PREDICTION OF DRILLABILITY OF ROCKS WITH STRENGTH PROPERTIES USING A HYBRID GA-ANN TECHNIQUE

Manoj Khandelwal[1*] and Danial Jahed Armaghani[2]

[1*]Faculty of Science and Technology, Federation University Australia, PO Box 663, Ballarat, Victoria 3353, Australia Phone: +61 3 5327 9821 Email: m.khandelwal@federation.edu.au.

[2]Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia, 81310, UTM, Skudai, Johor, Malaysia. Email: danialarmaghani@gmail.com.

Abstract

The purpose of this paper is to provide a proper, practical and convenient drilling rate index (DRI) prediction model based on rock material properties. In order to obtain this purpose, 47 DRI tests were conducted in the laboratory. In addition, the relevant strength properties i.e. uniaxial compressive strength (UCS) and Brazilian tensile strength (BTS) were determined and selected as input parameters to predict DRI. Examined simple regression analysis showed that the relationships between the DRI and predictors are statistically meaningful but not good enough for DRI estimation in practice. Moreover, multiple regression, artificial neural network (ANN) and hybrid genetic algorithm (GA)-ANN models were constructed to estimate DRI. Several performance indices i.e. coefficient of determination (R^2), root mean square error (RMSE) and variance account for (VAF) were used for evaluation of performance prediction the proposed methods. Based on these results and the use of simple ranking procedure, the best models were chosen. It was found that the hybrid GA-ANN technique can performed better in predicting DRI compared to other developed models. This is because of the fact that the proposed hybrid model can update the biases and weights of the network connection to train by ANN.

Keywords: Drilling rate index, Rock material properties, Artificial neural network, Hybrid model.

1. Introduction

Drillability is defined as the resistance of rock to penetrate the rock mass by a drilling system. Drilling rate index (DRI) is one of the tool to evaluate drillability of rocks. The drilling rate index (DRI) was proposed by Selmer-Olsen and Lien (1960) in order to evaluate the drillability of rocks by percussive drilling. The influential factors on DRI can be categorized into two parts, i.e. controllable and uncontrollable parameters. Bit type and diameter, thrust, blow frequency, rotational speed and flushing are considered as controllable factors on DRI, while some other parameters, like geological conditions and rock properties are defined as uncontrollable parameters of DRI (Yarali and Kahraman 2011). Drilling has a direct and may be close relationship with the rock mass and material properties (Hoseinie et al. 2008). Strength of rock has a considerable impact on drilling thrust. Strength properties of rocks play an important role in design, safety and stability of any rock structures (Khandelwal and Ranjith, 2010; Khandelwal, 2013). Therefore, recognition the most effective parameters on DRI and subsequently proper DRI prediction would help designers to select the appropriate type of drilling system.

Many studies have been conducted in order to demonstrate the effects of rock (mass and material) properties on DRI (e.g. Wijk 1989; Karpuz et al. 1990; Kahraman 1999; Kahraman et al. 2000; Kahraman et al. 2003; Hoseinie et al. 2009; Dahl et al. 2012; Yarali and Soyer 2013; Macias et al. 2014; Tripathy et al. 2015; Ataei et al. 2015). A penetration rate model was proposed using stepwise linear regression analysis in the study conducted by Selim and Bruce (1970). Schmidt (1972) related the penetration rate with tensile strength, density, Young's modulus, Shore hardness, shear modulus, longitudinal wave velocity, compressive strength, Poisson's ratio and shear wave velocity. A rating classification for DRI prediction was established in the study carried out by Hoseinie et al. (2008). They used six rock mass properties namely Mohs hardness, grain size, uniaxial compressive strength (UCS), joint filling, joint spacing and joint dipping to predict DRI. Yarali and Kahraman (2011) proposed new relations for predicting DRI by using brittleness values of 32 different rocks. Cheniany et al. (2012) developed linear and non-linear multiple regression to estimate specific rock mass drillability (SRMD) index. In their models, UCS, quartz content, Schmidt hammer hardness value, joint dip, alteration and fragment size (d80) were considered as predictors. Single regression models were introduced by Yarali and Soyer (2013) in order to relate DRI with several properties of rocks including UCS, Brazilian tensile strength (BTS), point load strength, Schmidt rebound hardness and Shore scleroscope hardness. They showed that rock strength is the most effective parameter on DRI. Moein et al. (2014) measured DRI values of carbonate rock in the laboratory and indicated good relationships for predicting DRI using the alteration index and specific energy.

In the field of artificial intelligent systems, there were also several attempts by previous researchers in order to predict penetration rate. An artificial neural network (ANN) approach was selected and proposed for predicting penetration rate by Akin and Karpuz (2008). They concluded that their developed approach can provide satisfactory results in estimating penetration rate. Arabjamaloei and Karimi Dehkordi (2012) utilized adaptive neuro-fuzzy inference system (ANFIS), ANN and statistical techniques in estimating penetration rate and concluded that ANN is the best model among all developed models. A penetration rate model based on ANFIS was proposed in the study conducted by Basarir et al. (2014). They successfully showed that ANFIS results are better than the results of statistical model. In the present study, several linear and non-linear models i.e. multiple regression analysis, ANN and hybrid genetic algorithm (GA)-ANN were applied and developed to predict the DRI values using strength properties of rocks.

2. Method

2.1 Artificial Neural Network

In ANNs, which are function approximation tools, the process of information-transfer in the human brain is imitated. Generally, ANNs are applicable to cases in which there is very complex and nonlinear contact nature between input variable(s) or predictor(s) and output of the system (Garrett 1994; Jahed Armaghani et al. 2015a). ANNs have been designed in many types, and the most commonly-used one is the multilayer feed-forward ANN that comprises multiple layers that are connected together by a number of hidden nodes (neurons) with different connection weights (Simpson 1990). For the achievement of a desirable outcome, ANNs should be trained by means of some learning algorithms. For training ANNs, the back-propagation (BP) algorithm is the most widely-used among other learning algorithms (Dreyfus 2005; Hajihassani et al. 2014; Jahed Armaghani et al. 2015b). By using BP algorithm, system error between desired and predicted values can be minimized. The output of each hidden node is determined subsequent to the application of a transfer function, which is mostly sigmoidal function, to the net input of the hidden node. A comparison is made between the desired output (targets) and the predicted one, and then the error is computed. If this error is bigger than mean square error (MSE) or root mean square error (RMSE) values, the network should be propagated back for adjusting the connection weights. Figure 1 shows structure of BP ANN algorithm with one hidden layer.

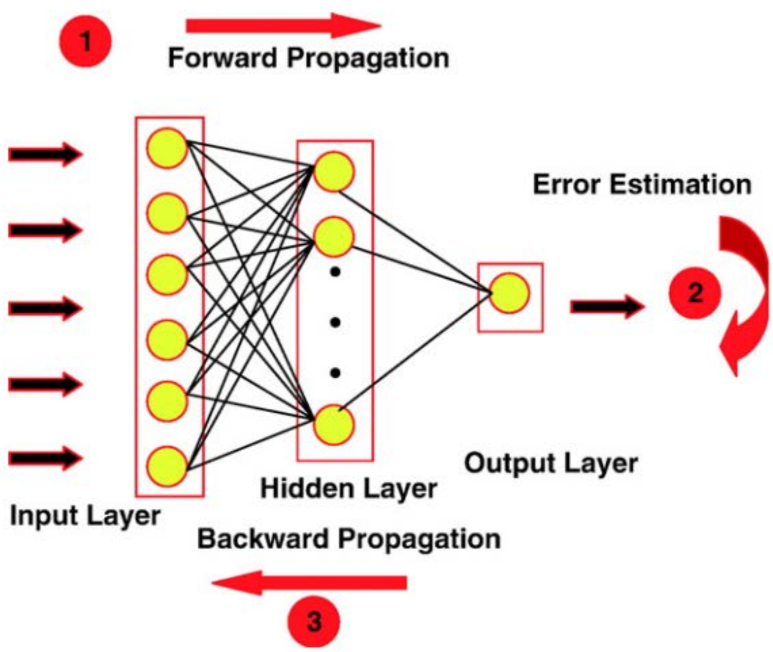

Figure 1. Structure of BP ANN algorithm with one hidden layer **(**Saemi et al. 2007)

2.2 Genetic Algorithm

Genetic algorithm (GA) which was developed by Holland (1975) is considered as an optimization technique. This algorithm mimics the natural selection mechanism and the biological species evolution. To advance, in each decision variable, objective function evaluation is needed by GA. This is because the stochastic-based technique of GA does not need any specific information for guiding the search (Chipperfield et al. 2006).

Generally, in GA, there are populations of individuals that are known as candidate solutions; each individual gradually converges over time to an optimal solution. Each candidate solution is denoted by a linear string that consists of chromosomes represented by 0s and 1s. Total solutions form the population size together with the optimization process of each iteration is known as a generation. In GA, for the creation of the next generation, three basic genetic operators i.e. reproduction, cross-over, and mutation should be applied. The first operator or reproduction is defined as a process through which the best chromosomes are selected according to their scaled values with considering the given criteria of fitness, and then the selected chromosomes are directly transferred to the next generation. Through the cross over operator, offspring or new individuals are produced through combining particular parts of individuals (parent). Recombination is done through several ways, including single-point cross over and two-point cross over. Nevertheless, during the process of cross over, a random cross over point and two parents are chosen. The creation of the first offspring is through the combination of the left side genes of the first parent with the right side genes of the second parent. To form the second offspring, an inverse procedure is repeated (Momeni et al. 2014). Mutation is defined as a process during which a random change occurs in elements of a chromosome.

Several studies have been conducted to enhance the performance quality and generalisation capabilities of ANNs through the use of GA algorithm (e.g. Monjezi et al. 2012; Aghajanloo et al. 2013; Momeni et al. 2014). GA is known as stochastic search algorithm; as a result, it can be performed for adjusting the biases and weights of the ANNs to increase the performance prediction of ANNs (Momeni et al. 2014). At a local minimum, by ANNs, there is normally more probability of convergence, while GA can find a global minimum. So, a combination of GA and ANN model (GA-ANN model) utilizes the search properties of both algorithms to enhance the network power. In this model, first, GA finds global minimum in search space, and then ANN employs it to discover the best results. A hybrid GA-ANN algorithm is displayed in Figure 2.

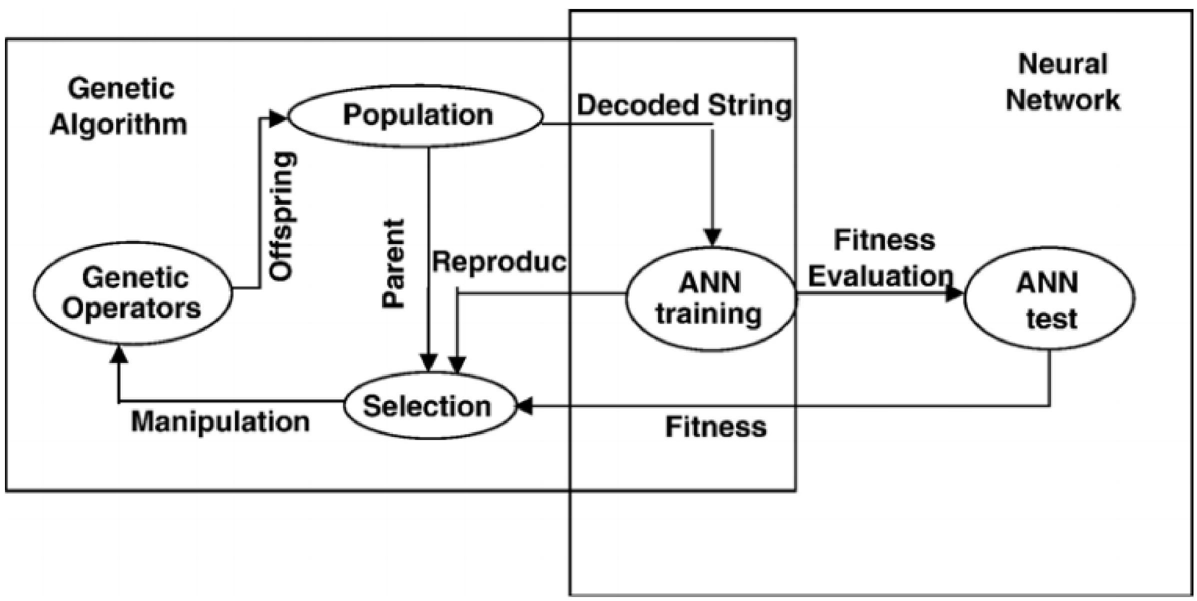

Figure 2. Combination of GA-ANN (Saemi et al. 2007)

3. Laboratory Testing

Rock mass samples were collected from different published literatures (Yarali and Kahraman, 2011; Adebayo et al, 2010; Ekincioglu et al, 2013) to fulfill the aim of this research.

3.1 Uniaxial compressive strength

Determination of UCS involves the use of a NX size (54 mm diameter) cylindrical specimen with length to diameter ratio of 2.5 which is loaded axially as suggested by ISRM (1979). UCS can be calculated with the help of following formula:

$$UCS = P / A \tag{1}$$

where,

P – Failure load, and

A – Cross-sectional area of the cylindrical specimen

3.2 Tensile strength

Brazilian test is used in order to determine tensile strength in the laboratory. This test is conducted based on the fact that mostly rocks in biaxial stress fail in tension at their uniaxial tensile strength (Jaeger 1967). The test should be conducted in accordance with ISRM (1978) standard. Tensile strength can be calculated with the help of following formula:

$$TS = 2.P / \pi.d.t \tag{2}$$

Where,

P = Failure load, and

d = Diameter of the disc

t = Thickness of the disc

3.3 Drilling Rate Index (DRI)

Drillability of rocks are examined on the basis of the DRI. The DRI is defined as a combination of the intact rock specimen brittleness value (S20) test which was proposed by Matern and Hjelmer (1943) and Sievers' J-Value (SJ) miniature drill-test which was proposed by Sievers (1950). The SJ test is considered as an indirect measure of rock resistance to tool indentation (surface hardness); the brittleness value, S20, is an indirect measure of rock resistance to crack growth and crushing.

3.3.1 The Brittleness Test

In this study, S20 values were measured by using the Swedish Stamp Test (see Figure. 3). The test is started by putting the rock aggregate in a mortar and then by using a 14 kg hammer, struck 20 times. The mortar aggregate volume corresponds to that of a 0.5 kg aggregate with a density of 2.6 5 tons/m3 in the fraction 11.2 - 16.0 mm. S20 equals the percentage of undersized material that passes through a 11.2 mm mesh after the drop-test. S20 should be taken as a mean value of three or four parallel tests.

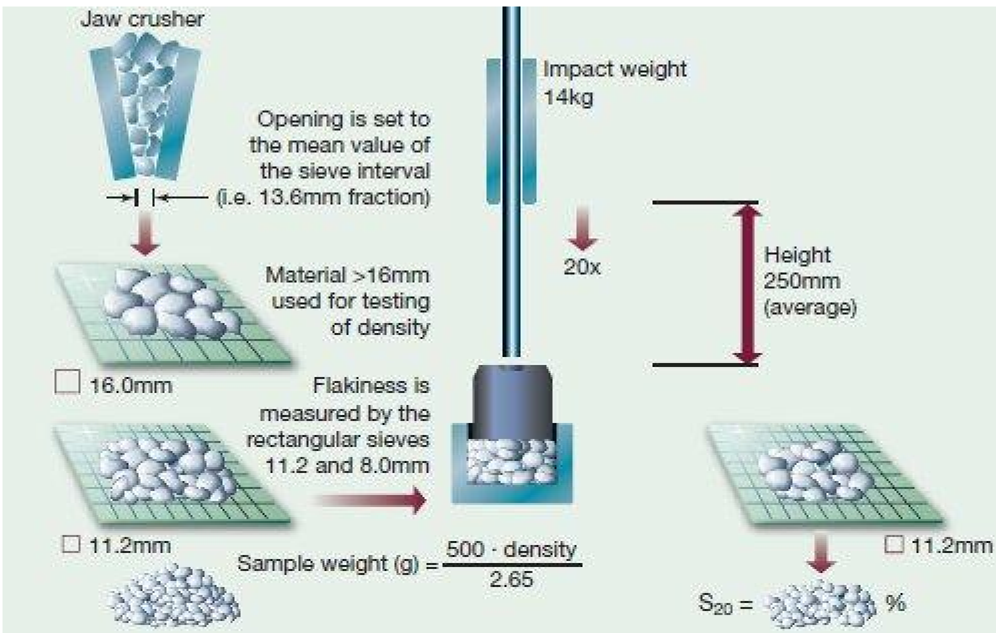

Figure 3. Outline of the brittleness test (Dahl 2003)

3.3.2 The Sievers' J (SJ) miniature drill test

The second DRI parameter which is the SJ value, can be obtained from a miniature drill test. After 200 revolutions, in the rock sample, the hole depth is measured in 1/10 mm. A mean value of four - eight test holes should be used. Parallel to rock foliation, the SJ values are always measured for created holes. Outline of the Sievers' J miniature drill test is shown in Figure 4.

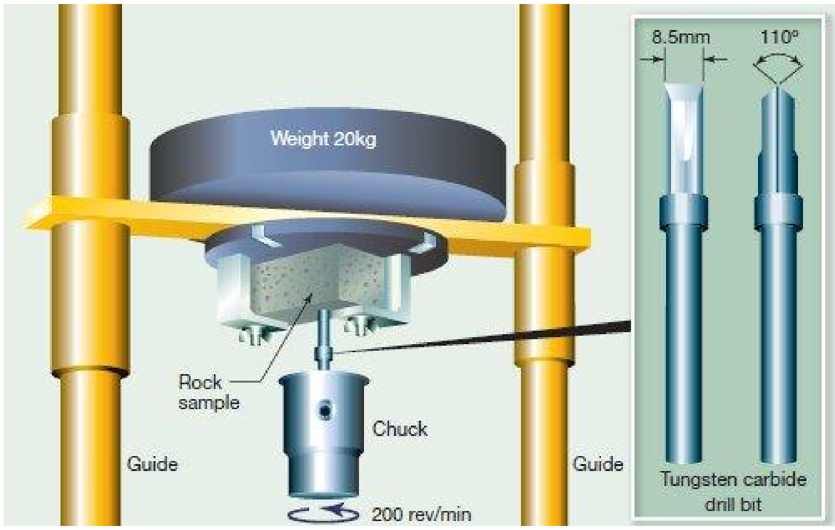

Figure. 4. Outline of the Sievers' J miniature drill test (Dahl 2003)

3.3.4 Assessment of DRI

After measuring S20 and SJ values, DRI can be determined by using the Figure 5. Based on this figure, DRI values can be determined using both brittleness and SJ values. Table 1 shows DRI classification rating for various categories.

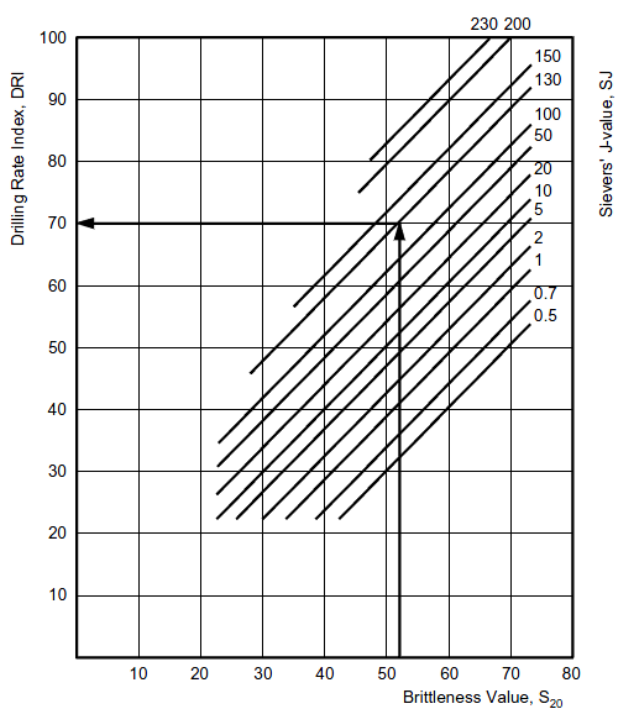

Figure. 5 The graph for determination of DRI using S20 and SJ (Bruland 1998)

Table 1 Classification of rocks considering DRI rating

S. No.	Category	DRI
1	Extremely low	21
2	Very low	28
3	Low	37
4	Medium	49
5	High	65
6	Very high	86
7	Extremely high	114

4. DRI Prediction

In order to solve the engineering problem, simple regression equations are conducted in the first step. The used parameters and their categories and ranges are shown in Table 2. Based on this table, UCS and BTS were considered as model inputs in this study to predict DRI.

Table 2 Basic statistical description of input and output parameters

Parameter	Unit	Category	Symbol	Min	Max	Mean
Uniaxial compressive strength	MPa	Input	UCS	28.6	182.1	95.5
Brazilian tensile strength	MPa	Input	BTS	2.57	17.07	8.68
Driling rate index	-	Output	DRI	22	86	55.26

The simple regression analyses were performed between the DRI and predictor parameters i.e. UCS and BTS. The obtained results from simple regression analysis are not good enough to be utilized to solve the problem. Due to this reason, to obtain the better model for prediction of DRI, multiple regression analysis, ANN and hybrid GA-ANN techniques were also conducted using established dataset. The procedure of each modelling technique was described in the following sections.

4.1 Simple Regression

In order to examine the effect of input parameters, the simple regression analyses were constructed between the DRI and other mentioned parameters including UCS and BTS. Subsequently, new equations introduced for estimation of DRI. In order to obtain equations with higher performance capacity, various simple regression analyses such as; linear, exponential, power and logarithmic were performed. The selected equations to predict DRI using UCS and BTS are presented in Equations 3 and 4, respectively.

$$DRI = -26.96 \times \ln(UCS) + 176.29 \qquad (R^2 = 0.396) \qquad (3)$$

$$DRI = -31.15 \times \ln(UCS) + 120.86 \qquad (R^2 = 0.411) \qquad (4)$$

The reliability of the developed relationships was evaluated by comparing the obtained coefficient of determination (R^2) values for each analysis. As it can be seen in Equations 3 and 4, the logarithmic relationships give the best relatively results in estimating DRI among all utilized-equation types. R^2 values of 0.396 and 0.411 were obtained for predicting DRI considering UCS and BTS data, respectively. The purposed relationships between the DRI and input parameters i.e. UCS and BTS are given in Figures 6 and 7. The results indicated that the relations between the input parameters and DRI are meaningful but not good enough for estimation of the DRI in practice. These relationships indicated that maybe multi-inputs are required to predict the DRI, so, various modelling techniques namely multiple regression analysis, ANN and GA-ANN were also constructed.

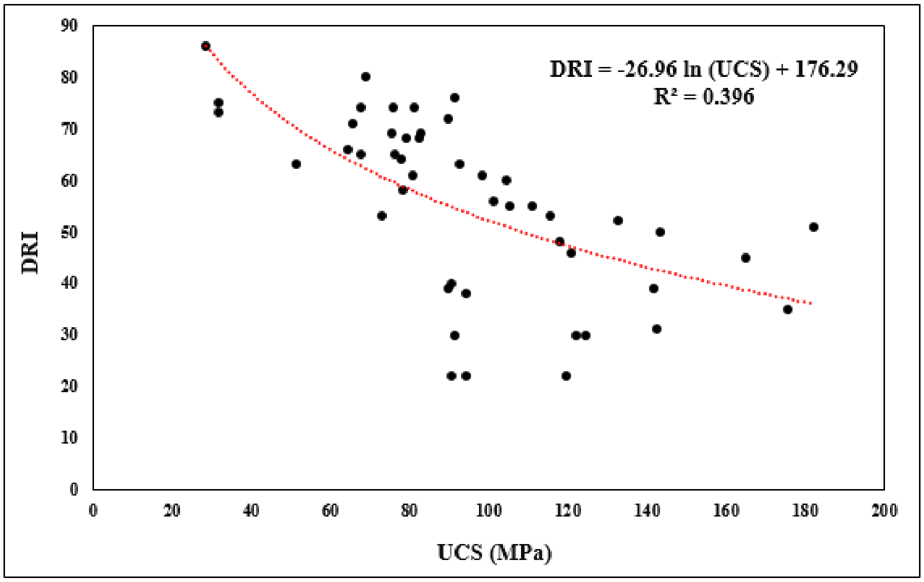

Figure 6. Relationship between measured DRI and UCS values

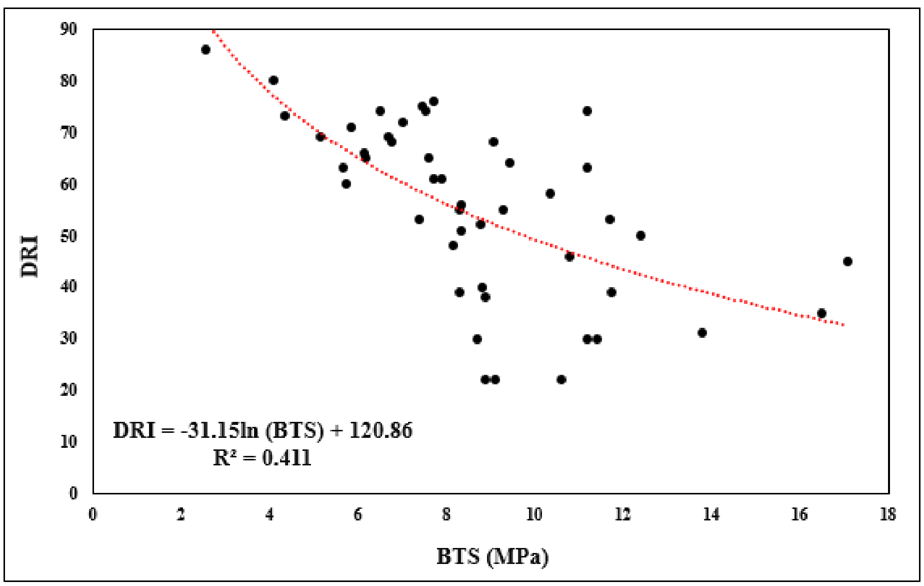

Figure 7. Relationship between measured DRI and BTS values

4.2 Multiple Regression

The multiple regression (MR) technique aims at determining the values of parameters for a function that causes the function to best fit a provided set of data observations. The function is a linear (straight-line) equation in this technique. In cases where more than one independent variable exists, MR is employed in order to achieve the best-fit equation. MR can solve the engineering problems through performing a least squares fit. By employing this techniques, some coefficients are suggested by means of the backslash operator (Khandelwal and Monjezi 2013). The MR equation type is presented as follows (Jahed Armaghani et al. 2015c):

$$y = a + b_1 x_1 + b_2 x_2 + b_3 x_3 + \cdots + b_n x_n \quad (5)$$

where,

$x_1, x_2, x_3, \ldots, x_n$ are independent variables,

$b_1, b_2, b_3, \ldots, b_n$ are coefficients of independent variables, and

y is output of the system.

To predict DRI using MR technique, actual DRI values are considered to be the product of the 2 input parameters namely UCS and BTS. As a first step of MR modelling, all data should be normalized considering the below equation:

Xnorm = (X – Xmin) / (Xmax-Xmin) (6)

Where,

Xnorm is the normalized value of the measured parameters,

X, Xmin and Xmax are the measured, minimum and maximum values of the measured parameters, respectively.

Afterwards, 5 datasets were chosen randomly to train and test for proposing MR models to evaluate the capability of the purposed model for estimation of the DRI as suggested by Zorlu et al. (2008), Yagiz et al. (2009). In the literature, 20% (Swingler 1996) of whole datasets and also a range of 20%-30% (Nelson and Illingworth 1990) of whole datasets were recommended for testing of the system. Based on above discussion, 80% (38 datasets) of whole datasets (47 datasets) was chosen randomly for developing the models, whereas the remained 20% (9 datasets) of data was assigned for testing. It should be noted that, an ANN code was used for the selection of the random data. Using the built datasets, five multiple input equations were developed as shown in Table 3.

It is concluded that, the R^2 values range from 0.391 to 0.451 for training and 0.325 to 0.760 for testing of the MR models. In these models, UCS and BTS were considered as inputs and then, the DRI was estimated as function of them. As a result, it is found that there is no salient difference among the developed models. More details regarding evaluation of the developed MR equations are given later. Note that, simple and MR regression analysis were performed using statistical software package of SPSS version 16 (SPSS 2007).

Table 3 MR equations together with the coefficient of correlation for testing and training

Dataset No.	Developed Relationship	Training R^2	Testing R^2
1	$\mathrm{DRI} = -0.342 \times \mathrm{UCS} - 0.451 \times \mathrm{BTS} + 0.845$	0.403	0.714
2	$\mathrm{DRI} = -0.638 \times \mathrm{UCS} - 0.315 \times \mathrm{BTS} + 0.927$	0.451	0.325
3	$\mathrm{DRI} = -0.370 \times \mathrm{UCS} - 0.447 \times \mathrm{BTS} + 0.892$	0.391	0.501
4	$\mathrm{DRI} = -0.391 \times \mathrm{UCS} - 0.493 \times \mathrm{BTS} + 0.898$	0.430	0.344
5	$\mathrm{DRI} = -0.406 \times \mathrm{UCS} - 0.447 \times \mathrm{BTS} +0.879$	0.398	0.760

4.3 ANN Modelling

In the ANN modeling, the same datasets utilized in the multiple regression part were performed. As mentioned by Kanellopoulas and Wilkinson (1997) and Hush (1989), ANN ability is directly related to its architecture. So, to design a desirable ANN model, determining the optimal architecture is needed. As a well-known fact, architecture of an ANN model is defined as the number of hidden layer or layers and the number of neuron or neurons in each hidden layer. Based on several scholars (e.g. Hecht-Nielsen 1987;

Hornik et al. 1989), hidden layer equal to 1 can approximate any complicated function. Then, hidden layer = 1 was chosen to construct the ANN networks. Additionally, Table 4 presents some of the available proposed equations for determining the number of neuron(s) together with their references. According to this table and considering N_i = 2 and N_o = 1, a range of 1-5 should be utilized in the hidden layer.

Table 4 The proposed number of neuron for hidden layer (Sonmez et al. 2006)

Heuristic	**Reference**
$\leq 2 \times N_i + 1$	Hecht-Nielsen (1987), Caudill (1988)
$(N_i + N_0)/2$	Ripley (1993)
$\dfrac{2 + N_0 \times N_i + 0.5\, N_0 \times \left(N_0^{\,2} + N_i\right) - 3}{N_i + N_0}$	Paola (1994)
$2N_i/3$	Wang (1994)
$\sqrt{N_i \times N_0}$	Masters (1994)
$2N_i$	Kaastra and Boyd (1996) Kannellopoulas and Wilkinson (1997)

N_i: number of input neuron, N_0: number of output neuron.

To determine the optimum number of neurons in the hidden layer, various ANN networks were modelled using one hidden layer and number of hidden neurons in the range of 1 to 5. The relevant results in terms of R^2 and RMSE can be seen in Tables 5 and 6, respectively. According to these tables, considering average R^2 and RMSE values of both training and testing datasets, model No. 3 with hidden neurons of 3 outperforms the other ANN models. Therefore, 3 was selected as number of hidden neuron in constructing ANN models in this study. Levenberg–Marquardt (LM) learning algorithm was used in constructing ANN models. The efficiency of the LM algorithm in comparison with the other conventional gradient descent techniques has been highlighted in the study conducted by Hagan and Menhaj (1994). ANN results of model No. 3 (all five iterations) were considered as the best ANN results for predicting DRI. More explanations regarding the selecting the best ANN network are given later.

Table 5 R^2 values of the constructed ANN models to predict DRI for selecting the optimum number of hidden node

Model No.	Nodes in hidden layers	Obtained Results of Network											
		Run 1		Run 2		Run 3		Run 4		Run 5		Average	
		R^2		R^2		R^2		R^2		R^2		R^2	
		Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
1	1	0.773	0.298	0.812	0.183	0.769	0.429	0.814	0.337	0.787	0.404	0.791	0.330
2	2	0.801	0.348	0.823	0.581	0.826	0.654	0.830	0.638	0.839	0.674	0.824	0.579
3	3	0.855	0.824	0.827	0.839	0.835	0.838	0.819	0.807	0.859	0.821	0.839	0.826
4	4	0.841	0.811	0.837	0.821	0.801	0.792	0.822	0.81	0.833	0.832	0.827	0.813
5	5	0.845	0.834	0.811	0.838	0.817	0.820	0.829	0.815	0.842	0.809	0.829	0.823

Table 6 RMSE values of the constructed ANN models to predict DRI for selecting the optimum number of hidden node

Model No.	Nodes in hidden layers	Obtained Results of Network											
		Run 1		Run 2		Run 3		Run 4		Run 5		Average	
		RMSE		RMSE		RMSE		RMSE		RMSE		RMSE	
		Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Train	Test
1	1	0.135	0.319	0.137	0.274	0.155	0.251	0.149	0.231	0.132	0.244	0.142	0.264
2	2	0.134	0.460	0.148	0.252	0.146	0.226	0.140	0.211	0.144	0.144	0.142	0.259
3	3	0.157	0.106	0.157	0.090	0.130	0.122	0.144	0.108	0.106	0.088	0.139	0.103
4	4	0.162	0.111	0.172	0.096	0.122	0.134	0.139	0.129	0.145	0.110	0.148	0.116
5	5	0.160	0.092	0.170	0.103	0.133	0.125	0.141	0.131	0.128	0.134	0.146	0.117

4.4 GA-ANN Modelling

As mentioned before, GA can efficiently improve the ANN performance and remove its limitations (e.g. Lee et al. 1991; Majdi and Beiki 2010; Rashidian and Hassanlourad 2013). The most frequently-cited advantage of GAs is the capability of these algorithms in escaping from being trapped in a local optimum (Chambers 2010). Chambers (2010) showed that with the use of a GA or at least a hybrid GA, an appropriate objective function can be freely selected. It can be concluded that the network connection weights and biases are optimized with GA instead of random generation. The hybrid GA-based ANN model can be referred to (Hagan and Menhaj 1994) for more details.

To propose hybrid GA-ANN model for DRI prediction, the most influential GA parameters should be designed. To do this, several parametric investigations were carried out to find optimum GA parameters. In the hybrid GA-ANN model, the mutation probability was set to 25% of the population size; whereas the percentage of recombination was fixed at 9% and value of 1% was applied as utilized by Momeni et al. (2014). The single point cross-over was used with 70%possibility. Numerous selection methods have been proposed in the literatures regarding cross-over operation; however, the tournament selection method was employed to generate two offspring from two parents (Momeni et al. 2014). It should be mentioned that the mutation probability and cross-over possibility were determined using trial-and-error method.

Finding the best population size is the next step of the hybrid GA-ANN. In this regard, several GA-ANN models were built with population sizes in range of 25 to 600 as shown in Table 7. In these models, the suggested ANN architecture and maximum generation of 100 were utilized. In the Table 7, the R^2 and RMSE values were tabulated for training and testing datasets of each model. Generally, increment in population size causes the increase in R^2 values and decrease in RMSE values. Since selection of the best model is too difficult, a simple ranking method proposed by Zorlu et al. (2008) was performed to obtain the optimum population size. Based on this method, each performance index was ordered in its class and the best performance index was assigned the highest rating. As an example, R^2 values of 0.426, 0.437, 0.425, 0.386, 0.420, 0.372, 0.443, 0.480, 0.661, 0.753, 0.842, 0.921, 0.927 and 0.931 were obtained for training datasets of models 1 to 14, respectively. Hence, their ratings were assigned as 5, 6, 4, 1, 3, 2, 7, 8, 9, 10, 11, 12, 13 and 14, respectively. This procedure was repeated for results of RMSE as well. After this process, the obtained ratings of performance indices for training and testing datasets were summed up in each model as shown in the last column of Table 7 (total rank). Based on obtained total rank values, model No. 12 can provide higher performance capacity compared to other models. Therefore, population size of 500 was chosen in modeling of GA-ANN technique.

Table 7 Effects of population size on network performance

Model No.	Population Size	Network Result				Ranking				Total Rank
		Train		Test		Train		Test		
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	25	0.426	0.200	0.223	0.217	5	5	1	2	13
2	50	0.437	0.194	0.561	0.181	6	7	6	4	23
3	75	0.425	0.182	0.341	0.253	4	8	2	1	15
4	100	0.386	0.195	0.486	0.213	1	6	4	3	14
5	150	0.420	0.201	0.506	0.175	3	4	5	5	17
6	200	0.372	0.207	0.658	0.153	2	2	9	7	20
7	250	0.443	0.203	0.456	0.158	7	3	3	6	19
8	300	0.480	0.182	0.632	0.147	8	8	8	9	33
9	350	0.661	0.171	0.592	0.152	9	9	7	8	33
10	400	0.753	0.154	0.778	0.137	10	10	10	11	41
11	450	0.842	0.148	0.851	0.131	11	11	11	13	46
12	500	0.921	0.139	0.932	0.122	12	13	14	14	53
13	550	0.927	0.140	0.921	0.135	13	12	13	12	50
14	600	0.931	0.138	0.913	0.144	14	14	12	10	50

Determination of maximum number of generation (G_{max}) is the next step of GA-ANN modelling procedure. To recognize the effect of G_{max} on the network's performance, one more parametric study was conducted. The number of generation was set to be 500 in order to determine the optimum number of generation. To do this, 14 models presented in Table 7 were constructed again using the mentioned maximum generation number (500). Figure 8 shows the importance of the number of generation to the network performance for predicting DRI. As displayed in this figure, there is no changes in the network performance (RMSE) after generation number = 300. Hence, the optimum number of generation was set to be 300 in design of GA-ANN models. It is worth mentioning that in determining number of generation, the other mentioned network parameters were kept constant.

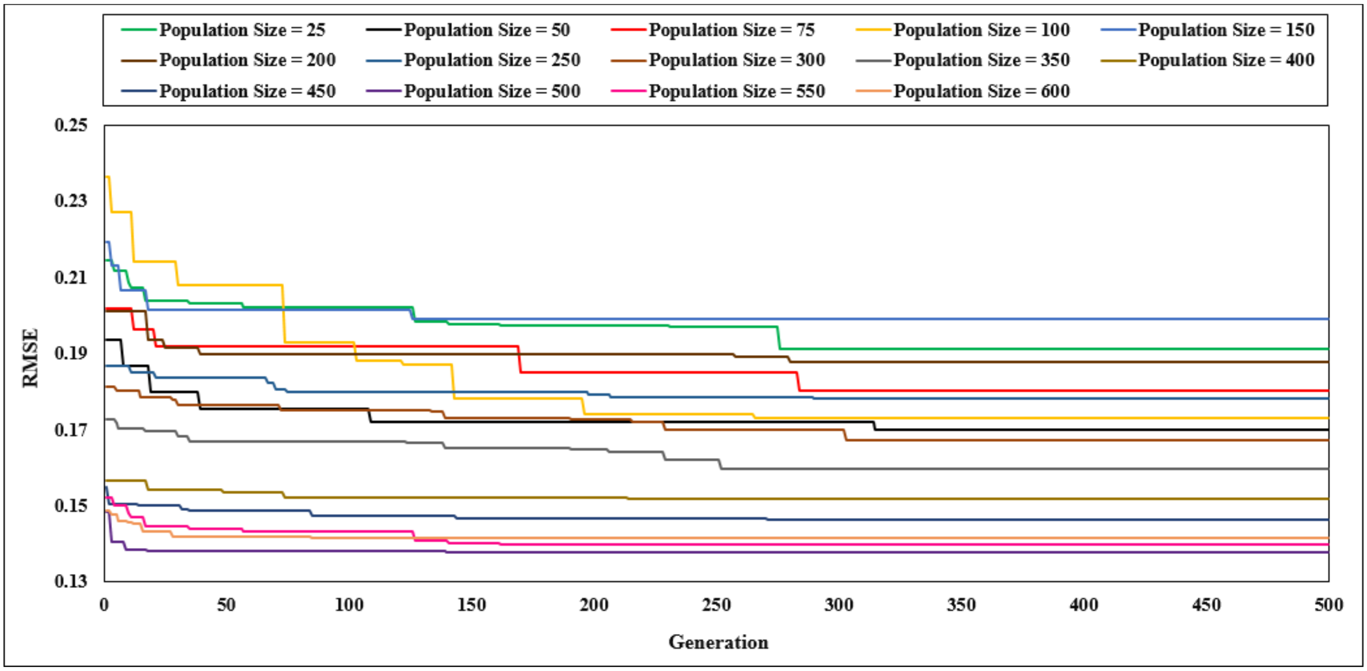

Figure 8. The effect of the number of generation on the network performance

In the final step of hybrid GA-ANN modelling, by using three different factors namely the suggested ANN structure (2 × 3 × 1), 5 randomly selected datasets, and determined GA parameters, five hybrid models were constructed. Evaluation of the obtained results of the hybrid models together with its discussion will be given later.

5. Evaluation of the Results

In this study, several techniques i.e. multiple regression, ANN and GA-ANN were applied and proposed for DRI prediction. Here, all 47 datasets were randomly selected to 5 datasets (to training and testing purposes) for developing the linear and non-linear models. For evaluation of the prediction performance, several performance indices including R^2, amount of variance account for (VAF) and RMSE were considered and computed:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y-y')^2}{\sum_{i=1}^{N}(y-\tilde{y})^2} \quad (7)$$

$$\mathrm{VAF} = [1- \frac{\mathrm{var}\,(y-y')}{\mathrm{var}\,(y)}] \times 100 \quad (8)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\,(y-y')^2} \quad (9)$$

Where,

y, y' and $\tilde{y}$ are the measured, predicted and mean of the y values respectively,

N is the total number of data and

P is the number of predictors.

Results of the mentioned indices for training and testing datasets are tabulated in Table 8. As shown in this table, selecting the best model for DRI estimation is not easy. To overcome this difficulty, as mentioned before, a simple ranking procedure developed by Zorlu et al. (2008) was used. A ranking value was computed and assigned for each training and testing dataset separately (see Table 8). The obtained total rank results for the developed models are shown in Table 9. Based on Table 9, model No. 4 exhibited the best performance of DRI prediction for MR technique, while models No. 5 and 1 yielded the best results of ANN and GA-ANN techniques, respectively. Therefore, the hybrid GA-ANN models can provide higher prediction performances in predicting DRI compared to other developed models (ANN and MR). The selected MR equation (model No. 4) is shown as follows:

$$\mathrm{DRI} = -0.391 \times \mathrm{UCS} - 0.493 \times \mathrm{BTS} + 0.898 \quad (10)$$

Table 8 The obtained performance indices for treaining antesting and their ranges for proposed models

Method	Model	R^2	RMSE	VAF	Rating for R^2	Rating for RMSE	Rating for VAF	Rank value
MR	Training 1	0.403	0.201	40.304	3	4	3	10
	Training 2	0.451	0.205	45.051	5	2	5	12
	Training 3	0.391	0.202	39.065	1	3	1	5
	Training 4	0.430	0.199	43.028	4	5	4	13
	Training 5	0.398	0.221	39.750	2	1	2	5
	Testing 1	0.714	0.204	45.537	4	1	3	8
	Testing 2	0.325	0.185	0.539	1	3	1	5
	Testing 3	0.501	0.195	48.802	3	2	4	9
	Testing 4	0.344	0.150	34.134	2	4	2	8
	Testing 5	0.760	0.093	71.843	5	5	5	15
ANN	Training 1	0.855	0.157	85.466	4	2	4	10
	Training 2	0.827	0.157	82.576	2	2	2	6
	Training 3	0.835	0.130	83.419	3	4	3	10
	Training 4	0.819	0.144	81.438	1	3	1	5
	Training 5	0.859	0.106	85.934	5	5	5	15
	Testing 1	0.824	0.106	82.316	3	3	3	9
	Testing 2	0.839	0.090	83.882	5	4	5	14
	Testing 3	0.838	0.122	82.773	4	1	4	9
	Testing 4	0.807	0.108	77.351	1	2	1	4
	Testing 5	0.821	0.088	82.061	2	5	2	9
GA-ANN	Training 1	0.933	0.071	93.066	3	4	4	11
	Training 2	0.926	0.111	92.090	2	2	2	6
	Training 3	0.948	0.066	94.772	5	5	5	15
	Training 4	0.937	0.076	93.046	4	3	3	10
	Training 5	0.921	0.119	91.909	1	1	1	3
	Testing 1	0.940	0.077	94.037	3	3	4	10
	Testing 2	0.945	0.058	94.457	4	4	5	13
	Testing 3	0.935	0.090	92.341	2	2	1	5
	Testing 4	0.929	0.053	92.845	1	5	2	8
	Testing 5	0.946	0.098	93.636	5	1	3	9

Table 9 Obtained total rank results for the developed models

Method	Model	Total rank
MR	1	18
	2	17
	3	14
	4	21
	5	20
ANN	1	19
	2	20
	3	19
	4	9
	5	24
GA-ANN	1	21
	2	19
	3	20
	4	18
	5	12

The graphs of predicted DRI using the MR, ANN and GA-ANN techniques against the measured DRI for training and testing datasets are shown in Figures 9 to 11, respectively. Based on the presented figures, the GA-ANN model can perform better in estimating DRI compared to other proposed models. Based on these figures, the R^2 equal to 0.940 for testing dataset suggests the superiority of the hybrid GA-ANN model, while these values are 0.821 and 0.344 for ANN and MR models, respectively. This shows the capability of the hybrid GA-ANN technique to predict DRI.

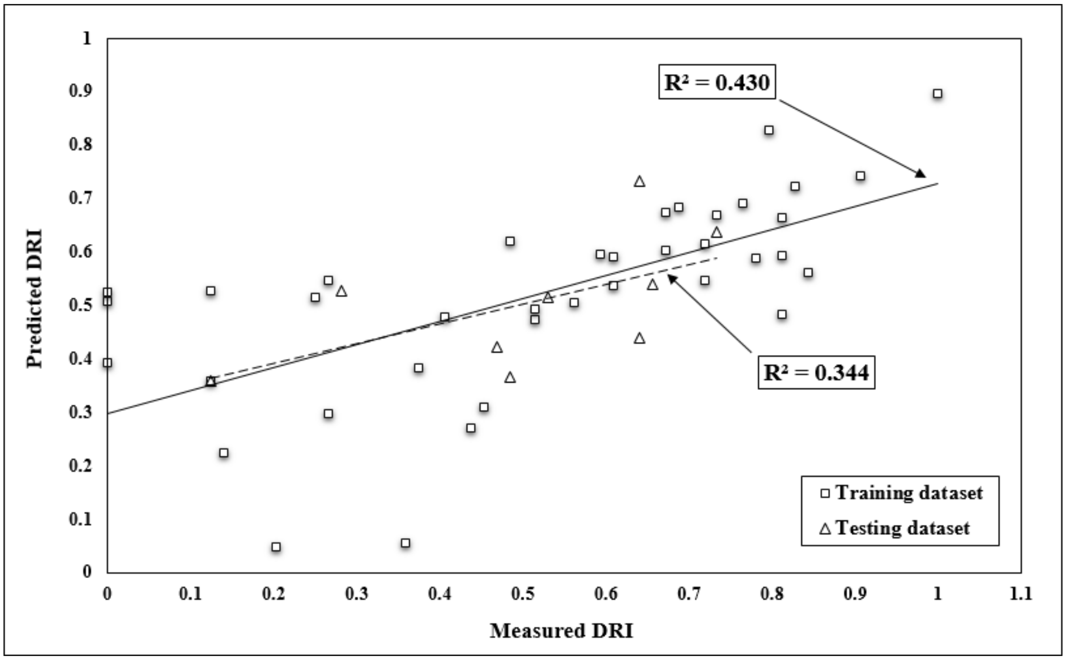

Figure 9. Predicted DRI values by MR model against the Measured DRI

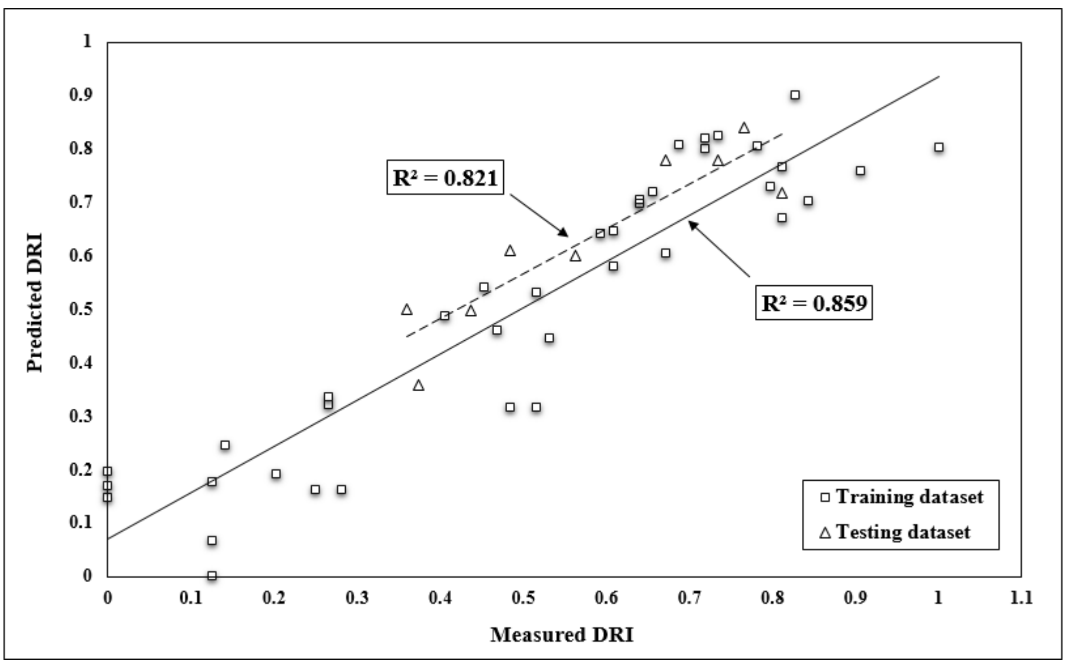

Figure 10. Predicted DRI values by ANN model against the Measured DRI

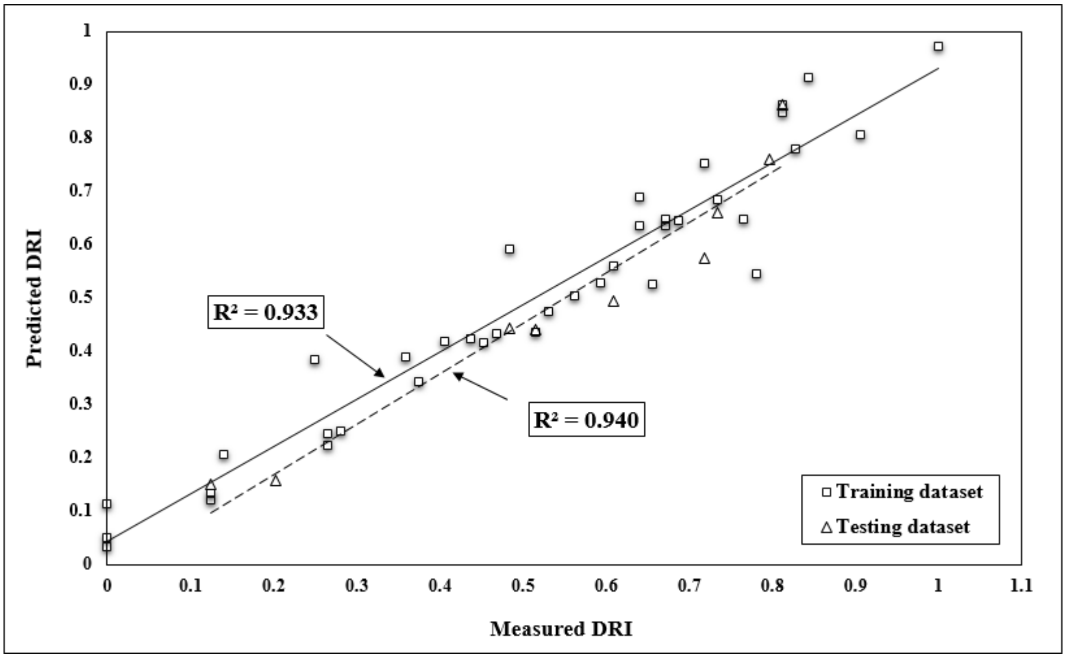

Figure 11. Predicted DRI values by GA-ANN model against the Measured DRI

6. Sensitivity Analysis

In this study, sensitivity analysis was performed to investigate the impacts of each input parameter on the output(s) using the cosine amplitude method (Yang and Zang 1997). All data pairs were utilized to construct a data array *X* as follows:

$$X = \{x_1, x_2, x_3, \dots, x_i, \dots, x_n\} \tag{11}$$

Variable x_i in array *X* is a length vector of m as:

$$x_i = \{x_{i1}, x_{i2}, x_{i3}, \dots, x_{im}\} \tag{12}$$

The strength of the relationship (r_{ij}) between datasets X_i and X_j can be expressed as follows:

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x^2{}_{ik} \sum_{k=1}^{m} x^2{}_{ik}}} \tag{12}$$

Figure 12 displays the strengths of the relationships between the input variables and output (DRI). The results show that among UCS and BTS, BTS is the most effective factor on the DRI.

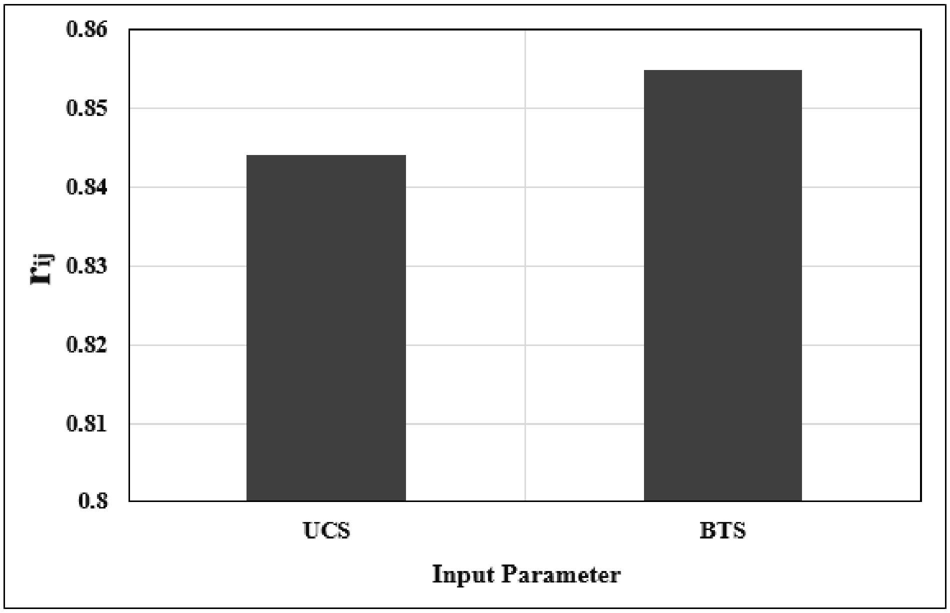

Figure 12. The effect of input parameters on the DRI

7. Conclusions

In this study, an attempt has been made to predict DRI by using strength properties of rock. To achieve this aim, DRI tests were conducted in the laboratory. In order to estimate DRI, two strength properties of rock namely UCS and BTS were chosen as model inputs. Based on simple regression models, the relationship between the DRI and input variables are acceptable and meaningful. Since each mentioned parameter has good relationship with the DRI, multiple regression, ANN and GA-ANN models were also generated to achieve the best accurate result.

In order to develop multiple-input models, the established datasets were divided into training and testing parts as suggested in the literature. Further, five different dataset for training and testing were established randomly to obtain the best models for each modeling technique. Developed models are compared to each other for choosing the best model among them. For selecting the best model, obtained R^2 and total rank for each model were computed and compared. As considering the testing datasets, the prediction performance of the GA-ANN model (R^2 = 0.940) is higher than that of the ANN model (R^2 = 0.821) and MR (R^2 = 0.344). Also, on taking into considering the training datasets, similar results were also obtained (R^2 = 0.430; 0.859; 0.933, respectively). It was found that the hybrid GA-ANN technique shows the best result compared to other models. Additionally, results of sensitivity analysis showed that the effect of BTS on DRI is slightly higher than the effect of UCS.

References

Adebayo B, Opafunso Z O, Akande J M (2010), Drillability and strength characteristics of selected rocks in Nigeria. AU Journal of Technology 14(1):56-60

Aghajanloo MB, Sabziparvar AA, Talaee PH (2013) Artificial neural network–genetic algorithm for estimation of crop evapotranspiration in a semi-arid region of Iran. Neural Comput Appl 23(5): 1387-1393

Akin S, Karpuz C (2008) Estimating drilling parameters for diamond bit drilling operations using artificial neural networks. Int J Geomech 8(1):68-73

Arabjamaloei R, Karimi Dehkordi B (2012) Investigation of the Most Efficient Approach of the Prediction of the Rate of Penetration. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects 34(7):581-590

Ataei M, KaKaie R, Ghavidel M, Saeidi O (2015) Drilling rate prediction of an open pit mine using the rock mass drillability index. Int J Rock Mech Min Sci 73:130-138

Basarir H, Tutluoglu L, Karpuz C (2014) Penetration rate prediction for diamond bit drilling by adaptive neuro-fuzzy inference system and multiple regressions. Eng Geol 173:1-9

Bruland A (1998) Drillability Test Methods. Trondheim: NTNU

Caudill M (1988) Neural networks primer part III. Al Expert 3:53–9

Chambers LD (2010) Practical Handbook of Genetic Algorithms: Complex Coding Systems, CRC Press

Cheniany A, Hasan KS, Shahriar K, Hamidi JK (2012) An estimation of the penetration rate of rotary drills using the Specific Rock Mass Drillability index. Int J Rock Mech Min Sci 22:187-193

Chipperfield A, Fleming P, Pohlheim H (2006) Genetic algorithm toolbox for use with MATLAB User's guide. version 1.2. University of Sheffield

Dahl F (2003) DRI, BWI, CLI Standards. NTNU, Angleggsdrift, Trondheim

Dahl F, Bruland A, Jakobsen PD, Nilsen B, Grøv E (2012) Classifications of properties influencing the drillability of rocks, based on the NTNU/SINTEF test method. Tunnel Undergr Sp Technol 28:150-158

Dreyfus G (2005) Neural Networks: Methodology and Application, Springer Berlin Heidelberg, Germany

Ekincioglu G, Altindag R, Sengun N, Demirdag S, Guney A (2013) The relationships between drilling rate index (DRI), physico-mechanical properties and specific cutting energy for some carbonate rocks, Rock Mechanics for Resources, Energy and Environment, Taylor & Francis group, London, 867-873

Garrett J (1994) Where and why artificial neural networks are applicable in civil engineering. J Comput Civil Eng 8:129–130

Hagan MT, Menhaj MB (1994) Training feed forward networks with the Marquardt algorithm, IEEE Trans. Neural Networks 5:861– 867

Hajihassani M., Jahed Armaghani D., Marto A., Tonnizam Mohamad E (2014) Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. Bull Eng Geol Environ doi:10.1007/s10064-014-0657-x

Hecht-Nielsen R (1987) Kolmogorov's mapping neural network existence theorem. In: Proceedings of the First IEEE International Conference on Neural Networks, San Diego, CA, USA, pp 11–14

Holland J (1975) Adaptation in Natural and Artificial Systems, The University of Michigan Press, Ann Arbor

Hornik K, Stinchcombe M, White H (1989) Multilayer feedforward networks are universal Approximators. Neural Networks 2:359-366

Hoseinie SH, Aghababaei H, Pourrahimian Y (2008) Development of a new classification system for assessing of rock mass drillability index (RDi). Int J Rock Mech Min Sci 45:1-10

Hoseinie SH, Ataei M, Osanloo M (2009) A new classification system for evaluating rock penetrability. Int J Rock Mech Min Sci 46:1329-1340

Hush DR (1989) Classification with neural networks: a performance analysis. In: Proceedings of the IEEE International Conference on Systems Engineering. Dayton, OH, USA, pp 277–280

ISRM (1978) Suggested methods for determining tensile strength of rock materials. Int. J. Rock Mech. Min. Sci. Geomech. Abstr 15:101-103

ISRM (1979) Suggested methods for determining the uniaxial compressive strength and deformability of rock materials. Int J Rock Mech Min Sci Geomech Abstr 16:135-140

Jaeger JC (1967) Failure of rocks under tensile strength. Int J Rock Mech Min Sci 4: 219-227

Jahed Armaghan D, Tonnizam Mohamad E, Hajihassani M, Alavi Nezhad Khalil Abad SV, Marto A, Moghaddam MR (2015b) Evaluation and prediction of flyrock resulting from blasting operations using empirical and computational methods. Eng Comput doi:10.1007/s00366-015-0402-5

Jahed Armaghani D, Hajihassani M, Sohaei H, Mohamad ET, Marto A, Motaghedi H, Moghaddam MR (2015c) Neuro-fuzzy technique to predict air-overpressure induced by blasting. Arab J Geosci 1-14

Jahed Armaghani D, Momeni E, Alavi Nezhad Khalil Abad SV, Khandelwal M (2015a) Feasibility of ANFIS model for prediction of ground vibrations resulting from quarry blasting. Environ Earth Sci. DOI 10.1007/s12665-015-4305-y

Kaastra I, Boyd M (1996) Designing a neural network for forecasting financial and economic time series. Neurocomputing 10:215-36

Kahraman S (1999) Rotary and percussive drilling prediction using regression analysis. Int J Rock Mech Min Sci 36: 981–989

Kahraman S, Balcı C, Yazıcı S, Bilgin N (2000) Prediction of the penetration rate of rotary blast hole drills using a new drillability index. Int J Rock Mech Min Sci 37:729-743

Kahraman S, Bilgin N, Feridunoglu C (2003) Dominant rock properties affecting the penetration rate of percussive drills. Int J Rock Mech Min Sci 40:711–723

Kanellopoulas I, Wilkinson GG (1997) Strategies and best practice for neural network image classification. Int J Remote Sens 18:711–725

Karpuz C, Pasamehmetoglu AG, Dincer T, Muftuoglu Y (1990) Drillability studies on the rotary blast hole drilling of lignite overburden series. Int. J Surf Min Recl 4:89–93

Khandelwal M (2013) Correlating P-wave velocity with the physico-mechanical properties of different rocks. Pure and Applied Geophysics 170(4):507-514

Khandelwal M, Monjezi M (2013) Prediction of backbreak in open-pit blasting operations using the machine learning method. Rock Mech Rock Eng 46(2):389-396

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

Lee Y, Oh SH, Kim MW (1991) The effect of initial weights on premature saturation in back-propagation learning, In: Proceedings of the International Joint Conference on Neural Networks 765–770

Macias FJ, Jakobsen PD, Seo Y, Bruland A (2014) Influence of rock mass fracturing on the net penetration rates of hard rock TBMs. Tunnel Undergr Sp Technol 44:108-120

Majdi A, Beiki M (2010) Evolving neural network using a genetic algorithm for predicting the deformation modulus of rock masses, Int J Rock. Mech. Min Sci 47:246–253

Masters T (1994) Practical neural network recipes in C++. Boston MA: Academic Press

Matern N von, Hjelmer A (1943) Försök med pågrus (‘‘Tests with Chippings’’), Medelande nr. 65, Statens väginstitut, Stockholm, 65 pp. (English summary, pp. 56–60).

Moein MJA, Shaabani E, Rezaeian M (2014) Experimental evaluation of hardness models by drillability tests for carbonate rocks. J Petroleum Sci Eng 113:104-108

Momeni E, Nazir R, Jahed Armaghani D, Maizir H (2014) Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN. Measurement 57:122-131

Monjezi M, Khoshalan HA, Varjani AY (2012). Prediction of flyrock and backbreak in open pit blasting operation: a neuro-genetic approach. Arab J Geosci 5(3):441-448

Nelson M, Illingworth WT (1990) A Practical Guide to Neural Nets. Addison- Wesley, Reading MA

Paola JD (1994) Neural network classification of multispectral imagery. MSc thesis, The University of Arizona, USA

Rashidian V, Hassanlourad M (2013) Predicting the shear behavior of cemented and uncemented carbonate sands using a genetic algorithm-based artificial neural network. Geotech. Geol Eng 2:1–18

Ripley BD (1993) Statistical aspects of neural networks. In: Barndoff- Neilsen OE, Jensen JL, Kendall WS, editors. Networks and chaos-statistical and probabilistic aspects. London: Chapman & Hall, pp 40-123

Saemi M, Ahmadi M, Varjani AY (2007) Design of neural networks using genetic algorithm for the permeability estimation of the reservoir. J Petroleum Sci Eng 59:97-105

Schmidt RL (1972) Drillability Studies – Percussive Drilling in the Field, US Bureau of Mines RI 7684

Selim AA, Bruce WE (1970) Prediction of penetration rate for percussive drilling. USBM. RI; p 7396

Selmer-Olsen R, Lien R (1960) Bergartens borbarhet og sprengbarhet, Teknisk Ukeblad, 34, Oslo, pp 3–11

Sievers H (1950) Die Bestimmung des Bohrwiderstandes von Gesteinen, Glückauf 86: 37/38, pp 776–784. Glückauf G.M.B.H., Essen

Simpson P (1990) Artificial Neural System: Foundation, Paradigms, Applications and Implementations, Pergamon, New York

Sonmez H, Gokceoglu C, Nefeslioglu HA, Kayabasi A (2006) Estimation of rock modulus: for intact rocks with an artificial neural network and for rock masses with a new empirical equation. Int. J. Rock Mech Min Sci 43:224-235

SPSS Inc. (2007). SPSS for Windows (Version 16.0). Chicago: SPSS Inc

Swingler K (1996) Applying Neural Networks: A Practical Guide. Academic Press, New York

Tripathy A, Singh TN, Kundu J (2015) Prediction of abrasiveness index of some Indian rocks using soft computing methods. Measurement 68: 302-309

Wang C (1994) A theory of generalization in learning machines with neural application. PhD thesis, The University of Pennsylvania, USA

Wijk G (1989) The stamp test for rock drillability classification. Int J Rock Mech Min Sci Geomech Abstracts 26:37-44

Yagiz S, Gokceoglu C, Sezer E, Iplikci S (2009) Application of two non-linear prediction tools to the estimation of tunnel boring machine performance. Eng Appl Artif Intel 22(4): 808-814

Yang Y, Zang O (1997) A hierarchical analysis for rock engineering using artificial neural networks. Rock Mech Rock Eng 30:207–222

Yarali O, Kahraman S (2011) The drillability assessment of rocks using the different brittleness values. Tunnel Undergr Sp Technol 26:406-414

Yarali O, Soyer E (2013) Assessment of relationships between drilling rate index and mechanical properties of rocks. Tunnel Undergr Sp Technol 33:46-53

Zorlu K, Gokceoglu C, Ocakoglu F, Nefeslioglu HA, Acikalin S (2008) Prediction of uniaxial compressive strength of sandstones using petrography-based models. Eng Geol 96(3):141-158