Rudarsko-geološko-naftni zbornik	Vol. 29	str. 69-79	Zagreb, 2014.

UDK 622.235+519.2
UDC 622.235+519.2

Orginalni znanstveni rad
Original scientific paper

Language/*Jezik:*Engleski/*English*

A NOVEL INVESTIGATION IN BLASTING OPERATION MANAGEMENT USING DECISION MAKING METHODS

M. Yari[1], M. Monjezi[2], R. Bagherpour[3]

[1] *Department of Mining Engineering, Isfahan University of Technology, Isfahan, Iran*
[2] *Faculty of Engineering, Tarbiat Modares University, Tehran, Iran*
[3] *Department of Mining Engineering, Isfahan University of Technology, Isfahan, Iran*

Key words: Numerical Taxonomy; Data Envelopment Analysis (DEA); Blasting Pattern; Sungun Copper Mine

Summary

Blasting is one of the most important operations in the mining projects. Inappropriate blasting pattern may lead to unwanted events such as poor fragmentation, back break, fly rock etc. and affect the whole operation physically and economically. In fact selecting of the most suitable pattern among previously performed patterns can be considered as a Multi Attribute Decision Making (MADM) problem. In this paper, firstly, from various already performed patterns, efficient and inefficient patterns were differentiated using Data Envelopment Analysis (DEA). In the second step numerical Taxonomy method was used for ranking the remaining efficient patterns and recognizing the most suitable pattern in the Sungun copper mine, Iran. According to the obtained results, blasting pattern with burden of 3 m, spacing of 4 m and stemming of 3.2 m was selected as the best pattern and suggested to be considered for the future operation..

1. Introduction

Blasting process plays significant role in the civil and mining projects. Incorrect blasting pattern can result in many technical, economical and safety problems (Hudaverdi, 2012; Kecojevic & Radomsky, 2005; Monjezi & Rezaei, 2011). In the mining activities, the prime aim of blasting operation is to achieve a suitable rock fragmentation necessary for subsequent processes such as transportation, crushing, etc. (Chakraborty et al., 2004; Crum & Crum, 1990; Latham, Van Meulen, & Dupray, 2006; Morin & Ficarazzo, 2006; Ozkahraman, 2006; Shim, Ryu, Chung, Synn, & Song, 2009). On the other hand, the explosive energy is not fully used for rock breakage and only 20–30% of the energy is practically consumed for the assigned purpose and the rest of the energy is exhausted in the form of unwanted phenomena such as ground vibration, air blast, flyrock, back break, etc. (Singh & Singh, 2005). Also, environmentalists are increasingly concerned about mining activities; hence, there should be much effort to control and eliminate the unwanted blast-induced environmental problems.

Conventional models can only provide an approximation to the solution for approaching perfect result of blasting considering technical, environmental and safety parameters and the final applicable design can be identified using a trial-error process (Inanloo Arabi Shad & Ahangari, 2012). Available experimental methods of designing blasting pattern are not accurate enough since they are site specific and therefore cannot be implemented in all the situations (Inanloo Arabi Shad & Ahangari, 2012). For finalizing a proposed initial pattern, an analysis of the obtained results would lead to adaptation of the design parameters (Jimeno, 1995). However, this approach is time consuming and imposes extra costs on the operation.

Given the existence of different parameters and multiple alternatives, it is relatively difficult to select the most suitable pattern among several patterns. So, it is necessary to employ a mechanism to optimize the design. The selected pattern should be reasonable from both technical and economical point of view. Safety and environment are the other important issues to be considered in the blasting operation (Hudaverdi, 2012; Kecojevic & Radomsky, 2005).

The main goal of the blasting is obtaining a proper fragmentation of materials while decreasing the unfavourable effects such as ground vibration, back break and fly rock (Monjezi & Rezaei, 2011). In the previous studies, fragmentation is regarded as the most important goal of the blasting (Ghasemi, Sari, & Ataei, 2012; Kulatilake, Qiong, Hudaverdi, & Kuzu, 2010; Michaux & Djordjevic, 2005; Morin & Ficarazzo, 2006; Sanchidrián, Segarra, & López, 2006) and Blasting experts have not paid enough attention to other effective parameters such as back break, fly rock, ground vibration and air blasting for evaluation of blasting patterns.

So far, many researches are focused on blasting operation management. Case in point, researchers portrayed some careful investigations noticing fly rock and presented causative components for the occasion to propose preventive measures (Amini, Gholami, Monjezi, Torabi, & Zadhesh, 2011; Bajpayee, Rehak, Mowrey, & Ingram, 2002; Bajpayee, Verakis, & Lobb, 2004; Bajpayee et al., 2003; Bajpayee, Rehak, Mowrey, & Ingram, 2004; Ghasemi, Amini, Ataei, & Khalokakaei, 2012; Ghasemi, Sari, et al., 2012; Kecojevic & Radomsky, 2005; Little & Blair, 2010; Monjezi, Amini Khoshalan, & Yazdian Varjani, 2012; Monjezi, Bahrami, Varjani, & Sayadi, 2011; Ning, 1999; Rehak, Bajpayee, Mowrey, & Ingram, 2001; Rezaei, Monjezi, & Yazdian Varjani, 2011; Stojadinović, Pantović, & Žikić, 2011; Tota et al., 2001). Wherever back break has been the blasting problem in a new bench, the lower amount of back break is considered as the blasting pattern evaluation factor (Gate, Ortiz, & Florez, 2005; Khandelwal & Monjezi, 2012; Monjezi, Amini Khoshalan, & Yazdian Varjani, 2011; Monjezi et al., 2012; Monjezi & Dehghani, 2008; Monjezi, Rezaei, & Yazdian, 2010). In addition, a few endeavours have been made to diminish ground vibration (Ak, Iphar, Yavuz, & Konuk, 2009; Ak & Konuk, 2008; Bakhshandeh Amnieh, Siamaki, & Soltani, 2012; Dehghani & Ataee-Pour, 2011; Erarslan, Uysal, Arpaz, & Cebi, 2008; Guosheng, Jiang, & Kui, 2011; Hudaverdi, 2012; Iphar, Yavuz, & Ak, 2008; Monjezi, Ahmadi, Sheikhan, Bahrami, & Salimi, 2010; Monjezi, Ghafurikalajahi, & Bahrami, 2011; Shuran & Shujin, 2011). The essential issue of these examinations is to recognize stand out of the impact criteria in the blasting operation enhancement.

DEA is a non-parametric method used for evaluating the relative efficiency of decision-making units (DMUs) according to multiple inputs and outputs (William Wager Cooper, Seiford, & Tone, 2007). It can also be employed to generate local weights of alternatives from pair-wise comparison judgment matrixes in the analytic hierarchy process (AHP) (Ramanathan, 2006).This method has been applied in different fields of science and engineering (Athanassopoulos, Lambroukos, & Seiford, 1999; Hermans, Brijs, Wets, & Vanhoof, 2009; Kao & Liu, 2009).

In order to achieve a global evaluation of blasting patterns, some aspects (criteria) such as fragmentation, back break, fly rock and blasting costs must be considered (Jimeno, 1995). Hence, due to the presence of various blasting effects (consequences), it is not easy to select the best applied alternative. For this reason, rather new mathematical based methods such as numerical Taxonomy, a branch of multi attribute decision making (MADM), can be employed. However, in cases where the number of alternatives is too high, it is better to limit the search space by omitting inefficient alternatives and considering only efficient ones. The work can be performed using methods such as data envelopment analysis (Li, Jahanshahloo, & Khodabakhshi, 2007). In this study, the most efficient applied blast patterns of mine were selected by DEA method. After that, among the selected patterns, the most suitable pattern was chosen using numerical Taxonomy method for Sungun Copper Mine (Fig. 1).

2. Data development Analysis (DEA)

Data Envelopment Analysis (DEA), was presented by Charnes et al in 1978 emphasizing researches of Farrel (1957). DEA systems are used as a linear or non-linear programming model. This model is implemented to evaluate the comparable decision making units (DMUs) efficiency considering multiple inputs and outputs (Sowlati, Paradi, & Suld, 2005). DEA and TOPSIS combined technique, can be practical for evaluating service operations using a ranking mechanism (William W Cooper, Seiford, & Tone, 2005). Generally, DEA models can be categorized into two main branches, i.e. input-orientated and output-orientated. Input orientated methods consists of the models in which input quantities can be regularly decreased without altering the outputs amounts produced, while in the second group, the output quantities can be proportionally increased by keeping the input quantities unchanged. Selection of the method depends on the nature of problem to be solved (Allen & Thanassoulis, 2004; Bal, Örkcü, & Çelebioğlu, 2010).

The efficiency is a ratio of the weighted sum of outputs to the weighted sum of inputs. The relative efficiency (w_o) of particular DMUs is obtained by solving the following fractional programming problem, $w_o = 1$. It means that DMU_0 is efficient while $w_o < 1$ shows the inefficiency of the DMU under evaluation.

$$w_0 = Max \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \qquad (1)$$

$$\begin{aligned} & j = 1,2,...,n \\ & u_r \ge 0, \qquad r = 1,2,...,s \\ & v_i \ge 0, \qquad i = 1,2,...,m \end{aligned}$$

Where:
j is the DMU index, j=1, ..., n;
r is the output index, r=1,..., s;
i is the input index, i = 1,...,m;

y_{rj} is the value of the r-th output for the j-th DMU,
x_{ij} is the value of the i-th input for the j-th DMU,
u_r is the weight given to the r-th output;
vi is the weight given to the i-th input.

The fractional program (1) can be converted into a linear programming problem (2) by forcing the weighted sum of the inputs to 1. This model, which is the first applicable type of DEA models, is called Charnes, Cooper and Rhodes (CCR) model. In this technique, all probable combinations are proportionally scaled up or down. Solution of the problem can be found with constant return to scale (CRS).

$$
\begin{aligned}
& w_0 = Max\sum_{r=1}^{s} u_r y_{r0} \\
& \sum_{i=1}^{m} v_i x_{i0} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \qquad (2) \\
& j = 1,2,...,n \\
& u_r \ge 0, \quad r = 1,2,...,s \\
& v_i \ge 0, \quad i = 1,2,...,m
\end{aligned}
$$

The second type of DEA models refers to Banker, Charnes and Cooper (BCC) model. Unlike CCR model, in the BCC approach, the solution comes with variable return to scale (VRS). The BCC model can be as follows:

$$
\begin{aligned}
& w_0 = Max\sum_{r=1}^{s} u_r y_{r0} + c_0 \\
& \sum_{i=1}^{m} v_i x_{i0} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + c_0 \le 0 \qquad (3) \\
& j = 1,2,...,n \\
& u_r \ge 0, \quad r = 1,2,...,s \\
& v_i \ge 0, \quad i = 1,2,...,m
\end{aligned}
$$

Where C_o indicates returns to scale (RS) and is free in sign.

When there is more than one efficient DMU, a complementary concept has to be employed to recognize the most efficient alternative. One of the applicable concepts is numerical Taxonomy technique, which can identify the most efficient DMU using a ranking mechanism.

3. Numerical Taxonomy

Taxonomy analysis method is one of the most applicable methods of ranking the zones in terms of development which has been widely used in geography. This method was posed by Adneson for the first time in 1763 and expanded by some mathematicians in 1950. In 1968, it was posed by Holling in UNESCO as an important way for classification of development degree of the different countries and has been posed in different fields of sciences at present. Taxonomy analysis is applied for different classifications in sciences of which special type is numerical taxonomy. In this method, a set is divided into relatively homogenous sets and gives the planners an acceptable scale for studying and measuring development rate of the zones. Taxonomy has been based on analysis of a series of predetermined indices which is used in prioritization of a series of alternatives and gives a full ranking for evaluation of alternatives (Eghbali, Zamarri, & Gaskari, 2007; Mohammadi, Shohani, & Borzooei, 2011). Different stages of taxonomy analysis are given in 9 steps as follows(Eghbali et al., 2007; Mohammadi et al., 2011):

Stage 1: specifying alternatives and determining attributes

Indices can be selected by analyst or experts group (by forming panel or Delphi method). In this stage, i alternatives is considered which will be evaluated by j attributes.

Stage 2: Forming Data Matrix and Calculating Mean and Standard Deviation

i alternatives and j attributes are ordered as the Table 1

Table 1. Data matrix

Attribute \ Alternatives	C_1	C_2	C_3	.	.	C_j
A_1	r_{11}	r_{12}	r_{13}	.	.	r_{1j}
A_2	r_{21}	r_{22}	r_{23}	.	.	r_{2j}
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
A_i	r_{i1}	r_{i2}	r_{i3}	.	.	r_{ij}
Mean	$\bar{x}_1$	$\bar{x}_2$	.	.	.	$\bar{x}_j$
Standard deviation	σ_1	σ_2	.	.	.	σ_j

In this matrix, r_{ij} is Compliance of the i-th alternative from each index view point, qualitatively or quantitatively. In this stage, one should note that the negative indices should be reversed or its negativity should be considered in other ways.

Stage 3: Normalizing the Obtained Matrix Data

In data matrix, alternatives have been expressed in terms of the indices which have different units (scales) and in this stage; attempt is made to remove its different units. It is used standard normal method described in (4).

$$Z_{ij} = (x_{ij} - \bar{x}_j) / \sigma_j \qquad (4)$$

Where

x_{ij}: arrays of matrix

x_j: mean indices for each one of the columns of matrix

σ_j: Standard deviation of each column of matrix

At this stage, matrix of the standard (normalized matrix) data is specified.

Stage 4: Determining Compound Distance between Alternatives

One can obtain distance (difference) of each alternative from other alternatives and determine distance between two alternatives using the (5).

$$D_{ab} = \sqrt{\sum_{j=1}^{m} \left(Z_{aj} - Z_{bj}\right)^2} \quad (5)$$

Where, a and b are the evaluated alternatives.

Distance of alternatives a and b is equal to distance of alternatives b and a. considering the above cases, one can form matrix of compound distances between alternatives of which main diagonal indicates difference (distance) of each alternative from itself which equals to zero.

Stage 5: Determining the Shortest Distance

In this stage, the shortest distance of each row of matrix is determined after calculating compound distances. Then, mean distance of the alternatives and their standard deviation are obtained and this is done for the shortest distance as well.

Stage 6: Delimiting the Alternatives (Homogenizing Alternatives)

There may be units which have longer or shorter distances from other alternatives; therefore, heterogeneous alternatives should be excluded from the set. In order to do so, upper and lower limits are obtained from (6), (7) and (8).

$$O_r = \bar{d}_r \pm 2\sigma_{dr} \quad (6)$$

$$O_r(+) = \bar{d}_r + 2\sigma_{dr} \quad \text{Upper limit} \quad (7)$$

$$O_r(-) = \bar{d}_r - 2\sigma_{dr} \quad \text{Lower limit} \quad (8)$$

In this case, d_r between upper and lower limits is coordinated and the alternatives which are out of this determined limit should be excluded.

Stage 7: Determining distance between alternatives and ideal value (C_{io})

In this stage, distance between each one of the alternatives and ideal value (specified in stage 4) is obtained as (9). short distance from ideal value indicates development (and its suitable condition) and long distance indicates that the alternative has not been developed.

$$C_{io} = \sqrt{\sum_{j=1}^{M} \left(Z_{ij} - Z_{bj}\right)^2} \quad (9)$$

Stage 8: Ranking of Alternatives Development Rate (Fi)

In this stage, ranking of development and condition of the alternatives are studied. Equation (10) indicates how to calculate alternatives development rate.

$$F_i = C_{io} / C_o \quad (10)$$

Where:

F_i: alternatives development rate

C_{io}: development model of each alternative

C_o :upper limit of development

In order to calculate C_o, one should specify mean and deviation of C_{io} and this is done at the end of stage 7 and it is calculated as (11):

$$C_o = \overline{C_{io}} + 2\sigma_{C_{io}} \quad (11)$$

F_i is between 0 and 1 and the closer alternative to zero, indicates the better development of that alternative and the closer the alternative to 1, the worse development of that alternative (no development). In this case, taxonomy problem is ended and rank of its alternatives are specified.

4. Sungun copper mine

The Sungun copper mine is the largest open-cast copper mine in Iran. It is located in East Azarbaijan province, 125 km North West of Tabriz (Fig1). This mine is in the primary stages of mining.

5. Model of Rock Blasting Patterns Evaluation for Sungun Copper Mine using DEA-Taxonomy method

For selecting the most economical, efficient and appropriate blasting pattern in terms of technical concepts using DEA-Taxonomy method, in first stage all alternatives should be determined.

Each pattern has been evaluated by considering 5 attributes (Yari, Monjezi, Bagherpour, & Sayadi, 2015):

- Powder factor: This parameter has been shown with PF (kg/m^3) in the second column in **Pogreška! Izvor reference nije pronađen.**. It should be noted that since the cost of explosive should be minimized, it is considered a negative attribute. It means that blasting system should be inclined to decrease it.
- Specific drilling: It is marked with SD (m/m^3) in the third column of **Pogreška! Izvor reference nije pronađen.**. This attribute is a negative index like PF. Increasing in specific drilling value improves fragmentation size.
- Fly rock: This index can be seen in the fourth column of **Pogreška! Izvor reference nije**

pronađen.. It has been marked with F (m). The smaller number indicates the suitable arrangement of the pattern.

- Back break: Back break is the maximum distance of crack propagation at the back of the last blast row. It is regarded as a negative attribute and shown with BB (m) in the fifth column of **Pogreška! Izvor reference nije pronađen.**.
- Fragmentation: It is the last index shown with letter K (cm) in **Pogreška! Izvor reference nije pronađen.**. This index is a negative parameter because the goal is to decrease fragmentation dimensions by aiming at the reduction of the future costs.

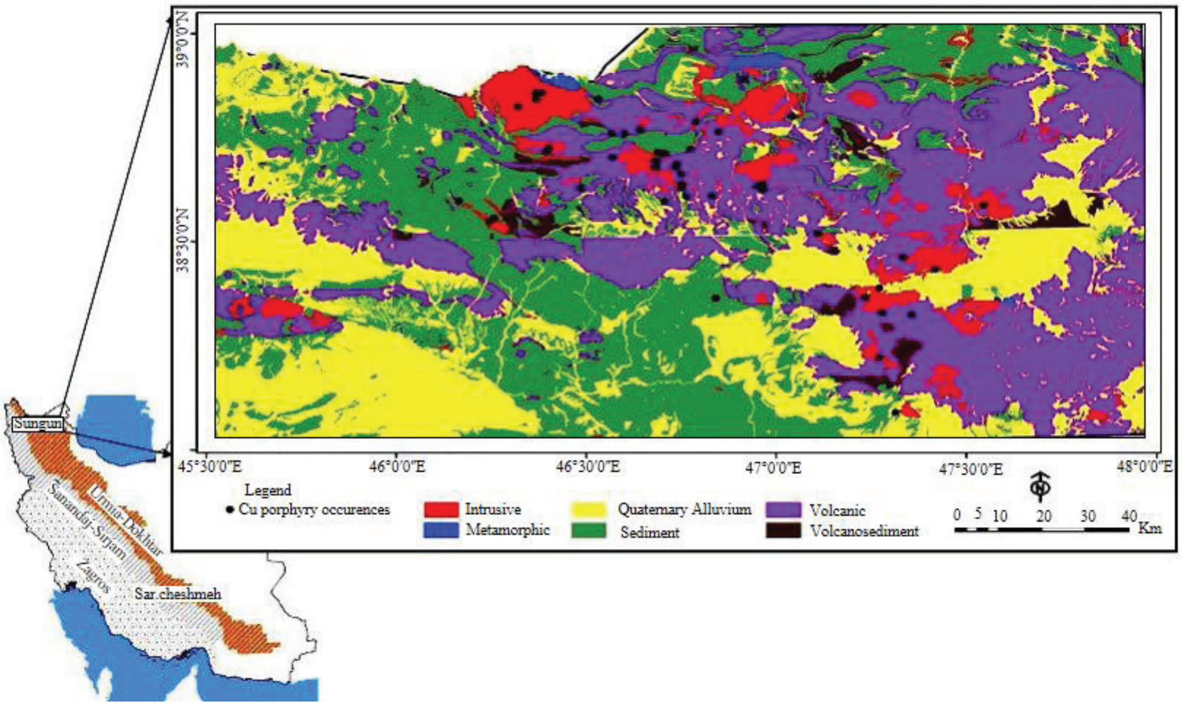

Figure 1: Geological map of Sungun copper mine (Pazand, Hezarkhani, & Ataei, 2012)

Table 2: Geometrical properties of blasting patterns

Pattern	D	H	S	B	Q
	inch	m	m	m	m
A1	5.5	12.1	4.5	3.5	3.8
A2	6	11.5	4.5	3.5	3
A3	5.5	12.5	4.5	3.5	3.6
A4	6	12.3	4.5	3.5	3.6
A5	5	13	5	4	3.8
A6	6	11.8	4.5	3.5	3.8
A7	5.5	12	4	3	3.2
A8	6	12.8	5	4	4.1
A9	5	13.5	5.5	5	4.5
A10	5.5	11.5	4	3	3.2
A11	5.5	11.5	4.5	3.5	3.6
A12	5	13.5	5	4	4.1
A13	6	13.2	5	4	3.5
A14	5	11	4.5	3.5	3.8
A15	5.5	13	4.5	3.5	4.1
A16	5.5	12	4.5	3.5	3.8
A17	5.5	13	5	4	3
A18	5	13.2	5.5	4.5	3.8
A19	6	12	5	4	4.1
A20	5.5	12.5	5	4	4.3
A21	5	13.2	5	4	4
A22	5	11	3.5	3	3
A23	5	12.8	4.5	3.5	4.1
A24	5	11.5	4	3	3
A25	6	12.9	5	4	4.1
A26	5.5	12.5	4.5	4	4
A27	5	11.8	4	3	3.2

For filtering inefficient blasting patterns output-orientated BCC has been used for 50 alternatives. As a result, 27 patterns have been selected as more efficient alternatives using DEA system (Table 2). Relative comparison of different attributes are shown in Fig 2 and more efficient patterns are mentioned in **Pogreška! Izvor reference nije pronađen.** with details.

In order to solve Multi Attribute Decision Making problem, it is necessary to form decision making matrix. This matrix consists of six columns and 28 rows. All attributes' values are expressed in

Pogreška! Izvor reference nije pronađen.. The first column is the pattern numbers while the other columns relate to the attributes including powder factor (column 2), specific drilling (column 3), fly rock (column 4), back break (column 5) and mean fragmentation size (column 6). Comparative values of attributes in different patterns of all 27 patterns are shown in Fig 2.

Table 3: Matrix of values, mean and standard deviation

Pattern	PF	SD	F	BB	K	Pattern	PF	SD	F	BB	K
A1	0.36	0.05	72	2.5	31	A16	0.4	0.05	75	3	30
A2	0.34	0.05	75	2	31.5	A17	0.59	0.06	80	5	24.7
A3	0.42	0.05	76	3	30	A18	0.59	0.07	80	5	24.6
A4	0.43	0.05	76	3	31	A19	0.59	0.07	82	5.5	24.9
A5	0.4	0.05	75	3	32	A20	0.52	0.06	79	5	26.3
A6	0.41	0.05	76	3	29	A21	0.54	0.06	79	5	25.7
A7	0.38	0.05	75	2	30.1	A22	0.34	0.05	73	2	31
A8	0.59	0.07	80	5	24.7	A23	0.52	0.06	78	5	26.7
A9	0.85	0.09	85	9	20.8	A24	0.34	0.05	73	2	31.6
A10	0.37	0.05	74	2	30.2	A25	0.52	0.06	79	5	26.8
A11	0.4	0.05	76	3	31	A26	0.46	0.06	75	4	28.2
A12	0.59	0.06	78	5.5	24.7	A27	0.37	0.05	74	2	30
A13	0.59	0.07	81	5.5	24.6	Average	0.478	0.0578	77.11	3.907	27.99
A14	0.4	0.05	76	3	30	STEV	0.12	0.0101	3.13	1.687	3.057
A15	0.59	0.07	80	5.5	24.7						

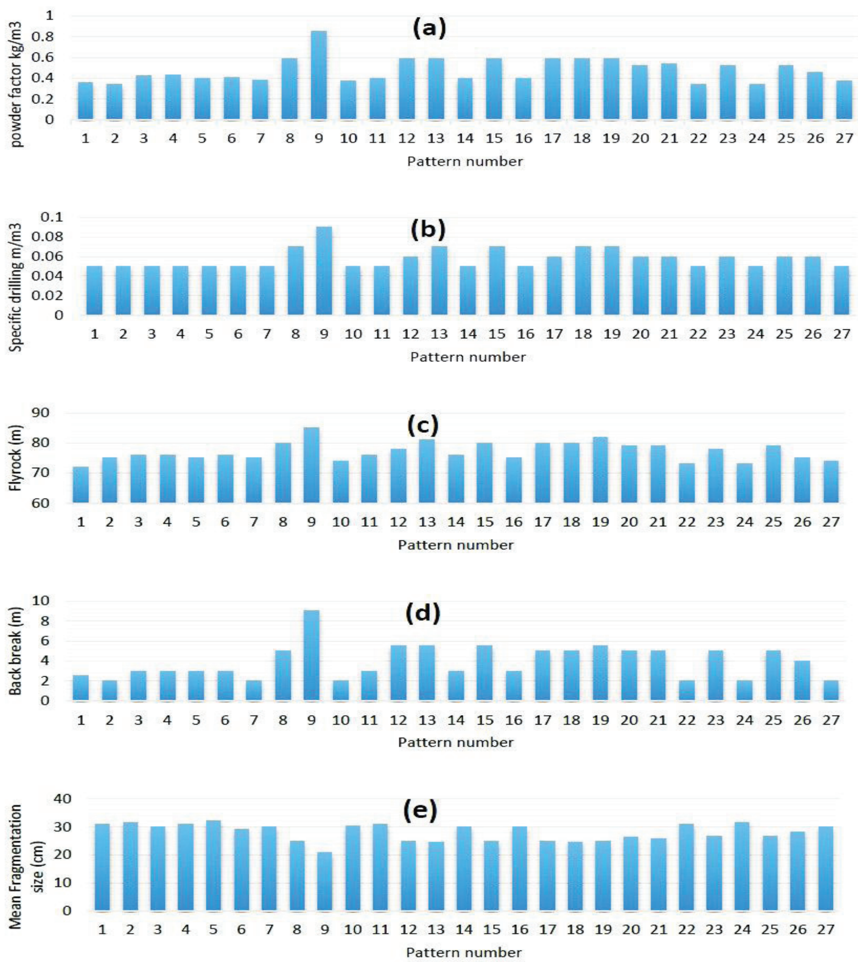

Fig 2 Comparative values of attributes in different patterns.
(a) Powder Factor (b) Specific Drilling (c) Fly rock (d) Back Break (e) Fragmentation

27 blasting performed patterns in Sungun Copper Mine have been measured with the 5 indices. 27 efficient patterns have been evaluated using Numerical Taxonomy analyze in following stages:

Stage 2: forming data matrix and calculating mean and standard deviation

Stage 1: specifying alternatives and determining attributes.

All affecting parameters on most appropriate blasting pattern selection are indicated in **Pogreška! Izvor reference nije pronađen.**.

27 operated blasting patterns and 5 indices as blasting evaluation factors are arranged in Table 3.

Table 3: Shortest distances in each row of paired distances matrix (d_r)

Pattern	d_r	Pattern	d_r	Pattern	d_r
A1	0.467	A11	0.25	A21	0.258
A2	0.566	A12	0.686	A22	0.196
A3	0.167	A13	0.321	A23	0.321
A4	0.25	A14	0.167	A24	0.196
A5	0.457	A15	0.296	A25	0.164
A6	0.338	A16	0.32	A26	1.292
A7	0.332	A17	0.619	A27	0.065
A8	0.033	A18	0.033	$\bar{d}_r$	0.456
A9	3.952	A19	0.334	σ_{dr}	0.744
A10	0.065	A20	0.164		

Stage 3: data matrix normalization

Stage 4: Determining Compound Distance between Alternatives:

Table 4: Cio calculation matrix

It has been calculated in a matrix of 27×27. After determining shortest distance for each row in paired distances matrix, Mean and standard deviation of short distances is calculated in Table 4.

	PF	SD	F	BB	K	
DOj / Pattern	-1.15	-0.768	-1.63	-1.13	-2.35	Cio
A1	0.028	0	0	0.088	11.13	3.354
A2	0	0	0.919	0	12.25	3.629
A3	0.445	0	1.634	0.351	9.058	3.389
A4	0.563	0	1.634	0.351	11.13	3.699
A5	0.25	0	0.919	0.351	13.42	3.866
A6	0.34	0	1.634	0.351	7.196	3.086
A7	0.111	0	0.919	0	9.256	3.207
A8	4.342	3.9	6.534	3.161	1.628	4.423
A9	18.07	15.6	17.25	17.21	0	8.254
A10	0.063	0	0.408	0	9.457	3.151
A11	0.25	0	1.634	0.351	11.13	3.656
A12	4.342	0.975	3.675	4.303	1.628	3.863
A13	4.342	3.9	8.27	4.303	1.545	4.729
A14	0.25	0	1.634	0.351	9.058	3.361
A15	4.342	3.9	6.534	4.303	1.628	4.55
A16	0.25	0	0.919	0.351	9.058	3.252
A17	4.342	0.975	6.534	3.161	1.628	4.079
A18	4.342	3.9	6.534	3.161	1.545	4.414
A19	4.342	3.9	10.21	4.303	1.799	4.955
A20	2.251	0.975	5.003	3.161	3.237	3.825
A21	2.779	0.975	5.003	3.161	2.57	3.806
A22	0	0	0.102	0	11.13	3.352
A23	2.251	0.975	3.675	3.161	3.725	3.713
A24	0	0	0.102	0	12.48	3.548
A25	2.251	0.975	5.003	3.161	3.853	3.904
A26	1	0.975	0.919	1.405	5.861	3.187
A27	0.063	0	0.408	0	9.058	3.087
$\overline{C_{io}}$						3.902
σ_{Cio}						1.01

Stage 5: Determining the Shortest Distance. After calculating normalized matrix, the negative ideal alternative (DOj) in terms of factors is evident in Table 3. In this stage distance of each alternative from DOj is calculated. Results are given in Table 4.

Stage 6: Homogenizing alternatives

Upper and lower boundaries are calculated as follow.

$O_r(+) = \ + 2\sigma_{dr} = 1.94$

$O_r(-) = \ - 2\sigma_{dr} = -1.03$

d_r between upper and lower limits is homogenous and the alternatives which are out of this interval should be excluded.

Stage 7: Determining model and alternatives (C_{io})

Values of C_{io} are calculated and mentioned for each alternative in Table 5.

Table 5: C_{io} and F_{io} calculation and final raking

Pattern num	Cio	Fio =Cio/co	Rank	Pattern num	Cio	Fio =Cio/co	Rank
A1	3.354	0.5664	8	A15	4.55	0.7683	24
A2	3.629	0.6128	12	A16	3.252	0.5492	6
A3	3.389	0.5723	10	A17	4.079	0.6888	21
A4	3.699	0.6246	14	A18	4.414	0.7453	22
A5	3.866	0.6528	19	A19	4.955	0.8367	26
A6	3.086	0.521	1	A20	3.825	0.6458	17
A7	3.207	0.5415	5	A21	3.806	0.6427	16
A8	4.423	0.7469	23	A22	3.352	0.566	7
A9	8.254	1.3938	27	A23	3.713	0.627	15
A10	3.151	0.532	3	A24	3.548	0.599	11
A11	3.656	0.6174	13	A25	3.904	0.6592	20
A12	3.863	0.6523	18	A26	3.187	0.5382	4
A13	4.729	0.7984	25	A27	3.087	0.5212	2
A14	3.361	0.5674	9				

6. Conclusion

Blasting operation in mines is one of the most important operations when considering technical, economical and safety effects. Blasting is a very important operation in all further mining stages. Safety in blasting operations is very important due to irreparable damages which inflict on people, equipment and environment in mine. Suitable management and the design of blasting patterns are all effective factors. MADM methods are useful methods for evaluating blasting patterns because it is very difficult to make decision about the most suitable blasting pattern. This complexity is due to the variety of the operated blasting patterns and the plurality of attributes which significantly influence the evaluation of blasting patterns. Among different patterns, TOPSIS model is one of the most applicable methods of MADM used to evaluate and rank blasting patterns in Sungun copper mine. Through this method, pattern 6 was selected as the most appropriate blasting pattern and alternative 9 was known as the most unsuitable blasting pattern. Based on the results, the selected pattern with burden of 3 m, spacing of 4 m and stemming rate of 3.2 m was selected as the most suitable blasting pattern for Sungun copper mine.

7. References

Ak, H., Iphar, M., Yavuz, M., & Konuk, A. (2009). Evaluation of ground vibration effect of blasting operations in a magnesite mine. *Soil Dynamics and Earthquake Engineering*, *29*(4), 669-676.

Ak, H., & Konuk, A. (2008). The effect of discontinuity frequency on ground vibrations produced from bench blasting: A case study. *Soil Dynamics and Earthquake Engineering*, *28*(9), 686-694.

Allen, Rachel, & Thanassoulis, Emmanuel. (2004). Improving envelopment in data envelopment analysis. *European Journal of Operational Research*, *154*(2), 363-379.

Amini, H., Gholami, R., Monjezi, M., Torabi, S.R., & Zadhesh, J. (2011). Evaluation of flyrock phenomenon due to blasting operation by support vector machine. *Neural Computing & Applications*, 1-9.

Athanassopoulos, Antreas D, Lambroukos, Nikos, & Seiford, Lawrence. (1999). Data envelopment scenario analysis for setting targets to electricity generating plants. *European Journal of Operational Research*, *115*(3), 413-428.

Bajpayee, T., Rehak, T., Mowrey, G., & Ingram, D. (2002). *A Summary of Fatal Accidents Due to Flyrock and Lack of Blast Area Security in Surface Mining, 1989 to 1999*. Paper presented at the PROCEEDINGS OF THE ANNUAL CONFERENCE ON EXPLOSIVES AND BLASTING TECHNIQUE.

Bajpayee, T., Verakis, H., & Lobb, T. (2004). *An Analysis and Prevention of Flyrock Accidents in Surface Blasting Operations*. Paper presented at the PROCEEDINGS OF THE ANNUAL CONFERENCE ON EXPLOSIVES AND BLASTING TECHNIQUE.

Bajpayee, TS, Bhatt, S.K., Rehak, T.R., Engineer, G., Mowrey, G.L., & Ingram, D.K. (2003). Fatal accidents due to flyrock and lack of blast area security and working practices in mining. *Journal of mines, metals and fuels*, *51*(11-12), 344-349.

Bajpayee, TS, Rehak, TR, Mowrey, GL, & Ingram, DK. (2004). Blasting injuries in surface mining with emphasis on flyrock and blast area security. *Journal of Safety Research*, *35*(1), 47-57.

Bakhshandeh Amnieh, H., Siamaki, A., & Soltani, S. (2012). Design of blasting pattern in proportion to the peak particle velocity (PPV): Artificial neural networks approach. *Safety Science*, *50*(9), 1913-1916.

Bal, Hasan, Örkcü, H Hasan, & Çelebioğlu, Salih. (2010). Improving the discrimination power and weights dispersion in the data envelopment analysis. *Computers & Operations Research*, *37*(1), 99-107.

Chakraborty, AK, Raina, AK, Ramulu, M, Choudhury, PB, Haldar, A, Sahu, P, & Bandopadhyay, C. (2004). Parametric study to develop guidelines for blast fragmentation improvement in jointed and massive formations. *Engineering geology*, *73*(1), 105-116.

Cooper, William W, Seiford, Lawrence M, & Tone, Kaoru. (2005). Introduction to data envelopment analysis and its uses: with DEA-solver software and references.

Cooper, William Wager, Seiford, Lawrence M, & Tone, Kaoru. (2007). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*: Springer.

Crum, SV, & Crum, SV. (1990). Fractal concepts applied to bench-blast fragmentation. *Proc. Rock Mechanics Contributions and Challenges*, *919*.

Dehghani, H., & Ataee-Pour, M. (2011). Development of a model to predict peak particle velocity in a blasting operation. *International Journal of Rock Mechanics and Mining Sciences*, *48*(1), 51-58.

Eghbali, A. R. , Zamarri, A. A. , & Gaskari, R. . (2007). the ranking iran's banks by taxonomy numerical analysis. *journal of international research publication: economy and business 2*.

Erarslan, Kaan, Uysal, Önder, Arpaz, Ercan, & Cebi, M Akif. (2008). Barrier holes and trench application to reduce blast induced vibration in Seyitomer coal mine. *Environmental Geology*, *54*(6), 1325-1331.

Gate, WC, Ortiz, BLT, & Florez, RM. (2005). *Analysis of rockfall and blasting backbreak problems*. Paper presented at the Paper ARMA/USRMS, proceedings of the American rock mechanics conference.

Ghasemi, E., Amini, H., Ataei, M., & Khalokakaei, R. (2012). Application of artificial intelligence techniques for predicting the flyrock distance caused by blasting operation. *Arabian Journal of Geosciences*, 1-10.

Ghasemi, E., Sari, M., & Ataei, M. (2012). Development of an empirical model for predicting the effects of controllable blasting parameters on flyrock distance in surface mines. *International Journal of Rock Mechanics and Mining Sciences*, *52*, 163-170.

Guosheng, Z., Jiang, L., & Kui, Z. (2011). Structural safety criteria for blasting vibration based on wavelet packet energy spectra. *Mining Science and Technology (China)*, *21*(1), 35-40.

Hermans, Elke, Brijs, Tom, Wets, Geert, & Vanhoof, Koen. (2009). Benchmarking road safety: lessons to learn from a data envelopment analysis. *Accident Analysis & Prevention*, *41*(1), 174-182.

Hudaverdi, T. (2012). Application of multivariate analysis for prediction of blast-induced ground vibrations. *Soil Dynamics and Earthquake Engineering*, *43*, 300-308.

Inanloo Arabi Shad, H., & Ahangari, K. (2012). An empirical relation to calculate the proper burden in blast design of open pit mines based on modification of the Konya relation. *International Journal of Rock Mechanics and Mining Sciences*, *56*, 121-126.

Iphar, M., Yavuz, M., & Ak, H. (2008). Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system. *Environmental Geology*, *56*(1), 97-107.

Jimeno, CL. (1995). Rock drilling and blasting: AA Balkema, Rotterdam, Brookfield.

Kao, Chiang, & Liu, Shiang-Tai. (2009). Stochastic data envelopment analysis in measuring the efficiency of Taiwan commercial banks. *European Journal of Operational Research*, *196*(1), 312-322.

Kecojevic, V., & Radomsky, M. (2005). Flyrock phenomena and area security in blasting-related accidents. *Safety science*, *43*(9), 739-750.

Khandelwal, M., & Monjezi, M. (2012). Prediction of Backbreak in Open-Pit Blasting Operations Using the Machine Learning Method. *Rock Mechanics and Rock Engineering*, 1-8.

Kulatilake, P., Qiong, W., Hudaverdi, T., & Kuzu, C. (2010). Mean particle size prediction in rock blast fragmentation using neural networks. *Engineering Geology*, *114*(3), 298-311.

Latham, John-Paul, Van Meulen, Jan, & Dupray, Sebastien. (2006). Prediction of fragmentation and yield curves with reference to armourstone production. *Engineering geology*, *87*(1), 60-74.

Li, Shanling, Jahanshahloo, Gholam Reza, & Khodabakhshi, M. (2007). A super-efficiency model for ranking efficient units in data envelopment analysis. *Applied Mathematics and Computation*, *184*(2), 638-648.

Little, TN, & Blair, DP. (2010). Mechanistic Monte Carlo models for analysis of flyrock risk. *Rock fragmentation by blasting*, 641-647.

Michaux, S., & Djordjevic, N. (2005). Influence of explosive energy on the strength of the rock fragments and SAG mill throughput. *Minerals engineering*, *18*(4), 439-448.

Mohammadi, A., Shohani, J., & Borzooei, R. (2011). Numerical taxonomy analysis with trapezoidal fuzzy data. *The Journal of*
Mathematics and Computer Science, *2*, 100-110.

Monjezi, M., Ahmadi, M., Sheikhan, M., Bahrami, A., & Salimi, AR. (2010). Predicting blast-induced ground vibration using various types of neural networks. *Soil Dynamics and Earthquake Engineering*, *30*(11), 1233-1236.

Monjezi, M., Amini Khoshalan, H., & Yazdian Varjani, A. (2011). Optimization of Open pit Blast Parameters using Genetic Algorithm. *International Journal of Rock Mechanics and Mining Sciences*, *48*(5), 864-869.

Monjezi, M., Amini Khoshalan, H., & Yazdian Varjani, A. (2012). Prediction of flyrock and backbreak in open pit blasting operation: a neuro-genetic approach. *Arabian Journal of Geosciences*, *5*(3), 441.

Monjezi, M., Bahrami, A., Varjani, A.Y., & Sayadi, A.R. (2011). Prediction and controlling of flyrock in blasting operation using artificial neural network. *Arabian Journal of Geosciences*, *4*(3), 421-425.

Monjezi, M., & Dehghani, H. (2008). Evaluation of effect of blasting pattern parameters on back break using neural networks. *International Journal of Rock Mechanics and Mining Sciences*, *45*(8), 1446-1453.

Monjezi, M., Ghafurikalajahi, M., & Bahrami, A. (2011). Prediction of blast-induced ground vibration using artificial neural networks. *Tunnelling and Underground Space Technology*, *26*(1), 46-50.

Monjezi, M., & Rezaei, M. (2011). Developing a new fuzzy model to predict burden from rock geomechanical properties. *Expert Systems with Applications*, *38*(8), 9266-9273.

Monjezi, M., Rezaei, M., & Yazdian, A. (2010). Prediction of backbreak in open-pit blasting using fuzzy set theory. *Expert Systems with Applications*, *37*(3), 2637-2643.

Morin, M.A., & Ficarazzo, F. (2006). Monte Carlo simulation as a tool to predict blasting fragmentation based on the Kuz–Ram model. *Computers & geosciences*, *32*(3), 352-359.

Ning, K. (1999). Prevention Measures for Controlling Flyrock in Engineering Blasting [J]: BLASTING.

Ozkahraman, HT. (2006). Fragmentation assessment and design of blast pattern at Goltas Limestone Quarry, Turkey. *International journal of rock mechanics and mining sciences*, *43*(4), 628-633.

Pazand, Kaveh, Hezarkhani, Ardeshir, & Ataei, Mohammad. (2012). Using TOPSIS approaches for predictive porphyry Cu potential mapping: A case study in Ahar-Arasbaran area (NW, Iran). *Computers & Geosciences*.

Ramanathan, Ramakrishnan. (2006). Data envelopment analysis for weight derivation and aggregation in the analytic hierarchy process. *Computers & Operations Research*, *33*(5), 1289-1307.

Rehak, T., Bajpayee, T., Mowrey, G., & Ingram, D. (2001). *Flyrock issues in blasting*. Paper presented at the PROCEEDINGS OF THE ANNUAL CONFERENCE ON EXPLOSIVES AND BLASTING TECHNIQUE.

Rezaei, M., Monjezi, M., & Yazdian Varjani, A. (2011). Development of a fuzzy model to predict flyrock in surface mining. *Safety Science*, *49*(2), 298-305.

Sanchidrián, JA, Segarra, P., & López, LM. (2006). A practical procedure for the measurement of fragmentation by blasting by image analysis. *Rock mechanics and rock engineering*, *39*(4), 359-382.

Shim, Hyun-Jin, Ryu, Dong-Woo, Chung, So-Keul, Synn, Joong-Ho, & Song, Jae-Joon. (2009). Optimized blasting design for large-scale quarrying based on a 3-D spatial distribution of rock factor. *International Journal of Rock Mechanics and Mining Sciences*, *46*(2), 326-332.

Shuran, L., & Shujin, L. (2011). Applying BP Neural Network Model to Forecast Peak Velocity of Blasting Ground Vibration. *Procedia Engineering*, *26*, 257-263.

Singh, TN, & Singh, Virendra. (2005). An intelligent approach to prediction and control ground vibration in mines. *Geotechnical & Geological Engineering*, *23*(3), 249-262.

Sowlati, Taraneh, Paradi, Joseph C, & Suld, C. (2005). Information systems project prioritization using data envelopment analysis. *Mathematical and Computer Modelling*, *41*(11), 1279-1298.

Stojadinović, S., Pantović, R., & Žikić, M. (2011). Prediction of flyrock trajectories for forensic applications using ballistic flight equations. *International Journal of Rock Mechanics and Mining Sciences*, *48*(7), 1086-1094.

Tota, E.W., Mudge, K., Branson, J.W., Georgiou, P.N., Gavrilovic, M., & Watson, J.D. (2001). Method and apparatus for flyrock control in small charge blasting: Google Patents.

Yari, M, Monjezi, M, Bagherpour, R, & Sayadi, AR. (2015). Blasting Operation Management Using Mathematical Methods *Engineering Geology for Society and Territory-Volume 1* (pp. 483-493): Springer (in print).