Shahrood University of Technology
Iranian Society of Mining Engineering (IRSME)
Journal of Mining and Environment (JME)
journal homepage: www.jme.shahroodut.ac.ir
THOMSON REUTERS
Vol. 10, No. 4, 2019, 917-928.
DOI: 10.22044/jme.2019.8141.1684

Development of a GEP model to assess CERCHAR abrasivity index of rocks based on geomechanical properties

M.H. Kadkhodaei and E. Ghasemi*

Department of Mining Engineering, Isfahan University of Technology, Isfahan, Iran

Received 25 February 2019; received in revised form 28 July 2019; accepted 30 July 2019

Keywords

CERCHAR Abrasivity Index

Rock Abrasivity Index

Brazilian Tensile Strength

Gene Expression Programming

Abstract

The CERCHAR abrasivity test is very popular for determination of rock abrasivity. An accurate estimation of the CERCHAR abrasivity index (CAI) is useful for excavation operation costs. This paper presents a model to calculate CAI based on the gene expression programming (GEP) approach. This model is trained and tested based on a database collected from the experimental results available in the literature. The proposed GEP model predicts CAI based on two basic geomechanical properties of rocks, i.e. rock abrasivity index (RAI) and Brazilian tensile strength (BTS). Root mean square error (RMSE), mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE), and coefficient of determination (R^2) are used to measure the model performance. Furthermore, the developed GEP model is compared with linear and non-linear multiple regression and other existing models in the literature. The results obtained show that GEP is a strong technique for the prediction of CAI.

1. Introduction

In the mining and civil projects, the abrasiveness of rocks plays a crucial role in the wear of cutting tools in any rock excavation operation including drilling-blasting and mechanical excavation. This feature can lead to an increase in costs, a decrease in efficiency, and an increase in the life of projects.

In order to estimate the rock abrasiveness, several tools and techniques have been developed by various researchers as well as international standards. Among them, the CERCHAR Abrasivity Index (CAI) test is the most commonly used method for the laboratory assessment of rock abrasivity due to its simple fast test procedure and economic merits [1]. This test has been introduced in the 1970s by the Centre d'Etudes et Recherches des Charbonages (CERCHAR) de France and standardized by French standard AFNOR (NF904-430-1), ASTM (D7625-10), and ISRM [2]. In the laboratory, CAI is determined while a rock sample is fixed on the sliding platform, over which a scratching pin of Rockwall Hardness 54-56 is fixed with a loading arrangement [3]. A static load of 70 N is applied on the fresh surface of the sample, and the sample is displaced at a rate of 1 mm/s over a length of 10 mm. The wear of the pin is determined through a high precision microscope. CAI is calculated by multiplying the value of the wear flat stated in units of 0.01 mm by 10. In order to eliminate the error, the test is repeated for five times and the arithmetic mean is reported in the result.

Rostami *et al.* [4] have reported that the CERCHAR testing is influenced by many parameters including the pin hardness, surface condition of specimens, petrographical and geomechanical properties, test speed, applied load, and method of measuring wear surface. During the last few decades, many researchers have studied the effects of these parameters on CAI. For example, Suana and Peters [5], West [6], and Yarali *et al.* [7] have mentioned that the quartz content of the rock is a main influencing parameter on CAI. Plinninger *et al.* [8] have

Corresponding author: e_ghasemi@cc.iut.ac.ir (E. Ghasemi).

shown that a combination of the Young's modulus and the equivalent quartz content (EQC) has a fair correlation with CAI. Lassnig *et al.* [9] have studied the impact of grain size on CAI. Al-Ameen and Waller [10], Alber [11], kahraman *et al.* [12], Dipova [13], and Deliormanli [14] investigated the relationship between the rock strength and CAI. Plinninger [15] developed an empirical correlation between CAI and the rock abrasivity index (RAI) based on 60 types of igneous, metamorphic, and sedimentary rocks. Altindag *et al.* [16] illustrated that the CAI value was related to the uniaxial compressive strength and brittleness of rocks. Khandelwal and Ranjith [17] proposed an empirical correlation between CAI and P wave velocity. The influence of the CERCHAR testing parameters such as pin hardness, surface condition of specimens, test speed, applied load, scratching distance, and method of measuring wear flat or CAI was examined by various researchers such as Rostami *et al.* [4], Plinninger *et al.* [8], Gharahbagh *et al.* [18], Lee *et al.* [19], Jacobs and Hagan [20], Stanford and Hagan [21], Michalakopoulos *et al.* [22], Käsling and Thuro [23], Yarali and Duru [24], Hamzaban *et al.* [25, 26], Aydin [27], and Tripathy *et al.* [3] investigated the correlation of CAI values of different rock types with uniaxial compressive strength (UCS), point load index, P wave velocity, and Young's modulus using multivariate regression analysis and artificial neural networking. Majeed and Abu Bakar [28] evaluated the CAI measurement methods and their dependence on the petrographic and mechanical properties of 64 rock units in Pakistan. Er and Tugrul [29, 30] developed empirical relationships between the geological and physico-mechanical properties and CAI of 12 different granitic rock samples using the simple regression analysis. He *et al.* [31] studied the correlations between CAI and mechanical properties together with the microstructure characteristic for 12 different rocks. Moradizadeh *et al.* [32] investigated the correlations between CAI and EQC, point load index, slake durability index, and percentage of water absorption of 36 samples of igneous, metamorphic, and sedimentary rocks using simple and multivariate regression. Undul and Er [33] examined the effects of the micro-textural and geomechanical properties on the CAI volcanic rocks. Abu Bakar *et al.* [2] investigated the influence of water saturation on CAI values based on laboratory testing of 33 sedimentary rock units. Ko *et al.* [1] evaluated the correlation between CAI and the geomechanical properties of rocks (including QC, UCS, BTS, and brittleness index) using a statistical analysis. Kahraman *et al.* [34] investigated the usability of CAI for the evaluation of triaxial strength of Misis Fault Breccia using the regression analysis. Capik and Yilmaz [35] developed new prediction models for CAI based on some rock properties using simple and multiple regression analysis. Moreover, they modeled the drill bit lifetime based on CAI. Balani *et al.* [36] investigated the effects of rock parameters on the CERCHAR abrasivity index using PFC3D modeling. Torrijo *et al.* [37] studied the relation between CAI and chemical compounds and petrographical properties of andesitic rocks from the central area of Ecuador. Ozdogan *et al.* [38] analyzed the relation between CAI and three geomechanical properties of building stones (including Shore hardness, porosity, and UCS) using simple and multiple regression analysis.

In this work, the correlation between CAI and the geomechanical properties of rocks including rock abrasivity index (RAI) and Brazilian tensile strength (BTS) was investigated using the Gene Expression Programming (GEP) technique. GEP is a new soft computing technique, first invented by Ferreira [39]. The main advantage of the GEP approach is the capability to generate prediction equations that can be easily manipulated in practical circumstances. An increase in the application of the GEP technique for solving many mining and rock mechanics problems has been observed in the recent years. For example, GEP has been successfully applied for prediction of tunneling-induced settlement [40], TBM and roadheader performance [41, 42], rock properties such as uniaxial compressive strength, tensile strength, modulus of elasticity [43-46], side-effects of blasting operation such as ground vibration and flyrock [47-50], and rockburst hazard [51]. All researchers have pointed out that GEP has the ability to solve complex problems.

The literature surveys show that there is no study about the application of GEP in the field of rock abrasiveness prediction. Hence, an effort was made, in this work, to make use of GEP for developing a prediction equation to estimate CAI based on the geomechanical properties of rocks (RAI and BTS).

2. Data collection

In this work, in order to develop and assess the performance of the GEP model, a database including 106 rock units was employed. This database was compiled from the published literature in this field [2, 4, 11, 28, 35, 36]. The examined rock types were from sedimentary, metamorphic, and igneous origins. The database contains two input parameters (RAI and BTS) and one output parameter (CAI). RAI can be calculated using an equation proposed by Plinninger *et al*. [52], as follows:

$$RAI = \frac{EQC \times UCS}{100} \quad (1)$$

where EQC = equivalent quartz content (%) and UCS = uniaxial compressive strength (MPa).

A summary of the statistical features for the input and output parameters is presented in Table 1. RAI ranged between 0.07 and 190.38; BTS ranged between 0.48 and 22.67 MPa, and CAI varied between 0.19 and 4.88.

It should be mentioned that among 106 data, 90 sets (85% of data) were randomly chosen as the training sets for the GEP modeling and 16 sets (15% of data) were used as testing the generalization capacity of the proposed model. The testing sets were not utilized in the training of the corresponding model.

Table 1. Statistical features of the input and output parameters used in this work.

Parameters	Symbol	Unit	Min.	Max.	Mean	Std. Dev.
Rock abrasivity index	RAI	-	0.07	190.38	30.803	32.738
Brazilian tensile strength	BTS	MPa	0.48	22.67	6.719	4.74
CERCHAR abrasivity index	CAI	0.1 mm	0.19	4.88	2.024	1.114

3. Gene expression programming (GEP)

GEP is a new evolutionary algorithm, first invented by Ferreira [26] based on the genetic algorithm (GA) and genetic programming (GP). GEP incorporates both the idea of a simple linear chromosome of a fixed length used in GAs and the tree structure of different sizes and shapes used in GP. According to Ferreira [39 53], the primary difference between GEP and its predecessors, GAs and GP, stems from the nature of the individuals: in GAs, the individuals are linear strings of fixed length (chromosomes). In GP, the individuals are non-linear entities of different sizes and shapes (parse trees). In GEP, the individuals are encoded as linear strings of fixed length (chromosomes) that are expressed as non-linear entities of different sizes and shapes.

The basic GEP algorithm is depicted in Figure 1. In order to develop a GEP model, the five components function set, terminal set, fitness function, control parameters, and stop condition are required. After the problem has been encoded for the candidate solution and the fitness function has been specified, the algorithm randomly creates an initial population of viable individuals (chromosomes) and then converts each chromosome into an expression tree corresponding to a mathematical expression. Afterwards the predicted target is compared with the actual one, and the fitness score for each chromosome is determined.

If it is sufficiently good, the algorithm stops; otherwise, some of the chromosomes are selected using roulette wheel sampling and then mutated to obtain the new generations. This closed loop is continued until the desired fitness score is achieved and then the chromosomes are decoded for the best solution of the problem. The readers can refer to Ferreira [55] for more details about GEP.

4. GEP model development

The fundamental aim of developing the GEP model is to generate a mathematical function for prediction of CAI. In developing the phase of the GEP model, RAI and BTS are entered as the input variables, while the CAI value is used as the output variable. Thus a mathematical function is generated in the form of $y = f(RAI, BTS)$ for CAI based on the training datasets.

In this work, the GeneXpro Tools 5.0 program [56] was employed to develop the model based on GEP. The following steps were followed to estimate CAI using GEP [41, 42]. The first step is to select the fitness function, which is based on several functions. In this research work, the fitness function of root mean square error (RMSE) was used. The second step in GEP modeling involves determining the mathematical functions that chromosomes are allowed to use in their programs and in the final equation. There is no definitive rule in choosing a mathematical function combination. In this work, the function set is comprised of four basic arithmetic operators (×, −, /, +) as well as other more complex mathematical functions, e.g. Power (Pow), square root (Sqrt), exponential (Exp), natural logarithm (Ln), logarithm of base 10 (log), cubic root (3Rt), Sine (sin), Cosine (cos), Tangent (tan), Secant (sec), and Cosecant (csc). The third step determines the chromosomal architecture, which involves determining the head length and gene numbers. In the present work, the trial-and-error method was used to establish these two parameters. GEP was run for various head length and gene number combinations. The results obtained show that the GEP model with 3 genes and head length of 9 produces the most accurate results in modeling CAI. In addition, since an initial population in the 30–100 interval leads to acceptable results, an initial population of 65 was considered in the current work. In the fourth step, the genetic operators including mutation, inversion, transposition, and recombination are selected. The parameters employed in developing the different GEP models are presented in Table In fact, the mentioned parameters are borderlines of GEP, which can affect the performance of GEP. It must be said that all the mentioned parameters are selected by the user using the trial-and-error procedure to obtain the optimum structure of GEP. Finally, in the last step of the GEP modeling procedure, a proper linking function should be chosen to connect the expression trees. The functions +, −, ×, and / are the most common functions that are used for this aim. Each one of these four functions were examined, and multiplication (×) was selected as the best linking function.

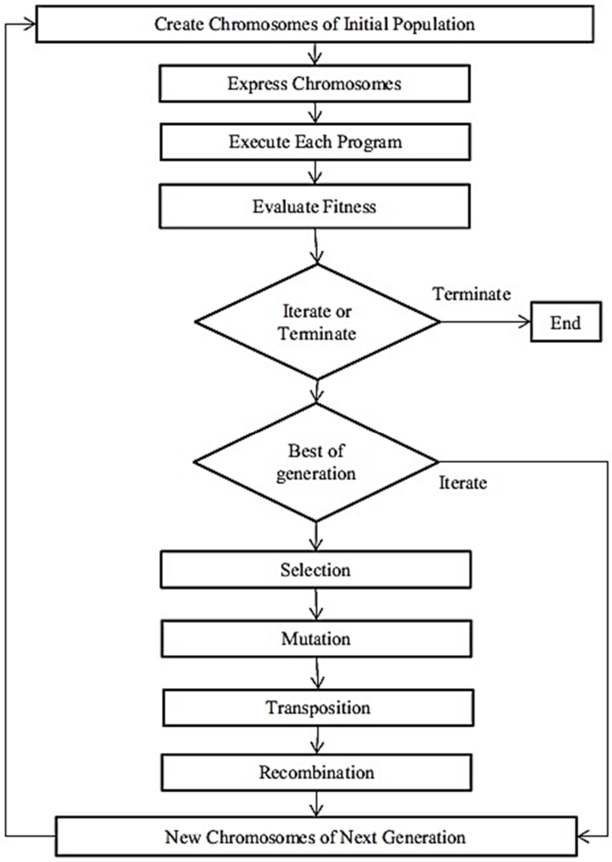

Figure 1. Flowchart of GEP [54].

Table 2. Parameters used in GEP model.

Parameter	Value
Mutation rate	0.044
Inversion rate	0.1
Gene recombination rate	0.2
One-point recombination rate	0.3
Two-point recombination rate	0.2
Gene transposition rate	0.1
Insertion sequence (IS) transposition rate	0.1
Root insertion sequence (RIS) transposition rate	0.1

After the performing steps 1–5, the adjusted GEP model was executed for 3000 iterations (generations) to predict CAI. ET of each gene (sub-ET) has been represented in Figure 2. The mathematical equations related to each gene can be extracted as Eqs. 2–4. These equations were then linked together via the chosen linking function (multiplication, in this work), and the final predictive model for CAI prediction was formulated as Eq. 5.

$$Sub-ET\,1=\frac{1}{\cosh\left(\cos\left(\cos\left(-0.23RAI\right)^{\frac{1}{3}}+\sin\left(\cos\left(BTS\right)\right)\right)\right)} \quad (2)$$

$$Sub-ET\,2=\left(\left(\cosh\left(\frac{0.63}{2.39-BTS}\right)\right)^{\frac{1}{3}}\times RAI\right)^{\frac{1}{3}} \quad (3)$$

$$Sub-ET\,3=\cos\left(\frac{1}{BTS+\left(\frac{\tan\left(4.84+BTS\right)}{BTS-9.26}\right)^{\frac{1}{3}}}\right) \quad (4)$$

$$CAI=Sub-ET1\times Sub-ET2\times Sub-ET3 \quad (5)$$

A comparison between the actual and predicted values for CAI (based on Eq. 5) for training datasets is shown in Figure 3. As it can be seen, the GEP model represents the acceptable prediction for CAI with the R^2 value of 0.875.

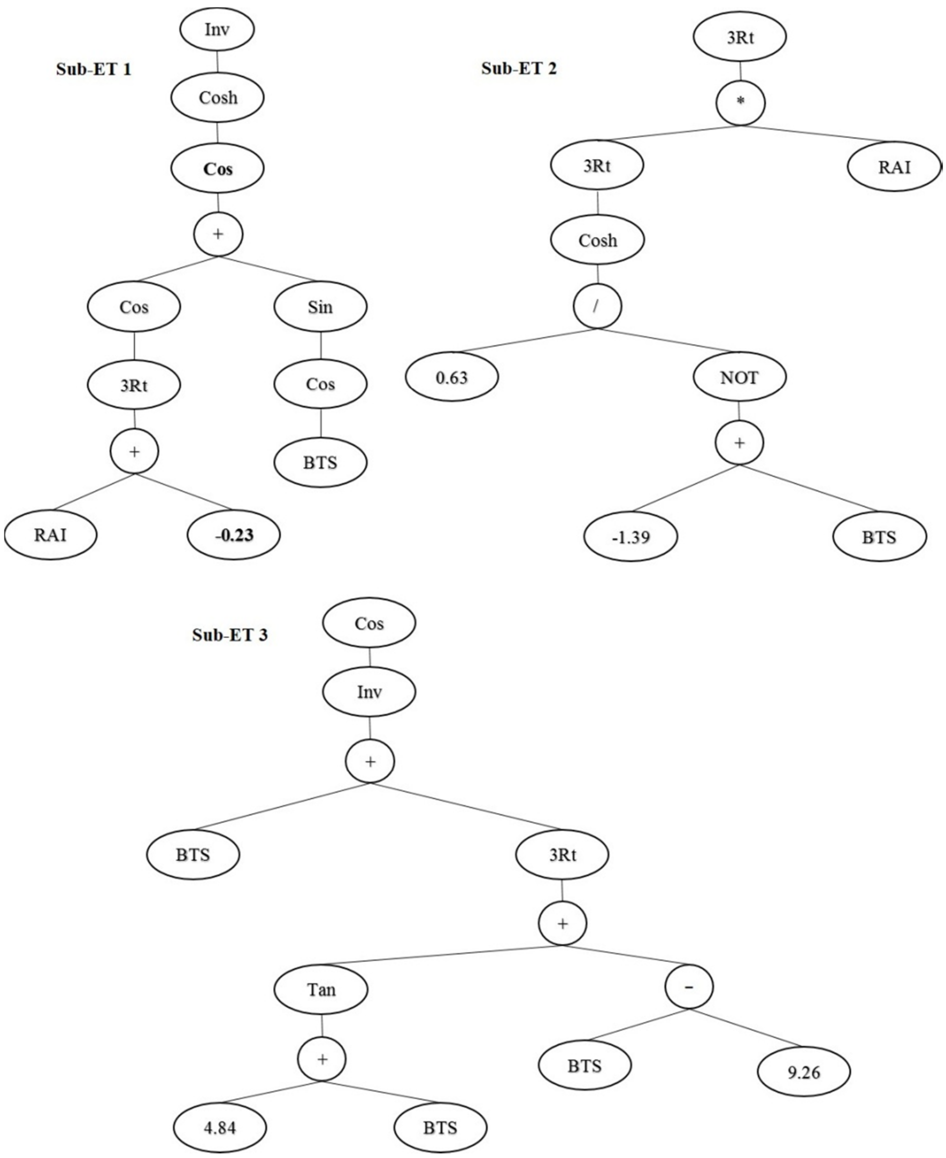

Figure 2. Expression tree for the CAI formulation.

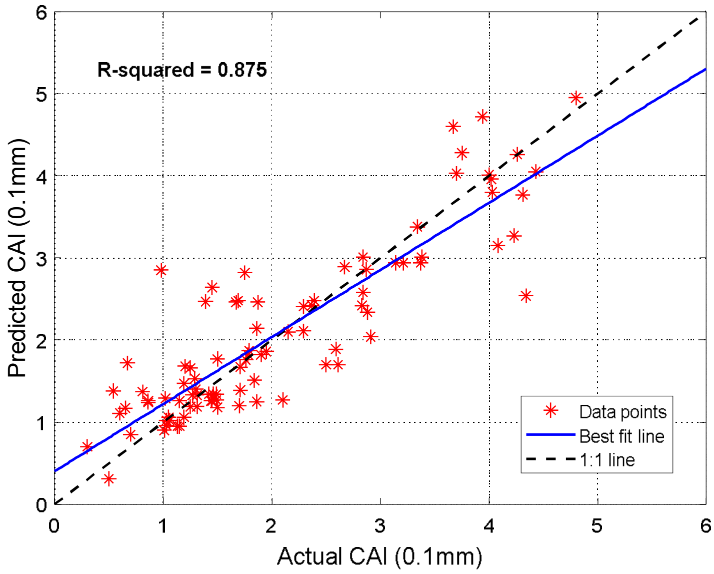

Figure 3. Relationship between the actual and predicted CAI for training datasets.

5. Results and discussion

5.1. GEP model assessment

As mentioned earlier, 16 sets out of 106 datasets were randomly selected for testing the GEP model. The testing data was unfamiliar to the model and thus was not included in its development. In this section, the GEP model performance is validated using the testing datasets. A comparison between the predicted and real values of CAI for the testing datasets has been given in Table 3.

Table 3. Comparison between the predicted and real values of CAI for the testing datasets.

No.	RAI	BTS (MPa)	Actual CAI (0.1 mm)	Predicted CAI (0.1 mm)		
				GEP	LMR	NLMR
1	33.72	2.8	2.28	2.88	2.03	2.26
2	190.38	18.65	3.59	3.74	6.80	4.96
3	21.02	9	1.87	2.27	1.90	2.20
4	25.52	1.4	1.22	1.57	1.77	1.90
5	39.59	1.6	1.81	1.83	2.15	2.24
6	1.3	0.8	0.19	0.76	1.09	0.66
7	80.19	6.76	3.19	2.78	3.42	3.32
8	26.5	13.7	1.99	1.95	2.21	2.49
9	38.65	4.2	2.91	2.82	2.22	2.47
10	3.71	6.5	1.61	1.52	1.35	1.19
11	21.01	9.02	1.98	2.28	1.98	2.19
12	7.32	12.53	2.11	1.83	1.61	1.60
13	0.6	7.8	0.25	0.70	1.31	0.66
14	6.05	9.45	1.00	1.23	1.49	1.45
15	2.49	4.6	0.94	0.96	1.25	1.00
16	13.76	13.5	1.15	1.81	1.86	1.99

Four standard statistical performance evaluation indices including the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Nash-Sutcliffe Efficiency (NSE), and coefficient of determination (R^2) were used to assess the model performance. The definitions of these evaluation indices are as follow [57]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - A_i)^2}{N}} \quad (6)$$

$$MAE = \frac{\sum_{i=1}^{N}|P_i - A_i|}{N} \quad (7)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(P_i - A_i)^2}{\sum_{i=1}^{N}(A_i - \bar{A})^2} \quad (8)$$

$$R^2 = \left(\frac{\sum_{i=1}^{N} (P_i - \bar{P})(A_i - \bar{A})}{\sqrt{\sum_{i=1}^{N} (P_i - \bar{P})^2 \sum_{i=1}^{N} (A_i - \bar{A})^2}} \right)^2 \quad (9)$$

where P_i is the ith estimated CAI using GEP, A_i is the ith actual CAI, $\bar{P}$ is the average of P_i, $\bar{A}$ is the average of A_i, and N is the number of testing datasets.

The lowest values for RMSE and MAE indicate the high performance of the model. An R^2 value equal to 1 indicates that the regression line perfectly fits the data. An NSE of 1 corresponds to a perfect match of estimated values to the observed data; to the contrary, an NSE of 0 indicates that the model predictions are as accurate as the mean of the observed data. The statistical indices for the developed GEP model are summarized in Table 4. The high values for R^2 (0.895) and NSE (0.806) and the low values for RMSE (0.357) and MAE (0.293) show that the GEP model is suitable and can predict CAI with an acceptable error. The CAI values predicted from the GEP model were graphically compared with their actual values in Figure 4. As it can be seen, there is a close match between the actual and predicted values.

Table 4. Statistical performance indices for the developed GEP model.

Model	RMSE	MAE	NSE	R^2
GEP	0.357	0.293	0.806	0.895
LMR	0.865	0.584	0.130	0.567
NLMR	0.494	0.428	0.647	0.785

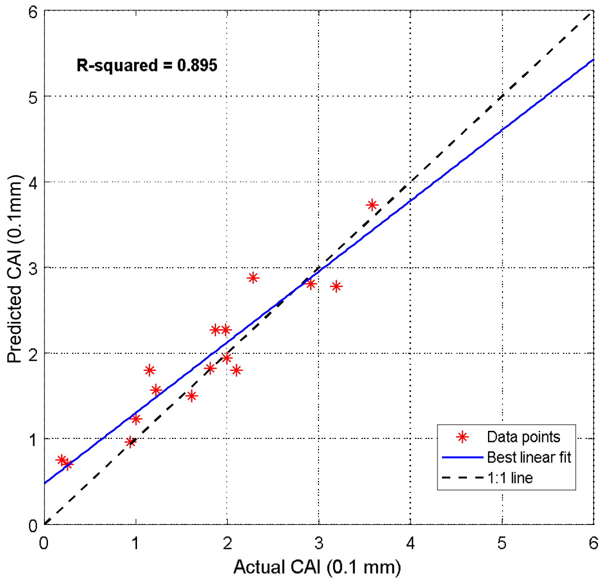

Figure 4. Relationship between the actual and predicted CAI for testing datasets.

5.2. Comparison of GEP model with multiple regression models

In this section, in order to verify the accuracy of the GEP model, it is compared with the multiple regression models. The multiple regression analysis is one of the popular statistical techniques used for developing the prediction equations. In the following, based on the training datasets, two multiple regression models are developed, and then, based on the testing datasets, their accuracies are determined and compared with the GEP model. To develop the models, both the linear and non-linear models were considered. In these models, CAI was taken as the dependent or response variable, whereas BTS and RAI were taken as the independent or explanatory variables. The linear (LMR) and non-linear (NLMR) equations can be expressed as Eqs. 10 and 11, respectively:

$$CAI = A + C_1 \cdot RAI + C_2 \cdot BTS \quad (10)$$

$$CAI = A \cdot RAI^{C_1} \cdot BTS^{C_2} \quad (11)$$

where A, C_1, and C_2 are the regression coefficients. These coefficients are determined using the regression analysis on the training datasets in the SPSS 16 software [58]. The final form of the LMR and NLMR equations is shown below:

$$CAI = 1.030 + 0.027RAI + 0.034BTS \tag{12}$$

$$CAI = 0.623RAI^{0.333}BTS^{0.112} \tag{13}$$

The predicted values for CAI based on Eqs. 12 and 13 for testing the datasets are presented in Table 3. Figure 5 shows a comparison between the predicted CAI values using the GEP, LMR, and NLMR models, and the actual CAI values. As it can be seen in Figure 5, the predicted CAI by the GEP model is closer to the actual CAI in comparison to the LMR and NLMR models. This indicates that the prediction of CAI using the GEP model is more accurate than that of the LMR and NLMR models. Furthermore, the statistical performance indices (RMSE, MAE, NSE, and R^2) for the developed multiple regression models in the testing phase are given in Table 4. A comparison of the LMR and NLMR models indicates that the NLMR model gives more reliable predictions that the LMR model. Furthermore, the LMR and NLMR models show a low prediction capacity, whereas the GEP model can predict CAI with an acceptable accuracy.

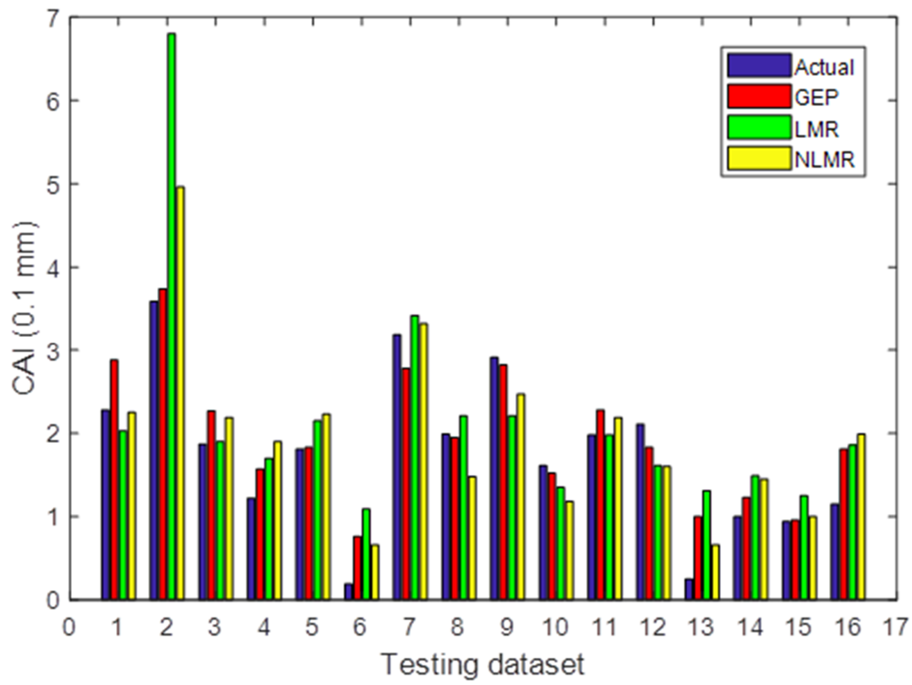

Figure 5. Comparison of the predicted CAI values using the GEP, LMR, and NLMR models and the actual CAI values.

5.3. Comparison of GEP model with other models

As mentioned in Section 1, many researchers have studied the relationship between the rock properties and CAI, and developed different models for the prediction of CAI using various techniques such as the regression analysis and the artificial neural network (ANN). In this section, in order to verify the accuracy of the GEP model, it was compared with other existing models in the literature (see Table 5). As it can be seen in Table 5, the GEP model has a higher accuracy in comparison with the classic statistical models, which indicates the superiority of the GEP technique over the simple and multiple regression analysis. Although the accuracy of the GEP model is less than that for the ANN model, the main advantage of GEP in comparison with ANN is that it suggests a practical and explicit equation between the inputs and output parameters.

5.4. Effect of input parameters on CAI

Determining the importance of the input parameters (variables) for the output parameter is one of the main features of the GeneXpro Tools 5.0 program. Generally, variable importance is computed based on the reduction of the model accuracy when the variable is removed. The importance of each variable ranges from 0 to 1; the higher this number, the more important is the variable. Based upon the developed GEP model, the importance of the input parameters for CAI has been shown in Figure 6. As it can be seen, the importance values for RAI and BTS are 0.627 and 0.373, respectively. This result shows that RAI is the most effective parameter to predict the CAI value and then BTS.

Furthermore, the influence of RAI and BTS on CAI was investigated by the sensitivity analysis based on the developed GEP model. This was performed by variation in one input parameter across from a minimum to maximum range, while the other input parameter was kept constant on its mean value. The results of the sensitivity analysis for RAI and BTS have been indicated in Figure 7. As it can be seen, there are direct relationships between the input parameters and the CAI value. In other words, for a specific rock type, the CAI value increases with increase in RAI and BTS.

Table 5. Comparison of the proposed GEP model with some other models reported in the literature.

Reference	Techniques	Input parameters	Accuracy (R^2)
Tripathy *et al.*[3]	RA	UCS, VP, E	63
Tripathy *et al.*[3]	ANN	UCS, VP, E, PLI	97
Khandelwal and Ranjith [17]	RA	V_P	76.46
Yarali *et al.* [7]	RA	Q	57.98
Yarali *et al.* [7]	RA	Q_{eq}	57.85
Rostami *et al.* [4]	RA	UCS, EQC	79.32
Torrijo *et al.* [37]	RA	Chemical compounds	66.8-88.3
Moradizadeh *et al.* [32]	RA	EQC	77
Ozdogan *et al.* [38]	RA	UCS, SH	83.1
Ozdogan *et al.* [38]	RA	SH, PR	82.2
Ozdogan *et al.* [38]	RA	SH	84.3
This study	GEP	RAI, BTS	89.5

V_P = P-wave velocity, E = Young's modulus, PLI = Point load index, Q = quartz content, Q_{eq} = equivalent quartz percentage, EQC = equivalent quartz content, SH = Shore hardness, PR = porosity, RA = regression analysis, and ANN = artificial neural networks.

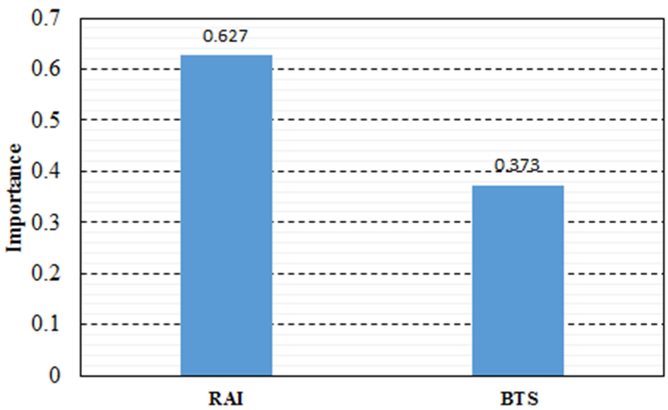

Figure 6. Importance of RAI and BTS for CAI.

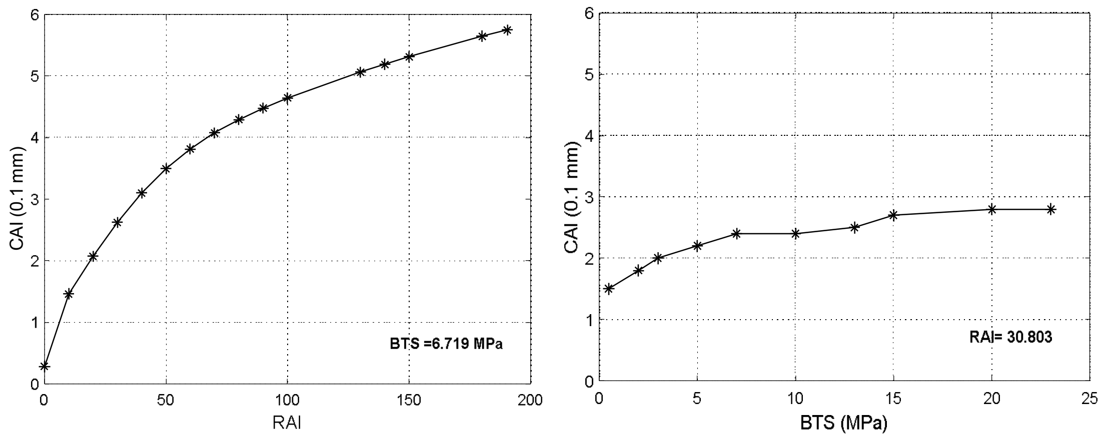

Figure 7. Effect of RAI and BTS on CAI.

6. Conclusions

This work has explored the potential of GEP in the prediction of CAI value that has a great role in the wear of cutting tools in any rock excavation operation including drilling-blasting and mechanical excavation. This work has presented the first application of GEP for CAI prediction of rocks. A database including 106 rock units was employed to develop and assess the performance of the GEP model. This database was compiled from the experimental results available in the literature. The GEP model was trained on 85% of the available data and tested using the remaining 15%. Two basic geomechanical properties of rocks, i.e. rock abrasivity index (RAI) and Brazilian tensile strength (BTS), were entered into the GEP model as the input parameters. The performance of the model was evaluated using four statistical performance evaluation indices (RMSE, MAE, NSE, and R^2). In the testing phase of the GEP model, the values for RMSE, MAE, NSE, and R^2 were obtained to be 0.357, 0.293, 0.806, and 0.895, respectively. A comparison of the developed GEP model with the multiple regression models and other existing models in the literature indicated that the prediction accuracy of the proposed model was as good as the others. These findings revealed that GEP was an efficient and useful technique for CAI prediction. Thus the developed model could be employed for the preliminary estimation of rock abrasivity in mining and civil projects with an acceptable accuracy.

The results of the sensitivity analysis illustrated that there was a direct relationship between the input parameters and the CAI value. It means that an increase in RAI and BTS of rocks results in a CAI increase. Also among the input parameters, RAI is the most effective parameter for predicting the CAI value.

Finally, it should be noted that the ignorance of other influencing parameters on CAI such as chemical compounds and petrographical properties of rocks is a clear limitation of the present work. A further limitation is that the compiled database is still relatively small. Accumulation of more data can lead to the development of more general models.

References

[1]. Ko, T.Y., Kim, T.K., Son, Y. and Jeon, S. (2016). Effect of geomechanical properties on Cerchar Abrasivity Index (CAI) and its application to TBM tunnelling. Tunnelling and Underground Space Technology. 57: 99-111.

[2]. Abu Bakar, M.Z., Majeed, Y. and Rostami, J. (2016). Effects of rock water content on CERCHAR Abrasivity Index. Wear. 368-369: 132-145.

[3]. Tripathy, A., Singh, T.N. and Kundu, J. (2015). Prediction of abrasiveness index of some Indian rocks using soft computing methods. Measurement. 68: 302-309.

[4]. Rostami, J., Ghasemi, A., Alavi Gharahbagh, E., Dogruoz, C. and Dahl, F. (2014). Study of Dominant Factors Affecting Cerchar Abrasivity Index. Rock Mechanics Rock Engineering. 47 (5): 1905-1919.

[5]. Suana, M. and Peters, T. (1982). The Cerchar Abrasivity Index and its relation to rock mineralogy and petrography. Rock mechanics. 15 (1): 1-8.

[6]. West, G. (1989). Rock abrasiveness testing for tunnelling. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts. 26 (2): 151-160.

[7]. Yaralı, O., Yaşar, E., Bacak, G. and Ranjith, P.G. (2008). A study of rock abrasivity and tool wear in Coal Measures Rocks. International Journal of Coal Geology. 74 (1): 53-66.

[8]. Plinninger, R., Käsling, H., Thuro, K. and Spaun, G. (2003). Testing conditions and geomechanical properties influencing the CERCHAR abrasiveness index (CAI) value. International Journal of Rock Mechanics and Mining Sciences. 40 (2): 259-263.

[9]. Lassnig, K., Latal, C. and Klima, K. (2008). Impact of Grain Size on the Cerchar Abrasiveness Test, Geomechanics and Tunnelling. 1: 71-76.

[10]. Al-Ameen, S.I. and Waller, M.D. (1994). The influence of rock strength and abrasive mineral content on the Cerchar Abrasive Index. Engineering Geology. 36 (3): 293-301.

[11]. Alber, M. (2008). Stress dependency of the Cerchar abrasivity index (CAI) and its effects on wear of selected rock cutting tools. Tunnelling and Underground Space Technology. 23 (4): 351-359.

[12]. Kahraman, S., Alber, M., Fener, M. and Gunaydin, O. (2010). The usability of Cerchar abrasivity index for the prediction of UCS and E of Misis Fault Breccia: Regression and artificial neural networks analysis. Expert Systems with Applications. 37 (12): 8750-8756.

[13]. Dipova, N. (2012). Investigation of the relationships between abrasiveness and strength properties of weak limestone along a tunnel route. Geology Engineering. 36: 23-34.

[14]. Deliormanlı, A.H. (2012). Cerchar abrasivity index (CAI) and its relation to strength and abrasion test methods for marble stones. Construction and Building Materials. 30: 16-21.

[15]. Plinninger, R. (2010). Hardrock Abrasivity Investigation using the Rock Abrasiveness Index

(RAI). In: Williams, A.L., Pinches, G.M., Chin, C.Y., McMorran, T.J. & Massey, C.I. (eds) Geologically Active: Proceedings of the 11th IAEG Congress, 5-10 September, Auckland, New Zealand. Taylor & Francis, London. pp. 3445-3452.

[16]. Altindag, R., Sengun, N. and Sarac, S. (2009). Evaluating the relations between brittleness and Cerchar abrasion index of rocks. In: EUROCK, Cavtat, Croatia.

[17]. Khandelwal, M. and Ranjith, P.G. (2010). Correlating index properties of rocks with P-wave measurements. Journal of Applied Geophysics. 71 (1): 1-5.

[18]. Gharahbagh, A.E, Rostami, J., Ghasemi, A.R. and Tonon, F. (2011). Review of Rock Abrasion Testing. Paper presented at the 45th U.S. Rock Mechanics / Geomechanics Symposium, San Francisco, California.

[19]. Lee, S.D., Jung, H.Y. and Jeon, S.W. (2012). Determination of rock abrasiveness using Cerchar abrasiveness test. Journal of Korean Society For Rock Mechanics. 22: 284-295.

[20]. Jacobs, N. and Hagan, P. (2009). The effect of stylus hardness and some test parameters on CERCHAR Abrasivity Index. In: ARMA, Asheville, North Carolina.

[21]. Stanford, J. and Hagan, P. (2009). An Assessment of the Impact of Stylus Metallurgy on Cerchar Abrasiveness Index. Coal Operators' Conference, University of Wollongong & the Australasian Institute of Mining and Metallurgy. pp. 348-355.

[22]. Michalakopoulos, T.N., Anagnostou, V.G., Bassanou, M.E. and Panagiotou, G.N. (2006). The influence of steel styli hardness on the Cerchar abrasiveness index value. International Journal of Rock Mechanics and Mining Sciences. 43 (2): 321-327.

[23]. Kasling, H. and Thuro, K. (2010). Determining rock abrasivity in the laboratory. In: EUROCK, Lausanne, Switzerland.

[24]. Yaralı, O. and Duru, H. (2016). Investigation into effect of scratch length and surface condition on Cerchar abrasivity index. Tunnelling and Underground Space Technology. 60: 111-120.

[25]. Hamzaban, M.T., Memarian, H., Rostami, J. and Ghasemi-Monfared, H. (2014). Study of rock-pin interaction in cerchar abrasivity test. International Journal of Rock Mechanics and Mining Sciences. 72: 100-108.

[26]. Hamzaban, M.T., Memarian, H. and Rostami, J. (2014). Continuous monitoring of pin tip wear and penetration into rock surface using a new Cerchar abrasivity testing device. Rock Mechanichs and Rock Engineering. 47 (2): 689-701.

[27]. Aydin, H. (2019). Investigating the effects of various testing parameters on Cerchar abrasivity index and its repeatability. Wear. 418-419: 61-74.

[28]. Majeed, Y. and Abu Bakar, M.Z. (2016). Statistical evaluation of CERCHAR Abrasivity Index (CAI) measurement methods and dependence on petrographic and mechanical properties of selected rocks of Pakistan. Bulletin of Engineering Geology and the Environment. 75 (3): 1341-1360.

[29]. Er, S. and Tuğrul, A. (2016). Correlation of physico-mechanical properties of granitic rocks with Cerchar Abrasivity Index in Turkey. Measurement. 91: 114-123.

[30]. Er, S. and Tuğrul, A. (2016). Estimation of Cerchar abrasivity index of granitic rocks in Turkey by geological properties using regression analysis. Bulletin of Engineering Geology and the Environment. 75 (3): 1325-1339.

[31]. He, J., Li, S., Li, X., Wang, X. and Guo, J. (2016). Study on the correlations between abrasiveness and mechanical properties of rocks combining with the microstructure characteristic. Rock Mechanichs and Rock Engineering. 49 (7): 2945-2951.

[32]. Moradizadeh, M., Cheshomi, A., Ghafoori, M. and TrighAzali, S. (2016). Correlation of equivalent quartz content, Slake durability index and Is50 with Cerchar abrasiveness index for different types of rock. International Journal of Rock Mechanics and Mining Sciences. 86: 42-47.

[33]. Undul, O. and Er, S. (2017). Investigating the effects of micro-texture and geo-mechanical properties on the abrasiveness of volcanic rocks. Engineering Geology. 229: 85-94.

[34]. Kahraman, S., Alber, M., Gunaydin, O. and Fener, M. (2015). The usability of the Cerchar abrasivity index for the evaluation of the triaxial strength of Misis Fault Breccia. Bulletin of Engineering Geology and the Environment. 74: 163-170.

[35]. Capik, M. and Yilmaz, A.O. (2017). Modeling of Micro Deval abrasion loss based on some rock properties. Journal of African Earth Sciences. 134: 549-556.

[36]. Balani, A., Chakeri, H., Barzegari, G. and Ozcelik, Y. (2017). Investigation of Various Parameters Effect on Cerchar Abrasivity Index with PFC3D Modeling. Geotechnical Geological Engineering. 35 (6): 2747-2762.

[37]. Torrijo, F.J., Garzón-Roca, J., Company, J. and Cobos, G. (2019). Estimation of Cerchar abrasivity index of andesitic rocks in Ecuador from chemical compounds and petrographical properties using regression analyses. Bulletin of Engineering Geology and the Environment. 78 (4): 2331-2344.

[38]. Ozdogan, M.V., Deliormanli, A.H. and Yenice, H. (2018). The correlations between the Cerchar abrasivity index and the geomechanical properties of building stones. Arabian Journal of Geosciences. 11 (20): 604.

[39]. Ferreira, C. (2001). Gene Expression Programming in Problem Solving. Paper presented at the invited tutorial of the 6th Online World Conference on Soft Computing in Industrial Applications, Santiago, Chile.

[40]. Ahangari, K., Moeinossada,t S.R. and Behnia, D. (2015). Estimation of tunnelling-induced settlement by modern intelligent methods. Soils and Foundations. 55 (4):737-748.

[41]. Faradonbeh, R.S., Salimi, A., Monjezi, M., Ebrahimabadi, A. and Moormann, C. (2017). Roadheader performance prediction using genetic programming (GP) and gene expression programming (GEP) techniques. Environmental Earth Sciences. 76 (16): 584.

[42]. Zare Naghadehi, M., Samaei, M., Ranjbarnia, M. and Nourani, V. (2018). State-of-the-art predictive modeling of TBM performance in changing geological conditions through gene expression programming. Measurement. 126: 46-57.

[43]. Baykasoğlu, A., Güllü, H., Çanakçı, H. and Özbakır, L. (2008). Prediction of compressive and tensile strength of limestone via genetic programming. Expert Systems with Applications. 35 (1): 111-123.

[44]. Çanakcı, H., Baykasoğlu, A. and Güllü, H. (2008). Prediction of compressive and tensile strength of Gaziantep basalts via neural networks and gene expression programming. Neural Computing Application. 18 (8): 1031-1041.

[45]. Ozbek, A., Unsal, M. and Dikec, A. (2013). Estimating uniaxial compressive strength of rocks using genetic expression programming. Journal of Rock Mechanics and Geotechnical Engineering. 5 (4): 325-329.

[46]. Dindarloo, S. and Siami-Irdemoosa, E. (2015). Estimating the unconfined compressive strength of carbonate rocks using gene expression programming. European Journal of Scientific Research 135 (3):309-316.

[47]. Güllü, H. (2012). Prediction of peak ground acceleration by genetic expression programming and regression: A comparison using likelihood-based measure. Engineering Geology. 141-142: 92-113.

[48]. Faradonbeh, R.S. and Monjezi, M. (2017). Prediction and minimization of blast-induced ground vibration using two robust meta-heuristic algorithms. Engineering with Computers. 33 (4): 835-851.

[49]. Faradonbeh, R.S., Hasanipanah, M., Amnieh, H.B., Armaghani, D.J. and Monjezi, M. (2018). Development of GP and GEP models to estimate an environmental issue induced by blasting operation. Environmental Monitoring Assessment. 190 (6): 351.

[50]. Faradonbeh, R.S., Armaghani, D.J, Amnieh, H.B. and Mohamad, E.T. (2016). Prediction and minimization of blast-induced flyrock using gene expression programming and firefly algorithm. Neural Computing Applications. 29 (6): 269-281.

[51]. Faradonbeh, R.S. and Taheri, A. (2019). Long-term prediction of rockburst hazard in deep underground openings using three robust data mining techniques. Engineering with Computers. 35 (2): 659-675.

[52]. Plinninger, R.J., Kasling, H. and Thuro, K. (2004). Wear prediction in hardrock excavation using the CERCHAR abrasiveness index (CAI). In: EUROCK 2004 & 53rd Geomechanics Colloquium, Salzburg.

[53]. Ferreira, C. (2001). Gene Expression Programming: A new Adaptive Algorithm for Solving Problems. Complex Systems. 13 (2): 87-129.

[54]. Yassin, M.A., Alazba, A.A. and Mattar, M.A. (2016). A new predictive model for furrow irrigation infiltration using gene expression programming. Computers and Electronics in Agriculture. 122: 168-175.

[55]. Ferreira, C. (2006). Gene expression programming: mathematical modeling by an artificial intelligence. Springer.

[56]. GeneXpro Tools 5.0 (2014), GEPSOFT.

[57]. Mehdizadeh, S., Behmanesh, J. and Khalili, K. (2017). Application of gene expression programming to predict daily dew point temperature. Applied Thermal Engineering. 112: 1097-1107.

[58]. SPSS 16.0 (2007). Statistical analysis software (Standard Version), SPSS Inc.

توسعه یک مدل GEP به منظور ارزیابی شاخص سایش سرشار سنگ‌ها بر اساس خواص ژئومکانیکی

محمدحسین کدخدایی و ابراهیم قاسمی*

دانشکده مهندسی معدن، دانشگاه صنعتی اصفهان، ایران

ارسال ۲۰۱۹/۲/۲۵، پذیرش ۲۰۱۹/۷/۳۰

* نویسنده مسئول مکاتبات: e_ghasemi@cc.iut.ac.ir

چکیده:

آزمایش سایش سرشار یکی از متداول‌ترین آزمایش‌ها به منظور تعیین سایندگی سنگ است. تخمین دقیق شاخص سایش سرشار (CAI) در هزینه‌های عملیاتی حفاری بسیار مفید است. این پژوهش مدلی برای محاسبه CAI بر اساس رویکرد برنامه‌نویسی بیان- ژنی (GEP) ارائه کرده است. این مدل بر اساس یک پایگاه داده گردآوری شده از نتایج آزمایشگاهی موجود در مقالات، آموزش و آزمایش شده است. مدل پیشنهادی GEP، CAI را بر اساس دو ویژگی اساسی ژئومکانیکی سنگ‌ها، یعنی شاخص سایش سنگ (RAI) و مقاومت کشش برزیلی (BTS) پیش‌بینی می‌کند. به منظور ارزیابی عملکرد مدل، خطای جذر میانگین مربعات (RMSE)، خطای میانگین مطلق (MAE)، کارایی نش- ساتکلیف (NSE) و ضریب تعیین (R^2) استفاده شده است. علاوه بر این، مدل GEP توسعه یافته با مدل‌های رگرسیون خطی و غیرخطی چندگانه و سایر مدل‌های موجود در مقالات مقایسه شده است. نتایج به دست آمده نشان می‌دهد که GEP یک روش قوی برای پیش‌بینی CAI است.

کلمات کلیدی: شاخص سایش سرشار، شاخص سایش سنگ، مقاومت کشش برزیلی، برنامه‌نویسی بیان-ژنی.