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PREDICTING AND MINIMIZING THE BLASTING COST IN LIMESTONE MINES USING A COMBINATION OF GENE EXPRESSION PROGRAMMING AND PARTICLE SWARM OPTIMIZATION

Blasting cost prediction and optimization is of great importance and significance to achieve optimal fragmentation through controlling the adverse consequences of the blasting process. By gathering explosive data from six limestone mines in Iran, the present study aimed to develop a model to predict blasting cost, by gene expression programming method. The model presented a higher correlation coefficient (0.933) and a lower root mean square error (1088) comparing to the linear and nonlinear multivariate regression models. Based on the sensitivity analysis, spacing and ANFO value had the most and least impact on blasting cost, respectively. In addition to achieving blasting cost equation, the constraints such as fragmentation, fly rock, and back break were considered and analyzed by the gene expression programming method for blasting cost optimization. The results showed that the ANFO value was 9634 kg, hole diameter 76 mm, hole number 398, hole length 8.8 m, burden 2.8 m, spacing 3.4 m, hardness 3 Mhos, and uniaxial compressive strength 530 kg/cm^2 as the blast design parameters, and blasting cost was obtained as 6072 Rials/ton, by taking into account all the constraints. Compared to the lowest blasting cost among the 146-research data (7157 Rials/ton), this cost led to a 15.2% reduction in the blasting cost and optimal control of the adverse consequences of the blasting process.

Keywords: Blasting cost, Limestone mines, Gene expression programming, Non-linear multivariate regression, Particle swarm optimization algorithm, Environmental impacts

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1. Introduction

Optimal fragmentation and displacement of crushed rocks are the initial purposes of the blasting process. It has been reported that only 20 to 30% of the total energy from explosion is spent on fragmentation and rock displacement while the remaining energy is wasted as the environmental destructive phenomena such as ground vibration, air blast, fly rock, and back break (Singh & Singh, 2005). Calculation of blasting cost (BC) is meaningless and unreasonable without considering the adverse consequences of the blasting process. The impact of blasting on the cost of minerals extraction has necessitated providing a model to predict BC. Therefore, calculating the optimal cost of a blasting process is regarded as a fundamental problem in the mining industry in order to achieve optimal fragmentation by observing the blasting constraints.

In the following, the most important studies conducted by researchers regarding BC and related issues are reviewed. In an article entitled „Optimum Blasting? The minimum cost or maximum value per ton of broken rock", Kanchibotla (2003) studied maximum profitability, costs, and optimum blasting in a gold mine and an open-pit coal mine by computer simulation models and field studies. Rajpot (2009) surveyed the effects of fragmentation characteristics on BC and presented a model for examining the impact of hole diameter on the blasting requirements in order to achieve the d_{80} fragmentation and calculate the blasting design parameters for a grain size of 75-350 mm. Through optimizing the blasting process and using the Kuz-Ram model, Afum & Temeng (2015) studied reducing the cost of drilling and blasting operations in an open-pit gold mine in Ghana in three pits, and finally, obtained the moderate fragmentation of 25 to 56 cm. Adebayo & Mutandwa (2015) addressed the relationship between the blasting hole diversion and the size of the rocks and the fragmentation cost. They used the ANFO, heavy ANFO, and emulsion in holes with a diameter of 191 to 311 mm. The results indicated that an increase in the hole deviation decreases the average size of the rocks, resulting in increasing the cost of drilling and blasting processes. By collecting the data from three copper mines in Iran as a function of the hole diameter, bench height, uniaxial compressive strength, and joint set direction, Ghanizadeh Zarghami et al. (2018) calculated BC in m^3 as a linear model using the Comfar software and statistical methods. Bakhshandeh Amnieh et al. (2019) proposed a mathematical model for estimation of BC at the gypsum mine of Baghak. The used input variables were burden, spacing, hole diameter, stemming length, charge density and charge weight. Finally, the nonlinear model was optimized considering the constraints by the simulated annealing.

During the last few decades, Artificial Intelligence (AI) methods such as Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Support Vector Machine (SVM), and Neuro-fuzzy Inference System (ANFIS) have been widely used in earth sciences to predict target parameters. These methods have significant features comparing to the traditional methods (Singh & Verma, 2010; Sharma et al., 2017). Although these intelligent techniques are considered as powerful methods in predicting parameters, they do not provide mathematical equations for engineering operations (Faradonbeh et al., 2016c). Gene Expression Programming (GEP) is able to solve non-linear engineering problems by suggesting a formula to predict a specific output using the related inputs of its model. In a study in Malaysia, Faradonbeh et al. (2016a) used 76 blast data of three granite mines and the GEP model to predict the flyrock caused by the blast. They employed the firefly algorithm to minimize the flyrock. Again in Malaysia, Hasanipanah et al. (2016a) applied 76 blast data of three granite mines to predict flyrock using particle swarm optimization (PSO) and linear multivariate regression (LMR). The proposed PSO equation was more reliable using several statistical functions. Faradonbeh et al. (2016b), with the help of GEP model, attempted to predict ground vibration caused by 102 blasting of a granite mine in Malaysia. They concluded that GEP has a higher R^2 than the nonlinear multiple regression (NLMR) model. Faradonbeh et al. (2016d) used genetic programming (GP) and GEP models to evaluate the flyrock caused by 97 stages of a blast in Delkan iron ore mine in Iran. The input data were burden, spacing, stemming, hole depth, and powder factor. It was finally revealed that GEP outperformed the other models. In the Pahang-Selangor water transfer tunnel in Malaysia, Armaghani et al. (2017a) employed GEP to evaluate the penetration rate of the tunnel boring machine (TBM) and compared the obtained results with those of the LMR model. The results indicated that GEP equation can be introduced as a new equation in predicting TBM performance. In a comprehensive review, Hajihassani et al. (2017) examined the application of PSO in geotechnical engineering (slope stability analysis, soil and rock mechanics, tunneling, etc.). They concluded that PSO has been used more in geotechnical engineering than in other fields of civil engineering due to the uncertainty and complexity of issues.

The above studies have been, generally, conducted on calculating the drilling cost, evaluating the relationship between BC and the cost of carrying minerals, considering the impact of fragmentation on BC, reducing drilling and BCs, and presenting the BC model in a particular mine and adverse effects of the blast. By reviewing the previous research, it is necessary to provide a model for predicting and optimizing BC in limestone mines. In the present study, GEP was used to predict BC in limestone mines and the results were compared with the actual data collected from six limestone mines in Iran, as well as LMR and NLMR. Finally, the ratio of spacing to burden ($S \geq B$), the relation of hole length and burden ($H = (3-4) \times$ B), BC, and optimal design parameters were obtained using PSO algorithm and applying the constraint functions of fragmentation, fly rock, and back break.

2. Methodology

2.1. GEP method

This method is a combination of the two methods of genetic algorithm (GA) and GP (Ferreira, 2001). In this method, linear and simple chromosomes with constant length are combined similar to GAs and branch structures with different size and shape are integrated similar to parse trees in GP, which are known as an expression tree (ET) in GEP (Steeb, 2014).

In this method, various phenomena are modeled using a set of functions and terminals. The set of functions usually contain the main Arithmetic functions $\{+,-,\times,/\}$, trigonometric functions, mathematical functions $\{\sqrt{}, x_2, \exp, \log, \sin, \cos, ...\}$, or functions defined by the user, who believes they can be suitable to change the model. On the other hand, the set of terminals are composed of constant values and independent variables of the problem (Ferreira, 2001; Khandelwal et al., 2016).

In GEP algorithm, the genes consist of two head and tail components; the former can contain functions and terminals while the latter can only contain terminals. The codes related to each gene result in the formation of a sub-expression tree (sub-ET). The sub-ETs interact together to form a larger and more complex ET. They are linked together by a function called linking function in order to form this complex structure. Addition (+), subtraction (–), multiplication (×), and division (/) are the most pronounced linking functions in this regard (Ferreira, 2001; Ferreira, 2006). As for GEP algorithm, the operators of mutation, inversion, transposition and insertion sequence elements, and recombination are applied on the chromosomes, respectively (Ferreira, 2001; Ferreira, 2006; Brownlee, 2011; Steeb, 2014).

2.2. PSO algorithm

PSO algorithm, invented in 1995 by James Kennedy (a social psychologist) and Russell C. Eberhart (an electrical engineer) is regarded as one of the meta-heuristic algorithms inspired by the principles governing the behavior of social species in nature, such as the group of birds and fishes (Kennedy et al., 2001; Tian et al., 2019). In the PSO algorithm, there are a number of particles distributed in the search space. Each particle calculates the objective function value in its location in the space. Ultimately, the particle chooses a direction for movement using the combination of the current location information, the best previous location contained in the space, and the information of one or more particles of the best available particles. After a collective movement, one step of the algorithm ends, and this trend is repeated several times until reaching the desired result (Kennedy et al., 2001; Tian et al., 2019).

3. Database

In the present study, the data of six limestone mines in Iran were collected to analyze the prediction results and validate the GEP method and the PSO meta-heuristic algorithm. Table 1 presents the geographic coordinates and specifications of these mines. The BC data of six limestone mines related to the period of 2011-2018 were collected to obtain real data. Then they were updated based on the price of explosives and costs in January 2019, which eventually became the basis for the research. According to the available data, the cost of purchasing explosives was 62.9%, the total cost of transport, escort, personnel, consumption monitoring, and container was 16.8%, the salary of blasting company was 8.5%, and the cost of secondary fragmentation and adverse effects of blasting was 11.8% of the total cost of each blasting. Table 2 reports the input and outputs parameters, as well as their constraints and statistical data, which have been recorded and collected in these case studies.

The outlier data were identified and eliminated from the collected data so that the number of data reached 146 patterns. The Laser distance meter and the Total Station surveying camera were used for measuring back break and fly rock, respectively, and the image analysis was done for rock fragmentation measurement using the Split Desktop V.5 software.

TABLE 1

Geographical coordinates and specifications of the studied limestone mines
(*Source:* http://ime.org.ir)

Row	Name of mine	Proven reserve (ton)	Annual extraction capacity (ton)	Geographical coordinates (WGS 84)		
				Nearest city	Latitude	Longitude
1	Abelou	89340000	4000000	Neka	36° 38’ 5“	53° 21’ 3“
2	Tajareh	4300000	150000	Khorramabad	33° 30’ 5“	48° 29’ 44“
3	Moslem Abad	7000000	300000	Hamedan	34° 39’ 37“	48° 54’ 22“
4	Tang Fani	900000	100000	Pol Dokhtar	33° 1’ 24“	47° 46’ 43“
5	Sepahan Mobarakeh	13500000	600000	Esfahan	32° 26’ 28.37“	51° 28’ 4.63“
6	Barkhordar1	1600000	160000	Nurabad	34° 3’ 8“	48° 12’ 53“

TABLE 2

Input and outputs parameters and their constraints and statistical data

Parameter type		Unit	Symbol	Max	Min	Mean	Standard Deviation
Input	ANFO	Kg	AN	12400	1020	8551.3	2598.5
	Number of electric detonators	—	Det	650	45	348	122.4
	Emolite	Kg	EM	600	40	295.4	115.4
	Hole number	—	N	553	29	271.5	136.6
	Hole length	m	H	20.5	4	9.5	3.2
	Hole diameter	mm	D	100	76	83	8.2
	Burden	m	B	3.5	1.7	2.36	0.53
	Spacing	m	S	4	1.9	2.8	0.61
	Stemming	m	T	3.6	0.85	1.83	0.53
	Sub-drilling	m	J	1.5	0.2	0.82	0.42
	Specific gravity	ton/m^3	Yr	2.7	2.6	2.66	0.04
	Rock hardness	Mhos	HA	3.5	3	3.27	0.16
	Uniaxial compressive strength	Kg/cm^2	σ_c	671	530	600.6	49.9
Constraints	Fragmentation	cm	Fr	47	20	36	7.94
	Fly rock	m	Fl	140	60	97	19.2
	Back break	m	BB	6	1	3.4	1.4
Output	Blast cost	Rials/ton	BC	23481	7157	13468	3995

4. BC prediction

4.1. Modeling with GEP

In the first stage, for the performance measurement of BC prediction equation based on the gathering data, the correlation between the input variables was measured by the Pearson's correlation coefficient (Table 3). Considering the 146 blastings recorded in the six limestone mines, 80% of the data were used for modeling and 20% were applied randomly to test the model. This section aims to find a function in the form of $BC = f(AN, Det, EM, H, N, D, B, S, T, J, Yr, HA, \sigma c)$ to predict BC, in which $AN, Det, EM, H, N, D, B, S, T, J, Yr, HA$ and σc represent independent (inputs) variables and BC indicates the dependent variable (Steeb, 2014).

Given that the input and output parameters have different units and range of variations, data should be normalized in intelligent methods before any modeling; this increases the speed, decreases the error of modeling, and prevents over-fitting phenomenon. In this research, the data were normalized by Equation 1 at interval (0-1):

$$X_{\text{norm}} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Where, X_i represents the initial data, $X_{\min}$ indicates the minimum variable value, $X_{\max}$ shows the maximum variable value, and X_{norm} is the normalized value.

TABLE 3

Pearson's correlation coefficients matrix for input parameters

Varia-bles	AN	Det	EM	N	H	D	B	S	T	J	Yr	HA	σc
AN	1	0.554	0.567	0.34	0.295	0.206	–0.194	–0.254	–0.037	–0.031	0.424	0.376	0.194
Det	0.554	1	0.759	0.845	–0.394	–0.473	–0.59	–0.598	–0.559	–0.35	0.423	0.581	0.494
EM	0.567	0.759	1	0.699	–0.241	– 0.34	–0.518	–0.526	–0.431	–0.105	0.704	0.785	0.723
N	0.34	0.845	0.699	1	0.703	–0.681	–0.724	–0.711	–0.765	–0.542	0.294	0.579	0.51
H	0.295	–0.394	–0.241	0.703	1	0.675	0.569	0.535	0.757	0.579	0.061	–0.254	–0.27
D	0.206	–0.473	– 0.34	–0.681	0.675	1	0.631	0.514	0.647	0.47	–0.014	–0.249	–0.319
B	–0.194	– 0.59	–0.518	–0.724	0.569	0.631	1	0.964	0.802	0.747	–0.197	–0.544	–0.384
S	–0.254	–0.598	–0.526	–0.711	0.535	0.514	0.964	1	0.787	0.745	–0.217	–0.574	–0.391
T	–0.037	–0.559	–0.431	–0.765	0.757	0.647	0.802	0.787	1	0.769	–0.074	–0.47	–0.377
J	–0.031	– 0.35	–0.105	–0.542	0.579	0.47	0.747	0.745	0.769	1	0.398	0.07	0.114
Yr	0.424	0.423	0.704	0.294	0.061	–0.014	–0.197	–0.217	–0.074	0.398	1	0.842	0.848
HA	0.376	0.581	0.785	0.579	–0.254	–0.249	–0.544	–0.574	–0.47	–0.07	0.842	1	0.945
σc	0.194	0.494	0.723	0.51	– 0.27	–0.319	–0.384	–0.391	–0.377	0.114	0.848	0.945	1

The modeling process can be expressed using the GEP algorithm in the following five steps (Faradonbeh & Monjezi, 2017; Faradonbeh et al., 2016b):

A) Step 1: The cost function is determined to evaluate the fitness of the generated chromosomes (problem responses). For this purpose, RMSE function is used as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - T_i\right)^2} \tag{2}$$

Where, O_i depicts the i-th real value, T_i demonstrates the i-the predicted value, and n is the number of data series.

B) Step 2: The terminals (problem inputs) and functions are determined to generate the GEP chromosomes. In the present study, the terminals have 13 input parameters, as presented in Table 2. By studying the structure of experimental relations and examining the correlation relationship between the inputs and outputs, the following important functions were selected:

$$\text{Functions set} = \left\{+, -, \times, \div, sqrt, Inv, {}^\wedge 2, {}^\wedge 3, {}^\wedge 4, 3Rt, 4Rt, \cos, \text{tg}, Not\right\} \tag{3}$$

Where, $3Rt$ and $4Rt$ are the cube and fourth roots of the variable, respectively.

C) Step 3: The structure of the chromosomes should be determined at this stage. The structure of each chromosome depends on the size of the head and the number of genes (sub-ETs). In general, an increase in the number of genes and chromosomes improves the performance of the GEP model to a certain extent. However, the increase of the number of genes beyond the optimal number raises the complexity of modeling and the possibility of the occurrence of over-fitting phenomenon. In this study, the number of genes and head sizes were considered 4 and 10, respectively to obtain BC function, and 3 and 8 to derive the functions of fragmentation, fly rock, and back break (Faradonbeh & Monjezi, 2017).

D) Step 4: Genetic operators and their rates are determined at this step. In the present study, all genetic operators were considered according to Ferreira's suggestion and other researchers (Ferreira, 2001; Teodorescu & Sherwood, 2008; Güllü, 2012; Keshavarz & Mehramiri, 2015). To determine the operators' rate, Ferreira proposed values, which are suitable for most engineering issues (Ferreira, 2001; Ferreira, 2006). The research has shown that the values proposed by Ferreira are suitable for the present study. Table 4 presents the rate of genetic operators for BC, and fragmentation limitations, fly rock, and back break.

TABLE 4

Genetic operators' rate of BC function and limitations

Type of setting	**Parameter**	**Value**			
		BC	**Fr**	**FL**	**BB**
Basic settings	Fitness function	RMSE	RMSE	RMSE	RMSE
	Number of chromosomes	30	30	30	30
	Number of generations	9000	9000	9000	9000
	Head size	10	8	8	8
	Number of genes	4	3	3	3
	Linking function	Addition	Addition	Addition	Addition
Genetic operators	Mutation rate	0.00138	0.00138	0.00138	0.00138
	Inversion rate	0.00546	0.00546	0.00546	0.00546
	IS transposition rate	0.00546	0.00546	0.00546	0.00546
	RIS transposition rate	0.00546	0.00546	0.00546	0.00546
	Gene transposition rate	0.00277	0.00277	0.00277	0.00277
	One-point recombination rate	0.00277	0.00277	0.00277	0.00277
	Two-point recombination rate	0.00277	0.00277	0.00277	0.00277
	Gene recombination rate	0.00277	0.00277	0.00277	0.00277

E) Step 5: A linking function is required to connect the genes. The four basic functions of addition, multiplication, subtraction, and division are the most common linking functions in this regard. In the present research, the addition function was used for better performance. In BC function, the superior chromosome has four genes, and each gene represents a sub-ET (see Fig. 1). The connection of these four sub-ETs by the addition function forms a large tree. Equations related to each gene can be extracted as Equations 4-7. Finally, GEP equation for BC prediction can be expressed as Equation 8:

$$Sub-ET_1 : H'\times\left(1-\left(N'\times\cos\left(HA'\times\sigma c'-B'\times\sigma c'\right)\right)\right) \tag{4}$$

$$Sub-ET_2 : 0.154\times\left(\frac{D'^{\left(\frac{1}{3}\right)}}{\left(D'-O.154\right)}\times\left(D'-H'\right)+1-N'\right) \tag{5}$$

$$Sub-ET_3 : \left(S'\times\cos\left(\cos\left(\left(D'-B'\right)^3+\cos\left(AN'+B'\right)\right)\right)\right)^3 \tag{6}$$

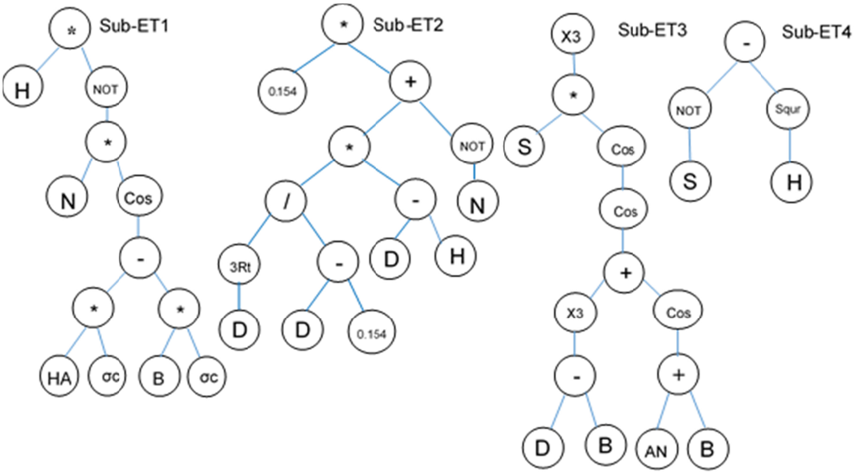

Fig. 1. The tree structure related to each gene in the GEP model for predicting BC

$$Sub - ET_4 : 1 - S' - H'^{0.5} \tag{7}$$

$$BC = \left(\left(Sub - ET_1 \right) + \left(Sub - ET_2 \right) + \left(Sub - ET_3 \right) + \left(Sub - ET_4 \right) \right) \times 16324 + 7157 \tag{8}$$

In addition, using the GeneXproTools software and following the above steps, Equations 9-11 were used to obtain fragmentation, fly rock, and back break, respectively:

$$Fr = \left(\begin{array}{l} -3.06 \times \dfrac{D'}{\left(\mathrm{tg}\left(\cos\left(AN' \right) \right) - 9.24 \right)} + \\ \left(0.5 \times \dfrac{H'^3}{\left(H' + \sigma c' \right)} \right)^{\frac{1}{4}} + \left(B' \times \left(HA'^4 + B' \right)^4 \right)^{\frac{1}{2}} \times N' \end{array} \right) \times 27 + 20 \tag{9}$$

$$FL = \left(\begin{array}{l} \left(\cos\left(\left(\mathrm{H}' + \sigma c' + H'^2 \right)^{\frac{1}{4}} \right) \right)^3 + \\ \left(\cos\left(\cos\left(\sigma c'^2 \times \cos\left(-2.86 \right) + \sigma c' \times S' \right) \right) \right)^3 + \\ AN' \times B' \times \left(\cos\left(\sigma c' + S' \right) - 1 + AN' \right) \end{array} \right) \times 80 + 60 \tag{10}$$

$$BB = \left(AN' - \sigma c' + \frac{B' - \left(N' \times H' \right)}{2.78} \times \left(1 - B' + HA' \right) + \sigma c'^6 \right) \times 5 + 1 \tag{11}$$

Regarding the models presented for BC function and constraint functions of fragmentation, fly rock, back break, the values of the decision variables (AN', N', H', D', B', S', HA', and $\sigma c'$) are normal numbers between zero and one, and the outputs represent a natural value by applying the coefficients and the entered integer. In order to simplify the process and to enter natural numbers, the following equations were used instead of decision variables (AN', N', H', D', B', S', HA′, and $\sigma c'$):

$$AN' = \frac{AN - 1020}{11380} \tag{12}$$

$$N' = \frac{N - 29}{524} \tag{13}$$

$$H' = \frac{H - 3.99}{16.38} \tag{14}$$

$$D' = \frac{D - 76}{24} \tag{15}$$

$$S' = \frac{S - 1.9}{2.1} \tag{16}$$

$$HA' = \frac{HA - 3}{0.5} \tag{17}$$

$$B' = \frac{B - 1.7}{1.8} \tag{18}$$

$$\sigma c' = \frac{\sigma c - 530}{14} \tag{19}$$

4.2. Modeling with multivariate regression

Multivariate regression is a statistical method, which is used to find out the relationship between dependent and independent variables, as well as for data analysis in modeling. It allows predicting the dependent variable from the independent variables and their relationship (Jakubowski & Tajduś, 2014; Enayatollahi et al., 2014; Esmaeili et al., 2014; Jakubowski et al., 2017). Given 146 blastings recorded in the studied six limestone mines, 80% of the data were utilized for modeling while the other 20% were randomly used to test the model. Regarding the constraints of fragmentation, fly rock, and back break, LMR models were constructed in the form of Equations 20-23 using the SPSS 24 software and the Forward method to predict BC:

$$BC = 22148.722 - 6624.528S - 0.597AN + 217.96D - 1711.786T \tag{20}$$

$$Fr = -26.776 + 0.529D + 4.901S + 0.001AN \tag{21}$$

$$FL = 85.95 - 41.097T + 12.176S + 0.62D \tag{22}$$

$$BB = -2.912 + 0.000186AN - 2.465T + 0.086D + 0.756S \tag{23}$$

In addition to linear model, polynomial, power, exponential, and logarithmic nonlinear models were also processed with these data. Considering the higher R^2 of logarithmic model comparing to other nonlinear models, this model was used for predicting BC and other constraints as Equations 24-27:

$$BC = \frac{10^{5.648}}{S^{1.627} \times N^{0.28} \times H^{0.176}} \tag{24}$$

$$Fr = 10^{1.089} \times H^{0.313} \times S^{0.362} \tag{25}$$

$$FL = \frac{10^{2.262}}{H^{0.3}} \tag{26}$$

$$BB = \frac{N^{0.23}}{10^{0.056}} \tag{27}$$

5. Comparison of BC prediction models

Comparing the results with each other and with actual data is the basis for evaluating the performance of models in the present study (Majdi &Rezaei, 2013). For this purpose, the statistical indicators of RMSE, decision coefficient (R^2) and variance account for (VAF) were used. In addition, a newly proposed engineering index, namely a10-index, has been used to assess the reliability of the developed models (Hasanipanah et al., 2019; Duan et al., 2020):

$$a10 - index = \frac{m10}{M} \tag{28}$$

Where, M is the number of dataset sample, and $m10$ is the number of samples along with a value of experimental rate value/estimated value between of 0.90 and 1.10. It is worth noting that, for a complete predictive approach, a10-index values were considered to be unity.

Based on the training and test data, the performance evaluation indicators were calculated for the proposed models and the results are presented in Table 5.

TABLE 5

Performance indicators for three models

Model	Training stage				Testing stage			
	R^2	RMSE	VAF (%)	a10-Index	R^2	RMSE	VAF (%)	a10-Index
LMR	0.885	1210	90.58	0.699	0.855	1161	92.02	0.822
NLMR	0.913	1089	98.02	0.931	0.931	1098	91.59	0.759
GEP	0.943	961	94.08	0.896	0.933	1088	93.29	0.793

Figure 2 demonstrates the conformity of the results of LMR and NLMR models and GEP with the actual data. As observed, the degree of conformity of GEP with actual data, and its accuracy are significantly greater than those of LMR and NLMR models.

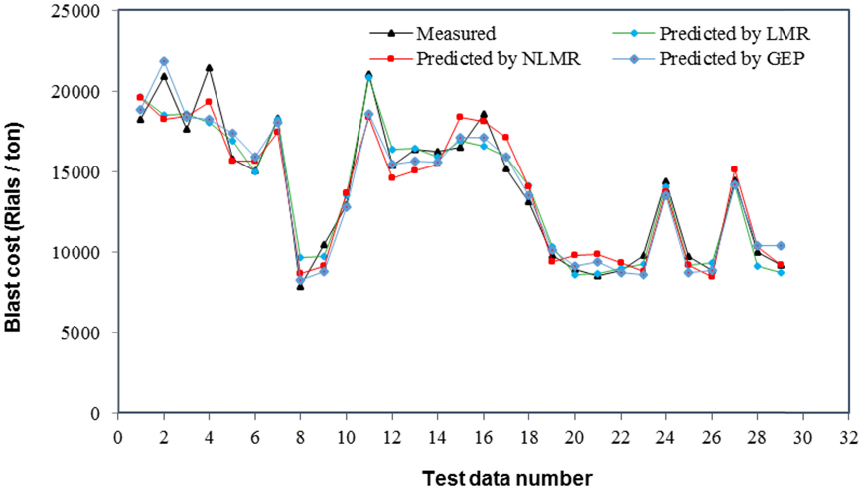

Fig. 2. Comparing the predicted cost of the three models with the actual cost

6. Sensitivity analysis

Using the sensitivity analysis method (relevancy factor (RF) method in this research), the relative effect of input parameters on BC function and the developed GEP model can be determined by actual values and Equation 29 (Sebastian et al., 1985; Saltelli et al., 2008):

$$r(P_k,\mu)=\frac{\sum_{i=1}^{n}\left(P_{k,i}-\bar{P}_k\right)\times\left(\mu_i-\bar{\mu}\right)}{\sqrt{\sum_{i=1}^{n}\left(P_{k,i}-\bar{P}_k\right)^2\times\sum_{i=1}^{n}\left(\mu_i-\bar{\mu}\right)^2}} \tag{29}$$

Where, $P_{k,i}$ represents the i-th value of the k-th input parameter, $\bar{P}_k$ indicates the mean value of the k-th input parameter, μ_i shows the i-th value of the output parameter, $\bar{\mu}$ depicts the mean value of the output parameter, and n is the number of input variables. Figure 3 shows the results of the sensitivity analysis of the GEP model, using Equation 28. As illustrated, the spacing and ANFO values have the greatest and least effect on the objective function (BC), respectively.

7. Optimization with PSO algorithm

The process of PSO algorithm is according to Figure 4. The inertia coefficient and its adjustment rate, personal learning rate, and collective learning rate are considered as the parameters of PSO algorithm. Particle size based on the number of samples used in the study was 146, and there were eight decision variables including ANFO, hole length, hole diameter, number of holes, hardness, uniaxial compressive strength of the rock, burden, and spacing (Shi & Eberhart, 1998; Jiang et al., 2007; Abad et al., 2016; Armaghani et al., 2016; Hasanipanah et al., 2016b; Armaghani et al., 2017b). The optimal result was obtained when all these parameters were selected as shown in Table 6.

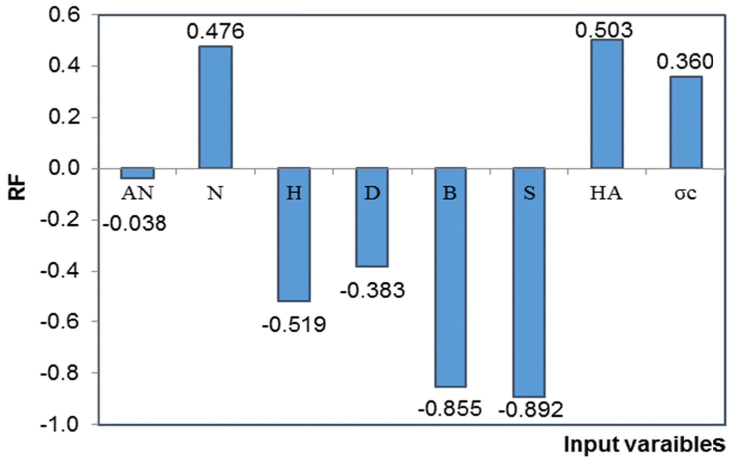

Fig. 3. Sensitivity analysis of BC with respect to input variables

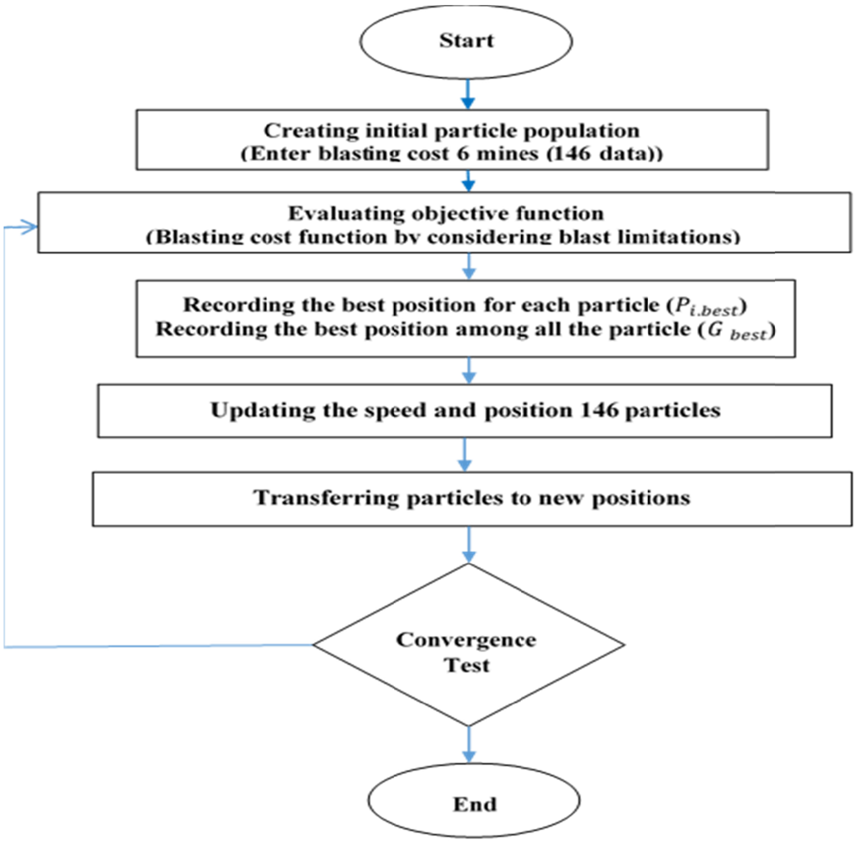

Fig. 4. Optimization process using the PSO algorithm

TABLE 6

Controllable parameters of the PSO algorithm used in this research

Parameter	Symbol	Value
Maximum number of iterations	MaxIt	200
Number of particles	Npop	146
Number of input variables	Nvar	8
Inertia coefficient	W	1
Inertia coefficient adjustment factor	Wdamp	0.99
Personal learning rate	C_1	2
Collective learning rate	C_2	2

The proposed model was run with a number of different iterations including 200, 500, 1000, 2000 and even higher. Based on the obtained results, the value of the target function remained constant after the tenth iteration. Figure 5 denotes the lowest value obtained for BC function from the beginning of the program implementation to the repetition number inserted on the horizontal axis. Table 7 suggests the parameters of the blasting model using the PSO method, in which the best value for BC function is 6072 Rials/ton.

TABLE 7

The parameters of pattern optimization using the PSO algorithm

Type	Parameter	Unit	Optimized value
Suggested pattern	AN	kg	9634
	D	mm	76
	N	–	398
	H	m	8.8
	B	m	2.8
	S	m	3.4
	HA	Mosh	3
	$\sigma c'$	Kg/m²	530
Constraints	Fr	cm	37.8
	FL	m	119.86
	BB	m	5
Blasting cost	BC	Rials/ton	6072

8. Results and Discussion

As shown in Table 5, the R^2 value was obtained as 0.855, 0.931, and 0.933 for the LMR and NLMR and GEP models, Also, according to this table, for the three models, the VAF values were calculated as 92.02, 91.59 and 93.29%, respectively, and the a10-index values as 0.822, 0.759 and 0.792, respectively. The RMSE values for these three models were obtained as 1161, 1098, and 1088, respectively. Comparison of the values obtained for the above statistical indicators shows the superiority of the GEP model over other models. However, during the extraction process in these mines, the average blasting cost, fragmentation, fly rock, and back break were 13468 Rials/ton, 36 cm, 97 m, and 3.4 m, respectively. Among the 146 blast models, this research

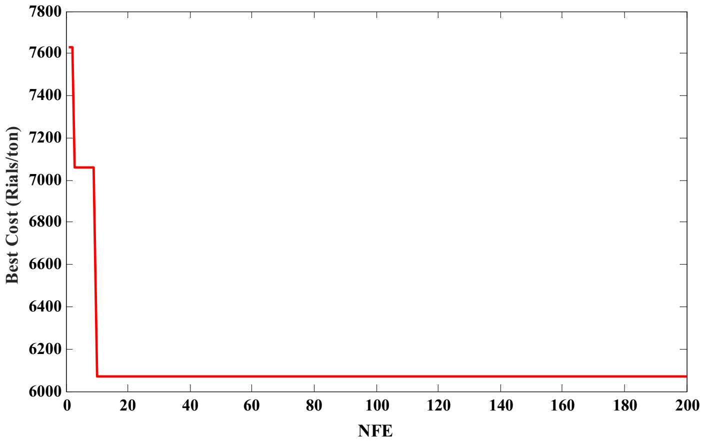

Fig. 5. The lowest value obtained for BC function resulted from GEP after 200 repetitions

has the lowest BC of 7157 Rials/ton with fragmentation 40 cm, fly rock 110 m, and back break 5 m. Table 8 shows comparing the values obtained from the GEP-PSO method with the mean and minimum actual values.

According to Tables 7 and 8 and based on the optimization performed by the PSO algorithm, the pattern suggested by this algorithm indicates a 15.1% reduction in BC from 7157 to 6072 Rials/ton. A 9% increase in fly rock compared to a 5.5% reduction in fragmentation from the blasting, which is regarded as the most important objective of a blasting, is negligible along with a 15.5% reduction in BC. Finally, comparing the results obtained for BB, FL, Fr, and BC in Table 8 shows the satisfactory results of the GEP-PSO model.

TABLE 8

Comparing the values obtained from the GEP-PSO method with the mean and minimum actual values

Model	BC		Fr		FL		BB	
	Value (Rials /ton)	Difference with minimum data (%)	Value (Rials /ton)	Difference with minimum data (%)	Value (Rials /ton)	Difference with minimum data (%)	Value (Rials /ton)	Difference with minimum data (%)
GEP-PSO	6072	–15.2	37.8	–5.5	119.86	9	5	0
Average of data	13468	88.2	36	–10	97	–11.8	3.4	–32
Minimum of data	7157	0	40	0	110	0	5	0

9. Conclusions

Comparing to LMR and NLMR, the GEP model provided higher R^2 (0.933) and VAF (93.29), lower RMSE (1088), and an acceptable a10-index value (0.793). Furthermore, it showed higher compatibility with the actual BC.

According to the sensitivity analysis carried out using the RF method on BC in the GEP model, the spacing and ANFO values had the maximum and minimum effect on the objective function, respectively. A positive correlation was observed between the number of holes, hardness, and uniaxial compressive strength of the rock with BC function, while there was a negative correlation between ANFO, hole length, hole diameter, burden, and spacing.

Comparing the results obtained for BC, fragmentation, fly rock, and back break using the GEP-PSO model and the lowest BC among the 146 research data (7157 Rials/ton), which resulted in a 15.2% reduction in BC and the optimal control of the devastating environmental consequences of blasting, indicated the suitability of this model for BC prediction and optimization.

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