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EVALUATION OF BLASTING PATTERNS USING OPERATIONAL RESEARCH MODELS

OCENA PLANÓW PRAC STRZAŁOWYCH W OPARCIU O METODY BADAŃ OPERACYJNYCH

Blasting is one of the most important operations, which has a great technical and economical effect on the mining projects. Criteria such as fragmentation (operation ultimate objective) and ground vibration, flyrock, airblast, etc. (operation side effects) should be considered in the assessment of blasting operation. A suitable pattern should be able to provide both reasonable (required) fragmentation and blasting side effects. In order to evaluate blasting performance, operational research models such as multi attribute decision making technique (MADM) can be applied. Technique for order preference by similarity to an ideal solution (TOPSIS), a branch of MADM, is a strong method for pattern ranking. The other quantitative method which is applied in the evaluation of systems' efficiency is data envelopment analysis (DEA) model. In this paper, an attempt has been made to develop a new hybrid MADM model for selecting the most appropriate blasting pattern in Chadormalu iron mine, Iran. In this regard, DEA method was utilized to select the efficient blast patterns thereafter TOPSIS was used to recognize the most suitable pattern amongst the selected patterns by DEA method. It was concluded that the patterns J, G and B are the most appropriate patterns for blasting operations in the Chadormalu iron mine.

Keywords: fragmentation, ground vibration, flyrock, airblast, TOPSIS, DEA

Prace strzałowe to jedne z kluczowych operacji w znacznym stopniu determinujące efektywność ekonomiczną wielu projektów górniczych. W planowaniu prac strzałowych uwzględnić należy podstawowe kryteria, takie jak rozdrobnienie skał (ostateczny cel operacji), wibracje podłoża, występowanie rozrzutu skał, i podmuchów powietrza (efekty uboczne). Odpowiedni harmonogram prac zapewnić powinien zarówno odpowiedni poziom rozdrobnienia (wymiary brył) jak i ograniczenie skutków ubocznych prac. Dla oceny skuteczności prac strzałowych zastosować można modele badań operacyjnych, np. modele oparte o wielokryterialną technikę decyzyjną MADM, a technika ustalania kolejności preferowanych rozwiązań oparta o podobieństwo do rozwiązania idealnego (TOPSIS), wywodząca się z MADM, jest skuteczną metodą ustalania rankingu wzorców. Inną metodą ilościową stosowaną do oceny efektywności systemów jest metoda analizy danych DEA. W niniejszym artykule dokonano próby opracowania hybrydowego modelu MADM do wyboru najbardziej korzystnego planu prac strzałowych w kopalni rud żelaza Chadormalu, w Iranie. W ramach badań wykorzystano metodę DEA do wyboru skutecznego planu

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prac strzałowych, następnie zastosowano podejście TOPSIS dla rozpoznania najbardziej odpowiedniego wzorca spośród tych wybranych przy pomocy metody DEA. Stwierdzono, że wzorce oznaczone jako J, G i B są najodpowiedniejsze do zastosowania przy pracach strzałowych prowadzonych w kopalni rud żelaza Chadormalu.

Słowa kluczowe: rozdrobnienie skał, drgania podłoża, rozrzut skał, podmuchy powietrza, TOPSIS, DEA

Introduction

In the mining activities the prime aim of blasting operation is rock fragmentation that is necessary for subsequent processes such as transportation, crushing, etc. hence, achieving a higher efficiency (Bozich, 1998; Chakraborty, 2004; Latham et al., 2006; Mario & Ficarazzo, 2006; Ozkahraman, 2006; Shim et al., 2009)

As a matter of fact, the explosive energy is not fully utilized for rock breakage and only 20-30% of the energy is practically consumed for the assigned purpose and rest of the energy is exhausted in the form of unwanted phenomena such as ground vibration, air blast, fly rock, etc (Singh et al., 2005). On the other hand, environmental constraints are increasingly concerned for mining activities, hence, there should be a great deal to control and eliminate the unwanted blast-induced environmental problems. An optimized blast design can satisfy both the technical and environmental issues. Normally, traditional empirical methods are used to design blast geometry. These methods are site specific and for general applicability require trial and error mechanism. In this way, once a blast is carried out, analyzing the obtained consequences would result in modification of the design parameters for the successive rounds (Lopez et al., 1995). This approach is time consuming and imposes extra costs to the operation. Moreover, many investigations have been performed for blast optimization. For example, Bajpayee et al. described several case studies regarding to flyrock and introduced causative factors for the event and proposed preventive measures (Bajpayee et al., 2004). In other research, Hyun-Jin Shim et al. tried to optimize fragmentation for a quarry mine (Shim et al., 2009). Also, airblast impact on the adjacent buildings annoying habitants was reduced (Kuzu et al., 2009). Moreover, several attempts have been done for attenuating ground vibration (Erarslan et al., 2008; Hakan & Konuk, 2008; Hakan et al., 2009; Khandelwal & Singh, 2006; Khandelwal & Singh, 2009; Khandelwal et al., 2010). The main drawback of these investigations is considering only one of the blast criteria in optimization process. While because of interrelation exist amongst the blasting criteria, it must be tried to incorporate all of them simultaneously.

To achieve a global evaluation some aspects (criteria) such as fragmentation, ground vibration, flyrock and airblast must be considered (Lopez et al., 1995). Hence, due to presence of various blasting effects (consequences) selection of the best applied alternative is not an easy task. For this, rather new mathematical based methods such as technique for order preference by similarity to an ideal solution (TOPSIS), a branch of multi attribute decision making (MADM) can be employed. However, in circumstances when 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 (Jahanshahloo & Khodabakhshi, 2007).

DEA is a non-parametric method for evaluating the relative efficiency of decision-making units (DMUs) on the basis of multiple inputs and outputs (Cooper et al., 2006). It can also be used to generate local weights of alternatives from pair-wise comparison judgment matrices in the analytic hierarchy process (AHP) (Ramanathan, 2006).This method has been applied in different field of science and engineering (Athanassopoulosa et al., 1999; Hermans et al., 2009; Kao & Liu, 2009). It has been extensively applied in performance evaluation and benchmarking of schools, hospitals, bank branches, production plants, etc. (Cooper et al., 2006).

TOPSIS, the most practical method of MADM, is a practical technique for ranking a number of relevant alternatives and selecting the best one considering certain decision criteria. This technique has been applied for solving many complicated problems in the various fields of science and technology (Chen &Tzeng, 2004; Lin et al., 2008; Monjezi et al., 2010; Yang & Chou, 2005).

In this study, the most efficient applied blast patterns of Chadomalu iron mine were selected using DEA method. Thereafter, among the selected patterns, the most suitable pattern was chosen with the help of TOPSIS.

DEA

Data envelopment analysis (DEA), a linear or non-linear programming based model, was developed in 1978 by Charnes et al (Post & Spronk, 1999) based on the earlier work of Farrell (1957). The linear programming is appropriate when dealing with imprecise data (Despotis & Smirlis, 2002).This model is applied for evaluating relative efficiency of comparable decision making units (DMUs) by considering multiple inputs and outputs (Sowlati et al., 2005). Also, this technique in combination to TOPSIS technique can be implemented in benchmarking the performance of service operations using a ranking mechanism (Cooper et al., 2006). As a whole, DEA models can be divided in two groups, i.e. input-orientated and output-orientated. The first group are the models in which input quantities can be proportionally reduced without changing the outputs quantities produced, whereas in the second group the output quantities can be proportionally expanded keeping the input quantities unchanged. Selection of the method is depending on the nature of problem to be solved (Allen & Thanassoulis, 2004; Bal et al., 2010).

The efficiency is indicated as 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, $w_o = 1$ means that DMU_0 is efficient while $w_o < 1$ shows inefficiency of the DMU under evaluation:

$$
\begin{aligned}
& w_0 = Max \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad j = 1, 2, ..., n \\
& u_r \ge 0, \quad r = 1, 2, ..., s \\
& v_i \ge 0, \quad i = 1, 2, ..., m
\end{aligned}
\tag{1}
$$

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; v_i 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 made with constant return to scale (CRS).

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

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

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

where, C_0 indicates returns to scale (RS) and is free in sign

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

TOPSIS

TOPSIS model which was first introduced by Yoon and Hwang (1981) is one of the most practical techniques in MADM. In this mathematical model selection of the best alternative is performed on the basis of various influential criteria or decision makers' ideals. According to This technique the best alternative has the shortest Euclidean distance from the positive ideal solution

(PIS) and the farthest Euclidean distance from the negative ideal solution (NIS) (Kim & Choi, 2001; Li et al., 2009; Shih et al., 2007; Triantaphyllou et al., 1998; Xu, 2008).

Normally, in all of the MADM techniques, a decision matrix has to be formed in the first step. The matrix is composed of competitive alternatives row-wise and their attributes' scores column-wise. Each alternative is compared and evaluated with all other present attributes.

Decision matrix, **D**, which refers to "n" alternatives and "m" criteria, is defined as:

$$\mathbf{D} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ . & & & . \\ . & & & . \\ x_{n!} & x_{n2} & \dots & x_{nm} \end{bmatrix}$$

where x_{ij} denotes the evaluations of the i-th alternative with respect to the j-th criterion.

Since each of the attribute has its own dimension, comparison is possible only after normalization of the decision matrix to make it dimensionless. During normalization process, the scores are really conformed or reduced to a norm or standard to convert them in to a positive normalized value within range [0, 1]. The normalized value of an element, r_{ij}, can be calculated as follows:

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

Weighted normalized value of r_{ij}, v_{ij}, can be obtained by:

$$v_{ij} = w_j r_{ij}, \quad j = 1, \dots, m; \quad i = 1, \dots, n$$

In the next step, a set of weights is defined to produce weighted normalized decision matrix **V**, keeping a constraint $\Sigma w_i = 1$ for the weights.

$$\mathbf{V} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1m} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2m} \\ . & & & . \\ . & & & . \\ w_1 r_{n1} & w_2 r_{n2} & \dots & w_n x_{nm} \end{bmatrix}$$

The ideal solution or alternative can be hypothetically defined and in case of presence of an alternative identical to the defined hypothetical alternative, decision is easily made. However, presence of an alternative exactly identical to the ideal solution is rarely occurred. On the contrary, the anti-ideal alternative is also a hypothetical alternative in which all attribute values correspond to the worst level. However the ideal alternative, A^+, and the anti-ideal alternative, A^-, can be denoted as follows:

$$A^+ = \left\{ \left(\underset{i}{max}\, v_{ij} \,|\, j \in J \right), \left(\underset{i}{min}\, v_{ij} \,|\, j \in J' \right) \middle| i \in n \right\} = \left[v_1^+, v_2^+, \dots, v_m^+ \right]$$

and

$$A^{-}=\left\{\left(\min_{i} v_{ij} \mid j\in J\right),\left(\max_{i} v_{ij} \mid j\in J'\right) \middle| i\in n\right\}=\left[v_1^{-},v_2^{-},\ldots,v_m^{-}\right]$$

where J and J' are the attribute sets of the larger-the better type (such as benefit) and the smaller-the better type (such as cost), respectively.

To recognize the distance of each solution from the ideal solution, d_i^+, and negative ideal solution can be calculated by Euclidean method, as follows:

$$d_i^{+}=\left[\sum_{j=1}^{m}\left(v_{ij}-v_j^{+}\right)^2\right]^{1/2}, \qquad i=1,2,\ldots,n$$

$$d_i^{-}=\left[\sum_{j=1}^{m}\left(v_{ij}-v_j^{-}\right)^2\right]^{1/2}, \qquad i=1,2,\ldots,n$$

Finally, to select the best solution relative closeness (Ci) to the ideal solution has to be determined for all the alternatives. The best alternative is the one that has the greatest relative closeness. The relative closeness is determined as below:

$$C_i=\frac{d_i^{-}}{d_i^{+}+d_i^{-}}, \qquad i=1,2,\ldots,n$$

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

In the last step, all of the alternatives are listed according to their calculated relative closeness. Tong and Su 1997; Parkan and Wu 1999

Case study

The Chadormalu iron mine is situated 180 km northeast of Yazd province, Iran, between 30.55 longitudes and 17.32 latitudes. In the blasting operation of ore faces blastholes of 250 mm diameter are drilled in a staggered pattern. ANFO is used as the main explosive whereas pentolite is used for priming and detonating cord for initiating. Also drill cuts are used as stemming materials. Figure 1 shows a view of blasting operation in the mine. The other blasting design parameters of the mine are listed in Table 1.

TABLE 1

Blasting parameters of the Chadormalu iron ore mine

Parameter	Value
Burden	5-7 (m)
Spacing	6-8 (m)
Stemming	5-6 (m)
Bench height	15 (m)

Fig. 1. A view of blasting operation in the Chadormalu mine

Input and output parameters for DEA model

In this study, a database of blasting patterns of Chadormalu iron mine including 78 different patterns has been collected and implemented in the DEA model.

- **Input parameters**

Considering blast design parameters indexes specific charge (CE), the quantity of explosive necessary for fragmenting 1 m^3 or 1 ton of rock, and specific drilling (Sd), the drilled hole volume or drilled hole length drilled per volume unit of rock, were calculated for all of the blasting rounds. Table 2 shows details of the calculated indexes.

TABLE 2

Details of the calculated indexes

Index	Minimum	Maximum	Average
specific charge (Kg/m^3)	0.56	1.27	0.87
specific drilling (m/m^3)	0.018	0.038	0.03

- **Output parameters**

The blasting effects of fragmentation, ground vibration, flyrock and airblast were estimated using relevant empirical methods. Details of calculation of each parameter are given in the following:

– Fragmentation

Estimating rock fragmentation can be performed using Kuz-Ram model, Bond-Ram model, EBT model and Kuznetsov-Cunningham-Ouchterlony (KCO) model (Latham et al., 2006). Since the Kuz-Ram model is widely adopted, it is preferred to be used for fragmentation estimation. This model is a combination of Kuznetsov and Rosin-Rammler. Mean fragment size (X_m) is calculated using kuznetsov equation (Eq. 4) and and fragmentation distribution (R) is calculated using Rosin-Rammler equation (Eq. 5):

$$X_m = A(K^{-0.8})Q_e^{1/6}\left(\frac{115}{S_{ANFO}}\right)^{19/30} \tag{4}$$

where X_m = mean fragment size (cm), A = rock factor (8-12), K = specific charge (kg of explosives/m^3 of rock), Q_e = mass of explosive being used (kg), S_{ANFO} = relative weight strength of the explosive relative to ANFO (ANFO = 100).

$$R = e^{-(X/Xc)^n} \tag{5}$$

where X = screen size (cm), X_c = characteristic size (cm), e = base of natural logarithms (2/7183), n = index of uniformity (0.8-1.5).

Since the Kuznetsov formula gives the screen size X_m for which 50% of the material would pass, substituting $X = X_m$ and $R = 0.5$ into Eq. (6) one finds that:

$$X_c = \frac{X_m}{(0.693)^{1/n}} \tag{6}$$

The exponent n for the Rosin-Rammler equation is estimated as follows:

$$n = (2.2 - 14\frac{B}{D})[\frac{1 + S/B}{2}]^{0.5}(1 - \frac{W}{B})(\frac{L}{H}) \tag{7}$$

where B is the blasting burden (m), S the blasthole spacing (m), D the blasthole diameter (mm), W the standard deviation of drilling accuracy (m), L the total charge length (m), and H the bench height (m).

– Ground vibration

Scaled distance equation widely suggested for cylindrical charges was used for prediction of peak particle velocity (Kahriman, 2004; Erarslan et al., 2008). The general form of this equation is given below:

$$SD = R / W_d^{0.5} \tag{8}$$

where SD = scaled distance; R = distance between the shot and the station (m); W_d = maximum charge per delay (kg).

– Air blast

Airblast overpressure for confined blasthole was estimated using the following equation:

$$P = 3.3\left(\frac{D}{w^{\frac{1}{3}}}\right)^{-\frac{1}{2}} \tag{9}$$

where P = pressure (Kpa), w = mass of explosive (Kg), D = distance from the explosive (m).

– Flyrock

Lundborg empirical model was used for predicting flyrock. This model is applicable for hard rock blasting (Lopez et al., 1995). According to the Lundborg model, the maximum throw (L) is a function of hole diameter (d) and specific charge (q) and is given as below:

$$L = 143d\,(q - 0.2) \tag{10}$$

where d = hole diameter (ins), q = specific charge (Kg/m^3), L = maximum throw (m).

Selection of the most efficient blast pattern

In this study, in the first step the most efficient blasting patterns were recognized with the help of DEA model and in the second step, the best pattern was selected using TOPSIS technique.

Recognizing the most efficient blast patterns using DEA

DEA-BCC output oriented model has been applied to recognize the most efficient blast patterns in the collected database. For this, considering the relevant inputs and outputs, the most efficient blast patterns were determined using software DEA solver (Table 3). It should be mentioned that the unwanted environmental related outputs which have intrinsically minus values must be converted to a positive value by deducting from a constant number, greater than the maximum recorded value. For example if the maximum value for flyrock is 1435 then all the flyrock values should be deducted from 1500. After running the software, the patterns with efficiency 1 were considered efficient and the rest of the patterns with efficiency less than 1 were considered inefficient. As it is seen in the Table 3, fourteen patterns were recognized as efficient.

After contracting the search space by DEA, to include expert's experiences TOPSIS was utilized for selecting the best alternative.

TABLE 3

Efficient blast patterns recognized by DEA Solver

Pattern	Specific charge (m/m^3)	Specific Drilling (Kg/m^3)	X_{mean} (cm)	(100 – R) %	Scale distance	Air Blast (Kp)	Fly rock (m)	Efficiency
A	0.58	0.018	47.6	25.7	93	0.0078	537	1
B	0.70	0.021	41.2	30.7	86	0.0084	699	1
C	0.56	0.018	49.3	25.3	96	0.0077	503	1
D	1.22	0.038	26.0	48.2	91	0.0080	1435	1
E	1.15	0.034	27.9	44.6	92	0.0079	1335	1
F	0.91	0.029	30.9	41.6	102	0.0073	1007	1
G	0.73	0.029	34.3	41.1	124	0.0062	750	1
H	0.93	0.028	30.9	42.0	95	0.0077	1028	1
I	1.19	0.037	26.5	47.3	91	0.0080	1404	1
J	0.73	0.024	36.9	36.8	96	0.0077	742	1
K	0.90	0.029	30.6	41.2	97	0.0076	988	1
L	1.27	0.038	26.0	48.1	84	0.0085	1055	1
M	0.83	0.024	36.7	33.6	81	0.0088	890	1
N	0.92	0.026	33.8	35.9	84	0.0085	1017	1

Selection of the best pattern using TOPSIS

The DEA outputs were considered as inputs for TOPSIS by which the decision matrix was constructed. Here, there are fourteen alternatives and seven attributes. Using expert's experience a weight was assigned to each of the attributes, the more important the attribute, the bigger is the assigned weight. To do so, local priority for each pair of attributes was separately determined by experts. Then, using Eigen vector method, a part or branch of analytic hierarchy process (AHP) was applied to determine the final weights, Table (4).

TABLE 4

Weights of criteria

Criteria	**Specific charge**	**Specific drilling**	**Fragment size**	**Fragmentation distribution**	**Scaled distance**	**Airblast**	**Flyrock**
Weight	25.5%	21.8%	24.6%	6.6%	9.1%	6.2%	6.2%

Considering the obtained weights, the decision process was set to run in the Microsoft Excel software environment. The ranked alternatives are shown in the Table 5. As it is seen from this Table, patterns J, G and B are getting the highest ranking therefore are selected as the most appropriate patterns for blasting operations in the Chadormalu iron mine.

TABLE 5

Final ranking of patterns by TOPSIS

Ranking	**Pattern**	**B×S** (m×m)	**Stemming** (m)	**Specific charge** (m/m^3)	**Specific Drilling** (Kg/m^3)	$\mathbf{X_{mean}}$ (cm)	**(100 – R)** %	**Scaled distance**	**Air blast** (Kp)	**Fly rock** (m)
J	1220	7×8	6	0.73	0.024	36.9	36.8	96	0.0077	742
G	1248	7×8	6	0.73	0.029	34.3	41.1	124	0.0062	750
B	1304	7×8	6	0.70	0.021	41.2	30.7	86	0.0084	699
A	1328	6×7	6	0.58	0.018	47.6	25.7	93	0.0078	537
C	1302	7×8	6	0.56	0.018	49.3	25.3	96	0.0077	503
M	1190	6×7	6	0.83	0.024	36.7	33.6	81	0.0088	890
K	1204	6×7	6	0.90	0.029	30.6	41.2	97	0.0076	988
F	1258	6×7	5	0.91	0.029	30.9	41.6	102	0.0073	1007
H	1227	6×7	5	0.93	0.028	30.9	42	95	0.0077	1028
N	1298	6×7	5	0.92	0.026	33.8	35.9	84	0.0085	1017
E	1287	5×6	5	1.15	0.034	27.9	44.6	92	0.0079	1335
I	1224	5×6	6	1.19	0.037	26.5	47.3	91	0.0080	1404
D	1300	5×6	6	1.22	0.038	26.0	48.2	91	0.0080	1435
L	1192	5×6	6	1.27	0.038	26.0	48.1	84	0.0085	1055

Conclusion

Combination of TOPSIS and DEA can efficiently be utilized for blasting pattern ranking and selection. In this paper, 78 blasting patterns operated in the Chadomalu iron mine were assessed to recognize the patterns satisfying (providing) required fragmentation and minimizing operation unwanted phenomena such as flyrock and airblast. In this regard, in the first step, using DEA method fourteen efficient patterns of various categories were recognized and in the second step, the identified efficient patterns were ranked by TOPSIS so as to reach a more realistic outcome by incorporating the experts' experience in the selection process. According to the obtained results, the patterns J, G and B with the highest ranting score were selected as the most appropriate patterns for blasting operations in the Chadormalu iron mine.

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