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RESEARCH PAPER

Prediction of Q-Value by Multi-Variable Regression and Novel Genetic Algorithm Based on the Most Influential Parameters

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ABSTRACT: Determination of tunnel support, required for tunnel stability and safety, is an important debate in tunnel engineering field. Q-system classification is a technique used to determine the support system of a tunnel in rock. The problem is that all the required parameters of support system are not accessible. On the other hand, such accesses are very costly and time consuming. Therefore, it is impossible to determine the Q-value in all cases. This paper identifies the most influential parameters of Q-system using SPSS program. Then, it adopts multi-variable regression (MVR) and genetic algorithm (GA) methods to propose a relation for predicting the Q-value using three influential parameters. To this end, 140 experimental data are used. To assess the obtained models, 34 new experimental data, which are not in the primary dataset, are used. The innovation of this paper is that instead of six parameters, the Q-value is determined using three parameters with the highest impact on it instead of six parameters. In this study, the MVR model, with RMSE = 2.68 and correlation coefficient = 0.81 for train data and RMSE = 2.55 and correlation coefficient = 0.80 for test data, showed better performance than GA model, with RMSE = 2.90 and correlation coefficient = 0.82 for train data and RMSE = 2.61 and correlation coefficient = 0.84 for test data.

Keywords: Genetic Algorithm, Influential Parameters, Multi-Variable Regression, Q-System, Tunnel Support.

1. Introduction

Today, underground spaces are increasingly used in developed and developing countries. Limitation on surface spaces, constructing nuclear power plants, and constructing ammunition and weapon depots make it inevitable to use underground spaces and to design tunnels. Different classification systems have been proposed for tunnel design from the past till now. Some researches proposed the empirical methods for designing tunnel supports (Terzaghi, 1946); Wickham et al., 1972; Bieniawki, 1973; Barton et al., 1974). Liu et al. (2004) predicted required tunnel support using Support Vector Regression (SVR) technique. They showed that SVR

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can yield acceptable results. Tzamos and Sofianos (2006) used fuzzy logic and predicted tunnel support in Q-system. They used collected data and concluded that fuzzy system shows higher accuracy in predicting tunnel support. Chun et al. (2009) used multinomial regression analysis and multiple regression method to predict the deformation modulus of a rock mass using RMR-system. They showed that the results of both methods almost agree with each other. Majdi and Beiki (2010) used neural network to optimize the estimation of the deformation modulus of rock. They optimized the number of neurons of each layer, the momentum coefficient and the learning rate of hidden and output layers using GA. They showed that the GA method optimizes results and yields better results than neural networks.

Jalalifar et al. (2011) used the fuzzy-neural inference system and predicted RMR-value. They used three types of fuzzy-neural networks and showed that the subtractive clustering method is more efficient in predicting RMR-value. Ding et al. (2013) used hybrid encoding method to propose an algorithm for optimizing the RBF neural network learning based on GA. Jang and Topal (2013) used MVR model and neural network to predict the load-failure curve. They compared the performance of linear MVR, non-linear MVR and neural network in predicting load-failure curve and showed that neural network yields more accurate results than MVR models.

Beiki et al. (2013) used genetic programming method to predict the uniaxial compressive strength and the elastic modulus of carbonated rocks. They used collected data and offered relations based on regression and genetic programming models. They showed that genetic programing yields better results than regression models. Jalalifar et al. (2014) predicted RMR-value using MVR model and fuzzy inference system. They resulted that the latter shows higher accuracy than the former in predicting RMR.

Park et al. (2015) used GA to predict the settlement of thick clay layers and showed that GA could better predict settlement than graphical methods and could serve as a useful tool for reducing calculation time. Miyamoto and Motoshita (2015) attempted to develop a decision support system for rehabilitation strategies of existing concrete bridges, based on the life cycle analysis. They presented a new bridge management system that can be used to evaluate the serviceability of existing concrete bridges. GA technique was used to search for an approximation of the optimal maintenance plan. They showed that this system can accurately predict optimal maintenance planning, as well as bridge rating. Karimaee Tabarestani and Zarrati (2015) was studied the stability of riprap stones around circular as well as aligned and skewed round-nose and tail rectangular bridge piers based on a large amount of experimental data. Alemdag et al. (2016) studied experimental and numerical simulation results to estimate the deformation modulus of stratified rock masses. They used neural networks, fuzzy-neural network and genetic programming. They resulted that genetic programming has higher accuracy than other methods. However, both the neural network and fuzzy-neural network methods show a satisfactory performance.

Erdik and Pektas (2019) for predicting the damage level of armor blocks of breakwaters used the Multivariate Adaptive Regression Splines (MARS) approach. This technique presents a flexible regression by the use of separate regression slopes in distinct intervals of the independent variable. Abdollahzadeh et al. (2017) used two models based on Gene Expression Programming to predict compressive strength of high strength concrete. They used experimental results from a widely spread database that have been used for developing the models. They showed that the suggested GEP models can predict the compressive strength amounts of high strength concrete for each of the training and testing phases according to the statistical parameters.

Dastorani et al. (2018) used a number of machine learning and data mining methods including support vector machine, regression trees, model trees and artificial neural networks to simulate rainfall-runoff process in Zayandeh Rood dam basin in Iran. Yagiz et al. (2018) developed predictive models for estimating the rock brittleness using two techniques, genetic algorithm, and particle swarm optimization. They developed four different models including linear and non-linear using GA and particle swarm optimization techniques. Hassan (2019) used a GA technique, integrated with the FEM to compute the optimal cut-off location and angle of inclination for barrages constructed on homogenous anisotropic soil foundations. Bhandary et al. (2019) proposed a procedure to determine the safety factor (SF) using the FEM in conjunction with GA. They concluded that the elastic parameters have impact on the value of SF in non-homogenous slope's stability analysis using FEM.

This study implements GA and MVR models to predict the value of Q using the most influential three parameters. Then the results are compared with each other. In this way, Q is calculated by fewer parameters to save costs and time for tunnel design.

2. Q-System

There are different analytical, empirical and numerical approaches to determining tunnel supports. The use of analytical methods depends on the continuum assumption of the domain. In the other hand, numerical methods demand initial data sets which are not easily determinable. In majority of cases, therefore, empirical methods are used to determine tunnel supports. However, the combinations of empirical and numerical methods yield better results. Proposed by Barton et al. (1974), Q-system is the most reputable empirical method with six parameters shown in Eq. (1).

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

where *RQD*: is the rock quality designation, J_n: is the joint set number, J_r: is the joint roughness number, J_a: is the joint alteration number, J_w: is the joint water reduction factor and *SRF*: is the stress reduction factor. The numerical value of the index *Q* varies on a logarithmic scale from 0.001 to a maximum of 1000.

3. Materials and Methods

3.1. Used Data

The data used in this study were collected from valid references (Goel et al., 1996; Barton, 2002; Anbalagana et al., 2003; Makurat et al., 2006; Dadkhah et al., 2010; Dadkhah and Hoseeinmirzaee, 2014). Totally, 140 data were used in this study. Table 1 shows the range of data used by each reference for modeling purposes. For each data, the values of *RQD, Jn, Jr, Ja, Jw and SRF* were measured. In addition, 34 test data (Schwingenschloegl and Lehmann, 2009; Barton and Gammelsaeter, 2010; Barton and Grimstad, 2014; Barton and Grimstad, 2014; Fereidooni et al., 2015) were used to assess results.

3.2. Multi-Variable Regression (MVR)

In statistical models, regression analysis is a statistical process used to estimate the relationship between variables. It aims to estimate a function from independent variables which are called regression function. Dozens of techniques have been developed for regression analysis. Pearson correlation coefficient is a parametrical method used for data with a normal distribution (Mardia et al., 1979). Pearson correlation analysis was used to determine the effect of all six parameters on Q-system. Table 2 shows the results of Pearson correlation analysis conducted on the parameters of Eq. (1). According to Table 2, the relationship between each parameter and itself is equal to one where Pearson correlation for *Q* is 1 for example. This means that there is a direct and complete relationship between any parameter with itself. In the process of assessing the correlation of the mentioned 6 parameters with *Q*, if the obtained value is positive, the relationship will be a direct relationship; otherwise, it will be an inverse relationship. Moreover, the closer positive numbers to 1, and the closer negative numbers to -1, the higher is the relationship of that parameter with *Q*. According to Table 2, *RQD, Jn, Jr* and *Ja* have the highest impact on Q. Therefore, the impact of three parameters is first studied, and then the impact of the 4 parameters is evaluated.

The most influential parameters are RQD, J_n, J_r and J_a. Therefore, three possible combinations are considered as follows: 1) RQD, J_n, J_r, 2) RQD, J_n, J_a; and 3) RQD, J_n, J_r, J_a (Table 3). It should be mentioned that the obtained results and relationships are valid only in the scope of this study.

3.3. Genetic Algorithm (GA)

As a comprehensive probabilistic search method, GA was introduced by Holland (1975). GA is a programming technique that uses genetic evolution as a problem-solving model. It is an iteration-based algorithm the majority parts of which are selected randomly (Rezae and Rangbaran, 2012). Figure 1 shows the flowchart of the genetic algorithm (Safarzadeh et al., 2017). Visual Basic was used to develop codes for GA model. Table 4 shows the range of parameters used for developing codes for GA. The best model was obtained using these parameters as well as try and error technique. The number of iterations was selected to be 500.

3.4. Accuracy of Assessment

In this study, some statistical parameters including root mean squared error (RMSE), mean squared error (MSE), mean absolute error (MAE) and average absolute deviation (δ) and Nash number were used to assess the accuracy of the obtained models.

Table 1. Variation of collected data for parameter in present study

	Test data				Train data			
Parameters	**STD**	**Mean**	**Maximum**	**Minimum**	**STD**	**Mean**	**Maximum**	**Minimum**
Q	6.53	9.21	19.35	0.006	6.75	9.84	25	0.008
RQD	28.86	78.42	100	10	23.49	79.45	100	10
Jn	4.63	7.64	20	2.5	3.22	6.66	20	3
Jr	0.80	2.25	4	1	0.72	2.39	3.1	1
Ja	2.31	2.65	13	1	1.10	2.26	8	0.75
Jw	0.17	0.90	1	0.5	0.11	0.95	1	0.5
SRF	0.92	2	5	1	0.87	2.15	10	1

Table 2. Result of Pearson correlation analysis

Parameters	Q	RQD	J_n	J_r	J_a	J_w	SRF
Q	1	0.69	-0.64	0.56	-0.53	0.36	-0.23
RQD	0.69	1	-0.67	0.36	-0.56	0.32	-0.40
J_n	-0.64	-0.67	1	-0.47	0.58	-0.25	0.28
J_r	0.56	0.39	-0.47	1	-0.40	0.18	-0.14
J_a	-0.53	-0.56	0.58	-0.40	1	-0.30	0.38
J_w	0.36	0.32	-0.25	0.18	-0.30	1	-0.23
SRF	-0.23	-0.40	0.28	-0.14	0.38	-0.23	1

Table 3. Three types of possible combination of effective parameters on Q value

Models	Parameters
Combination 1	*RQD – Jn – Jr*
Combination 2	*RQD – Jn – Ja*
Combination 3	*RQD – Jn – Jr – Ja*

Table 4. Variation of GA parameters

Parameters	Value
Population size	100 - 400
Mutaion rate	0.01 – 0.99
Repeat Number	500
Intersection	0.01 – 0.99

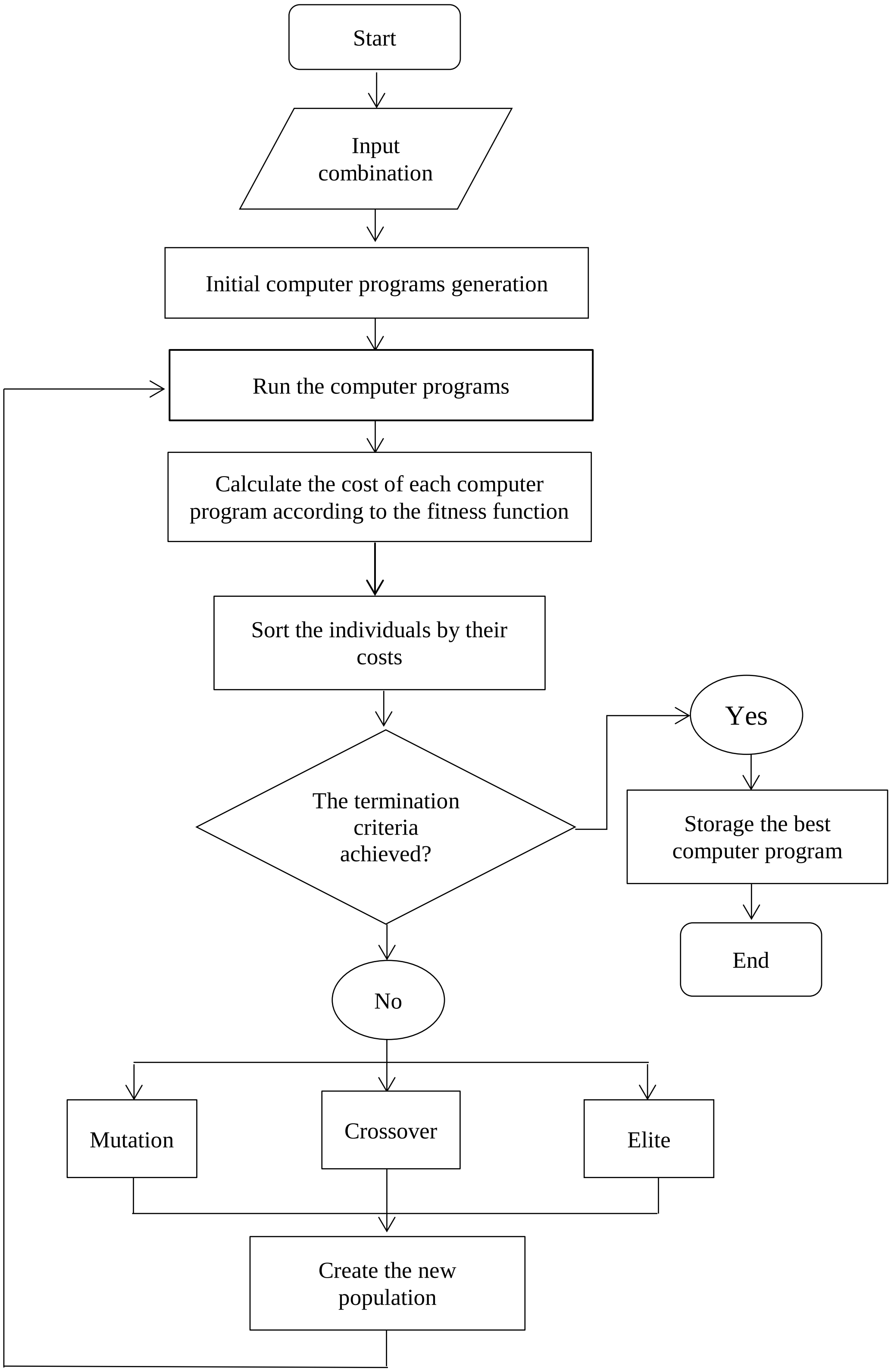


Fig. 1. GA flowchart

The mentioned functions show the difference of predicted deviations and real deviations. The lower values of the functions imply the higher performance of the model. The used statistical parameters are shown in the following:

$$MSE = \frac{\sum_{i=1}^{n}(Y_{p-}Y_{m})^2}{n} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(Y_{p-}Y_{m})| \quad (3)$$

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

$$\delta = \frac{\sum_{i=1}^{n} |(Y_p - Y_m)|}{\sum_{i=1}^{n} Y_p} \times 100 \quad (5)$$

$$R^2 = [\sum_{i=1}^{n} \frac{(y_m - \bar{y}_m)(y_p - \bar{y}_p)}{\sqrt{\sum_{i=1}^{n}(y_m - \bar{y}_m)^2 \sum_{i=1}^{n}(y_p - \bar{y}_p)^2}}]^2 \quad (6)$$

$$NASH = 1 - \frac{\sum_{i=1}^{n}(Y_p - Y_m)^2}{\sum_{i=1}^{n}(Y_m - \bar{Y}_m)^2} \quad (7)$$

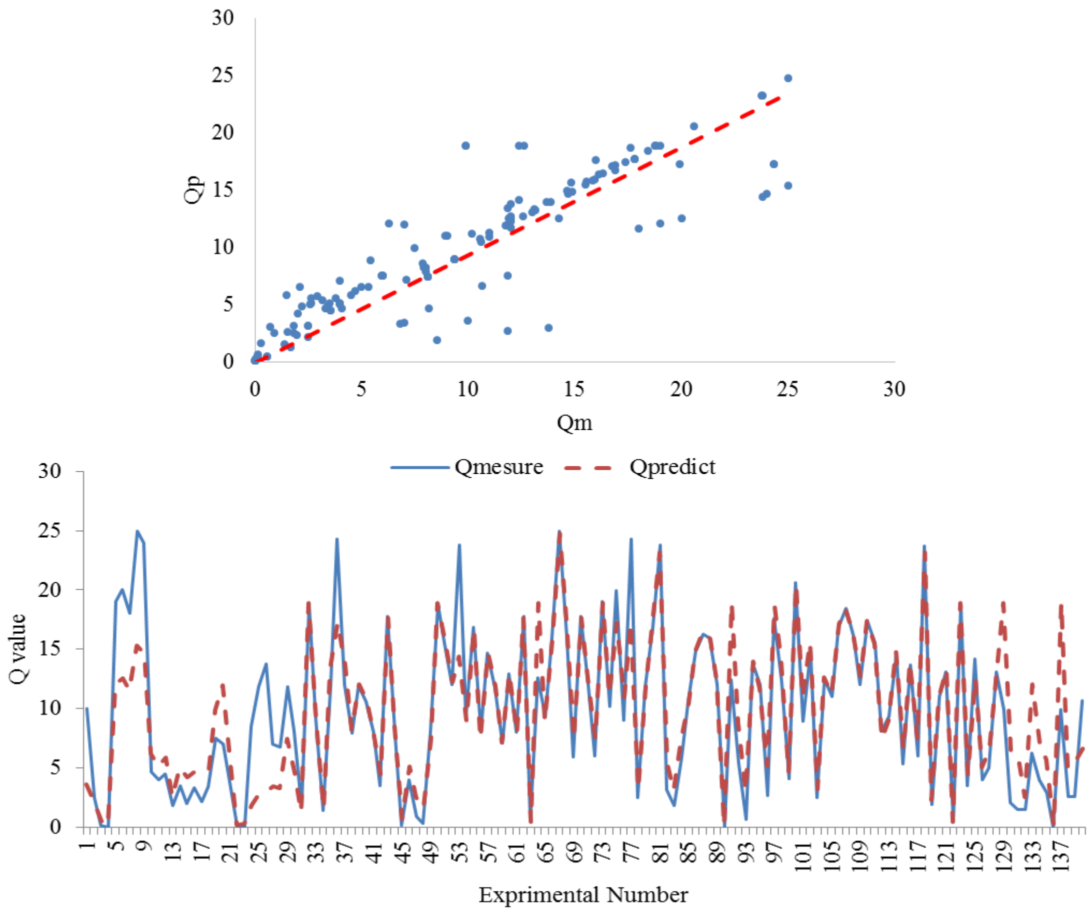
where Y_m, Y_p: are the observed and calculated values for Q, and $\bar{y}_m$, $\bar{y}_p$ and n: are the mean observed value, mean calculated value and number of data, respectively.

4. Results

4.1. Determination of Optimal Models for MVR and GA

In MVR and GA-based modeling, optimal values are proposed by a number of fit functions. Table 5 shows conventional MVR models used in this study for predicting Q-value (Beiki et al., 2013). According to Table 5, the Power equation yields the best result in all models. Figure 2 shows the MVR results of the Power model for all combinations.

In the GA model, the optimum value of parameters was defined after 27 tries and errors. Then, a fitness function was obtained for the optimum values. Table 6 shows the optimum values of GA parameters. RMSE, MAE and Nash function were assessed to select a suitable fitness function for the GA model. Table 7 compares three different fitness functions by statistical parameters. According to Table 7, fitness functions show almost close performances in all models but Nash function yields better results. Figure 3 shows the results of different combinations for Nash fitness function.



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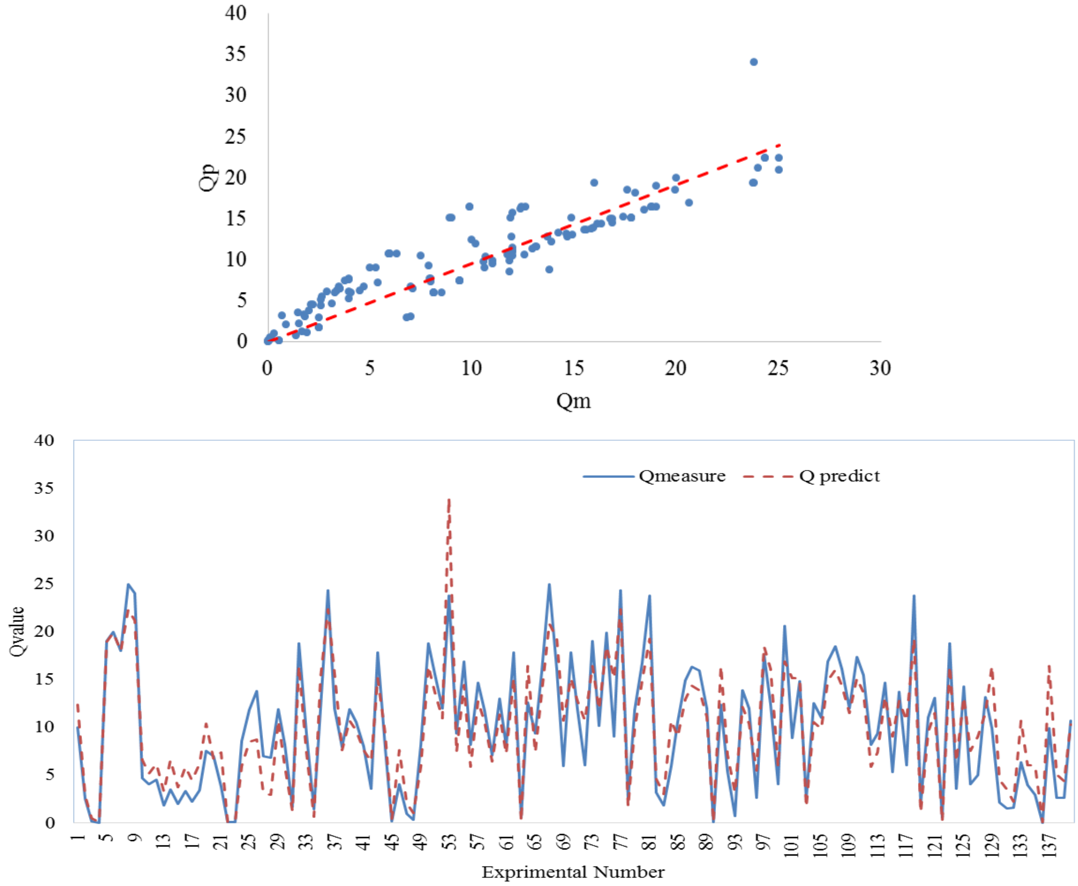

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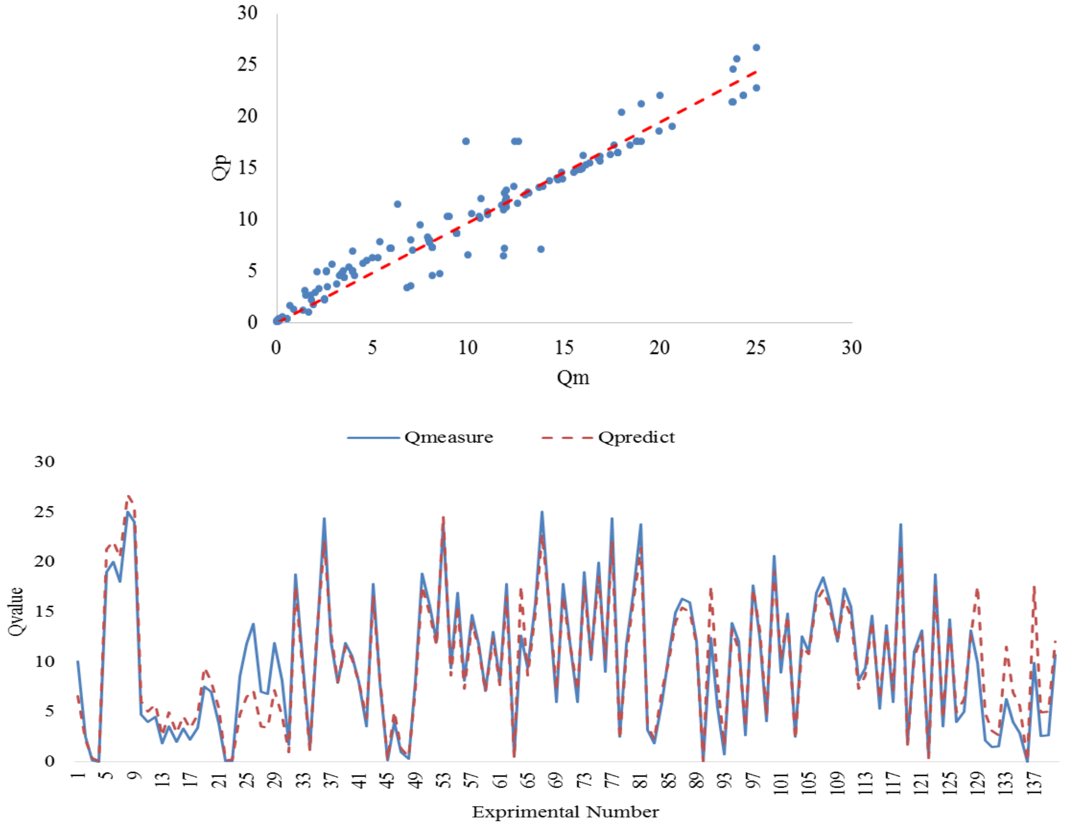
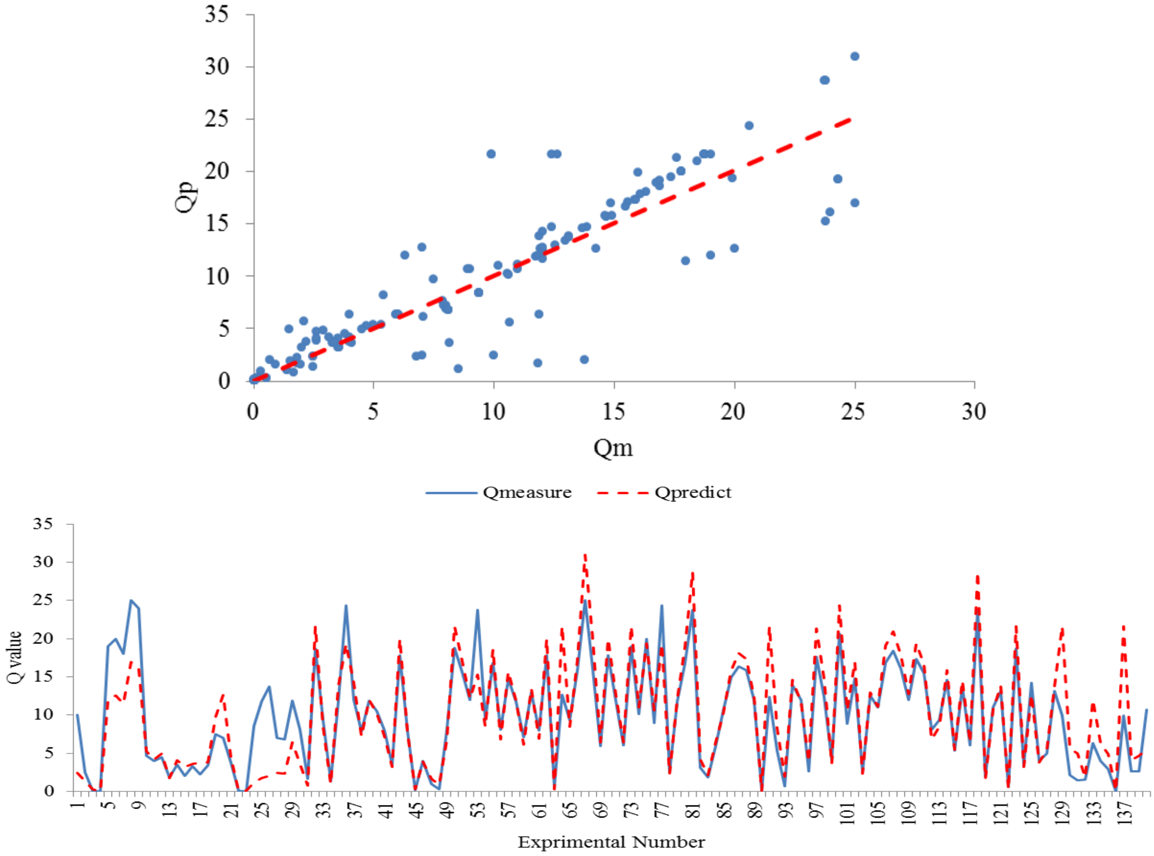


(c)

Fig. 2. Measured against predicted value of Q by power model for: a) Combination 1; b) Combination 2; and c) Combination 3 of effective parameters (Table 3)


Qp
Qm
Qmeasure
Qpredict
Q value
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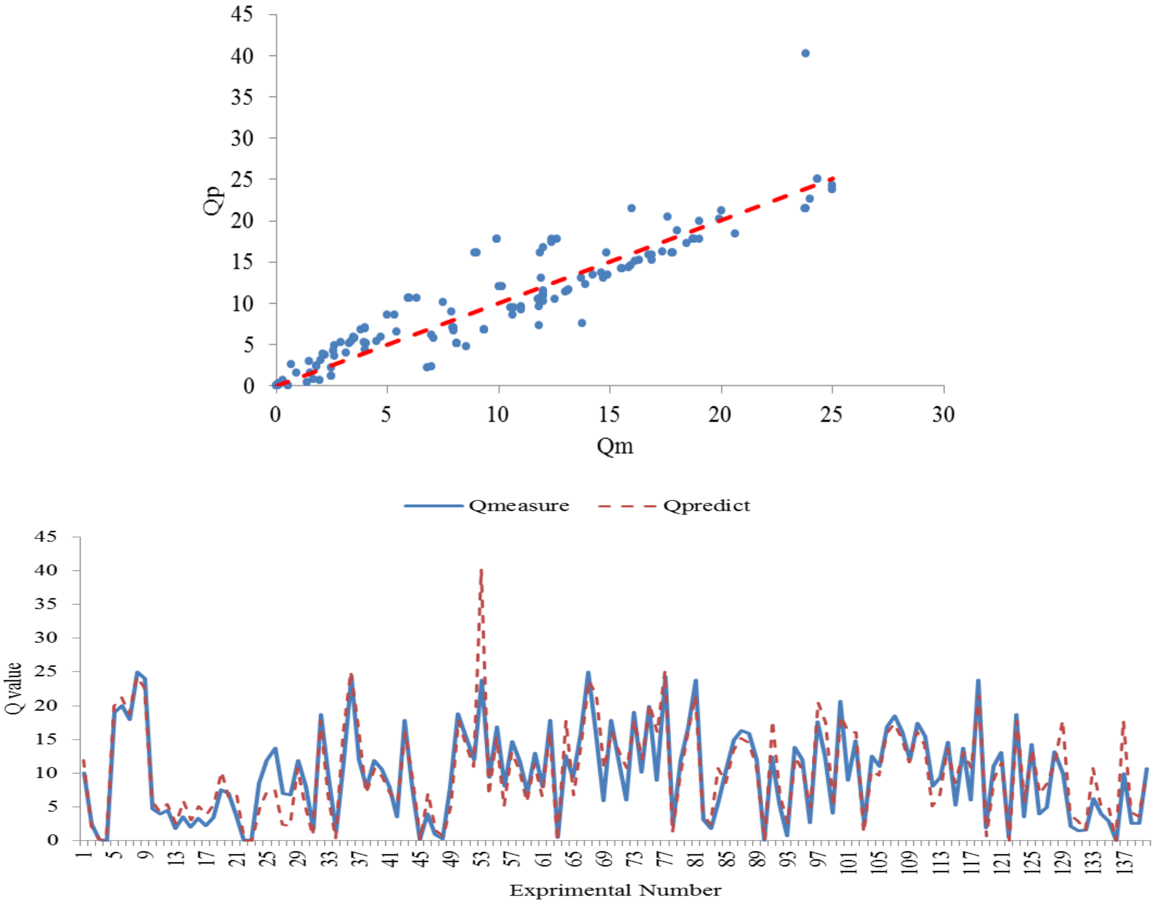
(a)


Qp
Qm
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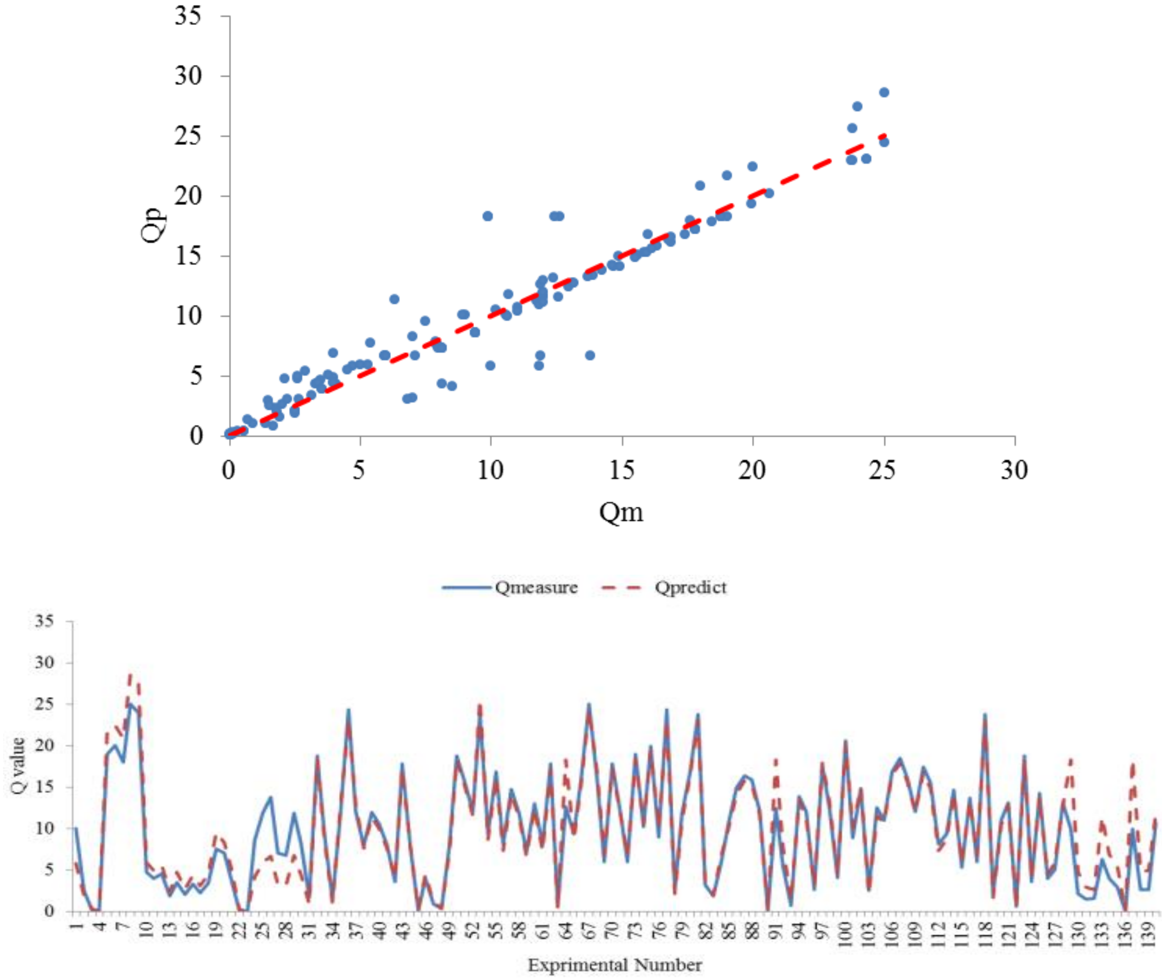
Qpredict
Q value
Exprimental Number

(b)



(c)

Fig. 3. Measured against predicted value of *Q* by GA model when using Nash fitness function for: a) Combination 1; b) Combination 2; and c) Combination 3 of effective parameters (Table 3)

Table 5. Statistical parameters for different regression model in prediction of Q values

Regression model	**Eqution**	**Model**		**Model**		**Model**	
		R	**RMSE**	**R**	**RMSE**	**R**	**RMSE**
Linear	$y = \sum_{i=1}^{n} a_i x_i + b$	0.39	4.25	0.27	4.55	0.42	4.23
Inverse	$y = \sum_{i=1}^{n} \frac{a_i}{x_i} + b$	0.35	3.92	0.69	3.36	0.74	3.13
Logarithmic	$y = \sum_{i=1}^{n} a_i \ln(x_i) + b$	0.41	4.19	0.50	4.04	0.56	3.85
Growth	$y = \sum_{i=1}^{n} \exp(a_i)^2 + b$	0.68	4.06	0.33	4.44	0.50	4.01
Power	$y = b \prod_{i=1}^{n} x_i^{a_i}$	0.74	3.12	0.81	2.68	0.91	1.94

Table 6. Optimum values of GA parameters

Parameters	**Value**
Population size	400
Mutaion rate	0.05
Repeat number	500
Intersection	0

Table 7. Statistical parameters for different fitness function for each model

Models	Fitness function	%δ	GA		
			MAE	RMSE	R
Model 1	RMSE	18.84	1.86	3.13	0.73
	MAE	18.41	1.64	3.19	0.75
	Nash	21.40	2.21	3.47	0.77
Model 2	RMSE	22.94	2.25	2.72	0.81
	MAE	18.53	2	3.03	0.82
	Nash	20.45	2.07	2.90	0.82
Model 3	RMSE	13.86	1.36	1.95	0.91
	MAE	10.10	1.05	2.13	0.90
	Nash	12.03	1.22	2	0.91

4.2. Comparison of Finalized Models

This section compares MVR and GA models in order to determine that which model shows a better performance in predicting the Q-value. Table 8 shows the comparison results. According to this table, train data are very close to each other in all combinations and both models have almost the same performance. Therefore, 34 test data were used to compare results. Table 9 shows the results derived from GA and MVR models for test data. This table reveals that GA and MVR models show close performances in all models where the performance of MVR model is slightly better. Figure 4 compares the results of MVR and GA models for test data where both models show almost the same performance in predicting Q-value by test data. However, the results of MVR model are slightly better than those of GA.

Despite the fact that GA and MVR models yield almost close results, the output results indicate that MVR model yields better results in all models. According to Tables 8-9, both GA and MVR models well assess all types of data. In addition, the Q-value predicted by the proposed models agrees with empirical data. Table 10 shows the coefficients of the equation proposed for the best MVR and GA models. Amongst the three combinations, the second one is proposed due to having fewer parameters with a correlation coefficient of 0.81 and 0.80 for train and test data, respectively. Furthermore, RMSE of train and test data is 2.68 and 2.55, respectively in this combination. In other words, given *RDQ*, J_n and J_a parameters, the Q-value can be obtained with an acceptable approximation.

Table 8. Statistical comparison of GA and MVR models for training data

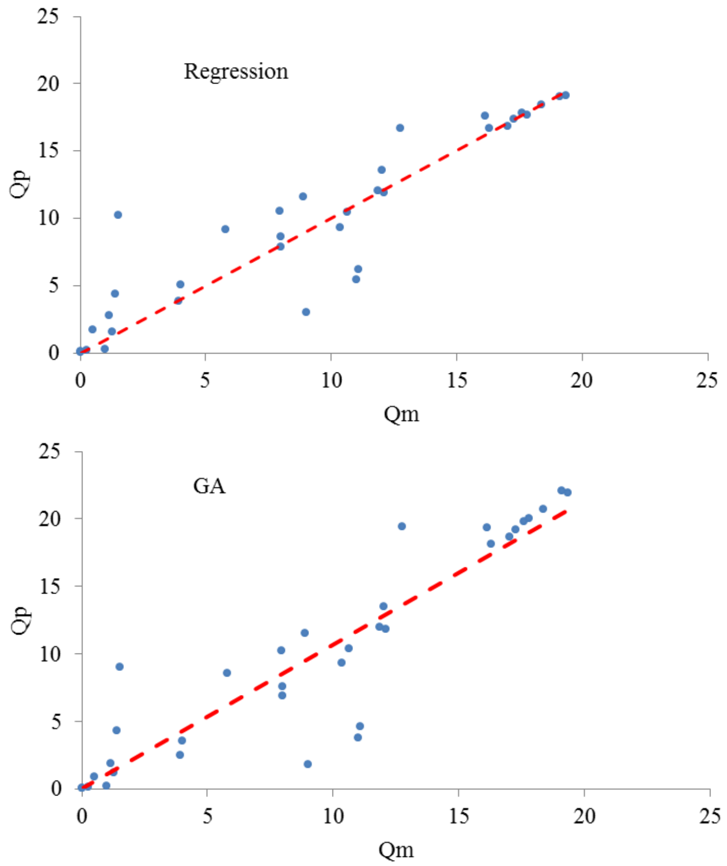
Statistical parameters	Regression			GA		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
R^2	0.74	0.81	0.91	0.77	0.82	0.91
RMSE	3.12	2.68	1.94	3.47	2.90	2

Table 9. Statistical comparison of GA and MVR models for test data

Statistical parameters	Regression			GA		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
R^2	0.83	0.80	0.93	0.83	0.84	0.93
RMSE	2.55	2.55	1.55	3.13	2.71	1.66

Table 10. Best derived equations for each combination of effective parameters

Models	Proposed equation	a	b	c	d	e	f
Model	$Q = a * \left(\frac{RQD^b}{J_n^c}\right) * \left(\frac{J_r^d}{1}\right) + e$	0.094	1.272	0.944	0.686	0	-
Model	$Q = a * \left(\frac{RQD^b}{J_n^c}\right) * \left(\frac{1}{J_a^d}\right) + e$	0.063	1.585	0.843	0.822	0	-
Model	$Q = a * \left(\frac{RQD^b}{J_n^c}\right) * \left(\frac{J_r^d}{J_a^e}\right) + f$	0.214	1.197	0.895	0.683	0.886	0



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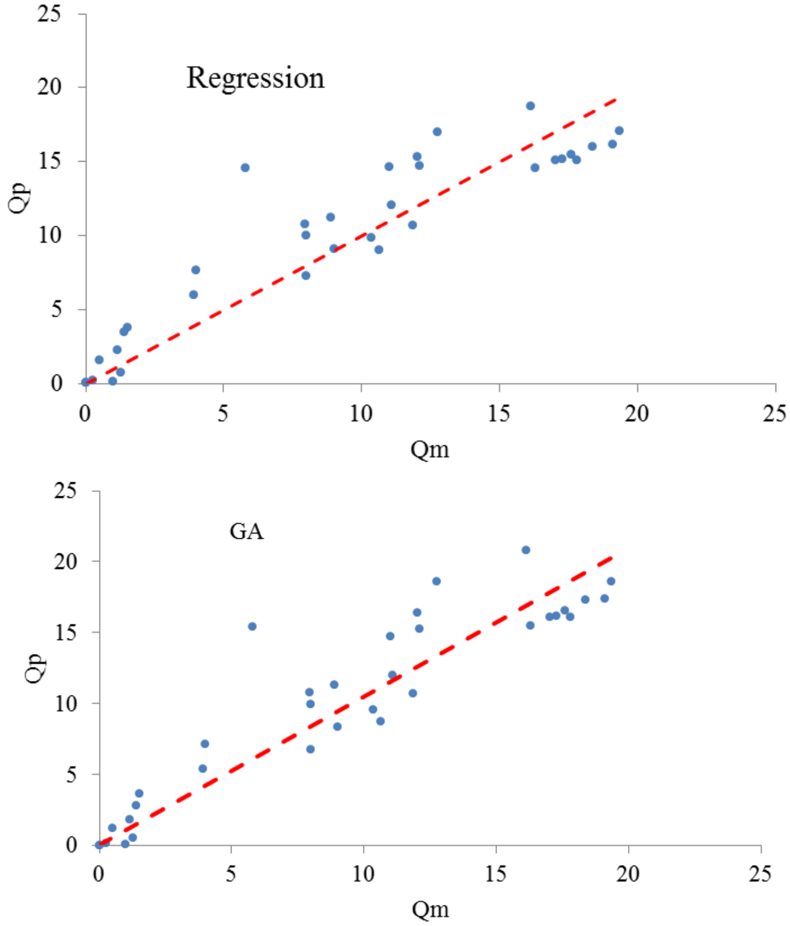

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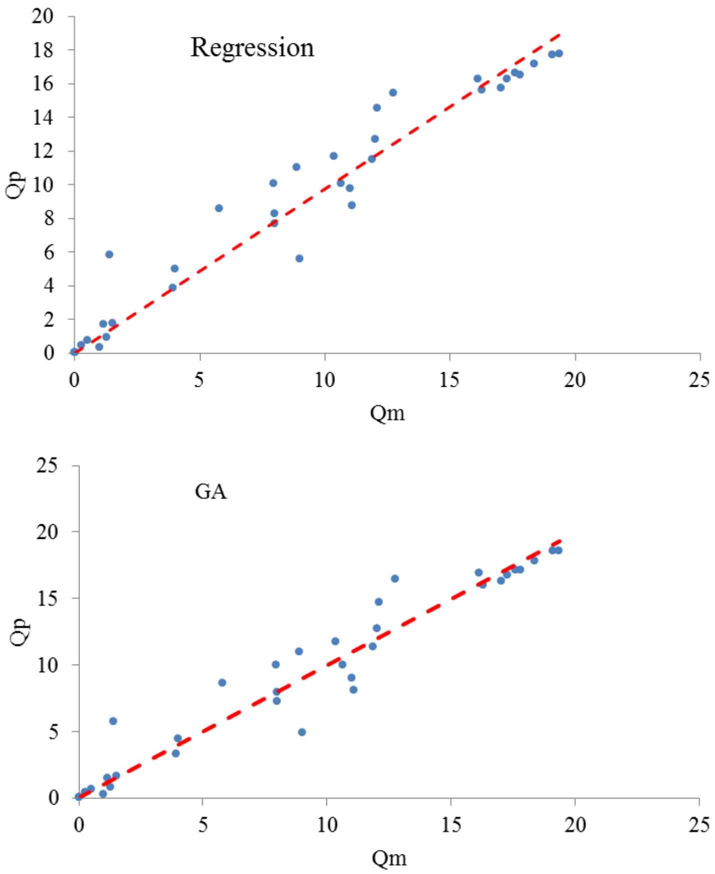

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Fig. 4. . Measured against predicted value of *Q* by GA model when using Nash fitness function for: a) Combination 1; b) Combination 2; and c) Combination 3 of effective parameters (Table 3)

5. Summary and Conclusions

This study evaluated the capabilities of MVR and GA techniques in estimating the Q-value. To this end, 140 experimental data, collected from different tunnels, were used. In addition, three combinations with the highest impact on Q were applied on the models. The effect of each parameter on Q was obtained using Pearson analysis. In MVR model, frequently-used equations were adopted to obtain the best model. In the GA model, however, different fitness functions were used, after obtaining optimal parameters, to obtain the best model. In the MVR and GA models, Power equation and Nash function yielded the best results, respectively. The extracted models, then, were compared with each other. According to the obtained results, both models show an acceptable performance. However, MVR model works slightly better. In addition, the results of both models were assessed by 34 test data which were not among the primary data set.

Finally, the second combination of MVR model with RMSE=2.68 and 2.55 for train and test data, respectively, was elected as the best combination due to showing more acceptable performance and having fewer parameters. The determination of all parameters of Q is a costly and time-consuming process which is not always accessible. However, the results of this study indicated that the Q-value could be calculated only by three parameters by which acceptable results could be obtained.

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