Available online at www.sciencedirect.com
ScienceDirect
Trans. Nonferrous Met. Soc. China 29(2019) 2160−2169
Transactions of Nonferrous Metals Society of China
www.tnmsc.cn

Optimization of mining method in subsea deep gold mines: A case study

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Received 28 February 2018; accepted 31 August 2019

Abstract: The mining method optimization in subsea deep gold mines was studied. First, an index system for subsea mining method selection was established based on technical feasibility, security status, economic benefit, and management complexity. Next, an evaluation matrix containing crisp numbers and triangular fuzzy numbers (TFNs) was constructed to describe quantitative and qualitative information simultaneously. Then, a hybrid model combining fuzzy theory and the Tomada de Decisão Interativa Multicritério (TODIM) method was proposed. Finally, the feasibility of the proposed approach was validated by an illustrative example of selecting the optimal mining method in the Sanshandao Gold Mine (China). The robustness of this approach was demonstrated through a sensitivity analysis. The results show that the proposed hybrid TODIM method is reliable and stable for choosing the optimal mining method in subsea deep gold mines and provides references for mining method optimization in other similar undersea mines.

Key words: subsea deep mining; mining method; fuzzy theory; hybrid TODIM method

1 Introduction

With the substantial reduction of available land resources, the exploitation of marine resources has measurably increased [1]. Mineral resources in oceans are mainly distributed in seawater, marine mud and bedrock. In particular, plentiful mineral resources are found in the bedrock near coastlines with many countries interested in accessing them [2]. Selecting suitable mining methods is one of the most important processes in mining and directly influences the safety and efficiency of the work. Problems may arise because of an inappropriate mining method choice, such as inefficiency, high production costs, and even water inrush disasters [3]. Mining methods must adapt for different mining depth. When mining near the sea floor, due to water inrush hazards, it is essential to retain enough pillars and prevent roof damage [4]. In comparison, it is possible to cancel pillars and change support measures for deep mining because the mining disturbance on the waterproof rock formation is diminished [5]. Moreover, owing to the distinctiveness of subsea mining, the mining technology used in land is not easily utilized directly. Hence, it is significant to research mining method optimization in subsea deep mines.

On the basis of statistics, more than 100 subsea coal mines exist globally [6]. The history of subsea coal mining is rich, long wall mining and room and pillar mining methods are widely employed. In contrast, there are relatively few subsea metal mines. Examples include the Qajasalolcroix Iron Mine in Finland, Levent Tin Mine in England, Dove Tungsten Mine in Australia, and Sanshandao Gold Mine in China [4,6]. As the filling material can restrict the deformation of the surrounding rock, several filling methods are chief subsea mining methods. Additionally, certain methods for mining under rivers or reservoirs can be used for reference. However, as conditions between mines vary, mining methods cannot be used indiscriminately.

Many researchers regard mining method selection as a multi-criterion decision making (MCDM) problem because it is affected by multiple factors [7,8]. In the process of mining method selection, two vital components are contained: the index system and decision making method. It is essential to establish an index

Foundation item: Project (2018dcyj052) supported by Survey Research Funds of Central South University, China; Project (51774321) supported by the National Natural Science Foundation of China; Project (2018YFC0604606) supported by the National Key Research and Development Program of China
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DOI: 10.1016/S1003-6326(19)65122-8

system first [9]. However, few researchers have established an index system for subsea mining method selection. LIU et al [10] selected 10 indicators in consideration of the geologic conditions, technology, economy and safety production in a subsea gold deposit. Nevertheless, their index system does not reflect the significant risk of water inrush with subsea bedrock mining due to the disturbance to overlying rock formations. This is an essential consideration for optimizing subsea mining methods.

With regard to the decision making method, BALUSA and SINGAM [7] combined wavelet packet modulation (WPM) and the preference ranking organization method for enrichment evaluations (PROMETHEE) to select an applicable mining method for a bauxite mine. LIU et al [10] considered a large amount of uncertain information and proposed a mining method optimization model based on unascertained measurement theory. KARIMNIA and BAGLOO [11] proposed a fuzzy analytic hierarchy process (FAHP) approach to determine the most appropriate mining method in the Qapiliq Salt Mine. KABWE [12] selected the optimal mining method for Nchanga's Upper Orebody using an analytic hierarchy process (AHP) and Yager's method. Furthermore, SITORUS et al [13] discussed the applications and trends of MCDM for the choice problem in mining and mineral processing. Nevertheless, the assessment values in these methods are only expressed by crisp or fuzzy numbers, which cannot indicate qualitative and quantitative information simultaneously.

Generally, the qualitative indexes expressed using the scoring method do not adequately reflect fuzzy information. In this case, fuzzy theory can be well-adopted to solve such ambiguous problems. For convenience, the fuzzy information is often transformed into triangular fuzzy numbers (TFNs) in the decision making process [14]. Thus, many MCDM methods have been combined with TFNs to solve fuzzy decision making problems. For instance, DONG et al [15] modified an analytic network process (ANP) with TFNs to identify the key influencing factors in the power generation market; OCAMPO [16] built a decision model for manufacturing sustainability with an FAHP in a triangular fuzzy environment; ZHAO et al [17] assessed battery energy storage systems based on TFNs, the best−worst method, and fuzzy-cumulative prospect theory.

In addition to the above methods, the Tomada de Decisão Interativa Multicritério (TODIM) method was presented by GOMES and LIMA [18] to rank alternatives on the basis of prospect theory [19,20]. In recent years, this method has been successfully modified with various fuzzy sets to address realistic issues. For example, JI et al [21] selected personnel by integrating multi-valued neutrosophic numbers with the TODIM method; BISWAS and SARKAR [22] proposed an interval-valued Pythagorean fuzzy TODIM approach to deal with multi-criteria group decision making problems; ZHANG et al [23] evaluated water security by employing TODIM with probabilistic linguistic term sets. Considering the complexity of mining method selection and the diversity of indicators, a hybrid TODIM method for selecting the optimal mining method is presented in this study.

The goal of this study is to propose an approach for mining method optimization in subsea deep gold mines. First, an evaluation index system for subsea mining method selection is established. Then, a hybrid methodology combining fuzzy theory and the TODIM method is presented. Afterwards, the proposed methodology is adopted to select the optimal mining method in the Sanshandao Gold Mine, China. Finally, the effectiveness and robustness of the approach is demonstrated.

2 Evaluation index system

The index system is established in this section according to the specific characteristics of subsea mining methods. It is comprised of four criteria: technical feasibility (B_1), security status (B_2), economic benefit (B_3), and management complexity (B_4). The detailed evaluation index system for subsea mining method selection is shown in Fig. 1.

(1) Technical feasibility (B_1)

Due to the complex mining conditions, the selected mining method should be feasible in the technical level first [7]. Furthermore, because of variation in orebody morphology, the method chosen must be strongly adaptable. Thus, the sub-criteria of technical feasibility include the degree of feasibility (B_{11}) and degree of adaptability (B_{12}).

(2) Security status (B_2)

There is a particularly high risk of water inrush in subsea mining. Hence, it is essential that disturbances to overlying rock formations should be minimized when employing any mining method [5]. The safety of the working surface also needs to be guaranteed, as it directly affects the operation security [10]. Therefore, the sub-criteria of security status include the degree of safety of the working surface (B_{21}), ventilation conditions (B_{22}), and degree of disturbance to the overlying rock formation (B_{23}).

(3) Economic benefit (B_3)

The performance of a mining method should be reflected in terms of economic benefit. That is to say, high efficiency and low cost should be achieved with the

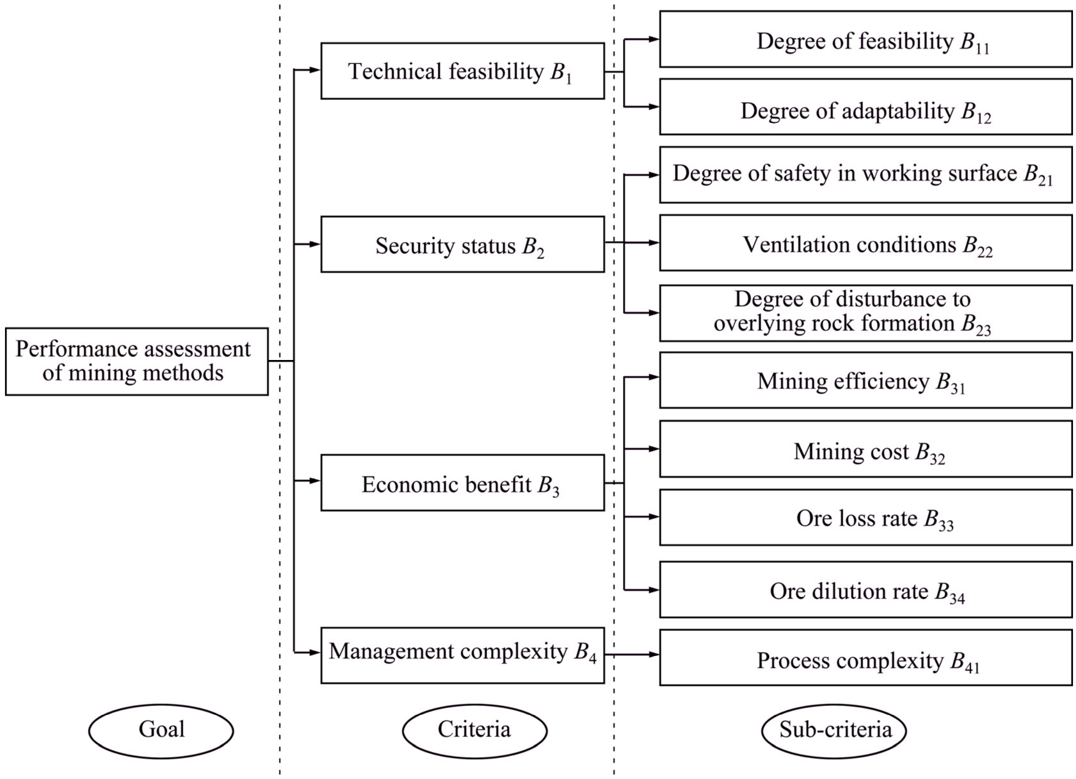

Fig. 1 Evaluation index system for subsea mining method selection

optimal mining method [10]. Consequently, the sub-criteria of economic benefit contain the mining efficiency (B_{31}), mining cost (B_{32}), ore loss rate (B_{33}), and ore dilution rate (B_{34}).

(4) Management complexity (B_4)

As mining is a complex engineering system, excellent manageability is required. More easily managed systems generally are correlated to smoother operations. Mining methods with less complexity in process management are weighted higher [8]. Accordingly, the sub-criterion of management complexity is the process complexity (B_{41}).

3 Hybrid TODIM method

A hybrid model combining fuzzy theory and the TODIM method is presented. The framework of this hybrid TODIM method is illustrated in Fig. 2.

The specific steps of the hybrid TODIM model for ranking mining methods are described as follows:

(1) Step 1: Establish initial evaluation matrix

For the comprehensive assessment of mining methods, several sub-criteria, e.g., B_{31}, B_{32}, B_{33} and B_{34}, can be denoted by quantitative values. Nevertheless, sub-criteria with uncertain information including B_{11}, B_{12}, B_{21}, B_{22}, B_{23} and B_{41} are more suitably denoted by qualitative values. However, most decision makers are accustomed to using linguistic phrases, such as "very good", "good", "poor", and so on [24]. In this study, the linguistic terms were converted into TFNs according to the transformation rule shown in Table 1 [25].

The triangular fuzzy number (TFN) $\tilde{s}$ can be denoted as a triplet $\tilde{s}=[s^{\mathrm{O}}, s^{\mathrm{P}}, s^{\mathrm{T}}]$, and the membership function $\mu_{\tilde{s}}(x)$ is represented as follows [26]:

$$\mu_{\tilde{s}}(x)=\begin{cases}0, & x<s^{\mathrm{O}} \\ \dfrac{x-s^{\mathrm{O}}}{s^{\mathrm{P}}-s^{\mathrm{O}}}, & s^{\mathrm{O}}<x<s^{\mathrm{P}} \\ \dfrac{s^{\mathrm{T}}-x}{s^{\mathrm{T}}-s^{\mathrm{P}}}, & s^{\mathrm{P}}<x<s^{\mathrm{T}} \\ 0, & x>s^{\mathrm{T}}\end{cases} \tag{1}$$

where s^{O} and s^{T} are the lower and upper bounds of the available area, respectively, and $s^{\mathrm{O}}<s^{\mathrm{P}}<s^{\mathrm{T}}$.

Thus, the basic elements in the initial evaluation matrix $\boldsymbol{S}$ are composed of crisp values and TFNs, which are expressed as follows:

$$\boldsymbol{S}=\begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1r} & \tilde{s}_{1,r+1} & \cdots & \tilde{s}_{1,n} \\ s_{21} & s_{22} & \cdots & s_{2r} & \tilde{s}_{2,r+1} & \cdots & \tilde{s}_{2,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mr} & \tilde{s}_{m,r+1} & \cdots & \tilde{s}_{m,n} \end{bmatrix} \tag{2}$$

where s_{ij} is a crisp value that represents the assessment information of alternative A_i (i=1, 2, ⋯, m) relating to objective sub-criterion B_j (j=1, 2, ⋯, r); $\tilde{s}_{i,j}$ is a TFN

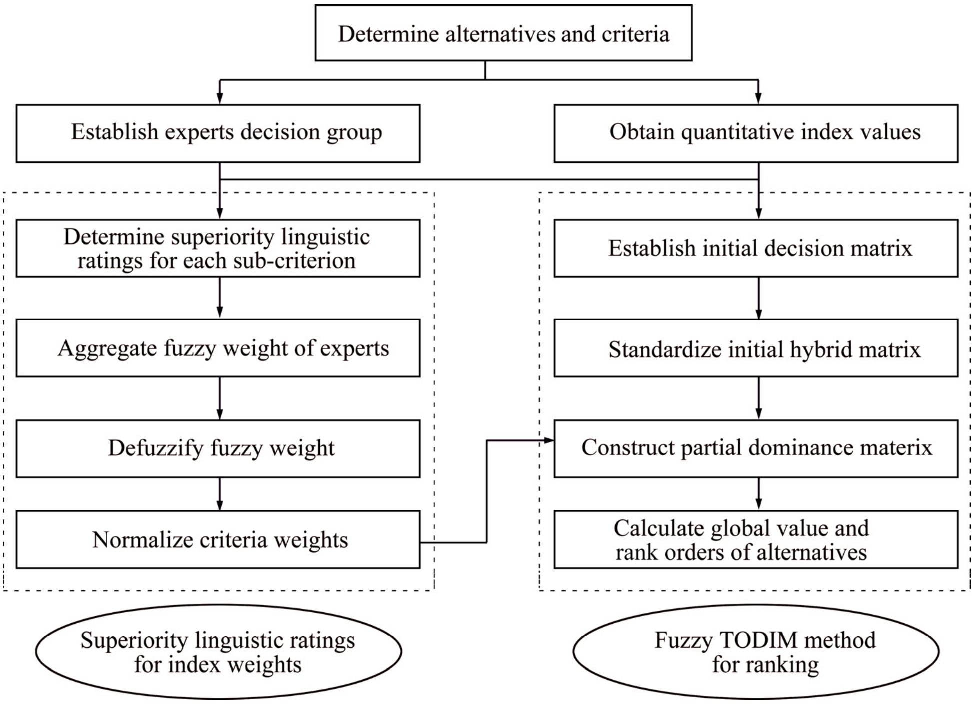

Fig. 2 Framework of hybrid TODIM method

Table 1 Transformation rule between linguistic terms and TFNs

Linguistic term	TFNs
Very poor (VP)/Very low (VL)	(0.1, 0.2, 0.3)
Poor (P)/Low (L)	(0.2, 0.3, 0.4)
Slightly poor (SP)/Slightly low (SL)	(0.3, 0.4, 0.5)
Fair (F)/Medium (M)	(0.4, 0.5, 0.6)
Slightly good (SG)/Slightly high (SH)	(0.5, 0.6, 0.7)
Good (G)/High (H)	(0.6, 0.7, 0.8)
Very good (VG)/Very high (VH)	(0.7, 0.8, 0.9)

that represents the evaluation data of alternative A_i (i=1, 2, ⋯, m) with reference to subjective sub-criterion B_j (j=r+1, r+2, ⋯, n).

(2) Step 2: Standardize initial evaluation matrix

Because of the diverse dimensions and units of criteria, standardizing the initial evaluation matrix is necessary. For the performance evaluation of mining methods, the sub-criteria include two types: benefit and cost. As such, the initial decision matrix can be normalized by Eqs. (3)−(6) [25,27]:

For crisp numbers of the benefit sub-criteria, the normalization value can be calculated by

$$z_{ij}=\frac{s_{ij}}{\sum_{i=1}^{m}s_{ij}} \tag{3}$$

For crisp numbers of the cost sub-criteria, the normalization value can be calculated by

$$z_{ij}=\frac{1/s_{ij}}{\sum_{i=1}^{m}1/s_{ij}} \tag{4}$$

For TFNs of the benefit sub-criteria, the normalization value can be calculated by

$$\tilde{z}_{i,j}=[z_{i,j}^{\mathrm{O}},\ z_{i,j}^{\mathrm{P}},\ z_{i,j}^{\mathrm{T}}]=[\frac{s_{i,j}^{\mathrm{O}}}{\sum_{i=1}^{m}s_{i,j}^{\mathrm{T}}},\ \frac{s_{i,j}^{\mathrm{P}}}{\sum_{i=1}^{m}s_{i,j}^{\mathrm{P}}},\ \frac{z_{i,j}^{\mathrm{T}}}{\sum_{i=1}^{m}z_{i,j}^{\mathrm{O}}}] \tag{5}$$

For TFNs of the cost sub-criteria, the normalization value can be calculated by

$$\tilde{z}_{i,j}=[z_{i,j}^{\mathrm{O}},\ z_{i,j}^{\mathrm{P}},\ z_{i,j}^{\mathrm{T}}]=[\frac{1/s_{i,j}^{\mathrm{O}}}{\sum_{i=1}^{m}1/s_{i,j}^{\mathrm{T}}},\ \frac{1/s_{i,j}^{\mathrm{P}}}{\sum_{i=1}^{m}1/s_{i,j}^{\mathrm{P}}},\ \frac{1/z_{i,j}^{\mathrm{T}}}{\sum_{i=1}^{m}1/z_{i,j}^{\mathrm{O}}}] \tag{6}$$

Subsequently, the standardized evaluation matrix can be obtained as follows:

$$\boldsymbol{Z}^{\mathrm{S}}=\begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1r} & \tilde{z}_{1,r+1} & \cdots & \tilde{z}_{1,n} \\ z_{21} & z_{22} & \cdots & z_{2r} & \tilde{z}_{2,r+1} & \cdots & \tilde{z}_{2,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ z_{m1} & z_{m2} & \cdots & z_{mr} & \tilde{z}_{m,r+1} & \cdots & \tilde{z}_{m,n} \end{bmatrix} \tag{7}$$

To simplify the calculation, TFNs can be converted into crisp numbers. CHEN and HSIEH [28] advanced the graded mean integration representation method to transform TFNs into crisp numbers, and the transformation rule is shown as follows:

$$H(\tilde{z}_{i,j})=\frac{z_{i,j}^{\mathrm{O}}+4z_{i,j}^{\mathrm{P}}+z_{i,j}^{\mathrm{T}}}{6} \tag{8}$$

Accordingly, the ultimate standardized decision matrix can be denoted as

$$\boldsymbol{Z}=\begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1r} & H(\tilde{z}_{1,r+1}) & \cdots & H(\tilde{z}_{1,n}) \\ z_{21} & z_{22} & \cdots & z_{2r} & H(\tilde{z}_{2,r+1}) & \cdots & H(\tilde{z}_{2,n}) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ z_{m1} & z_{m2} & \cdots & z_{mr} & H(\tilde{z}_{m,r+1}) & \cdots & H(\tilde{z}_{m,n}) \end{bmatrix} \tag{9}$$

(3) Step 3: Determine index weight vector

In most cases, the importance of each index is not equal. Therefore, an algorithm for weight determination based on the superiority linguistic ratings is employed. As given in Table 1, the importance of each sub-criterion can be expressed using linguistic terms, like "very low", "low" and "high", and these linguistic terms can be converted into TFNs.

Suppose the superiority linguistic rating of sub-criteria B_j denoted by decision maker D_k (k=1, 2, ⋯, e) is expressed as

$$\tilde{w}_{kj}=(w_{kj}^{\mathrm{O}},\ w_{kj}^{\mathrm{P}},\ w_{kj}^{\mathrm{T}}) \tag{10}$$

Then, the aggregated fuzzy weight of all professionals can be calculated by

$$\tilde{w}_j=(1/e)\otimes(\tilde{w}_{1j}\oplus\cdots\oplus\tilde{w}_{kj}\oplus\cdots\oplus\tilde{w}_{ej}) \tag{11}$$

where $\tilde{w}_j=(w_j^{\mathrm{O}},w_j^{\mathrm{P}},w_j^{\mathrm{T}})$, $w_j^{\mathrm{O}}=\sum_{k=1}^{e}\frac{w_{kj}^{\mathrm{O}}}{e}$, $w_j^{\mathrm{P}}=\sum_{k=1}^{e}\frac{w_{kj}^{\mathrm{P}}}{e}$ and $w_j^{\mathrm{T}}=\sum_{k=1}^{e}\frac{w_{kj}^{\mathrm{T}}}{e}$.

Finally, the weight w_j of each sub-criterion can be normalized with

$$w_j=\frac{H(\tilde{w}_j)}{\sum_{j}^{n}H(\tilde{w}_j)} \tag{12}$$

(4) Step 4: Calculate dominance of each alternative over other alternatives

First, the criterion with the largest weight value is chosen as a reference criterion B_l. Subsequently, a partial dominance matrix $\boldsymbol{\phi}_c(A_i, A_p)$ is built, which indicates the superiority degree of alternative A_i over alternative A_p (p=1, 2, ⋯, m) under criterion B_c. The final dominance matrix $\boldsymbol{\delta}(A_i, A_p)$ is then determined by summing all the partial dominance matrices under each criterion.

The dominance matrix of alternative A_i over A_p is calculated as follows:

$$\boldsymbol{\phi}_c(A_i,A_p)=\begin{cases}\sqrt{\dfrac{w_{lc}}{\sum_{c=1}^{n}w_{lc}}}\cdot d(z_{ic},z_{pc}), & z_{ic}>z_{pc}\\ 0, & z_{ic}=z_{pc}\\ \dfrac{-1}{\theta}\sqrt{\dfrac{\sum_{c=1}^{n}w_{lc}}{w_{lc}}}\cdot d(z_{ic},z_{pc}), & z_{ic}<z_{pc}\end{cases} \tag{13}$$

$$\boldsymbol{\delta}(A_i,A_p)=\sum_{c=1}^{n}\boldsymbol{\phi}_c(A_i,A_p) \tag{14}$$

where w_{lc} is the weight of criterion B_c divided by the weight of reference criterion B_l (l=1, 2, ⋯, r), i.e., w_{lc}=w_c/w_l; θ indicates the attenuation factor of the losses, which can be adjusted in specific conditions; and $d(z_{ic}, z_{pc})$ represents the distance between z_{ic} and z_{pc}, i.e., $d(z_{ic}, z_{pc})=z_{ic}-z_{pc}$.

(5) Step 5: Select optimal alternative

The global value of each alternative is determined by normalizing the final dominance matrix, and the normalization equation is

$$\eta_i=\frac{\sum_{p=1}^{m}\boldsymbol{\delta}(A_i,A_p)-\min\sum_{p=1}^{m}\boldsymbol{\delta}(A_i,A_p)}{\max\sum_{p=1}^{m}\boldsymbol{\delta}(A_i,A_p)-\min\sum_{p=1}^{m}\boldsymbol{\delta}(A_i,A_p)} \tag{15}$$

After the values of η_i are determined, the ranking of the alternatives can be obtained based on η_i. The higher the value of η_i, the better the alternative.

4 Case study

4.1 Engineering background

The Sanshandao Gold Mine lies in Laizhou City within Shandong Province of China and consists of three districts: Xinli, Xishan, and Xiling. The Xinli district, which occurs in the subsea bedrock of the Bohai Sea, is the first subsea hard rock mine developed in China. This deposit is located in the Sanshandao−Cangshang fault zone, as shown in Fig. 3(a). The exterior view of the Xinli district is displayed in Fig. 3(b).

The development method in the Xinli district is indicated in Fig. 4. The shaft is located on the coast and the wellhead lies above sea level. Several cross adits are excavated through the orebody so that the minerals situated under the sea can be mined efficiently. According to a geological survey, the main orebody is distributed in a fractured rock zone within 35 m below the fault, and extends downward from a level of 40−700 m at an inclination angle of 40°−50° southeast. Above the orebody is 35 m of Quaternary weathering gravel layer that terminates at a sea water depth of about

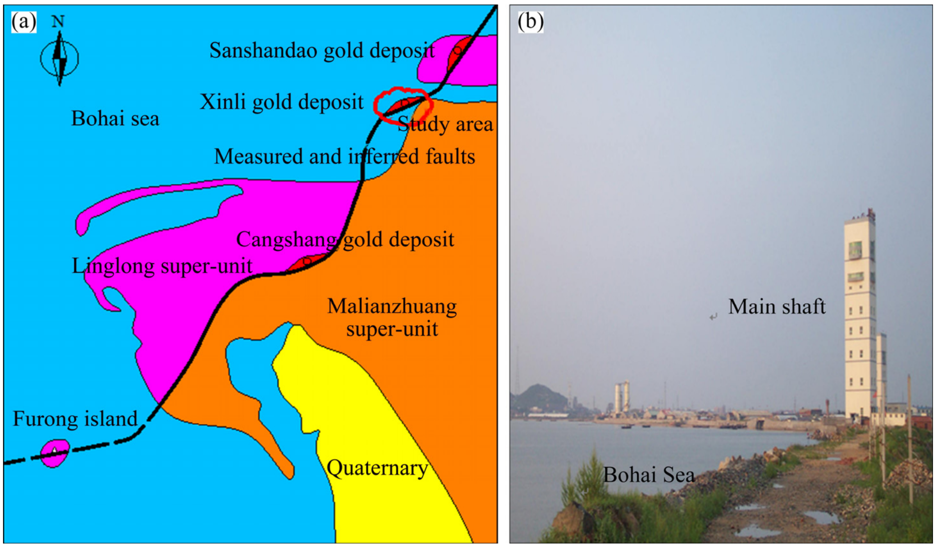

Fig. 3 Position of Xinli district: (a) Geologic scheme of Sanshandao−Cangshang fault; (b) Exterior view of Xinli district

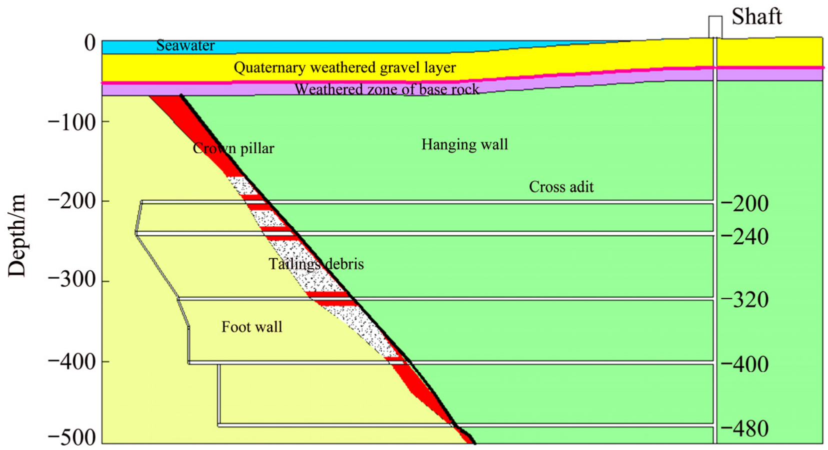

Fig. 4 Development method in Xinli district

10 m. The Quaternary weathering gravel layer including gravel, sand, mild clay and sludge provides some protections to the mine but is bondless. Fortunately, 2−3 m of silty clay, which has been proven to have significant impermeability, is widely distributed in the contact site between the Quaternary weathering gravel layer and bedrock. However, silty clay can be easily damaged because of its low strength. Therefore, a crown pillar with a thickness of approximately 120 m has been retained to ensure the safety of undersea mining.

The point-pillar sublevel filling method was adopted in the Xinli district from level −165 to −465 m, which has been proven effective in the field. Whereas, many ore pillars are reserved to prevent the movement of rock mass, which have brought heavy losses. As the depth increases, the mining location moves gradually away from the sea, and the mining disturbances on the isolation layer decrease. Indeed, this mining method becomes less effective at greater depths. Therefore, it is possible to cancel point pillars and employ other mining methods. The feasibility of cancelling ore pillars in the Xinli district has been analyzed based on numerical simulation and mining conditions [5]. It was determined that ore pillars could be progressively reduced from the level −465 to −555 m, and then completely eliminated below the level −555 m. Accordingly, research on the optimization for selecting a non-pillar method for deep mining in the Xinli district is required.

4.2 An illustrative example

According to the mining technical conditions, four feasible mining methods for a subsea deep gold deposit were designed: the room-pillar alternation upward level cut and fill stopping method (A_1), room and pillar sublevel filling method (A_2), medium and deep hole caving with subsequent filling method (A_3), and high access back-filling method (A_4). Meanwhile, the point-pillar sublevel filling method (A_5) was also used for comparison. The hybrid TODIM model was adopted to select the optimal mining method for the Xinli district, and the concrete evaluation procedure is described as follows:

(1) Step 1: Construct initial evaluation matrix

A group of professionals were invited to evaluate the performance of each mining method. Based on the outcome of in-depth investigations and focused discussion, the sub-criteria of the five mining methods were determined, as given in Table 2.

(2) Step 2: Standardise initial evaluation matrix to account for differences of index dimensions

The normalization values were calculated by Eqs. (3)−(6). Subsequently, the TFNs were defuzzified by Eq. (8). Accordingly, the evaluation matrix after normalization and defuzzification was derived as follows:

$$\boldsymbol{Z}=\begin{bmatrix} 0.2222 & 0.2038 & 0.2315 & 0.2222 & 0.1956 & 0.2623 & 0.1918 & 0.2781 & 0.2262 & 0.2708 \\ 0.2222 & 0.2375 & 0.2028 & 0.2222 & 0.2476 & 0.2384 & 0.1951 & 0.2035 & 0.1939 & 0.1772 \\ 0.1592 & 0.1029 & 0.1740 & 0.2222 & 0.1381 & 0.2659 & 0.2182 & 0.0878 & 0.1597 & 0.2141 \\ 0.1907 & 0.2375 & 0.2028 & 0.1592 & 0.1205 & 0.1262 & 0.1785 & 0.3337 & 0.1939 & 0.1513 \\ 0.2222 & 0.2375 & 0.2028 & 0.1907 & 0.3390 & 0.1071 & 0.2164 & 0.0970 & 0.2262 & 0.2141 \end{bmatrix}$$

(3) Step 3: Determine weights of sub-criteria using superiority linguistic ratings

The linguistic ratings for the sub-criteria were provided by five professionals, as given in Table 3. It can be seen that all professionals believed the weight of sub-criteria B_{23} was very high for subsea mining. Subsequently, the aggregated fuzzy weights were calculated by Eqs. (10)−(11). The weights after normalization were then obtained according to Eq. (12) as follows:

$$\boldsymbol{w}=[0.0950\ 0.0890\ 0.1039\ 0.0950\ 0.1187\ 0.1068\ 0.1098\ 0.1068\ 0.0890\ 0.0861]$$

(4) Step 4: Establish dominance matrix

As the weight value of B_{23} was the largest, it was selected as the reference criterion. Subsequently, all partial dominance matrices were obtained by Eq. (13). The final dominance matrix was then derived by Eq. (14), as shown in Table 4.

(5) Step 5: Select optimal mining method

The global values of alternatives were determined by Eq. (15), and the calculation results were η_1=1.0000, η_2=0.7753, η_3=0, η_4=0.1349 and η_5=0.6483. As $\eta_1>\eta_2>\eta_5>\eta_4>\eta_3$, the optimal mining method was A_1.

Consequently, the room-pillar alternation upward level cut and fill stopping method was selected as the optimal mining method in the Xinli district, which is detailed in Fig. 5. The practice demonstrates that the selected mining method is effective and capable of greater economic benefit.

Table 2 Sub-criteria of five mining methods

Mining method	Sub-criteria									
	B_{11}	B_{12}	B_{21}	B_{22}	B_{23}	B_{31}/(t·shift^{-1})	B_{32}/(YUAN·t^{-1})	B_{33}/%	B_{34}/%	B_{41}
A_1	G	SG	VG	G	F	42.12	60.24	6.0	6.0	SP
A_2	G	G	G	G	SP	38.27	59.23	8.2	7.0	SG
A_3	F	P	SG	G	VG	42.70	52.97	19.0	8.5	F
A_4	SG	G	G	F	G	20.27	64.73	5.0	7.0	G
A_5	G	G	G	SG	P	17.20	53.40	17.2	6.0	F

Table 3 Linguistic ratings of all sub-criteria

Professional	Sub-criteria									
	B_{11}	B_{12}	B_{21}	B_{22}	B_{23}	B_{31}	B_{32}	B_{33}	B_{34}	B_{41}
D_1	SH	M	H	SH	VH	H	H	H	SH	M
D_2	H	H	H	H	VH	H	VH	H	M	SH
D_3	SH	SH	H	H	VH	H	VH	H	H	SH
D_4	SH	SH	H	SH	VH	H	H	VH	SH	H
D_5	H	SH	H	SH	VH	VH	H	H	SH	M

Table 4 Dominance of each alternative over other alternatives

Parameter	A_1	A_2	A_3	A_4	A_5
A_1	0	−1.1129	−0.0526	−0.7421	−1.7409
A_2	−3.3273	0	−1.0990	−0.6499	−2.2954
A_3	−6.2567	−5.0312	0	−4.0848	−4.8307
A_4	−5.8371	−4.2695	−3.3626	0	−4.3485
A_5	−4.1836	−2.4209	−1.4192	−1.4496	0

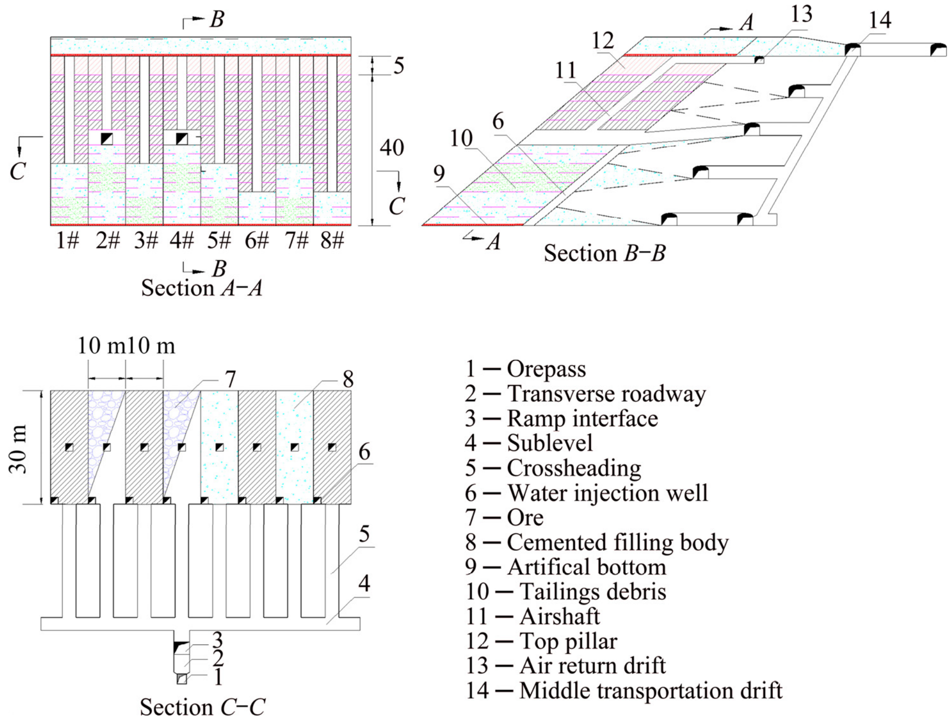

Fig. 5 Room-pillar alternation upward level cut and fill stopping method

5 Discussion

Tapping the resources of subsea bedrock deposits is becoming increasingly vital and widespread. To account for the distinctiveness of subsea bedrock deposits, a hybrid TODIM model was proposed to select the optimal mining method.

Considering the influence of parameter θ in Eq. (13), a sensitivity analysis is provided to demonstrate the robustness of the proposed method. Here, the value of θ is assumed to be θ=1. However, other values of θ have been adopted in the literatures [29,30]. Therefore, to verify the stability of the results, other θ values were also chosen for comparison. In general, if θ>1, the influence of loss is weakened; if θ<1, the influence of loss is exacerbated. Thus, the values of θ were sorted into two conditions: 0<θ<1 and θ>1. The global values of the alternatives for different θ values are given in Table 5. It can be seen that the trends of the global values for different θ values are consistent. The global values decreased with the increase of θ, except that the maximum and minimum values were invariant. The ranking results of the different θ values are given in Table 6. All ranking results were consistent. That is to say, the ranking result was not sensitive to θ when using the hybrid TODIM method. Thus, the sensitivity analysis validates the robustness of the proposed method to a certain degree.

Table 5 Global values of alternatives for different θ values

θ	η_1	η_2	η_3	η_4	η_5
0.2	1	0.7917	0	0.1394	0.6541
0.4	1	0.7874	0	0.1382	0.6526
0.6	1	0.7832	0	0.1371	0.6511
0.8	1	0.7792	0	0.1359	0.6497
1.0	1	0.7753	0	0.1349	0.6483
2.0	1	0.7572	0	0.1299	0.6420
4.0	1	0.7275	0	0.1217	0.6316
6.0	1	0.7040	0	0.1152	0.6233
8.0	1	0.6850	0	0.1100	0.6167

Table 6 Ranking results with different θ values

θ	Ranking result	Optimal alternative	Worst alternative
0.2	A_1>A_2>A_5>A_4>A_3	A_1	A_3
0.4	A_1>A_2>A_5>A_4>A_3	A_1	A_3
0.6	A_1>A_2>A_5>A_4>A_3	A_1	A_3
0.8	A_1>A_2>A_5>A_4>A_3	A_1	A_3
1.0	A_1>A_2>A_5>A_4>A_3	A_1	A_3
2.0	A_1>A_2>A_5>A_4>A_3	A_1	A_3
4.0	A_1>A_2>A_5>A_4>A_3	A_1	A_3
6.0	A_1>A_2>A_5>A_4>A_3	A_1	A_3
8.0	A_1>A_2>A_5>A_4>A_3	A_1	A_3

The hybrid TODIM method was employed to select the optimal mining method for the Xinli district of the Sanshandao Gold Mine. Alternative A_1 was chosen as the best mining method. Currently, the mine is producing ore, both safely and efficiently. The selected filling methods are being used, whereas certain deformations may still occur, especially in steep and thick orebody. MA et al [31] monitored the surface settlement in the Jinchuan Nickel Mine using global positioning system (GPS) monitoring system. Their results showed that the maximum settlement reached 2403 mm, despite the use of the back-filling method. The consequences would be extremely serious if a similar situation were to occur in subsea mines. Thus, several monitoring methods have been adopted, such as hydraulic discharge, micro-seismic, and displacement monitoring. Additionally, because of the potential for water inrush and its extremely serious consequences, several emergency rescue measures have been implemented, including an alarm system, waterproof structures, and escape routes.

Further, to reduce the amount of settlement, it is necessary to fill the goaf compactly. Considering the conditions in the Xinli district, several measures for reducing settlement are proposed as follows:

(1) Improve concentration of filling material

Currently, the filling materials in the Xinli district are composed of tailings, cement, water, etc. However, the volume concentration is only in the range of 52%−54%. Because of the effect of water, achieving a roof-contact filling is difficult. Therefore, high-density filling or paste filling should be adopted.

(2) Fill goafs at multiple points

Generally, attle is difficult to distribute evenly, especially when filling a large goaf from only one point. Filling the goaf from multiple points can effectively improve the attle distribution. There are two ways to achieve this: drill several holes in the stowing pipe, or use multiple stowing pipes. Regardless, it is necessary to fill from the bottom.

(3) Fill goafs forcibly with injection pump

Because the filling slurry may be compressed by external stress or shrink after dehydrating, it is difficult to fully fill the goaf. Thus, an injection pump could be used to fill the goaf forcibly.

6 Conclusions

(1) According to the specific conditions of subsea mines, an index system for subsea mining method selection was established with four criteria and ten sub-criteria. To describe the uncertain information more fully and accurately, qualitative index values were represented by TFNs instead of scores.

(2) The index weights were determined using superiority linguistic ratings. Comprehensively considering the knowledge, experience and preferences of five experts, the degree of disturbance on overlying rock formation was assigned a maximum weight value.

(3) A hybrid model combining fuzzy theory and the TODIM method was proposed to select the optimal mining method in the Xinli district of the Sanshandao Gold Mine, and the room-pillar alternation upward level cut and fill stopping method was selected. A sensitivity analysis indicated that the proposed model was robust, and the practice showed that the optimized mining method was useful for safe mining.

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海底深部金矿采矿方法优化

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摘 要：对海底深部金矿开采方法的优化进行研究。首先，综合考虑技术可行性、安全状况、经济效益和管理复杂性 4 个方面，建立海底采矿方法优化的指标体系。其次，构建一个同时包含实数和三角模糊数的评价矩阵，对定性及定量信息进行综合表征。然后，提出一种模糊理论与 TODIM 方法相结合的混合模型。最后，以三山岛金矿为例，对该方法的可行性进行验证，并通过灵敏度分析证实该方法具有较好的鲁棒性。结果表明，所提出的混合 TODIM 方法能可靠有效地用于海底深部金矿采矿方法的选择，并可为其他类似海底矿山采矿方法优化提供参考。

关键词：海底深部采矿；采矿方法；模糊理论；混合 TODIM 方法

(Edited by Bing YANG)