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A. AGHAJANI BAZZAZI*, M. OSANLOO**, H. SOLTANMOHAMMADI**

Loading-haulage equipment selection in open pit mines based on fuzzy-TOPSIS method

Introduction

Equipment selection is one of the most important aspects of open pit design. Mining costs are mainly affected by the number and capacity of equipment. Equipment selection for open-pit mines is definitely a major decision which will impact greatly the economic viability of an operation (Aghajani et al. 2007).

Equipment selection effects 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. Mining costs are a function of site conditions, operating scale and equipment. The purpose of equipment selection is to select optimum equipment with minimum cost (Lizotte 1988).

The equipment selection process begins with the initial conception of mine development. In many industries, materials handling represents a significant component of the operational cost, making equipment selection an important challenge to management. To meet this challenge, extensive research has taken place in the mining and construction industries which are heavily dependent on equipment.

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

* Department of Mining Engineering, Islamic Azad University, Savadkooh Branch, Iran.
** Department of Mining and Metallurgy Engineering, Amirkabir University of technology, Tehran, Iran.

costs of looking after the equipment during its useful life are not taken into account (Blanchard et al. 1981).

Various types of cost model have been proposed for application to the selection of mining equipment. Expert system as decision aid in surface mine equipment selection was applied by Bandopadhyay, Venkatasubramanian (Bandopadhyay, Venkatasubramanian 1987) and Denby, Schofield (Denby, Schofield 1990). Hrebar (Hrebar 1990) and Sevim, Sharma used net present value analysis for selection of a dragline and surface transportation system (Sevim, Sharma 1991).

Use of a linear breakeven model has been proposed by Cebesory (Cebesory 1997). Models for equipment selection and evaluation described by Celebi were aimed at selection of the equipment fleet on the basis of minimizing the unit stripping cost and maximizing production (Celebi 1998). Hall et.al illustrated how reliability analysis can provide mine management with quantitative information of value for decision making about surface mining equipment (Hall et al. 2003). Analytical hierarchy process have proposed for application to selection of equipment by some researchers (Samanta et al. 2002; Bascetin 2004).

Bascetin et al used fuzzy logic for selection mining method and surface transportation system. EQuipment Selection (EQS) is computer software that used fuzzy logic for equipment selection in surface mines and proposed by bascetinn et al (Bascetin et al. 2006). Application of AHP-TOPSIS method for loading-haulage equipment selection in open pit mines was used by Aghajani, Osanloo (Aghajani, Osanloo 2007).

Most of these decision-making tools either rely on objective input data, with little or no subjective judgment, or focus on a single parameter. Also, because of incomplete or non-obtainable information, the data (attributes) are often not so deterministic; there for they usually are fuzzy-imprecise and application of fuzzy logic for surface mine equipment selection is exigent. Multi-criteria decision-making (MCDM) techniques, such as the Analytical Hierarchy Process (AHP) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method, can be very useful in encompassing several subjective criteria with conflicting objectives to arrive at an eclectic decision. A hierarchical fuzzy Technique for Order Performance by Similarity to Ideal Solution method is developed to cope with this multi-attribute selection problem.

1. Analytical hierarchy process (AHP)

This method has been developed by Saaty (Saaty 1990, 1994). The AHP structures the decision problem in levels which correspond to one understands of the situation: goals, criterion, sub-criterion, and alternatives. By breaking the problem into levels, the decision-maker can focus on smaller sets of decisions. In AHP technique the elements of each level compared to its related element in upper level inform by pair-wise comparison method.

It must be noted that, in pair comparison of criterion if the priority of element i compared to element j is equal to w_{ij} then the priority of element j compared to element i is equal to $1/w_{ij}$. The priority of element compared to it is equal to one.

AHP method is applied in this research for criteria weighting. So, at first, set up n criteria in the rows and columns of $n \times n$ matrix. Then, Perform pair wise comparisons of all the criteria according to the goal. The fundamental scale used for this purpose is shown in Table 1. For a matrix of order n, $((n) \times (n-1)/2)$ comparisons are required. Use average over normalized columns to estimate the Eigen values of the matrix. The redundancy of the pair wise comparisons (Table 1) makes the AHP much less sensitive to judgment errors; it also lets one measure judgment errors by calculating the consistency index of the comparison matrix, and then calculating the consistency ratio.

TABLE 1

Scale for pair wise comparisons

TABELA 1

Skala dla porównań parami

Numerical assessment	Linguistic meaning
1	Equal important
3	Moderately more important
5	Strongly more important
7	Very strongly important
9	Extremely more important
2, 4, 6, 8	Intermediate values of importance

In spite of its popularity and simplicity in concept, this method is often criticized for its inability to adequately handle the inherent uncertainty and imprecision associated with the mapping of the decision-makers perception to crisp values. In the traditional formulation of the AHP, human judgments are represented as crisp values. However, in many practical cases the human preference model is uncertain and decision makers might be reluctant or unable to assign crisp values to the comparison judgments (Chan, Kumar 2007).

The use of fuzzy set theory allows the decision-makers to incorporate unquantifiable information, incomplete information, non-obtainable information, and partial facts into the decision model.

2. Fuzzy TOPSIS model

2.1. Fuzzy TOPSIS model

It is often difficult for a decision-maker to assign a precise performance rating to an alternative for the attributes under consideration. The merit of using a fuzzy approach is to assign the relative importance of attributes using fuzzy numbers instead of precise numbers.

This section extends the TOPSIS to the fuzzy environment. We briefly review the rationale of fuzzy theory before the development of fuzzy TOPSIS; as follows:

Definition 5.1. A fuzzy set $\tilde{a}$ a in a universe of discourse X is characterized by a membership function $\mu_{\tilde{a}}(x)$ $\mu_{\tilde{a}}(x)$ which associates with each element x in X, a real number in the interval [0, 1]. The function value $\mu_{\tilde{a}}(x)$ is termed the grade of membership of x in $\tilde{a}$ (Zadeh 1965).

The present study uses triangular fuzzy numbers. A triangular fuzzy number $\tilde{a}$ can be defined by a triplet (a1, a2, a3). Its conceptual schema and mathematical form are shown by Equation 1 (Kaufmann, Gupta 1985):

$$\mu_{\tilde{a}}(x) = \begin{cases} 0 & x \le a_1 \\ \dfrac{x-a_1}{a_2-a_1} & a_1 < x \le a_2 \\ \dfrac{a_3-x}{a_3-a_2} & a_2 < x \le a_3 \\ 0 & x > a_3 \end{cases} \tag{1}$$

Definition 5.2. Let $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ be two triangular fuzzy numbers, then the vertex method is defined to calculate the distance between them, as Equation 2:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \tag{2}$$

Let $\tilde{a}$, $\tilde{b}$, $\tilde{c}$ be three triangular fuzzy numbers. The fuzzy number $\tilde{b}$ is closer to fuzzy number $\tilde{a}$ than the other fuzzy number $\tilde{c}$ if, and only if, $d(\tilde{a}, \tilde{b}) < d(\tilde{a}, \tilde{c})$.

The basic operations on fuzzy triangular numbers are as follows:

$$\tilde{a} \cdot \tilde{b} = (a_1 \cdot b_1, a_2 \cdot b_2, a_3 \cdot b_3) \quad \text{for multiplication} \tag{3}$$

$$\tilde{a} + \tilde{b} = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \quad \text{for addition} \tag{4}$$

The fuzzy MADM can be concisely expressed in matrix format as Equations 5 and 6.

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \cdots & \tilde{x}_{2n} \\ \tilde{x}_{31} & \tilde{x}_{32} & \tilde{x}_{33} & \cdots & \tilde{x}_{3n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m22} & \tilde{x}_{m3} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \tag{5}$$

$$\widetilde{W} = [\widetilde{w}_1, \widetilde{w}_2, \widetilde{w}_3, \ldots, \widetilde{w}_n] \tag{6}$$

where $\widetilde{x}_{ij}$, i = 1, 2, …, m, j = 1, 2, …, n and $\widetilde{w}_j$ = 1, 2, …, n are linguistic triangular fuzzy numbers, $\widetilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\widetilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$. Note that $\widetilde{x}_{ij}$ is the performance rating of the ith alternative, Ai, with respect to the jth attribute, Cj and $\widetilde{w}_j$ represents the weight of the jth attribute, Cj.

The normalized fuzzy decision matrix denoted by $\widetilde{R}$ is shown as Equation 7.

$$\widetilde{R} = [r_{ij}]_{m \times n} \tag{7}$$

The weighted fuzzy normalized decision matrix is shown as Equation 8.

$$\widetilde{v} = \begin{bmatrix} \widetilde{v}_{11} & \widetilde{v}_{12} & \cdots & \widetilde{v}_{1j} & \cdots & \widetilde{v}_{1n} \\ \widetilde{v}_{21} & \widetilde{v}_{22} & \cdots & \widetilde{v}_{2j} & \cdots & \widetilde{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{v}_{i1} & \widetilde{v}_{i2} & \cdots & \widetilde{v}_{ij} & \cdots & \widetilde{v}_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{v}_{m1} & \widetilde{v}_{m2} & \cdots & \widetilde{v}_{mj} & \cdots & \widetilde{v}_{mn} \end{bmatrix} = \begin{bmatrix} \widetilde{v}_1\widetilde{r}_{11} & \widetilde{v}_2\widetilde{r}_{12} & \cdots & \widetilde{v}_j\widetilde{r}_{1j} & \cdots & \widetilde{v}_n\widetilde{r}_{1n} \\ \widetilde{v}_1\widetilde{r}_{21} & \widetilde{v}_2\widetilde{r}_{22} & \cdots & \widetilde{v}_j\widetilde{r}_{2j} & \cdots & \widetilde{v}_n\widetilde{r}_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{v}_1\widetilde{r}_{i1} & \widetilde{v}_2\widetilde{r}_{i2} & \cdots & \widetilde{v}_j\widetilde{r}_{ij} & \cdots & \widetilde{v}_n\widetilde{r}_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{v}_1\widetilde{r}_{m1} & \widetilde{v}_2\widetilde{r}_{m2} & \cdots & \widetilde{v}_j\widetilde{r}_{mj} & \cdots & \widetilde{v}_n\widetilde{r}_{mn} \end{bmatrix} \tag{8}$$

Given the above fuzzy theory, the fuzzy TOPSIS procedure is then defined as follows:

Step 1: Choose the linguistic ratings ($\widetilde{x}_{ij}$, i = 1, 2, …, m, j = 1, 2, …, n) for alternatives with respect to criteria and the appropriate linguistic variables ($\widetilde{w}_j$, j = 1, 2, …, n) for the weight of the criteria.

The fuzzy linguistic rating $\widetilde{x}_{ij}$ preserves the property that the ranges of normalized triangular fuzzy numbers belong to [0, 1]; thus, there is no need for a normalization procedure. For this instance, the $\widetilde{D}$ defined by Equation 13 is equivalent to the $\widetilde{R}$ defined by Equation 15.

Step 2: Construct the weighted normalized fuzzy decision matrix. The weighted normalized value $\widetilde{v}$ is calculated by Equation 16.

Step 3: Identify positive ideal (A*) and negative ideal (A$^-$) solutions. The fuzzy positive--ideal solution (FPIS, A*) and the fuzzy negative-ideal solution (FNIS, A$^-$) are shown as Equations 9 and 10:

$$A^* = (\widetilde{v}^*_1, \widetilde{v}^*_2, \widetilde{v}^*_3, \ldots, \widetilde{v}^*_n) = \left\{ \max_i v_{ij} \middle| i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \right\} \tag{9}$$

$$A^- = (\widetilde{v}_1^-, \widetilde{v}_2^-, \widetilde{v}_3^-, \ldots, \widetilde{v}_n^-) = \left\{ \min_i v_{ij} \middle| i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \right\} \tag{10}$$

Step 4: Calculate separation measures. The distance of each alternative from A^* and A^- can be currently calculated using Equations 11 and 12.

$$d^*_j = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}^*_j) \qquad i = 1, 2, ..., m \tag{11}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \qquad i = 1, 2, ..., m \tag{12}$$

Step 5: Calculate similarities to ideal solution. This step solves the similarities to an ideal solution by Equation 13:

$$CC_i = \frac{d_i^-}{d_i^- + d^*_i} \tag{13}$$

Step 6: Rank preference order. Choose an alternative with maximum CC_i^* or rank alternatives according to CC_i^* in descending order.

2.2. Fuzzy membership function

The decision makers use the linguistic variables to evaluate the importance of attributes and the ratings of alternatives with respect to various attributes. The present study has only precise values for the performance ratings and for the attribute weights. In order to illustrate the idea of fuzzy MACD, we deliberately transform the existing precise values to five-levels, fuzzy linguistic variables-very low (VL), low (L), medium (M), high (H) and very high (VH).

Among the commonly used fuzzy numbers, triangular and trapezoidal fuzzy numbers are likely to be the most adoptive ones due to their simplicity in modeling and easy of interpretation. Both triangular and trapezoidal fuzzy numbers are applicable to the present study. We feel that a triangular fuzzy number can adequately represent the five-level fuzzy linguistic variables and thus, is used for the analysis hereafter.

As a rule of thumb, each rank is assigned an evenly spread membership function that has an interval of 0.30 or 0.25. Based on these assumptions, a transformation table can be found as shown in Table 2. For example, the fuzzy variable-Very Low has its associated triangular fuzzy number with minimum of 0.00, mode of 0.10 and maximum of 0.25. The same definition is then applied to the other fuzzy variables-Low, Medium, High and Very High.

TABLE 2

Transformation for fuzzy membership functions

TABELA 2

Przekształcenie dla funkcji rozmytych

Rank	Attribute grade	Membership function
Very Low (VL)	1	(0.00, 0.10, 0.25)
Low (L)	2	(0.15, 0.30, 0.45)
Medium (M)	3	(0.35, 0.50, 0.65)
High (H)	4	(0.55, 0.70, 0.85)
Very High (VH)	5	(0.75, 0.90, 1.00)

3. Applicaion of fuzzy TOPSIS method in sungun copper mine

3.1. Sungun copper mine location

Sungun mine is one of the largest copper deposits of Iran which is located in the north-west of the country close to Azerbaijan, Armenia and Turkey borders. Technical and economical studies were shown that the most appropriate of mining method for this deposit is open pit mining method. By this method 384 million tons of ore with 0.665 percentage of copper grade can be mined. Total mine's life estimated to be 31 years with annual production of 7 million tons in first 5 years and 14 million tons for 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. These are loader-truck (A_1), shovel-truck (A_2) and shovel-truck-belt conveyor (A_3) systems.

3.2. Weighting criteria by AHP model for haulage-loading equipment selection

The structure of the problem according to Saaty's hierarchy is given in Figure 1. The goal is to select the loading-hauling system that can meet optimal production requirements. This goal is placed on the first level of the hierarchy. Two strategic factors, namely cost and operational/technical factors, are identified to achieve this goal, which form the second level of the hierarchy. The third level of the hierarchy covers the criteria defining the two strategic factors of cost and operational/technical factors of the second level. Some criteria are divided into some sub criteria (Fig. 1). Expert Choice software is used to determine the global priority weights.

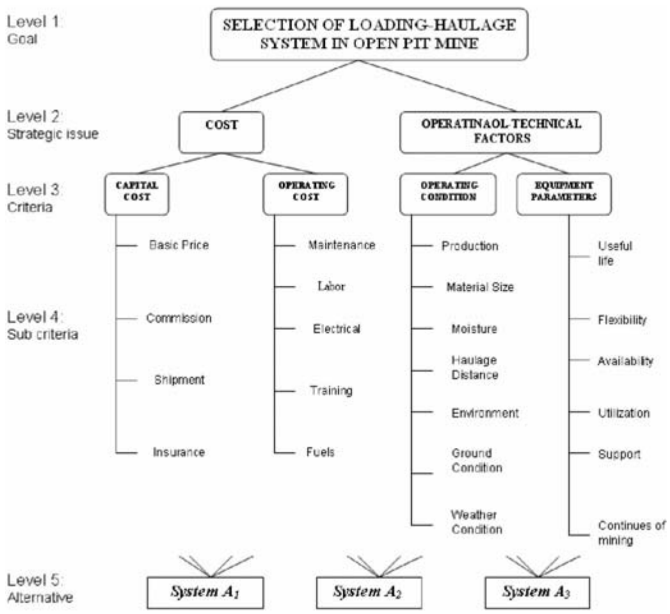

Fig. 1. AHP model for loading-hauling system selection

Rys. 1. Model AHP dla wyboru systemu załadunku odstawy

These matrices are constructed by an expert team. Using this approach, an evaluation team of four members who are frequently involved in equipment selection in the particular open pit mine operation was used. It deserved mention; all of them have equal impression in decision making process.

3.3. Evaluation procedure by fuzzy TOPSIS in sungun copper mine

In this study, twenty two attributes and three alternatives were considered. AHP model was used to attribute weighting because Weight of attribute should be given to decision makers for application fuzzy TOPSIS method.

For the first step of this methodology, the decision matrix, representing the performance values of each alternative with respect to each criterion, is computed.

Table 3 is showing thirteen attributes are the smaller the better type criteria and nine attributes are the larger the better type criteria.

In order to transform the performance ratings to fuzzy linguistic variables as discussed in the previous section, the performance ratings in Table 3 are normalized into the range of [0,1] by Equations 14 and 15 (Cheng 1999):

$$r_{ij} = \frac{x_{ij} - \min\{x_{ij}\}}{[\max\{x_{ij}\} - \min\{x_{ij}\}]} \quad \text{the larger the better type} \tag{14}$$

$$r_{ij} = \frac{\max\{x_{ij}\} - x_{ij}}{[\max\{x_{ij}\} - \min\{x_{ij}\}]} \quad \text{the smaller the better type} \tag{15}$$

Normalized decision matrix for fuzzy TOPSIS analysis is illustrated in Table 4.

By using fuzzy membership function discussed in Section 5.2, the crisp values of global weight and performance of each alternative, exchange to fuzzy number. The fuzzy linguistic

TABLE 3

Normalized decision matrix for TOPSIS analysis

TABELA 3

Macierz znormalizowanej decyzji dla analizy TOPSIS

Criteria \ Alternative	System A1	System A2	System A3
Basic price (c1)	0.235	0.281	0.292
Commission (c2)	0.141	0.161	0.146
Shipment (c3)	0.235	0.281	0.292
Insurance (c4)	0.141	0.161	0.146
Maintenance (c5)	0.188	0.201	0.175
Labor (c6)	0.188	0.161	0.146
Electrical (c7)	0.047	0.201	0.263
Training (c8)	0.094	0.120	0.088
Fuels (c9)	0.282	0.120	0.146
Production (c10)	0.188	0.321	0.292
Material size (c11)	0.235	0.080	0.233
Moisture (c12)	0.141	0.161	0.204
Haulage distance (c13)	0.188	0.120	0.117
Environment (c14)	0.235	0.161	0.117
Ground condition (c15)	0.329	0.201	0.117
Weather condition (c16)	0.329	0.201	0.175
Useful life (c17)	0.235	0.361	0.379
Flexibility (c18)	0.282	0.161	0.058
Availability (c19)	0.235	0.241	0.204
Utilization (c20)	0.188	0.321	0.263
Support (c21)	0.141	0.201	0.233
Continues of mining (c22)	0.141	0.201	0.292

TABLE 4

Normalized decision matrix for fuzzy TOPSIS analysis

TABELA 4

Macierz znormalizowanej decyzji dla rozmytej analizy TOPSIS

Criteria \ Alternative	System A1	System A2	System A3	Criteria weight (w_j)
Basic price	0.333	0.286	0.273	0.167
Commission	0.667	0.714	0.727	0.015
Shipment	0.333	0.286	0.273	0.052
Insurance	0.667	0.714	0.727	0.047
Maintenance	0.500	0.571	0.636	0.091
Labor	0.500	0.714	0.727	0.051
Electrical	1.000	0.571	0.364	0.074
Training	0.833	0.857	0.909	0.029
Fuels	0.167	0.857	0.727	0.131
Production	0.500	0.857	0.727	0.026
Material size	0.667	0.000	0.545	0.024
Moisture	0.667	0.714	0.545	0.019
Haulage distance	0.500	0.857	0.818	0.060
Environment	0.667	0.286	0.182	0.016
Ground condition	1.000	0.429	0.182	0.046
Weather condition	0.000	0.571	0.636	0.018
Useful life	0.667	1.000	1.000	0.010
Flexibility	0.833	0.286	0.000	0.028
Availability	0.667	0.571	0.455	0.019
Utilization	0.500	0.857	0.636	0.036
Support	0.667	0.571	0.455	0.025
Continues of mining	0.333	0.429	0.727	0.017

variable is then transformed into a fuzzy triangular membership function as shown in Table 5. This is the first step of the fuzzy TOPSIS analysis. The fuzzy attribute weight is also collected in Table 5.

The second step in the analysis is to find the weighted fuzzy decision matrix. The resulting fuzzy weighted decision matrix is shown as Table 6 by using Equation 3.

According to Table 6, we know that the elements $v_{ij}, \forall i, j$ are normalized positive triangular fuzzy numbers and their ranges belong to the closed interval [0,1]. Thus, we

TABLE 5

Decision matrix using fuzzy linguistic variables

TABELA 5

Macierz decyzji z wykorzystaniem rozmytych zmiennych lingwistycznych

Criteria \ Alternative	System A1	System A2	System A3	Criteria weight (w_j)
Basic price	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)	(0.75, 0.90, 1.00)
Commission	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)	(0.00, 0.10, 0.25)
Shipment	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)	(0.55, 0.70, 0.85)
Insurance	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)
Maintenance	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.55, 0.70, 0.85)	(0.75, 0.90, 1.00)
Labor	(0.35, 0.50, 0.65)	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)
Electrical	(0.75, 0.90, 1.00)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)	(0.55, 0.70, 0.85)
Training	(0.75, 0.90, 1.00)	(0.75, 0.90, 1.00)	(0.75, 0.90, 1.00)	(0.35, 0.50, 0.65)
Fuels	(0.00, 0.10, 0.25)	(0.75, 0.90, 1.00)	(0.55, 0.70, 0.85)	(0.75, 0.90, 1.00)
Production	(0.35, 0.50, 0.65)	(0.75, 0.90, 1.00)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)
Material size	(0.55, 0.70, 0.85)	(0.00, 0.10, 0.25)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)
Moisture	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)
Haulage distance	(0.35, 0.50, 0.65)	(0.75, 0.90, 1.00)	(0.75, 0.90, 1.00)	(0.55, 0.70, 0.85)
Environment	(0.55, 0.70, 0.85)	(0.15, 0.30, 0.45)	(0.00, 0.10, 0.25)	(0.00, 0.10, 0.25)
Ground condition	(0.75, 0.90, 1.00)	(0.35, 0.50, 0.65)	(0.00, 0.10, 0.25)	(0.35, 0.50, 0.65)
Weather condition	(0.00, 0.10, 0.25)	(0.35, 0.50, 0.65)	(0.55, 0.70, 0.85)	(0.15, 0.30, 0.45)
Useful life	(0.55, 0.70, 0.85)	(0.75, 0.90, 1.00)	(0.75, 0.90, 1.00)	(0.00, 0.10, 0.25)
Flexibility	(0.75, 0.90, 1.00)	(0.15, 0.30, 0.45)	(0.00, 0.10, 0.25)	(0.35, 0.50, 0.65)
Availability	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)
Utilization	(0.35, 0.50, 0.65)	(0.75, 0.90, 1.00)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)
Support	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)
Continues of mining	(0.15, 0.30, 0.45)	(0.35, 0.50, 0.65)	(0.55, 0.70, 0.85)	(0.15, 0.30, 0.45)

TABLE 6

Fuzzy-weighted decision matrix

TABELA 6

Macierz decyzji rozmytych ważonych

Alternative / Criteria	System A1	System A2	System A3
Basic price	(0.11, 0.27, 0.45)	(0.11, 0.27, 0.45)	(0.11, 0.27, 0.45)
Commission	(0.00, 0.07, 0.21)	(0.00, 0.07, 0.21)	(0.00, 0.07, 0.21)
Shipment	(0.08, 0.21, 0.38)	(0.08, 0.21, 0.38)	(0.08, 0.21, 0.38)
Insurance	(0.30, 0.49, 0.72)	(0.30, 0.49, 0.72)	(0.30, 0.49, 0.72)
Maintenance	(0.26, 0.45, 0.65)	(0.26, 0.45, 0.65)	(0.41, 0.63, 0.85)
Labor	(0.19, 0.35, 0.55)	(0.30, 0.49, 0.72)	(0.30, 0.49, 0.72)
Electrical	(0.71, 0.63, 0.85)	(0.19, 0.35, 0.55)	(0.08, 0.21, 0.38)
Training	(0.26, 0.45, 0.65)	(0.26, 0.45, 0.65)	(0.26, 0.45, 0.65)
Fuels	(0.00, 0.09, 0.25)	(0.56, 0.81, 1.00)	(0.41, 0.63, 0.85)
Production	(0.12, 0.25, 0.42)	(0.26, 0.45, 0.65)	(0.19, 0.35, 0.55)
Material size	(0.19, 0.35, 0.55)	(0.00, 0.05, 0.16)	(0.12, 0.25, 0.42)
Moisture	(0.08, 0.21, 0.38)	(0.08, 0.21, 0.38)	(0.05, 0.15, 0.29)
Haulage distance	(0.19, 0.35, 0.55)	(0.41, 0.63, 0.85)	(0.41, 0.63, 0.85)
anEnvironment	(0.00, 0.07, 0.21)	(0.00, 0.03, 0.11)	(0.00, 0.01, 0.06)
Ground condition	(0.26, 0.45, 0.65)	(0.12, 0.25, 0.42)	(0.00, 0.05, 0.16)
Weather condition	(0.00, 0.03, 0.11)	(0.05, 0.15, 0.29)	(0.08, 0.21, 0.38)
Useful life	(0.00, 0.07, 0.21)	(0.00, 0.09, 0.25)	(0.00, 0.09, 0.25)
Flexibility	(0.26, 0.45, 0.65)	(0.05, 0.15, 0.29)	(0.00, 0.05, 0.16)
Availability	(0.08, 0.21, 0.38)	(0.05, 0.15, 029)	(0.05, 0.15, 0.29)
Utilization	(0.12, 0.25, 0.42)	(0.26, 0.45, 0.65)	(0.19, 0.35, 0.55)
Support	(0.19, 0.35, 0.55)	(0.12, 0.25, 0.42)	(0.12, 0.25, 0.42)
Continues of mining	(0.02, 0.09, 0.20)	(0.05, 0.15, 0.29)	(0.08, 0.21, 0.38)

can define the fuzzy positive-ideal solution (FPIS, A*) and the fuzzy negative-ideal solution (FNIS, A⁻) as: $\tilde{v}^*_j = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$ j = 1, 2, ..., n. This is the third step of the fuzzy TOPSIS analysis.

For the fourth step, the distance of each alternative from A* and A⁻ can be currently calculated using Equations 11 and 12. The fifth step solves the similarities to an ideal solution by Equation 13. The resulting fuzzy TOPSIS analyses are summarized in Table 7.

An example is used in order to illustrate Steps 4 and 5 calculations as follows:

$$d^*_1 = \sqrt{\frac{1}{3}[(1-0.11)^2 + (1-0.27)^2 + (1-0.45)^2]} + \tag{16}$$

$$+\sqrt{\frac{1}{3}[(1-0)^2 + (1-0.07)^2 + (1-0.21)^2]} + \sqrt{\frac{1}{3}[(1-0.08)^2 + (1-0.21)^2 + (1-0.38)^2]} + \ldots +$$

$$+\sqrt{\frac{1}{3}[(1-0.02)^2 + (1-0.09)^2 + (1-0.20)^2]} = 15.770$$

$$d_1^- = \sqrt{\frac{1}{3}[(0-0.11)^2 + (0-0.27)^2 + (0-0.45)^2]} +$$

$$+\sqrt{\frac{1}{3}[(0-0)^2 + (0-0.07)^2 + (0-0.21)^2]} + \sqrt{\frac{1}{3}[(0-0.08)^2 + (0-0.21)^2 + (0-0.38)^2]} + \ldots +$$

$$+\sqrt{\frac{1}{3}[(0-0.02)^2 + (0-0.09)^2 + (0-0.20)^2]} = 7.143$$

CC_1 is calculated for this example as follows:

TABLE 7

Fuzzy TOPSIS analysis

TABELA 7

Rozmyta analiza TOPSIS

Alternative	di^+	di^-	CC_i	Ranking
A1	15.770	7.143	0.311	2
A2	15.533	7.450	0.324	1
A3	15.939	7.056	0.306	3

$$CC_1 = \frac{d_1^-}{d_1^- + d_1^+} = \frac{7.143}{7.143 + 15.770} = 0.311 \tag{17}$$

In conclusion, Shovel-Truck (A_2) has become the most desirable system among three alternatives with the final performance value of 0.324; while loader-Truck and Shovel--Truck-Conveyor belt have positioned at the second and third ranks with 0.311 and 0.306 as the final performance values, respectively.

Conclusions

The open pit equipment selection problem is a strategic issue and has significant impacts to the open-pit design and production planning. Most of exiting open pit equipment selection rely on objective input data, with little or no subjective judgment, or focus on a single parameter; and therefore lead to a poor equipment selection due to the MADM nature of equipment selection problem.

In this study, combination of AHP, TOPSIS and fuzzy set theory techniques is introduced to select the suitable loading-haulage equipment in large open pit mines. The methods and experiences learned from the study can be valuable to the open pit mines future strategic planning. Empirical results showed that the proposed methods are viable approaches in solving the proposed mining equipment selection problem. TOPSIS is a viable method for the proposed problem and is suitable for the use of precise performance ratings. When the performance ratings are vague and inaccurate, then the fuzzy TOPSIS is the preferred technique.

Each mining equipment selection is unique in nature; thus, the success of the present study has no guarantee for its applicability to other applications. Judicious use of proposed method is advised in solving a specific application. In addition, there exists other worth investigating MADM methods for mining equipment selection problem. This becomes one of the future research opportunities in this classical yet important research area.

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DOBÓR URZĄDZEŃ DO ZAŁADUNKU ODSTAWY W KOPALNIACH ODKRYWKOWYCH OPARTY NA METODZIE ROZMYTEJ – TOPSIS

Słowa kluczowe

Metoda rozmyta, kopalnia odkrywkowa, odstawa, maszyny i urządzenia

Streszczenie

Dobór urządzeń w inżynierii górnictwa jest jedną z najważniejszych decyzji uwzględniających projekt kopalni, planowanie produkcji i parametry ekonomiczne górnictwa odkrywkowego. Inżynierowie planujący kopalnię zwykle polegają na swej intuicji i doświadczeniu w podejmowaniu decyzji, mimo że dobór urządzeń jest zagadnieniem złożonym opartym na wielu kryteriach i obejmującym wiele osób. W niniejszym opracowaniu, spośród wielu modeli kryteriów w podejmowaniu złożonych decyzji i modeli wieloatrybutowych dla najbardziej preferowanego wyboru, wybrano technikę preferencji kolejności poprzez podobieństwo do rozwiązania idealnego

(TOPSIS). W warunkach rzeczywistych, ze względu na niepełne lub niedostępne informacje, dane (atrybuty) często nie są tak decydujące, gdyż zwykle są rozmycie-niedokładne. Z tego względu celem niniejszego opracowania jest rozszerzenie metody TOPSIS w zagadnieniach podejmowania decyzji o dane rozmyte. W niniejszym opracowaniu dane zebrane w kopalni miedzi Sungun wykorzystano do ukazania procedury proponowanego podejścia odnośnie doboru urządzeń do załadunku odstawy.

LOADING-HAULAGE EQUIPMENT SELECTION IN OPEN PIT MINES BASED ON FUZZY-TOPSIS METHOD

Key words

Fuzzy method, open pit mine, haulage, machines and equipment

Abstract

Equipment selection in mining engineering is one of the most important decision that is affected the mine design, production planning and economic parameters in open pit mining. Mine planning engineers generally use of their intuition and experiences in decision making even though equipment selection is a complex multi person, multi-criteria decision problem. In this paper, from among multi criteria models in making complex decisions and multiple attribute models for the most preferable choice, technique for order preference by similarity to ideal solution (TOPSIS) approach has been dealt with. In real-world situation, because of incomplete or non-obtainable information, the data (attributes) are often not so deterministic, there for they usually are fuzzy-imprecise. Therefore, the aim of this paper is to extend the TOPSIS method to decision-making problems with fuzzy data. In this paper, gathering data from Sungun copper mine is used to illustrate the procedure of the proposed approach for loading-haulage equipment selection.