A new model for mining method selection of mineral deposit based on fuzzy decision making

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Synopsis

One of the main tasks in exploitation of mines is to select a method suitable for the deposits, specific features including geometric, geo-mechanical and geological features. The purpose of selecting a mining method at this stage is to choose one or more method(s) having the most coordination with the deposit's conditions and external factors, including the allocated budget and local technology for detailed feasibility studies. Several methods have been developed in the past to evaluate suitable mining methods for an ore deposit, based on its physical characteristics. These approaches can be classified into three groups: (1) profile and checklist methods, (2) numerical ranking (scoring) methods, and (3) decision-making models. Most of these methods have shortcomings. Considering the fact that most of the specifications of mineral deposits, such as dip and depth, are linguistic variables, absoluteness of the explaining parameters by previous methods can be mentioned as the most important disadvantage of these methods. This paper discusses the Fuzzy technique for order performance by similarity to ideal solution (Fuzzy TOPSIS) to determine the mining method. The fuzzy decision making (FDM) software tool is employed to develop a Fuzzy TOPSIS based model. Application of this model with various values (crisp, linguistic and fuzzy) of the deposit eliminated the existing disadvantages of other methods. Two empirical illustrations demonstrate the effectiveness and feasibility of the evaluation procedure. These show that the proposed model performs better than its alternatives.

Keywords: mining method selection, fuzzy TOPSIS, decision making, mining engineering, linguistic variables.

Introduction

Mining method selection is a critical point and a strategic issue in the mining engineering process. Selection of a method unsuitable for deposit characteristics may make exploitation of the orebody troublesome and sometimes uneconomical. So, available deposits should be evaluated carefully in an optimum manner. In the process, the selection of the most appropriate mining method is of great importance from the economical, technical and safety points of view. In the method selection process, many controllable and uncontrollable parameters should be taken into account. Therefore, these parameters must be obtained with scientific and technical studies for each ore deposit[1].

In the past, selection of an extraction method was based primarily on operating experience at a similar type of mine and on methods already in use in the districts of the deposit. The approach of adopting the same mining method as that of a neighbouring operation is not always appropriate. However, this does not mean that one cannot learn from comparing mining plans of existing operations in the district, or of similar deposits[2].

There is no single appropriate mining method for a deposit. Usually two or more feasible methods are possible. Each method entails some inherent problems. Consequently, the optimal method is the one that offers the minimum numbers of problems. The key issue for mining method selection is to maximize the profit by selecting the method with the highest recovery of the mineral resources and the lowest cost among the feasible alternatives.

The approaches to the selection of the mining method can be classified in three categories: profile and checklist methods, numerical ranking (scoring) methods, and decision making models. In this paper, the problems with these methods are discussed and the results of applying fuzzy decision making software tool in the process of selecting the extraction method for several cases are offered. The main purpose of this paper is to present a fuzzy multi-criteria decision making model for the mining method selection. In order to introduce the suggested fuzzy decision making model, firstly, the existing mining method selection models and their disadvantages are presented. Then, the

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basic concepts of the technique for order preference by similarity to an ideal solution (TOPSIS) and the Fuzzy TOPSIS are introduced. Moreover, the fuzzy decision making (FDM) software tool is introduced based on the Fuzzy TOPSIS. An application of the FDM software tool is carried out through several case studies.

Existing mining method selection models and their limitations

Several methods have been developed in the past to evaluate a suitable mining method for an ore deposit based on its physical characteristics such as shape, grade and geo-mechanical properties of the enclosing rock and ore deposit itself. The approaches to the solution of mining method selection problems can be classified in three groups: (1) profile and checklist methods, (2) numerical ranking (scoring) methods and (3) decision making models.

A group of mining specialists such as Peele[3], Boshkov and Wright[4], Morrison[5], Hartman[6] and Agoshkov[7] suggested a series of approaches for selecting a suitable mining method. This group of studies was neither enough nor complete, as it is not possible to design a methodology that will automatically choose a mining method for the orebody studied.[2]

Various approaches have been offered by researchers such as Labscher[8], Nicholas[9,10], Pakalnis *et al.*[11] to select the mining method. These attempts led to the development of a numerical approach to select the method of extracting mineral deposits. Numerical ranking (scoring) methods rely on ranking a finite number of geometric, geomechanical and geologic parameters to arrive at a rating value for different alternatives. In these methods, in addition to the limitation of criteria number and alternatives, ambiguity and simultaneous influence of criteria have been neglected in the decision making process.

This group of methods, such as University of British Columbia (UBC) method[11] or the method offered by Nicholas[10], are based on ranking parameters, which explain the mineral deposit status. Disadvantages of these approaches include limitations in the number of criteria and the selection of alternatives. In the method offered by Nicholas, geometric parameters such as general shape, thickness, dip and grade distribution manner are considered. Although in this method, the deposit depth is considered an effective parameter in selecting the method of deposit extraction, no point is considered for its influence. Furthermore, only the geomechanic criteria of joint frequency, rock quality designation (RQD), rock substance strength (RSS) and the shear strength factor of joints in the ore deposit and its surrounding rocks are considered. In the UBC method, although the depth and the rock mass rating (RMR) score are added, this limitation is still binding. Criteria such as deposit dimensions, thickness changes or its uniformity, availability of expert personnel in extraction, recovery in any mining method, subsidence effect or gas leak effect, underground water status and so on, are neglected in both methods. This limitation also exists in the choices and alternatives of selection. In the scoring approach, ten mining methods are considered for selection. These methods in the order of increasing operating costs are: open pit mining, block caving, sublevel stoping, sublevel caving, longwall, room and pillar, shrinkage, cut and fill, top slicing and square-set. Although the traditional mining methods are divided into eighteen extraction methods, each of which may include several different alternatives.[12] Among the methods not included in the above list are the stope and pillar mining, vertical crater retreat mining (VCR), strip mining and novel extraction methods such as hydraulic mining and borehole mining. Moreover, underground methods such as longwall may be performed in the retreat or advance mode and the ground control may be performed by caving or filling. Therefore choices in the mining method selection process are much more numerous than the ten considered methods.

Considering the fact that parameters affecting selection of the mine extraction method are divided into three classes of crisp (deterministic), linguistic and fuzzy parameters, the deterministic explanation in numerical ranking methods can be mentioned as the most important disadvantage, because in the method offered by Nicholas and the UBC method, parameters are explained by crisp values. But most of the statements introducing the mineral deposit are linguistic statements. For example, for the dip of an orebody, usually low dip (flat), moderate dip (intermediate) or high dip (steep) terms are used and for the cavability of the deposit hanging wall, the terms appropriate, moderate or inappropriate cavability are used. Also criteria introducing a mineral deposit are divided into classes, which have no exact definition in boundary status and have some ambiguities. In numerical ranking methods, the influence of each parameter is verified separately and the mutual effects of parameters are ignored. For example, dip, thickness and depth parameters are simultaneously effective on determination of the open pit method. In numerical ranking methods, as the orebody's dip increases, the probability of choosing the open pit method decreases. When the thickness is increased, the decreasing score of the dip should compensate each other. For an inclined and thick deposit, the open pit method maybe preferred. Also in these methods, all the criteria are assumed to have equal weights in decision making, but considering the status of each deposit makes such an assumption unrealistic.

Considering these limitations and disadvantages, efforts have recently been made in order to develop decision making models for selecting the mining method. Among these efforts are studies of researchers such as Wei-Xuan and Yiming[13,14], Kesimal and Bascetin[15] Miranda *et al.*.[16], Samimi and Shahriar[17,18], Bitarafan and Ataei[2], Bascetin *et al.*[19], Karadogan *et al.*[1].

Recent methods for decision making processes have enabled decision-makers to decide more quickly, easily and sensitively[1]. Although the disadvantages of numerical ranking methods have been removed partly in the decision making models offered, these methods have their own disadvantages.

In decision making models, which are based on multi-criteria decision making (MCDM) techniques, there is no limitation on the number of criteria and alternatives, but these models face the problem of time-consuming calculations.

Most of these methods are based on the Yager model. The Yager model[20] follows the max-min method of Bellman and Zadeh[21], with the improvement of the analytical hierarchy process (AHP) method, which considers the use of a reciprocal matrix to express the pair-wise comparison criteria

and the resulting eigenvector as subjective weights.[2] The disadvantages of the AHP technique is that it focuses mainly on the decision maker who has to make many pair-wise comparisons to reach a decision, while possibly using subjective preferences. Furthermore, an important disadvantage of the AHP method is the artificial limitation of the use of the nine-point scale. For instance, if Alternative A is five times more important than Alternative B, which in turn is five times more important than Alternative C, a serious evaluation problem arises. The Saaty method[22] cannot cope with the fact that Alternative A is twenty five times more important than Alternative C.[23] The methodology is useful only when the decision making framework has a unidirectional hierarchical relationship among decision levels. Moreover, AHP is not practically usable if the number of alternatives and criteria are large since the repetitive assessments may cause fatigue in the decision maker.[24,25]

The existing decision making models for mining method selection are useful but have restricted applications. These methods cannot deal with decision maker ambiguities, uncertainties and vagueness, which cannot be handled by crisp values. Having to use crisp values is one of the important problematic points in their process.

In this article, the concept of the approach used for solving the mining method selection problem is based on the fuzzy technique for order preference by similarity to ideal solution (Fuzzy TOPSIS). This is because four advantages are addressed: (1) a sound logic that represents the rationale of human choice, (2) a scalar value that accounts for both the best and worst alternatives simultaneously, (3) a simple computation process that can be easily programmed, and (4) the performance measures of all alternatives on attributes can be visualized as a polyhedron, at least for any two dimensions. These advantages make TOPSIS a major decision making technique as compared with other related techniques such as AHP.[26,27]

Methodology and the proposed model

TOPSIS and fuzzy TOPSIS

TOPSIS is a popular approach to the MCDM method and has been widely used in the literature (Abo-Sinna and Amer[28]; Agrawal *et al.*[29]; Cheng *et al.*[30]; Deng *et al.*[31]; Feng and Wang[32,33]; Hwang and Yoon[34]; Jee and Kang[35]; Kim *et al.*[36]; Lai *et al.*[37]; Liao[38]; Olson[39]; Opricovic and Tzeng[40]; Parkan and Wu,[41,42]; Tong and Su[43]; Tzeng *et al.*[44]; Zanakis *et al.*[45]). The method has also been extended to deal with Fuzzy MCDM problems. For example, Chen[46] first converted a fuzzy MCDM problem into a crisp one via centroid defuzzification and then solved the nonfuzzy MCDM problem using the method. Chen and Tzeng[47] transformed a fuzzy MCDM problem into a nonfuzzy MCDM using a fuzzy integral. Instead of using distance, they employed the grey relation grade to define the relative closeness of each alternative. Chu[48,49] and Chu and Lin[50] also changed a fuzzy MCDM problem into a crisp one and solved the crisp MCDM problem using the method. Differing from the others, they first derived the membership functions of all the weighted rankings in a weighted normalization decision matrix using interval arithmetics of fuzzy numbers and then defuzzified them into crisp values using the ranking method of mean of removals (Kaufmann and Gupta[51]).

Chen[46] extended the method to fuzzy group decision making situations by defining a crisp Euclidean distance between any two fuzzy numbers. Triantaphyllou and Lin[52] developed a fuzzy version of the method based on fuzzy arithmetic operations, which led to a fuzzy relative closeness for each alternative proposed by Wang and Elhag[53].

The TOPSIS method is a technique for order preference by similarity to ideal solution and proposed by Hwang and Yoon[34]. The ideal solution (also called the positive ideal solution) is a solution that maximizes the benefit criteria/attributes and minimizes the cost criteria/attributes, whereas the negative ideal solution (also called the anti-ideal solution) maximizes the cost criteria/attributes and minimizes the benefit criteria/attributes. The so-called benefit criteria/attributes are those for maximization, while the cost criteria/attributes are those for minimization. The best alternative is the one that is closest to the ideal solution and farthest from the negative ideal solution.

Suppose a MCDM problem with m alternatives, $A_1,\ldots,A_m$, and n decision criteria/attributes, $C_1,\ldots,C_n$. Each alternative is evaluated with respect to m criteria/attributes.

All the values/ratings assigned to the alternatives with respect to each criterion form a decision matrix denoted by $X = (x_{ij})_{n\times m}$. Let $W = (w_1,\ldots,w_n)$ be the relative weight vector for the criteria, satisfying $\sum_{i=1}^{n} w_i = 1$, then the method can be summarized as follows:[24]

a) Calculate the decision matrix (D) as:

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \cdots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad [1]$$

b) Calculate the normalized decision matrix or R matrix. The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1,\ldots,n,\ j = 1,\ldots,m \quad [2]$$

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \cdots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \quad [3]$$

c) Calculate the criteria weighted matrix as:

$$W = \begin{bmatrix} w_1 & \cdots & 0 \\ \vdots & w_2 \cdots & \vdots \\ 0 & \cdots & w_n \end{bmatrix} \quad [4]$$

d) Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as:

$$v_{ij} = w_i r_{ij} = W \times R \quad j = 1,\ldots,m, i = 1,\ldots,n \quad [5]$$

where w_j is the weight of the jth criterion and $\sum_{i=1}^{n} w_i = 1$.

e) Determine the positive ideal and negative ideal solution, A^+ and A^- respectively.

$$A^+ = \{v_1^+,\ldots,v_n^+\} = \left\{\left(\max_j v_{ij} | i \in I\right),\left(\min_j v_{ij} | i \in J\right)\right\} \quad [6]$$

$$A^- = \{v_1^-, \ldots, v_n^-\} = \left\{\left(\min_j v_{ij} | i \in I\right), \left(\max_j v_{ij} | i \in J\right)\right\} \quad [7]$$

where I is associated with benefit criteria, and J is associated with cost criteria.

f) Calculate the separation measures, using the n-dimensional Euclidean distance. The distance of each alternative from the ideal solution is given as:

$$d_j^+ = \sqrt{\sum_{i=1}^{n}\left(v_{ij} - v_i^+\right)^2} \quad j = 1, \ldots, m \quad [8]$$

Similarly, the distance from the negative ideal solution is given as:

$$d_j^- = \sqrt{\sum_{i=1}^{n}\left(v_{ij} - v_i^-\right)^2} \quad j = 1, \ldots, m \quad [9]$$

g) Calculate the relative closeness to the ideal solution. The relative closeness of the alternative A_j with respect to A^+ is defined as:

$$RC_j = \frac{d_j^-}{d_j^+ + d_j^-} \quad j = 1, \ldots, m \quad [10]$$

Since $d_j^- \geq 0$ and $d_j^+ \geq 0$, then clearly $RC_j \in [0,1]$.

h) Rank the alternatives according to the relative closeness to the ideal solution: the higher RC_j, the better alternative A_j.[53]

The fuzzy theory is a modern theory, which was proposed by Zadeh[54]. In classic logic, events have two values: to be or not to be, to exist or not to exist, black or white, and one or zero. But in fuzzy logic, in order to answer to events, a consistent spectrum is considered between 'to exist' and 'not to exist' and world phenomena are seen as gray—neither black nor white. The use of fuzzy theory allows us to incorporate unquantifiable information, incomplete information, non-obtainable information, and partial facts into the decision model. The fuzzy decision matrix ($\tilde{D}$) and criteria weighted ($\tilde{W}$) can be concisely expressed in matrix format as:

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad [11]$$

$$\tilde{W} = \begin{bmatrix} \tilde{w}_1 & \cdots & 0 \\ \vdots & \cdots & \vdots \\ 0 & \cdots & \tilde{w}_n \end{bmatrix} \quad [12]$$

where $\tilde{x}_{ij}$, $i = (1,2,\ldots,m)$, $j = (1,2,\ldots,n)$ and $\tilde{w}_j$, $j = (1,2,\ldots,n)$ are fuzzy numbers, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$. That $\tilde{x}_{ij}$ is the performance rating of the ith alternative, A_i, with respect to the jth criteria, C_j and $\tilde{w}_j$ represents the weight of the jth attribute, C_j.

The normalized fuzzy decision matrix denoted by $\tilde{R}$ is shown as:

$$\tilde{R} = \begin{bmatrix} \tilde{r}_{11} & \cdots & \tilde{r}_{1n} \\ \vdots & \cdots & \vdots \\ \tilde{r}_{m1} & \cdots & \tilde{r}_{mn} \end{bmatrix} \quad [13]$$

If $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$, $i = (1,2,\ldots,m)$ and $j = (1,2,\ldots,n)$ are triangular fuzzy numbers, then the normalization process can be conducted by:[53]

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), \; i = 1,2,\ldots,m; j \in \Omega_b \quad [14]$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \; i = 1,2,\ldots,m; j \in \Omega_c \quad [15]$$

where Ω_b and Ω_c are the sets of benefit criteria and cost criteria, respectively and $c_j^+ = \max_i c_{ij}, j \in \Omega_b$ and $a_j^- = \min_i a_{ij}$, $j \in \Omega_c$.

The weighted fuzzy normalized decision matrix is shown as:

$$\tilde{v}_{ij} = \tilde{w}_j \tilde{r}_{ij} = \tilde{W} \times \tilde{R} \; j = 1,\ldots,m, \; i = 1,\ldots,n \quad [16]$$

The fuzzy positive-ideal (A^+) and the fuzzy negative-ideal (A^-) solutions are shown as:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+) = \left\{\max_1 v_{ij} \middle| \begin{matrix} i = 1,2,\ldots,m \\ j = 1,2,\ldots,n \end{matrix}\right\} \quad [17]$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-) = \left\{\min_1 v_{ij} \middle| \begin{matrix} i = 1,2,\ldots,m \\ j = 1,2,\ldots,n \end{matrix}\right\} \quad [18]$$

The distance of each alternative from A^+ and can be currently calculated using Equations [19] and [20].

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), i = 1,2,\ldots,m \quad [19]$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), 1 = 1,2,\ldots,m \quad [20]$$

If $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ are two triangular fuzzy numbers, then the vertex method is used to calculate the distance between them and is calculated as:

$$d(\tilde{a}, \tilde{b}) = \sqrt{[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \quad [21]$$

At the end, the relative closeness of each alternative to the ideal solution is calculated as below:

$$RC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad [22]$$

RC_i is then used to rank the alternatives. The higher the RC_i, the more suitable the mining method. The higher value of RC_i indicates that an alternative is closer to the positive ideal solution and farther from the negative ideal solution simultaneously. A value of 1 (or 100 per cent) for an alternative indicates that the alternative is equal to the positive ideal solution and a value of 0 (or 0 per cent) is equal to the negative ideal solution. The best alternative is the one with the greatest relative closeness to the positive ideal solution.

The fuzzy decision making (FDM) software tool

The fuzzy decision making (FDM) software tool[55] has been prepared to make decisions considering specific criteria and the effect of qualitative parameters and in the situation where the decision maker does not have access to precise

information, by Meamareiani at the engineering faculty of Tarbiat-modares University in Iran. The FDM software tool has been designed based on the Fuzzy TOPSIS technique, presented in the previous section. In this section, it is attempted to remove the defects in existing mining method selection models by using this software tool and applying it systematically. The most important advantage of applying this software tool is its ability in cases where diversity of data exists. This tool can receive three types of information, including deterministic, linguistic, and fuzzy information. These three types of data are indeed parameters affecting the decision making process for selecting the mining method. But in previous methods only the crisp (ordinary) values constitute the decision making process input. For example, in Table I, the variety of the data that can be explained in the extraction method selection has been offered.

Regarding fuzzy numbers related to the mine costs mentioned in the last line of Table I, it should be added that the costs are related to the block caving method, and it is meant that the mine costs in block caving method is about $12.5 per ton and *a* and *b* values are left and right limits, respectively.[6] Moreover, there is no limitation on the number of alternatives and criteria.

The evaluation procedure can be applied to the mining method selection, as shown in Figure 1.

The proposed model consists of several steps. The first step is to identify the criteria that are considered in the mining method selection process and mining methods as alternatives. Then the weights of the criteria are determined and a decision matrix is created. In order to perform the fuzzy decision making process, the scores for each criterion and all of the weights are converted to fuzzy numbers (fuzzification). In this step, crisp values and linguistic variables are converted to fuzzy numbers. This step is called fuzzification because fuzzy sets are used to convert linguistic variables to fuzzy variables.

The decision makers use the linguistic variables to evaluate the relative importance or weights of criteria and the ratings of alternatives for various attributes. For this reason, the linguistic variable is transformed into a fuzzy triangular membership function. This is the first step of the Fuzzy TOPSIS analysis. In the FDM software tool, the linguistic variables divided to seven-levels, fuzzy linguistic values 'very low', 'low', 'more or less (MoL) low', 'medium', 'more or less (MoL) high', 'high' and 'very high'. Based on these assumptions, a transformation table can be created as shown in Table II. For example, the fuzzy variable 'low' has its associated triangular fuzzy number with the minimum value of 0.00, the mode value of 0.10, and the maximum value of 0.3. The same definition is then applied to the other fuzzy variables very low, MoL low, medium, MoL high, high and very high.

The next step is fuzzy deduction. In this step, the result is determined by the Fuzzy TOPSIS technique. The decision making process in a fuzzy environment is the same as the decision making process in the human brain, because in everyday life, people analyses much inaccurate fuzzy information and then makes decisions. Before any calculation, linguistic and crisp values are converted to fuzzy numbers with transformation of fuzzy membership functions (by using Table II).

Transformation of the decision matrix to fuzzy numbers is carried out by the software tool for user convenience and the user has any role here. This action is carried out for all inputs including criteria, weights and the decision matrix information. Then, in order to remove a dimension, the decision matrix is normalized and calculated using weighted normalized ratings automatically.

The next action is to find the negative as well as the positive ideal solutions. After finding the ideal and negative solutions, the distance of each alternative is obtained in an *n*-dimensional space (*n* is the number of criteria affecting decision making).

Table I

Various data input to FDM software

Data type	Description	Value
Crisp value	Annum production	300 000 (ton per year)
Linguistic	Deposit thickness	Intermediate
Fuzzy value	Mine costs	(m=12.5,a=5,b=20)

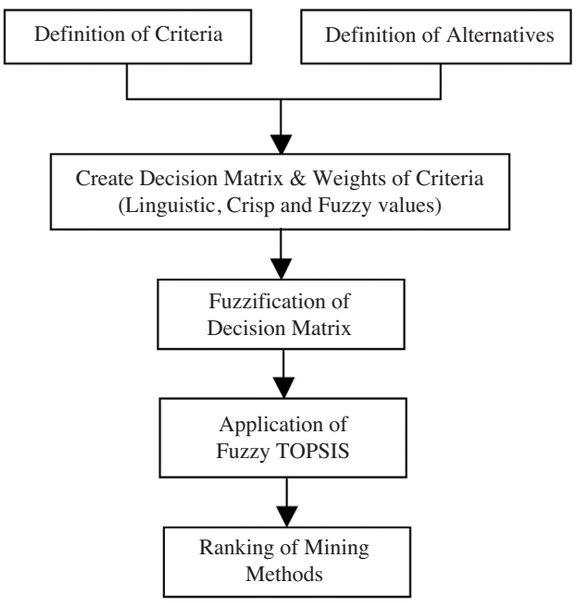

Figure 1—Selection framework of mining methods

Table II

Transformation for fuzzy membership functions

Rank	Membership function
Very low	(0.0, 0.0, 0.1)
Low	(0.0, 0.1, 0.3)
MoL low	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
MoL high	(0.5, 0.7, 1.0)
High	(0.7, 0.9, 1.0)
Very high	(0.9, 1.0, 1.0)

The final scores of each parameter is its relative closeness to the positive ideal solution. These processes are performed by the software tool itself and the user enters only the input information such as selection criteria, their effective weight and selection alternatives.

Empirical illustration

In this section, three empirical examples are examined using the proposed model. The first example is taken from Nicholas[10]. Other case studies are a real application of the proposed model to mining method selection.

Example 1: This example reconsiders the one investigated by Nicholas[10]. Used data are given in Table III.

Let us suppose the ratings (criteria values and their relative importance weights) for numeric ranking methods according to Table IV. After evaluation the top four alternatives are determined, according to the proposed model as well as the results of Nicholas method. The results are summarized in Table V.

The Nicholas and proposed model lead to the choice of open pit as the first priority.

Case study 1:[56,57] In order to investigate the competence of the proposed model, the Gol-e-Gohar (GEG) deposit, south of Iran, was chosen as the first case. This iron ore district is located in 55 km south-west of Sirjan (Figure 2).

The above mentioned iron ore district includes six anomalies. Anomaly No. 1 has been extracted for many years with open pit mining. Recently, exploitation of anomaly No. 3 has been considered. Deposit No. 3 has a length of 2 200 m in a north-south line and an average width of 1 800 m in the west of anomaly No. 1, which is located under a relatively flat field. The geometric and some geomechanic specifications of anomaly No.3 are represented in Table VI based on the latest detailed exploration results. In order to select the most suitable extraction method for this deposit, 11 methods are considered for comparison and competition.

Examined extraction methods include: open pit mining, block caving, sublevel stoping, sublevel caving, longwall, room and pillar, shrinkage, cut and fill, top slicing, square-set and stope and pillar methods.

These methods are entered into the FDM model as alternatives. Criteria involved in this selection include the suitability of deposit shape, grade distribution, deposit dip, deposit thickness, deposit depth, hangingwall rock mass rating (RMR), deposit RMR, hangingwall rock substance strength (RSS) (RSS = overburden pressure/ uniaxial compressive strength UCS), deposit RSS, footwall RSS, mining method recovery, access to expert work force, production capacity, hangingwall rock quality designation (RQD), shear strength of deposit joint, hangingwall joint shear resistance and mine costs.

Table III

Nicholas example input parameters[10]

	Criteria	Description
Ore zone	Deposit shape	tabular or platy
	Ore thickness	90 meters (thick)
	Ore dip	15 degree(flat)
	Grade distribution	uniform
	Depth	130 meters
	RQD	40 %
	RSS	Strong
	Joint condition	Clean with a rough surface
Hangingwall	RQD	65%
	RSS	Strong
	Joint condition	Clean with a rough surface
Foot wall	RQD	40%
	RSS	moderate
	Joint condition	Coated with thin clay

Table IV

Linguistic value of Nicholas scores and weights

Description		Linguistic rank
Criteria values	-49	Very low
	0	Low
	1	MoL low
	2	Medium
	3	MoL high
	4	High
Weighting factor	0.5	Medium
	0.8	High
	1	Very high

Table V

Summary of evaluation for example 1

Method	OP	TS	BC	SQ	SC	SH
Nicholas	33.8	28.3	27.3	26.6	26.3	25.8
FDM	70.74	58.13	57.26	56.49	55.91	56.34

* Where OP: open pit, TS: top slicing, BC: block caving, SQ: square set, SC: sublevel caving and SH: shrinkage mining method

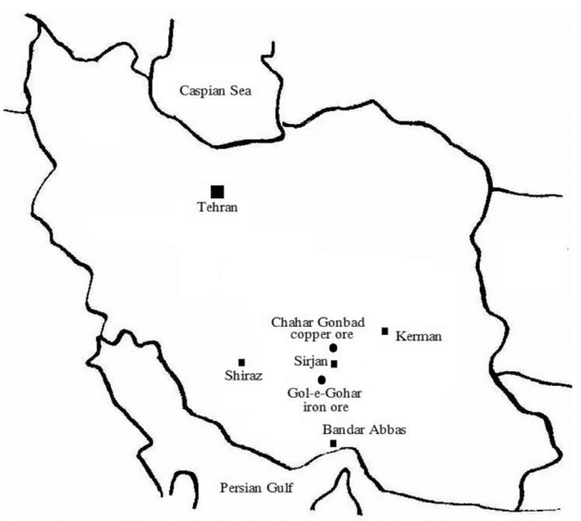

Figure 2—Location of GEG and Chahar Gonbad mines

These parameters are entered as attributes. The first step is to gather input information for the model. The decision matrix for GEG anomaly No. 3 was entered into the FDM model according to Figure 3.

In this process, mining cost is entered as cost criteria (negative effect on decision making) and the other parameters are entered as profit. The decision making matrix and related weight of criteria are shown in Figure 3. The simplicity of changing these weights and studying different decision making situations are advantages of this model.

Table VI

Specifications of GEG Iron Ore anomaly No. 3

	Criteria	Description
Ore zone	General shape	Tabular
	Ore thickness	15–130, Average 40 meters
	Ore dip	20 degree
	Grade distribution	Gradational
	Depth	95 ~ 600 meters
	RQD	75%
	RSS	8.9
	RMR	Good (60-80)
	Ore reserve	643 million tons
	Joint condition	Filled (low strength)
Hanging wall	RQD	38%
	RSS	6
	RMR	Good (60–80)
	Joint condition	Clean with a smooth surface
Footwall	RQD	15%
	RSS	6.5
	RMR	Good (60–80)
	Joint condition	Clean with a rough surface

Figure 4 shows the scores obtained by each mining method in fuzzy decision making, after the data has been processed by the FDM model. The open pit mining method stands first with a score of 75.71and the square-set method is last with a score of 30.86.

Case study 2: [56,57] The Chahar Gonbad copper ore deposit is located 50 km north of Sirjan, south of Iran (Figures 2). Table VII shows the physical and mechanical characteristics of this deposit.

In order to select a mining method for this deposit, 11 methods are proposed for comparison such as the GEG mining method selection process. The criteria that affect the selection, considered in this study, are presented in Figure 5.

The final scores obtained by each mining method in the fuzzy decision making method are shown in Figure 6. The open pit mining method is first with 78.90 and the square-set method is last with 28.03.

Results and discussion

In example 1, there is only one difference between the results of the Nicholas and proposed model in the ranking of the sublevel caving and shrinkage (Table V). The Fuzzy TOPSIS is one of the compensatory decision making methods. As mentioned before, in this method decreasing the score of one parameter is compensated by increasing the score of other parameter(s) and vice versa. In fact the shrinkage is closer than the sublevel caving to the ideal solution so it is rational to prefer the shrinkage method to sublevel caving.

The resulting alternatives for GEG anomaly No. 3 vary among the different methods to some extent. The eight alternatives, according to the numerical ranking methods

Fuzzy Decision Making V4.0 - [Gol-E-Gohar No. 3]

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No.	Attribute Name / Attribute Data Type / Attribute Weight	Deposit shape	Grade distribution	Ore dip	Ore thickness	Depth	Hangwall RMR	Ore RMR	Hangwall RSS
	Attribute Data Type	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic
	Attribute Weight	Medium	MoL Low	MoL High	MoL High	MoL High	MoL High	Medium	MoL High
1	Block caving	Medium	Medium	Medium	MoL High	MoL High	MoL High	Low	High
2	Cut & fill	High	MoL High	MoL High	MoL Low	MoL High	High	MoL High	MoL High
3	Longwall	High	MoL Low	Low	Very Low	Medium	High	Medium	Very High
4	Open pit	Medium	MoL High	MoL High	High	Low	High	MoL High	MoL High
5	Room & pillar	High	Medium	Low	Very Low	MoL High	MoL High	Very High	Low
6	Shirinkage	High	Medium	Low	Very Low	MoL High	Medium	MoL High	Low
7	Square-set	MoL Low	MoL Low	MoL High	Low	MoL Low	MoL Low	Low	High
8	Stope & pillar	High	MoL High	Medium	MoL High	MoL High	MoL High	Very High	Low
9	Sublevel caving	High	Medium	MoL Low	High	Medium	MoL High	MoL Low	High
10	Sublevel stoping	High	High	MoL Low	High	High	MoL High	High	Low
11	Top slicing	Medium	MoL Low	Medium	Medium	MoL Low	Medium	MoL Low	High

CAPS INS

Fuzzy Decision Making V4.0 - [Gol-E-Gohar No. 3]

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No.	Attribute Name / Attribute Data Type / Attribute Weight	Ore RSS	Footwall RSS	Recovery	Skilled man power	Output per man shift	Hangwall RQD	Mining cost
	Attribute Data Type	Linguistic	Linguistic	Deterministic	Linguistic	Deterministic	Linguistic	Triangular Fuzzy
	Attribute Weight	Medium	Medium	High	High	MoL High	Medium	MoL High
1	Block caving	Medium	Medium	90	Very Low	90	Very High	m:12.5, a:5, b:20
2	Cut & fill	MoL Low	Medium	100	Medium	30	High	m:32.5, a:15, b:50
3	Longwall	Very High	MoL High	95	Medium	40	Very High	m:15, a:5, b:25
4	Open pit	MoL High	High	100	Very High	90	High	m:11.5, a:3, b:20
5	Room & pillar	Low	Medium	60	MoL High	35	MoL Low	m:20, a:10, b:30
6	Shirinkage	MoL Low	MoL High	85	MoL High	12	Very High	m:27.5, a:15, b:40
7	Square-set	MoL High	Low	100	Very Low	8	High	m:77.5, a:30, b:125
8	Stope & pillar	Low	Medium	60	MoL Low	40	MoL Low	m:19, a:8, b:30
9	Sublevel caving	MoL High	Medium	85	MoL Low	35	Very High	m:26, a:12, b:40
10	Sublevel stoping	Medium	MoL High	85	MoL High	45	Low	m:23.5, a:12, b:35
11	Top slicing	Medium	MoL Low	95	Medium	10	High	m:42.5, a:20, b:65

CAPS INS

Figure 3—Geometrical and geomechanical input data of GEG deposit No. 3

Ranking

Rank	Name	Score
1	Open pit	75.71
2	Sublevel stoping	60.88
3	Block caving	58.36
4	Longwall	56.83
5	Sublevel caving	56.02
6	Cut & fill	55.43
7	Stope & pillar	52.44
8	Room & pillar	49.10
9	Shirinkage	46.85
10	Top slicing	45.40
11	Square-set	30.86

OK

Figure 4—The scores obtained by each mining method for GEG deposit No. 3

Table VII

Specifications of Chahar Gonbad copper ore

	Criteria	Description
Ore zone	General shape	Platy
	Ore thickness	Average 8.5 metres
	Ore dip	70 degree
	Grade distribution	Irregular
	Depth	Low depth (<100 metres)
	RQD	75%
	RSS	8.7
	RMR	Good (60–80)
	Ore reserve	700 million tons
	Joint condition	Filled (low strength)
Hangingwall	RQD	38%
	RSS	15.63
	RMR	Good (60–80)
	Joint condition	Clean with a smooth surface
Footwall	RQD	15%
	RSS	9.1
	RMR	Average (40–60)
	Joint condition	Clean with a rough surface

Fuzzy Decision Making V4.0 - [Chahar Gonbad Deposit]

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Run

No.	Attribute Name	Deposit shape	Grade distribution	Ore dip	Ore thickness	Depth	Hangwall RMR	Ore RMR	Hangwall RSS
	Attribute Data Type	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic	Linguistic
	Attribute Weight	Medium	MoL Low	MoL High	MoL High	MoL High	MoL High	Medium	MoL High
1	Block caving	Medium	Medium	High	Low	Medium	MoL High	Low	Medium
2	Cut & fill	High	High	High	High	Medium	High	MoL High	High
3	Longwall	High	Low	Very Low	Low	Medium	High	Medium	Medium
4	Open pit	Medium	Medium	MoL Low	MoL High	High	High	MoL High	High
5	Room & pillar	High	Low	Very Low	MoL Low	MoL High	MoL High	Very High	Medium
6	Shirinkage	High	Medium	High	Low	MoL High	Medium	MoL High	MoL High
7	Square-set	MoL Low	MoL High	Medium	Medium	MoL Low	MoL Low	Low	MoL Low
8	Stope & pillar	High	MoL High	Medium	MoL High	MoL High	MoL High	Very High	Low
9	Sublevel caving	High	Medium	High	Low	MoL High	MoL High	MoL Low	Medium
10	Sublevel stoping	High	MoL High	High	MoL High	MoL High	MoL High	High	High
11	Top slicing	Medium	MoL Low	Low	Low	Medium	Medium	MoL Low	Medium

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Fuzzy Decision Making V4.0 - [Chahar Gonbad Deposit]

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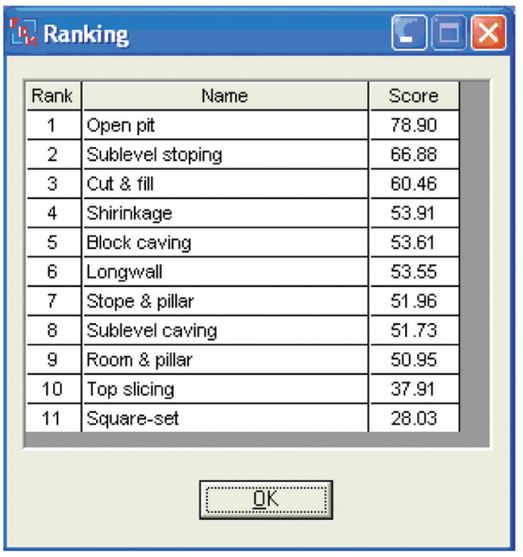
Run

No.	Attribute Name	Ore RSS	Footwall RSS	Recovery	Skilled man power	Output per man shift	Hangwall RQD	Mining cost
	Attribute Data Type	Linguistic	Linguistic	Deterministic	Linguistic	Deterministic	Linguistic	Triangular Fuzzy
	Attribute Weight	Medium	Medium	High	High	MoL High	Medium	MoL High
1	Block caving	Medium	Medium	90	Very Low	90	Very High	m:12.5, a:5, b:20
2	Cut & fill	MoL Low	Medium	100	Medium	30	High	m:32.5, a:15, b:50
3	Longwall	Very High	MoL High	95	Medium	40	Very High	m:15, a:5, b:25
4	Open pit	MoL High	High	100	Very High	90	High	m:11.5, a:3, b:20
5	Room & pillar	Low	Medium	60	MoL High	35	MoL Low	m:20, a:10, b:30
6	Shirinkage	MoL Low	MoL High	85	MoL High	12	Very High	m:27.5, a:15, b:40
7	Square-set	MoL High	Low	100	Very Low	8	High	m:77.5, a:30, b:125
8	Stope & pillar	Low	Medium	60	MoL Low	40	MoL Low	m:19, a:8, b:30
9	Sublevel caving	MoL High	Medium	85	MoL Low	35	Very High	m:26, a:12, b:40
10	Sublevel stoping	Medium	MoL High	85	MoL High	45	Low	m:23.5, a:12, b:35
11	Top slicing	Medium	MoL Low	95	Medium	10	High	m:42.5, a:20, b:65

NUM CAPS INS

Figure 5—Geometrical and geomechanical input data of Chahar Gonbad deposit



Rank	Name	Score
1	Open pit	78.90
2	Sublevel stoping	66.88
3	Cut & fill	60.46
4	Shirinkage	53.91
5	Block caving	53.61
6	Longwall	53.55
7	Stope & pillar	51.96
8	Sublevel caving	51.73
9	Room & pillar	50.95
10	Top slicing	37.91
11	Square-set	28.03

Figure 6—The score obtained by each mining method for the Chahar Gonbad deposit

Table VIII

Scores of different exploitation methods according to the methods prevalent in GEG deposit No. 3

Methods		Open pit	Cut and fill	Shrinkage	Sublevel stoping	Top slicing	Square-set	Block caving	Sublevel caving
Case 1	Nicholas	32.9	30	29.1	28.8	28.8	28	26.1	20.7
	UBC	33	33	22	34	16	10	24	28
	FDM	75.71	55.43	46.85	60.88	45.40	30.86	58.36	56.02
Case 2	Nicholas	32	30	25	21	-	25	-	-
	UBC	33	34	34	32	13	15	-	-
	FDM	78.9	60.46	53.91	66.88	37.91	28.03	53.61	51.73

(Nicholas and UBC), as well as the results by FDM, are presented in Table VIII. Considering Table VIII: the open pit mining in the Nicholas method has obtained the best score. This result is not surprising considering the fact that in the UBC method, scoring has been done with reference to Canadian mining and gives priority to open stoping methods such as sublevel stoping. Because the UBC mining method selection is a modification of the Nicholas approach, which places more emphasis on stoping methods (sublevel stoping, room and pillar and cut and fill), thus better representing typical Canadian mining design practices.[11] Considering the results of the mining method selection for Chahar Gonbad (case 2), open pit mining in the Nicholas method has obtained the best score.

By applying the FDM model, based on Fuzzy TOPSIS, a strategy was offered to extract mineral deposits. This strategy has advantages in comparison with previous numerical ranking (scoring) methods such as Nicholas and UBC. These advantages are a strong theoretical base on fuzzy logic, the high speed in achieving the result, the ability of sensitivity analysis, the direct usage of linguistic variables in the mining method selection process, unlimited alternatives and criteria, and, most important of all, the possibility of considering the mutual effects of different parameters in the selection process. In fact, TOPSIS is one of the compensatory multi-attribute decision making models. Moreover, this model considers the uncertainty associated with the input parameters (linguistic variables) used in the selection process. The model has a potential to become a suitable tool in mining method selection.

Conclusions

The mining method selection of an explored orebody is a critical point and strategic issue in the mining engineering process. This decision involves many parameters that are interrelated in that changes in some parameters affect the others. This paper has discussed mining method selection in a fuzzy environment and uncertain linguistic value of variables. Fuzzy TOPSIS is a viable method for the proposed problem and is suitable for the use of linguistic variables. When the decision making condition is vague and inaccurate, then this method is the preferred technique.

The present study explored the use of Fuzzy TOPSIS in mining method selection. The proposed model can be a suitable tool to select the mining method. The mining method selection of GEG anomaly No.3 and Chahar Gonbad were examined by this model. At the end of this examination, open pit mining was assigned as the best extraction method for these iron and copper ore deposits. The systematic evaluation by Fuzzy TOPSIS of mining method selection problems can reduce the risk of a poor choice.

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PLATINUM 2008

Johnson Matthey releases 'Platinum 2008' industry review*

Platinum market in deficit by 480-000 oz in 2007

The platinum market was in deficit by 480-000 oz in 2007 according to Platinum 2008, released today by Johnson Matthey. Disruption to production in South Africa drove global platinum supplies down to 6.55 million ounces. Demand for platinum rose by 8.6 per cent to 7.03 million ounces with increased purchases of metal for autocatalysts and for industrial use. The platinum price rose by 35 per cent in response, hitting a series of record highs. Jewellery demand fell marginally under pressure from the high price.

South African supply falls

Platinum supplies in 2007 fell by 4.1 per cent to 6.55 million ounces. South African supplies fell by 4.9 per cent to 5.04 million ounces; unscheduled smelter closures, safety problems and a difficult industrial relations climate had a negative impact on. Supplies of platinum from Russia and elsewhere fell slightly.

Autocatalyst purchases of platinum rise to new record

Global platinum purchases by the autocatalyst sector rose by 8.2 per cent in 2007 to 4.23 million ounces. The number of diesel vehicles produced in Europe, Japan and North America fitted with platinum-based exhaust aftertreatment to meet emissions rules continued to increase, outweighing the effect of substitution of platinum by palladium in some gasoline and diesel catalysts.

High prices have little impact on jewellery demand

Despite a rising price, purchases of platinum by the jewellery industry, excluding scrap, fell only marginally to 1.59 million ounces. Retail sales and manufacturing volumes were resilient in most geographical markets. Chinese demand for manufacturing platinum jewellery rose modestly from 760-000 oz to 780-000 oz. The quantity of second-hand jewellery and unsold retail stock returned for recycling in both China and Japan increased due to the high metal price.

Exchange traded funds boost investment demand

Platinum investment demand climbed sharply to 170-000 oz in 2007 from net disinvestment of 40-000 oz the previous year. The launch of two new platinum-based exchange traded funds in Europe in the first half of 2007 created significant new investment demand. Platinum industrial demand rose to 1.94 million ounces, six per cent up from the 2006 total. This was aided by booming retail sales of electronic goods, which increased platinum requirements for hard disks and for the manufacture of flat panel display glass.

Platinum price to remain volatile

The countrywide power supply crisis in South Africa and the temporary closure of the Amandelbult mine due to flooding in early 2008 will affect production of platinum this year. With industrial and automotive demand expected to remain strong and supplies set to underperform, the platinum market is likely to be in a substantial deficit in 2008. The global economic slowdown and any strengthening in the US dollar could cause the platinum price to soften but high volatility is expected to continue during the next six months. Johnson Matthey forecasts that platinum will trade within a wide range of $1-775 to $2-500 over this period. ◆