Comprehensive Evaluation of Land Reclamation Schemes in Mining Area based on Linguistic Intuitionistic Fuzzy Group Decision Making

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Manuscript

Comprehensive Evaluation of Land Reclamation Schemes in Mining Area based on Linguistic Intuitionistic Fuzzy Group Decision Making

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Abstract

Mine geological environment protection and land reclamation schemes are the core requirements for mining right application, which play an important role in regulating mining activities and supervising mining enterprises to fulfill their obligations of mine reclamation. In order to give full play to the guidance function of the schemes, provide reference for the compilation and review of the schemes, this paper attempts to make comprehensive evaluation of land reclamation schemes in mining area with multi-attribute group decision making method. First, linguistic intuitionistic fuzzy numbers are utilized to describe the evaluation information. Considering the authority and preference attitude of experts, the determination methods of expert weights in four cases are established. Then max-min deviation method is used to determine the attribute weights. Thereafter, a method for

Linguistic intuitionistic fuzzy group decision making problem is proposed. Finally, the practicability of this method is verified by land reclamation schemes of four mining areas in Sichuan Province and comparative analysis is made. The research results show that the evaluation process of this method is simple and effective, so it can be reasonably applied to compile and review of land reclamation schemes.

Keywords: Land reclamation scheme, Multi-attribute group decision making, Linguistic Intuitionistic Fuzzy, Expert weight, Attribute weight

1 Introduction

With the increasing attention to environmental governance and ecological sustainable development, land reclamation and ecological restoration in mining areas have become a hot research issue at home and abroad(Feng et al, 2019; Yu et al, 2020; Peco et al, 2021). As early as the beginning of 20th century, the countries such as USA, Germany, Australia, Britain and Canada have recognized the seriousness of land damage, and began to study the mining land reclamation. Now, they have perfect laws and regulations, strict implementation and supervision systems and advanced reclamation technologies, and have made outstanding achievements in mining land reclamation. The land reclamation of mining areas in China started relatively late, and the related theoretical research began in the 1980s. Although China has issued a series of laws and regulations since 1988, which have made land reclamation and ecological restoration on a legal track, and the speed and quality of reclamation have been greatly improved, the overall reclamation rate is still very low, only about 20%. Compared with the world advanced level of $70\% - 80\%$, there is still a big gap, land reclamation task is still quite heavy(Guo et al, 2015).

In 2017, the Ministry of Land and Resources issued the Notice on Compilation and Review of Schemes for Geological Environment Protection and Land Reclamation in Mines, and simultaneously issued the Guide for Compilation of Schemes for Geological Environment Protection and Land Reclamation in Mines (hereinafter referred to as the Guide) to clarify technical requirements for compilation of schemes. The combined compilation and reporting system of mining enterprises' schemes for mine geological environment protection, control and restoration and their schemes for land reclamation was formally implemented. Subsequently, the State amended the Provisions on The Protection of the Geological Environment of Mines and the Measures for the Implementation of the Regulations on Land Reclamation, explicitly stipulating that "when mining right applicants apply for mining licenses, they shall work out schemes for the protection of the geological environment of mines and land reclamation". The compilation and review of the schemes are the important prerequisite for rational exploitation and utilization of mineral resources and minimizing the disturbance of mining activities to the ecological environment of the mining areas. It is an important task for the administrative departments in charge of resource utilization from the source. On the one hand, mining enterprises mainly formulate schemes in accordance with the Provisions on protection of mine geological Environment, Implementation Measures of Land Reclamation Regulations, Guidelines and Quality Control Standards for Land Reclamation, etc., and carry out mining activities according to the approved schemes to fulfill obligations of mine geological environment protection and land reclamation. On the other hand, local natural resources authorities at all levels supervise and manage the review and implementation of the schemes.

As a prerequisite for obtaining mining license, the land reclamation scheme mainly aims to control the development and utilization of mineral resources from the source, guide and standardize mining activities, promote scientific and reasonable exploitation of resources, and protect the ecological environment of the mining area. However, in reality, due to the unclear positioning of the schemes, mining enterprises did not pay enough attention to it. They only regarded the schemes review as a process of mining right acquisition, and had insufficient understanding of the importance of the schemes. In the compilation process, there were perfunctory responses, not seeking truth from facts, and the guidance of the scheme failed to play an effective role.

Therefore, in the process of scheme review, it is necessary to evaluate the quality of the scheme and find out the existing problems. So many decision making methods have been applied to the evaluation of the land reclamation schemes in mine areas(Yavuz and Altay, 2015; Zhou et al, 2016; Cheng et al, 2017; Liang et al, 2018; Ye et al, 2021). The common characteristic of these methods is that they all treat the evaluation problem as multi-attribute decision making(MADM) problem and the difference lies in the different describing the evaluation information. The evaluation information in (Yavuz and Altay, 2015; Zhou et al, 2016) is represented by fuzzy number(Zadeh, 1965), that in (Cheng et al, 2017) is represented by linguistic neutrosophic number(Fang and Ye, 2017), that in (Liang et al, 2018) is represented by triangular fuzzy number(Ban and Coroianu, 2015), and that in (Ye et al, 2021) is represented by fuzzy credibility number.

Since there are many experts participating in the review of the schemes, we are more inclined to think that scheme evaluation is a multi-attribute group decision making (MAGDM) problem(Ding et al, 2020; Deng et al, 2021; Li et al, 2021b). Linguistic intuitionistic fuzzy numbers (LIFNs)(Chen et al, 2015) combine the advantages of both linguistic term sets(Merigo and Gil-Lafuente, 2013) and intuitionistic fuzzy numbers(IFNs)(Atanassov, 1986; Xu, 2013) and can better process imprecise or vague information because the membership and nonmembership degrees only need to be expressed as linguistic variables rather than exact values. In order to better deal with the uncertainty and fuzziness in the process of scheme evaluation, we consider using LIFNs to process the evaluation information. So the main research idea of this paper is to establish a linguistic intuitionistic fuzzy multi-attribute group decision making(LIFMAGDM) method to solve the evaluation problem of land reclamation schemes, which expert weights and attribute weights are unknown.

The novelties and contributions of this paper are listed as follows. (1) The scheme evaluation of land reclamation is regarded as a MAGDM problem, which is expressed by using LIFNs. (2) Considering the preference attitude and authority of experts, the determination methods of expert weights in four cases are established. (3) Attribute weights are solved by an optimization model. (4) The evaluation index system of land reclamation scheme in four mining areas is established. (5) A new LIFMAGDM method is proposed to solve the evaluation problem of land reclamation schemes. (6) According to the evaluation results, some reasonable suggestions are put forward for the compilation of land reclamation schemes.

The rest part of this paper is allocated as follows. Section 2 reviews some basic concepts and notations about LIFNs, such as operator, score function and distance measure. Section 3 introduces the determination method of weights and application process of the new LIFMAGDM method in detail. Section 4 describes the land reclamation schemes of four mining areas, establishes the evaluation index system and gives an illustrative example of appraising land reclamation schemes in mine areas. In Section 5, the sensitivity and comparison analyses are respectively undertaken. Section 6 gives some suggestions for the compilation of land reclamation schemes.

2 Preliminaries

This section mainly reviews the concepts related to linguistic intuitionistic fuzzy set(LIFS) and lays a foundation for the subsequent research.

2.1 LIFN

Language variables are a practical way of expressing the subjectivity and uncertainty inherent in individual preferences. In many practical problems such as management, engineering, psychology and sociology, the use of ordered qualitative scales composed of language terms is a common way to gather evaluators' opinions on alternatives.

Assuming that $S = \{s_i \mid i = 0, 1, \cdots, h\}$ is a linguistic term set with odd cardinality, where h is the even value. We can use the linguistic term set(Merigo and Gil-Lafuente, 2013)

$$\begin{aligned} S =& \{s_0(extremelylow), s_1(verylow), s_2(low), s_3(slightlylow), s_4(medium), \\ & s_5(slightlyhigh), s_6(high), s_7(veryhigh), s_8(extremelyhigh)\}. \end{aligned} \tag{1}$$

For the convenience of computation between languages, discrete language sets can be extended into continuous language sets $S_{[0,h]} = \{s_\theta \mid \theta \in [0, h]\}$.

Definition 1 (Atanassov, 1986) Let X be a finite reference set, $\psi = \{< x, \mu(x), \nu(x) >| \ x \in X\}$ is called intuitionistic fuzzy set(IFS), where $\mu(x)$ and $\nu(x)$ are the membership degree and non-membership degree of x to ψ respectively, $\mu(x) : X \to [0,1]$,$\nu(x) : X \to [0,1]$ and $0 \le \mu(x) + \nu(x) \le 1$, $\forall x \in X$.

For convenience, $\psi =< \mu, \nu >$ is called an IFN (Xu, 2013), which is used to represent the elements in IFS, where $0 \le \mu \le 1, 0 \le \nu \le 1, 0 \le \mu + \nu \le 1$.

Definition 2 (Xu, 2013) Let s_α, $s_\beta \in S_{[0,h]}$, $\psi =< s_\alpha, s_\beta >$,if $0 \le \alpha + \beta \le h$, then ψ is called the LIFN.

For the sake of description, suppose $\Gamma_{[0,h]}$ is the set of all LIFNs.

LIFN is a special IFN which membership and non-membership are expressed by linguistic terms, so it can more easily express the uncertainty and the vagueness information existing in the real world.

2.2 Operator of LIFNs

Chen et al (2015) developed some operators of LIFNs to solve MAGDM problems, involving LIFWA operator, LIFOWA operator and LIFHA operator, etc. But there is a flaw in these operators that may lead to unreasonable results. If the non-membership degree of an attribute value was s_0, the non-membership degree of the aggregation result for this decision making problem was also s_0, regardless of the value of the other attributes. So Yuan et al (2018) redefined the operation rules and aggregation operators of LIFNs.

Definition 3 (Yuan et al, 2018) Let $\psi_1 =< s_{\alpha_1}, s_{\beta_1} >$, $\psi_2 =< s_{\alpha_2}, s_{\beta_2} >$, $\psi =< s_\alpha, s_\beta >\in \Gamma_{[0,h]}$, the operation rules are defined as belows:

$$\psi_1 \oplus \psi_2 =< s_{\alpha_1+\alpha_2}, s_{\beta_1+\beta_2} >, m\psi =< s_{m\alpha}, s_{m\beta} > . \tag{2}$$

Definition 4 (Yuan et al, 2018) Assume $\psi_j =< s_{\alpha_j}, s_{\beta_j} >\in \Gamma_{[0,h]}$, the linguistic intuitionistic fuzzy weighted arithmetical averaging (LIFWAA) operator is given as follows:

$$LIFWAA(\psi_1, \psi_2, \cdots, \psi_n) = \bigoplus_{j=1}^{n} \tau_j \psi_j =< s_{\sum_{j=1}^{n} \tau_j \alpha_j}, s_{\sum_{j=1}^{n} \tau_j \beta_j} > . \tag{3}$$

where τ_j be the weight vector of ψ_j, satisfying that $0 \le \tau_j \le 1, \sum_{j=1}^{t} \tau_j = 1$.

2.3 Score function and distance measure

Chen et al (2015) introduced the LIF score function and accuracy function of $\psi =< s_\alpha, s_\beta >$ as $Ls(\psi) = \alpha - \beta, Lh(\psi) = \alpha + \beta$. Meng and Dong (2021) noticed that the sorting results obtained by Chen et al (2015)'s method might be unreasonable in some cases and proposed new score function and accuracy function to construct the sorting rules between LIFNs.

Definition 5 (Meng and Dong, 2021) Let $\psi =< s_\alpha, s_\beta >\in \Gamma_{[0,h]}$, the preference attitudinal score function(PASF) is given as

$$S_\lambda(\psi) = \frac{\alpha - 2\beta - 2h}{3} + \frac{\lambda}{3}(\alpha + \beta + 4h) = \lambda\frac{2\alpha - \beta + 2h}{3} + (1-\lambda)\frac{\alpha - 2\beta - 2h}{3}, \quad (4)$$

the preference attitudinal accuracy function(PAAF) is

$$H_\lambda(\psi) = \frac{2h - \alpha + 2\beta}{3} + \lambda(\alpha - \beta) = \lambda\frac{2\alpha - \beta + 2h}{3} + (1-\lambda)\frac{2\beta - \alpha + 2h}{3}, \quad (5)$$

where $\lambda \in [0, 1]$.

For $\psi_1 =< s_{\alpha_1}, s_{\beta_1} >$, $\psi_2 =< s_{\alpha_2}, s_{\beta_2} >\in \Gamma_{[0,h]}$,

(i)if $S_\lambda(\psi_1) < S_\lambda(\psi_2)$,then $\psi_1 \prec \psi_2$;

(ii)if $S_\lambda(\psi_1) = S_\lambda(\psi_2)$,then

if $H_\lambda(\psi_1) < H_\lambda(\psi_2)$,then $\psi_1 \prec \psi_2$; if $H_\lambda(\psi_1) = H_\lambda(\psi_2)$,then $\psi_1 = \psi_2$.

The parameter λ can be seen as the level of the expert¡¯s preference attitude towards the qualitative preferred and non-preferred judgments. The corresponding values of λ and expert¡¯s preference attitudes are shown in Table 1.

Table 1 Values of λ and expert¡¯s preference attitudes

λ	expert¡¯s preference attitudes
0	Expert has an absolutely preference for negative information
0.1	Expert has an extremely preference for negative information
0.2	Expert has a strongly preference for negative information
0.3	Expert has a moderately preference for negative information
0.4	Expert has a slightly preference for negative information
0.5	Expert has a neutral view for the positive and negative information
0.6	Expert has a slightly preference for positive information
0.7	Expert has a moderately preference for positive information
0.8	Expert has a strongly preference for positive information
0.9	Expert has an extremely preference for positive information
1	Expert has an absolutely preference for positive information

Definition 6 (Liu and Qin, 2017) Assume $\psi_1 =< s_{\alpha_1}, s_{\beta_1} >$, $\psi_2 =< s_{\alpha_2}, s_{\beta_2} >\in \Gamma_{[0,h]}$, then the Euclidean distance between ψ_1 and ψ_2 is defined as follows:

$$\tilde{d}(\psi_1, \psi_2) = \frac{1}{2h}\{\mid \alpha_1 - \alpha_2 \mid + \mid \beta_1 - \beta_2 \mid\}. \quad (6)$$

3 A new LIFMAGDM method

MADM is an important branch in the field of decision research. The main content of MADM is to synthesize the values of several alternatives according to the evaluation information of alternatives w.r.t. multiple attributes, order the alternatives, and give the optimal solution. The process in which a group of experts prioritize a limited number of alternatives based on multiple attributes is called MAGDM problem. MAGDM is an extension of traditional MADM, which makes up for the deficiency of single decision-maker's evaluation information and improves the accuracy of decision results. At present, many scholars have devoted themselves to the research of MAGDM, which mainly includes information representation(Rao et al, 2016; Lin et al, 2018b), group consensus analysis(Chen et al, 2019; Li et al, 2021a), experts' information integration(Meng et al, 2015), alternatives' information integration(Fu et al, 2020) and ranking methods(Mahmoudi et al, 2016; Pramanik and Mallick, 2019; Wang et al, 2020). In this paper, we will focus on the determination of expert weights and attribute weights in the process of information aggregation.

A LIFMAGDM problem can be described as follows: $X = \{Q_1, Q_2, \cdots, Q_m\}$ is the set of alternatives, $Y = \{\Upsilon_1, \Upsilon_2, \cdots, \Upsilon_n\}$ is the set of decision attributes, $E = \{e^1, e^2, \cdots, e^r\}$ is the set of decision experts. According to the linguistic term set S, the expert $e^k (k = 1, 2, \cdots, r)$ uses LIFN $\psi^k_{xy} (x = 1, 2, \cdots, m;\ y = 1, 2, \cdots, n)$ to represent his evaluation information for alternative Q_x w.r.t. attribute Υ_y. So his evaluation information for each alternative w.r.t. different attributes can be expressed by the LIFN decision matrix $\Omega^k = (\psi^k_{xy})_{m\times n}$, where $\psi^k_{xy} =< s_{\alpha^k_{xy}}, s_{\beta^k_{xy}} >\in \Gamma_{[0,h]}$.

3.1 Expert weights

In MAGDM problems, it is usually necessary to measure the relative importance of experts objectively based on their provided information, according to specific techniques such as entropies, distance measures, and optimization models. For example, Wang (2021) defined the attitude-based individual consensus index of expert to determine expert weights, Yang and Ding (2021) devised a novel dynamic expert weight calculation model by Hausdorff distance measure for q-rung orthopair fuzzy sets, Liu et al (2020)obtained the expert weights through Jousselme distance, Yin et al (2017) used the maximum proximity method based on the projection values between the interval grey trapezoid fuzzy linguistic variables vectors to obtain expert weights an so on.

Experts may come from different fields with different background and professional knowledge, which may have preference tendency. To overcome the shortages of existing methods, Lin et al (2018a) proposed a preference attitudinal method for ranking IFNs based on PASF and PAAF. The proposed ranking method considers not only the preference attitude of expert, but also all the possible values in feasible domain. Then Meng and Dong (2021) presented PASF and PAAF to build the ranking orders between LIFNs in terms of the preference attitude. In this section, we use PASF and PAAF not only to rank LIFNs, but also to establish methods for determining expert weights.

Definition 7 For the decision matrix $\Omega^k = (\psi_{xy}^k)_{m\times n}$ of expert $e^k(k = 1, 2, \cdots, r)$, $\psi_{xy}^k =< s_{\alpha_{xy}^k}, s_{\beta_{xy}^k} >$, the deviation in alternative $Q_x(x = 1, 2, \cdots, m)$ is defined as

$$\xi_x^k = \sum_{y=1}^{n-1}\sum_{z=y+1}^{n}(S_\lambda(\psi_{xy}^k) - S_\lambda(\psi_{zy}^k))^2 + \sum_{y=1}^{n-1}\sum_{z=y+1}^{n}(H_\lambda(\psi_{xy}^k) - H_\lambda(\psi_{zy}^k))^2. \quad (7)$$

the deviation in attribute $\Upsilon_y(y = 1, 2, \cdots, n)$ is defined as

$$\zeta_y^k = \sum_{x=1}^{m-1}\sum_{z=x+1}^{m}(S_\lambda(\psi_{xy}^k) - S_\lambda(\psi_{zy}^k))^2 + \sum_{x=1}^{m-1}\sum_{z=x+1}^{m}(H_\lambda(\psi_{xy}^k) - H_\lambda(\psi_{zy}^k))^2. \quad (8)$$

According to the Definition 5, ξ_x and ζ_y can also be described as:

$$\begin{aligned}\xi_x^k =& \sum_{y=1}^{n-1}\sum_{z=y+1}^{n}\{(\frac{\lambda}{3}+\frac{1}{3})(\alpha_{xy}^k - \alpha_{zy}^k) + (\frac{\lambda}{3}-\frac{2}{3})(\beta_{xy}^k - \beta_{zy}^k)\}^2 \\ &+ \sum_{y=1}^{n-1}\sum_{z=y+1}^{n}\{(\lambda-\frac{1}{3})(\alpha_{xy}^k - \alpha_{zy}^k) - (\lambda-\frac{2}{3})(\beta_{xy}^k - \beta_{zy}^k)\}^2, \end{aligned} \quad (9)$$

$$\begin{aligned}\zeta_y^k =& \sum_{x=1}^{m-1}\sum_{z=x+1}^{m}\{(\frac{\lambda}{3}+\frac{1}{3})(\alpha_{xy}^k - \alpha_{zy}^k) + (\frac{\lambda}{3}-\frac{2}{3})(\beta_{xy}^k - \beta_{zy}^k)\}^2 \\ &+ \sum_{x=1}^{m-1}\sum_{z=x+1}^{m}\{(\lambda-\frac{1}{3})(\alpha_{xy}^k - \alpha_{zy}^k) - (\lambda-\frac{2}{3})(\beta_{xy}^k - \beta_{zy}^k)\}^2. \end{aligned} \quad (10)$$

For expert $e^k(k = 1, 2, \cdots, r)$, the smaller the deviation in evaluation values of alternatives and attributes, the smaller the role he plays in decision-making and ranking, so he should be given a smaller weight. Taking into account the authority of experts for each attribute, the weight determination methods in four cases are proposed.

(**Case I**) When there is no absolute authoritative expert in the evaluation expert group, if $\bar{\xi_x} = \frac{1}{r}\sum_{k=1}^{r}\xi_x^k$ is the deviation from average of alternative $Q_x(x = 1, 2, \cdots, m)$, $\bar{\zeta_y} = \frac{1}{r}\sum_{k=1}^{r}\zeta_y^k$ is the deviation from average of attribute $\Upsilon_y(y = 1, 2, \cdots, n)$, the deviation rate of alternative $Q_x(x = 1, 2, \cdots, m)$ for the expert $e^k(k = 1, 2, \cdots, r)$ is $\mid \xi_x^k - \bar{\xi_x} \mid / \sum_{k=1}^{r} \mid \xi_x^k - \bar{\xi_x} \mid$, the deviation rate of attribute $\Upsilon_y(y = 1, 2, \cdots, n)$ for the expert $e^k(k = 1, 2, \cdots, r)$ is $\mid \zeta_y^k - \bar{\zeta_y} \mid / \sum_{k=1}^{r} \mid \zeta_y^k - \bar{\zeta_y} \mid$.

Then the weight of expert $e^k(k = 1, 2, \cdots, r)$ is

$$\varpi_k = \frac{1}{m+n}\left(\sum_{x=1}^{m}\frac{\mid \xi_x^k - \bar{\xi_x} \mid}{\sum_{k=1}^{r}\mid \xi_x^k - \bar{\xi_x} \mid} + \sum_{y=1}^{n}\frac{\mid \zeta_y^k - \bar{\zeta_y} \mid}{\sum_{k=1}^{r}\mid \zeta_y^k - \bar{\zeta_y} \mid}\right). \quad (11)$$

(**Case II**) When there is an absolute authoritative expert in the evaluation expert group, assume that expert e^l is the absolute authority whose weight is known to be ϖ_l, the deviation rate of alternative $Q_x(x = 1, 2, \cdots, m)$ for the expert $e^k(k = 1, 2, \cdots, r)$ and e^l is $\mid \xi_x^k - \xi_x^l \mid / \sum_{k=1}^r \mid \xi_x^k - \xi_x^l \mid$, the deviation rate of attribute $\Upsilon_y(y = 1, 2, \cdots, n)$ for the expert $e^k(k = 1, 2, \cdots, r)$ is $\mid \zeta_y^k - \zeta_y^l \mid / \sum_{k=1}^r \mid \zeta_y^k - \zeta_y^l \mid$.

Then the weight of expert $e^k(k = 1, 2, \cdots, r, k \neq l)$ is

$$\varpi_k = \frac{(1 - \varpi_l)}{m + n} \left(\sum_{x=1}^{m} \frac{\mid \xi_x^k - \xi_x^l \mid}{\sum_{k=1}^r \mid \xi_x^k - \xi_x^l \mid} + \sum_{y=1}^{n} \frac{\mid \zeta_y^k - \zeta_y^l \mid}{\sum_{k=1}^r \mid \zeta_y^k - \zeta_y^l \mid} \right). \tag{12}$$

(**Case III**) When expert e^l is the relative authority of attribute $\Upsilon_j(j = 1, 2, \cdots, n)$ and has no significant difference in other attributes, then the weight of expert $e^k(k = 1, 2, \cdots, r)$ is

$$\varpi_k = \frac{1}{m + n} \left(\frac{\mid \xi_j^k - \xi_j^l \mid}{\sum_{k=1}^r \mid \xi_j^k - \xi_j^l \mid} + \sum_{\substack{x=1 \\ x \neq l}}^{m} \frac{\mid \xi_x^k - \bar{\xi_x} \mid}{\sum_{k=1}^r \mid \xi_x^k - \bar{\xi_x} \mid} + \sum_{y=1}^{n} \frac{\mid \zeta_y^k - \bar{\zeta_y} \mid}{\sum_{k=1}^r \mid \zeta_y^k - \bar{\zeta_y} \mid} \right). \tag{13}$$

(**Case IV**) When expert e^l is the relative authority on alternative $Q_j(j = 1, 2, \cdots, m)$, and has no significant difference in other alternatives, then the weight of expert $e^k(k = 1, 2, \cdots, r)$ is

$$\varpi_k = \frac{1}{m + n} \left(\sum_{x=1}^{m} \frac{\mid \xi_x^k - \bar{\xi_x} \mid}{\sum_{k=1}^r \mid \xi_x^k - \bar{\xi_x} \mid} + \frac{\mid \zeta_j^k - \zeta_j^l \mid}{\sum_{k=1}^r \mid \zeta_j^k - \zeta_j^l \mid} + \sum_{\substack{y=1 \\ y \neq l}}^{n} \frac{\mid \zeta_y^k - \bar{\zeta_y} \mid}{\sum_{k=1}^r \mid \zeta_y^k - \bar{\zeta_y} \mid} \right). \tag{14}$$

3.2 Attribute weights

Current methods to obtain the attribute weights are largely divided into three types: the subjective methods, the objective methods and the comprehensive methods. The subjective methods such as AHP(Sirisawat and Kiatcharoenpol, 2018), BWM(Liu et al, 2021a) and Delphi method(Lin et al, 2021) determine the attribute weights according to the subjective will of experts. The objective methods such as entropy method(Jain et al, 2020), linear programming model(Yu et al, 2019) and maximizing deviation method(Pang et al, 2020) determine the attribute weights according to objective information of decision matrix. The comprehensive methods determine the attribute weights according to the subjective will of experts and objective information of decision matrix. Dong et al (2019) established the optimization model, and got the linear combination weights of subjective weights obtained by least square method and objective weights obtained by correlation coefficient-based method. Liu et al (2020) combined subjective weights obtained by AHP method and objective weights obtained by entropy weight method into comprehensive weights through the linear goal programming method.

The idea of attribute weight determination model in this paper is that when the deviation of evaluation values among all alternatives w.r.t. a certain attribute is big, it means such attribute can greatly affect the ranking order. Thus, a large weight value can be assigned to this attribute. Therefore, the optimal weight should maximize the deviation of all attribute values. Under the same attribute, the minimum deviation between the $Q_x(x = 1, 2, \cdots, m)$ and the $Q_z(z = 1, 2, \cdots, m)$ scheme is maximized. This method is called max-min deviation method.

Assume the decision matrix is $\Omega = (\psi_{xy})_{m\times n}$, $\tilde{d}(\psi_{xy}, \psi_{zy})(x = 1, 2, \cdots, m-1, z = x, x+1, \cdots, m, y = 1, 2, \cdots, n)$ is the distance between ψ_{xy} and ψ_{zy} . If $\psi_{xy} =< s_{\alpha_{xy}}, s_{\beta_{xy}} >$ and $\psi_{zy} =< s_{\alpha_{zy}}, s_{\beta_{zy}} >$, the distance between ψ_{xy} and ψ_{zy} can also be described as:

$$\tilde{d}(\psi_{xy}, \psi_{zy}) = \frac{1}{2h}\{| \alpha_{xy} - \alpha_{zy} | + | \beta_{xy} - \beta_{zy} |\}. \tag{15}$$

Suppose that $U = \{u_1, u_2, \cdots, u_n\}$ is the attribute weighted vector, where u_y denotes the weight of the attribute Υ_y such that $0 \le u_y \le 1$, $\sum_{y=1}^{r} u_y = 1$, we need to determine the value of U to maximize the difference of all attribute values. Thus, the optimization problem can be written as:

Model 1:

$$\begin{aligned} &\max\min \quad \tilde{d}(\psi_{xy}, \psi_{zy}) * u_y \\ &s.t. \begin{cases} x = 1, 2, \cdots, m-1, z = x, 2, \cdots, m, \\ \sum_{y=1}^{n} u_y = 1, u_y \ge 0, y = 1, 2, \cdots, n. \end{cases} \end{aligned} \tag{16}$$

Let the minimum deviation of two different alternatives w.r.t. the same attribute be represented by $\delta = \min \quad \tilde{d}(\psi_{xy}, \psi_{zy}) * u_y, x = 1, 2, \cdots, m-1, z = x, x+1, \cdots, m, y = 1, 2, \cdots, n$, so $\tilde{d}(\psi_{xy}, \psi_{zy}) * u_y \ge \delta, x = 1, 2, \cdots, m-1, z = x, 2, \cdots, m, y = 1, 2, \cdots, n$. Therefore, Model 1 can be transformed into the following form:

Model 2:

$$\begin{aligned} &\max \quad \delta \\ &s.t. \begin{cases} \tilde{d}(\psi_{xy}, \psi_{zy}) * u_y \ge \delta, \\ x = 1, 2, \cdots, m-1, z = x, x+1, \cdots, m, \\ \sum_{y=1}^{n} u_y = 1, u_y \ge 0, y = 1, 2, \cdots, n. \end{cases} \end{aligned} \tag{17}$$

3.3 Evaluation process

Step 1. Analyze the specific problem and determine the attribute set $X = \{Q_1, Q_2, \cdots, Q_m\}$ and alternative set $Y = \{\Upsilon_1, \Upsilon_2, \cdots, \Upsilon_n\}$. Each expert gives the LIFN decision matrix $\Omega^k(k = 1, \cdots, r)$ as shown in Table 2.

Table 2 LIFN decision matrix Ω^k of the expert e^k

	Υ_1	Υ_2	$\cdots$	Υ_n
Q_1	$\psi_{11}^k =< s_{\alpha_{11}^k}, s_{\beta_{11}^k} >$	$\psi_{12}^k =< s_{\alpha_{12}^k}, s_{\beta_{12}^k} >$	$\cdots$	$\psi_{1n}^k =< s_{\alpha_{1n}^k}, s_{\beta_{1n}^k} >$
Q_2	$\psi_{21}^k =< s_{\alpha_{21}^k}, s_{\beta_{21}^k} >$	$\psi_{22}^k =< s_{\alpha_{22}^k}, s_{\beta_{22}^k} >$	$\cdots$	$\psi_{2n}^k =< s_{\alpha_{2n}^k}, s_{\beta_{2n}^k} >$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Q_m	$\psi_{m1}^k =< s_{\alpha_{m1}^k}, s_{\beta_{m1}^k} >$	$\psi_{m2}^k =< s_{\alpha_{m2}^k}, s_{\beta_{m2}^k} >$	$\cdots$	$\psi_{mn}^k =< s_{\alpha_{mn}^k}, s_{\beta_{mn}^k} >$

Step 2. Standardize the initial group evaluating matrix $\Omega^k = (\psi_{xy}^k)_{m\times n}$ to get the normalized matrix $\widetilde{\Omega^k} = (\widetilde{\psi_{xy}^k})_{m\times n}$, where

$$\widetilde{\psi_{xy}^k} =< s_{\widetilde{\alpha}_{xy}^k}, s_{\widetilde{\beta}_{xy}^k} >= \begin{cases} < s_{\alpha_{xy}^k}, s_{\beta_{xy}^k} >, & \Upsilon_y \text{ is a benefit attribute,} \\ < s_{\beta_{xy}^k}, s_{\alpha_{xy}^k} >, & \Upsilon_y \text{ is a cost attribute.} \end{cases} \tag{18}$$

Obviously, $\widetilde{\psi_{xy}^k}$ is also a LIFN.

Step 3. Calculate the weight vector $T = \{\tau_1, \tau_2, \cdots, \tau_r\}$ of the experts according to Eq.(11)-(14) for different cases. Then combine $\widetilde{\Omega^k} = (\widetilde{\psi_{xy}^k})_{m\times n}, k = 1, \cdots, r$ to get $\Omega = (\psi_{xy})_{m\times n}$ by using Eq.(3) as shown in Table 3, where $\psi_{xy} = LIFWAA(\widetilde{\psi_{xy}^1}, \widetilde{\psi_{xy}^2}, \cdots, \widetilde{\psi_{xy}^r}) =< s_{\sum_{k=1}^r \tau_k \widetilde{\alpha}_{xy}^k}, s_{\sum_{k=1}^r \tau_k \widetilde{\beta}_{xy}^k} >$.

Step 4. Calculate the weight vector $U = \{u_1, u_2, \cdots, u_n\}$ of the attributes by using **Model 2**. Using the Eq.(3) again, aggregate into a LIFN $q_x(x = 1, 2, \cdots, m)$ for each alternative $Q_x(x = 1, 2, \cdots, m)$ as shown in Table 3. If $\psi_{xy} =< s_{\alpha_{xy}}, s_{\beta_{xy}} >$, then

$$q_x = LIFWAA((\psi_{x1}), (\psi_{x2}), \cdots, (\psi_{xn})) =< s_{\sum_{y=1}^n u_y \alpha_{xy}}, s_{\sum_{y=1}^n u_y \beta_{xy}} > . \tag{19}$$

Step 5. Determine $S_\lambda(q_x)$ according to Eq.(4) and compare. The order of the alternatives $Q_x(x = 1, 2, \cdots, m)$ is given by the size of $S_\lambda(q_x)(x = 1, 2, \cdots, m)$. That means the bigger $S_\lambda(q_x)$ is, the better alternative Q_x is.

4 Illustrative example

In this section, the land reclamation schemes of four mining areas in Sichuan province are sorted by using the evaluation method proposed in this paper.

4.1 Evaluation objects

Combined with the scheme review work of Sichuan Provincial Department of Natural Resources, by analyzing the problems existing in the process of scheme compilation and review, the land reclamation schemes of the following four mining areas are selected for evaluation.

Table 3 LIFN decision matrix Ω and integrated results

	Q_1	Q_2	$\cdots$	Q_m
Υ_1	$\psi_{11} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{11}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{11}^k} >$	$\psi_{21} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{21}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{21}^k} >$	$\cdots$	$\psi_{m1} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{m1}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{m1}^k} >$
Υ_2	$\psi_{12} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{12}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{12}^k} >$	$\psi_{22} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{22}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{22}^k} >$	$\cdots$	$\psi_{m2} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{m2}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{m2}^k} >$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Υ_n	$\psi_{1n} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{1n}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{1n}^k} >$	$\psi_{2n} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{2n}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{2n}^k} >$	$\cdots$	$\psi_{mn} =< s_{\sum_{k=1}^{r} \tau_k \widetilde{\alpha}_{mn}^k}, s_{\sum_{k=1}^{r} \tau_k \widetilde{\beta}_{mn}^k} >$
q_x	$q_1 =< s_{\sum_{y=1}^{n} u_y \alpha_{1y}}, s_{\sum_{y=1}^{n} u_y \beta_{1y}} >$	$q_2 =< s_{\sum_{y=1}^{n} u_y \alpha_{2y}}, s_{\sum_{y=1}^{n} u_y \beta_{2y}} >$	$\cdots$	$q_m =< s_{\sum_{y=1}^{n} u_y \alpha_{my}}, s_{\sum_{y=1}^{n} u_y \beta_{my}} >$

Q_1: Luohedong Gold mine in Danba County has a mining concession area of $4.6km^2$ and a production scale of 30 thousand tons per age. The mine design service life is 17 years and the remaining service life is 13.7 years. The mining method is underground mining. Mine geological environment protection and prevention measures mainly include cutting drainage ditch, retaining wall, active protection net, passive protection net and related monitoring projects. The land occupied by the mine is collectively owned and does not involve basic farmland. The mining land area of the mine is $3.58hm^2$, the reclamation area is $3.58hm^2$, and the reclamation responsibility area is $3.58hm^2$. The main types of reclaimed land are cultivated land and forest land. The static investment of the program is 4.27 million yuan and the dynamic investment is 5.54 million yuan.

Suggestions on revising the land reclamation scheme mainly include:(1) evaluating the collapse risk of air shaft industrial sites; (2) further improving the monitoring measures and preplans within the mine area; (3) reducing the occupation of river channels to ensure safety of flood discharge; (4) the specification of drawings and written reports and so on.

Q_2: Yinchanggou lead-zinc mine in Luding County has a mining concession area of $0.4415km^2$ and a production scale of 10 thousand tons per age. The mine design service life is 7.5 years and the remaining service life is 7.5 years. The mining method is underground mining. Mine geological environment protection and prevention measures mainly include cutting drainage ditch, retaining wall, active flexible protective net, protective dike, concrete slope protection and silt removal of ditches and other projects. The land occupied by the mine is collectively owned and does not involve basic farmland. The mining land area of the mine is $1.5258hm^2$, the reclamation area is $1.5258hm^2$, and the reclamation responsibility area is $1.5258hm^2$. The main types of reclaimed land are dry land, forest land and shrub land. The static investment of the program is 6.04 million yuan and the dynamic investment is 6.82 million yuan.

Suggestions on revising the land reclamation scheme mainly include: (1) the addition of certification materials that do not occupy the basic farmland; (2) rechecking the price of materials according to the recent price and verifying the quantity of the plugging project; (3) improving current analysis and distribution of geological disasters; (4) refining monitoring measures and adding graphic representations and so on.

Q_3: Tangfanggou Iron Mine in Yanyuan County has a mining concession area of $0.1119km^2$ and a production scale of 100 thousand tons per age. The mine design service life is 10.5 years and the remaining service life is 9.68 years. The mining method is underground mining. Mine geological environment protection and prevention measures mainly include intercepting ditches, sinking sand, retaining walls, flood intercepting dam and rock blocking dam, etc. The land occupied by the mine is collectively owned and does not involve basic farmland. The mining land area of the mine is $19.1505hm^2$, the reclamation area is $7.9606hm^2$, and the reclamation responsibility area is $2.6910hm^2$.

The main types of reclaimed land are dry land, forest land and grassland. The static investment of the program is 4.36 million yuan and the dynamic investment is 4.93 million yuan.

Suggestions on revising the land reclamation scheme mainly include: (1) strengthening the analysis and prediction of the current situation of water and soil environment in the mining area; (2) reviewing topsoil demand and revising the purchase amount accordingly; (3) adding profiles of each slag yard and specifying slag height and slope; (4) discussing the possibility of slag dump becoming debris flow source and calculating dynamic and static reserves; (5) revising the land reclamation adaptability evaluation index and improving the reclamation planning map and so on.

Q_4**:** Caiyuanzi magnetite mine in Huidong County has a mining concession area of $0.4705km^2$ and a production scale of 270 thousand tons per age. The mine design service life is 14.01 years and the remaining service life is 13.4 years. The mining method is underground mining. Mine geological environment protection and prevention measures mainly include drainage ditch, slag dam, sewage dam, drainage tunnel and so on. The land occupied by the mine is collectively owned and does not involve basic farmland. The mining land area of the mine is $12.643hm^2$, the reclamation area is $12.643hm^2$, and the reclamation responsibility area is $12.643hm^2$. The main types of reclaimed land are dry land, forest land, shrub land and other grassland. The static investment of the program is 10.50 million yuan and the dynamic investment is 14.00 million yuan.

Suggestions on revising the land reclamation scheme mainly include: (1) reviewing the types and physical and chemical properties of the soil in the project area; (2) improving the design of agricultural irrigation and drainage facilities in reclaimed dry land areas; (3) re-evaluation of the stability of the temporary reactor mine; (4) providing data related to ground collapse prediction; (5) automatic monitoring of tailings pond deformation and so on.

4.2 Evaluation attributes

According to the regulations for the compilation of land reclamation schemes, the contents of land reclamation schemes mainly include 10 parts, such as preface, compilation general principles, project overview, feasibility analysis, quality requirements and reclamation measures, project design and engineering quantity calculation, investment estimation, service life and work plan, benefit analysis and safeguard measures. At present, the main problems in land reclamation scheme compilation are as follows: (1) The basic background of the mining area is not clear. (2) Land damage assessment and analysis are weak. (3) The project deployment is not perfect. (4) The cost of reclamation is unreasonable. (5) Planning is not scientific.

After field investigation and inquiry of relevant experts, the evaluation indexes of mining land reclamation schemes are determined.

Υ_1: Clarity of reclamation projects. This attribute is the requirement of the preliminary work, to check whether the mine geological environment problems have been identified, and whether the area, form and degree of land damage are clear. On the basis of mine geological environment assessment and land damage prediction and assessment, the scheme of mine geological environment protection and land reclamation is put forward.

Υ_2: Integrity of reclamation schemes. The contents of the 10 parts should be linked and closely related to each other. For example, the project overview is to clarify the project type, project area, reclamation area, reclamation responsibility, service period, etc. The analysis of land use status serves the reclamation target and the reclamation quality. Adaptability evaluation provides support for clarifying the direction and target tasks of reclamation. The analysis of soil and water balance provides the basis for the design of reclamation engineering measures.

Υ_3: Feasibility of reclamation technologies. At present, relatively mature mine reclamation measures include soil reconstruction engineering, geomorphic remolding engineering, vegetation reconstruction engineering, supporting engineering and monitoring management engineering, etc. According to the types and ways of land damage and the degree of difficulty of reclamation, the reclamation technology should be determined according to local conditions so as to meet the principle of technical feasibility and rationality.

Υ_4: Pertinency of reclamation measures. The pollution and damage degree of resources and environment are different in different areas, different mineral species and different exploitation and utilization methods. On the basis of the current situation investigation, current situation assessment and forecast assessment, according to the mine current situation and the future geological environment problems, the selection of targeted restoration measures and land reclamation measures should not only conform to the mine reality, but also accord with the requirements of relevant norms and regulations.

Υ_5: Rationality of reclamation funds. The scientificity, rationality and feasibility of the land reclamation scheme are ultimately determined by the investment and use of reclamation funds. The scientific and reasonable estimation of reclamation investment affects the implementation and effectiveness of land reclamation to a great extent.

4.3 Selection optimal land reclamation scheme

The LIFMAGDM method proposed in this paper will be used to select the mining area with the best land reclamation scheme. The steps are as follows:

Step 1. The decision expert group $E = \{e^1, e^2, e^3, e^4\}$ composed of 4 experts evaluate the 5 attributes using LIFNs. So the experts¡¯ assessment information is presented in Table 4.

Step 2. As all the attributes have the same type (benefit), so the standardization are not needed.

Step 3. According to Eq.(11), we calculate the weight vector $T = \{\tau_1, \tau_2, \tau_3, \tau_4\}$ of the experts. When $\lambda = 0.5$, $T = \{0.3476, 0.1847, 0.2238, 0.2439\}$. Then using Eq.(3), the comprehensive evaluation matrix Ω obtained is shown in Table 5.

Table 4 Decision matrices

experts	Alternatives	Υ_1	Υ_2	Υ_3	Υ_4	Υ_5
e^1	Q_1	$< s_7, s_1 >$	$< s_6, s_2 >$	$< s_4, s_3 >$	$< s_7, s_1 >$	$< s_5, s_2 >$
	Q_2	$< s_6, s_2 >$	$< s_5, s_2 >$	$< s_6, s_1 >$	$< s_6, s_2 >$	$< s_7, s_1 >$
	Q_3	$< s_6, s_1 >$	$< s_5, s_3 >$	$< s_7, s_1 >$	$< s_5, s_1 >$	$< s_3, s_4 >$
	Q_4	$< s_5, s_2 >$	$< s_7, s_1 >$	$< s_4, s_3 >$	$< s_6, s_1 >$	$< s_4, s_4 >$
e^2	Q_1	$< s_7, s_1 >$	$< s_4, s_4 >$	$< s_6, s_2 >$	$< s_5, s_2 >$	$< s_3, s_5 >$
	Q_2	$< s_7, s_1 >$	$< s_5, s_1 >$	$< s_6, s_1 >$	$< s_5, s_2 >$	$< s_4, s_3 >$
	Q_3	$< s_5, s_2 >$	$< s_6, s_1 >$	$< s_7, s_1 >$	$< s_5, s_3 >$	$< s_4, s_4 >$
	Q_4	$< s_6, s_2 >$	$< s_4, s_3 >$	$< s_5, s_2 >$	$< s_7, s_1 >$	$< s_5, s_3 >$
e^3	Q_1	$< s_6, s_1 >$	$< s_5, s_2 >$	$< s_3, s_4 >$	$< s_7, s_1 >$	$< s_5, s_2 >$
	Q_2	$< s_7, s_1 >$	$< s_6, s_2 >$	$< s_7, s_1 >$	$< s_6, s_2 >$	$< s_5, s_1 >$
	Q_3	$< s_5, s_3 >$	$< s_5, s_2 >$	$< s_6, s_1 >$	$< s_4, s_3 >$	$< s_3, s_1 >$
	Q_4	$< s_6, s_2 >$	$< s_7, s_1 >$	$< s_5, s_1 >$	$< s_5, s_2 >$	$< s_5, s_3 >$
e^4	Q_1	$< s_5, s_3 >$	$< s_4, s_4 >$	$< s_7, s_1 >$	$< s_5, s_1 >$	$< s_4, s_2 >$
	Q_2	$< s_6, s_1 >$	$< s_7, s_1 >$	$< s_6, s_1 >$	$< s_5, s_2 >$	$< s_6, s_1 >$
	Q_3	$< s_5, s_2 >$	$< s_3, s_4 >$	$< s_6, s_2 >$	$< s_3, s_3 >$	$< s_5, s_2 >$
	Q_4	$< s_4, s_3 >$	$< s_5, s_1 >$	$< s_4, s_2 >$	$< s_6, s_2 >$	$< s_5, s_2 >$

Step 4. We calculate the weight vector $U = \{u_1, u_2, u_3, u_4, u_5\}$ of the attributes according to **Model 2** and aggregate into a LIFN $q_x(x = 1, 2, 3, 4)$ for each alternative $Q_x(x = 1, 2, 3, 4)$ by using the Eq.(3). When $\lambda = 0.5$, $U = \{0.3276, 0.1990, 0.1544, 0.1836, 0.1354\}$, $q_1 =< s_{5.51}, s_{2.01} >$, $q_2 =< s_{6.00}, s_{1.46} >$, $q_3 =< s_{4.98}, s_{2.14} >$, $q_4 =< s_{5.28}, s_{2.00} >$.

Step 5. Using Eq.(4), we obtain $S_{0.5}(q_1) = 1.7503$, $S_{0.5}(q_2) = 2.2689$, $S_{0.5}(q_3) = 1.4189$,$S_{0.5}(q_4) = 1.6412$. According to the comparison rule of LIFNs, the sorting results can be obtained as follows: $Q_2 \succ Q_1 \succ Q_4 \succ Q_3$ and the best land reclamation scheme is Q_2 .

5 Results Analysis

5.1 Sensitivity analysis

In order to analyze the influence of λ during the evaluation process, we take different values of $\lambda(\lambda = 0, 1, \cdots, 1)$ for experiments, and the different results obtained are shown in Table 6.

Firstly, the influence of λ on expert weights and attribute weights. As can be seen from Figure 1-2, the different values of λ have different influences on weights. With the change of λ, some weight values do not change much, while others fluctuate greatly. Because the value of λ reflects the expert's preference for membership and non-membership, therefore, Figure 1 also indirectly reflects the influence of expert's preference attitude on the change of weight values.

Secondly, the influence of λ on the alternative scores. Figure 3-6 shows the relationship between λ and the scores of the four alternatives. Obviously,

Table 5 Comprehensive evaluation matrix Ω corresponding to $\lambda = 0.5$

Alternative	Υ_1	Υ_2	Υ_3	Υ_4	Υ_5
Q_1	$< s_{6.29}, s_{1.49} >$	$< s_{4.92}, s_{2.86} >$	$< s_{4.88}, s_{2.55} >$	$< s_{6.14}, s_{1.18} >$	$< s_{4.39}, s_{2.55} >$
Q_2	$< s_{6.41}, s_{1.35} >$	$< s_{5.71}, s_{1.57} >$	$< s_{6.22}, s_{1.00} >$	$< s_{5.57}, s_{2.00} >$	$< s_{5.75}, s_{1.37} >$
Q_3	$< s_{5.35}, s_{1.88} >$	$< s_{4.70}, s_{2.65} >$	$< s_{6.53}, s_{1.24} >$	$< s_{4.29}, s_{2.30} >$	$< s_{3.67}, s_{2.84} >$
Q_4	$< s_{5.16}, s_{2.24} >$	$< s_{5.96}, s_{1.37} >$	$< s_{4.41}, s_{2.12} >$	$< s_{5.96}, s_{1.47} >$	$< s_{4.65}, s_{2.92} >$

Table 6 λ and results

Parameter	λ	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Expert weights	e_1	0.3423	0.3427	0.3439	0.3455	0.3467	0.3476	0.3460	0.3452	0.3448	0.3447	0.3446
	e_2	0.2280	0.2270	0.2230	0.2146	0.2008	0.1847	0.1736	0.1644	0.1585	0.1555	0.1548
	e_3	0.1957	0.1960	0.1974	0.2022	0.2117	0.2238	0.2352	0.2446	0.2506	0.2535	0.2543
	e_4	0.2340	0.2343	0.2356	0.2378	0.2408	0.2439	0.2452	0.2459	0.2462	0.2463	0.2463
Attribute weights	Υ_1	0.2932	0.2951	0.3019	0.3129	0.3238	0.3276	0.3180	0.3109	0.3066	0.3045	0.3040
	Υ_2	0.2346	0.2332	0.2279	0.2184	0.2053	0.1990	0.2117	0.2212	0.2270	0.2297	0.2304
	Υ_3	0.1026	0.1038	0.1079	0.1179	0.1352	0.1544	0.1674	0.1776	0.1841	0.1872	0.1881
	Υ_4	0.2548	0.2524	0.2444	0.2278	0.2054	0.1836	0.1670	0.1550	0.1479	0.1446	0.1437
	Υ_5	0.1148	0.1155	0.1179	0.1230	0.1303	0.1354	0.1359	0.1353	0.1344	0.1340	0.1338
Alternative scores	Q_1	-4.8110	-3.4927	-2.1735	-0.8580	0.4512	1.7503	3.0346	4.3278	5.6306	6.9409	8.2562
	Q_2	-4.3851	-3.0678	-1.7444	-0.4116	0.9293	2.2689	3.5962	4.9206	6.2415	7.5594	8.8753
	Q_3	-5.1737	-3.8684	-2.5573	-1.2375	0.0910	1.4189	2.7321	4.0449	5.3557	6.6636	7.9697
	Q_4	-4.8015	-3.4941	-2.1962	-0.9117	0.3617	1.6412	2.9463	4.2537	5.5622	6.8706	8.1789
Sorting		(2413)	(2143)	(2143)	(2143)	(2143)	(2143)	(2143)	(2143)	(2143)	(2143)	(2143)

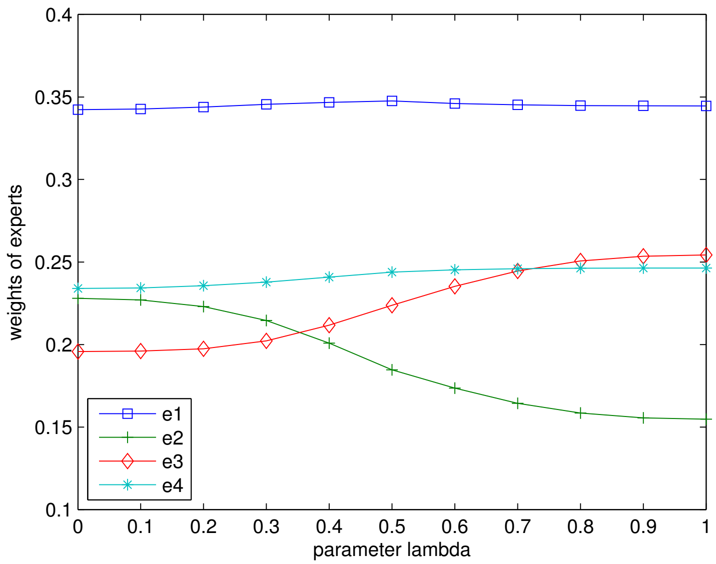

Fig. 1 λ and expert weights

each of these scores has a monotonically increasing linear relationship with λ. The fitting functions are as follows: $S_\lambda(Q_1) = 13.0398 * \lambda - 4.7875$, $S_\lambda(Q_2) = 13.2818*\lambda-4.388$, $S_\lambda(Q_3) = 13.1627*\lambda-5.1778$, $S_\lambda(Q_4) = 12.9592*\lambda-4.8059$.

Thirdly, the influence of λ on the ranking results. Table 6 shows the variation of the ranking results with λ. We can find that the ranking of the alternatives may change when λ changes. With κ increase, the ranking results change from $Q_2 \succ Q_4 \succ Q_1 \succ Q_3$ to $Q_2 \succ Q_1 \succ Q_4 \succ Q_3$. The method we proposed to determine the expert weights and attribute weights can effectively reduce human¡¯s subjective factors and improve the accuracy and stability of decision results due to the introduction of parameter λ.

Lastly, comparison of expert weights in four cases. According to Eq.(11)-(14), we can get the corresponding results in four cases, as shown in Table 7. In Case II, it is assumed that expert e^1 has absolute authority, that is, the weight of expert e^1 is known and is set to 0.3364. In Case III, it is assumed that expert e^1 is relative authority of attribute Υ_1. In Case IV, it is assumed that expert e^1 is relative authority of alternative Q_1.

As can be seen from the results, considering the authority of experts will have impacts on expert weights and attribute weights. This is in line with the expectation of real life, and also shows the effectiveness and practicability of the method.

5.2 Comparisons with existing approach

The above results indicate the effectiveness of our method, which can be solved LIFMAGDM problems. To further prove the superiority of our method, this

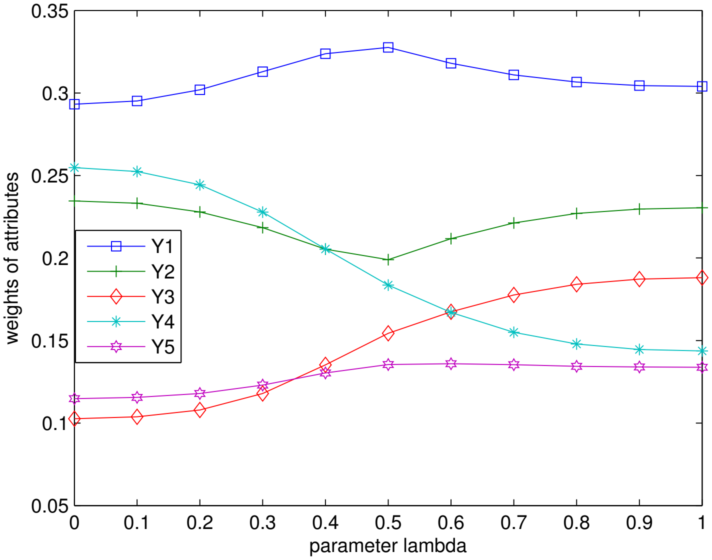

Fig. 2 λ and expert weights

Table 7 Results in four cases corresponding to $\lambda = 0.5$

	Case I	Case II	Case III	Case IV
Expert weights	0.3364 0.1885 0.2235 0.2516	0.3364 0.2494 0.1979 0.2163	0.3001 0.1863 0.2500 0.2636	0.3454 0.2094 0.2180 0.2273
Attribute weights	0.2837 0.2238 0.1568 0.1964 0.1393	0.2966 0.2305 0.0857 0.2841 0.1031	0.2047 0.2873 0.1805 0.1837 0.1438	0.3534 0.1897 0.1309 0.1990 0.1270
Alternative scores	1.6992 2.2479 1.3837 1.6648	1.8237 2.1683 1.3368 1.7951	1.5564 2.2423 1.3428 1.7047	1.8054 2.2562 1.4175 1.6657
Sorting	(2143)	(2143)	(2413)	(2143)

section compares the existing methods with our proposed method. The previous methods include Chen et al (2015)'s method, Yuan et al (2018)'s method and Liu et al (2020)'s method. The differences between these methods are shown in Table 8 and sorting results are listed in Table 9.

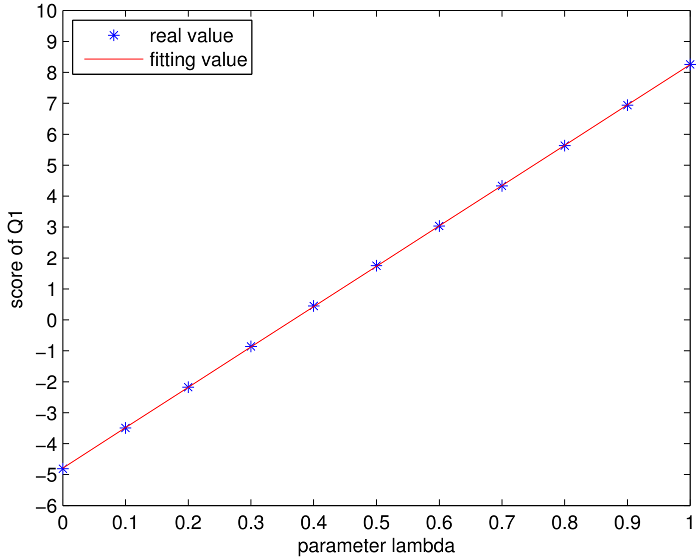

Fig. 3 λ and expert weights

Table 8 Results in four cases corresponding to $\lambda = 0.5$

Method	Expert weight	Attribute weight	Aggregation method	Sorting basis
Chen et al (2015)	Known	Known	LIFWA operator	Score function and accuracy function
Yuan et al (2018)	Incompletely known	Incompletely known	LIFWAA operator	Score function and accuracy function
Liu et al (2020)	Unknown	Unknown	Combination rule of DST	Mass function and belief function
Ours	Unknown	Unknown	LIFWAA operator	PASF and PAAF

By comparing and analyzing the four methods about the determination of weights, aggregation method and sorting basis, the main advantages of the proposed method are as follows:

(1) It can handle effectively LIFMAGDM problems with unknown expert weights and attribute weights. (Chen et al, 2015) requires that the weights be known, and (Yuan et al, 2018) needs to know the range of the weights. Both (Liu et al, 2020) and our proposed method can solve the problem of unknown weights, but calculations of (Liu et al, 2020) are a bit complicated. First the subjective weight of attributes is obtained by using AHP method and the objective weight of attributes is obtained by fuzzy entropy. Then the

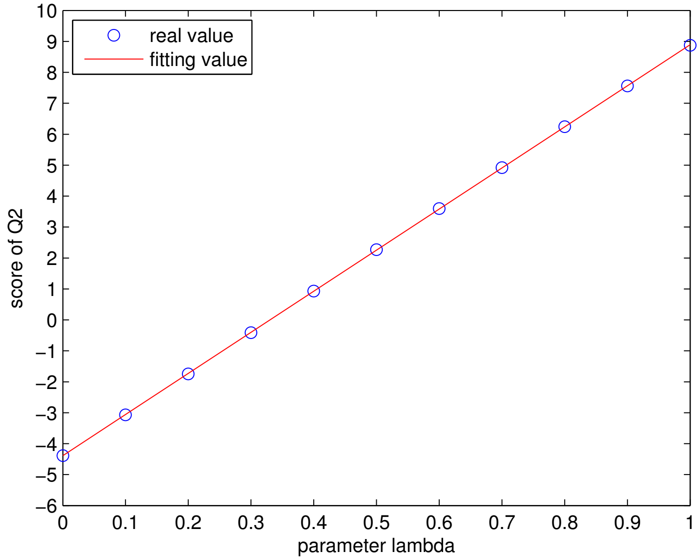

Fig. 4 λ and expert weights

Table 9 Results in four cases

Method	Alternative scores	Sorting
Chen et al (2015)	$Ls(Q_1) = 3.7114, Ls(Q_2) = 4.7089,$ $Ls(Q_3) = 3.1368, Ls(Q_4) = 3.5521.$	(2143)
Yuan et al (2018)	$S(Q_1) = 3.0355, S(Q_2) = 4.4105,$ $S(Q_3) = 2.6120, S(Q_4) = 3.2055.$	(2143)
Liu et al (2020)	$Bel(Q_1) = 0.9939, Bel(Q_2) = 0.9988,$ $Bel(Q_3) = 0.9853, Bel(Q_4) = 0.9928.$	(2143)
Ours	$S_{0.5}(Q_1) = 1.7503, S_{0.5}(Q_2) = 2.2689,$ $S_{0.5}(Q_3) = 1.4189, S_{0.5}(Q_4) = 1.6412.$	(2143)

combination weight of attributes is obtained according to the model by using the distance. Our proposed method only needs an optimization model, which is more straightforward and simpler than (Liu et al, 2020).

(2) Its aggregation method is more reasonable and efficient. (Chen et al, 2015) has the problem of failure under extreme value. To overcome the shortcoming, (Yuan et al, 2018) and our proposed method improve the aggregation operator, (Liu et al, 2020) use an aggregation formula of Dempster-Shafer evidence theory. But (Liu et al, 2020) need to convert the LIFNs into the

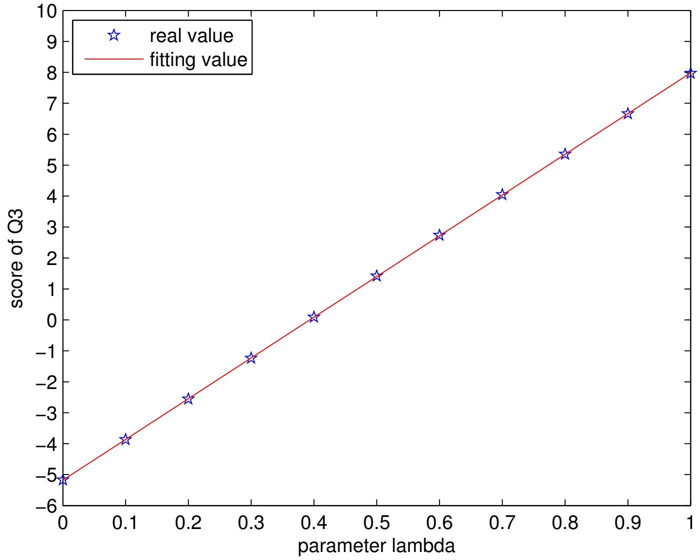

Fig. 5 λ and expert weights

form of basic probability assignments. This virtually increases the computational workload, and it is not clear whether there is information loss in the transformation process.

(3) Its sorting basis is more comprehensive and flexible. The parameter λ in PASF and PAAF not only reflects the preference attitude of experts, but also has a functional relationship with alternative scores, so that the scores can be flexibly and readily modified based on the actual situation. When different parameter values are endowed, the variation of alternative scores and sorting results can be manifested dynamically. Then, the inherent rules for change can be displayed better.

Based on the above comparative analysis, it can be seen our method is effective and superior to some existing methods. Of course, our method can be further studied. For example, if there are enough experts involved in the evaluation, we can regard the scheme evaluation problem as a large-scale group decision making problem and study the clustering and consensus reaching of experts(Liu et al, 2021c). In addition, the determination method of expert weights is based on LIFN score function and distance measure, so we can consider applying the method to other fuzzy numbers(Liu et al, 2021b).

6 Conclusions

According to the evaluation results and the problems existing in the four evaluation objects, we believe that strengthening the comprehensive evaluation of the scheme is an effective method to better complete the compilation and

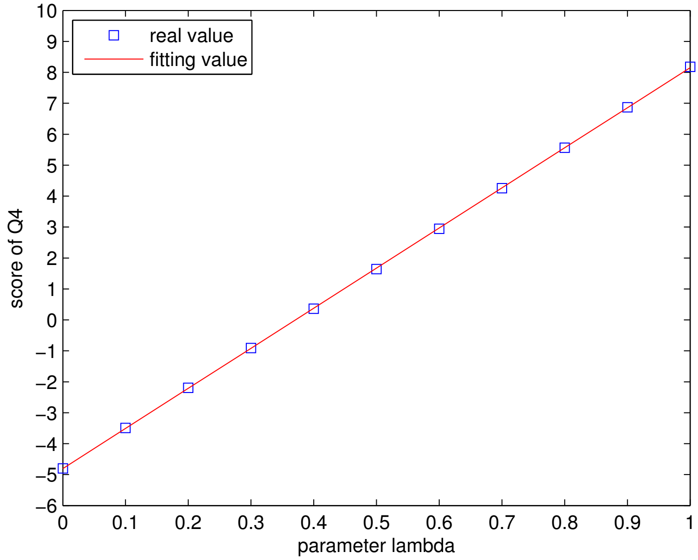

Fig. 6 λ and expert weights

review of the schemes. The compilation and review of the schemes are the important part of the natural resources department to strengthen the pre-management of mineral resources, standardize and supervise the mining order. It is of great significance to mining right management and sustainable development of mineral resources. In order to better complete the relevant work, we put forward some suggestions as follows: (1) Make clear the positioning of the scheme and give full play to its guiding role. (2) Revise the Guide of land reclamation scheme in due time to expand the scheme connotation. (3) Cause the mine enterprise and the compilation unit to attach importance, earnestly completes the mining area reconnaissance and the ecological environment background investigation. (4) Carry out regular professional training for the compilation staffs and reviewers to improve the quality of scheme compilation and review. (5) Strengthen supervision over the implementation of the scheme to ensure its effective implementation.

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Declarations

Some journals require declarations to be submitted in a standardised format. Please check the Instructions for Authors of the journal to which you are submitting to see if you need to complete this section. If yes, your manuscript must contain the following sections under the heading ‘Declarations’:

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- Ethics approval
  Ethics approval is not involved in this study.
- Consent to participate
  All authors agree to participate.
- Consent for publication
  All authors agree to publish this paper.
- Availability of data and materials
  All data generated or analyzed in this study may be provided by the corresponding author upon reasonable request.
- Code availability
  Code can be provided if required.
- Authors' contributions
  All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Yi Liu, Fang Liu and Hao Gong. The first draft of the manuscript was written by Ju Wu and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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