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Preliminary communication

Selection of the most proper drilling and blasting pattern by using MADM methods (A case study: Sangan Iron Ore Mine, Iran)

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Abstract

Drilling is the first stage of open pit mining that has a considerable effect on the other stages of mining, including blasting, loading, hauling and crushing. An unsuitable drilling pattern may lead to undesirable results such as poor fragmentation, back break and fly rock that not only results in technical and safety issues but also increases the operating cost of the mine. Multi-Attribute Decision-Making (MADM) methods can be useful approaches to select the appropriate drilling pattern among various alternatives, performed previously. This paper aims to select the most proper drilling and blasting pattern for Sangan Iron Mine, Iran. To achieve this, in the first step, rock fragmentation, back break, fly rock, specific charge and specific drilling were considered as the decision criteria and their degree of importance was calculated using the AHP method under a fuzzy environment. Then, TOPSIS and PROMETHEE methods were used to select the most proper alternative. The results of this study show that the drilling pattern with a spacing of 5 m, burden 4 m, hole depth 10 m, and hole diameter 15 cm is the most suitable one. The stemming length and powder factor of the suggested pattern are 2.3 m and 2.6 gr/cm3, respectively.

Keywords:

Drilling and blasting pattern; Sangan Iron Ore Mine; AHP; TOPSIS; PROMETHEE

1. Introduction

Drilling and blasting play a vital role in mining projects. The quality of the blasting operation and subsequently, the adequate rock fragmentation are effective parameters that have a considerable effect on the mine productivity (**Shi et al. 2012**). Reduction of the mineral size to suitable fragmentation is necessary for either hauling or crushing processes. Poor fragmentation increases the operating cost of a mine and also the amount of dust in the mine atmosphere. The main aim of drilling and blasting pattern (DBP) selection is to reduce the costs of rock crushing and then improve the operational effectiveness. Nowadays, many researchers have been trying to propose the most suitable DBP. In some studies, back break was considered as a destructive phenomenon (**Gate et al. 2005**; **Khandelwal and Monjezi 2012**; **Monjezi et al. 2012a, Ghasemi et al. 2016**). Some studies focused on the fly rock and tried to reduce this parameter (**Bajpayee et al. 2003**; **Bajpayee et al. 2004**; **Gate et al. 2005**; **Little and Blair 2010**; **Stojadinovi et al. 2011**; **Monjezi et al. 2007, 2012**). Moreover, there have been some attempts to reduce ground vibration (**Guosheng et al. 2011**; **Hudaverdi 2012**; **Bakhshandeh Amnieh et al. 2012**). Regarding the past studies, effective factors in selecting the most appropriate DBP can be categorized into technical (fragmentation and back break), economical (specific charge and drilling) and safety parameters (such as fly rock, ground and air vibrations). Drilling patterns suggested by the experimental methods are not accurate enough and cannot consider all the effective criteria, mentioned earlier, simultaneously. These parameters are varied from one site to another and their degree of importance is also not the same in all cases. In such conditions, using multi-criteria decision-making (MCDM) methods to select the most proper pattern among all the options seems essential. **Monjezi et al. (2012b)** used the Technique for Order of Preference by Similarity to Ideal Solution, the TOPSIS method for the selection of the most appropriate DBP in the limestone Tajareh mine in Iran. In this study, drilling and blasting cost, fragmentation and fly rock were considered as decision criteria and the most proper DBP was selected among 19 patterns, performed previously. In other studies, the most suitable DBP was proposed for the Sungun Copper Mine in Azerbaijan Sharghi Province, Iran using MADM methods among 27 performed patterns (**Yari et al. 2013, 2014a, 2014b, 2015, 2017**). In these studies, specific drilling, powder factor, fly rock, back break and fragmentation were considered as attributes. Regarding the results of these studies, the TOPSIS method showed that the drilling pattern with a diameter of 12.7 cm, burden of 3 m, spacing of 4 m and hole

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length of 11.8 m was the most proper one (**Yari et al. 2013**). Based on the Taxonomy method, the selected pattern with a hole diameter of 15.24 cm, burden of 3 m, spacing of 4 m and stemming rate of 3.2 m was selected as the most suitable drilling pattern (**Yari et al. 2014a, 2015**) that was consistent with the ELECTRE method results (**Yari et al. 2013**). At the same time, the application of the liner assignment method showed that the pattern with a burden of 3.5 m, spacing of 4.5 m, stemming of 3.8 m and hole length of 12.1 m was selected as the most suitable pattern (**Yari et al. 2015, 2017**). These results indicate that, a single MADM method is not efficient to enable a complete and correct analysis and therefore to obtain a more reliable result, two or more methods should be used by utilizing the strengths of each one.

A review of past studies, mentioned above, shows that the conventional MCDM methods were used to select the most appropriate DBP is some cases. However, in most cases, it is difficult for experts and decision-makers to compute verbal and linguistic variables. In such circumstances, the uncertainties should be interpreted in a fuzzy environment. This paper aims to select the most appropriate DBP for the Sangan Iron Ore Mine in Razavi Khorasan Province, Iran among different proposed drilling patterns, performed previously. To achieve this, fragmentation, fly rock, specific drilling, back break, and specific charge have been selected as the decision criteria. To avoid ambiguities and uncertainties in obtaining the importance weight of each criterion, calculations should be done under a fuzzy environment instead of crisp values. Therefore, the degree of importance of each criterion is determined using the Analytical Hierarchy Process (AHP) method under a fuzzy environment. To select the most proper DBP, the technique for the order of preference by similarity to an ideal solution (TOPSIS) and the preference ranking organization method for enrichment evaluation (PROMETHEE) methods are used. TOPSIS is an understandable and straightforward method that is applicable to handle both qualitative and quantitative data sets. PROMETHEE is one of the new and simple MCDM methods that can derive the partial and full ranking of alternatives. This method includes both qualitative and quantitative criteria and supports group-level decision-making to identify the positive and negative aspects of the alternatives. PROMETHEE is a clear and stable MADM and there is no need for preferences to be expressed as linear relationships. Characterized by different types of preference functions, being a user-friendly method, and the successful application in real-life planning problems are the main advantages of this method. Nowadays, PROMETHEE has been applied in many applications in the field of mining engineering such as mining method selection (**Bogdanovic et al. 2012**, **Kant et al. 2016**, **Balusa and Singam 2018**, **Iphar and Alpay 2019**), prioritization of the mineral resources (**Rahimdel and Noferesti 2020**), mining equipment selection (**Sousa Junior et al. 2014**, **Wang and Tu 2015**), mechanization of coal mining (**Ghadernejad et al. 2019**) and post-mining land-use selection (Amirshenava and Osanloo 2017). TOPSIS is an understandable and straightforward method that deals with either qualitative or quantitative criteria. In the application of TOPSIS, determination of the best alternative is possible with simple calculations. TOPSIS is extremely flexible and therefore, it is possible to accommodate a further extension to make a better choice in different situations. TOPSIS has also been used in numerous mining applications such as equipment selection (**Adebimpe et al. 2013**, **Yazdani-Chamzini 2014**, **Yavuz 2016**), mining method selection (**Gligoric and Gligoric 2015**, **Ooriad et al. 2018**, **Iphar and Alpay 2019**), mining site selection (**Hekmat et al. 2008**, **Golestanifar and Aghajani Bazzazi 2010**), mine reclamation planning (**Alavi 2014**), and choice problems in mineral processing (**Kostovic and Gligoric 2015**). Although, the TOPSIS and PROMETHEE methods have been used in various fields of mining engineering, the application of these methods to select the most suitable DBP has not yet been reported. This paper aims to integrate the fuzzy-AHP-TOPSIS and also the fuzzy-AHP-PROMETHEE methods for the selection of the most proper drilling pattern for the Sangan Iron Ore mine in Razavi Khorasan Province, Iran.

This paper is divided into four sections. In section 2, the Fuzzy AHP, TOPSIS and PROMETHEE methods are represented. In section 3, the case study and the geometrical specifics of all the performed DBP are presented. Finally, in section 4, first the weight of each criterion is obtained by using the fuzzy AHP method and then the TOPSIS and PROMETHEE methods are applied to find the most proper DBP.

2. Theoretical foundation; MCDM methods

Multi-criteria decision-making (MCDM) is one of the branches of operation research used to prioritize and select the best available alternative considering various criteria which are sometimes opposite indices. Multi-objective decision-making (MODM) and multi-attribute decision-making (MADM) are two kinds of MCDM (**Pohekar and Ramachandran 2004**). MODM methods are generally used to design and optimize problems while the MADM methods are applied to select the most proper alternative among different options. Nowadays, different methods have been presented for MADM problems. This section is devoted to representing the steps of the fuzzy AHP, TOPSIS, and PROMETHEE, as the most applied MADM methods in selection problems.

2.1. AHP under fuzzy environment

AHP is one of the most powerful and simplest methods used to define a criteria's degree of importance in

MADM problems. Nowadays, many successful applications of AHP have been reported in vague decision-making problems such as the selection of opencast mining equipment (**Samanta et al. 2002**), underground mining method selection (**Gupta and Kumar 2012**), the selection of a primary crusher (**Rahimdel and Ataei 2014**), the selection of a transportation system (**Despodov et al. 2011**), plant species selection for mine reclamation (**Alavi 2014**) and groundwater potential zones in coal mining (**Kumar and Krishna, 2018**). In the first step of AHP, the hierarchy structure of the problem is constructed and then pairwise comparison matrixes are created. Finally, the relative weights are calculated. In conventional AHP, the pairwise comparison is made using crisp scale values. A nine-point scale is a frequently used scale (ranging from 1 for equally important to 9 for extremely preferred). Although the application of crisp values is simple and straightforward, it does not consider uncertainties and vagueness in expert judgments. To overcome this scarcity, fuzzy numbers ($\tilde{a}$) are used in order to capture ambiguous. In this study, a triangular fuzzy number (TFN) is used. A character "~" represents a fuzzy set and the TFN is expressed with $\tilde{a}$ = (a,b,c). The parameters a, b and c indicate the smallest possible, most promising and largest possible values, respectively (**Alavi 2014**; **Kumar and Krishna 2018**).

The steps of AHP under a fuzzy environment are given as below (**Rahimdel and Bagherpour 2018**):

2.1.1. Constructing the Fuzzy Judgment Matrix

In the first step of the fuzzy AHP, a fuzzy decision matrix with TFNs ($\tilde{A} = (\tilde{a})_{n \times n}$) is constructed as **Equation 1**:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \ldots \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \ldots \tilde{a}_{2n} \\ \vdots & \vdots & 1 \ \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} \ldots & 1 \end{bmatrix}$$

This matrix contains fuzzy numbers $\tilde{a}_{ji} = 1/\tilde{a}_{ij}$. The fuzzy linguistic variables include just equal to extremely preferred and the fuzzy numbers corresponding to them are given in **Table 1**.

Table 1: Linguistic variables and their corresponding TFN

Linguistic scale for importance	TFN
Just equal	(1,1,1)
Equal importance	(1,1,3)
Weak importance of one over another	(1,3,5)
Moderately importance	(3,5,7)
Essential or strong importance	(5,7,9)
Very strong importance	(7,9,10)
Extremely preferred	(9,10,10)

2.1.2. Calculating the fuzzy synthetic extent value

After forming the fuzzy decision-making matrix, the synthetic extent value (S_i), a triangle fuzzy number, is calculated for the i^{th} criterion as shown in **Equations 2** and **3**:

$$S_i = \sum_{J=1}^{m} M_{gi}^{j} \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \quad (2)$$

$$\sum_{j=1}^{m} M_{gi}^{j} = \left[\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right], \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} =$$

$$= \left(\frac{1}{\sum_{j=1}^{m} u_j}, \frac{1}{\sum_{j=1}^{m} m_j}, \frac{1}{\sum_{j=1}^{m} l_j} \right) \quad (3)$$

Where:

Symbol g - the row number

Symbols i and j - the alternatives and criteria

2.1.3. Calculating the degree of possibility

In this step, the degree of possibility for each criterion is calculated. The possibility degree of two TFNs, $M_1=(l_1,m_1,u_1) \geq M_2=(l_2,m_2,u_2)$, is defined as **Equation 4**:

$$V(M_2 \geq M_1) = \begin{cases} 1, & if \ \ m_2 > m_1 \\ 0, & if \ \ l_1 < u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \quad (4)$$

Where:

d - the highest intersection point of μ_{M1} and μ_{M2} as shown in **Figure 1**.

To compare M_1 and M_2, both values $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ are required.

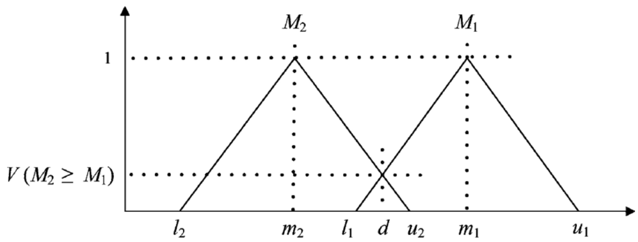

Figure 1: Intersection point d between two fuzzy number M_1 and M_2

2.1.4. Calculating the weight vectors

With $d'(A_i)$=min $V(S_i \geq S_k)$ for k = 1, 2, …, n; $k \neq i$ in consideration, the non-normalized weight vector (W') is calculated as **Equation 5**:

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^T \quad (5)$$

Where:

A_i (i= 1, 2, …, n) - n elements.

The normalized weight vector (W) is calculated as **Equation 6**:

$$W = (d(A_1), d(A_2), \dots, d(A_n))^T \tag{6}$$

2.2. *TOPSIS method*

TOPSIS is another MADM method offered by **Hwang and Yoon (1981)**. In this technique, alternatives are ranked based on the distance from an ideal solution and negative ideal solution. On the other hand, the alternative with the shortest distance from the positive ideal solution (the best one) and the biggest distance from the negative ideal solution (the worst case) is ranked in a higher order. This method is understandable and straightforward, and it is used to handle both qualitative and quantitative data sets. The TOPSIS method has been applied to different mining-related decision problems (**Wu et. al 2007**; **Li et al. 2011**; **Alavi and Alinejad-Rokny 2011**; **Rahimdel and Karamoozian 2014**; **Yavuz 2016**; **Rahimdel and Mirzaei 2020**]. Steps of the TOPSIS method are represented below (**Rahimdel and Mirzaei 2020**):

2.2.1. Calculating the weighted normalized decision matrix

In this step, the decision matrix (A) for n alternative and m criterion is formed as **Equation 7:**

$$A = \begin{bmatrix} x_{11} & \dots & x_{1j} \\ \vdots & \ddots & \dots \\ x_{i1} & \dots & x_{ij} \end{bmatrix}, j = 1, \dots, n, j = 1, \dots, m \tag{7}$$

The normalized decision matrix (R) is created as **Equation 8**:

$$R = \left[r_{ij} \right]_{m \times n} = \begin{bmatrix} r_{11} & \dots & r_{1n} \\ \vdots & \ddots & \dots \\ r_{m1} & \dots & r_{mn} \end{bmatrix}, j = 1, \dots, n, j = 1, \dots, m \tag{8}$$

Where:

r_{ij} - the normalized value, calculated as **Equation 9**:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x^2{}_{ij}}} \tag{9}$$

The weighted normalized decision matrix, with v_{ij} as weighted normalized values, is calculated as **Equation 10**:

$$V = \left[v_{ij} \right]_{m \times n} = \begin{bmatrix} w_1 . r_{11} & \dots & w_n . r_{1n} \\ \vdots & \ddots & \dots \\ w_1 . r_{m1} & \dots & w_n . r_{mn} \end{bmatrix},$$

$$i = 1, 2, \dots, m . j = 1, 2, \dots, n \tag{10}$$

Where:

W_j - the weight of j criterion that are calculated from the fuzzy AHP method.

2.2.2. Determine the positive-ideal and negative-ideal solution

Positive ideal solution (A^*) and negative ideal solution (A^-) for benefit (I) and cost (J) criteria are respectively calculated from the following **Equation 11**.

$$A^* = \left\{ v_1^*, v_2^*, \dots, v_n^* \right\} = \left\{ (\min_j v_{ij} \mid i \in I) \right\},$$

$$A^- = \left\{ v_1^-, v_2^-, \dots, v_n^- \right\} = \left\{ (\max_j v_{ij} \mid i \in J) \right\} \tag{11}$$

2.2.3. Calculating the separation measures and ranking the preference order

To calculate the separation measures, the n-dimensional Euclidean distance is used. In this way, the separation of each alternative from the positive-ideal solution (S_i^*) and negative-ideal solution (S_i^-) are calculated as **Equation 12**:

$$S_j^* = \sqrt{\sum_{i=1}^{n} \left(V_{ij} - V_i^* \right)^2}, \quad S_j^- = \sqrt{\sum_{i=1}^{n} \left(V_{ij} - V_j^- \right)^2}, \tag{12}$$

For ranking the alternatives, relative closeness (C_j^*) to the ideal solution is used as **Equation 13**:

$$C_j^* = \frac{S_j^-}{S_j^* + S_j^-} \tag{13}$$

The order of all alternatives is determined by considering the descending order of C_j^* such that the higher C_j^*, the better is the alternative.

2.3. *PROMETHEE method*

PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) is a new MADM method proposed by **Brans (1982)** and then developed by **Brans and Vincke (1985)**. PROMETHEE shows the opposition between all alternatives and considers both qualitative and quantitative attributes with high flexibility and accurate calculations. It also has simpler and more straightforward equations in comparison to other MADM methods. PROMETHEE has been applied in different fields of mining engineering such as the selection of an ore transport system for an underground mine (**Elevli and Demirci 2004**), the selection of the main mine shaft location (**Hudej et al. 2013**), management of mine action projects (**Mladineo et al. 2016**), underground mining method selection (**Balusa and Singam 2018**; **Iphar and Alpay 2019**) and safety risk assessment of the mining industry (**Gul et al. 2019**). This method requires three factors including a decision-making matrix, a degree of importance of the criteria and information related to the preference function, determined by the decision-makers. The preference function is used to define how one object is prioritized in comparison to others. In fact, this function represents an increasing function of deviation. On the other hand, smaller deviations mean weaker preference degrees and larger ones indicate a stronger preference. Six preference functions with specific shapes have been presented in PROMETHEE. The shape of each function is dependent on two thresholds, named P and Q. Threshold Q represents the largest deviation, considered negligible while, P (cannot be smaller than Q) indicates the smallest deviation, considered as decisive (**Brans 1982**; **Brans and Vincke 1985**). In PROMETHEE, two parameters, named positive flow (φ^+) and negative flow (φ^-), are calculated for each alternative regarding the given importance degree for each criterion. The character φ^+ expresses how much each alternative is higher than all other ones. This means the higher the φ^+, the better the alternative. On the other hand, φ^- indicates the superiority of an alternative over the other ones (**Behzadian et al. 2010**). The steps of the PROMETHEE method are represented below.

2.3.1. Implementing the preference function and calculating overall preference

After constructing a decision matrix, the preference function in the creation j, ($P_j(a,b)$), is applied to decide how much the value a is preferred to b for this criterion. Then, the overall preference index ($\pi(a,b)$), which takes all the criteria into account, is calculated as **Equation 14**:

$$\pi(a,b) = \sum_{j=1}^{k} W_j . P_j(a,b) \tag{14}$$

Where:

W_j - the weight of criteria j.

2.3.2. Calculating positive and negative flows for each alternative

The positive flow (φ^+) and negative flow (φ^-) for each alternative $a \in A$ are respectively, calculated as **Equation 15**:

$$\varphi^+(a) = \frac{1}{n-1}\sum_{x\in A}\pi(a,x), \quad \varphi^-(a) = \frac{1}{n-1}\sum_{x\in A}\pi(x,a) \tag{15}$$

It is noted that the PROMETHEE I provides a partial ranking of the alternatives while, PROMETHEE II used the net flow ($\varphi(a) = \varphi^+(a) - \varphi^-(a)$) for the ranking of alternatives such that, the alternatives are ranked based on their net flow (**Anand and Kodali 2008**).

2.4. *Final rank of alternatives*

When there is a difference between the achieved scores for alternatives in applying different MCDM methods, a robust aggregation method needs to be considered. Since, there is no guarantee to obtain the optimum results in averaging the obtained ranks, other methods such as Borda and Copeland rules are applied (**Pomerol and Barba-Romero 2012**). In the Borda method, a pairwise comparison matrix between the alternatives is constructed regarding their scores obtained from the MCDM methods. This matrix is a zero-one matrix. If the alternative in that row is more rational than the alternative in that column, then the alternative obtains one. Otherwise, it obtains zero. Then, the row sum for each row is calculated for alternative ranking. In the Copeland method, that is a modified version of the Borda, the number of times that an alternative is preferred over the others is subtracted (row-sum) from the number of times that an alternative is subordinated. A column-

Figure 2: Location of the Sangan Iron Ore Mine

sum is calculated and used for the alternative ranking (**Phelipe et al. 2016**).

3. Case study; Sangan Iron Ore Mine

The Sangan iron ore mine is located 16 km north of Sangan city and 300 km southeast of Mashhad in Razavi Khorasan Province, Iran. The location of this mine is shown in **Figure 2**. The total geological reserve of this mine was evaluated to be about 1.2 billion tons of iron ore with an average grade of 50 percent Fe_3O_4. The annual production of the mine is 4.5 million tons of which 2.6 million tons of iron pellets are produced per year. Drilling equipment is used for blasting holes with different diameters from 76 to 200 mm. In the blasting operation of the mine, vertical blast holes with a diameter of 10, 15, and 20 cm are drilled in length ranging from 8.5 to 10.5 m. Pattern geometry is staggered and ANFO is the main explosive. The dynamite cartridges are used as a primer and a detonating cord is utilized as the initiation system. The consumed charge per period is 159-964 kg and the burden to spacing ratio is about 0.65 to 0.87. More details on these patterns are given in **Table 2**.

Table 2: Geometrical specifications of a drilling pattern considered to select the most proper ones

Pattern No.	Hole diameter (mm)	Stemming (m)	Hole depth (m)	Spacing (m)	Burden (m)
P1	10	2.2	8.7	3	3
P2	10	2.3	8.7	3	2.5
P3	15	2.8	9.2	3	2.5
P4	20	2.7	10.5	4.5	4
P5	15	2.2	9.8	3.5	3
P6	20	2.5	9.8	4.5	4
P7	15	1.9	10.2	4	3.5
P8	15	1.7	8.7	3.5	3
P9	15	2.2	8.3	3.5	3
P10	20	3.4	9.6	6	5
P11	15	2.2	8.5	5	4
P12	15	2.1	10	5	4
P13	20	2.6	9.7	6	6
P14	15	2.3	9.6	4	3.5
P15	15	2.7	10.3	4	3.5
P16	15	2.3	10	5	4
P17	15	2.5	9.3	5	4

In the first step of the research, the decision-making criteria are defined. In this study, to evaluate DPB, five criteria including specific charge (SC), specific drilling (SD), rock fragmentation (RF), Flyrock (FR) and back break (BB) were considered regarding the past studies and experts' opinions. Specific charge (SC) is the amount of explosives needed to break one ton of rock. This parameter represents the distribution of explosives in the rock mass and has a considerable impact on the blasting results. Specific drilling (SD) is the hole length drilled per one cubic volume of the rock. With an increase in SD, mining costs increase, therefore this parameter has a negative effect on the drilling operation. Rock fragmentation (RF) has a direct effect on the drilling and blasting costs and also on future mining operations such as material transportation and crushing process. RF depends on both rock mass properties (that are uncontrollable) and drilling and blasting design parameters, which can be controlled. An efficient blasting operation can be reached by investigating the relationship between blast design parameters and rock fragmentation. Fly rock (FR) refers to rock pieces that fly beyond the blast site which may cause injuries to people and also damage to equipment, machinery or even structures. This parameter is one of the major issues in blasting operations which must be efficiently controlled. Back break (BB) is defined as the broken rocks beyond the specified limits of the rear row of the drilled holes. This phenomenon is another negative issue resulting from a poor blasting operation. BB causes instability of the mine walls, falling down of machinery and improper fragmentation (**Gokhale 2010**; **Morin and Ficarazzo 2006**; **Cho and Kaneko 2004**). A description of the drilling pattern of the mine, performed previously, is considered as problem attributes.

4. Results and discussion

This section is devoted to the selection of the most proper drilling and blasting pattern for the Sangan Iron Ore mine. In the first step, the degree of importance (or weight) of criteria is calculated by using AHP in a fuzzy environment. Then, a decision matrix that includes values of the criteria for the 17 drilling pattern (see **Table 2**) is created and the TOPSIS and PROMETHEE methods are applied to find the most proper DBP pattern.

4.1. Calculation of the weight vector

In the first step of the fuzzy AHP, a decision-making group used linguistic scales (see **Table 1**) to obtain the TFN comparison matrix. To achieve this, data collected from 14 expert's opinions was applied. Then, the fuzzy comparison matrix for all criteria is created as given in **Table 3**.

The synthetic extent values (S_i) were calculated for each criterion and then, the possibility degrees of each pairwise criteria were calculated as follows:

Table 3: The pairwise comparison matrix for all criteria

	BB	FR	RF	SC	SD
BB	(1,1,1)	(1,3.17,6)	(0.11,0.69,3.00)	(0.14,0.41,1)	(0.17,1.05,4)
FR	(0.17,0.32,1)	(1,1,1)	(0.11,0.50,1)	(0.13,0.30,1)	(0.13,0.26,0.50)
RF	(0.33, 1.45, 9.01)	(1,2.01,9.01)	(1,1,1)	(1,5,9)	(1,4.14,9)
SC	(1,2.43,7.04)	(1,3.37,8)	(0.11,0.2,1)	(1,1,1)	(1,1.76,5)
SD	(0.25,0.95,6.03)	(2,3.82,8)	(0.11,0.24,1)	(0.10,0.20,0.57)	(1,1,1)

$V(S_1>S_2)=1$,	$V(S_1>S_3)=0.814$,	$V(S_1>S_4)=0.814$,	$V(S_1>S_5)=1.073$,
$V(S_2>S_1)=0.968$,	$V(S_2>S_3)=0.807$,	$V(S_2>S_4)=0.934$,	$V(S_2>S_5)=0.982$,
$V(S_3>S_1)=1$,	$V(S_3>S_2)=1$,	$V(S_3>S_4)=1$,	$V(S_3>S_5)=1$,
$V(S_4>S_1)=1$,	$V(S_4>S_2)=1$,	$V(S_4>S_3)=0.913$,	$V(S_4>S_5)=1$,
$V(S_5>S_1)=1$,	$V(S_5>S_2)=1$,	$V(S_5>S_3)=0.907$,	$V(S_5>S_4)=1.034$.

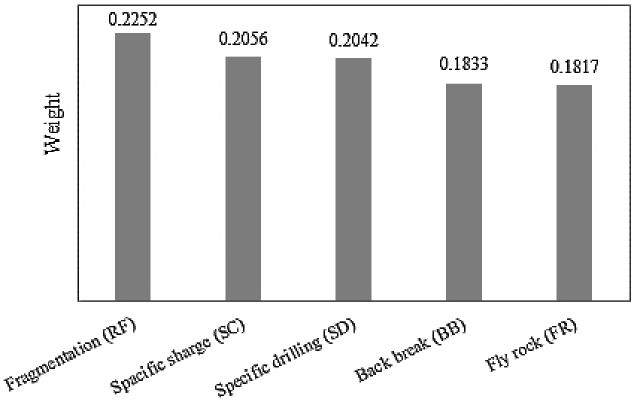

Figure 3: The weight of each decision criteria

According to the possibility degree values, the normalized weight of the criteria was calculated and shown in **Figure 3**. The results indicate that rock fragmentation and fly rock have the highest and lowest importance, respectively.

4.2. Selection of the most proper DBP using the TOPSIS method

This subsection tried to select the most proper DBP for the studied mine by using the TOPSIS method. To achieve this, the practical results of the formerly performed pattern were considered as the decision matrix as given in **Table 4**. It is noted that all criteria except RF and BB are expressed in the form of numerical values which means they are not measured systematically. Therefore, in the first step, the qualitative criteria (RF and BB) were converted to numerical values while considering values 1, 2 and 3 as acceptable, fairly acceptable and unacceptable levels, respectively. Then, a normalized decision matrix was created using **Equation (12)**. The weighted normalized decision matrix was formed using **Equation (13)** and **Table 4** and given in **Table 5**. The positive ideal solution () and negative-ideal solution () were computed using **Table 5** and **Equation (14)** and given in **Table 6**. The distance between each alternative and and was calculated and then the closeness coefficient of the alternatives was calculated to rank a drilling pattern. The results are given in **Table 6**. Regarding the results, alternatives P16 and P4 are the best and worst patterns, respectively.

Table 4: Decision matrix

DBP No.	BB	SD (m/m^3)	FR (m)	RF	SC (gr/m^3)
P1	Acceptable	0.111	30	Acceptable	205
P2	Fairly-acceptable	0.157	40	Acceptable	271
P3	Fairly-acceptable	0.133	29	Acceptable	252
P4	Unacceptable	0.070	155	Unacceptable	336
P5	Fairly-acceptable	0.092	38	Fairly-acceptable	244
P6	Unacceptable	0.058	103	Unacceptable	290
P7	Unacceptable	0.071	92	Fairly-acceptable	307
P8	Fairly-acceptable	0.095	44	Fairly-acceptable	252
P9	Fairly-acceptable	0.085	21	Fairly-acceptable	225
P10	Unacceptable	0.036	79	Unacceptable	269
P11	Acceptable	0.051	13	Fairly-acceptable	215
P12	Fairly-acceptable	0.055	38	Fairly-acceptable	245
P13	Fairly-acceptable	0.031	34	Unacceptable	230
P14	Fairly-acceptable	0.037	26	Fairly-acceptable	231
P15	Acceptable	0.122	43	Fairly-acceptable	205
P16	Acceptable	0.047	52	Fairly-acceptable	206
P17	Acceptable	0.054	28	Fairly-acceptable	221

4.3. Selection of the most proper DBP using the PROMETHEE method

In this subsection, the most suitable drilling pattern is selected using the PROMETHEE method. In this meth-

Table 5: Weighted normalized matrix

DBP No.	BB	SD	RF	RF	SC
P1	0.0215	0.0649	0.0021	0.0802	0.0414
P2	0.0429	0.0918	0.0302	0.0802	0.0548
P3	0.0429	0.0778	0.0221	0.0802	0.0509
P4	0.0644	0.0409	0.1156	0.0267	0.0594
P5	0.0429	0.0538	0.0281	0.0535	0.0493
P6	0.0644	0.0339	0.0765	0.0267	0.0586
P7	0.0644	0.0415	0.0682	0.0535	0.0620
P8	0.0429	0.0556	0.0332	0.0535	0.0509
P9	0.0429	0.0497	0.0159	0.0535	0.0455
P10	0.0644	0.0211	0.0587	0.0267	0.0543
P11	0.0215	0.0298	0.0096	0.0535	0.0434
P12	0.0429	0.0322	0.0287	0.0535	0.0495
P13	0.0429	0.0181	0.0255	0.0267	0.0465
P14	0.0429	0.0216	0.0198	0.0535	0.0467
P15	0.0215	0.0713	0.0032	0.0535	0.0414
P16	0.0215	0.0275	0.0038	0.0535	0.0416
P17	0.0215	0.0316	0.0134	0.0535	0.0446

Table 6: Fuzzy positive and negative ideal solutions

	A^-	A^*
SC	0.0620	0.0414
RF	0.0802	0.0267
FR	0.1156	0.0021
SD	0.0918	0.0181
BB	0.0643	0.0214

od, to select the most proper alternative, the comparison matrix for all alternatives is created. Regarding the high volume of calculations and the limitation of page numbers, the details of the calculations have been omitted. The overall preference index (π(a,b)) is calculated by using **Equation (14)** and **Table 5** and given in **Table 8**. The positive, negative and net flows are calculated regarding **Table 8** and **Equation (15)**. The results are presented in **Table 9**. Regarding **Table 9**, pattern No. 16 is selected as the most proper drilling pattern, which is consistent with the TOPSIS results.

The final rank of the pattern in the application of the Copeland aggregation method is given in **Table 10**. Regarding the results, pattern No. 16 is selected as the most suitable alternative. It is worth noting that the specific charge and specific drilling of this pattern is 38.77 and 16.70 percent lower than the average ones, respectively. The rock fragmentation of the pattern no. 16 equals the average rock fragmentation of all studied patterns and the back break is acceptable.

Table 7: Closeness coefficient of alternatives

DBP No.	S_i^-	S_i^*	C_i
P1	0.1260	0.0710	0.6394
P2	0.0884	0.0985	0.4728
P3	0.0976	0.0858	0.5321
P4	0.0738	0.1247	0.3718
P5	0.1022	0.0564	0.6444
P6	0.0880	0.0890	0.4973
P7	0.0741	0.0889	0.4547
P8	0.0970	0.0602	0.6169
P9	0.1147	0.0488	0.7016
P10	0.1057	0.0722	0.5941
P11	0.1341	0.0302	0.8163
P12	0.1115	0.0463	0.7067
P13	0.1308	0.0321	0.8028
P14	0.1246	0.0391	0.7613
P15	0.1266	0.0596	0.6801
P16	**0.1400**	**0.0284**	**0.8315**
P17	0.1301	0.0321	0.8020

5. Conclusion

Drilling and blasting is the most common method applied in open pit mining which is a very important part of a mining operation. Improper drilling and blasting operations may lead to adverse technical and safety consequences such as fly rock, back break and therefore, increases in the operating costs of mines. In this paper, the most ideal drilling and blasting pattern was proposed for the Sangan Iron Mine, Iran. Specific charge, fly rock, rock fragmentation, back break and specific drilling were considered as decision criteria and the most suitable drilling pattern was selected among 17 patterns, all previously performed. The AHP method under a fuzzy environment was used to define the weight of criteria and the TOPSIS and PROMETHEE methods were applied to select the most ideal drilling and blasting pattern. Regarding the results of this study, rock fragmentation, specific charge and specific drilling have the highest degree of importance, respectively. A drilling and blasting pattern with a spacing of 5 m, a burden of 4 m, a hole depth of 10 m, and a hole diameter of 15 cm is proposed as the most proper alternative. Considering the effect of the suggested pattern on direct and indirect costs of the mining operation, studying the effect of the proposed pattern on ground vibration and air blast and applying other multi-attribute decision-making methods to find the most suitable alternative could be recommended for future studies.

Table 8: Matrix of preference function for drilling patterns

DBP No.	1	2	3	4	5	6	7	8	9
P1	0	0.583	0.583	0.618	0.618	0.618	0.618	0.618	0.618
P2	0.187	0	0	0.805	0.230	0.805	0.805	0.408	0.230
P3	0.187	0.583	0	0.805	0.408	0.805	0.805	0.408	0.230
P4	0.382	0.195	0.195	0	0.195	0	0.195	0.195	0.195
P5	0.382	0.583	0.405	0.805	0	0.805	0.575	0.583	0
P6	0.382	0.195	0.195	0.583	0.195	0	0.405	0.195	0.195
P7	0.382	0.195	0.195	0.618	0.195	0.408	0	0.195	0.195
P8	0.382	0.405	0.195	0.805	0	0.805	0.575	0	0
P9	0.382	0.583	0.583	0.805	0.583	0.805	0.575	0.583	0
P10	0.382	0.405	0.195	0.583	0.195	0.583	0.583	0.195	0.195
P11	0.195	0.770	0.592	1	0.770	1	0.770	0.770	0.770
P12	0.382	0.583	0.405	1	0.195	1	0.770	0.583	0.195
P13	0.382	0.583	0.405	0.770	0.583	0.770	0.770	0.583	0.195
P14	0.382	0.583	0.583	1	0.583	1	0.770	0.583	0.195
P15	0	0.770	0.770	0.805	0.575	0.805	0.575	0.575	0.195
P16	0.195	0.575	0.770	1	0.770	1	0.770	0.770	0.770
P17	0.195	0.770	0.770	1	0.770	1	0.770	0.770	0.770
DBP No.	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	
P1	0.618	0.618	0.618	0.618	0.618	0.618	0.618	0.618	
P2	0.595	0.230	0.230	0.230	0.230	0.230	0.425	0.230	
P3	0.805	0.408	0.408	0.408	0.230	0.230	0.230	0.230	
P4	0	0	0	0	0	0.195	0	0	
P5	0.805	0	0.388	0.230	0	0.195	0	0	
P6	0	0	0	0	0	0.195	0	0	
P7	0.230	0	0	0.230	0	0.195	0	0	
P8	0.805	0	0	0.230	0	0.195	0	0	
P9	0.805	0	0.388	0.618	0.388	0.195	0	0	
P10	0	0.195	0.195	0	0.195	0.195	0.195	0.195	
P11	0.805	0	0.770	0.805	0.575	0.195	0	0.583	
P12	0.805	0	0	0.230	0	0.195	0	0	
P13	0.770	0.195	0.583	0	0.405	0.195	0.195	0.195	
P14	0.805	0.195	0.583	0.408	0	0.195	0.195	0.195	
P15	0.805	0.388	0.575	0.805	0.575	0	0.388	0.388	
P16	0.805	0.583	0.770	0.805	0.575	0.195	0	0.583	
P17	0.805	0	0.770	0.805	0.575	0.195	0	0	

Table 9: The positive, negative and net flows for all alternatives

DBP No.	φ^+	φ^-	φ	DBP No.	φ^+	φ^-	φ
P1	0.6217	0.2867	0.3351	P10	0.2924	0.6277	-0.3353
P2	0.3708	0.5077	-0.1369	P11	0.6617	0.1690	0.4927
P3	0.4544	0.4124	0.0420	P12	0.4060	0.3714	0.0346
P4	0.1079	0.8122	-0.7043	P13	0.4863	0.3922	0.0941
P5	0.3742	0.4148	-0.0406	P14	0.5239	0.2652	0.2587
P6	0.1641	0.7457	-0.5816	P15	0.5955	0.2235	0.3720
P7	0.1744	0.6516	-0.4772	**P16**	**0.6931**	**0.1376**	**0.5555**
P8	0.2871	0.4904	-3.660	P17	0.6392	0.1915	0.4477
P9	0.4695	0.3196	-0.2033				

Table 10: Final ranking of the drilling and blasting pattern based on the Copeland method

DBP No.	Value	Rank	DBP No.	Value	Rank
P1	4	7	P10	-6	12
P2	-7	13	P11	14	2
P3	-2	11	P12	4	8
P4	-14	17	P13	10	4
P5	0	9	P14	8	5
P6	-10	15	P15	7	6
P7	-11	16	**P16**	**16**	**1**
P8	-9	14	P17	12	8
P9	0	10			

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SAŽETAK

Odabir najprikladnijega načina bušenja i miniranja upotrebom MADM metoda (studija slučaja: Rudnik željeza Sangan, Iran)

Bušenje je prva faza površinske eksploatacije koja ima znatan utjecaj na ostale faze rudarenja, uključujući miniranje, utovar, transport i drobljenje. Neprimjeren način bušenja može dovesti do nepoželjnih rezultata poput loše fragmentacije, povratnoga loma i odbacivanja stijena, što ne samo da rezultira tehničkim i sigurnosnim problemima, već i povećava operativne troškove rudnika. Metode donošenja odluka s više atributa (MADM) mogu biti korisne za odabir odgovarajućega načina bušenja među raznim prethodno izvedenim alternativama. Cilj je ovoga rada odabrati najpogodniji način bušenja i miniranja za rudnik željeza Sangan, Iran. Da bi se to postiglo, u prvome koraku kao kriteriji za odlučivanje razmatrani su fragmentacija stijena, povratno lomljenje, odbacivanje stijena, specifično punjenje i specifično bušenje, a njihova važnost izračunana je korištenjem AHP metode u neizrazitome okruženju. Zatim su korištene metode TOPSIS i PROMETHEE za odabir najprikladnije alternative. Rezultati ove studije pokazuju da je najprikladniji način bušenja s razmakom od 5 m, opterećenjem od 4 m, dubinom rupe od 10 m i promjerom rupe od 15 cm. Duljina čepa bušotine i specifična potrošnja eksploziva predloženoga uzorka iznose 2,3 m, odnosno 2,6 g/cm^3.

Ključne riječi:
način bušenja i miniranja, rudnik željeza Sangan, AHP, TOPSIS, PROMETHEE

Authors contribution

A. Aryafar and **M.J. Rahimdel** (Associate and Assistant Professor of Mining Engineering) contributed to the design and implementation of the research. **E. Tavakkoli** (M.Sc. of Mining Engineering) performed the field work.