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A NEW FUZZY MULTI CRITERIA DECISION MAKING MODEL FOR OPEN PIT MINES EQUIPMENT SELECTION

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Nowadays, the capital cost of open-pit mining equipment is very high so any mistake in the selection of quantity, type and capacity of equipment may cause irreparable impact on the net present value of mining project. Mine planning engineers generally use their intuition and experience in decision making even though equipment selection is a complex multi criteria decision problem. Considering the tangible along with intangible factors in the mine equipment selection problem, this paper proposes a new method of multi criteria decision making (MCDM) that makes it possible to select the optimal equipment that satisfies the decision maker. In a real-world situation, because of incomplete or non-obtainable information, the data (attributes) are often not deterministic but they are usually fuzzy-imprecise. Our proposed model considers objective, critical, and subjective factors as the three main common factors in equipment selection analysis. The last two factors, critical and subjective factors, are defined by decision maker's judgments for more adoption with real world problems. A case study is presented to illustrate the use of the proposed model and to demonstrate the capability of the model. The result of this study shows significant reduction of time consumption of calculation and good precision compared to customary methods such as Chang's fuzzy AHP method.

Keywords: Fuzzy sets; multiple criteria analysis; decision support systems; mining equipment selection.

1. Introduction

Equipment selection is one of the most important factors in open-pit design (pit slopes, bench height, block sizes and geometries, ramp layout as well as excavation sequences and open-pit layout) and production planning. Further, equipment selection also affects economic considerations in open-pit design, specifically overburden, waste rock and ore mining costs and cost escalation parameters as a function of plan location and depth. The purpose of equipment selection is to select the optimal equipment with minimum cost.

Mine planning engineers often use their intuition and experience in decision making. Linguistic variables (the weather is raining, soil is wet, etc.) are ambiguous and decision-makers may not know how these variables are computed. Since the advent of fuzzy set theory, these uncertainties are easily evaluated in decision making processes (Bascetin and Kesimal, 1999).

The selection of equipment for mining applications is not a well-defined process and because it involves the interaction of several subjective factors or criteria, decisions are often complicated and may even embody contradictions. Traditionally, procurement costs become elevated through a system of public tendering to appear as the primary criterion and the major costs of looking after the equipment during its useful life are not taken into account (Samanta *et al.*, 2002).

Various models have been proposed for application to the selection of mining equipment. General guidelines and a survey related to the selection of surface mining equipment were discussed by Martin *et al.* (1982). An expert system as decision aid in surface mine equipment selection was applied by Bandopadhyay and Venkatasubramanian (1987) and Denby and Schofield (1990). Hrebar (1990) and Sevim and Sharma (1991) used net present value analysis for selection of a dragline and surface transportation system. Chanda (1995) reviewed the fundamental concepts of equipment selection.

Use of a linear breakeven model has been proposed by Cebesory (1997). Models for equipment selection and evaluation described by Celebi (1998) were aimed at selection of the equipment fleet on the basis of minimizing the unit stripping cost and maximizing production.

Hall *et al.* (2003) illustrated how reliability analysis can provide mine management with quantitative information of value for decision making about surface mining equipment. The analytical hierarchy process has been proposed for application to the selection of equipment by some researchers (Samanta *et al.*, 2002; Bascetin, 2004).

EQuipment Selection (EQS) is computer software that uses fuzzy logic for equipment selection in surface mines and has been proposed by Bascetin *et al.* (2006). Application of fuzzy TOPSIS (technique for order preference similarity to ideal solution) method for optimal open pit mining equipment selection has been illustrated by Aghajani *et al.* (2009). Application of modified VIKOR method has been proposed by Aghajani Bazzazi *et al.* (2011) for deriving preference order of open pit mines equipment.

Most of these decision-making tools either rely on objective input data, with little or no subjective judgment, or spotlight on a single parameter. Also, because of incomplete or non-obtainable information, the data (attributes) are often not so deterministic; therefore they usually are fuzzy-imprecise and application of fuzzy logic (Zadeh, 1965) for surface mine equipment selection is exigent. Fuzzy multi-criteria decision-making (Fuzzy-MCDM) techniques can be very useful in encompassing several subjective criteria with conflicting objectives to arrive at an eclectic decision. In this paper, a combination of fuzzy set theory and the analytic hierarchy process (AHP) (Saaty, 1990) is developed to solve a multi-attribute open pit mining equipment selection problem.

The remainder of this paper is organized as follows: first, we review the selection of a multiple attribute decision making method. Then, we discuss the methodological issues related to this study and then this method is applied in real open pit mine. Finally, discussions and conclusions are listed.

2. Multiple Attribute Decision Making (MADM) Method

2.1. *MADM method*

MADM methods are developed to handle selection problems. In this class of problems, the "best" solution is determined from a finite and usually small set of alternatives. The selection is performed based on the evaluation of the attributes and their preference information.

In the decision making process, many MADM techniques use a decision matrix D (or goal achievement matrix) to describe the states of the attributes of each alternative. In decision matrix format, columns indicate attributes considered in a given problem and rows list the competing alternatives. Specifically, a MADM problem with m alternatives (A_1, A_2, ..., A_m) that are evaluated by n attributes (C_1, C_2, ..., C_n) can be viewed as a geometric system with m points in n-dimensional space. An element x_{ij} of the matrix indicates the performance rating of the ith alternative, A_i, with respect to the jth attribute, C_j, as shown in following equation (Hwang and Yoon, 1981):

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m22} & x_{m3} & \dots & x_{mn} \end{bmatrix} \end{array} \tag{1}$$

Generally, MADM methods can be classified into compensatory and non-compensatory methods based on the treatment of the attribute information. The compensatory methods allow trade-offs between criteria, assigning a number to each multidimensional representation of an alternative. The non-compensatory methods do not permit the trade-off between criteria, i.e. one unfavorable criterion value cannot be offset by reducing a favorable value of another criterion (Hwang and Yoon, 1981).

2.2. *MADM selection*

Many efforts have been made to facilitate the MCDM process so that various methods and techniques have been developed, such as Simple Additive Weighting (SAW), Weighted Product Model (WPM) and Technique for Ordered Preference by Similarity to the Ideal Solution (TOPSIS) (Hwang and Yoon, 1981).

Up to now, over 70 MCDM methods have been proposed (Roman *et al.*, 2004), and each method has a different analysis model intending to solve some class of problem. The existence of the various decision making methods implies that different methods have their own advantages and disadvantages and there is not a general, universal method capable of handling all types of problems. This fact indicates that in order to obtain a desired solution for the problem under consideration, a suitable method should be utilized since the existing methods have different degrees of appropriateness in handling a given problem. This statement can be further supported by the fact that for a given problem significantly different conclusions may be obtained from the application of the various methods.

Over the past decades, many efforts have been made to facilitate the selection of the most appropriate decision making method for a given problem. MacCrimmon (MacCrimmon, 1973) is probably the first researcher who recognized the importance of MCDM method selection. He proposed a classification of MCDM methods, created a method specification chart in the form of a tree diagram and provided an illustrative application example. A classification similar to the one MacCrimmon proposed was developed by Hwang and Yoon (Hwang and Yoon, 1981). This taxonomy is also represented by a tree diagram which consists of nodes and branches connected by choice rules.

Sen and Yang (1998) developed two similar tree diagrams to help select the appropriate MADM and Multi-Objective Decision Making (MODM) method among a few typically used methods.

Gershon and Duckstein (1984) were among the first to develop a MCDM algorithm approach. Their approach consists of evaluating the MCDM methods with respect to a set of criteria which fall into one of four categories: mandatory, non-mandatory, technique-dependent and application-dependent. The methods are evaluated by the criteria until the most suitable method for the given problem is found.

In the early 1990s, researchers began to employ the techniques of artificial intelligence to improve the quality of the decision making method selection. Ozernoy (1992) developed an expert system for choosing the best MCDM method, and presented a small example as a proof of implementation. The expert system works by asking the user a series of questions and then eliminating options to the most appropriate method based on the user's answers. An artificial neural network approach to multi criteria model selection was applied by Ulengin *et al.* (2000). Based on Ulengin *et al.* (2000) research, open pit mining equipment selection is a multi attribute decision making problem because decision makers want to choose the best alternative; decision makers consider a large number of attributes and a small number of alternatives and pairwise comparison. In this problem, model doesn't using thresholds and giving complete order and finally, all the performance values are qualitative and quantitative. Consequently, a fuzzy AHP method is the most appropriate method for solving open pit mining equipment selection problems.

3. Methodology

The proposed approach is developed within the AHP framework consisting of (1) hierarchy developments, (2) fuzzy pairwise comparisons and (3) relative weight calculations with regard to group decisions. These systematic procedures of the proposed method are similar to the process of human thinking and capable of turning the complex decision-making process into simple comparisons and rankings.

3.1. *Analytical hierarchy process*

Hierarchy is the structural frame in AHP (Saaty, 1990), which is used to determine the influence of all the decision criteria. The AHP structures the decision problem in levels which correspond to one's understanding the situation: goals, criteria, sub-criteria, and alternatives. At the highest level is the overall goal of the problem, and the alternatives are at the lowest level. Between them are criteria and sub-criteria. By breaking the problem into levels, the decision-maker can focus on smaller sets of decisions.

3.2. *Fuzzy pairwise comparison*

Once the hierarchy is established, the pairwise comparison evaluation takes place. All the criteria on the same level of the hierarchy are compared to each of the criteria of the preceding (upper) level. A pairwise comparison is performed by using linguistic terms. Based on Chen's definition (Chen, 2000), seven linguistic terms, "Very Low Important" (VLI), "Low Important" (LI), "Medium Low Important" (MLI), "Medium Important" (MI), "Medium High Important" (MHI), "High Important" (HI) and "Very High Important" (VHI) ranging from 0–10 are used to develop fuzzy comparison matrices. These seven linguistic variables are described by fuzzy numbers as denoted in Table 1 or by membership functions as illustrated in Fig. 1

Table 1. Fuzzy importance scale.

Verbal judgment	Explanation	Fuzzy number
Very Low Important (VLI)	A criterion is very strongly inferior to another	(0, 0, 1)
Low Important (LI)	A criterion is strongly inferior to another	(0, 1, 3)
Medium Low Important (MLI)	A criterion is slightly inferior to another	(1, 3, 5)
Medium Important (MI)	Two criteria contribute equally to the objective	(3, 5, 7)
Medium High Important (MHI)	Judgment slightly favors one criterion over another	(5, 7, 9)
High Important (HI)	Judgment strongly favors one criterion over another	(7, 9, 10)
Very High Important (VHI)	Judgment very strongly favors one criterion over another	(9, 10, 10)

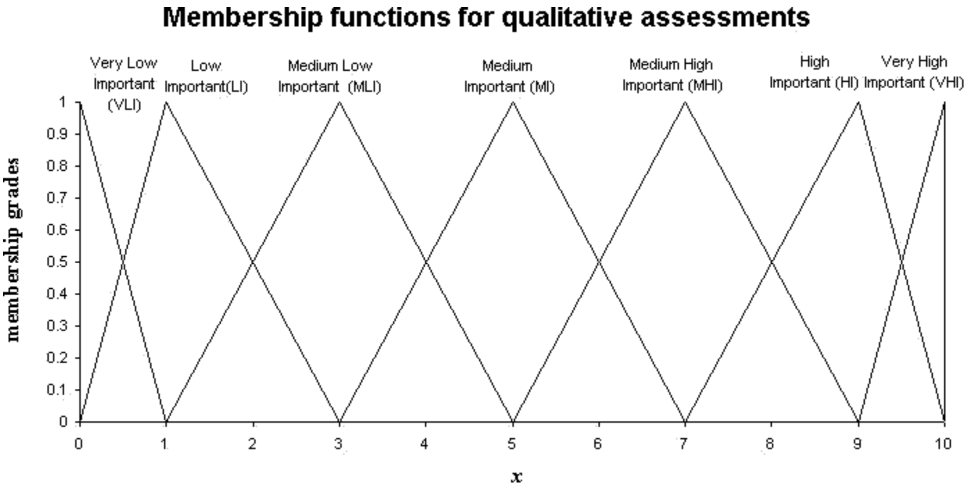

Fig. 1. Membership functions for linguistic values.

where levels are characterized by symmetric triangular membership functions. Fuzzy comparison matrix, Ã, is given by:

$$\tilde{A} = \begin{bmatrix} 1 & (x_{12,L}, x_{12,M}, x_{12,U}) & \cdots & (x_{1n,L}, x_{1n,M}, x_{1n,U}) \\ (x_{21,L}, x_{21,M}, x_{21,U}) & 1 & \cdots & (x_{2n,L}, x_{2n,M}, x_{2n,U}) \\ \vdots & \vdots & \ddots & \vdots \\ (x_{n1,L}, x_{n1,M}, x_{n1,U}) & (x_{n2,L}, x_{n2,M}, x_{n2,U}) & \cdots & 1 \end{bmatrix} \tag{2}$$

$(x_{ij,L}, x_{ij,M}, x_{ij,U})$ in Eq. (2) shows the lower, middle and upper value of the ith element compared with the jth element. In Chang's method (Chang, 1996), the element of the negative judgment is treated as an inverse and reversed order of the fuzzy number of the corresponding positive judgment. For example, suppose that criterion A compared to criterion B is "high important" denoted by fuzzy number (7, 9, 10), so that the negative judgment, "less important", is described by (1/10, 1/9, 1/7). Thus, it requires careful checks to avoid errors arising from such tedious manipulations while constructing a reciprocal matrix. To overcome this difficulty, each negative reciprocal element is characterized by its own representative fuzzy number as defined in Table 1.

To reflect particular degrees of uncertainty regarding the decision making process, the α-cut concept is applied. This is another development of the proposed method made to Chang's model. The value of α is between 0 and 1. $\alpha = 0$ and $\alpha = 1$ signify the degree of uncertainty is greatest and least, respectively.

In practical applications, $\alpha = 0, \alpha = 0.5$, and $\alpha = 1$ are used to indicate the decision-making condition that has pessimistic, moderate, and optimistic view,

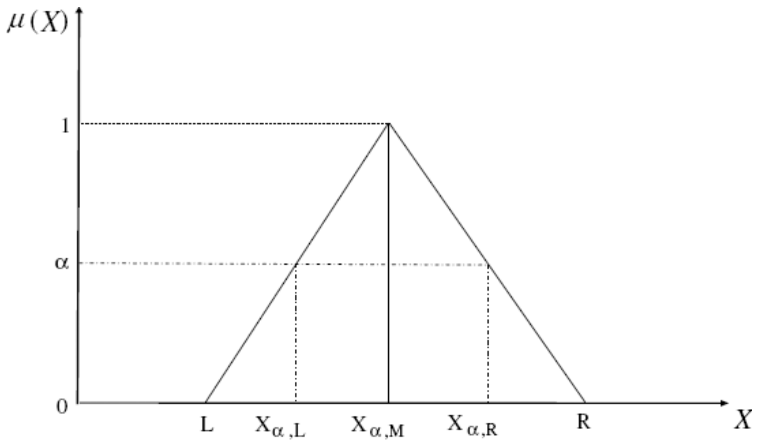

Fig. 2. Triangular fuzzy intervals under α-cut.

respectively. Figure 2 shows that a triangular fuzzy number regarding a given value can be denoted by $(X_{\alpha,L}, X_{\alpha,M}, X_{\alpha,R})$. $X_{\alpha,M}$, $X_{\alpha,L}$, and $X_{\alpha,R}$ represent the most-likely value, minimum value, and maximum value of the fuzzy number, respectively.

Seven membership functions shown in Fig. 1 under α-cut can also be mathematically expressed through Eqs. (3)–(9).

$$x_\alpha(\text{Very Low Important}) = \begin{cases} X_{\alpha,L} = 0 \\ X_{\alpha,M} = 0 \\ X_{\alpha,R} = 1 - \alpha \end{cases} \tag{3}$$

$$x_\alpha(\text{Low Important}) = \begin{cases} X_{\alpha,L} = \alpha \\ X_{\alpha,M} = 1 \\ X_{\alpha,R} = 3 - 2\alpha \end{cases} \tag{4}$$

$$x_\alpha(\text{Medium Low Important}) = \begin{cases} X_{\alpha,L} = 1 + 2\alpha \\ X_{\alpha,M} = 3 \\ X_{\alpha,R} = 5 - 2\alpha \end{cases} \tag{5}$$

$$x_\alpha(\text{Medium Important}) = \begin{cases} X_{\alpha,L} = 3 + 2\alpha \\ X_{\alpha,M} = 5 \\ X_{\alpha,R} = 7 - 2\alpha \end{cases} \tag{6}$$

$$x_\alpha(\text{Medium High Important}) = \begin{cases} X_{\alpha,L} = 5 + 2\alpha \\ X_{\alpha,M} = 7 \\ X_{\alpha,R} = 9 - 2\alpha \end{cases} \tag{7}$$

$$x_\alpha(\text{High Important}) = \begin{cases} X_{\alpha,L} = 7 + 2\alpha \\ X_{\alpha,M} = 9 \\ X_{\alpha,R} = 10 - \alpha \end{cases} \tag{8}$$

$$x_\alpha(\text{Very High Important}) = \begin{cases} X_{\alpha,L} = 9 + \alpha \\ X_{\alpha,M} = 10 \\ X_{\alpha,R} = 10 \end{cases} \tag{9}$$

To facilitate fuzzy weight computations, fuzzy comparison matrix $\tilde{\text{A}}$ in Eq. (2) is further decomposed into three crisp matrices: the lower bound matrix ($\tilde{\text{A}}^L$), most-likely matrix ($\tilde{\text{A}}^M$), and upper-bound matrix ($\tilde{\text{A}}^U$). Concerning $\tilde{\text{A}}^L$ as an example, $\tilde{\text{A}}^L$ is defined by:

$$\tilde{A}^L = \begin{bmatrix} 1 & x_{12,L} & \dots & x_{1n,L} \\ x_{21,L} & 1 & \dots & x_{2n,L} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1,L} & x_{n2,L} & \dots & 1 \end{bmatrix} \tag{10}$$

3.3. *Relative weight calculations with regard to group decisions*

Several methods can be used for element weight calculation such as normalization of geometric mean, eigenvalue, etc. In this research, normalization of arithmetic mean (NAM) is applied to compute local weights and given by:

$$w_i^L = \frac{g_i^L}{\sum_{i=1}^n g_i^L}; \quad w_i^M = \frac{g_i^M}{\sum_{i=1}^n g_i^M}; \quad w_i^U = \frac{g_i^U}{\sum_{i=1}^n g_i^U} \tag{11}$$

where

$$g_i^L = \frac{\sum_{j=1}^n x_{ij}^L}{n}; \quad g_i^M = \frac{\sum_{j=1}^n x_{ij}^M}{n}; \quad g_i^U = \frac{\sum_{j=1}^n x_{ij}^U}{n} \tag{12}$$

In the above equations, g_i^L, g_i^M and g_i^U are the lower, middle and upper value of arithmetic mean of criterion i, respectively. w_i^L, w_i^M and w_i^U are the lower, middle and upper value of ith criterion's weight, respectively, where $w_i^L > 0, w_i^M > 0$ and $w_i^U > 0$ and $\Sigma w_i = 1, 1 \leq i \leq n. x_{ij}^L$ is the comparison value of criterion i to criterion j in lower bound matrix ($\tilde{\text{A}}^L$), x_{ij}^M is the comparison value of criterion i to criterion j in most-likely matrix ($\tilde{\text{A}}^M$) and x_{ij}^U is the comparison value of criterion i to criterion j in upper-bound matrix ($\tilde{\text{A}}^U$).

Group decision making was applied for weight calculation. For group evaluation, because the assessment of alternative weights is usually made by multiple evaluators whose preference may vary based on the individual's perception, experience, and knowledge; it is required to aggregate different evaluators' opinions into one. To achieve this task, the pooled assessments of multiple evaluators represented by membership functions need to be defuzzified. Defuzzification plays an important role when a conversion of a fuzzy number to a single representative value is required. In the proposed method, at first, minimum and maximum values between evaluators are eliminated when one criterion is compared with another one. This procedure is done because in a real situation each evaluator may be interested in one main criterion such as economy, environment or price, so he/she considers this interest in the decision questionnaire used to criteria evaluation. The proposed model employs the Center of Sum (COS) technique because the COS approach involves the simplified algebraic sum of individual fuzzy sets, which is much faster than most related methods and easy to implement (Ross, 1995). Defuzzification is applied to the set of pairwise comparison matrices after eliminating the maximum and minimum values. This method is given by:

$$Z^* = \frac{\int z \sum_{k=1}^{K} \mu_k(z) dz}{\int \sum_{k=1}^{K} \mu_k(z) dz} \tag{13}$$

where Z^* is the defuzzified value or weighted average, K is the number of evaluations after eliminating maximum and minimum value, $\mu(z)$ is obtained from Fig. 2 and is the membership value of the element z in the subset and $\int$ denotes an algebraic integration. Accordingly, the synthetic weight of the l'th sub-criterion related to the ith main criterion ($S_{il'}$) can be determined as follows:

$$S_{il'} = w_i \times s_{il'}, \quad i = 1, 2, \ldots, n, \quad l' = 1, 2, \ldots, L^i \tag{14}$$

$s_{il'}$ is the overall weight of the l'th sub-criterion ($l' = 1, 2, \ldots, L^i$) with regard to the ith main criterion, L^i is the number of sub-criteria related to ith main criterion and w_i is overall weight of the ith main criterion. It deserved mention that the overall weight of sub-criteria and main criteria are calculated by Eq. (13).

By the same manner, the weight of the jth alternative ($j = 1, 2, \ldots, m$) with respect to the lth sub-criterion (e_{jl}) can be obtained by Eq. (13). Consequently, the overall weight of the jth alternative regarding to sub-criterion l (r_{jl}) is given by:

$$r_{jl} = S_{il'} \times e_{jl}\{i = 1, 2, \ldots, n; j = 1, 2, \ldots, m; l' = 1, 2, \ldots, L^i; l = 1, 2, \ldots, L_{\text{total}}\} \tag{15}$$

where L_{total} is the total number of sub-criteria and e_{jl} is the weight of the jth alternative with respect to the lth sub-criterion. Note that sub-criterion l is the l'th sub-criterion of main criterion i. e_{jl} is obtained from field information and depends on the multiple attribute selection problems. Finally, the overall weight of the jth alternative regarding all sub-criteria, R_j, can be found by the following:

$$R_j = \sum_{l=1}^{L_{\text{total}}} r_{jl} \tag{16}$$

Fig. 3. Geographical location of Sungun copper mine.

4. Case Study

The Sungun mine is one of the largest copper deposits of Iran which is located in the north-west of the country close to the Azerbaijan, Armenia and Turkey borders (Fig. 3).

Technical and economical studies showed that the most appropriate mining method for this deposit is open pit mining. By this method 384 million tons of ore with 0.665 percent of copper grade can be mined. The mine's total life is estimated to be 31 years with annual production of 7 million tons in the first 5 years and 14 million tons for the remaining years. During this period 680 million tons of waste must be removed. So, the waste to ore ratio in this mine is 1.8:1 (Hoseinie *et al.*, 2006).

Three potential transportation system alternatives have been evaluated for ore transportation. These are loader- truck (A_1), shovel-truck (A_2) and shovel-truck-belt conveyor (A_3) systems.

The basic hierarchy of the decision problem was constructed based on the experts' suggestions. Each expert was asked to identify possible factors that could somehow affect the final decision through several surveys, questionnaires and discussions. Also, the criteria used in the hierarchy were based on the suggestions from the references in (Samanta *et al.*, 2002; Bascetin, 2004; Bandopadhyay and Venkatasubramanian, 1987).

As shown in Fig. 4, the top level and the lowest level of the hierarchy denote the overall objective (selecting the suitable loading-haulage equipment for the open pit mine) and the candidates, respectively. The five main criteria, namely Financial Consideration (FC), Operating condition, Safety and Environment (OSE), Mine

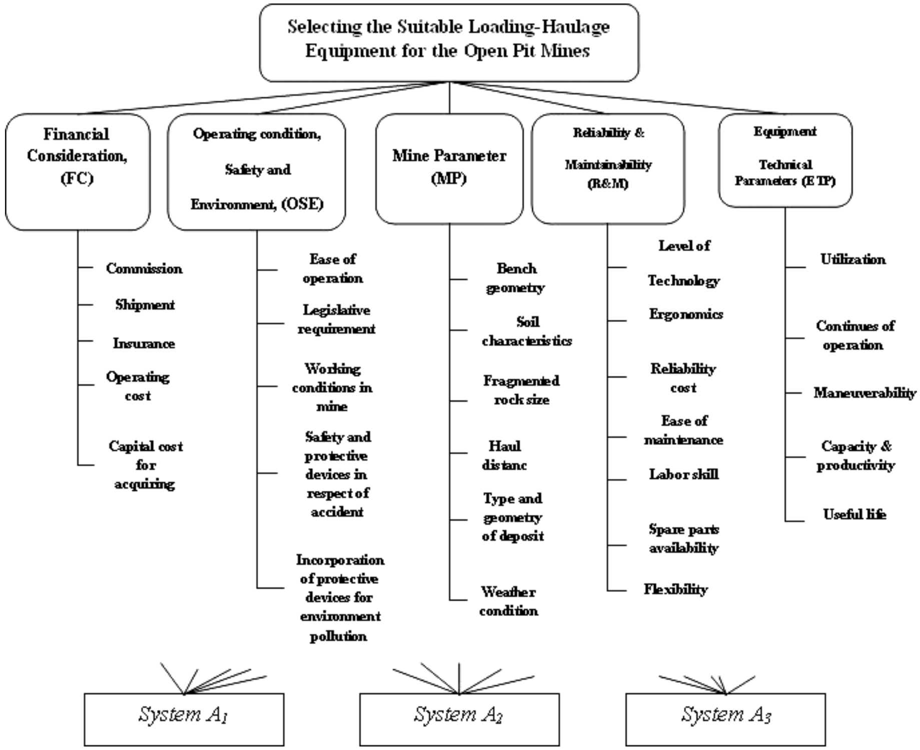

Fig. 4. The hierarchy for selecting the suitable loading-haulage equipment for the open pits mines.

Parameter (MP), Reliability and Maintainability (R&M) and Equipment Technical Parameters (ETP) were included at the second level. The main criteria were further broken down into sub-criteria. Financial consideration was characterized by commission, shipment, operating cost, insurance and capital cost for acquiring equipment. Operating condition, safety and environment was divided into ease of operation, legislative requirement, working conditions in mine, safety and protective devices in respect of accident and finally incorporation of protective devices for environment pollution.

Mine parameters was associated with bench geometry, soil characteristics, fragmented rock size, haul distance, type and geometry of deposit and weather conditions. Reliability and maintainability criterion was broken down into level of technology, ergonomics, ease of maintenance, reliability cost, labor skill, spare parts availability and flexibility. Equipment technical parameters were divided into utilization, continuity of operation, capacity and productivity, maneuverability and useful life.

Once the hierarchy was established, experts' knowledge was elicited through interviews and questionnaires. A series of questionnaires were designed and used to direct pairwise comparison judgments.

As an example, Table 2 depicts a particular questionnaire for evaluating main criteria with respect to the overall goal. By the use of Table 2, each expert performed a pairwise comparison to indicate his or her preference for each criterion. The assessment result can be found in Table 3. The team members included two sales managers of famous companies in Iran, two mine planning engineers and two academic professors. As mentioned before, minimum and maximum values in each pairwise compression were eliminated. The results are illustrated in Table 4.

Table 2. Questionnaire used to assess main criteria.

Q1. How important is FC when it is compared to OSE?
Q2. How important is FC when it is compared to MP?
Q3. How important is FC when it is compared to R&M?
Q4. How important is FC when it is compared to ETP?
Q5. How important is OSE when it is compared to MP?
Q6. How important is OSE when it is compared to R&M?
Q7. How important is OSE when it is compared to ETP?
Q8. How important is MP when it is compared to R&M?
Q9. How important is MP when it is compared to ETP?
Q10. How important is R&M when it is compared to ETP?

Table 3. Evaluation results of the main criteria with respect to the overall goal.

Pairwise criteria	1st exp	2nd exp	3rd exp	4th exp	5th exp	6th exp
FC vs. OSE	VHI	HI	VHI	MHI	HI	MI
FC vs. MP	VHI	HI	MI	MHI	MLI	MHI
FC vs. R&M	MI	MHI	MLI	MI	VHI	MI
FC vs. ETP	VHI	HI	MI	MI	MI	MHI
OSE vs. MP	VLI	LI	MLI	VLI	MLI	LI
OSE vs. R&M	VLI	VLI	LI	MI	MVI	LI
OSE vs. ETP	MI	MI	MHI	MI	LI	MLI
MP vs. R&M	MLI	MI	MLI	MI	LI	MI
MP vs. ETP	MI	MLI	MLI	MI	LI	MI
R&M vs. ETP	VHI	HI	HI	MI	HI	VHI

Table 4. Max and min eliminated from Table 3.

Pairwise criteria	1st	2nd	3rd	4th
FC vs. OSE	HI	VHI	MHI	HI
FC vs. MP	HI	MI	MHI	MHI
FC vs. R&M	MI	MHI	MI	MI
FC vs. ETP	HI	MI	MI	MHI
OSE vs. MP	VLI	LI	LI	MLI
OSE vs. R&M	VLI	LI	LI	MLI
OSE vs. ETP	MI	MI	MLI	MI
MP vs. R&M	MLI	MI	MLI	MI
MP vs. ETP	MI	MLI	MLI	MI
R&M vs. ETP	VHI	HI	HI	HI

It is notable that this case study has six experts (so that after elimination we have $K = 4$), five main criteria ($n = 5$), three alternatives ($m = 3$), financial consideration has five sub-criteria ($L^1 = 5$), operating condition, safety and environment has five sub-criteria ($L^2 = 5$), mine parameter, reliability and maintainability and equipment technical parameters has six, eight and five sub-criteria, respectively ($L^3 = 6, L^4 = 7$ and $L^5 = 5$). It is obvious that this problem have overall twenty eight sub-criteria ($L_{\text{total}} = 28$).

In Table 4, 1st, 2nd, 3rd and 4th replace 1st exp, 2nd exp, 3rd expert, 4th expert, 5th expert and 6th expert because minimum and maximum value in each pairwise comparison were eliminated so six experts (Table 3) reduce to four evaluations (Table 4).

To illustrate the use of the proposed model, the first column assessment in Table 4 is exemplified. First, the fuzzy comparison matrix based on the first column judgment in Table 4 is given by:

$$\tilde{A} = \begin{bmatrix} 1 & (7,9,10) & (7,9,10) & (3,5,7) & (7,9,10) \\ (0,1,3) & 1 & (0,0,1) & (0,0,1) & (3,5,7) \\ (0,1,3) & (9,10,10) & 1 & (1,3,5) & (3,5,7) \\ (3,5,7) & (9,10,10) & (5,7,9) & 1 & (9,10,10) \\ (0,1,3) & (3,5,7) & (3,5,7) & (0,0,1) & 1 \end{bmatrix} \tag{17}$$

Thus, the lower-bound, most-likely and upper-band comparison matrices are given by:

$$\tilde{A}_1^L = \begin{bmatrix} 1 & 7 & 7 & 3 & 7 \\ 0 & 1 & 0 & 0 & 3 \\ 0 & 9 & 1 & 1 & 3 \\ 3 & 9 & 5 & 1 & 9 \\ 0 & 3 & 3 & 0 & 1 \end{bmatrix} \quad \tilde{A}_1^M = \begin{bmatrix} 1 & 9 & 9 & 5 & 9 \\ 1 & 1 & 0 & 0 & 5 \\ 1 & 10 & 1 & 3 & 5 \\ 5 & 10 & 7 & 1 & 10 \\ 1 & 5 & 5 & 0 & 1 \end{bmatrix} \quad \tilde{A}_1^U = \begin{bmatrix} 1 & 10 & 10 & 7 & 10 \\ 3 & 1 & 1 & 1 & 7 \\ 3 & 10 & 1 & 5 & 7 \\ 7 & 10 & 9 & 1 & 10 \\ 3 & 7 & 7 & 1 & 1 \end{bmatrix} \tag{18}$$

Next, the arithmetic mean of FC with regard to OSE, MP, R&M and ETP can be calculated by using Eq. (12) to produce the following:

$$g_1^L = (1 + 7 + 7 + 3 + 7)/5 = 5 \tag{19}$$

In the same manner, the arithmetic mean (AM) for OSE, MP, R&M and ETP yields 0.8, 2.8, 5.4, and 1.4, respectively. Hence, the relative weight of FC can be estimated by using Eq. (11) to produce the following:

$$w_1^L = \frac{5}{5 + 0.8 + 2.8 + 5.4 + 1.4} = 0.324 \tag{20}$$

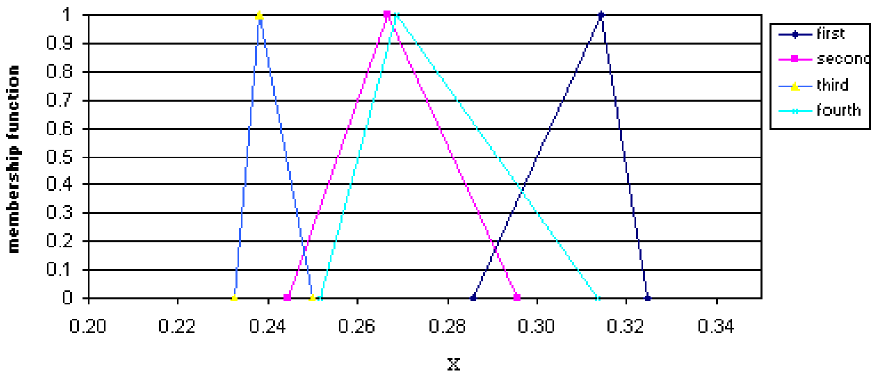

Fig. 5. Illustration of four assessments regarding financial consideration.

Similarly, the weights for OSE, MP, R&M and ETP yield 0.051, 0.181, 0.350 and 0.090, respectively. Also, regarding $\tilde{A}_1^M$ and $\tilde{A}_1^U$, the weights for FC, OSE, MP, R&M and ETP result in (0.314, 0.067, 0.190, 0.314, 0.114) and (0.286, 0.098, 0.195, 0.278, 0.143), respectively. Consequently, the minimum, mean, and maximum weight of FC yields (0.286, 0.314, 0.324). It is notable that these values didn't correspond to w_1^L, w_1^M and w_1^U respectively. By the same manner, the weight of FC deriving from the second, third and fourth judgment yields (0.245, 0.267, 0.296), (0.232, 0.238, 0.250) and (0.252, 0.269, 0.313) respectively. Four assessments regarding financial consideration can be obtained as shown in Fig. 5.

From Fig. 5, the representative weight of quality FC, $Z*$, can be found by using Eq. (13) to produce the following:

$$Z^* = \left\{ \begin{aligned} &\int_{0.286}^{0.314} \frac{1-0}{0.314-0.286}(x-0.286)x dx \\ &+ \int_{0.314}^{0.325} \left(\frac{0-1}{0.325-0.314}(x-0.314)+1 \right) x dx \end{aligned} \right\}$$

$$+ \left\{ \begin{aligned} &\int_{0.245}^{0.267} \frac{1-0}{0.267-0.245}(x-0.245)x dx \\ &+ \int_{0.267}^{0.296} \left(\frac{0-1}{0.296-0.267}(x-0.267)+1 \right) x dx \end{aligned} \right\}$$

$$+ \left\{ \begin{aligned} &\int_{0.232}^{0.238} \frac{1-0}{0238-0.232}(x-0.232)x dx \\ &+ \int_{0.238}^{0.250} \left(\frac{0-1}{0.250-0.238}(x-0.238)+1 \right) x dx \end{aligned} \right\}$$

$$+\left\{\begin{array}{l}\displaystyle\int_{0.252}^{0.269}\frac{1-0}{0.269-0.252}(x-0.252)xdx\\ \displaystyle+\int_{0.269}^{0.313}\left(\frac{0-1}{0.313-0.269}(x-0.269)+1\right)xdx\end{array}\right\}$$

$$\div\left\{\begin{array}{l}\displaystyle\int_{0.286}^{0.314}\frac{1-0}{0.314-0.286}(x-0.286)dx\\ \displaystyle+\int_{0.314}^{0.325}\left(\frac{0-1}{0.325-0.314}(x-0.314)+1\right)dx\end{array}\right\}$$

$$+\left\{\begin{array}{l}\displaystyle\int_{0.245}^{0.267}\frac{1-0}{0.267-0.245}(x-0.245)dx\\ \displaystyle+\int_{0.267}^{0.296}\left(\frac{0-1}{0.296-0.267}(x-0.267)+1\right)dx\end{array}\right\}$$

$$+\left\{\begin{array}{l}\displaystyle\int_{0.232}^{0.238}\frac{1-0}{0.238-0.232}(x-0.232)dx\\ \displaystyle+\int_{0.238}^{0.250}\left(\frac{0-1}{0.250-0.238}(x-0.238)+1\right)dx\end{array}\right\}$$

$$+\left\{\begin{array}{l}\displaystyle\int_{0.252}^{0.269}\frac{1-0}{0.269-0.252}(x-0.252)dx\\ \displaystyle+\int_{0.269}^{0.313}\left(\frac{0-1}{0.313-0.269}(x-0.269)+1\right)dx\end{array}\right\}=0.2783 \qquad (21)$$

By using the foregoing procedures and all evaluations (Table 4), the weights for OSE, MP, R&M and ETP yield (0.0892, 0.1948, 0.2890, 0.1412) regarding $\alpha = 0$. Regarding $\alpha = 0.5$ and $\alpha = 1.0$, calculating the main criteria weights yields (0.279, 0.091, 0.201, 0.289, 0.140) and (0.274, 0.088, 0.198, 0.281, 0.160), respectively (Table 6). The results indicate that FC and R&M are the two most important main criteria for selecting the suitable loading-haulage equipment for the open pit mine in this case study, whereas OSE is least important. Based on the main criteria weights, the overall weights of sub-criteria can be estimated by using Eq. (14).

Applying Eq. (15), the alternative weights relating to each sub-criterion can be obtained as shown in Table 6. Due to space limitations, only the results for $\alpha = 0$ are illustrated in Table 6 and the results for $\alpha = 0.5$ and $\alpha = 1$ are not shown.

Table 5. Synthetic weight of sub-criteria ($S_{il'}$) under $\alpha = 0$, 0.5, and 1.

	$\alpha = 0$	$\alpha = 0.5$	$\alpha = 1$
Commission (S_{11})	0.016	0.016	0.014
Shipment (S_{12})	0.037	0.037	0.038
Insurance (S_{13})	0.052	0.059	0.058
Operating cost (S_{14})	0.088	0.087	0.086
Capital cost (S_{15})	0.085	0.082	0.082
Ease of operation (S_{21})	0.016	0.014	0.017
Legislative requirement (S_{22})	0.015	0.015	0.015
Working conditions in mine (S_{23})	0.030	0.029	0.028
Safety and protective devices (S_{24})	0.015	0.016	0.016
Incorporation of protective devices for environment pollution (S_{25})	0.013	0.016	0.013
Bench geometry (S_{31})	0.037	0.038	0.036
Soil characteristics (S_{32})	0.018	0.019	0.019
Fragmented rock size (S_{33})	0.030	0.031	0.031
Haul distance (S_{34})	0.057	0.057	0.057
Type and geometry of deposit (S_{35})	0.034	0.033	0.033
Weather conditions (S_{36})	0.020	0.019	0.019
Level of technology (S_{41})	0.056	0.056	0.054
Ergonomics (S_{42})	0.029	0.030	0.031
Ease of maintenance (S_{43})	0.032	0.033	0.033
Reliability cost (S_{44})	0.069	0.069	0.068
Labor skill (S_{45})	0.022	0.024	0.023
Spare parts availability (S_{46})	0.048	0.045	0.046
Flexibility (S_{47})	0.033	0.035	0.034
Utilization (S_{51})	0.013	0.011	0.012
Continuity of operation (S_{52})	0.042	0.039	0.043
Capacity and productivity (S_{53})	0.039	0.038	0.040
Maneuverability (S_{54})	0.019	0.023	0.021
Useful life (S_{55})	0.028	0.030	0.025

The final alternative weight can be obtained by summing all the weights up using Eq. (16). It can be found in the last row of Table 7, that the weights for loader-truck, shovel-truck and shovel-truck-conveyor belt regarding $\alpha = 0$ yield (0.327, 0.349, 0.323). The weights for Loader-truck, shovel-truck and shovel-truck-conveyor belt regarding $\alpha = 0.5$ and $\alpha = 1$ yield (0.325, 0.353, 0.321) and (0.326, 0.352, 0.320), respectively.

The results suggest that shovel-truck is the most desirable alternative; whereas shovel-truck-conveyor belt is the last one that will be considered to select.

5. Discussions

This paper presents a new fuzzy AHP model to tackle the open pit equipment selection problem. The proposed model characterizes each negative reciprocal fuzzy number by its own representative membership value, rather than an inverse and reversed order of its corresponding positive fuzzy number in Buckley's method (Buckly, 1985) that requires tedious manipulations. For example in Chang's method equally important is denoted by (1/2, 1, 3/2) and the triangular fuzzy reciprocal scale is denoted

Table 6. Overall weights of the alternatives estimated by the proposed model regarding $\alpha = 0$.

Sub criteria	System A $_1$ $(j = 1)$		System A$_2$ $(j = 2)$		System A$_3$ $(j = 3)$	
	e_{jl}	$r_{jl} = (S_{il'} * e_{jl})$	e_{jl}	$r_{jl} = (S_{il'} * e_{jl})$	e_{jl}	$r_{jl} = (S_{il'} * e_{jl})$
Commission	0.334	0.005	0.355	0.006	0.311	0.005
Shipment	0.578	0.021	0.261	0.005	0.578	0.021
Insurance	0.568	0.030	0.163	0.021	0.261	0.010
Operating cost	0.424	0.037	0.568	0.010	0.163	0.006
Capital cost	0.370	0.031	0.252	0.006	0.568	0.030
Ease of operation	0.422	0.007	0.182	0.030	0.252	0.013
Legislative requirement	0.301	0.005	0.424	0.013	0.182	0.009
Working conditions in mine	0.329	0.010	0.380	0.009	0.424	0.037
Safety and protective devices	0.108	0.002	0.188	0.037	0.380	0.033
Incorporation of protective. . .	0.179	0.002	0.370	0.033	0.188	0.017
Bench geometry	0.098	0.004	0.316	0.017	0.370	0.031
Soil characteristics	0.562	0.010	0.311	0.031	0.316	0.027
Fragmented rock size	0.093	0.003	0.422	0.027	0.311	0.026
Haul distance	0.218	0.012	0.445	0.026	0.422	0.007
Type and geometry of deposit	0.146	0.005	0.137	0.007	0.445	0.007
Weather conditions	0.078	0.002	0.301	0.007	0.137	0.002
Level of technology	0.130	0.007	0.399	0.002	0.301	0.005
Ergonomics	0.593	0.017	0.309	0.005	0.399	0.006
Ease of maintenance	0.593	0.019	0.329	0.006	0.309	0.005
Reliability cost	0.324	0.022	0.525	0.005	0.329	0.010
Labor skill	0.556	0.012	0.124	0.010	0.525	0.016
Spare parts availability	0.401	0.019	0.108	0.016	0.124	0.004
Flexibility	0.486	0.016	0.323	0.004	0.108	0.002
Utilization	0.154	0.002	0.551	0.002	0.323	0.005
Continuity of operation	0.120	0.005	0.179	0.005	0.551	0.008
Capacity and productivity	0.082	0.003	0.379	0.008	0.179	0.002
Maneuverability	0.565	0.011	0.439	0.002	0.379	0.005
Useful life	0.166	0.005	0.098	0.005	0.439	0.006
Overall weight of the alternative regarding all sub-criteria (R$_j$)		0.327		0.349		0.323

Table 7. Relationship between the random index (RI) and matrix order (n).

Matrix order (N)	1	2	3	4	5	6	7	8	9	10
Random index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

by (2/3, 1, 2). This process should be used in all matrices so tedious manipulations occur in Chang's method. In the proposed model, if we have equally important that we mentioned by medium high important, we use (5, 7, 9) and triangular fuzzy reciprocal scale denoted by (1, 3, 5). Additionally, the proposed approach is easier to implement and faster than Buckley's (1985) and Chang's (1996) methods.

The model enables to tackle the difficulty in using Saaty's AHP method while transforming the imprecise judgment into an exact number. It should be noted that in the proposed model, minimum and maximum values between evaluators are eliminated when one criterion is compared with another one causing better attribute weighting.

Another advantage of the proposed model is normalizing scores when ranking alternatives so that the sum of overall weights of the alternative regarding all sub-criteria is equal to one. As is shown in Tables 5 and 6 the weight of the alternatives regarding to sub criteria is very close together when α change from 0 to 1 because in this model minimum and maximum value are eliminated when we calculate the weight of the alternative regarding to sub criteria.

As known, testing the validity of a proposed or developed model is an extremely important issue. In this study, the issue of validity of the proposed fuzzy AHP model is considered. Validity of the proposed model is evaluated from two perspectives. The first is the calculation of consistency ratios of the pairwise comparison matrices and entire model. A consistency ratio is computed, according to the consistency index and random index. The consistency index (CI) proposed by Saaty (1990), was used as described in Eq. (22):

$$CI = \frac{(\lambda_{\max} - 1)}{(N - 1)} \tag{22}$$

Here, $\lambda_{\max}$ is the maximum eigenvalue and N is the size of the matrix. The consistency ratio (CR) is obtained by Eq. (23):

$$CR = \frac{CI}{RI} \tag{23}$$

Values for the random index (RI), i.e., the average consistency rate, are listed in Table 7. When the value for the CR is less than 0.1, the judgment matrix is considered as consistent and satisfactory (Saaty, 1994).

However, consistency ratios of pairwise comparison matrices consisting of fuzzy numbers cannot be calculated by using the method described above. Different methods for computing this ratio can be found in the literature and in this study the algorithm proposed by Mikhailov is used (Mikhailov, 2004). According to Mikhailov algorithm, if the eigenvalue of fuzzy matrix (λ) value computed for pairwise comparison matrices consisting of fuzzy numbers is between 0 and 1, the matrix is assumed to be consistent and if λ is less than 0 the matrix is assumed to be inconsistent. Consistencies of pairwise comparison matrices are analyzed and λ values are calculated with Mikhailov algorithm.

Table 8. Final ranking of three alternatives by different decision making teams.

	First team	Second team	Third team
Loader-truck	0.327	0.321	0.331
Shovel-truck	0.349	0.363	0.354
Shovel-truck-Belt conveyor	0.323	0.316	0.325

The validity of the model is tested in second step by investigating whether or not the same results are found by different decision making teams. The application presented in this study was repeated by three different decision making teams that included academic professors, sales managers of famous companies and mine planning engineers. The results are given in Table 7 as a comparison.

All the decision making teams gave the decision of "shovel-truck" is the best alternative for this mine. "Loader-truck" and "shovel-truck-conveyor belt" are other alternatives that will be considered to select, respectively. It is an important indicator for the validity of the model that all decision making teams gave the same decisions.

6. Conclusion

Nowadays, the capital cost of open pit mining equipment is very high so any mistake in the selection of quantity, type and capacity of equipment may cause irreparable impact on the mining project. The open pit equipment selection problem is a strategic issue and has significant impacts to the open-pit design and production planning.

The outputs produced by the model are the weights of sub-criteria, main criteria, and alternatives. The input requirements include the hierarchy of the decision problem, and the pairwise comparison judgments. A suitable level of experience on the part of the expert is crucial because the expert usually relies heavily on experience and knowledge while evaluating alternatives. Likewise, a judgment of the quality of information regarding design and construction, and sufficient knowledge of the expertise is also significant for the assessments. The results derived by using the model depend on the expert's pairwise assessments; thus, a suitable level of experience on the part of the expert and adequate knowledge of the expertise is essential. The proposed method may be applied in different areas of mining engineering and other alternative selection problems such as mining method selection, waste dump selection and selection of loading-haulage equipment for the underground mines.

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