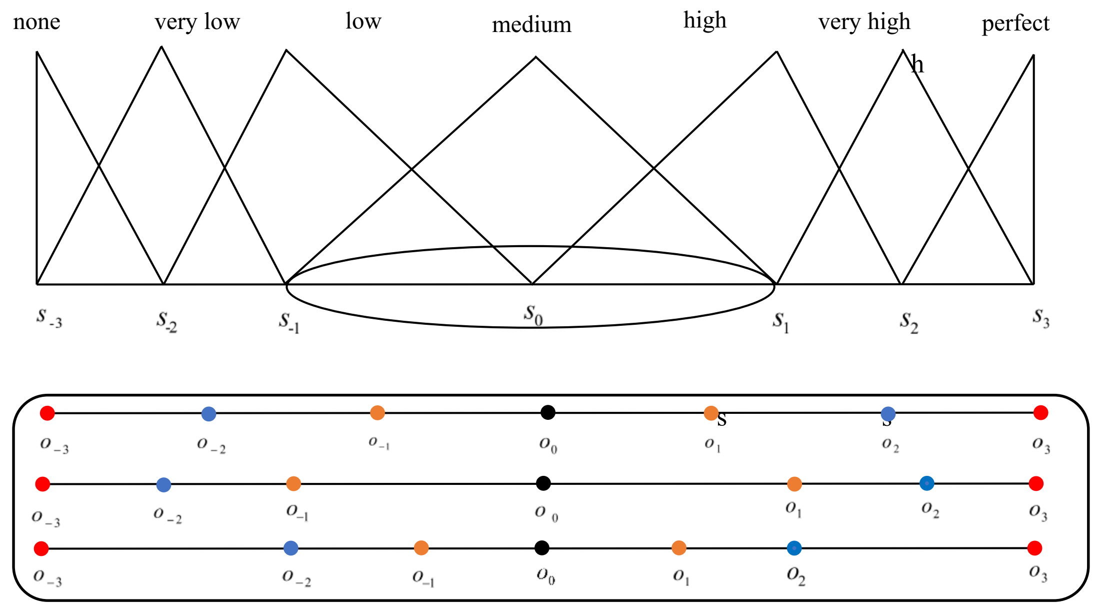

Fig. 6 Information expression form of DHLTSs

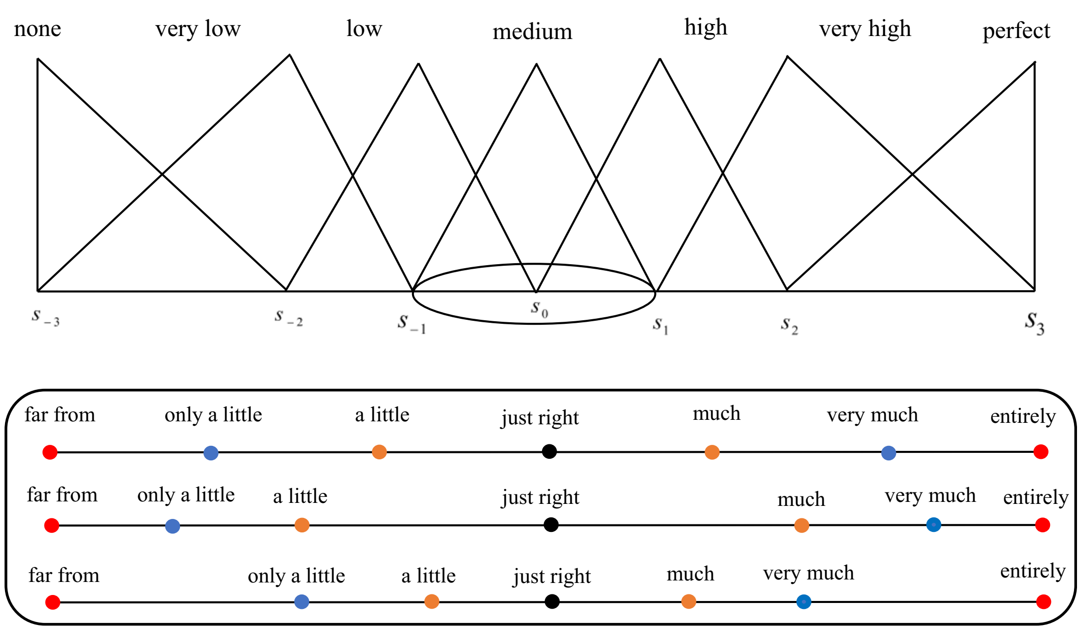

Fig. 7 The unbalanced distributed LTS with increasing deviation

where $2\alpha + 1$ is the granularity of the second hierarchy LTS. $\sigma \geq 0$ is the risk appetite parameters of "negative" and "positive," when the unbalanced situation is increasing deviation (see Fig. 2), $\sigma \in (0, 1)$; when the unbalanced situation is decreasing deviation (see Fig. 3), $\sigma \in (1, +\infty)$. The representations of linguistic terms are shown in Figs. 6 and 7.

Example 1 Let σ be 0.7 and 1.3, respectively. Figure 8 shows the different cognitive bias. From Fig. 8, we can see that the parameter σ indicates different cognitive biases. When $\sigma \in (0, 1)$, the risk attitude of the DMs decreases with the increasing performance of the object. When $\sigma \in (1, +\infty)$, the risk attitude of the DMs increases with the increasing performance of the object.

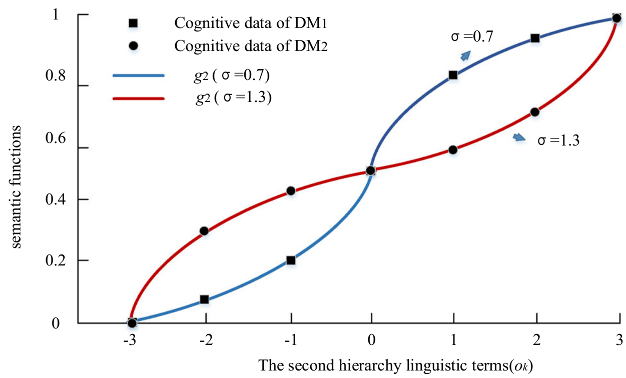

Fig. 8 The unbalanced semantics with different cognitive bias

Remark 1 Let $S=\{s_\kappa|\kappa=-t,\cdots,-1,0,1,\cdots,t;\}$ be the first hierarchy LTS, $s_\kappa\in S$; $O=\{o_v|v=-\alpha,\cdots,-1,0,1,\cdots,\alpha\}$ be the second hierarchy LTS,$o_v\in O$,$s_{\kappa_1\langle o_{v_1}\rangle}$ and $s_{\kappa_2\langle o_{v2}\rangle}$ be two unbalanced double hierarchy linguistic elements, The LSFs are $f_{1,2}$ and $g_{1,2}$ when the linguistic terms are uniformly and non-uniformly distributed, then.

(1) If $f_{1,2}(s_{\kappa_1})+g_{1,2}(o_{v_1})>f_{1,2}(s_{\kappa_2})+g_{1,2}(o_{v_2})$, then $s_{\kappa_1\langle o_{v_1}\rangle}$ is larger than $s_{\kappa_2\langle o_{v2}\rangle}$.

(2) If $f_{1,2}(s_{\kappa_1})+g_{1,2}(o_{v_1})=f_{1,2}(s_{\kappa_2})+g_{1,2}(o_{v_2})$ then.

 1) If $f_{1,2}(s_{\kappa_1})>f_{1,2}(s_{\kappa_2})$, then $s_{\kappa_1\langle o_{v_1}\rangle}$ is larger than $s_{\kappa_2\langle o_{v2}\rangle}$.

 2) If $f_{1,2}(s_{\kappa_1})=f_{1,2}(s_{\kappa_2})$, then $s_{\kappa_1\langle o_{v_1}\rangle}$ is equal to $s_{\kappa_2\langle o_{v2}\rangle}$.

2.3 Unbalanced Double Hierarchy Linguistic Term Set

As we know, the semantic of a linguistic term can be represented by a LSF mathematically. In this subsection, the scale functions of UDHLTS consisting of first and second hierarchies are shown as follows.

Definition 3 Let $S=\{s_\kappa|\kappa=-t,\cdots,-1,0,1,\cdots,t\}$ be the first hierarchy LTS,$s_\kappa\in S$; $O=\{o_v|v=-\alpha,\cdots,-1,0,1,\cdots,\alpha\}$ be the second hierarchy LTS,$o_v\in O$. The $f_1(s_\kappa)$,$f_2(s_\kappa)$ and $g_1(o_v)$,$g_2(o_v)$ are their LSFs, respectively. $2t+1$ and $2\alpha+1$ are the granularity of the two hierarchy LTS, respectively. When S and O are non-uniformly distributed, the UDHLTS can be defined as:

$$U_{S_O}=\Big\{s_{\kappa_{\langle o_v\rangle}},u(\kappa,v)/\ u(\kappa,v)=f_1(s_\kappa)+g_1(o_v);\ \kappa=-t,\cdots,-1,0,1,\cdots,t;v=-\alpha,\cdots,-1,0,1,\cdots,\alpha\Big\} \tag{5}$$

when the UDHLTS is uniformly distributed;

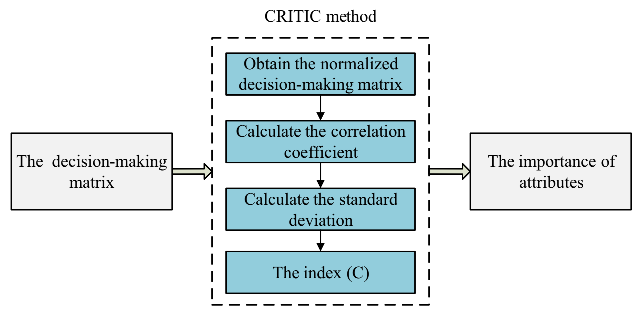

Fig. 9 The process of CRITIC method

$$U_{S_O}=\Big\{s_{\kappa_{\langle o_v\rangle}},u(\kappa,v)/\ u(\kappa,v)=f_2(s_\kappa)+\frac{g_2(o_v)}{2t\alpha};\ \kappa=-t,\cdots,-1,0,1,\cdots,t;v=-\alpha,\cdots,-1,0,1,\cdots,\alpha\Big\} \tag{6}$$

when the UDHLTS is non-uniformly distributed, where u denotes the semantic of the $s_{\kappa\langle o_v\rangle}$, called the unbalanced double hierarchy semantic value (UDHSV).

Definition 4 Let $S=\{s_\kappa|\kappa=-t,\cdots,-1,0,1,\cdots,t\}$ be the first hierarchy LTS,$s_\kappa\in S$; $O=\{o_v|v=-\alpha,\cdots,-1,0,1,\cdots,\alpha\}$ be the second hierarchy LTS,$o_v\in O$. The complement set of U_{S_O} is.

$$\tilde{U}_{S_O}=\{s_{-\kappa\langle o_{-v}\rangle}|s_{-\kappa\langle o_{-v}\rangle}\in S_O;\kappa=-t,\cdots,-1,0,1,\cdots,t;v=-\alpha,\cdots,-1,0,1,\cdots,\alpha\} \tag{7}$$

3 The FMEA-MACBETH Model under UDHLTS Context

In this section, a new fuzzy MADM approach called FMEA-MACBETH is presented. In this approach, the CRITIC method proposed by Diakoulaki, Mavrotas and Papayannakisin [40] is used to obtain the importance of different FMs, which overcomes the disadvantage of traditional FMEA model in ignoring the weights of different FMs. Furthermore, the MACBETH method [33] is utilized to calculating the ranking of alternatives and all FMs.

3.1 Weight Determination Method Based on CRITIC Approach

The CRITIC method [40] is an efficient tool in weight determination, which can transform the qualitative into quantitative attributes. This method takes the contrast intensity and the conflicting character of different criteria into account. The correlation coefficient is based on the correlation between different attributes. The characteristic of this method is considering the contrast intensity of each single criterion and the conflict of different attributes. This objective weight determination method avoids the experts' subjective views. Therefore, the weight determination method is more objective and reasonable.

The calculation steps of this method are as follows:

Step 1 Determine the decision-making problems, select basic linguistic term set U_{S_O}.

Step 2 Structure the decision-making matrix.

$$U_{ij} = \begin{bmatrix} \quad O & S & D \\ U_{S_O}^{11}, U_{S_O}^{12}, \cdots, U_{S_O}^{1m}; & U_{S_O}^{11}, U_{S_O}^{12}, \cdots, U_{S_O}^{1m}; & U_{S_O}^{11}, U_{S_O}^{12}, \cdots, U_{S_O}^{1m} \\ U_{S_O}^{21}, U_{S_O}^{22}, \cdots, U_{S_O}^{2m}; & U_{S_O}^{21}, U_{S_O}^{22}, \cdots, U_{S_O}^{2m}; & U_{S_O}^{21}, U_{S_O}^{22}, \cdots, U_{S_O}^{2m} \\ \cdots\cdots\cdots & \cdots\cdots\cdots & \cdots\cdots\cdots \\ U_{S_O}^{n1}, U_{S_O}^{n2}, \cdots, U_{S_O}^{nm}; & U_{S_O}^{n1}, U_{S_O}^{n2}, \cdots, U_{S_O}^{nm}; & U_{S_O}^{n1}, U_{S_O}^{n2}, \cdots, U_{S_O}^{nm} \end{bmatrix},$$

$i = 1, \cdots, n; j = 1, \cdots, m.$

Step 3 Normalize the decision-making matrix.

Step 4 Calculate the correlation coefficient between attributes [40].

$$\rho_{jk} = \sum_{i=1}^{m} \left(U_{S_O}^{ij} - \overline{U}_{S_O}^{j}\right)\left(U_{S_O}^{ik} - \overline{U}_{S_O}^{k}\right) \Bigg/ \sqrt{\sum_{i=1}^{m} \left(U_{S_O}^{ij} - \overline{U}_{S_O}^{j}\right) \overline{U}_{S_O}^{j^2} \sum_{i=1}^{m} \left(U_{S_O}^{ik} - \overline{U}_{S_O}^{k}\right)^2} \tag{8}$$

where $\overline{U}_{S_O}^{j}$ and $\overline{U}_{S_O}^{k}$ are the average values of evaluation information under the j'th and k'th attributes.

Then, $\overline{U}_{S_O}^{j}$ is determined by the following formula.

$$\overline{U}_{S_O}^{j} = \frac{1}{n} \sum_{j=1}^{n} U_{S_O}^{ij}, i = 1, \cdots, m \tag{9}$$

Step 5 Calculate the standard deviation.

$$\delta_j = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} \left(U_{S_O}^{ij} - \overline{U}_{S_O}^{j}\right)^2}, i = 1, \cdots, m \tag{10}$$

Step 6 Calculate the index C_j.

$$C_j = \delta_j \sum_{k=1}^{n} \left(1 - p_{jk}\right), j = 1, \cdots, n \tag{11}$$

Step 7 Calculate the weights of each attributes.

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}, \quad j = 1, 2, \cdots, j \tag{12}$$

In the following, the process of the CRITIC method is shown in Fig. 9.

The CRITIC method can calculate the importance of attributes through the contrast and conflict relationship. The standard deviation is used to get the contrast between attributes. The conflict of different attributes is reflected by the correlation coefficient. The usage of the weights produced in this subsection avoids the drawbacks of classical FMEA method. The CRITIC method is used to calculate the weight values of different failure modes.

3.2 The Application of FMEA Method in MADM Environment

FMEA is an efficient means to assess the risk factors. The classical FMEA method assess the risk problems by the RPN. Evaluating the risks faced by different research objects, the risk management and risk prevention can be carried out. The RPN reflects the priority of FMs. O, S and D are three important factors of the RPN, and determined by

$$RPN = O \times S \times D \tag{13}$$

The bigger RPN of the failure modes, the more significance of the risk factors. In classical FMEA approach, the FMs are ranked using the crisp RPNs, which is hard to apply in a complex fuzzy environment. The Fig. 10 exhibits the framework of FMEA method. However, with the raising diversity of the assessment problems, the FMEA approach is used in different fields [44]. So, the classical FMEA approach is used to UDHLTS context.

Compared with the traditional FMEA method, the combination of FMEA and weight determination method overcomes the disadvantage of ignoring attribute weights. In traditional FMEA method, there are some disadvantages in using the product of O, S, and D to measure the degree of risk factors. The ranking of risk factors only through RPN is a little simple without considering more factors in risk evaluation. The weight values of different risk factors need to be considered. Therefore, the combination of risk factors and weight determination method makes the risk assessment process more reasonable.

3.3 Extended Fuzzy MACBETH Approach under UDHLTS Context

The MACBETH method [33] is an efficient method in MADM, and it is applied in many cases such as health and behavioral factors analysis [45] and evaluation of supplier [19]. Meantime, this approach is based on the compensation principle, and its steps are shown as below.

Step 1 Obtain and summarize the information about the MADM problems, and select the basic linguistic term set.

Step 2 Obtain the initial decision matrix U_{ij} in which the collected decision information is preprocessed by the transformation function.

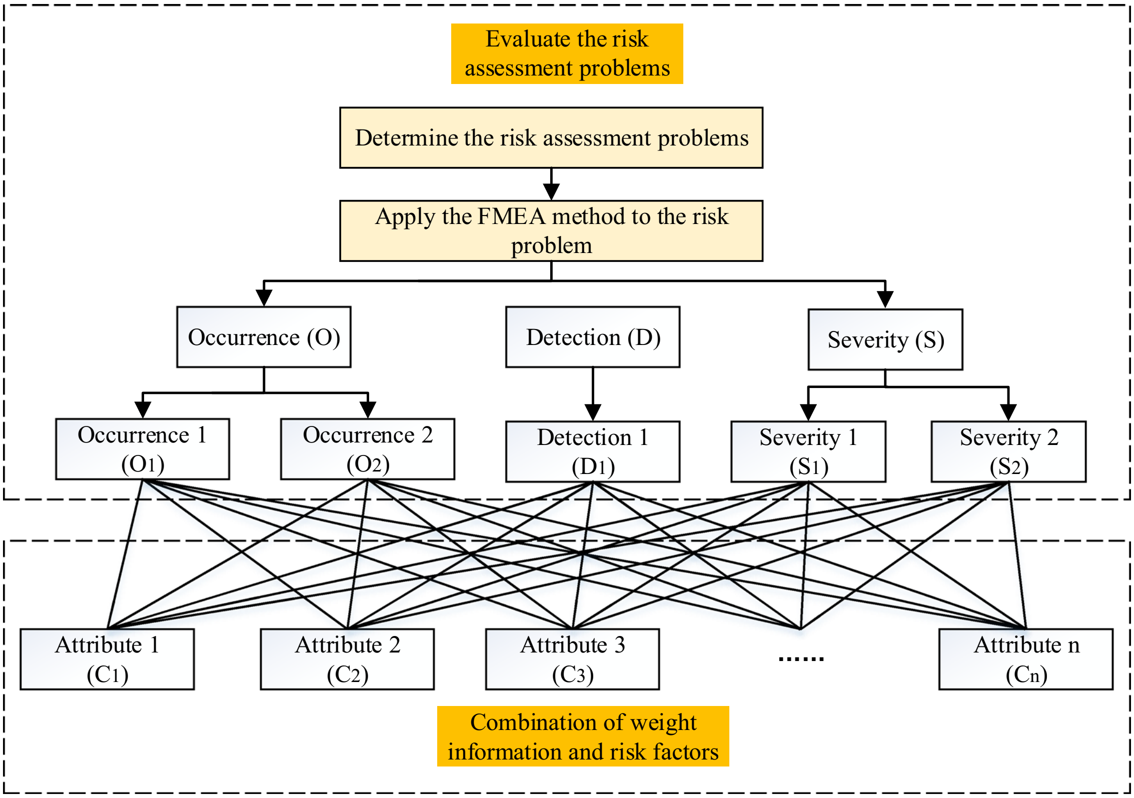

Fig. 10 Framework of FMEA method

$$U_{ij} = \begin{array}{c} \qquad\qquad O \qquad\qquad\qquad S \qquad\qquad\qquad D \\ \begin{bmatrix} U_{S_O}^{11}, U_{S_O}^{12}, \cdots, U_{S_O}^{1m};\ U_{S_O}^{11}, U_{S_O}^{12}, \cdots, U_{S_O}^{1m};\ U_{S_O}^{11}, U_{S_O}^{12}, \cdots, U_{S_O}^{1m} \\ U_{S_O}^{21}, U_{S_O}^{22}, \cdots, U_{S_O}^{2m}; U_{S_O}^{21}, U_{S_O}^{22}, \cdots, U_{S_O}^{2m}; U_{S_O}^{21}, U_{S_O}^{22}, \cdots, U_{S_O}^{2m} \\ \cdots\cdots\cdots \qquad \cdots\cdots\cdots \qquad \cdots\cdots\cdots \\ U_{S_O}^{n1}, U_{S_O}^{n2}, \cdots, U_{S_O}^{nm};\ U_{S_O}^{n1}, U_{S_O}^{n2}, \cdots, U_{S_O}^{nm};\ U_{S_O}^{n1}, U_{S_O}^{n2}, \cdots, U_{S_O}^{nm} \end{bmatrix} \end{array},$$
$$i = 1, \cdots, n; j = 1, \cdots, m.$$

Step 3 Standard the decision matrix and transform the original information into crisp number scale.

First, standard the decision matrix. Then, according to the LFSs of UDHLTS presented in Sect. 2, transform evaluation information obtained by different DMs into numerical scale.

Step 4 Determine the reference levels.

$$\begin{aligned} U_{S_O}^{j-} &= \min\ U_{S_O}^{ij}; \quad i = 1, \ldots, m; j = 1, \ldots, n \\ U_{S_O}^{j+} &= \max\ U_{S_O}^{ij}; \quad i = 1, \ldots, m; j = 1, \ldots, n \end{aligned} \tag{14}$$

Step 5 Normalize the criteria and calculate the MACBETH score $v\left(U_{S_O}^{ij}\right)$.

$$v\left(U_{S_O}^{ij}\right) = v\left(U_{S_O}^{j-}\right) + \frac{\left(\left[f_{1,2}\left(S_{\kappa_{ij}}\right) + g_{1,2}\left(O_{v_{ij}}\right)\right] - \left[f_{1,2}\left(S_{\kappa_j^-}\right) + g_{1,2}\left(O_{v_j^-}\right)\right]\right)}{\left(\left[f_{1,2}\left(S_{\kappa_j^-}\right) + g_{1,2}\left(O_{v_j^+}\right)\right] - \left[f_{1,2}\left(S_{\kappa_j^-}\right) + g_{1,2}\left(O_{v_j^-}\right)\right]\right)} \left[v\left(U_{S_O}^{j+}\right) - v\left(U_{S_O}^{j-}\right)\right]; \quad i = 1, \ldots, m; j = 1, \ldots, n \tag{15}$$

The f_1, g_1 are linguistic scale functions of $U_{S_O}^{ij}$ when the linguistic terms are uniformly and f_2, g_2 are linguistic scale functions of $U_{S_O}^{ij}$ when the semantics are unbalanced distributed.

Step 6 Calculate the overall score V_i.

$$V_i = \sum_{j=1}^{n} v\left(U_{S_O}^{ij}\right) \cdot w_j; \quad i = 1, \ldots, m; j = 1, \ldots, n \tag{16}$$

Step 7 Get the rankings of alternatives and select the optimal one. The bigger the overall score V_i, the better the alternative. It needs to be further explained: in the risk assessment, the bigger the value of V_i, the bigger the risk. In other words, decision makers need to take measures to avoid the risk factors with large score value.

Due to the complexity of the real evaluation environment, the USHLTS can be used to not only describe the DMs' evaluation information in more detail, but also reflect

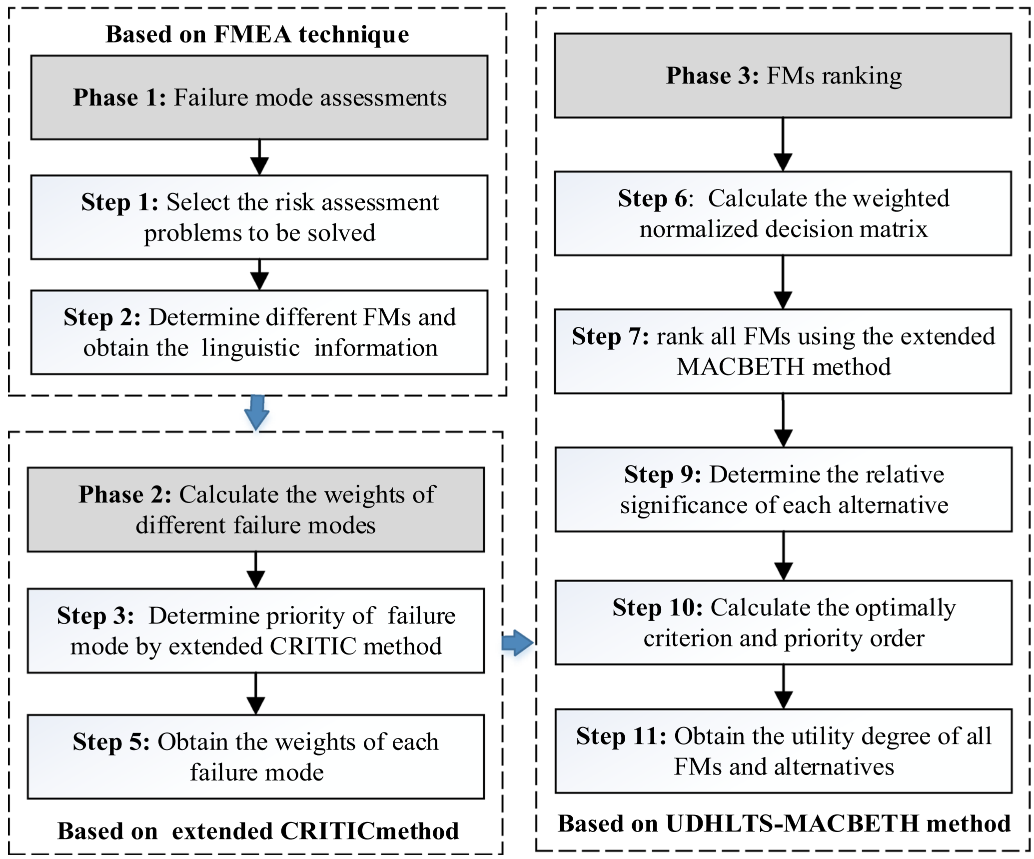

Fig. 11 Framework of the proposed method

unbalanced distribution of the LTS. Obviously, the USHLTS can make reasonable and meticulous description of linguistic information forms. Especially, the second hierarchy LTS increases the granularity of LTS and provides more evaluation information. In this subsection, the MACBETH method is extended to the UDHLTS environment.

3.4 The Proposed FMEA-MACBETH Method under UDHLTS Environment

When assessment risk problems using FMEA approach in the complex environment, the crisp numbers are the commonly used. However, it is hard to describe the information of FMs by crisp numbers. To deal with the risk assessment problem more efficiently, the UDHLTS is utilized to express the information of the FMs. At the same time, the MACBETH approach is an efficient tool to use to calculate the comprehensive scales and get the results of different FMs. Moreover, the importance of different FMs is obtained by CRITIC method. The steps of the presented approach are exhibited in Fig. 11. The process of the presented approach is shown in the following.

3.4.1 Phase 1: Failure Mode Assessment

Step 1–1 Determining the risk assessment problems and different failure modes, describing the details of failure modes.

Step 1–2 Constructing the decision-making matrix U_{ij} consisting three aspects of O, S and D.

Step 1–3 Standardizing the decision-making matrix U_{ij}. When all criteria are benefit type or cost type, it is no need to standardization. When there are benefit and cost type criteria, the LTS of cost type criteria should be its complement set.

$$\begin{cases} \overline{U}_{ij} = \left(U_{S_O}^{ij}\right)_{n\times\beta} & \text{for benefit type} \\ \overline{U}_{ij} = \left(\tilde{U}_{S_O}^{ij}\right)_{n\times\beta} & \text{for cost type} \end{cases} \tag{17}$$

3.4.2 Phase 2: Determine the Attribute Weights of FMs Using CRITIC Method

Step 2–1 Calculate the correlation coefficient among attributes according to the normalized decision-making matrix.

Table 1 Risk description of transportation forms

Types of FMs	Description of FMs
FM_1: Personnel risks	Safety skills and safety awareness of drivers and others
FM_2: Equipment Risks	Design and use safety and maintenance of the equipment
FM_3: Risks caused by road condition factors	Road disaster, road network density, slope, curve, etc.
FM_4: Risks caused by route planning	Is the route planning standard and reasonable
FM_5: Risks from weather factors	Risks caused by rainy, snowy, and foggy weather
FM_6: Risks of traffic management	Risks brought by traffic monitoring and management system
FM_7: Risks of driving environment	Traffic flow, guardrail, shading and other factors
FM_8: Risk factors of accidents	Frequency and severity of accidents

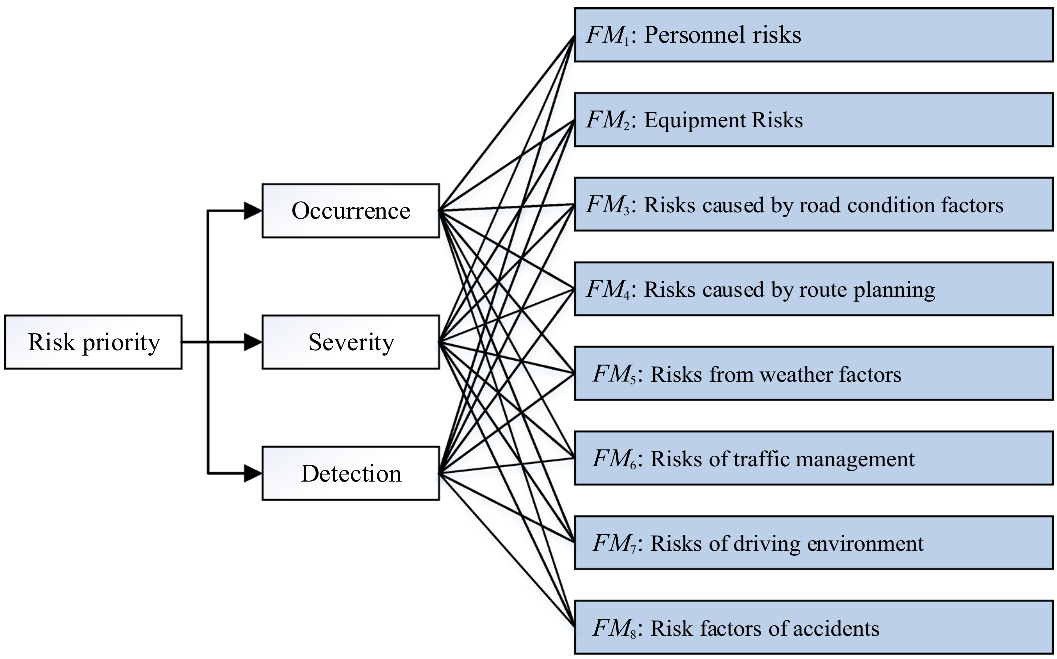

Fig. 12 The eight *FM*s of *O*, *S*, and *D* in FMEA method

Step 2–2 Calculate the standard deviation of each attribute.

Step 2–3 Calculate the index (C).

Step 2–4 Obtain the weights of attributes.

3.4.3 Phase 3: Failure Mode Ranking by FMEA-MACBETH Method

Step 3–1 Determine the reference levels

$$\begin{aligned} U_{S_O}^{j-} &= \min\ U_{S_O}^{ij}; \quad i = 1, \ldots, m; j = 1, \ldots, n \\ U_{S_O}^{j+} &= \max\ U_{S_O}^{ij}; \quad i = 1, \ldots, m; j = 1, \ldots, n \end{aligned} \tag{18}$$

Step 3–2 Calculate the MACBETH score (v) according to the steps of Sect. 3.3.

Step 3–3 Calculate the overall scores.

$$V_i = \sum_{j=1}^{n} v\left(U_{S_O}^{ij}\right) \cdot w_j; \quad i = 1, \ldots, m; j = 1, \ldots, n \tag{19}$$

Step 3–4 Ranking all FMs according to the overall scores. The larger overall score is, the greater the influence of this failure mode. Therefore, it is necessary to take corresponding risk avoidance measures for the risks with high scores.

The proposed method is the extension of the traditional FMEA, which can deal with the risk decision-making problems efficiently under UDHLTS context. Compared with traditional FMEA methods, the proposed method combines FMEA method with MACBETH method and

Table 2 Evaluation information of UDHLTSs

	Occurrence				Severity	
	T_1	T_2	T_3	T_4	T_1	T_2
FM_1	$\{s_{2\langle o_{0}^{2}\rangle}\}$	$\{s_{3\langle o_{-3}^{3}\rangle}\}$	$\{s_{2\langle o_{1}^{2}\rangle}\}$	$\{s_{1\langle o_{2}^{1}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{2\langle o_{1}^{2}\rangle}\}$
FM_2	$\{s_{-2\langle o_{0}^{-2}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$
FM_3	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{-2\langle o_{0}^{-2}\rangle}\}$	$\{s_{1\langle o_{-3}^{1}\rangle}\}$
FM_4	$\{s_{-2\langle o_{0}^{-2}\rangle}\}$	$\{s_{1\langle o_{-1}^{1}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{1}^{0}\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$
FM_5	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{2\langle o_{0}^{2}\rangle}\}$	$\{s_{1\langle o_{3}^{1}\rangle}\}$	$\{s_{2\langle o_{-1}^{2}\rangle}\}$	$\{s_{0\langle o_{2}^{0}\rangle}\}$	$\{s_{2\langle o_{2}^{2}\rangle}\}$
FM_6	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{0\langle o_{1}^{0}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$
FM_7	$\{s_{0\langle o_{1}^{0}\rangle}\}$	$\{s_{1\langle o_{1}^{1}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{0\langle o_{3}^{0}\rangle}\}$
FM_8	$\{s_{0\langle o_{2}^{0}\rangle}\}$	$\{s_{2\langle o_{-2}^{2}\rangle}\}$	$\{s_{0\langle o_{2}^{0}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{2\langle o_{0}^{2}\rangle}\}$

	Severity		Detection			
	T_3	T_4	T_1	T_2	T_3	T_4
FM_1	$\{s_{2\langle o_{-1}^{2}\rangle}\}$	$\{s_{1\langle o_{3}^{1}\rangle}\}$	$\{s_{1\langle o_{2}^{1}\rangle}\}$	$\{s_{2\langle o_{0}^{2}\rangle}\}$	$\{s_{1\langle o_{1}^{1}\rangle}\}$	$\{s_{2\langle o_{1}^{2}\rangle}\}$
FM_2	$\{s_{1\langle o_{-1}^{1}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{1\langle o_{1}^{1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$
FM_3	$\{s_{0\langle o_{-3}^{0}\rangle}\}$	$\{s_{0\langle o_{-2}^{0}\rangle}\}$	$\{s_{-2\langle o_{0}^{-2}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{-2}^{0}\rangle}\}$
FM_4	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{-1\langle o_{3}^{-1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$
FM_5	$\{s_{2\langle o_{1}^{2}\rangle}\}$	$\{s_{1\langle o_{2}^{1}\rangle}\}$	$\{s_{1\langle o_{1}^{1}\rangle}\}$	$\{s_{1\langle o_{3}^{1}\rangle}\}$	$\{s_{2\langle o_{-1}^{2}\rangle}\}$	$\{s_{2\langle o_{-1}^{2}\rangle}\}$
FM_6	$\{s_{0\langle o_{1}^{0}\rangle}\}$	$\{s_{0\langle o_{1}^{0}\rangle}\}$	$\{s_{-2\langle o_{0}^{-2}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$
FM_7	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{-1\langle o_{0}^{-1}\rangle}\}$	$\{s_{1\langle o_{3}^{1}\rangle}\}$	$\{s_{0\langle o_{1}^{0}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$
FM_8	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{0}^{0}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{1\langle o_{0}^{1}\rangle}\}$	$\{s_{0\langle o_{2}^{0}\rangle}\}$

weight determination method to address the risk assessment problems. At the same time, the application of weight determination method overcomes the disadvantages of ignoring the weight of different failure modes. In FMEA method, it is only the multiplication of *O*, *S* and *D* to obtain the RPN value of a failure mode. The same MACBETM does not take into account the three aspects of *O*, *S,* and *D* of risk factors. So, the proposed can not only evaluate different risk factors from three aspects of *O*, *S,* and *D*, but also use multi-attribute decision-making methods to rank risks and alternatives. Therefore, the proposed method has wider applicability.

4 Case Study: The Risk Assessment of Transportation Forms

In this part, a case of risk assessment for four modes of transportation is analyzed by using the proposed model. Furthermore, we analyze the ranking results of eight FMs. Section 4.1 gives the background description of transportation risk assessment, Sect. 4.2 presents the process description of data collection, and Sects. 4.3 and 4.4 propose the weight calculation process and decision-making process of the presented method under UDHLTS context. The ranking results and results analysis are also shown in Sect. 4.4.

Table 3 Semantic value matrix of UDHLTSs

	Occurrence				Severity	
	T_1	T_2	T_3	T_4	T_1	T_2
FM_1	$\{\frac{33}{35}\}$	$\{\frac{71}{72}\}$	$\{\frac{20}{21}\}$	$\{\frac{34}{39}\}$	$\{\frac{2}{3}\}$	$\{\frac{31}{36}\}$
FM_2	$\{\frac{2}{35}\}$	$\{\frac{49}{57}\}$	$\{\frac{1}{2}\}$	$\{\frac{49}{57}\}$	$\{\frac{1}{3}\}$	$\{\frac{1}{2}\}$
FM_3	$\{\frac{8}{57}\}$	$\{\frac{1}{2}\}$	$\{\frac{49}{57}\}$	$\{\frac{1}{2}\}$	$\{\frac{1}{6}\}$	$\{\frac{7}{12}\}$
FM_4	$\{\frac{2}{35}\}$	$\{\frac{17}{20}\}$	$\{\frac{49}{57}\}$	$\{\frac{26}{51}\}$	$\{\frac{5}{18}\}$	$\{\frac{1}{3}\}$
FM_5	$\{\frac{49}{57}\}$	$\{\frac{33}{35}\}$	$\{\frac{76}{87}\}$	$\{\frac{14}{15}\}$	$\{\frac{5}{9}\}$	$\{\frac{8}{9}\}$
FM_6	$\{\frac{8}{57}\}$	$\{\frac{1}{2}\}$	$\{\frac{8}{57}\}$	$\{\frac{26}{51}\}$	$\{\frac{1}{2}\}$	$\{\frac{2}{3}\}$
FM_7	$\{\frac{26}{51}\}$	$\{\frac{20}{23}\}$	$\{\frac{49}{57}\}$	$\{\frac{49}{57}\}$	$\{\frac{1}{3}\}$	$\{\frac{7}{12}\}$
FM_8	$\{\frac{21}{41}\}$	$\{\frac{67}{72}\}$	$\{\frac{21}{41}\}$	$\{\frac{1}{2}\}$	$\{\frac{1}{2}\}$	$\{\frac{5}{6}\}$
	Severity		**Detection**			
	T_3	T_4	T_1	T_2	T_3	T_4
FM_1	$\{\frac{29}{36}\}$	$\{\frac{3}{4}\}$	$\{\frac{19}{33}\}$	$\{\frac{20}{27}\}$	$\{\frac{4}{7}\}$	$\{\frac{26}{35}\}$
FM_2	$\{\frac{23}{36}\}$	$\{\frac{2}{3}\}$	$\{\frac{14}{33}\}$	$\{\frac{1}{2}\}$	$\{\frac{4}{7}\}$	$\{\frac{1}{2}\}$
FM_3	$\{\frac{5}{12}\}$	$\{\frac{4}{9}\}$	$\{\frac{7}{27}\}$	$\{\frac{1}{2}\}$	$\{\frac{37}{65}\}$	$\{\frac{38}{75}\}$
FM_4	$\{\frac{2}{3}\}$	$\{\frac{1}{2}\}$	$\{\frac{28}{65}\}$	$\{\frac{4}{9}\}$	$\{\frac{1}{2}\}$	$\{\frac{37}{65}\}$
FM_5	$\{\frac{31}{36}\}$	$\{\frac{13}{18}\}$	$\{\frac{37}{65}\}$	$\{\frac{7}{12}\}$	$\{\frac{17}{23}\}$	$\{\frac{17}{23}\}$
FM_6	$\{\frac{19}{36}\}$	$\{\frac{19}{36}\}$	$\{\frac{7}{27}\}$	$\{\frac{1}{2}\}$	$\{\frac{28}{65}\}$	$\{\frac{1}{2}\}$
FM_7	$\{\frac{2}{3}\}$	$\{\frac{1}{2}\}$	$\{\frac{28}{65}\}$	$\{\frac{7}{12}\}$	$\{\frac{1}{2}\}$	$\{\frac{37}{65}\}$
FM_8	$\{\frac{2}{3}\}$	$\{\frac{2}{3}\}$	$\{\frac{1}{2}\}$	$\{\frac{37}{65}\}$	$\{\frac{37}{65}\}$	$\{\frac{38}{75}\}$

4.1 Background Description

Traffic mode risk evaluation has great significance to improve traffic safety. Studying and ranking the risk importance of different transportation modes are of great significance to improve the efficiency of risk control, reduce the repetition of traffic accidents and help passengers choose appropriate and effective transportation modes. To provide decision support for traffic management, scholars have carried out some studies on traffic risk assessment [1]. Ait-Mlouk et al. [18] and Arun et al. [20] did the related research on the road safety assessment. When construct the index system of traffic modes, it is necessary to do qualitative analysis of various factors on the impact of traffic safety. Risk identification and assessments in the preliminary stages is further challenging due to lack of complete and accurate risk information available. FMEA method [46] has its own unique advantages in identifying risks. It can consider different aspects of risks. It is more popular among scholars in identifying and evaluating risks.

Based on previous studies, we investigate and compare the different modes of transportations, and the four transportation forms (or called alternatives) are selected, they are railway traffic (T_1), highway (T_2), airplane (T_3),and ship (T_4). Furthermore, the risk factors in terms of personnel, transportation facilities, environment, management, etc. are analyzed, and the relevant factors are taken into account. Among the risk factors, the personnel factor is an important aspect, including driving skills of drivers, passenger factors, and safety awareness of pedestrians and other personnel. The second aspect is equipment risk factor, including equipment design, transportation safety and maintenance. The third is the risk caused by road conditions, including road disasters, road network density, slope, etc. Further, whether the route planning is standardized and reasonable is also an important part of traffic safety. Subsequently, weather risk factors are also very important, and they include rain, snow, fog, ice, and other weather risks. Then the other risk factors are shown as follows. The traffic management risk includes the risk brought by traffic monitoring and management system. In addition, the hidden risks of driving environment include traffic flow,

Table 4 RPN matrix of eight FMs

	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8
T1	0.3670	0.0153	0.0092	0.0130	0.2520	0.0275	0.0642	0.1276
T2	0.6752	0.1728	0.1458	0.0953	0.4937	0.1667	0.2729	0.4473
T3	0.4432	0.1991	0.1890	0.2439	0.5084	0.0538	0.2455	0.2109
T4	0.4445	0.2439	0.1129	0.1570	0.4975	0.1336	0.2268	0.1694

Table 5 Correlation coefficient between FMs

Coefficients	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8
FM_1	1.0000	0.3629	0.4997	0.0337	0.5472	0.8290	0.7150	0.9903
FM_2	0.3629	1.0000	0.8057	0.7962	0.9557	0.6305	0.8783	0.2774
FM_3	0.4997	0.8057	1.0000	0.8767	0.9282	0.4134	0.9222	0.4947
FM_4	0.0337	0.7962	0.8767	1.0000	0.8105	0.0919	0.7007	0.0171
FM_5	0.5472	0.9557	0.9282	0.8105	1.0000	0.6540	0.9748	0.4919
FM_6	0.8290	0.6305	0.4134	0.0919	0.6540	1.0000	0.7330	0.7435
FM_7	0.7150	0.8783	0.9222	0.7007	0.9748	0.7330	1.0000	0.6731
FM_8	0.5257	0.1472	0.2626	0.0091	0.2611	0.3946	0.3573	0.5308

Table 6 Scores of MACBETH in eight FMs

	Occurrence				Severity	
	T_1	T_2	T_3	T_4	T_1	T_2
FM_1	100.00	100.00	100.00	65.45	100.00	95.00
FM_2	0.00	47.67	37.70	62.63	33.33	25.00
FM_3	19.22	0.00	75.41	0.00	0.00	45.00
FM_4	0.00	46.35	75.41	1.74	22.22	0.00
FM_5	80.78	77.44	77.67	100.00	77.78	100.00
FM_6	19.22	0.00	0.00	1.74	66.67	60.00
FM_7	50.85	48.99	75.41	62.63	33.33	45.00
FM_8	51.39	75.29	39.40	0.00	66.67	90.00

	Severity		Detection			
	T_3	T_4	T_1	T_2	T_3	T_4
FM_1	87.50	100.00	100.00	100.00	59.04	100.00
FM_2	50.00	72.73	39.48	26.42	59.04	0.00
FM_3	0.00	0.00	0.00	26.42	58.23	2.75
FM_4	56.25	18.18	41.42	0.00	29.12	40.16
FM_5	100.00	90.91	98.06	59.77	100.00	97.77
FM_6	25.00	27.27	0.00	26.42	0.00	0.00
FM_7	56.25	18.18	41.42	59.77	29.93	40.16
FM_8	56.25	72.73	69.74	56.30	58.23	2.75

Table 7 Overall scores and ranking of eight FMs

FMs	Overall scores each FMs	Ranking
Overall scores	$N(FM_1) = 215.69, N(FM_2) = 45.78, N(FM_3) = 16.69, N(FM_4) = 49.74,$ $N(FM_5) = 102.91, N(FM_6) = 20.19, N(FM_7) = 38.02, N(FM_8) = 144.68.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ$ $FM_2 \succ FM_7 \succ FM_6 \succ FM_3$
The standardized scores	$N(FM_1) = 1, N(FM_2) = 0.2122, N(FM_3) = 0.0774, N(FM_4) = 0.2306,$ $N(FM_5) = 0.4771, N(FM_6) = 0.0936, N(FM_7) = 0.1763, N(FM_8) = 0.6708.$	

Table 8 RPN matrix of overall scores and ranking of eight FMs

	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8
T_1	0.3670	0.0153	0.0092	0.0130	0.2520	0.0275	0.0642	0.1276
T_2	0.6752	0.1728	0.1458	0.0953	0.4937	0.1667	0.2729	0.4473
T_3	0.4432	0.1991	0.1890	0.2439	0.5084	0.0538	0.2455	0.2109
T_4	0.4445	0.2439	0.1129	0.1570	0.4975	0.1336	0.2268	0.1694

Table 9 RPN matrix of eight FMs

	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8
T_1	0.3670	0.0153	0.0092	0.0130	0.2520	0.0275	0.0642	0.1276
T_2	0.6752	0.1728	0.1458	0.0953	0.4937	0.1667	0.2729	0.4473
T_3	0.4432	0.1991	0.1890	0.2439	0.5084	0.0538	0.2455	0.2109
T_4	0.4445	0.2439	0.1129	0.1570	0.4975	0.1336	0.2268	0.1694

guardrail, shading and other factors. Finally, accident risk factors are also important indicators to measure the risk of transportation forms, including accident frequency and severity. Therefore, according to the above risk factors, FMs of this case are divided into the following eight categories. These eight FMs are FM_1: Personnel risks, FM_2: Equipment Risks, FM_3: Risks caused by road condition factors, FM_4: Risks caused by route planning, FM_5: Risks from weather factors, FM_6: Risks of traffic management, FM_7: Risks of driving environment, FM_8: Risk factors of accidents. Different risks and descriptions are exhibited in Table 1. The structural relationship of eight FMs and O, S, and D is exhibited in Fig. 12. According to the rules of FMEA method, eight failure modes of four alternatives are scored by experts from three aspects of *O, S,* and *D*, and the original evaluation information can be collected. In addition, the traditional traffic risk assessment method is too simple to ensure the accuracy and comprehensiveness of the evaluation, and the operability of the evaluation process and the objectivity of the evaluation results does not be considered. In this paper, the UDHLTS is utilized to describe the linguistic information of these eight risk failure modes of different transportation forms, and the FMEA-MACBETH method is used to comprehensively evaluate the traffic risks under UDHLTS environment.

4.2 Data Collection

In this case study, the original data are accepted by expert scoring. Experts evaluate the four modes of transportations (T_1: railway, T_2: highway, T_3: airplane, T_4: ship) as alternatives for their risk factors through their own knowledge and background effectively, and the second hierarchy of linguistic evaluation information is given under the first hierarchy. The failure modes are divided into eight categories which are shown as follows: FM_1: Personnel risks; FM_2: Equipment Risks; FM_3: Risks caused by road condition factors; FM_4: Risks caused by route planning; FM_5:

Table 10 Overall scores and ranking of eight FMs

FMs	utility degree N of each FM	Ranking
Traditional FMEA method	$N(T_1) = 0.1546, N(T_2) = 0.4693,$ $N(T_3) = 0.3291, N(T_4) = 0.3059.$	$T_2 \succ T_3 \succ T_4 \succ T_1$
The proposed method	$N(T_1) = 0, N(T_2) = 1, N(T_3) = 0.7958, N(T_4) = 0.7531.$	
The standardized scores	$N(FM_1) = 1, N(FM_2) = 0.2122, N(FM_3) = 0.0774, N(FM_4) = 0.2306,$ $N(FM_5) = 0.4771, N(FM_6) = 0.0936, N(FM_7) = 0.1763, N(FM_8) = 0.6708.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$

Table 11 Overall scores and ranking of eight FMs

LTSs	Comprehensive values	Ranking
Method of Fu and Liao [32] based on TOPSIS for the UDHLTSs	$s(FM_1) = 0.9872, s(FM_2) = 0.1544,$ $s(FM_3) = 0.0357, s(FM_4) = 0.2562,$ $s(FM_5) = 0.3983, s(FM_6) = 0.0640,$ $s(FM_7) = 0.0883, s(FM_8) = 0.6629.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$
Traditional FMEA [47] for the UDHLTSs ($\lambda_1 = 0.7, \lambda_2 = 1.3$)	$s(FM_1) = 0.4981, s(FM_2) = 0.0704,$ $s(FM_3) = 0.0363, s(FM_4) = 0.0834,$ $s(FM_5) = 0.2230, s(FM_6) = 0.0363,$ $s(FM_7) = 0.0619, s(FM_8) = 0.2495.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$
Our proposed method for the UDHLTSs ($\lambda_1 = 0.7, \lambda_2 = 1.3$)	$s(FM_1) = 1, s(FM_2) = 0.2123,$ $s(FM_3) = 0.0774, s(FM_4) = 0.2306,$ $s(FM_5) = 0.4771, s(FM_6) = 0.0936,$ $s(FM_7) = 0.1763, s(FM_8) = 0.6708.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$

Risks from weather factors; FM_6: Risks of traffic management; FM_7: Risks of the driving environment; FM_8: Risk factors of accidents. Based on the eight risk failure modes, experts evaluated the Occurrence, Severity, and Detection of risk factors. There are three important factors of the risks and can be regarded as “probability of occurrence,” “degree of severity,” and “degree of detectability.” These eight FMs and their description are shown in Fig. 12. According to UDHLTSs, experts give two hierarchy evaluation information in turn. And the linguistic information of O, S, and D for four traffic modes can be obtained, which are shown in Table 2. According to the information of different experts, when evaluating Severity, the LTS is uniformly distributed with equal deviation, $\eta = \sigma = 1$. When evaluating Occurrence, the LTS is unbalanced distributed with increasing deviation, $0 < \eta = \sigma < 1$. When evaluating Detection, the LTS is unbalanced distributed with decreasing deviation, $\eta = \sigma > 1$. The matrix of semantic values is shown in Table. 3.

4.3 Calculate the Weights of Criteria

According to the semantic value matrix in Table 3, we can obtain the following matrix. To calculating the weights of eight FMs, the overall values are obtained according to the FMEA model, which is shown in Table 4.

Based on the previous steps, calculate the standard value under each attribute, that is, the mean value u, and get $u = \{0.4825, 0.1578, 0.1142, 0.1273, 0.4379, 0.0954, 0.2023, 0.2388\}$. Then, calculate the correlation coefficient between FMs, which is shown in Table 5.

Next, calculate the standard deviation of computed properties.

$$\partial = \{0.1156, 0.0861, 0.0664, 0.0845, 0.1075, 0.0568, 0.0814, 0.1239\}$$

Furthermore, calculate the index C_j.

$$C_j = \{0.4031, 0.2086, 0.1521, 0.3111, 0.2008, 0.1847, 0.1400, 0.4686\}$$

Finally, calculate the weights of eight FMs.

Table 12 A set of evaluation information of UDHLTSs

	Occurrence				Severity				Detection			
	T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4
FM_1	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{3\langle o_{-3}^3\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{1\langle o_2^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{0\langle o_{-1}^0\rangle}\}$	$\{s_{1\langle o_3^1\rangle}\}$	$\{s_{1\langle o_2^1\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{1\langle o_1^1\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$
FM_2	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_{-1}^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$
FM_3	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{1\langle o_{-3}^1\rangle}\}$	$\{s_{0\langle o_{-3}^0\rangle}\}$	$\{s_{0\langle o_{-2}^0\rangle}\}$	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_{-2}^0\rangle}\}$
FM_4	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{1\langle o_{-1}^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{-1\langle o_3^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$
FM_5	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{1\langle o_3^1\rangle}\}$	$\{s_{0\langle o_{-1}^0\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{2\langle o_2^2\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{1\langle o_2^1\rangle}\}$	$\{s_{1\langle o_1^1\rangle}\}$	$\{s_{1\langle o_3^1\rangle}\}$	$\{s_{2\langle o_{-1}^2\rangle}\}$	$\{s_{2\langle o_{-1}^2\rangle}\}$

$$w_j = \{0.1948, 0.1008, 0.0735, 0.1503, 0.097, 0.0892, 0.0677, 0.2265\}$$

4.4 Rank the FMs of Different Transportation Modes

According to the weight results of Sect. 4.3, we can determine the reference levels.

$$r^- = \begin{array}{c} \qquad\qquad\qquad\qquad O \qquad\qquad\qquad S \qquad\qquad\qquad D \\ \left[\frac{11}{89}, \frac{1}{2}, \frac{11}{41}, \frac{1}{2}; \quad \frac{1}{6}, \frac{1}{3}, \frac{5}{12}, \frac{4}{9}; \quad \frac{17}{83}, \frac{13}{33}, \frac{19}{50}, \frac{1}{2}\right] \end{array}$$

$$r^+ = \begin{array}{c} \qquad\qquad\qquad\qquad O \qquad\qquad\qquad S \qquad\qquad\qquad D \\ \left[\frac{78}{89}, \frac{71}{72}, \frac{83}{94}, \frac{67}{77}; \quad \frac{2}{3}, \frac{8}{9}, \frac{31}{36}, \frac{3}{4}; \quad \frac{27}{43}, \frac{66}{83}, \frac{19}{24}, \frac{4}{5}\right] \end{array}$$

Then the scores of MACBETH can be obtained as shown in Table 6.

Moreover, the overall scores and final ranking can be obtained as shown in Table 7.

Therefore, according to the overall scales of all FMs, the ranking result with the descending order is: $FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$. So, we can see that the personnel risks (FM_1) are the highest risk factors, so, they should be paid the most attention. Furthermore, the results of risk ranking from high to low are as follows: FM_1: Personnel risks; FM_8: Risk factors of accidents; FM_5: Risks from weather factors; FM_4: Risks caused by route planning; FM_2: Equipment Risks; FM_7: Risks of the driving environment; FM_6: Risks of traffic management; FM_3: Risks caused by road condition factors.

Further, we analyze the eight FMs and four traffic modes. According to the proposed decision-making model, the results of eight FMs are shown in Sect. 4.3 and Sect. 4.4. Moreover, the steps and results of four traffic modes are exhibited as follows.

First, according to the decision-making matrix in Table 3, the overall scores and ranking of eight FMs in four traffic modes are exhibited in Table 8.

Then, according to the produce of MACBETH method, the reference levels are obtained as

$$r^- = \begin{array}{c} \begin{array}{cccccccc} FM_1 & FM_2 & FM_3 & FM_4 & FM_5 & FM_6 & FM_7 & FM_8 \end{array} \\ \left[\begin{array}{cccccccc} 0.3670, & 0.0153, & 0.0092, & 0.0130, & 0.2520, & 0.0275, & 0.0642, & 0.1276 \end{array}\right] \end{array}$$

$$r^+ = \begin{array}{c} \begin{array}{cccccccc} FM_1 & FM_2 & FM_3 & FM_4 & FM_5 & FM_6 & FM_7 & FM_8 \end{array} \\ \left[\begin{array}{cccccccc} 0.6752, & 0.2439, & 0.1890, & 0.2439, & 0.5084, & 0.1667, & 0.2729, & 0.4473 \end{array}\right] \end{array}$$

Furthermore, the overall values of four traffic modes are obtained shown as

$$N(T_1) = 0, N(T_2) = 1, N(T_3) = 0.7958, N(T_4) = 0.7531$$

Finally, the ranking result of four alternatives can be calculated as $T_2 \succ T_3 \succ T_4 \succ T_1$.

Table 13 Overall scores and ranking of failure modes

LTSs	Comprehensive values	Ranking
Method of Fu and Liao [32] based on TOPSIS for the UDHLTSs	$s(FM_1)=0.8171$,$s(FM_2)=0.2869$, $s(FM_3)=0.1283$,$s(FM_4)=0.1846$, $s(FM_5)=0.7394$.	$FM_1 \succ FM_5 \succ FM_2 \succ FM_4 \succ FM_3$
Our proposed method for the UDHLTSs ($\lambda_1 = 0.7$,$\lambda_2 = 1.3$)	$s(FM_1)=1$,$s(FM_2)=0.4853$, $s(FM_3)=0.1991$,$s(FM_4)=0.2872$, $s(FM_5)=0.9535$.	$FM_1 \succ FM_5 \succ FM_2 \succ FM_4 \succ FM_3$

Table 14 A set of evaluation information of UDHLTSs

	Occurrence				Severity				Detection			
	T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4
FM_1	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{1\langle o_{-3}^1\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{1\langle o_1^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{0\langle o_{-1}^0\rangle}\}$	$\{s_{1\langle o_3^1\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{1\langle o_1^1\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$
FM_2	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_{-1}^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$
FM_3	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{2\langle o_{-1}^2\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{1\langle o_{-3}^1\rangle}\}$	$\{s_{0\langle o_{-2}^0\rangle}\}$	$\{s_{0\langle o_{-2}^0\rangle}\}$	d	$\{s_{0\langle o_{-1}^0\rangle}\}$	$\{s_{1\langle o_{-1}^1\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$
FM_4	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{1\langle o_{-1}^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{-1\langle o_3^{-1}\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$
FM_5	$\{s_{-2\langle o_1^{-2}\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{1\langle o_3^1\rangle}\}$	$\{s_{0\langle o_{-1}^0\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{2\langle o_{-1}^2\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_2^1\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$

To reflect the availability of the presented approach, we make comparisons with the traditional FMEA method. Firstly, we get the ranking result of the four traffic modes in this case by the traditional FMEA method.

First, according to the risk decision-making matrix, the RPN matrix of this problem is exhibited in Table 9.

Then, the RPN values of each traffic mode can be obtained.

$$N(T_1)=0.1546, N(T_2)=0.4693, N(T_3)=0.3291, N(T_4)=0.3059$$

Finally, the ranking result of four traffic modes is $T_2 \succ T_3 \succ T_4 \succ T_1$ under the traffic FMEA context.

Therefore, the rankings of four traffic modes and eight risk FMs are as exhibited in Table 10.

In Table 10, the ranking result $T_2 \succ T_3 \succ T_4 \succ T_1$ of four traffic modes is obtained and the ranking of eight risk FMs is $FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$. Therefore, among the four traffic modes, the risk of railway traffic (T_1) is the lowest, followed by ship (T_4), airplane (T_3), and highway (T_2), and highway (T_2) is highest. Among these eight failure modes, the risk of FM_1 (Personnel risks) is the greatest. Next, the second highest risk factor is FM_8 (Risk factors of accidents). So, these two risk factors should be paid more attention. Then, the risks of FM_6 (Risks of traffic management) and FM_3 (Risks caused by road condition factors) are relatively low.

Table 15 Overall scores and ranking of failure modes

LTSs	Comprehensive values	Ranking
Method of Fu and Liao [32] based on TOPSIS for the UDHLTSs	$s(FM_1) = 0.6914, s(FM_2) = 0.3949, s(FM_3) = 0.2680, s(FM_4) = 0.1963, s(FM_5) = 0.5739.$	$FM_1 \succ FM_5 \succ FM_2 \succ FM_3 \succ FM_4$
Our proposed method for the UDHLTSs ($\lambda_1 = 0.7, \lambda_2 = 1.3$)	$s(FM_1) = 1, s(FM_2) = 0.6197, s(FM_3) = 0.4363, s(FM_4) = 0.3474, s(FM_5) = 0.8648.$	$FM_1 \succ FM_5 \succ FM_2 \succ FM_3 \succ FM_4$

Table 16 Overall scores and ranking of eight FMs and four alternatives with different weights

Different weights	Overall scores	Ranking results
Under the weight calculated by CRITIC method	$s(FM_1) = 1, s(FM_2) = 0.2123, s(FM_3) = 0.0774, s(FM_4) = 0.2306, s(FM_5) = 0.4771, s(FM_6) = 0.0936, s(FM_7) = 0.1763, s(FM_8) = 0.6708.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$
In the case of average weight	$s(FM_1) = 1, s(FM_2) = 0.4101, s(FM_3) = 0.2051, s(FM_4) = 0.2989, s(FM_5) = 0.9577, s(FM_6) = 0.2044, s(FM_7) = 0.5076, s(FM_8) = 0.5770.$	$FM_1 \succ FM_5 \succ FM_8 \succ FM_7 \succ FM_2 \succ FM_4 \succ FM_3 \succ FM_6$
Under the weight calculated by CRITIC method	$N(T_1) = 0, N(T_2) = 1, N(T_3) = 0.7958, N(T_4) = 0.7531.$	$T_2 \succ T_3 \succ T_4 \succ T_1$
In the case of average weight	$N(T_1) = 0, N(T_2) = 1, N(T_3) = 0.7958, N(T_4) = 0.7531.$	$T_2 \succ T_3 \succ T_4 \succ T_1$

5 Comparison and Discussion

In this section, we discuss and analyze the feasibility of the new method, the sensitivity of weights, the advantages of the method and the linguistic term set used. We first analyze the feasibility of the presented approach in Sect. 5.1. Compared with the TOPSIS method [32] and traditional FMEA model in the same linguistic information environment (UDHLTS), the feasibility of the proposed method is illustrated. In the second part, we add the analysis of weight sensitivity of the proposed decision-making framework. The sensitivity of the proposed framework to different weights is analyzed. Then, in Sect. 5.3, the comparison between the presented approach and the existing MADM methods is used to illustrate the validity and superiority. The proposed method can evaluate the risk problems more efficiently. Furthermore, two examples are used to illustrate the difference and superiority of the presented approach. Moreover, in Sect. 5.4, the comparison between the UDHLTS and unbalanced linguistic term sets is shown. The comparison shows that the UDHLTS can provide more unbalanced information in decision-making process.

5.1 Feasibility Analysis

In this subsection, the presented approach is compared with the UDHLTS-TOPSIS method proposed by Fu and Liao [32] and the traditional FMEA method [47]. Fu and Liao [32] have studied the TOPSIS method under the UDHLTS environment. So, it is feasible. We compare the existing TOPSIS methods in the same linguistic information environment (UDHLTS) and analyze the results to prove the feasibility of the new method. Furthermore, to illustrate the feasibility of the proposed method, two examples are used in the following part. The following Table 11 shows the results of different methods.

From Table 11, we can see that the three methods have the same ranking result $FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$, So, the ranking order of eight risk FMs is FM_1: Personnel risks; FM_8: Risk factors of accidents; FM_5: Risks from weather factors; FM_4: Risks caused by

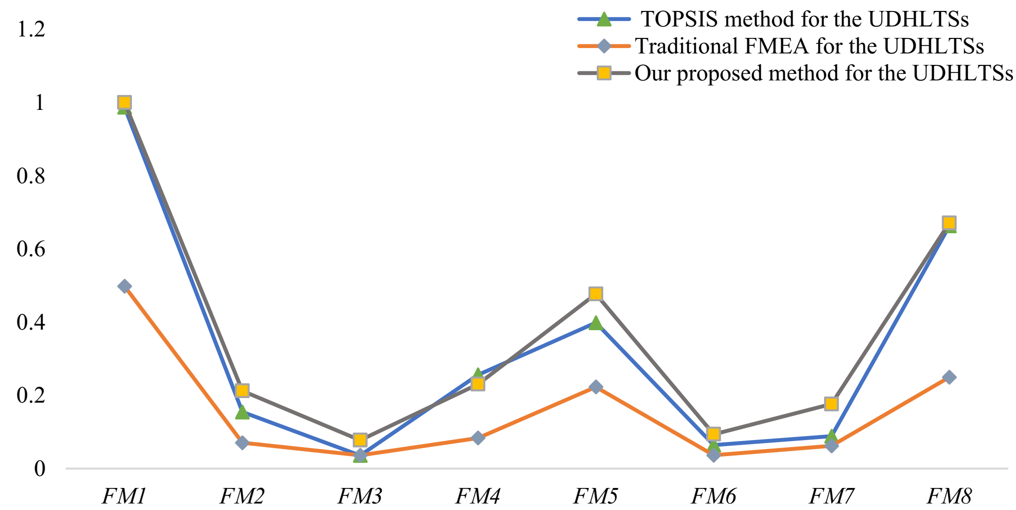

Fig. 13 Ranking results of different methods

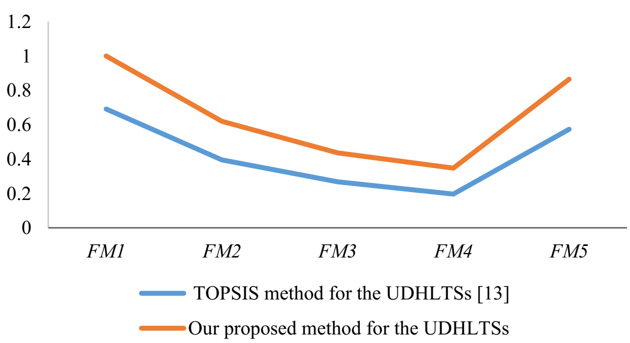

Fig. 14 Ranking results of TOPSIS and the proposed methods

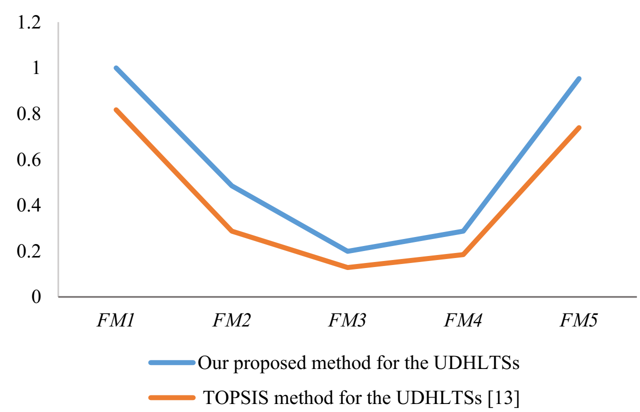

Fig. 15 Ranking results of TOPSIS and the proposed methods

route planning; FM_2: Equipment Risks; FM_7: Risks of driving environment; FM_6: Risks of traffic management; FM_3: Risks caused by road condition factors. According to the previous analysis of the deviation parameter, in our case, the parameter value is $\lambda_1 = 0.7, \lambda_2 = 1.3$. So, it is needed to choose the appropriate parameters according to the actual problems and the environment. The same ranking in Table 11 reflects the feasibility of the presented approach.

From Table 11 and Fig. 13, it can be found that these three methods have the same ranking results, i.e., $FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$. According to the previous analysis of the deviation parameter, choosing the appropriate parameters according to problems and the environment is of importance. So, in this case, the parameter values are $\lambda_1 = 0.7, \lambda_2 = 1.3$. For method of Fu and Liao [32] based on TOPSIS and the traditional FMEA [47] under the UDHLTSs environment, the highest failure mode is FM_1 (Personnel risks). The Comprehensive values of FM_1 is 1. Then, the highest failure mode of traditional FMEA and TOPSIS method under the same linguistic environment is also FM_1. And the result is the same with our proposed method. Therefore, the

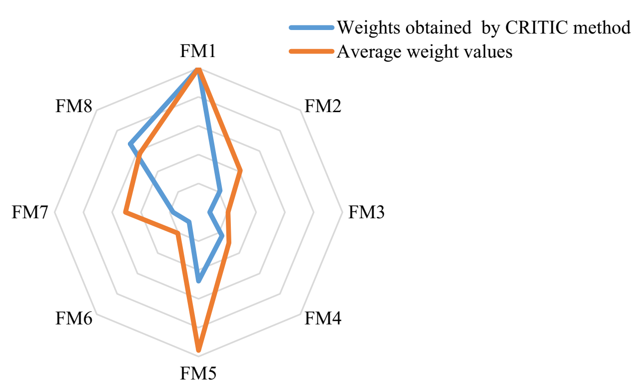

Fig. 16 Ranking results of eight FMs with different weights

Table 17 Comparison results for different methods

Linguistic term sets	Comprehensive values	Ranking
The traditional FMEA [47] for UDHLTSs	$s(FM_1) = 0.4981, s(FM_2) = 0.0704,$ $s(FM_3) = 0.0363, s(FM_4) = 0.0834,$ $s(FM_5) = 0.2230, s(FM_6) = 0.0363,$ $s(FM_7) = 0.0619, s(FM_8) = 0.2495.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \approx FM_3$
The MACBETH method [19] for UDHLTSs	$s(FM_1) = 1, s(FM_2) = 0.2027,$ $s(FM_3) = 0.0987, s(FM_4) = 0.2654,$ $s(FM_5) = 0.4618, s(FM_6) = 0.0264,$ $s(FM_7) = 0.2265, s(FM_8) = 0.5287.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_7 \succ FM_2 \succ FM_3 \succ FM_6$
Our proposed framework for UDHLTSs	$s(FM_1) = 1, s(FM_2) = 0.2123,$ $s(FM_3) = 0.0774, s(FM_4) = 0.2306,$ $s(FM_5) = 0.4771, s(FM_6) = 0.0936,$ $s(FM_7) = 0.1763, s(FM_8) = 0.6708.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$

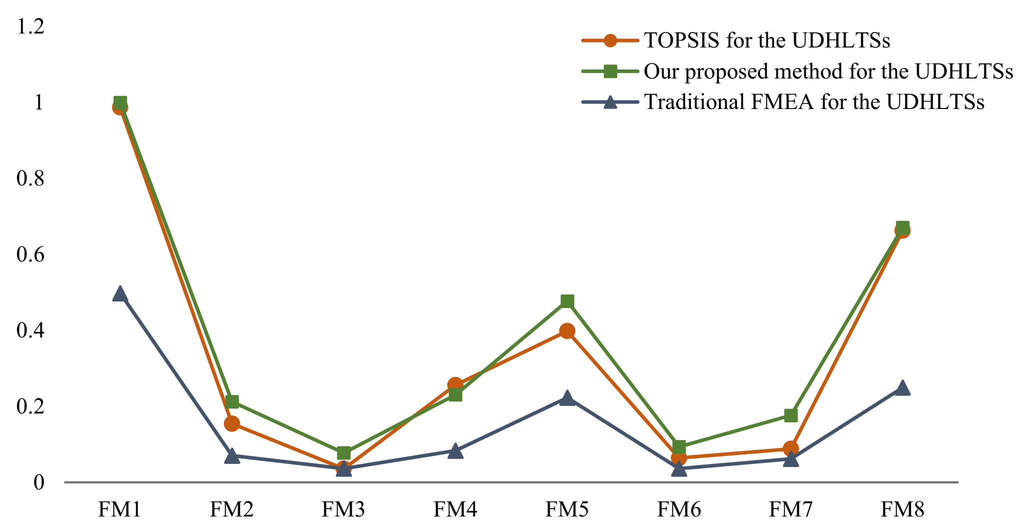

Fig. 17 The ranking results of eight failure modes

same ranking in Table 11 and Fig. 13 illustrates the feasibility of the presented approach.

In order to further illustrate the feasibility of the method, we added two groups of data to compare the TOPSIS method with the proposed method. The TOPSIS method has been applied in the UDHLTS environment by Fu and Liao [32]. So, to illustrate the validity of our presented method, we further compare the two methods.

There are five kinds of risk factors: FM_1, FM_2, FM_3, FM_4, and FM_5, and we take four alternatives T_1, T_2, T_3, and T_4 as the research object, and evaluate these five types of risk failure modes by the way of expert scoring. The initial evaluation matrix is as follows: the linguistic evaluation information under UDHLTSs of first group are shown in the following Table 12.

By using two different methods for calculation, we get the evaluation results of the two methods: $FM_1 \succ FM_5 \succ FM_2 \succ FM_4 \succ FM_3$. The ranking results are shown in the following Table 13 and Fig. 14.

From above Table 13 and Fig. 14, we can see that the same ranking result $FM_1 \succ FM_5 \succ FM_2 \succ FM_4 \succ FM_3$ is obtained in this example. It can be seen that the factor with the highest risk among the two methods is FM_1. Then, the risk level of FM_5, FM_2, FM_4, and FM_3 is reduced in turn.

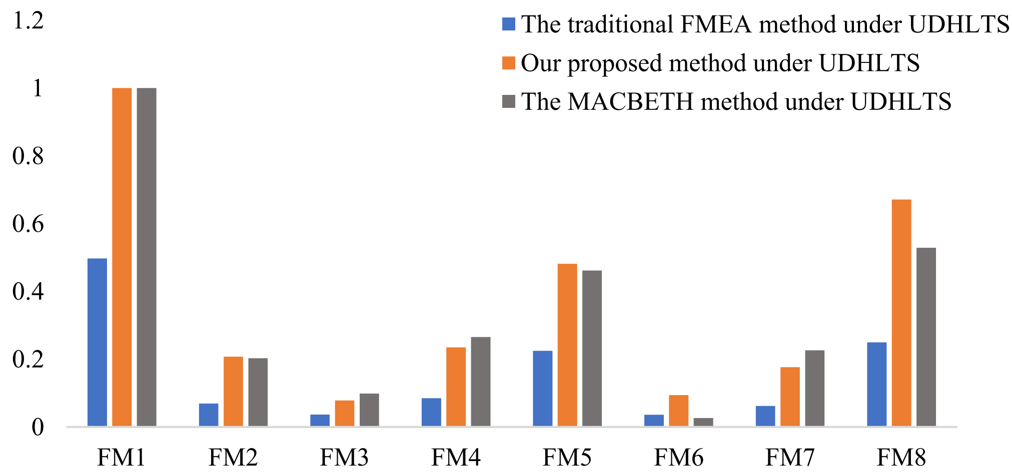

Fig. 18 Ranking results of different methods

Then, the linguistic evaluation information under UDHLTSs of first group are shown in the following Table 14.

By using these two different methods for calculation, we get the same ranking results of the two methods: $FM_1 \succ FM_5 \succ FM_2 \succ FM_3 \succ FM_4$. The ranking results are shown in the following Table 15 and Fig. 15.

From the calculation results of this group of evaluation information, we can see that the same ranking result $FM_1 \succ FM_5 \succ FM_2 \succ FM_3 \succ FM_4$ is obtained in this example. It can be seen that the factor with the highest risk among the two methods is $FM_{1.}$ Then, the risk level of FM_5, FM_2, FM_3,and FM_4 is reduced in turn.

From above Table 13, Fig. 14, Table 15, Fig. 15, and the case study, we can see that the same ranking results are obtained in these two examples, which illustrate the feasibility of the presented model. The UDHLTS-TOPSIS method proposed by Fu and Liao [32] has been proved to be feasible in the same linguistic evaluation environment. From the ranking results of Table 13 and Fig. 14, we obtained the same ranking results in different numerical examples. So, we can get that the proposed method meets the feasibility in UDHLTS environment.

5.2 Weight Sensitivity Analysis

In this subsection, we further analysis the robustness of the proposed method. Robustness explains the steadiness of the results produced by a method. The sensitivity analysis is a popular tool to examine the robustness of various MCDM methods. In this part, we analyze the sensitivity of the ranking result about different weights. The results are shown in the following Table 16 and Fig. 13.

From the Table 16 and Fig. 16, the ranking results of different FMs are changed. According to the above table, the top three FMs are FM_1, FM_8 and FM_5. The results of FM_8 and FM_5 can be seen changed when we use different weights. While, the ranking results of four alternatives are robust. In other words, for the four alternatives, the ranking results are robust, and for the eight FMs, the ranking results are sensitive to the change of weight. However, the top three risk factors remains and unchanged. So, the decision makers need to be paid great attention and avoidance. Therefore, it is necessary to apply the weight determination method in the process of risk evaluation.

5.3 Advantage Analysis by Comparing with Different Methods

In this subsection, we compare the presented method with other existing methods (the traditional FMEA method and the simple MACBETH method) and illustrate the advantages of our proposed method. The proposed method contains the FMEA method and MACBETH method. Compared with the traditional FMEA method, our new framework is more complete. The proposed method overcomes the disadvantage of simple multiplication of O, S, and D and evaluation the failure modes according to the RPN values. The weights of different failure modes are considered. Besides, the simple MADM method cannot better address the problem of risk assessment. So, the proposed method combines these two methods and addresses the risk assessment problems more effectively. Therefore, the presented framework is compared with the traditional FMEA model and the classical MAEBETH method under UDHLTS context. The results are exhibited

Table 18 Evaluation information of example 2 under UDHLTS

	Occurrence				Severity	
	T_1	T_2	T_3	T_4	T_1	T_2
FM_1	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{3\langle o_{-3}^3\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$	$\{s_{1\langle o_2^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$
FM_2	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$
FM_3	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$
FM_4	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{1\langle o_{-1}^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$
FM_5	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{2\langle o_{-2}^2\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$
FM_6	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{0\langle o_{-2}^0\rangle}\}$
FM_7	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{1\langle o_1^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_3^0\rangle}\}$
FM_8	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{2\langle o_{-2}^2\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$

	Severity		Detection			
	T_3	T_4	T_1	T_2	T_3	T_4
FM_1	$\{s_{2\langle o_{-1}^2\rangle}\}$	$\{s_{1\langle o_3^1\rangle}\}$	$\{s_{1\langle o_2^1\rangle}\}$	$\{s_{2\langle o_0^2\rangle}\}$	$\{s_{1\langle o_1^1\rangle}\}$	$\{s_{2\langle o_1^2\rangle}\}$
FM_2	$\{s_{1\langle o_{-1}^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{-1\langle o_{-2}^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_1^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$
FM_3	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{0\langle o_{-2}^0\rangle}\}$	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_{-2}^0\rangle}\}$
FM_4	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{-1\langle o_3^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$
FM_5	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$
FM_6	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{-2\langle o_0^{-2}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$
FM_7	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{-1\langle o_0^{-1}\rangle}\}$	$\{s_{1\langle o_3^1\rangle}\}$	$\{s_{0\langle o_1^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$
FM_8	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_0^0\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{1\langle o_0^1\rangle}\}$	$\{s_{0\langle o_2^0\rangle}\}$

in Table 17, and Fig. 17 shows the ranking of different methods based on Table 17.

From Table 17 and Fig. 18, the ranking results of FM_3 and FM_6 can be seen changed when we use MACBETH-FMEA method and classical MACBETH method, and the orders of FM_7 and FM_2 also have changed. The reasons for different results are explained as below. Firstly, the MACBETH approach does not consider the relationship between O, S, D, and risk factors, which leads to the inaccuracy of decision-making results. Secondly, from the Table 17, when we use the traditional FMEA method, we cannot choose the FM_6 and FM_3. Moreover, the weights of each failure mode are not considered. So, the traditional FMEA method has some disadvantages. Because the presented approach takes the attributes of failure modes into account and determines the attribute weights through reasonable weight determination method, which overcomes the shortcomings of the classical method, therefore, the ranking of presented approach is reasonable and feasible.

To further compare these three methods, two numerical examples are used to reflect the characteristics and differences. The evaluation information of Example 2 is given by the UDHLTSs obtained by expert scoring, and the results are obtained by the above three methods.

Example 2 In order to make further comparative analysis and reflect the benefits of the presented approach, the following is another set of data obtained by expert scoring. In this example, T_1, T_2, T_3, and T_4 are four alternatives. FM_1, FM_2, FM_3, FM_4, FM_5, FM_6, FM_7, and FM_8 are eight failure modes of these four alternatives. The evaluation information of this example is shown in the following Table 18.

Table 19 Comparison results for different methods

Linguistic term sets	Comprehensive values	Ranking
The traditional FMEA [47] for UDHLTSs	$s(FM_1)=0.5019, s(FM_2)=0.0906$, $s(FM_3)=0.0735, s(FM_4)=0.0327$, $s(FM_5)=0.3382, s(FM_6)=0.0238$, $s(FM_7)=0.0598, s(FM_8)=0.2598$.	$FM_1 \succ FM_5 \succ FM_8 \succ FM_2 \succ FM_3 \succ FM_7 \succ FM_4 \succ FM_6$
The MACBETH method [19] for UDHLTSs	$s(FM_1)=1, s(FM_2)=0.3012$, $s(FM_3)=0.3030, s(FM_4)=0.1061$, $s(FM_5)=0.7106, s(FM_6)=0.0250$, $s(FM_7)=0.2055, s(FM_8)=0.5448$.	$FM_1 \succ FM_5 \succ FM_8 \succ FM_2 \approx FM_3 \succ FM_7 \succ FM_4 \succ FM_6$
Our proposed framework for UDHLTSs	$s(FM_1)=1, s(FM_2)=0.309222$, $s(FM_3)=0.1850, s(FM_4)=0.1045$, $s(FM_5)=0.7517, s(FM_6)=0.0547$, $s(FM_7)=0.1743, s(FM_8)=0.7241$.	$FM_1 \succ FM_5 \succ FM_8 \succ FM_2 \succ FM_3 \succ FM_7 \succ FM_4 \succ FM_6$

Table 20 Crisp evaluation information of example 3

	Occurrence				Severity	
	T_1	T_2	T_3	T_4	T_1	T_2
FM_1	0.8764	0.9861	0.8829	0.7422	0.6667	0.8611
FM_2	0.1236	0.7317	0.5000	0.7317	0.3333	0.5000
FM_3	0.2683	0.5000	0.7317	0.5000	0.1667	0.5833
FM_4	0.1236	0.7253	0.7317	0.5064	0.2778	0.3333
FM_5	0.7317	0.8764	0.7456	0.8700	0.5556	0.8889
FM_6	0.2683	0.5000	0.2683	0.5064	0.5000	0.6667
FM_7	0.5064	0.7382	0.7317	0.7317	0.3333	0.5833
FM_8	0.5105	0.8660	0.5105	0.5000	0.5000	0.8333

	Severity		Detection			
	T_3	T_4	T_1	T_2	T_3	T_4
FM_1	0.8056	0.7500	0.6281	0.7952	0.6232	0.7985
FM_2	0.6389	0.6667	0.3719	0.5000	0.6232	0.5000
FM_3	0.4167	0.4444	0.2048	0.5000	0.6199	0.5082
FM_4	0.6667	0.5000	0.3801	0.3940	0.5000	0.6199
FM_5	0.8611	0.7222	0.6199	0.6338	0.7918	0.7918
FM_6	0.5278	0.5278	0.2048	0.5000	0.3801	0.5000
FM_7	0.6667	0.5000	0.3801	0.6338	0.5033	0.6199
FM_8	0.6667	0.6667	0.5000	0.6199	0.6199	0.5082

According to the process of the different decision-making methods, the results are shown in the following Table 19.

From Table 19, we can see that the ranking result of these three methods is $FM_1 \succ FM_5 \succ FM_8 \succ FM_2 \succ FM_3 \succ FM_7 \succ FM_4 \succ FM_6$. But we can also see that it is hard to distinguish between FM_2 and FM_3 in the MACBETH method because the Severity, Occurrence, and Detection is hard to express in the classical MACBETH method.

Example 3 For further comparative analysis, the following example is utilized to reflect the advantages of the presented method. In this example, the evaluation information is crisp number obtained by experts. T_1, T_2, T_3, and T_4 are four alternatives, FM_1, FM_2, FM_3, FM_4, FM_5,

Table 21 Comparison results for different methods

Linguistic term sets	Comprehensive values	Ranking
The traditional FMEA [47] for UDHLTSs	$s(FM_1) = 0.4981, s(FM_2) = 0.0704,$ $s(FM_3) = 0.0363, s(FM_4) = 0.0834,$ $s(FM_5) = 0.2230, s(FM_6) = 0.0363,$ $s(FM_7) = 0.0619, s(FM_8) = 0.2495.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \approx FM_3$
The MACBETH method [19] for UDHLTSs	$s(FM_1) = 1, s(FM_2) = 0.2027,$ $s(FM_3) = 0.0987, s(FM_4) = 0.2654,$ $s(FM_5) = 0.4618, s(FM_6) = 0.0264,$ $s(FM_7) = 0.2265, s(FM_8) = 0.5287.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_7 \succ FM_2 \succ FM_3 \succ FM_6$
Our proposed framework for UDHLTSs	$s(FM_1) = 1, s(FM_2) = 0.2123,$ $s(FM_3) = 0.0774, s(FM_4) = 0.2306,$ $s(FM_5) = 0.4771, s(FM_6) = 0.0936,$ $s(FM_7) = 0.1763, s(FM_8) = 0.6708.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$

Table 22 Comparison results for different linguistic term sets

Linguistic term sets	Comprehensive values	Ranking
The traditional FMEA for ULTSs	$s(FM_1) = 0.3469, s(FM_2) = 0.0833,$ $s(FM_3) = 0.0538, s(FM_4) = 0.0788,$ $s(FM_5) = 0.2169, s(FM_6) = 0.0427,$ $s(FM_7) = 0.0626, s(FM_8) = 0.2456.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_2 \succ FM_4 \succ FM_7 \succ FM_3 \succ FM_6$
Our proposed framework for ULTSs	$s(FM_1) = 1, s(FM_2) = 0.3663,$ $s(FM_3) = 0.1491, s(FM_4) = 0.2912,$ $s(FM_5) = 0.7073, s(FM_6) = 0.1268,$ $s(FM_7) = 0.2362, s(FM_8) = 0.9576.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_2 \succ FM_4 \succ FM_7 \succ FM_3 \succ FM_6$
The traditional FMEA for UDHLTSs	$s(FM_1) = 0.4981, s(FM_2) = 0.0704,$ $s(FM_3) = 0.0363, s(FM_4) = 0.0834,$ $s(FM_5) = 0.2230, s(FM_6) = 0.0363,$ $s(FM_7) = 0.0619, s(FM_8) = 0.2495.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$
Our proposed framework for UDHLTSs	$s(FM_1) = 1, s(FM_2) = 0.2123,$ $s(FM_3) = 0.0774, s(FM_4) = 0.2306,$ $s(FM_5) = 0.4771, s(FM_6) = 0.0936,$ $s(FM_7) = 0.1763, s(FM_8) = 0.6708.$	$FM_1 \succ FM_8 \succ FM_5 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_6 \succ FM_3$

FM_6, $FM_{7,}$ and FM_8 are eight failure mode of these four alternatives. The evaluation matrix is obtained by scoring according to experts' cognition for alternatives and risk failure modes, which is shown in Table 20.

According to the evaluation information obtained by experts, this risk assessment problem is processed and calculated by three methods, and the results are as follows.

From the Table 21, we can see that it is difficult to distinguish between FM_6 and FM_3 in the traditional FMEA method for UDHLTSs. Because the traditional FMEA method has some drawbacks in considering the importance and weight values of different failure modes. In a word, from the above comparisons and analysis, we can see that the presented approach overcomes the drawbacks of the traditional FMEA method and classic MACBETH method.

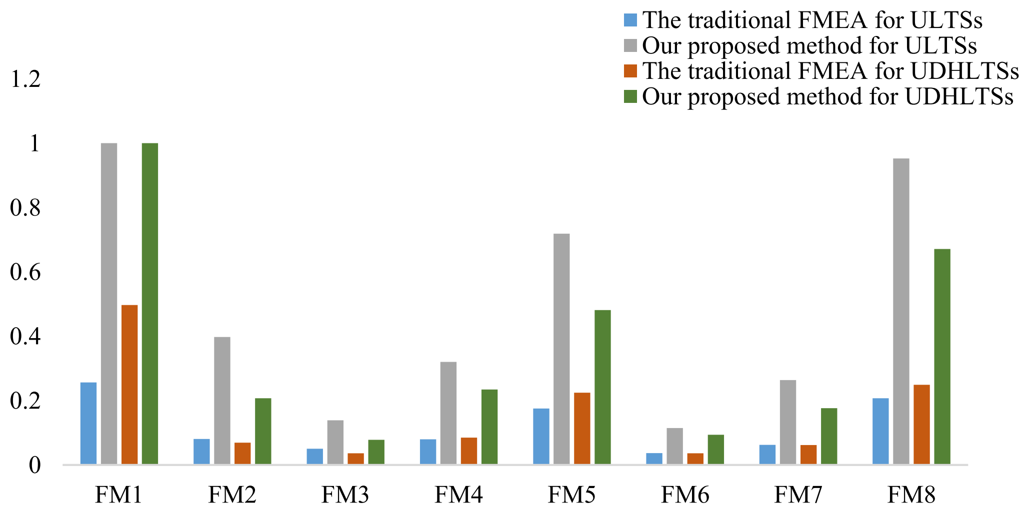

Fig. 19 Ranking results of different linguistic term sets

Compared with FMEA method, our proposed approach can solve risk assessment problems more feasible by using the MACBETH method. Moreover, the weight-determined model overcomes the defect that the FMEA method does not consider the weight factors. The proposed approach has more feasibility in dealing with risk issues compared with the MACBETH method. The proposed FMEA-MACBETH can evaluate the risk factor from OSD and the UDHLTSs is more convenient and more suitable for real decision-making environment. Besides, the weight determination method avoids the weaknesses of classical FMEA that ignores the weight of different FMs, because the weight of FMs also plays an important role in the process of risk assessment. Therefore, the presented method is more reasonable than the classical method.

5.4 Further Comparison with Different LTSs

In this part, the advantages of this UDHLTS are illustrated by comparing with the different linguistic term set (Unbalanced linguistic term sets). Compared with the ULTS, the UDHLTS [32] is more detailed in describing the complex and fuzzy linguistic information than ULTSs [48]. In this subsection, the decision-making results under two linguistic information forms is analyzed, and the results are exhibited in Table 22.

Table 22 shows the scale values and the results in two different LTSs environment, and Fig. 19 reflects the results with different LTSs based on Table 22. Different LSTs result in different ranking results. From Table 22, we can see that the ranking results of A_4 and A_2, A_6, and A_3 have changed when we use UDHLTS and ULTS. The UDHLTS can not only consider the unbalanced semantics of the first hierarchy but also the second hierarchy, and the two hierarchies of UDHLTS can reflect the linguistic information more precisely by increasing the granularity of the LTS. So, UDHLTS can provide more details of evaluation information. The different precision of the LTS can result in different results, which illustrate the advantages of our UDHLTSs.

Therefore, different precision of linguistic sets affects the ranking results. The advantages of the UDHLTS are as follows: (1) UDHLTS can descript the complex information more detailed because the second hierarchy LTS adds more details of information. (2) The UDHLTS can describe the fuzzy information with non-uniformly distribution and risk appetite. (3) The UDHLTS can describe the non-uniformly distributed linguistic information more detailed because two hierarchy LTSs can express the unbalanced linguistic information. Therefore, the UDHLTS is an efficient tool to describe complex evaluation information with unbalanced distribution.

6 Conclusions

To describe the complex linguistic evaluation information more accurately and completely, we use UDHLTSs to express fuzzy and complex information with non-uniformly distributed evaluation information, then three scale functions of the first and second hierarchy LTS are improved and unified. To evaluate the risk information effectively in fuzzy environment, a new framework combing FMEA method with MACBETH method is presented under the unbalanced double hierarchy linguistic environment. In addition, a weight determination model based on the CRITIC method is used under UDHLTS context, and the weight is applied in the FMEA method. Furthermore, the presented approach is used to the risk assessment of different transportation forms. Lastly, the comparison between the proposed approach and the traditional methods is utilized to reflect the feasibility and excellence of the presented method.

In future, we will apply the FMEA-MACBETH model to more linguistic decision-making environment, such as double hierarchy hesitant fuzzy linguistic environment. The weight determination method can be further improved by considering the combination of subjective and objective weights. Furthermore, other aggregation criteria can be considered in risk assessment in a fuzzy environment. And the proposed approach can also be applied to different group decision-making situations and real decision-making, such as marine safety risk assessment, environmental risk assessment, and so on.

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