Predicting the value of the rock quality index in the Q-system using gene expression programming

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Abstract:

Among the methods used to design the tunnel, the Q-system is a comprehensive method that has attracted the attention of many researchers today. However, the limitations of the Q-system make it impossible to access all the required parameters as well as the time and cost of them, which has made it impossible to classify the rock mass using the Q-system. This paper attempts to predict the value of Q by parameters that have the highest coefficient of importance in the value of Q, using the Gene Expression Programming (GEP) technique. The most effective parameters involved in the Q value have been identified using Pearson correlation analysis (PCA), and then three different input models have been used to obtain Q value so that they are more closely related to experimental values. A total number of 159 experimental data were used for training and testing of the models, respectively. The innovation of this paper is that instead of 6 parameters, only three influential ones were used for determining the value of Q. Using the three parameters RQD, Jn and Ja, which have been determined as the most effective parameters and applying Pearson correlation analysis method, the value of Q can be determined with an acceptable approximation. In the suggested relation, the coefficients of determination (R²), root mean square error (RMSE), BIAS and the scatter index (SI) obtained were 0.917, 2.31, 1.74 and 0.43, respectively that show the new equation presented by GEP, can be undoubtedly used to predict the value of Q.

1. Introduction

The scope of the field and the diversity of underground engineering projects in design and implementation have made tremendous progress. Based on the observations and the results of statistical surveys, the criteria for sustainability of spaces should be prepared and the prediction of support tunnel should be executed with sufficient reliability. Considering the properties of rocks, a kind of classification called the engineering classification of rock was proposed [1]. Different classification methods used in rock engineering underpin the design of underground spaces. Geological and geotechnical studies are essential for proper assessment and determination of rock classification values [2]. Terzaghi's classification [1], which is considered as the first classification system, is suitable for estimating the load on steel arched frames, and has been used in the U.S. for designing steel-framed supports for more than 35 years.

RSR classification system [1] is another pioneer comprehensive classification system, preceded only by Terzaghi's system. Rock mass rating (RMR) technique [1] was introduced by Bieniawski with information from drilling in South Africa and founded on determining five parameters namely: uniaxial compressive strength of rock, quality of rock index, distance between joints, status of joints and the conditions of ground water. Q-system [1] is based on the quality of rock mass. It is currently used as the most conventional method for designing tunnel supports. RMI index was first proposed by Palmstrom [3] to determine rock mass strength that represents the uniaxial compressive strength of the rock mass from the size parameters of the blocks marked with the joints, the strength of the block material, the shear strength of the block surfaces and the size and end of the joints. Ozbek et al. [4] used GEP to predict uniaxial compressive strength of rock. Adopting experimental data and five GEP models, they showed that there is a good concordance between experimental results and predicted ones. Shirani et al. [5] used genetic

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programming (GP) and GEP to evaluate fly rock during mine explosion. They used the data of 97 mine explosions in Iran and five influential parameters, which proved that GEP has a better performance in predicting fly rock compared to GA. Alemdag et al. [6] evaluated the results of experimental and numerical simulations in order to estimate the deformation modulus of stratified sedimentary rock masses. They used neural networks, neural fuzzy (NF) and GP to determin the deformation modulus of stratified sedimentary rock masses. According to their results, GP has a higher accuracy compared to other methods whereas, the performance of neural network and neural fuzzy was satisfactory as well. Yang et al. [7] used two-dimensional finite element method (2DFEM) to predict the behavior of excavated rock mass. They minimized the difference between measured results and GA results in order to find the optimal specifications of rock mass. Monjezi et al. [8] optimized open-explosion parameters using GA. They applied 32 models to get the best results for throwing stones in an explosion. Beiki et al. [9] predicted uniaxial compressive strength as well as the modulus of elasticity of carbonated rocks using GP and regression model. According to their results, GP yielded better results than the regression model. Feng et al. [10] combined GP and modified particle swarm optimization algorithm (MPSOA) and determined the specifications of the viscoelastic model of rocks. Fahimifar et al. [11] used the genetic algorithm to optimally design tunnel stabilization systems. They showed that optimization significantly reduces costs. Li et al. [12] predicted underground excavation-induced ground displacement using fuzzy genetic programming method (FGPM). They showed that FGPM yields satisfactory results and can be used to predict excavation-induced displacements, especially in coal mines. Majdi and Beiki [13] optimized the number of neurons of each layer, momentum factor and learning rate of latent and output layers using GP. They demonstrated that GP is more optimized and yields better results compared to NN to estimate the deformation modulus of rock. Beiki et al. [14] used GP to determine the deformation modulus of rock mass. They showed that GP yields better estimations than other experimental methods. Park et al. [15] used genetic algorithm (GA) and predicted the subsidence of thick deposits in some areas of Southern Korea. They showed that GA can better predict subsidence compared to conventional graphical methods and can cut calculation time. Gullu [16] predicted peak ground acceleration by GEP and regression. Ghobadian and Hajiabadi [17] estimated soil compaction in fine grained soil by using GEP technique and compared it with experimental method. Liu et al. [18] predicted tunnel support system used by applying the Support Vector Regression (SVR) method. They showed that SVR algorithm has appropriate capability of yielding satisfactory

results and yields better results than Multi-Layer Perceptron (MLP) algorithm. Mobarra and Hassaninia [19] used Multivariate regression and fuzzy neural network to predict the penetration rate of all-cross machines (TBM). They demonstrated that the neural-fuzzy network method has a higher accuracy than multivariate regression for assessing the penetration rate. Jalalifar et al. [20] predicted Rock Mass Rating (RMR) using Fuzzy Inference System (FIS) and model. They indicated that the FIS model is better than multi-variable regression for estimating the RMR value. Jalalifar et al. [21] predicted rock engineering classification system using adaptive neuro-fuzzy inference system (ANFIS). They used three ANFIS networks and demonstrated that subtractive clustering method shows higher efficiency and capability in predicting RMR. In addition, GEP has been used to solve dozens of problems such as the simulation of water table fluctuations [22], concrete technology [23], composite material fatigue modeling [24] and determining rock strength [25]. Also, Naderpour and Mirrashid [26] demonstrated the capability of a neuro-fuzzy system to predict the shear strength of reinforced concrete beams with steel stirrups. They indicated that the Neuro-Fuzzy system can predict the shear strength of the RC beams which are reinforced with steel stirrups. Taban et al. [27] presented Genetic Programming to predict the Van Genuchten model fitting parameters for unsaturated clean sand soils. Alikhani and Alvanchi [28] presented an improved maintenance planning model based on Genetic Algorithm for a network of bridges to predict a long-term perspective for the lifespan of bridges. Z. Li and B. Li [29] presented a novel class of bi-level fuzzy random programming problem for insuring critical path. They assumed each task duration as a fuzzy random variable and followed the known possibility and probability distributions. This study predicts Q-value using GEP and the most influential parameters so that it can be predicted by 3 parameters instead of 6. This saves the time and cost required for obtaining relevant parameters.

2. Q-system

Experimental, numerical and analytical methods are some of the tools used to design tunnels. Experimental methods are experiences obtained in different projects and are widely used in rock classification systems. In many projects, experimental classification of rocks is the only criterion used to design complex underground structures. Experimental classification systems are built based on two objectives: simplicity and organizing the unknowns. However, it is possible to overcome the uncertainty of geological and geotechnical problems using specific classifications [30]. The Q system method is one of experimental methods suggested by Barton et al [31-32] and used to evaluate the

experimental design of tunnel support system. This index has six parameters mentioned in Equation (1).

$$Q = \frac{RQD}{J_n} \frac{J_r}{J_a} \frac{J_w}{SRF} \tag{1}$$

Where RQD is Rock Quality Designation, Jn is joint set number, Jr is joint roughness number, Ja is joint alteration number, Jw is joint water parameter and SRF is Stress Reduction Factor. Most of the research in this field has examined the correlation and relationships between different classification methods. Based on the study, researchers have proposed several relationships in different situations between Q and RMR.

3. Gene expression programming (GEP)

Gene expression programming requires computer programs with different shapes and lengths encoded in linear chromosomes with constant size. Further, the chromosomes' information is decoded into expression trees (ET) called translation. The encoding procedure is very straightforward, where the ET reads the chromosomes from left to right and from top to bottom. An example of chromosome translation to ET is presented in Fig. 1. Each gene begins in the first position. However, the termination point is not always the last gene position and open reading frames are used.
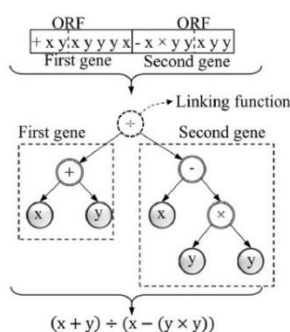

Fig. 1: Presentation of chromosomes GEP [32]

ETs are complex computer programs that are commonly extended for the purpose of dissolving a special problem and they are chosen based on their appropriateness to resolve the problem. Diverse genetic variations detect the characteristics of the existing population and as a result it is fitted to the specific problem that was meant to be solved. This means there is a suitable solution to solve the intended problem provided, there is adequate time and accurate particulars.

The gene expression programming process consists of some major steps. At first, chromosomes from the initial population are produced randomly and then the chromosomes are represented such that, the worth of each chromosome is considered according to its fitness function. The chromosomes are then selected keeping in view their worth to be generated again or to be revised. Catering new

individuals through a similar approach including genome expression, composition of the environmental selection, and reproduction with correction, comprises the next stage. The mentioned approach is iterated until the considered number of generations or acceptable model error is gained [33]. The chromosomes in each production are optimized by genetic operators. The genetic operators applied in the GEP method are jump, inversion, IS transposition, crossover, and gene transposition. Jump can occur anyplace in the chromosome. In the chromosome's head, each identity could be replaced by functions or terminals. However, in the chromosome's tail the terminals are only allowed to be replaced with other terminals. Despite the jump, inversion is only done in the chromosome's head. In the inversion approach, a sequence is selected randomly and inverted. The IS transposition selects a random subsequence from a chromosome and copies it to any location of the chromosome's head despite the start location. In crossover, the parent chromosomes are mixed with each other and two new children are generated. In gene transposition, a whole gene performs as a transposon and transposes itself to the chromosome's start location. Subsequently, in order to prevent chromosome length change, the transposon gene is removed from the original location. The algorithm of GEP is shown in Fig. 2.
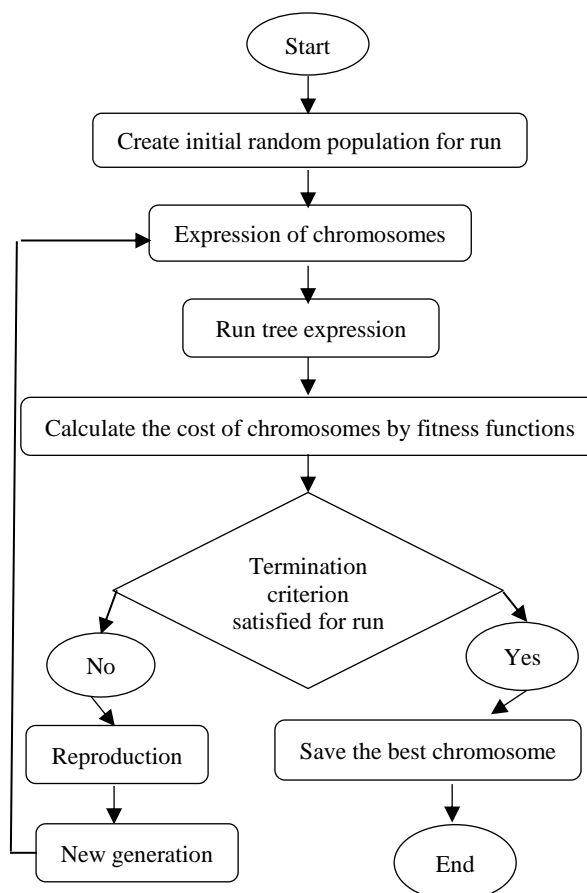

Fig. 2: Algorithm of GEP [32]

4. Used data

This study used 140 data collected from reputable references [34-39]. Table 1 shows the range of data. For each data, the value of Q, ROD, Jn, Jr, Jw and SRF was measured. In addition, 19 test data [40-43] which were not included in the initial data set were used to evaluate the built model. Table 1 shows the range of these parameters.

5. Methodology

Pearson correlation analysis was used to obtain the effect of each aforementioned 6 parameters on Q-system. This study used 140 data of different tunnels. Table 2 shows the results of Pearson correlation analysis conducted on the parameters of relation 1. According to table 2, the relationship of any parameter with itself is unit. This means that there is a direct and complete relationship between any parameter and itself. In the process of investigating the correlation of parameters with Q, if the correlation is positive, this means that there is a direct relationship; otherwise the relationship is reverse. Moreover, the closer the positive values to 1 and the negative values to -1, the stronger is the relationship of the parameter with Q. According to table 2, considering the values of RQD, Jn, Jr and Ja parameters, they have the highest impact factor on Q. Therefore, the effect of three parameters is first evaluated and then the effect of all four parameters will be evaluated.

Table. 1: The range of measured parameters from reputable references [39-44].

Data Type	Train data				Test data			
	Minimum	Maximum	Average	Standard Deviation	Minimum	Maximum	Average	Standard Deviation
Q	0.008	25	9.84	6.75	0.006	12.75	5.26	4.79
RQD	10	100	79.45	23.49	10	100	65.18	33.11
Jn	3	20	6.66	3.22	2.5	20	9.70	5.15
Jr	1	3.1	2.39	0.72	1	4	1.91	0.844
Ja	0.75	8	2.26	1.10	1	13	3.16	3.03
Jw	0.5	1	0.95	0.11	0.5	1	0.821	0.194
SRF	1	10	2.15	0.87	1	5	2.01	1.25

Table. 2: The results of Pearson correlation analysis conducted on the parameters of Equation 1.

	Q	RQD	J_n	J_r	J_a	J_w	SRF
Q	1	0.692	-0.64	0.567	-0.531	0.360	-0.238
RQD	0.692	1	-0.679	0.360	-0.560	0.329	-0.402
Jn	-0.64	-0.679	1	-0.471	0.588	-0.254	0.283
Jr	0.567	0.396	-0.471	1	-0.402	0.185	-0.149
Ja	-0.531	-0.560	0.588	-0.402	1	-0.301	0.381
Jw	0.360	0.329	-0.254	0.185	-0.301	1	-0.230
SRF	-0.238	-0.402	0.283	-0.149	0.381	-0.230	1

This paper aims to determine Q-value using the most influential parameters. To this end, three different models are considered (table 3). Model 1 includes RQD, Jn and Jr parameters, model 2 includes RQD, Jn and Ja parameters and model 3 includes all four parameters i.e. RQD, Jn, Jr and Ja.

Table. 3: Three different models are considered in GEP.

Model name	Model components
Model 1	Q = f (RQD, Jn, Jr)
Model 2	Q = f (RQD, Jn, Ja)
Model 3	Q = f (RQD, Jn, Jr, Ja)

The coefficients of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), Scatter Index (SI) and BIAS were used to assess the accuracy of obtained models. These functions show the variance of predicted values with actual ones as follows:

$$R^2 = [\sum_{i=1}^{n} \frac{(y_m - \bar{y}_m)(y_p - \bar{y}_p)}{\sqrt{\sum_{i=1}^{n}(y_m - \bar{y}_m)^2 \sum_{i=1}^{n}(y_p - \bar{y}_p)^2}}]^2 \qquad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_p - Y_m)^2}{n}} \qquad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(Y_p - Y_m)| \qquad (4)$$

$$MSE = \frac{\sum_{i=1}^{n}(Y_p - Y_m)^2}{n} \qquad (5)$$

$$SI = \frac{RMSE}{\bar{y}_m} \qquad (6)$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}|(Y_p - Y_m)| \qquad (7)$$

where y_m, y_p are observed and measured values of Q and n, $\bar{y}_m$, $\bar{y}_p$ are number of data, mean observed values and mean measured values, respectively.

This section explains GEP modeling used to estimate the quality of rock mass. GEP was trained by 140 experimental

data. To assess model performance, its results were re-examined by 19 new data. GEP modeling consists of five essential stages. The first stage determines the fitness function used to calculate chromosome cost. This study used try and error method to obtain suitable fitness function. Table 4 shows the results. According to this table, the fitness function of MAE shows the best performance in model 1 while that of RMSE is better in models 2 and 3. The second stage is to determine the mathematical functions that chromosomes are allowed to use. There is no mathematical rule in the process of selecting the mix of a mathematical function. This study uses four basic mathematical functions i.e. {×.+.-./} as well as other complex functions. The third stage involves the determination of chromosome architecture including the length of chromosome head and the number of genes. This study used trial and error technique to determine both. GEP model was built for different head length and different combinations of chromosome number. The results show that GEP with 3 genes and the head length of 7 best models the Q-value in models 1 and 2, while GEP with 3 genes and the head length of 8 yields the best results in model 3. The increase of both parameters has no considerable effect on the models performance. The 4th stage is to select a proper linking function. After trial and error, it was revealed that multiplication linking function yields the best results.

Table 5 shows trial and error results were used to select the best linking function. In the last stage, the genetic operators which are used by GEP in reproduction process are determined. The genetic operators are the product of the diversity of generation evolution. This study determined mutation rate using trial and error technique and found other genetic operators to be in accordance with the initial values set for GEP.

Table. 4: Results of different fitness functions in estimate the rock quality

Fitness Function	Model 1							
	Train data				Test data			
	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE
Relative with SR	0.774	1.64	10.73	3.27	0.575	2.10	10.28	3.20
MSE	0.808	1.92	8.66	2.94	0.327	3.09	24.14	4.91
MAE	0.785	1.58	9.95	3.15	0.603	2.09	8.83	2.97
RMSE	0.798	1.90	9.13	3.02	0.573	2.56	11.58	3.40
	Model 2							
Fitness Function	Train data				Test data			
	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE
Relative with SR	0.826	2.07	9.27	3.04	0.834	1.93	8.39	2.89
MSE	0.842	2.16	7.20	2.68	0.878	1.79	5.78	2.40
MAE	0.838	1.94	8.5	2.91	0.870	2.11	9.31	3.05
RMSE	0.856	2.09	6.54	2.55	0.917	1.74	5.37	2.31
	Model 3							
Fitness Function	Train data				Test data			
	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE
Relative with SR	0.91	1.07	5.07	2.25	0.834	1.43	4.12	2.03
MSE	0.938	0.983	2.80	1.67	0.878	1.37	3.19	1.78
MAE	0.939	0.695	2.88	1.69	0.795	1.80	5.95	2.44
RMSE	0.931	1.13	3.12	1.76	0.930	1.03	2.03	1.42

Table. 5: Try and error results used to select the best linking function.

Fitness Function	Model 1				Model 2				Model 3			
	Train data		Test data		Train data		Test data		Train data		Test data	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Addition	0.794	3.07	0.594	3.12	0.842	2.68	0.834	3.26	0.93	1.77	0.841	2.46
Subtraction	0.771	3.25	0.622	3.15	0.834	2.73	0.840	2.93	0.93	1.78	0.004	167.1
Multiplication	0.785	3.15	0.603	2.97	0.856	2.55	0.917	2.31	0.93	1.76	0.93	1.42
Division	0.786	3.14	0.552	3.32	0.855	5.57	0.855	3.15	0.92	1.81	0.909	1.68

Table 6 shows the values of the final parameters of genetic operators and other specifications.

6. Programs and results

Considering above explanation of Q prediction and adopting statistical indices, the aim is to obtain the best model for predicting Q-value. Table 7 shows the results of the best models obtained for training data. According to this table, all models show acceptable performance considering their input parameters. Fig. 3 shows predicted and observed Q values of training data. Table 8 shows the results of the best models obtained for different parameters and test data. According to this table, all models yield acceptable results considering their parameters. The best results for different models for test data are shown in Fig. 4.

Table. 6: The values of the final parameters of genetic operators and other specifications.

Parameter	Detail
Number of generations	30000
Number of chromosomes	30
Number of genes	3
mutation rate	0.045
Inversion rate	0.1
One-point coupling rate	0.3
Two-point coupling rate	0.3
Gene Coupling Rate	0.1
Gene transposition rate	0.1
Functions used	×, ÷, +, -, ln, sqrt, exp, Inv, x2, x3, x4, x5, cube root, quartic root, quintic root
Link function	Multiplication
Fitness function	MAE, RMSE

**Table. 7:** The results of the best models obtained for training data.

Models	R^2	RMSE	MAE	SI	BIAS
Model 1	0.785	3.15	1.58	0.32	1.58
Model 2	0.856	2.55	2.09	0.25	2.09
Model 3	0.931	1.76	1.13	0.17	1.13

This section provides different equations obtained for different models for Q-value prediction. Equation 8 shows formula derived for model 1 and Equations 9 and 10 show formulas obtained for model 2 and model 3.
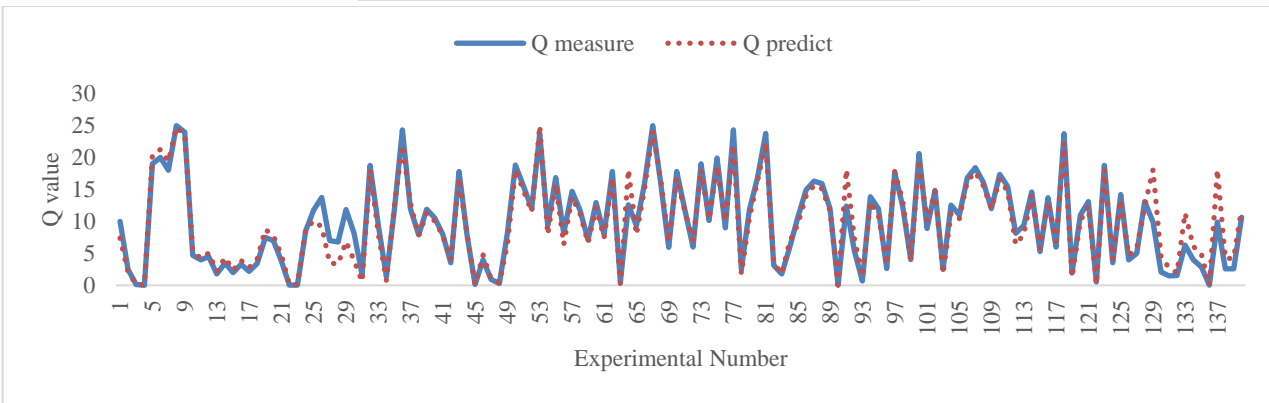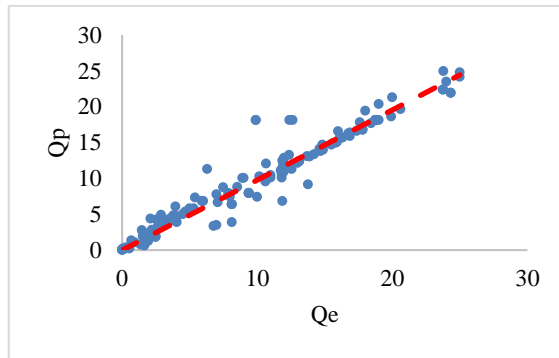
Table. 8: The results of the best models obtained for test data.

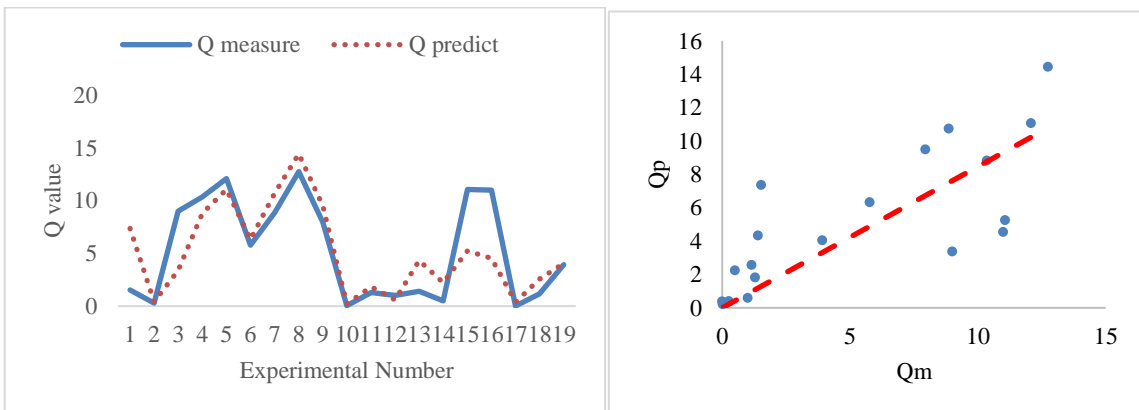| Models	R^2	RMSE	MAE	SI	BIAS
Model 1	0.603	2.97	2.09	0.56	2.09
Model 2	0.917	2.31	1.74	0.43	1.74
Model 3	0.930	1.42	1.03	0.26	1.03

(A)
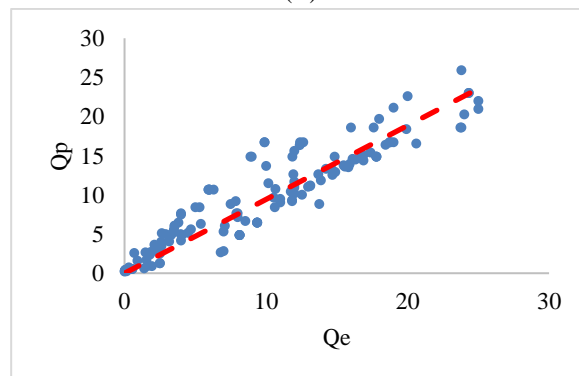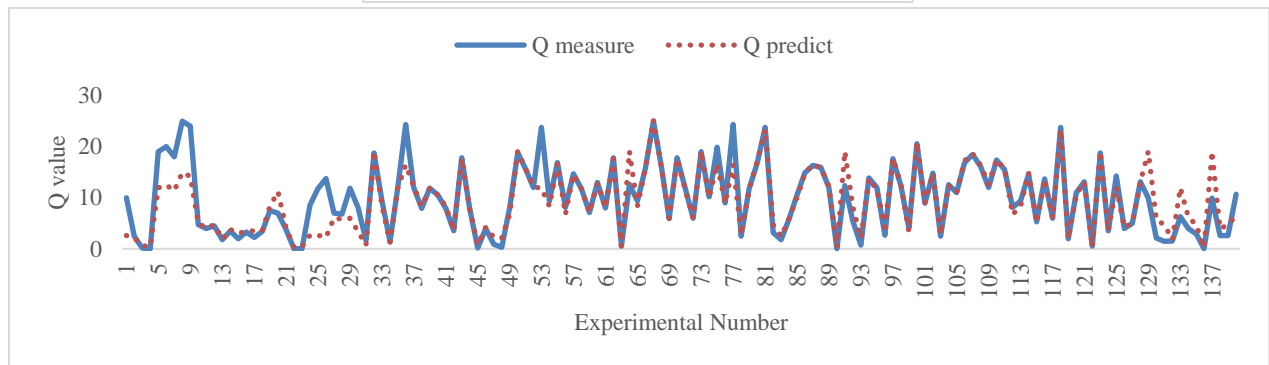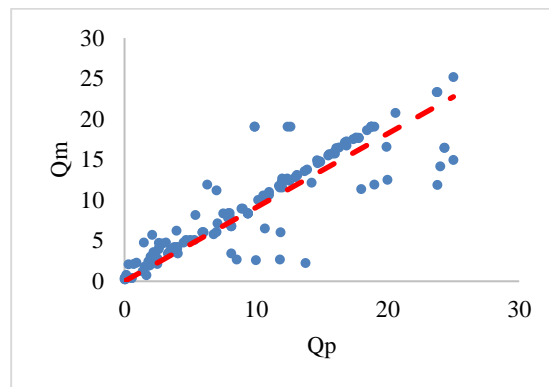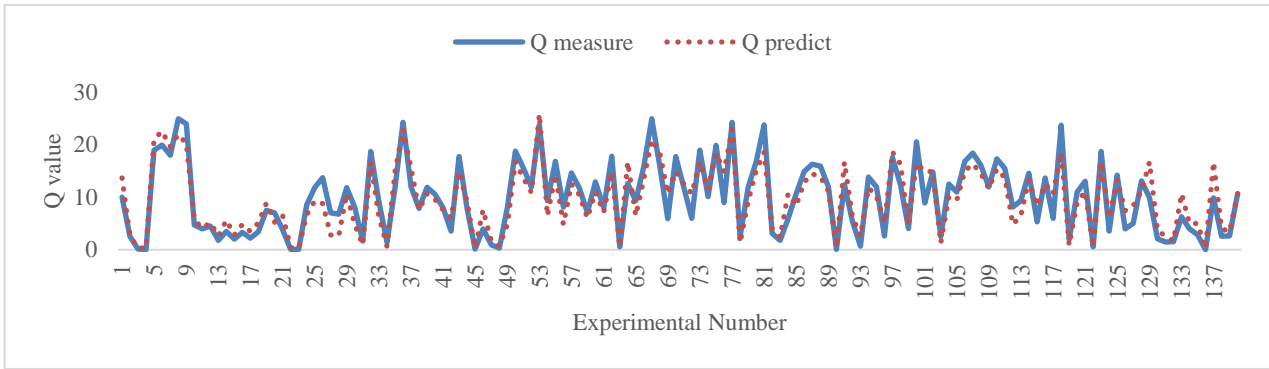
(B)

(C)

Fig. 3: Measured against predicted value of Q for train data A) Model 1, B) Model 2 and C) Model 3 (Table 3)
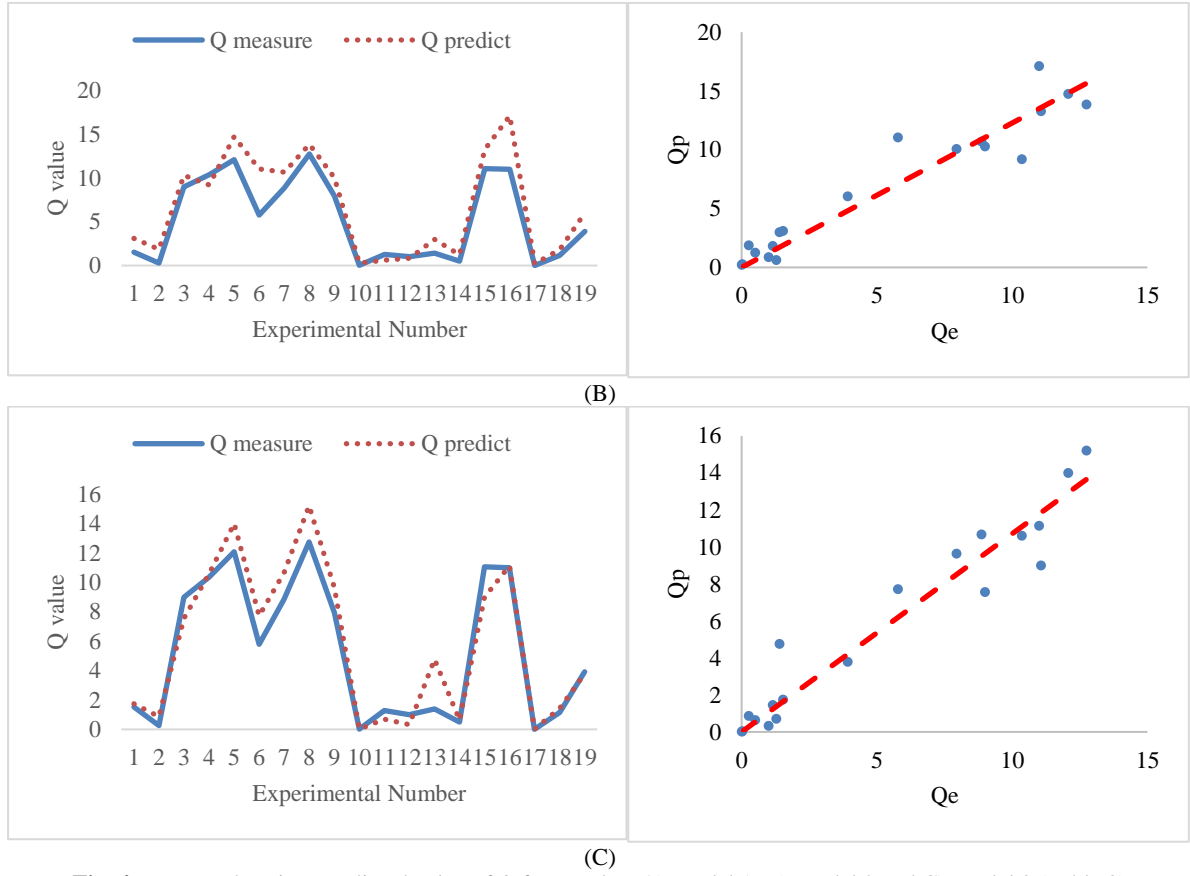
(A)

Fig. 4: Measured against predicted value of Q for test data A) Model 1, B) Model 2 and C) Model 3 (Table 3)

$$Q = \left(\frac{sqrt\left(\left(\left(\frac{1}{\left(\frac{RQD}{55.005462}\right)}\right)\right)\right)}{\left((55.009429 * Jn) + Jr\right)^2} \right) * \left(sqrt\left(\left(98.320984 + \left(\frac{\exp(Jn)}{RQD + 81.909363}\right)\right)\right)\right)^{\frac{1}{4}}$$

$$* \left(Jr * \left(\left((Jn - RQD)^3\right) + \left((Jn + RQD)^3\right)\right)\right) \tag{8}$$

$$Q = \left(\left(\left(\frac{1}{\left(\left(Ja^{\frac{1}{3}}\right) * (RQD * Ja)\right)}\right) + \left(\frac{1}{(Jn * Ja)}\right)\right) * \left(\left(RQD + \log\left(\left(\left((Ja - 3.984375) + Jn\right)^2\right)\right)\right)\right)^4\right)$$

$$* sqrt\left(\left(\frac{1}{\left(\left(\left(\log\left(\left(\left(RQD^{\frac{1}{3}}\right)^4\right)\right)\right)^5\right)^3\right)}\right)\right) \tag{9}$$

$$Q = sqrt\left(\left(RQD - \left(Ja - \left(\left(\frac{Jn - Jr}{Ja}\right)^2\right)\right)\right)\right) * \left(\log\left(\left(\left(\frac{10.408966 + Ja}{Jr}\right) + Ja\right)\right) * \left(\frac{1}{Ja}\right)\right)$$

$$* \left(\left(\left(\frac{Jr}{42.006591 * Jn}\right) * RQD\right) * \left(\left(Jr^{\frac{1}{3}}\right)^{\frac{1}{3}}\right)\right) \tag{10}$$

Considering the available parameters, all models have acceptable results. Among the models, model 2 is introduced as the elite relation because, in addition to having fewer parameters, it yields more acceptable results. For training and test data, R^2 and RMSE obtained from model 2 are 0.856, 2.55 and 0.917, 2.31, respectively. In other words, Q-value can be acceptably obtained via RQD, Jn and Ja parameters. Fig. 5 shows expression tree of model 2. According to this figure, ×, +, -, 3Rt, Inv, X2, X3, X4, X5, Ln and Sqrt functions were used in this model. Table 9 shows the value of parameters and constants used in expression tree.

7. Conclusion

This study used GEP technique to predict Q by 140 variable experimental data. Pearson correlation analysis was used to obtain the effect of parameters. Three models were used to predict Q-value. The best state of each model was obtained through the step by step GEP method. Furthermore, 19 new test data which were not included in initial data were used to assess the models. The results show that all three models show acceptable capability in predicting Q-value. Finally, model 2 was selected as the better model for test data because it has fewer parameters and shows better performance with the R^2 and RMSE of 0.917 and 2.31, respectively. The results of this study revealed that considering the fact that the determination of all parameters of Q is a difficult, time-consuming and costly process where all parameters are not available, the value of Q can be determined and acceptable results can be obtained through only three parameters.

Table. 9: The value of parameters and constants used in expression tree.

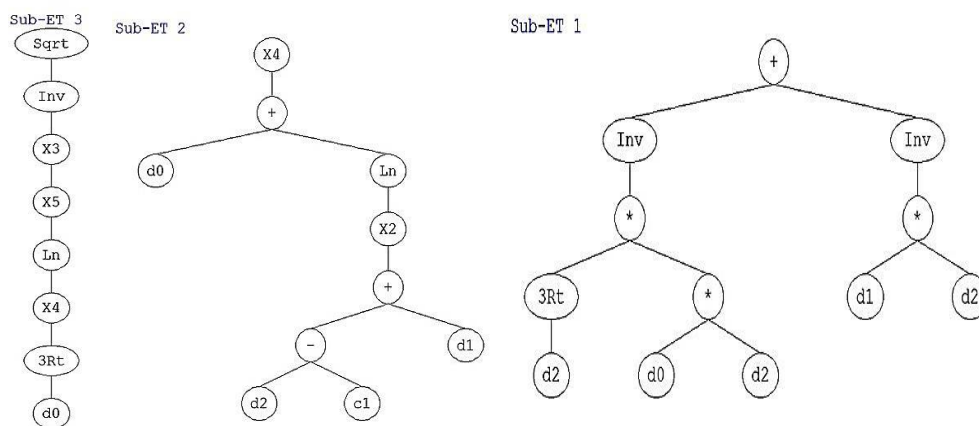| d0	d1	d2	G2 / C1
RQD	Jn	Ja	3.984375

Fig. 5: Expression tree of model 2 in GEP

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