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Prediction of Fly-rock using Gene Expression Programming and Teaching–learning-based Optimization Algorithm

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Abstract

This work attempts to estimate the amount of fly-rock in the Angoran mine in the Zanjan province (Iran) using the gene expression programming (GEP) predictive technique. For this, the input data including the fly-rock, mean depth of the hole, powder factor, stemming, explosive weight, number of holes, and booster is collected from the mine. Then using GEP, a series of intelligent equations are proposed in order to predict the fly-rock distance. The best GEP equation is selected based on some well-established statistical indices in the next stage. The coefficient of determination for the training and testing datasets of the GEP equation are 0.890 and 0.798, respectively. The model obtained from the GEP method is then optimized using the teaching–learning-based optimization (TLBO) algorithm. Based on the results obtained, the correlation coefficient of the training and testing data increase to 91% and 89%, which increase the accuracy of the equation. This new intelligent equation could forecast fly-rock resulting from mine blasting with a high level of accuracy. The capabilities of this intelligent technique could be further extended to the other blasting environmental issues.

1. Introduction

Surface mines are sometimes close to the residential areas due to the population growth and restricted land resource use. For having a green mining strategy, it is significant to consider a safe blasting operation in these mines [1, 2]. The drilling and blasting methods are extensively practiced for fragmentation rocks in surface mining, tunnels, and construction projects [3]. Among all environmental issues of blasting, fly-rock is considered the most hazardous event in surface mining excavated by blasting [4]. Hence, predicting the fly-rock distance plays an outstanding role in controlling and minimizing blasting accidents in surface mines [5]. The previous researchers proposed several experimental methods to predict fly-rock [6]. However, the complexity of the fly-rock analysis causes a low-performance prediction of such practical methods [4]. The inaccuracy of empirical models is mainly caused by different effective and vital parameters and their unknown relationships [7]. In the recent years, the use of new approaches such as artificial intelligence (AI) and machine learning (ML) in solving problems related to blasting environmental issues, e.g. fly-rock is highly recommended [8, 9; 10; 11, 12]. The performance of the AI and ML techniques show that these methods are proper tools to minimize uncertainty in blasting operations [13]. In addition, the use of the AI and ML techniques in solving other issues related to science and engineering has been highlighted in the literature [14, 15, 16, 17, 18, 19; 20; 21; 22; 23; 24; 25; 26; 27, 28, 29; 30, 31; 32; 33, 34; 35, 36, 37, 38, 39].

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Adhikari (1999) has examined the amount of fly-rock from 47 explosions in six limestone mines. After analyzing the results, he provided some suggestions to minimize the risks of fly-rock in limestone mines [40]. Bajpayee *et al*. (2004) have examined several case studies about fatal injuries caused by flyrock during 21 years, from 1978 to 1998. This study concluded that the causes of these injuries are essentially personal and, to some extent, environmental [1]. Kecojevic and Radomsky (2005) have investigated the results of a research study on the fly-rock phenomena and safety-related incidents in the blasting region of surface mining. This study indicated that 45 fatal and 367 non-fatal accidents happened in the coal, metal, and non-metallic surface mines between 1978 and 1998, which was essentially due to the insecurity of the blast region, the fly-rock, an early explosion, and a non-explosive pit [41]. Investigations conducted on fly-rock showed that one or more of the following vital factors affected significantly fly-rock, which are: 1) discontinuities in the geological structure, 2) inappropriate charging, and 3) arrangement of holes, inadequate overburden, excessive density of explosives, and insufficient stemming [41, 42]. Rezaei *et al*. (2011) have developed a fuzzy model to predict fly-rock at the Gol Gohar iron mine. In this respect, a database including 490 datasets of explosion operations was provided and used. The performance of the fuzzy model was compared using the statistical method. It was perceived that the efficiency of the developed fuzzy model was much better than the statistical model [43].

Additionally, the sensitivity analysis revealed that the powder factor and rock density parameters had the most and the most negligible influence on fly-rock distance, respectively. Monjezi *et al*. (2012) have attempted to develop a model based on an artificial neural network (ANN) and genetic algorithm (GA) to predict fly-rock at the Sungun copper mine. The model provided using this method is faster and more accessible than the conventional ANN. The sensitivity analysis revealed that the most influential parameters on fly-rock were powder factor and stemming [44]. Amini *et al*. (2012) have predicted fly-rock at the Songun copper mine by applying another ML model, namely support vector machine (SVM). It was concluded that the SVM method was faster and more precise than the ANN method [45]. Armaghani *et al*. (2014) have proposed a new approach of combining particle swarm optimization (PSO) with ANN to succeed in the PSO-ANN constraints. In this regard, 44 datasets obtained from three granite mining sites in Malaysia were used to create the mentioned model. The results revealed that the proposed method could predict fly-rock caused by blasting with a high accuracy rate. The sensitivity analysis determined that the powder factor and maximum charge per delay were the most efficient parameters in fly-rock [42]. Ghasemi *et al*. (2014) have developed two prediction models, namely ANN and fuzzy logic techniques, to predict fly-rock at the Songun copper mine. The results determined that both models were beneficial and efficient, while the fuzzy model had a better performance than the ANN model in predicting fly-rock. The performance of the models revealed that the developed AI models were a good device to minimize uncertainty in blasting operations [13]. Dehghani and Shafaghi (2017) have predicted the explosion-induced fly-rock by combining the differential evolution (DE) algorithm and the dimensional analysis (DA) algorithm. Accordingly, the parameters of 300 blasting operations were estimated. The results determined the superiority of the proposed DE-DA model compared to the experimental approaches [46]. Hasanipanah *et al*. (2017b) have acted to model to create an accurate and efficient model based on the regression tree (RT) to predict fly-rock caused by explosions in the Ulu Tiram mines (Malaysia). In this respect, 65 blasting operations were examined, and the most effective parameters available on the rock-fly were measured. The results revealed that RT could be introduced as a powerful method to predict fly-rock [47]. Rad *et al*. (2018) have indicated the amount of fly-rock applying the least squares support vector machine (LS-SVM) method. The support vector regression (SVR) method was also used to compare them. A case study was conducted in the Golgohar iron mine to measure the required parameters of 90 explosions to meet the desired goal. According to the results obtained, the LS-SVM method with a correlation coefficient of 0.969 and a mean squared error of 16.25 can be more efficient than the SVR method with a correlation coefficient of 0.945 and mean squared error of 31.58 in estimating the fly-rock caused by blasting [48]. Kumar *et al*. (2018) have proposed a combined PSO-ANN prediction model to predict fly-rock. The developed model results were compared with the imperialist competitive algorithm (ICA)-ANN, BP-ANN methods, experimental equation, and multivariate regression analysis (MRA). The results revealed that the PSO-ANN method gave a more accurate prediction than the other methods [49]. Koopialipoor *et al*. (2018)

have used the ICA, GA, and PSO methods with an ANN to predict the explosion-induced fly-rock. A database consisting of 262 datasets was collected to meet this objective. The results determined that although all predictor models could estimate the fly-rock, the PSO-ANN prediction model performed better than other models [50]. Han *et al*. (2020) have conducted a two-part study on fly-rock prediction. The first part was associated with evaluating and selecting the most effective fly-rock parameters utilizing the random forest technique. Using this technique, they removed the "maximum charge per delay" from the input variables. The second part estimated fly-rock using the Bayesian network technique [51]. it still needs some new model/direction for predicting or minimizing fly-rock, which is one of the most significant issues related to blasting. Shakeri *et al*. (2021) have determined blast ground vibration (BGV) by applying ANNs and LMR [32]. Dehghani *et al*. (2021) have used a combination of TLBO and GEP to predict PPV at the Galali iron mine in Iran. For this purpose, they built a dataset including 13 parameters collected from 34 blasting blocks in the area. After finding the most influential factors using statistical analyses, they applied GEP in order to suggest an empirical relationship. Eventually, the TLBO algorithm was utilized to optimize the suggested relationship [33]. Moomivand (2022) has investigated the influences of blast hole parameters such as burden, blast hole diameter, and stemming, which have been investigated in the previous empirical research work [52]. For this purpose, as an example the fly-rock has been estimated up to 3512 m by Lundborg *et al*. (1975), which is much higher than the real results (Moomivand 2022) that is because there are not some crucial parameters in the Lundborg *et al*. (1975) relation.

In this study, the idea is to propose an empirical relationship for predicting the fly-rock distance, which is essential to determine the blast safety regions. The relationship is suggested with the help of a powerful AI method, namely GEP. The GEP relationship is proposed using the most influential parameters on fly-rock. Then the relationship is optimized using the TLBO algorithm in order to increase the prediction accuracy. Before the blasting operations, the proposed relationship can be utilized to identify the safe area for blasting. The remaining parts of this study are as follows:

The second part is related to some principles of the GEP model and TLBO in predicting issues. Then the third section describes the studied area, database establishment, and modeling procedure of the fly-rock prediction. Section 4 provides some critical discussions of the obtained fly-rock prediction results, and the sensitivity analysis results are presented in Section 5. Eventually, some critical conclusions and limitations will be discussed in the last section.

2. Materials and Methods

In order to provide a mathematical equation, the amount of fly-rock in the Angoran mine was collected using the methods of gene expression algorithm and the teaching and learning-based optimization algorithm of all required parameters. Then 70% of the data was randomly used to construct the model, and 30% of the data for validation. An equation between the parameters and the dependent variable was then developed using the gene expression algorithm. The obtained equations for optimization of prediction accuracy entered the teaching and learning-based optimization algorithm. The steps for conducting the research work are shown in Figure 1.

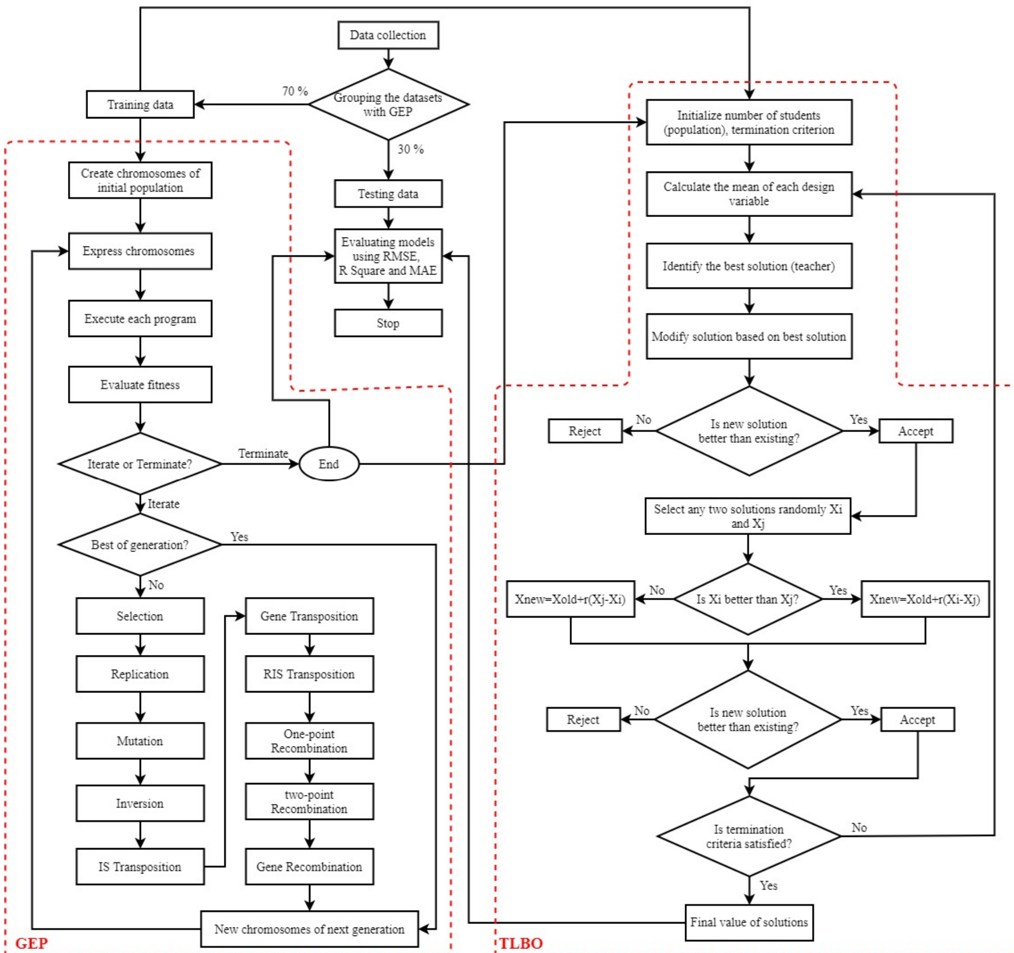


Figure 1. Flowchart of fly-rock prediction.

2.1. GEP

One of the most significant subfields of AI is the evolutionary algorithm (EA). EAs are inspired by biological evolution in order to solve the engineering and science problems [53, 54]. EAs themselves include several different sub-classes that are based on the principles of biological evolution. GA is one of the EA methods, and it is considered as a simple natural evolution. In the computer science, GA is a search method to find approximate solutions for optimization purposes. The search problems are a particular type of EA that utilize the biological evolution techniques such as heritage and mutation to solve the problems. In general, GA uses a genetic technique as a problem-solving model. It tries to find the best solution to the problem by genetically modifying the population of solutions in successive generations [55]. In GA, several individuals will first generate randomly a problem where this set of individuals is called the "initial population". Each individual is regarded as a chromosome. The chromosomes are combined, and mutations are made in them after evaluating the initial population's fitness to organize and reproduce better chromosomes utilizing genetic actuators, and eventually combining the current population with a new population emerging from a combination and mutation in chromosomes [56]. The method is a new regression technique with a high capability for the automatic evolution of programs. Koza (1995) invented genetic programming in the late 1980s after performing experiments on symbolic regression [57].

Ferreira (2001) has developed a new algorithm based on GA and genetic programming, namely gene expression programming (GEP) [58]. It is a new technique to create computer programs based on trained models and genetic programming. GEP is an evolutionary algorithm to defeat many constraints of GA and genetic programming (GP). GEP is a learning algorithm that particularly learns the relationship between variables in a set of data and creates models among these variables in more simplistic terms. One of its strengths is its high speed and ability in complicated modeling; therefore, it can be considered the most robust learning algorithm [59]. GEP is a new and powerful EA algorithm with a high capability to find the function and discover non-linear regression models. The statistical coefficients gained by this method present high productivity and great results. The three methods GA, GP, and GEP belong to the same family, and are different in the individuals' nature. The individuals are symbolic strings of constant size in GA (chromosomes). The individuals in non-linear inputs have different sizes and shapes in GP (parse tree). In GEP, the individuals are still non-linear inputs with different sizes and shapes (expression tree, ET) but complex inputs are encoded as simple strings of constant size. This process starts with the production of a random generation of chromosomes and a certain number of individuals or programs as the initial population. The initial population of models is first created for mathematical modeling, and these chromosomes are then displayed as a decomposition tree, and the fitness of all models is estimated. Based on their value, the programs are selected based on their value to create new generations with new features by modifying and replicating. This process is repeated for many generations until a proper solution is determined [59].

2.2. TLBO algorithm

Introduced by Rao *et al.* in 2011, the TLBO algorithm is among the newest developments in the field of intelligent optimization [60]. An outstanding feature of this algorithm is its independence of the parameters, as it works with the minimum possible number of parameters, making it a unique approach. Inspired by the teaching-learning process in a conventional classroom, this algorithm considers the population of solutions as a group of students in a class and takes the best member of the population as the teacher. The teacher then attempts to train the students to add to their knowledge, with the students further adding to their own knowledge upon training by communicating with one another. This algorithm goes through two stages, namely the teacher and the student stages [60].

3.1. Teacher stage

At this stage, the teacher improves the students' information and knowledge through teaching and training. The following Equation describes this stage:

$$X_{new,i} = X_{old,i} + r(X_i^{best} - T_F\, M_i) \quad (1)$$

where:

r: a random number in the [0, 1] interval;
T_F: teaching factor;
X_i^{best}: the best member of the population at the i^{th} iteration (selected as teacher);
M_i: mean of the class at the i^{th} iteration;
$X_{old,\,i}$: a member that needs to be taught;
$X_{new,\,i}$: a taught member.

$X_{new,\,i}$ would be accepted if it is somehow better than $X_{old,\,i}$ [60].

3.2. Student stage

At this stage, each student exchanges information with another randomly-selected student to enhance his/her own deal of knowledge. For the i^{th} member of the population, a member is selected randomly. Then if $f(X_i) < f(X_j)$, the i^{th} member is taught based on Equation 6, while Equation 7 is applied otherwise. This stage is performed for each and any member of the population.

$$X_{new,i} = X_{old,i} + r(X_i - X_j) \quad (2)$$

$$X_{new,i} = X_{old,i} + r(X_j - X_i) \quad (3)$$

where:

r: a random number in the [0, 1] interval;
$X_{old,\,i}$: a member that needs to be taught;
$X_{new,\,i}$: a taught member.

If $X_{new,\,i}$ is better than $X_{old,\,i}$, it replaces $X_{old,\,I}$, [60].

4. Case Study

Angoran lead and zinc mine is located in the Zanjan state (Iran) 136 km SW of the Zanjan city. The mine is located 36 degrees and 66 minutes north and 48 degrees and 48 minutes east [61]. The Angoran concentrate plant is located near the city of Dandi. The oxide part is placed in the highest part of the deposit, the sulfur part is in the lowest part, and the mixed part (a mixture of oxide and sulfur) is located between these two parts. This mine is a part of the complex metamorphic NE of Takab in Iran's geological divisions, an important part of the Central region in Iran. This complex includes Gneiss, Amphibolite, and Greenschist. The Angoran mine schists have been introduced in stratigraphy under Angoran schists' names including mica schist, chlorite schist, graphite schist, sediment schist [62]. As mentioned earlier, fly-rock is one of the unwanted environmental issues of blasting, which causes damage to the personnel, buildings, and equipment. Therefore, it is possible to transfer the personnel and equipment to safer locations to minimize damage by predicting the amount of fly-rock from each model. The required data was collected from 33 patterns to investigate, predict, and control this unwanted phenomenon. A view of the open-pit of Angoran mine in Zanjan is shown in Figure 2.

Figure 2. General view of open-pit of Angoran mine in Zanjan.

4.1. Data collection

All the required parameters were collected from the mentioned mine to provide a mathematical equation for the prediction of the fly-rock distance using GEP and TLBO. The symbols were assigned to each one of the collected parameters to understand them better. Table 1 shows the input and output parameters along with the signs assigned to these parameters and their ranges. As observed, the amount of fly-rock varies from 102 to 192 m. Considering that the range of fly-rock changing is high, hence, the possibility of damage caused by this phenomenon is also considered a high level.

Table 1. Input and output parameters and their statistical information.

Parameter	Unit	Symbol	Range	Median	Standard deviation	Parameter type
Burden	m	B	3.80-4.80	4.2	0.15	
Average depth of holes	m	H	5-11	11	1.34	
Maximum power factor per delay	kg	Q	30-95	85	12.84	
Stemming	m	T	2.23-4.90	3.25	0.56	Input
Total amount of ANFO	kg	ANFO	1800-8145	3870	1755	
Number of holes	-	N	24-170	46	30.19	
Number of boosters	-	Bo	30-180	50	30.86	
Fly-rock	m	F	102-192	160	22.75	Output

4.2. GEP modeling

In this study, the gene expression algorithm software (GeneXproTools v5.0) was utilized to obtain a relationship between the input and output parameters. Originally, the GeneXproTools software was used to divide the data into the model data and validation data, each one containing 70% and 30% of the original dataset, respectively. It should be remarked that the validation data was selected randomly.

The first GEP step is to choose the fit function. In this study, Equation (4) was considered as a fitness function:

In the above equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (4)$$

n: number of data;
P_i: estimated data;
O_i: real data.

After identifying the fitness function, sets of functions were chosen to form chromosomes. The next step includes selecting the chromosomal structure, selecting the critical function, and determining the genetic operators' coefficients. The models can be created after the specified steps. In this research work, 42 GEP models were created to obtain the relationship between fly-rock and the input parameters. The number of iterations were fixed as 3000 to create these models. Table 2 shows the top five GEP model structures among all constructed models. In addition, Table 3 defines the functions applied in the GEP models to predict the fly-rock distance.

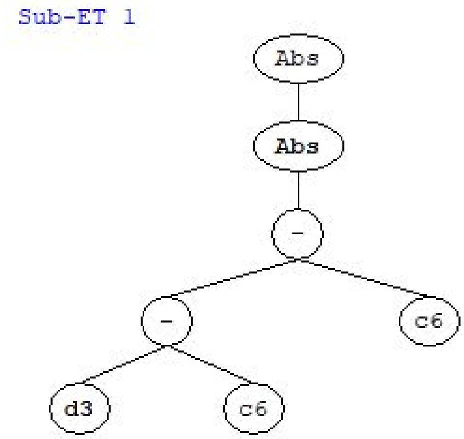
Table 2. Structure of GEP models.

Model number	Number of mhromosomes	Head size	Number of genes	Linking function	Genetic operators	Used functions	R^2	RMSE
1	39	10	7	Multiplication	Optimal evolution	+, -, ×, ÷, Sqrt, Exp, Log, Abs, X2, X3, 3Rt, 4Rt, Avg2	0.74	9.38
2	55	15	10	Multiplication	Optimal evolution	+, -, ×, ÷, Sqrt, Exp, Log, Abs, X2, X3, 3Rt, 4Rt, Avg2	0.79	8.51
3	55	15	10	Multiplication	Optimal evolution	+, -, ×, ÷, Sqrt, Exp, Ln, Log, Abs, Inv, X2, X3, 3Rt, 4Rt, Avg2	0.80	8.26
4	54	16	8	Addition	Optimal evolution	+, -, ×, ÷, Sqrt, Exp, Ln, Abs, Inv, X2, 3Rt, 4Rt	0.83	7.77
5	39	10	7	Addition	Optimal evolution	+, -, ×, ÷, Sqrt, Exp, Log, Abs, X2, X3, 3Rt, 4Rt, Avg2	0.89	5.99

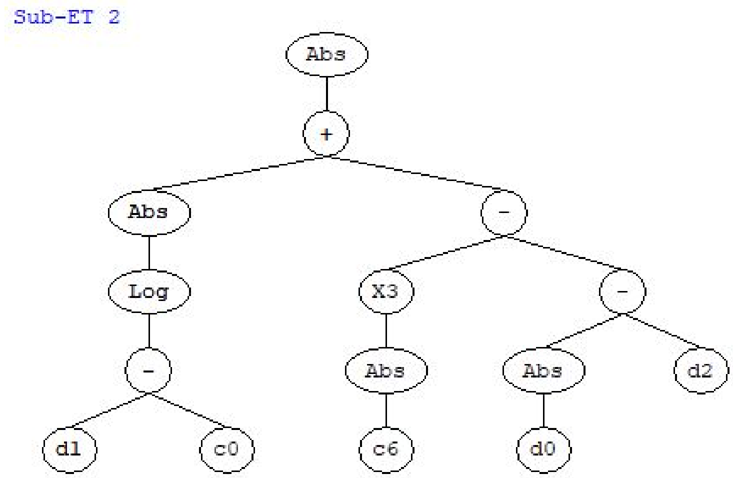
Table 3. GEP functions definition.

Name	Representation	Definition
Addition	+	(x+y)
Subtraction	-	(x-y)
Multiplication	×	(x×y)
Division	/	(x/y)
Square root	Sqrt	sqrt(x)
Exponential	Exp	exp(x)
Logarithm of base 10	Log	log(x)
Natural logarithm	Ln	ln(x)
Absolute value	Abs	abs(x)
Inverse	Inv	1/x
x to the power of 2	X2	x^2
x to the power of 3	X3	x^3
Cube root	3Rt	x^(1/3)
Quartic root	4Rt	x^(1/4)
Average of 2 inputs	Avg2	avg(x,y)

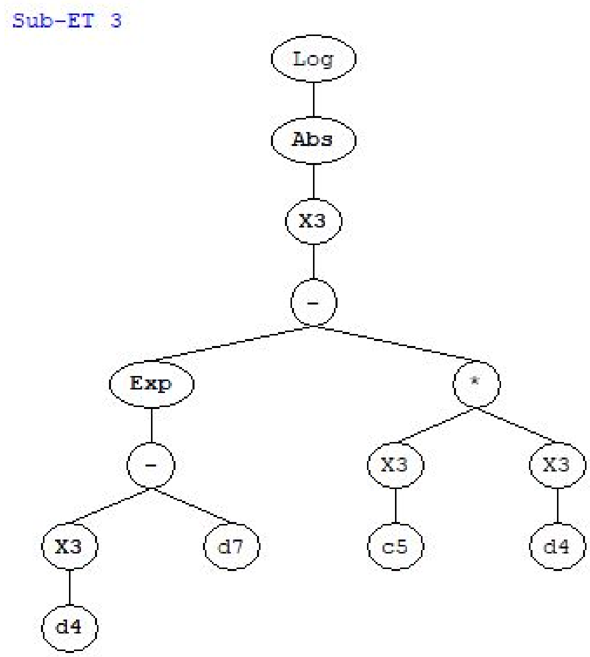
According to the statistical criteria (root mean square error, RMSE, coefficient of determination, R^2), GEP model number 1 was selected as the best model. Figure 3 shows the final equation obtained using the GEP algorithm to estimate the amount of fly-rock as an expression tree. The equation of each tree is shown individually in Equations 5-11.



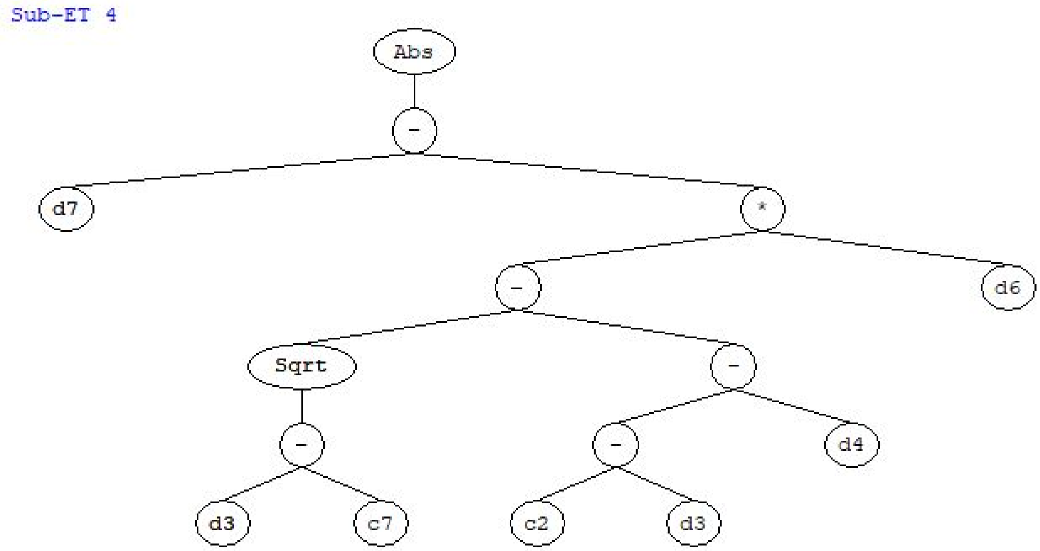
Sub-ET 1 = ABS(ABS(((H-10.482)-10.482))) **(5)**



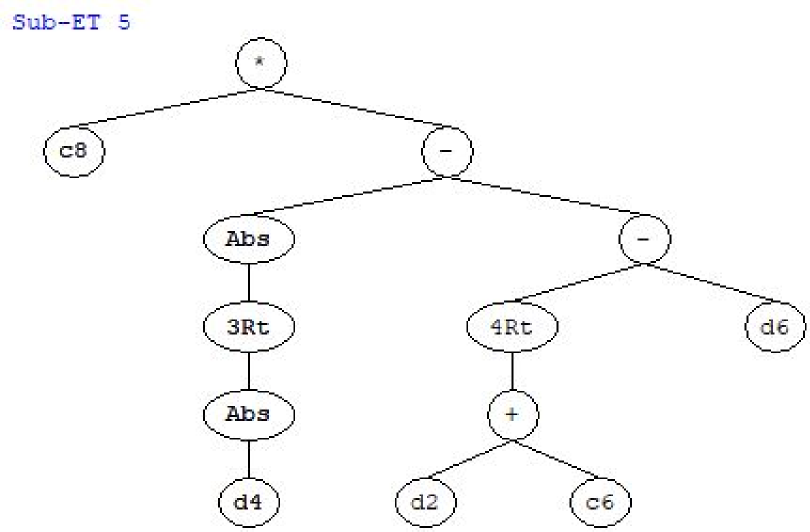
Sub-ET 2 = ABS ((ABS((Log((ANFO-(-8.185)))/Log(10))) + ((ABS(-2.782)^3) - (ABS(N) - Bo)))) **(6)**



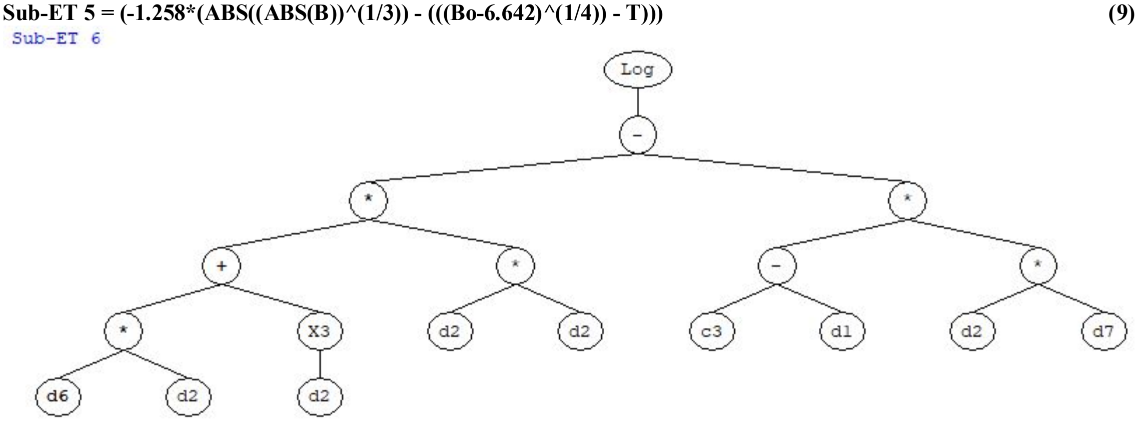
Sub-ET 3 = (Log(ABS(((EXP(((B^3) - Q)) - ((8.728^3)*(B ^ 3)))^3)))/Log(10)) **(7)**



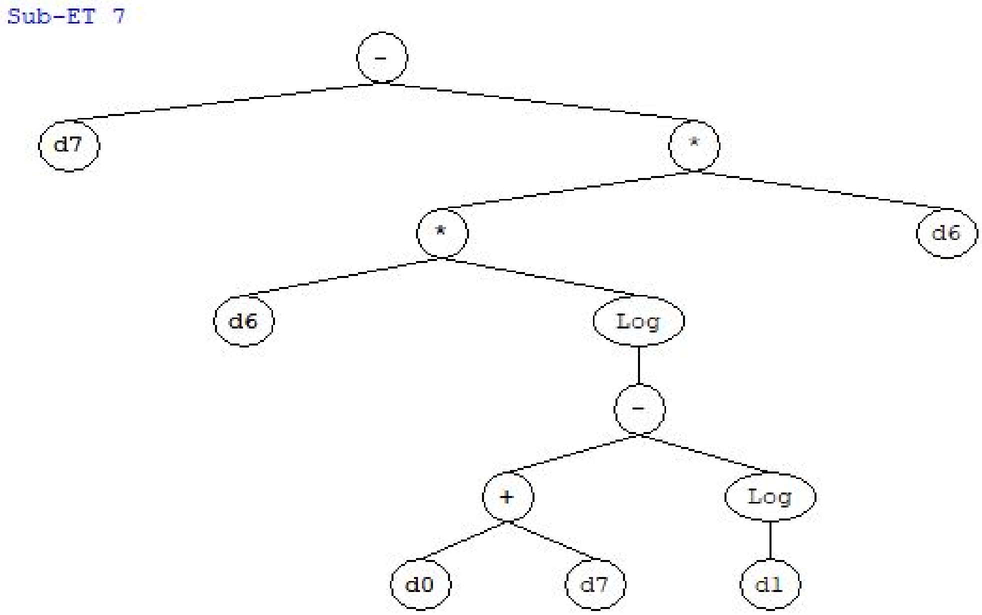
Sub-ET 4 = ABS((Q - ((SQRT((H - 3.979)) - ((5.185 - H) - B))*T))) **(8)**



Sub-ET 5 = (-1.258*(ABS((ABS(B))^(1/3)) - (((Bo-6.642)^(1/4)) - T))) **(9)**



Sub-ET 6 = (Log(((((T*Bo) + (Bo^3))*(Bo*Bo)) - ((-1.408-ANFO)*(Bo*Q))))/Log(10)) **(10)**



Sub-ET 7 = (Q - ((T*(Log(((N + Q) - (Log(ANFO)/Log(10))))/Log(10)))*T)) **(11)**

Figure 3. A statement tree for estimating amount of fly-rock.

Considering that (+) has been used in this model as a connection function, the final equation can be obtained by adding the expression trees 1 to 7. The final mathematical equation obtained by GEP to estimate the amount of fly-rock is shown in Equation 12.

$$F = \text{Sub-ET1} + \text{Sub-ET2} + \text{Sub-ET3} + \text{Sub-ET4} + \text{Sub-ET5} + \text{Sub-ET6} + \text{Sub-ET7} \quad (12)$$

4.3. TLBO modeling

Based on Equation 12, the mathematical relationship of fly-rock prediction was optimized using the teaching and learning-based optimization algorithm. In this algorithm, the RMSE function (Equation 4) was considered as the objective function. In the MATLAB 2017b software model, the number of populations was 100, and the number of repetitions was 1000 considered. Reduction of the RMSE error during the performance of the teaching and learning-based optimization algorithm is shown in Fig. 4.

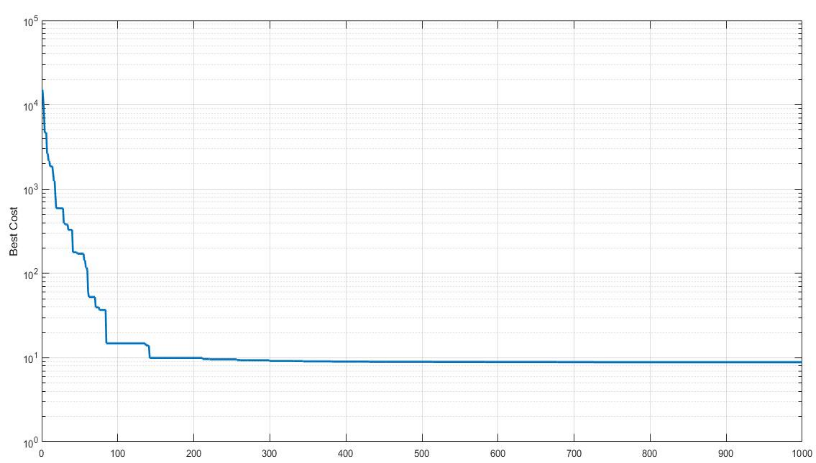


Figure 4. Amount of RMSE error during performance of optimization by TLBO.

Using the teaching and learning-based optimization algorithm, Equation (13) was obtained for PPV prediction .

$$F = -1.60 - 4.34\text{Sub-ET1} + 1.71\text{Sub-ET2} + 1.27\text{Sub-ET3} + 5.38\text{Sub-ET4} - 10.11\text{Sub-ET5} + 4.08\text{Sub-ET6} - 2.58\text{Sub-ET7} \quad (12)$$

5. Discussion

In this work, developing a new model to estimate the fly-rock rate was examined using the mean depth of holes, power factor on the delay, stemming, amount of ANFO, number of hopes, and number of boosters, with the help of GEP and TLBO algorithms. A mathematical equation was first created with the help of the GEP algorithm and using 70% of the data or training datasets to present the above model. The developed model was validated/tested using the remaining 30%. Next, the results obtained were compared by calculating R^2, RMSE, and mean absolute error (MAE), and then the best model was selected to predict the amount of fly-rock. Then the obtained equations are optimized using the TLBO algorithm. Table 4 shows the value of the statistical parameters.

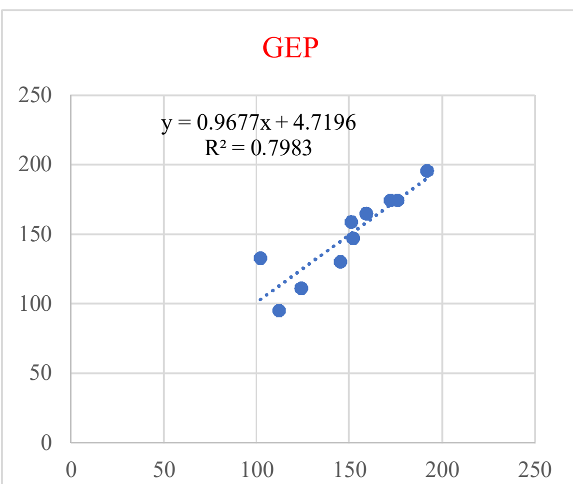
Table 4. Results from GEP and TLBO.

Stage	Parameter	GEP	TLBO
Training	RMSE	5.99	5.47
	R-square	0.89	0.91
	MAE	4.31	3.99
Testing	RMSE	13.30	9.53
	R-square	0.80	0.89
	MAE	10.15	6.20

Figure 5 displays the relationship between the results of the predicted and measured fly-rock using the testing data samples. The presented results showed that the proposed GEP equation was well-developed in the training stage ($R^2 = 0.89$), and due to that, a high level of accuracy was obtained in the model testing stage ($R^2 = 0.798$).

The model obtained from the GEP method was optimized using the TLBO method.

Additionally, Figure 5 illustrates a diagram of the actual amount of fly-rock with the predicted amount of fly-rock in testing the data samples using the GEP and TLBO algorithms. The results identified that the proposed model accurately estimates the fly-rock distance. According to Figure 6, the predicted fly-rock values are close to the actual values, which confirms that GEP and TLBO are powerful and applicable techniques for blasting environmental issues.



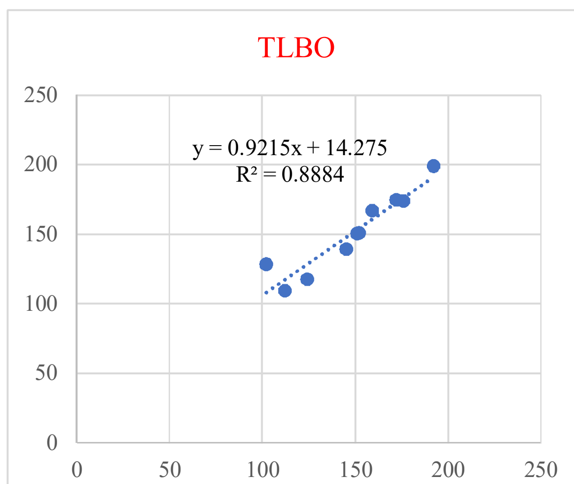


Figure 5. Relationship between model testing data and target values.

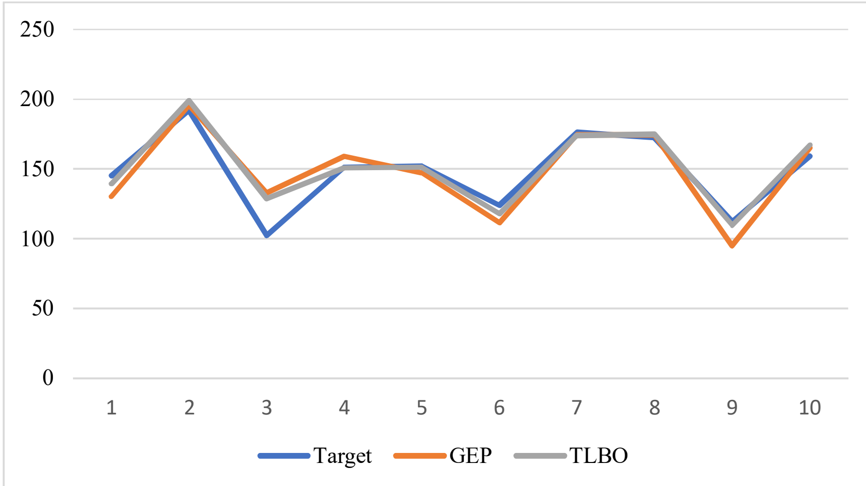


Figure 6. Diagram of predicted fly-rock and actual value for testing data samples.

6. Sensitivity Analysis

The sensitivity analysis is called the study of the influence of input variables on the system output in a statistical model. It is useful to identify each input parameter's importance and influence on the output parameter (fly-rock). This allows us to recognize the most sensitive parameters hierarchically affecting fly-rock. Two types of sensitivity analyses, tornado and spider, were performed to meet this objective. The correlation ranges are between -1 and +1 in a tornado sensitivity analysis. Figure 7 shows the tornado sensitivity analysis, and Figure 8 shows the spider sensitivity analysis for identifying the most influential parameters on fly-rock. These figures show that the number of boosters, the maximum power factor per delay, and stemming are the most efficient fly-rock parameters. Additionally, the burden and the number of holes have the least influence.

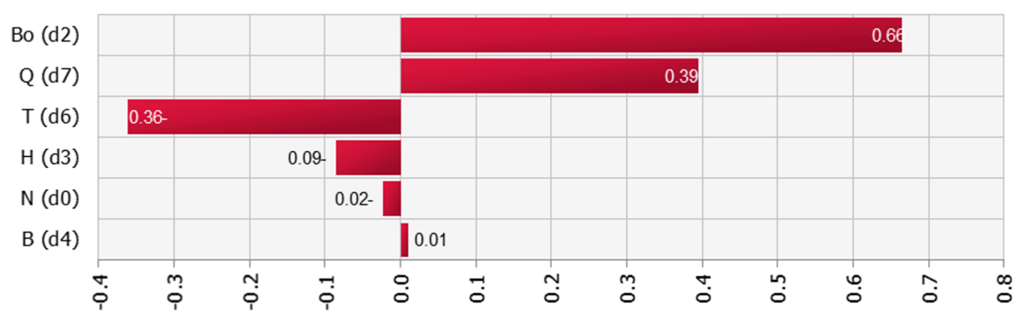


Figure 7. Tornado sensitivity analysis.

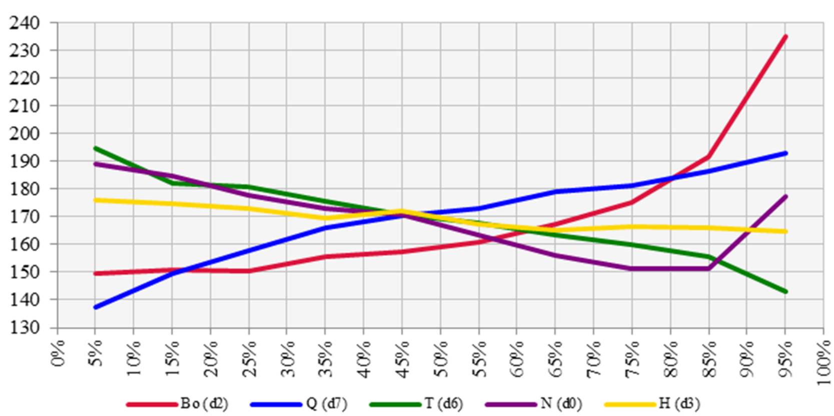


Figure 8. Spider sensitivity analysis.

7. Conclusions

In this work, a new mathematical equation based on GEP and TLBO model was developed to estimate the fly-rock distance using the mean depth of holes, power factor on the delay, stemming, amount of ANFO, number of holes, and number of boosters. Several models were developed using a series of parametric studies, and the following results were obtained and highlighted:

• Based on the results obtained, it can be concluded that the GEP and TLBO algorithm have a satisfying capacity to estimate the amount of fly-rock. Consequently, this method can be employed to estimate the number of other consequences of the explosion such as ground vibration, air blast, and rock fragmentation.

• The results of this modeling can be utilized to determine the blast safety areas, which reduces the amount of damage caused by a fly-rock.

• It is cost-effective due to the lower cost of modeling than the operational methods, and a good feasibility study can be obtained at the lowest budget.

• According to the performed sensitivity analysis, the number of boosters, a maximum power factor per delay, and stemming are the most influential parameters on the fly-rock distance. Furthermore, the burden and the number of holes have the most negligible influence in this regard.

• Due to the variability of each region's geological and mechanical characteristics, the results obtained from this work are associated with the Angoran mine. Nevertheless, the developed GEP and TLBO equation can also be generalized to other regions.

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پیش‌بینی پرتاب سنگ با استفاده از روش الگوریتم بیان ژن و الگوریتم بهینه‌سازی یادگیری معلم

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چکیده:

در این مقاله، میزان پرتاب سنگ در معدن انگوران در استان زنجان (ایران) با استفاده از روش الگوریتم بیان ژن، پیش‌بینی شده است. برای این منظور، داده‌های ورودی شامل، میانگین عمق چال‌ها، فاکتور پودرشوندگی، میزان مواد منفجره، تعداد چال‌ها، ارتقا دهنده انفجار، جمع آوری شدند. سپس، با استفاده از روش الگوریتم بیان ژن، مجموعه‌ای از رابطه‌های ریاضی برای پیش‌بینی فاصله پرتاب سنگ، ارائه شدند. در ادامه، با استفاده از پارامترهای آماری، بهترین رابطه انتخاب شد. میزان ضرایب تعیین، برای داده‌های آموزش و آزمایش، بترتیب ۰/۸۹ و ۰/۷۹۸ بودند. سپس با استفاده از روش الگوریتم بهینه‌سازی یادگیری معلم، رابطه بدست آمده از الگوریتم بیان ژن، بهبود داده شد. نتایج بدست آمده حاکی از آن است، که میزان ضرایب بدست آمده با استفاده از روش الگوریتم یادگیری معلم برای داده‌های آموزش و آزمایش، افزایش یافته و بترتیب به‌میزان، ۹۱ در صد و ۸۹ در صد ر سیدند. برا ساس نتایج می‌توان دریافت که این رابطه می‌تواند به‌عنوان معیار جدیدی در پیش بینی حاصل از انفجار، با دقت بالا، مورد استفاده قرار گیرد. همچنین، با استفاده از قابلیت این روش هوشمند، می‌توان سایر ملاحظات زیست محیطی ناشی از عملیات آتشکاری را نیز، مورد بررسی قرار داد.

کلمات کلیدی: عملیات آتش‌کاری، پرتاب سنگ، الگوریتم بیان ژن، الگوریتم بهبود دهنده یادگیری معلم.