Improved Failure Mode and Effect Analysis: Implementing Risk Assessment and Conflict Risk Mitigation with Probabilistic Linguistic Information

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Abstract: Failure mode and effect analysis (FMEA) is a system reliability analysis technique that has been widely used in various industries to reduce the failure risk of products, systems, and services. However, traditional FMEA methods have limitations in managing the complex uncertain environment as well as the aggregation and weight allocation of FMEA attributes. Complex real-world problems usually involve multiple decision-makers. Individual perceptions and subjective factors are likely to lead to the differences in opinion, and even the conflict risk, which can ultimately become a challenge to achieve a highly recognized solution. This paper proposes an improved FMEA method to implement the risk assessment, which integrates probabilistic linguistic information and conflict risk mitigation. Probabilistic linguistic term sets (PLTSs) are used to describe the risk assessments, and a comprehensive method is applied to determine the weights of the FMEA attributes. Several new operations and distance measures related to PLTSs are defined. Then, a conflict risk mitigation model is developed to reduce the differences among decision-makers’ FMEA risk assessments. Finally, a case study on global production base selection is presented to illustrate the feasibility and effectiveness of the proposed method. Comparative analysis and discussion verify features and advantages of the method.

Keywords: failure mode and effects analysis (FMEA); risk assessment; conflict risk mitigation; probabilistic linguistic term sets (PLTSs); global production base selection; decision support

1. Introduction

Failure mode and effects analysis (FMEA) is a structured method used during a given stage of the system life cycle to evaluate all probable failure modes and the effects of their occurrences [1]. Since FMEA was first developed in the 1960s by the aerospace industry, it has been widely used in various industrial fields for risk assessment, such as sustainable supplier selection [2,3], remote diagnosis of the street cleaning vehicle [4], security assessment of the supply chain system [5], and so forth. Traditional FMEA usually employs the risk priority number (RPN) to compute the risk ranking of failure modes or risk objects [6]. There are often three FMEA attributes for failure modes, including occurrence (O), detectability (D), and severity (S). Each FMEA attribute is scored using a ten-point scale. Then, we multiply the three FMEA attributes’ scores to obtain the RPN values of failure modes. Finally, the ranking of failure modes can be obtained by the RPN values.

The research on the improvement of FMEA is always ongoing. Liu et al. [7] proposed an integrated FMEA approach for accurate risk assessment under uncertainty. Wang et al. [8] developed a risk evaluation and prioritization method for FMEA with prospect theory and the Choquet integral. Qin et al. [9] extended the FMEA by introducing the evidential reasoning method. However, there are still some issues to be further addressed:
Due to the complexity and uncertainty of decision-making problems, it is difficult for
decision-makers (DMs) to express their quantitative judgments of failure mode risk
with precise values.

In traditional FMEA methods, the relative importance of O, D, and S is not considered
in the risk analysis, but simply multiplied (this can be seen as giving equal importance
to all three FMEA attributes).

Individual FMEA risk assessments may have significant differences, which may lead
to an aggregation of the collective risk assessment that is not reliable enough.

The complexity and uncertainty of decision-making in the real world often require
the participation of multiple DMs to ensure the reliability of decision results, especially
when public interests or major economic interests of enterprises are involved [10–12]. In
this study, we define the group decision-making (GDM) as a situation where several DMs
provide their individual FMEA risk assessments about a set of feasible alternatives and
achieve a widely accepted solution. Because DMs come from different industries and have
different professional knowledge, individual FMEA risk assessments may be different.
When this difference is great, there will be a conflict risk on the individual risk assessments.

Conflict risk in group decision-making is defined as the opposite of consensus. Usually,
a decision with the zero conflict risk can be obtained nearly under ideal situations, and
impossible in practical operations [13,14]. However, a high level of conflict is certainly
not allowed. Generally, the concept of conflict risk threshold should be predefined, which
is used to determine whether the level of conflict risk is acceptable. If the conflict level
is greater than the threshold, it indicates that the differences among DMs’ assessments
are sufficiently large, and conflict risk exists. Conflict risk results from different opinions
about a thing/issue caused by people’s cognitive differences and diverse professional
backgrounds. With these discussions, the following research question emerges: How to
measure, assess, and mitigate the conflict risk in the individual FMEA assessments.

Linguistic assessment information is one of the most commonly used forms of informa-
tion expression in reality decision-making modeling because it is close to people’s natural
language [15–18]. Traditional linguistic expression models only allow DMs to express
their assessments with single linguistic terms. However, in terms of multiple linguistic
terms, DMs might hesitate. Consequently, Rodriguez et al. [19] introduced the concept of
hesitant fuzzy linguistic term sets (HFLTSs), in which all linguistic terms had the same
weight. However, in practical decisions, DMs may have different preferences over differ-
ent linguistic terms when judging an object, rather than just vacillating among multiple
linguistic terms. To this end, Pang et al. [20] defined the probabilistic linguistic term sets
(PLTSs), which could make DMs to express the possible linguistic terms with different
importance degrees. Studies on operation laws, distance measures, and decision applica-
tions of PLTSs begin to emerge. Pang et al. [20] developed an extended TOPSIS method
and an aggregation-based method, respectively, for multi-attribute group decision-making
with probabilistic linguistic information. The consistency and consensus of probabilistic
linguistic preference relations were investigated [21–23].

Motivated by the above analysis and literature reviews, we highlight the contributions
of this study to the existing FMEA methods as follows:

1. PLTSs are used to deal with the uncertainty and fuzziness of FMEA risk assessments.
Several new operations and distance measures related to PLTSs are defined. A
comprehensive method is proposed to determine the weights of FMEA attributes.
2. A conflict risk mitigation model is developed to reduce the conflict risk among
individual risk assessments. The model takes account of the interaction between
DMs.
3. We discuss the determination of some important parameters, including the group
conflict risk threshold and the importance degree of subjective weights in calculating
the weights of FMEA attributes.

The remainder of this paper is organized as follows. Section 2 presents several new
operational rules and distance measures related to PLTSs. Section 3 proposes an improved
FMEA method to conduct the risk assessment by implementing the conflict risk mitigation with probabilistic linguistic information. In Section 4, a case study shows the utility and applicability of the proposed improved FMEA method. Section 5 presents the comparative analysis and sensitivity analysis. Section 6 draws the conclusions.

2. New Operational Rules and Distance Measures Related to PLTSs

As an extension form of HFLTs, the concept of PLTS was originally proposed in Pang et al. [20], and then improved by Zhang et al. [23].

Definition 1. Let \( S = \{ s_\alpha | \alpha = -T, \ldots, -1, 0, 1, \ldots, T \} \) (\( T \) is a positive integer) be a linguistic term set, a PLTS is defined as

\[
L(p) = \left\{ L^{(k)}(p^{(k)}) \mid L^{(k)} \in S, p^{(k)} \geq 0, k = 1, 2, \ldots, \#L(p), \sum_{k=1}^{\#L(p)} p^{(k)} \leq 1 \right\},
\]

where \( L^{(k)}(p^{(k)}) \) is a probabilistic linguistic element, including the linguistic term \( L^{(k)} \) and the probability \( p^{(k)} \). \( \#L(p) \) is the number of all different linguistic terms in \( L(p) \).

We redefine the normalization and basic operation laws of PLTSs. The normalization of PLTSs includes the following two steps.

Step 1: Full display of linguistic terms in \( 2T + 1 \) linguistic scale. \( L(p) \) can be changed as

\[
L(p) = \left\{ s_{-T}(p^{(1)}), \ldots, s_{-1}(p^{(T)}), s_0(p^{(T+1)}), s_1(p^{(T+2)}), \ldots, s_{T}(p^{(2T+1)}) \right\},
\]

Step 2: Probability redistribution. If \( \sum_{k=1}^{2T+1} p^{(k)} < 1 \), then we have

\[
p^{(k)} = p^{(k)} + \frac{1 - \sum_{k=1}^{2T+1} p^{(k)}}{2T + 1}.
\]

By Equation (3), the sum of the probability values of all linguistic terms is equal to 1. Through the above steps, a normalized PLTS can be obtained. For simplicity, the normalized PLTS (NPLTS) is still written as \( L(p) \).

Example 1. Given a PLTS \( L(p) = \{ s_0(0.2), s_1(0.4) \} \), in which the linguistic terms come from \( S = \{ s_{-2}, s_{-1}, s_0, s_1, s_2 \} \). Then, the normalization of the PLTS can be obtained by the following steps:

Step 1: Let \( L(p) = \{ s_{-2}(0), s_{-1}(0), s_0(0.2), s_1(0.4), s_2(0) \} \).
Step 2: Let \( L(p) = \{ s_{-2}(0.08), s_{-1}(0.08), s_0(0.28), s_1(0.48), s_2(0.08) \} \).

Definition 2. Given two NPLTSs, \( L(p)_1 = \left\{ L^{(k)}_1(p^{(k)}_1) \mid L^{(k)}_1 \in S, k_1 = 1, 2, \ldots, 2T + 1 \right\} \) and \( L(p)_2 = \left\{ L^{(k)}_2(p^{(k)}_2) \mid L^{(k)}_2 \in S, k_2 = 1, 2, \ldots, 2T + 1 \right\} \), \( \lambda, \lambda_1, \lambda_2 \geq 0 \). Then we have

1. \( L(p)_1 \oplus L(p)_2 = \left\{ L^{(k)}_3(p^{(k)}_3) \mid L^{(k)}_3 \in S, k_3 = 1, 2, \ldots, 2T + 1 \right\} \),
2. \( \lambda L(p)_1 = \left\{ L^{(k)}_4(\lambda p^{(k)}_1) \mid L^{(k)}_4 \in S, k_4 = 1, 2, \ldots, 2T + 1 \right\} \),
3. \( \lambda_1 L(p)_1 \oplus \lambda_2 L(p)_2 = \left\{ L^{(k)}_5(p^{(k)}_5) \mid L^{(k)}_5 \in S, k_5 = 1, 2, \ldots, 2T + 1 \right\} \),

where \( L^{(k)}_3 = L^{(k)}_1, L^{(k)}_4 = L^{(k)}_1, L^{(k)}_5 = L^{(k)}_1 + p^{(k)}_2 - p^{(k)}_1 p^{(k)}_2, p^{(k)}_3 = p^{(k)}_1 + p^{(k)}_2 - p^{(k)}_1, p^{(k)}_4 = \lambda_1 p^{(k)}_1 + \lambda_2 p^{(k)}_2 - \lambda_1 \lambda_2 p^{(k)}_1 p^{(k)}_2 \).

Theorem 1. Let \( L(p)_1, L(p)_2 \) and \( L(p)_3 \) be any three NPLTSs, \( \lambda_1, \lambda_2, \lambda_3 \geq 0 \). Then

1. \( L(p)_1 \oplus L(p)_2 = L(p)_3 \oplus L(p)_1, \)
2. \( (L(p)_1 \oplus L(p)_2) \oplus L(p)_3 = L(p)_1 \oplus (L(p)_2 \oplus L(p)_3) \).
3. \( \lambda (L(p)_1 \oplus L(p)_2) = \lambda L(p)_1 \oplus \lambda L(p)_2 \), \\
4. \((\lambda_1 + \lambda_2)L(p)_1 = \lambda_1 L(p)_1 \oplus \lambda_2 L(p)_2 \).

It is easy to know that the operational laws presented in Theorem 1 are true.

**Remark 1.** We consider the PLTS to be a special form of linguistic expression. Unlike the scalar multiplication formula presented in [20] or [23], we use the scalar to multiply the probability value. A probabilistic linguistic element contains a linguistic term and its corresponding probability. If the scalar is multiplied by the linguistic term and the probability remains unchanged, the ordinary linguistic term will be distorted to some extent. Furthermore, the aggregated linguistic term may exceed the given linguistic scale.

**Example 2.** Based on the linguistic set \( S = \{s_{-2}, s_{-1}, s_0, s_1, s_2\} \) and given two PLTSs \( L(p)_1 = \{s_0(0.2), s_1(0.8)\} \) and \( L(p)_2 = \{s_1(0.5), s_2(0.5)\} \), \( \lambda_1 = 0.8, \lambda_2 = 0.7 \), we have

- Pang et al.’s method [20]:
  \[
  \lambda_1 L(p)_1 \oplus \lambda_2 L(p)_2 = \{0.8 \times 0.25s_0 \oplus 0.7 \times 0.5s_1, 0.8 \times 0.8s_1 \oplus 0.7 \times 0.5s_2\}
  = \{0.16s_0 \oplus 0.35s_1, 0.64s_1 \oplus 0.35s_2\}
  = \{s_0, s_1, s_2\}.
  \]

- Zhang et al.’s method [23]:
  \[
  \lambda_1 L(p)_1 \oplus \lambda_2 L(p)_2 = \{s_0(0.2), s_0(0.8)\} \oplus \{s_1, s_2\}{(0.5)}
  = \{s_{0.5}(0.4), s_{1.2}(0.4), s_{1.4}(0.1), s_{2.7}(0.1)\}
  = \{s_{-2}(0), s_{1.0}(16), s_{1.6}(s), s_{2.0}(s)\} \oplus \{s_{-2}(0), s_{1.0}(0), s_{1.0}(0.35), s_{2.0}(0.35)\}
  = \{s_{-2}(0), s_{1.0}(0), s_{0.1254}(s), s_{1.6003}(s), s_{2.2743}(s)\}.
  \]

We can see that the probabilities of linguistic terms are not reflected in the result by using Pang et al.’s method [20]. In this case, the unique feature of PLTSs compared with the ordinary linguistic term sets cannot be reflected. In Zhang et al.’s method [23], probability elements are preserved, nonetheless some of their corresponding linguistic terms may be converted to virtual linguistic terms, rather than the ordinary discrete linguistic terms. In general, the DMs use the ordinary linguistic terms to evaluate alternatives, and the virtual linguistic terms can only appear in the operation and ranking [24]. In the conflict risk mitigation process (namely the reverse of the consensus-reaching process), compared with ordinary discrete linguistic terms, the virtual ones make the DMs more difficult to understand and determine the degree to which preferences are adjusted. In this study, the ordinary linguistic terms remain unchanged and yet the associated probabilities always change. If different normalization methods and operational laws are used to process the probabilistic linguistic information, inconsistent decision results will be obtained. The relevant analysis will be discussed in Section 5.1.1.

In order to make a better application of PLTSs in decision making, the following averaging operators for PLTSs are defined.

**Definition 3.** Let \( L(p)_i = \{L^{(k)} (p)^{(k)}_i \}_{k_1 = 1, 2, \ldots, 2T + 1} \) be \( m \) NPLTSs, \( \theta = (\theta_1, \theta_2, \ldots, \theta_m)^T \) be the weight vector of \( L(p)_i (i = 1, 2, \ldots, m) \), \( \theta_i \geq 0, i = 1, 2, \ldots, m, \sum_{i=1}^{m} \theta_i = 1 \), then the probabilistic linguistic weighted averaging (PLWA) operator is defined as

\[
  CL(p) = PLWA (L(p)_1, L(p)_2, \ldots, L(p)_m) = \theta_1 L(p)_1 \oplus \theta_2 L(p)_2 \oplus \cdots \oplus \theta_m L(p)_m.
\]
The probability value for each linguistic term in \( CL(p) \) can be computed recursively. Suppose \( p_m^{(k)} \) is the probability of \( k_i \) in \( CL(p) \). Then, we have

\[
p_m^{(k)} = p_{m-1}^{(k)} + \theta_m p_m^{(k)} - \theta_m p_{m-1}^{(k)}.
\]  

(5)

As \( m \) goes down to 2, we get

\[
p_2^{(k)} = \theta_1 p_1^{(k)} + \theta_2 p_2^{(k)} - \theta_1 \theta_2 p_1^{(k)} p_2^{(k)}.
\]

Definition 4. Let \( L(p)_1 \) and \( L(p)_2 \) be any two NPLTSs, then the distance between \( L(p)_1 \) and \( L(p)_2 \) can be defined as

\[
d(L(p)_1, L(p)_2) = \left( \frac{\sum_{i=1}^{2T+1} \left( \theta_i \left| p_1^{(k)} - p_2^{(k)} \right| \right)^{1/\lambda}}{2T} \right)
\]

where \( i_1^{(k)} \) is the subscript of linguistic term \( L_1^{(k)} \).

This study makes \( \lambda = 2 \), and thus Equation (6) is changed to the Euclidean distance. It is evident that the distance measures between PLTSs satisfy the following properties:

1. \( 0 \leq d(L(p)_1, L(p)_2) \leq 1 \),
2. \( d(L(p)_1, L(p)_2) = 0 \) if and only if \( L(p)_1 = L(p)_2 \),
3. \( d(L(p)_1, L(p)_2) = d(L(p)_2, L(p)_1) \).

3. Materials and Methods

This section develops an improved FMEA method to conduct the risk assessments. Figure 1 summarizes the research framework of this study.

**Figure 1.** The research framework of this paper.

3.1. FMEA Risk Assessment Without Considering the Conflict Risk

Given an FMEA risk assessment problem with probabilistic linguistic information: Let \( X = \{x_1, x_2, \ldots, x_m\} \) be a set of alternatives, which are possible solutions to the problem, \( R = \{r_1, r_2, \ldots, r_n\} \) be a set of risk factors, \( E = \{e_1, e_2, \ldots, e_q\} \) be a set of DMs, and \( C = \{c_1, c_2, \ldots, c_n\} \) be a set of FMEA attributes. Usually, FMEA attributes include three elements, the occurrence (O) that represents the probability of the risk, the severity (S) of the risk, and the detection (D) that means the probability of the risk not being detected.
Thus, we rewrite the set \( C \) as \( C = \{ c_1, c_2, c_3 \} = \{ O, S, D \} \). The weight vector of the attributes is denoted as \( \mathbf{\theta} = (\theta_1, \theta_2, \theta_3)^T \), where \( \theta_j \geq 0, j = 1, 2, 3 \) and \( \sum_{j=1}^{3} \theta_j = 1 \).

Let \( B^h = \left( B^h_{ij} \right)_{u \times n} \) be the FMEA assessment information given by DM \( e_k \in E \), where \( B^h_{ij} = \left( b^h_{ij,1}, b^h_{ij,2}, \ldots, b^h_{ij,m} \right) \) represents the evaluation of alternatives under the risk factor \( r_j \in R \) with respect to the attribute \( c_j \in C \). To refine, \( b^h_{ij} \) (\( i = 1, 2, \ldots, m \)) is a PLTS that can be according to risk scales with five-label linguistic terms presented in Table 1, denoting the evaluation of alternative \( x_j \) under the risk factor \( r_j \in R \) with respect to the attribute \( c_j \in C \). Table 2 details the information \( B^h \) provided by DM \( e_k \). Through using the PLWA operator to aggregate the DMs’ risk assessments, the group risk assessment is obtained as \( B^c = \left( B^c_{ij} \right)_{u \times n} = \left( \left( b^c_{ij,1}, b^c_{ij,2}, \ldots, b^c_{ij,m} \right) \right)_{u \times n} \), where \( b^c_{ij} = PLWA \left( b^1_{ij}, b^2_{ij}, \ldots, b^m_{ij} \right) \).

### Table 1. Linguistic evaluation scale.

| Scale       | s−2       | s−1       | s0        | s1        | s2        |
|-------------|-----------|-----------|-----------|-----------|-----------|
| Severity    | No effect | Minor effect | Moderate effect | Major effect | Catastrophic effect |
| Frequency of occurrence | Almost never | Infrequency | Occasionally | Frequently | Almost always |
| Detection of hazard | Certain | Moderately easy | Moderate | Difficult | Impossible to detect |

### Table 2. FMEA decision information \( B^h \) provided by DM \( e_k \).

| \( r_1 \) | \( b^h_{1,11}, b^h_{1,12}, \ldots, b^h_{1,m1} \) | \( b^h_{1,12}, b^h_{2,12}, \ldots, b^h_{m,12} \) | \( b^h_{1,13}, b^h_{2,12}, \ldots, b^h_{m,13} \) |
| \( r_1 \) | \( b^h_{1,21}, b^h_{2,21}, \ldots, b^h_{m,21} \) | \( b^h_{1,22}, b^h_{2,22}, \ldots, b^h_{m,22} \) | \( b^h_{1,23}, b^h_{2,23}, \ldots, b^h_{m,23} \) |
| …       | \( b^h_{1,u1}, b^h_{2,u1}, \ldots, b^h_{m,u1} \) | \( b^h_{1,u2}, b^h_{2,u2}, \ldots, b^h_{m,u2} \) | \( b^h_{1,u3}, b^h_{2,u3}, \ldots, b^h_{m,u3} \) |

Many literatures have studied the effect of the weights of FMEA attributes on evaluation results, and this effect was considered to be very significant. Generally, the weight calculation is divided into three categories: subjective weighting method (the common equal-weight method is regarded as a special case of this method), objective weighting method, and comprehensive weighting method. The subjective weighting method is simple and practical, but it relies too much on the knowledge and experience of DMs, and fails to consider the role of evaluation information in weight determination, whereas the objective weighting method makes full use of evaluation information. The comprehensive weighting method combines the advantages of subjective and objective weighting methods, which is more accurate and flexible by adjusting the weight distribution of the first two methods. Thus, we adopt the comprehensive weighting method to determine the weights of the FMEA attributes.

According to the information theory, in the multi-attribute decision making, if the deviation degree among DMs’ risk assessments is smaller for an attribute, then a small weight should be assigned to the attribute. This is due to the fact that such an attribute does not help in differentiating alternatives. Otherwise, the attribute should be assigned a larger weight [25]. Thus, we calculate the difference for each FMEA attribute as
where \( \xi \) will present the sensitivity analysis of the parameter \( \rho \)

To highlight our focus on conflict risk, we refer to the process of reducing the information, measuring conflict risk is followed to determine whether DMs have achieved differences between DMs’ assessments as conflict risk mitigation rather than consensus

By solving Equation (9), the optimal weight is obtained as \( \theta^O = (\theta_1^O, \theta_2^O, \ldots, \theta_n^O)^T \), where

\[
\theta_j^O = \frac{\sum_{l=1}^{n} \sum_{m=1}^{q} \sum_{g=1}^{d} d(B_{ljg}^h, B_{ljg}^s)}{\sqrt{\sum_{j=1}^{n} \left( \sum_{l=1}^{n} \sum_{m=1}^{q} \sum_{g=1}^{d} d(B_{ljg}^h, B_{ljg}^s)^2 \right)^2}}, j = 1, 2,\ldots, n
\]

normalizing the objective weights as

\[
\theta_j^O = \frac{\sum_{l=1}^{n} \sum_{m=1}^{q} \sum_{g=1}^{d} d(B_{ljg}^h, B_{ljg}^s)}{\sum_{j=1}^{n} \sum_{l=1}^{n} \sum_{m=1}^{q} \sum_{g=1}^{d} d(B_{ljg}^h, B_{ljg}^s)}, j = 1, 2,\ldots, n
\]

Clearly, \( 0 \leq \theta_j^O \leq 1 \) and \( \sum_{j=1}^{n} \theta_j^O = 1 \). We see that the more differences between DMs’ opinions on one FMEA attribute, the more weight should be assigned. Following the above calculation, the comprehensive weight \( \theta_j \) \( (j = 1, 2,\ldots, n) \) can be obtained through a linear combination of subjective weight \( \theta_j^s \) and objective weight \( \theta_j^O \), i.e., \( \theta_j = \rho \theta_j^s + (1 - \rho) \theta_j^O \), where \( \rho \) is the importance degree of subjective weight, meeting that \( 0 \leq \rho \leq 1 \). Section 5.2 will present the sensitivity analysis of the parameter \( \rho \).

3.2. Conflict Risk Mitigation Model

Since DMs usually have different knowledge backgrounds and experiences, some DMs’ opinions are likely to be significantly different from others [26,27]. At this point, the conflict risk appears, which means that there are large differences between DMs’ FMEA risk assessments. The higher the conflict risk, the lower the reliability of the decision. As the reverse of conflict, the concept of consensus has been widely adopted in the adoption process [28]. To highlight our focus on conflict risk, we refer to the process of reducing the differences between DMs’ assessments as conflict risk mitigation rather than consensus building, although these two terms are the same. After obtaining FMEA risk assessment information, measuring conflict risk is followed to determine whether DMs have achieved a decision outcome that is sufficiently low in conflict risk.
Two rules for calculating conflict risk measures exist: The first is based on the distance to the group opinion, and the second is based on the distance between DMs’ opinions [13,29]. We adopt the second rule, because it can eliminate the impact of DMs’ weights, and only focus on the differences between DMs’ assessments.

Definition 5. The conflict risk level of $e_h$ in the $t$-th iteration is defined as

$$CR_h^t = \frac{1}{q-1} \sum_{g=1, h \neq g}^{q} d\left(B_h^t, B_g^t\right),$$  \hspace{1cm} (12)

where $d\left(B_h^t, B_g^t\right)$ is the Euclidean distance between $B_h^t$ and $B_g^t$, such that

$$d\left(B_h^t, B_g^t\right) = \frac{1}{m \times u \times n} \left(\sum_{i=1}^{m} \sum_{l=1}^{u} \sum_{j=1}^{n} \left(b_{h_i}^{t_l} - b_{g_i}^{t_l}\right)^2\right).$$  \hspace{1cm} (13)

The group conflict risk level in the $t$-th iteration is obtained as

$$GCR^t = \frac{1}{q} \sum_{h=1}^{q} CR_h^t,$$  \hspace{1cm} (14)

Obviously, $0 \leq GCR^t \leq 1$. If the group conflict risk level is sufficiently low (smaller than the threshold $\overline{GCR}$), then the selection process can be followed; otherwise, the conflict risk mitigation process should be applied to manage the opinion differences. The conflict risk threshold $\overline{GCR}$ is an important parameter used to determine whether the current group conflict risk level is acceptable. The proper assignment of $\overline{GCR}$ is related to the operation of the whole conflict risk mitigation process and the final decision result. At present, the main method is to use computer software to simulate the impact of different values on the process of conflict risk mitigation, and finally determine the threshold range based on the actual decision-making problem. We will present the analysis on the conflict risk threshold in Section 5.3.

The reason for entering into the conflict risk mitigation process is that there is a large degree of conflict risk between DMs’ opinions. This is because some DMs’ opinions are quite different from those of the majority. These DMs must modify their opinions to reduce the risk level of group conflict. This modification should not be viewed as a distortion of the original opinion, but as a timely correction of the inappropriate opinion and a convergence of individual opinions through interaction and discussion among DMs. This study employs three phases to address the conflict risk: identification, interaction, and proper modification.

3.2.1. Identification of the Individual Opinion with the Highest Conflict Risk

Based on the majority principle, the first step should be to find the DM with the highest level of conflict risk. Suppose $B_{h_i}^t$ contributes more to the conflict risk, i.e., $CR_{h_i}^t = \max_h \left\{ CR_h^t \mid h = 1, 2, \ldots, q \right\}$. Thus, DM $e_h$’s risk assessment $B_{h_i}^t$ is asked to be adjusted. Generally, the more difference between an individual opinion and others, the larger adjustment should be carried out. For simplicity, an individual risk assessment is also called an individual opinion in the following.

3.2.2. Interaction and Discussion

This step includes two operations: the calculation of the adjustment reference and the interaction among DMs. The former aims to provide a mathematical reference for the identified DM to modify its individual opinion, as well as for the following interaction. The latter is used to make all DMs, especially the identified one, more aware of decision problem and current conflict risks, and then guide adjustment operations. By constructing the
mathematical relationship between the conflict risk level and the acceptable conflict threshold, we propose the concept of objective adjustment coefficient. This type of adjustment coefficient depends on the given calculation rather than DMs’ subjective judgments.

**Definition 6.** Given the conflict risk threshold $GCR$ and individual conflict risk level in the $t$-th iteration $CR_{h,t}$, the objective adjustment coefficient can be defined as

$$\delta_{h,t} = \frac{CR_{h,t} - GCR}{CR_{h,t}},$$

(15)

where $\delta_{h,t}$ represents the degree of respect that DM $e_h$ should have for the collective opinion in the $t$-th iteration according to the defined calculation rule. Clearly, $0 \leq \delta_{h,t} \leq 1$. The larger the individual conflict risk, the more the objective adjustment coefficient.

Table 3 presents the issues that should be answered by the identified DM or all DMs in each round of iteration. This study assumes that DMs can answer questions honestly and objectively. The following outcomes must be clarified.

1. (For the first issue) If the high level of conflict risk is due to a lack of understanding of the decision problem, then a deeper discussion should be carried out. If this is due to a DM insisting on his/her own opinion, the following conflict risk mitigation process may incur a large cost, including interaction cost and opinion adjustment cost.

2. (For the second issue) The identified DM is asked to indicate whether or not he/she agrees with the objective adjustment coefficient and to what extent. Note that the objective adjustment coefficient is a reference, not a mandatory parameter.

3. (For the third issue) The identified DM needs to inform others of his/her subjective willingness to implement the opinion adjustment clearly.

4. (For the fourth issue) The identified DM needs to answer clearly whether the opinion adjustment is distorted, and if so, whether it is acceptable. If acceptable, the decision continues; otherwise, the exit mechanism is activated to determine whether the identified DM exits or the entire decision is terminated.

5. (For the five issue) All DMs need to assess the impact of individual conflict risk on group conflict risk, including the contribution degree of individual conflict risk to group conflict risk and the extent to which identified DMs need to make adjustments.

6. (For the sixth issue) All DMs need to clarify the activation condition of the exit mechanism. Then, in each iteration, whether the current situation requires the activation of the exit mechanism can be determined.

**Table 3. Issues involved in interaction and discussion.**

| Issues that should be answered for the identified DM | Detailed Description |
|-----------------------------------------------------|----------------------|
| 1. What causes you to have the highest level of conflict risk? Lack of clarity about the decision? Or firmly adhere to your own opinion? |
| 2. Do you agree with the objective adjustment coefficient? To what extent? |
| 3. What is the extent to which you are willing to adjust your opinion? |
| 4. Do you think there is any distortion in the adjusted opinion? If there is distortion, can you accept it? |

| Issues that should be answered for all DMs |
|------------------------------------------|
| 5. How much does this individual conflict risk affect the overall group conflict risk? |
| 6. Does the exit mechanism need to be activated? |
3.2.3. Exit Mechanism

An exit mechanism is essential to the conflict risk mitigation process, which can be divided into the following two choices:

- DMs with high risk of conflict and unwilling to adjust their opinions are required to withdraw from the decision. Note that the decision that requires the exit of a single DM must be made with great care and approval from all DMs, including that DM.
- If no agreement is reached on a single DM’s exit, the decision can be terminated. Or, if all DMs feel that the current level of conflict risk is too high, any degree of adjustment is not enough to meet the threshold requirements, but will increase the decision cost and increase the possibility of opinion distortion, at which time, DMs can choose to terminate the decision after deliberation. Next, three things need to be done: (i) reflect on the reasons why the decision cannot be reached, (ii) redefine the DMs involved in decision-making, and (iii) conduct a reassessment of all alternatives.

Remark 2. Objective adjustment coefficient is used as a reference for the DM to give the adjustment coefficient. In practical decisions, the DM can directly give the adjustment coefficient according to the current conflict risk level.

Remark 3. The interaction between the DMs is a very important step in the conflict risk mitigation process, because it has the following good effects. (i) It helps reduce or eliminate bias among DMs and promote the smooth process of decision making; (ii) It helps the DMs to have a clearer understanding of the decision issue and the current level of conflict risk; (iii) It can help and guide the identified DMs to give appropriate adjustment coefficients to reduce the risk level of group conflict. If the interaction between DMs is not involved in conflict risk mitigation, it is likely that the decision information of some DMs may be distorted for the purpose of reducing conflict risk.

3.2.4. Proper Modification

Following the in-depth discussion among the DMs, the identified DM $e_h$ provides the adjustment coefficient $c_h^{i, t}$ and uses it to modify its opinion as follows:

$$ p_{i,j}^{h,t+1} = c_h^{i, t} \cdot p_{i,j}^{c \rightarrow h,t} + \left(1 - c_h^{i, t}\right) \cdot p_{i,j}^{h,t} \tag{16} $$

where $p_{i,j}^{c \rightarrow h,t} = \sum_{g=1}^{q} p_{i,j}^{g} \cdot \pi_g$ is the collective probability used to guide the adjustment of $e_h$’s opinion, and $\pi_g$ is the remaining DM $e_g$’s weight such that $\pi_g = w_g / \sum_{g=1}^{q} w_g$. Through Equation (16), we can obtain the adjusted opinion $B_{i,j}^{h,t+1} = \left[B_{i,j}^{h,t+1}\right]_{u \times 3}$, where $L_{i,j}^{h,t+1} = L_{i,j}^{h,t} ; i = 1, 2, \ldots, m; \ L = 1, 2, \ldots, u; \ j = 1, 2, 3$.

Remark 4. The adjustment operation presented in Equation (16) is based on the proposed new operation laws and distance measures related to PLTSs. Different from the definition of normalization rules and operation laws of PLTSs in [20] or [23], this paper always holds that the discrete linguistic term is used to evaluate information, while the continuous linguistic term is used for the calculation operation. The comparative analysis of the effect of different normalization methods on the conflict risk mitigation process and selection process will be presented in Section 5.1.

Algorithm 1 presents the procedure of the proposed conflict risk mitigation model.
Algorithm 1. Conflict risk mitigation model with FMEA risk assessments.

Input: Initial normalized FMEA risk assessments \( B^{h,0} \), \( h = 1, 2, \ldots, q \), and the acceptable conflict risk threshold \( GCR \).
Output: Final individual FMEA risk assessments.
Step 1. Set \( t = 0 \).
Step 2. Compute the conflict measures by using Equations (12)–(14). If \( GCR^t \leq GCR \), proceed to Step 4; otherwise proceed to the next step.
Step 3. Conflict risk mitigation process.
Step 3.1. Identify the individual assessment with the highest conflict risk, denoted as \( CR^{h,t} = \max_h \{ CR^{h,t} | h = 1, 2, \ldots, q \} \).
Step 3.2. Apply Equation (15) to calculate the objective adjustment coefficient \( \delta^{h,t} \) and enter into the interaction and discussion process.
Step 3.3. Use Equation (16) to adjust \( \epsilon_h \)'s assessment and obtain the adjusted opinion \( B^{h,t+1} \). Let \( t = t + 1 \) and return to Step 2.
Step 4. Let \( t^* = t \). Output the final FMEA risk assessments \( B^{h,t^*} \), \( h = 1, 2, \ldots, q \).
Step 5. End.

3.3. Proposed Improved FMEA Risk Assessment and Conflict Risk Mitigation

The proposed improved FMEA method aims to obtain a widely accepted risk assessment with probabilistic linguistic information. An algorithm for the method is summarized as Algorithm 2.

Algorithm 2. Improved FMEA method with probabilistic linguistic information.

Input: Individual FMEA risk assessments \( B^{h,0} \) (\( h = 1, 2, \ldots, q \)), the acceptable conflict risk \( GCR \), and the parameter \( \rho \).
Step 1: Normalize the DMs’ FMEA risk assessments, still denoted as \( B^{h,0} \) (\( h = 1, 2, \ldots, q \)).
Step 2: Use Algorithm 1 to manage the conflict risk mitigation and obtain the final iterative time \( t^* \) and the final DMs’ opinions \( B^{h,t^*} \) (\( h = 1, 2, \ldots, q \)). For simplicity, let \( B^{h,t^*} \) be denoted as \( B^h \) (\( h = 1, 2, \ldots, q \)).
Step 3: Use Equation (11) to calculate the objective weight vector of FMEA attribute \( \theta^O \). Then, use the formula \( \theta_i = \rho \theta_{1i} + (1 - \rho) \theta_{2i} \) to obtain the comprehensive weight vector \( \theta \).
Step 4: Aggregation of individual FMEA risk assessments.
- First layer (the aggregation of DMs’ opinions): let \( B^{r_j}_{ij} = \left( b^{r_j}_{1ij}, b^{r_j}_{2ij}, \ldots, b^{r_j}_{m_{ij}} \right) \) be the collective opinion under the risk factor \( r_j \) with respect to the attribute \( c_{ij} \), where \( b^{r_j}_{ij} = PLWA_w \left( b^{r_j}_{1ij}, b^{r_j}_{2ij}, \ldots, b^{r_j}_{m_{ij}} \right) \).
- Second layer (the aggregation of FMEA attributes): let \( B^c_i = \left( b^c_{1i}, b^c_{2i}, \ldots, b^c_{m_i} \right) \) be the aggregated FMEA evaluation matrix, where \( b^c_{ij} = PLWA \left( b^{r_j}_{1ij}, b^{r_j}_{2ij}, \ldots, b^{r_j}_{ij} \right) \).
- Third layer (the aggregation of risk factors): let \( RV = (rv_1, rv_2, \ldots, rv_m) \) be the risk values of alternatives after aggregating all risk factors, where \( rv_i = PLWA \left( b^c_{ij}, b^c_{ij}, \ldots, b^c_{ij} \right) \).
Step 5: Calculate the score of each risk value as

\[
rs_i = E(rv_i) = s_{p_i}^{(17)}
\]

where \( rv_i \) is a PLTS and \( p_i = \sum_{k=1}^{m+1} r_i^{(k)} I_{p_i}^{(k)} \). Rank the alternatives according to the ascending order of the evaluation scores.
Step 6: Output the final selected alternative.
Step 7: End.
4. Results

This section applies the proposed improved FMEA method to a case study on the global production base selection. The studied company is a Chinese sports equipment manufacturer focusing on the development and manufacture of classic American-style products. The company is committed to providing comfortable shoe styles and a high-quality dressing experience for young urbanites and teenagers, and its products are mainly sold to China and southeast Asian countries and regions. At present, the company’s main production bases are located in Fujian and Guangdong, China. Due to the company’s overall strategic adjustment and the increase in China’s domestic labor costs, the company decides to build a new production base overseas and initially chose seven locations in four countries (including Vietnam, Philippines, Malaysia, and Indonesia) as alternatives (denoted as \( X = \{x_1, x_2, x_3, x_4\} \)). Note that the original source of this figure is presented in https://SinoFrance.com (accessed on 4 May 2021). The reasons for preselecting these seven global production bases are as follows: (1) they are all located in southeast Asia, which overlaps with the main sales regions of the products, so as to facilitate the rapid realization of the process from production to sales; (2) production costs in these places are indeed lower than those in China, which is the main motivation for the company to choose overseas production bases.

To evaluate the seven alternative global production bases comprehensively, clarify the possible risks, and provide technical support for subsequent decision-making activities, a special committee is convened by inviting four DMs \( e_h \) (\( h = 1, 2, 3, 4 \)) from different departments to participate in the preliminary analysis. Suppose there is no opinion leader among the DMs, so the DMs are assigned to the same weight. Based on the research in [30–34] and business practices, four risk factors are used: economical risk (\( r_1 \)), such as tax policies, energy price fluctuation, financial crises, bribery, patent infringements; social risk (\( r_2 \)), including excessive working time; work-life imbalance, unfair wages, discrimination, healthy and safe working environment; demographic challenges/aging population; environmental risk (\( r_3 \)), such as environmental accidents, pollution (air, water, soil), natural disasters (e.g., hurricanes, floods, earthquakes), water scarcity; and global risk (\( r_4 \)), such as exchange rate fluctuations, tariff barriers, disruption risks through political instability, terrorism, and cultural incompatibility. The DMs provide the evaluation information of the alternatives by using the linguistic evaluation scale in Table 1. The decision process is as follows.

Step 1: Construction of individual FMEA risk assessments.

The whole DMs’ FMEA risk assessment information is presented in the supplementary materials. Only DM \( e_1 \)’s information with respect to the attribute \( c_1 \) under economical risk \( r_1 \) is listed here, i.e.,

\[
B_{11}^1 = \left( B_{11,11}^1, B_{12,11}^1, B_{13,11}^1, B_{14,11}^1 \right),
\]

where

\[
B_{11}^1 = (\{s_2-0.2, s_1(0.5), s_2(0.3)\}, \{s_2(1)\}, \{s_2-0.1, s_0(0.5), s_3(0.4)\}, \{s_1(0.6), s_1(0.4)\}).
\]

Step 2: Use Algorithm 1 to manage the conflict risk mitigation.

Some parameters are predetermined, i.e., the conflict level threshold \( \text{GCR} = 0.15 \) and the weight parameter \( \rho = 0.5 \). It is noted that how to determine these parameters is an important and complicated problem that will be analyzed in Section 5.3. The conflict risk mitigation process can be summarized in Table 4. We obtain that the final iterative time is \( t^* = 3 \). Due to space limitations, the final FMEA assessment information is not listed here (please see the Supplementary Material).

| Number of Iterations | GCR before CRMP \(^1\) | Identified Opinion | Subjective Adjustment Coefficient before Interaction | Objective Adjustment Coefficient | Subjective Adjustment Coefficient after Interaction | GCR after CRMP |
|----------------------|---------------------|------------------|-------------------------------------------------|---------------------------------|---------------------------------|----------------|
| Round 1              | 0.1961              | \( B^{3,0} \)    | 0.2                                             | 0.2693                          | 0.46                            | 0.1665          |
| Round 2              | 0.1665              | \( B^{4,1} \)    | 0.1                                             | 0.1495                          | 0.1                             | 0.1596          |
| Round 3              | 0.1596              | \( B^{5,2} \)    | 0.1                                             | 0.1135                          | 0.15                            | 0.1495          |

\(^1\) CRMP stands for conflict risk mitigation process.
Step 3: Use Equation (11) to calculate the objective weight vector of FMEA attributes as \( \theta^O = (0.3424, 0.363, 0.2946)^T \). The subjective weight vector is set as \( \theta^S = (0.4, 0.4, 0.2)^T \). Then, use \( \theta_j = \rho \theta^S_j + (1 - \rho) \theta^O_j \) to calculate the comprehensive weight vector as \( \theta = (0.3712, 0.3815, 0.3473)^T \).

Steps 4–6: Aggregate the final individual FMEA risk assessments and calculate the scores of risk values of alternatives as \( r_{s1} = s_1 - 0.0954, r_{s2} = s_2 - 0.1208, r_{s3} = s_3 - 0.0528, r_{s4} = s_4 - 0.0577 \). Therefore, \( x_2 \) is finally identified as the optimal solution. Namely, the production base should be established in the Philippines.

Step 7: End.

5. Discussion

This section first presents the further analysis of the improved FMEA method through the comparison with current research. Section 5.2 implements the sensitivity analysis of parameter \( \rho \). Section 5.3 discusses the determination of important parameters. Note that the data used in the comparative analysis come from the case study in Section 4.

5.1. Comparison with Other Decision Support Methods

We compare and analyze the difference between the proposed method and other studies from the following two aspects: the processing of probabilistic linguistic information, and the impact of effective interaction on conflict risk mitigation.

5.1.1. Compared with Pang et al.’s Research and Zhang et al.’s Research Regarding the Processing of Probabilistic Linguistic Information

So far, there are three main ways to normalize and aggregate probabilistic linguistic information, that is, Pang et al.’s research [20], Zhang et al.’s research [23], and this study. To normalize the number of linguistic terms in a PLTSs, Pang et al. [20] and Zhang et al. [23] made the numbers of linguistic terms in the two PLTSs be identical by adding several linguistic terms with zero probability, and repeated linguistic terms usually occurred in the normalized PLTSs. Our study makes the linguistic terms in both phrases equal not only in number but also in subscript. To implement the weighted averaging operation, in Pang et al.’s research [20], the PLTSs were integrated into an ordinary set of linguistic terms without any probability values. Zhang et al. [23] assembled the PLTSs into an ordinary set of linguistic terms associated with probability values. In this study, the aggregated PLTS is still composed of a set of original discrete linguistic terms associated with probability values. Figure 2 presents the comparison results of different processing approaches to probabilistic linguistic information. To avoid incomparability caused by the artificial adjustment coefficient, the objective adjustment coefficient is used to manage conflict risk mitigation in this subsection.

We can conclude the following observations and discussions:

1. All three methods yield the same alternative ranking. This indicates that all these methods can be used to solve the decision problem effectively. However, the final score of the risk value of each alternative is different, although it does not affect the selection of the best alternative.

2. The three methods lead to different conflict risk mitigation processes, which are reflected in the conflict risk measures and the final conflict risk levels.

3. No matter which method is used to deal with probabilistic linguistic information, the opinion adjustment faces some disadvantages and difficulties (see Table 5).
Table 5. Disadvantages/Difficulties of different methods for dealing with probabilistic linguistic information.

| Three Methods          | Results in The Normalization and Aggregation of PLTSs                                                                 | Disadvantages/Difficulties                                                                 |
|------------------------|-------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|
| Pang et al. [20]       | Multiple virtual linguistic term without any probability values                                                        | ● Virtual linguistic term will make it difficult for the DMs to understand the evaluation meaning corresponding to linguistic terms. |
| Zhang et al. [23]      | Multiple virtual linguistic term associated with probability values                                                  | ● The probabilities of linguistic terms are not reflected in the result. By this way, the unique point of PLTSs compared with the ordinary linguistic term sets disappears. |
| This study             | Multiple original discrete linguistic term associated with probability values                                        | ● The number of linguistic terms in a PLTS may increase.                                      |
|                        |                                                                                                                        | ● The sum of the probabilities in the aggregated PLTS may be less than 1.                     |

5.1.2. Compared with Zhang et al.’s Research Regarding the Impact of Effective Interaction on Conflict Risk Mitigation

The interaction and discussion between DMs are very important and necessary in the conflict risk mitigation process, aiming to guide the identified DMs to take a positive and cooperative attitude towards opinion adjustment. This attitude is voluntary rather than mandatory. We simulate the conflict risk mitigation process by using the objective
adjustment coefficient with/without interaction. Suppose the benchmark is the objective adjustment coefficient obtained by Equation (15). If an effective interaction exists in an iteration, we let the identified DM give an adjustment coefficient 30% larger than the objective adjustment coefficient. Contrarily, if the interaction is not good in an iteration, we let the identified DM give an adjustment coefficient 30% less than the objective adjustment coefficient. Figure 3 shows the results of conflict risk mitigation processes with/without interactions between DMs.

![Figure 3](image_url)

**Figure 3.** Results of conflict risk mitigation processes with/without interaction between DMs.

We can obtain the following observations and discussions:

- Effective interactions can significantly reduce the number of iterations of conflict risk mitigation. For example, if the benchmark is used to address conflict risk mitigation, the number of iterations is 5. If there is an effective interaction, the number of iterations drops sharply to 3. The interaction should be added to the conflict risk mitigation model, which not only helps increase the adjustment coefficient, but more importantly, enables the DM to feel that he/she is involved in the decision, and that the revision of his/her opinion is not mandatory, but an active adjustment after a clearer understanding of the decision problem.

- Ineffective interactions are likely to prolong the number of iterations of conflict risk mitigation. Ineffective or negative interactions also occur frequently in real decisions. In this case, an exit mechanism is introduced to require the DMs who are at greater conflict risk with the group and hold a negative attitude towards the risk mitigation to exit the decision (this operation should be cautious) or to terminate the entire decision.

5.2. Sensitivity Analysis

A sensitivity analysis is carried out to examine the influence of different weights of FMEA attributes on the decision result. For this purpose, we use MATLAB software to generate 1000 random numbers of the parameter \( \rho \) in the range \([0,1]\) and obtain the simulation results (see Figure 4). Figure 4a–d show four independent sub-graphs regarding the scores of risk values of the alternatives under different risk factors, and Figure 4f displays the scores of comprehensive risk values after aggregating all risk factors.
When the parameter \( \rho \) is set as different values, the ranking of risk scores of alternatives remains unchanged. However, if we examine the ranking under different risk factors, there will be a big difference. We make the following observations:

1. Under different risk factors, the optimal alternative may be different. For example, as shown in Figure 4b, under the risk factor \( r_2 \), the optimal alternative is \( x_4 \), while under the risk factors \( r_3 \) and \( r_4 \), \( x_2 \) will be selected as the optimal alternative (see Figure 4b,c).

2. Under different risk factors, the alternative ranking may be different. For example, in Figure 4b, the ranking is \( x_4 \succ x_2 \succ x_3 \succ x_1 \), while Figure 4c shows the ranking \( x_2 \succ x_3 \succ x_1 \succ x_4 \).

Determining the weights of FMEA attributes is a matter of concern, which will be presented in Section 5.3.

5.3. Determination of Important Parameters

In our proposed FMEA method, two important parameters must be predetermined, that is, \( \rho \) and \( GCR \). We use the objective adjustment coefficient to stimulate the change trajectory of the two indexes (the number of iterations and average adjustment amount) when setting \( GCR \) to change within the interval \([0.05, GCR^0]\). The lower limit 0.05 represents a very low level of conflict risk for DMs, very close to zero. If the threshold is set above the upper limit \( GCR^0 \), conflict risk mitigation is not required. Thus, we let the value of \( GCR \) change in the interval \([0.05, GCR^0]\). Consider the DMs’ attributes towards the opinion adjustment. We can regard the objective adjustment coefficient as a neutral attribute. The adjustment coefficient corresponding to a negative attitude is 30% larger than the objective adjustment coefficient, while the adjustment coefficient corresponding to a negative attitude is 30% smaller than the objective adjustment coefficient. Figure 5 shows the results of the iterative times and average adjustment amount when \( GCR \) changes. The total adjustment amount is used to measure the sum of the changes in the identified opinion before and after the implementation of the conflict risk mitigation model in each iteration. Given the final iterations \( t^* \), the total adjustment amount can be calculated as

\[
AD = \sum_{t=0}^{t^*} d\left(B^{h,t+1}, B^{h,t}\right),
\]

where \( B^{h,t} \) is the identified opinion that should be adjusted in
each iteration. We can conclude that the smaller the value of $GCR$, the larger the number of iterations and the average adjustment amount required. The determination of $GCR$ can be divided into two procedures:

1. Examine the average adjustment amount. The larger the average adjustment amount, the more likely the distortion is to occur. The average adjustment amount is generally required to be less than 0.5, and the threshold value should belong to the internal $[0.13, 0.1961]$.

2. Examine the number of iterations. Too many iterations will prolong the decision time and increase the uncertainty. It is assumed that the number of acceptable conflict risk mitigation iterations belongs to the interval $[2, 4]$. If the DMs are positive about adjustment, the threshold can be set within the interval $[0.13, 0.17]$ (see the green region in Figure 5). If the DMs are negative about adjustment, the internal is set as $[0.18, 0.19]$ (see the orange region in Figure 5). If the DMs are neutral about adjustment, $[0.13, 0.19]$ will be more appropriate (see the blue region in Figure 5).

![Figure 5. Comparative results when setting different threshold values of conflict risk.](image)

In essence, the FMEA risk assessment method is a multi-attribute decision-making technique, which contains three attributes, that is, occurrence probability ($O$), severity ($S$), and detection probability ($D$). Traditional FMEA methods generate quantitative evaluation results by using the risk priority number, which is calculated by multiplying the values of these three attributes (namely $RPN = O \times S \times D$). This indicates that the traditional FMEA risk assessment process does not consider the weight information of risk attributes, and regards occurrence probability, severity, and detection probability as equally important. However, this arrangement is sometimes out of line with reality. For example, in a group decision making, a DM thinks that the occurrence probability is more important, because any risk will produce actual damage only when it happens. Another DM holds that severity should be taken more seriously because it represents the extent to which that risk will impact once it occurs. Section 3.1 has presented three weight calculation method.

Since there are both subjective weight and objective weights, it is necessary to introduce a parameter $\rho$ to balance the importance of the above two weights. Figure 4 already shows the effect of the change of $\rho$ on the scores of the risk values of alternatives. The DMs can observe the risk score of each alternative when $\rho = 0$ and $\rho = 1$. $\rho = 0$ means that the DMs completely adopt the objective weight, while $\rho = 1$ indicates that the DMs completely adopt the subjective weight. Although these two different values of $\rho$ get
the same ranking of risk scores in Figure 4, different results will be obtained in many cases. Qualitatively speaking, if the DMs are uncertain or difficult to assess the weight information of risk criteria, we can set $\rho < 0.5$, and $\rho$ can be close to 0; otherwise, we can set $\rho \geq 0.5$, and $\rho$ can be close to 1. However, there is a problem that must be paid attention to: how to determine the weight of FMEA attributes when there is a big difference between subjective weight and objective weight. At this point, $\rho$ should be as close to 1 as possible (for example, let $\rho = 0.9$). Because the DMs are the core elements of the decision-making problem, they should choose to believe their own knowledge when there is a big difference between their subjective cognition and the result according to a certain law. If they choose to believe the very different ‘objective results’, it may indicate that their understanding of the decision-making problem is not clear and accurate. Conversely, if subjective and objective weights are similar (or nearly the same), then the objective weight can provide a good aid and reference. At this point, $\rho$ can be set smaller (for example, let $\rho = 0.3$).

5.4. Limitations of the Proposed Improved FMEA

The proposed FMEA improved traditional FMEA methods by introducing PLTSs to express risk assessments and considering the conflict risk mitigation of individual risk assessments. However, there still exist some limitations:

1. Although we propose a comprehensive method to calculate the weights of FMEA attributes, it is still subject to the subjective influence of the DMs.

2. PLTS can handle fuzziness and uncertainty well, but they increase the computational complexity due to the special construction.

6. Conclusions

This study develops an improved FMEA method to conduct the risk assessment, in which a conflict risk mitigation process is included. The main contributions of this study are as follows.

1. We use PLTSs to describe FMEA risk assessments due to the uncertainty and fuzziness of the decision problem. Several new operations and distance measures related to PLTSs are defined. We present a comprehensive method to calculate the weights of the risk criteria.

2. A conflict risk mitigation model is proposed to deal with the difference in the individual risk assessments. The model defines the objective adjustment coefficient used as a reference for the DM to give the adjustment coefficient. The interaction between DMs is emphasized, and its effective role in conflict risk mitigation is discussed.

3. An improved FMEA-based risk assessment is conducted, which first uses PLTSs to express the FMEA risk assessments, and then puts forward a conflict risk mitigation model to address the conflict risk among individual FMEA risk assessments.

In future research, we consider developing a decision support system so that many decision steps can be run automatically. In addition, the expansion of technological paradigms, such as social media and e-marketplaces, is causing large-scale GDM problems [35,36]. Compared with small-scale GDM, large-scale GDM has many different features, and thus the proposed method should be improved.

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