Geosciences Journal
Vol. 20, No. 5, p. 681 − 690, October 2016
DOI 10.1007/s12303-015-0065-7

Indirect estimation of deformation modulus of an in situ rock mass: an ANFIS model based on grid partitioning, fuzzy c-means clustering and subtractive clustering

Hadi Fattahi* *Department of Mining Engineering, Arak University of Technology, Arak 1000780654, Iran*

ABSTRACT: Deformability of rock masses influencing their behavior is an important geomechanical property for the rock structures design. Due to the problems in determining the deformability of jointed rock masses at the laboratory-scale, various in situ test methods such as plate loading tests, dilatometer etc. have been developed. Although these methods are currently the best techniques, they are expensive and time consuming, and present operational problems. Furthermore, the influence of the test volume on modulus of deformation depending on the technique used is also important. For these reasons, in this paper, the adaptive network-based fuzzy inference system (ANFIS) was used to build a prediction model for the indirect estimation of deformation modulus of a rock mass. Three ANFIS models were implemented by grid partitioning (GP), subtractive clustering method (SCM) and fuzzy c-means clustering method (FCM). The estimation abilities offered using three ANFIS models were presented by using field data of achieved from road and railway construction sites in Korea. In these models, rock mass rating (RMR), depth, uniaxial compressive strength of intact rock (UCS) and elastic modulus of intact rock (E_i) were utilized as the input parameters, while the deformation modulus of a rock mass was the output parameter. Various statistical performance indexes were utilized to compare the performance of those estimation models. The results achieved indicate that the ANFIS-SCM model has strong potential to indirect estimation of deformation modulus of a rock mass with high degree of accuracy and robustness.

Key words: deformation modulus, ANFIS, grid partitioning, subtractive clustering method, fuzzy c-means clustering method

1. INTRODUCTION

The deformation modulus (E_m) of rock masses is one of the important parameters utilized in the design stage of surface and underground rock engineering structures, where estimating of amount deformation is important (Sonmez et al., 2006). There are several methods to determine the deformation modulus of rock mass directly, by field or in situ tests; plate loading, like pressure meter (Chun et al., 2009), plate jacking, cable jack, flat jack, radial jacking and geophysical methods. Although in situ techniques are the best methods to determine deformability modulus of rock masses, they are expensive, time-consuming and can only be performed when the exploration space are excavated (Gholamnejad et al., 2013). This constraint forced the investigators to develop an empirical equation for indirect estimation of the deformation modulus of rock masses based on other rock mass properties that can be easily determined at low cost such as rock mass rating (RMR), geology strength index (GSI), the tunneling quality index (Q), etc. The number of empirical approaches uses for estimating the deformation modulus of rock masses has increased in recent years. The first empirical equation, which considers only RMR as an input parameter, was proposed by Bieniawski (1973). The main limitation of Bieniawski's approach is that it has to be used for rock masses with RMR > 50. Serafim and Pereira (1983) proposed an equation for rock masses with RMR < 50 to overcome the limitation of Bieniawski's equation. Mitri et al. (1995) and Nicholson and Bieniawski (1990) applied two empirical equations to estimate the deformation modulus of the rock mass by reducing elasticity modulus of the intact rock (E_i) based on the RMR value. Hoek and Brown (1997) proposed an empirical equation based on the GSI and uniaxial compressive strength of intact rock (UCS). Palmström and Singh (2001) proposed the relations based on rock mass index (RMI) classification system. Barton (2002) obtained a formula including Q system and UCS. Gokceoglu et al. (2003) proposed an empirical equation based on based on UCS, rock quality designation (RQD) and weathering degree of rock (WD). Kayabasi et al. (2003) presented the relation based on WD, E_i and RQD. Zhang and Einstein (2004) presented an empirical equation based on E_i and RQD. Sonmez et al. (2004) presented the formulas based on E_i, GSI and D (Factor of disturbance). Hoek and Diederichs (2006) introduced formulas based on GSI and D.

Although previous efforts are valuable but in many cases, the aforesaid empirical approaches are not capable of distinguishing the sophisticated structures involved in dataset. These reasons have been the main causes of interest to better find out the interaction between rock and machine and to propose a more precise and sure model for the indirect estimation of deformation modulus of a rock mass. For doing the purpose, recently, some techniques in fuzzy systems, artificial neural networks (ANN), and evolutionary computation have been successfully combined, and new techniques named computational intelligence or soft computing have been devel-

*Corresponding author: H.fattahi@arakut.ac.ir

oped. These techniques are attracting more and more attention in several research fields because they tolerate a wide range of uncertainty. One of these research areas is the rock mechanics. In this paper, the application of soft computing methods for data analysis named adaptive neuro-fuzzy inference system (grid partitioning (GP), subtractive clustering method (SCM) and fuzzy c-means clustering method (FCM)) to estimate of deformation modulus of a rock mass is demonstrated. Adaptive neuro-fuzzy inference system (ANFIS) hybrid systems combine the advantages of fuzzy systems, which deal with explicit knowledge which can be explained and understood, and ANNs which deal with implicit knowledge which can be acquired by learning. ANN learning provides a good way to adjust the expert's knowledge and automatically generate additional membership functions (MFs) and fuzzy rules, to meet certain specifications and reduce costs and design time. On the other hand, fuzzy logic enhances the generalization capability of an ANN by providing more reliable output when extrapolation is needed beyond the limits of the training data. The learning process is not knowledge based, but data driven. Recently, the ANFIS was used in the areas of rock mechanics and engineering geology by various researchers worldwide. In this study, the well-known research works are addressed. Grima et al. (2000) utilized ANFIS model for tunnel boring machine (TBM) performance prediction. Luis Rangel et al. (2005) presents an alternative approach to evaluate the tunnel stability during construction using ANFIS. Iphar et al. (2008) used ANFIS model for prediction of ground vibrations resulting from the blasting operations in an open-pit mine. Kalkan et al. (2009) proposed an ANFIS model to predict the unconfined compressive strength (UCS) of compacted granular soils. Kayadelen et al. (2009) have aimed to present the usability of an ANFIS approach for estimating swelling potential of the compacted soils. Pradhan et al. (2010) produced regional landslide susceptibility maps by ANFIS modeling. The results obtained from the study performed by Pradhan et al. (2010) showed that the ANFIS modeling is a very useful for the regional landslide susceptibility assessments. Sezer et al. (2010) trained an ANFIS approach for the sand permeability prediction. This approach has a great potential to be used by engineers to make precise permeability estimations. Jalalifar et al. (2011) used ANFIS model for prediction of a rock engineering classification system. Singh et al. (2013) proposed an ANFIS model to predict unconfined compressive strength of rocks. Fattahi et al. (2013) utilized ANFIS model for the assessment of damaged zone around underground spaces.

In this paper, in ANFIS models (ANFIS-SCM, ANFIS-FCM, ANFIS-GP), RMR, Depth, uniaxial compressive strength of intact rock (UCS) and elastic modulus of intact rock (E_i) are utilized as the input parameters, while deformation modulus of a rock mass is the output parameter. The estimation abilities offered using ANFIS models are presented by using field data of achieved from road and railway construction sites in Korea.

The scope of this paper is summarized in the following:

- Application and comparison between three models of the ANFIS (ANFIS-SCM, ANFIS-FCM, ANFIS-GP) for estimation of deformation modulus of a rock mass and investigation of the performance and convergence of ANFIS models.
- Investigation of the accuracy and flexibility of the approach when employed to specific real-world data sets. Additionally, exploration of the data sets and testing the quality of the data.

2. THE METHODOLOGY OF ADAPTIVE NETWORK-BASED FUZZY INFERENCE SYSTEM

A fuzzy inference system can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. Neural networks (NNs) are information-processing programs inspired by mammalian brain processes. NN are composed of a number of interconnected processing elements analogous to neurons. The training algorithm inputs to the NNs a set of input data and checks the NN output desired result. Combining NNs with fuzzy logic (FL) has been shown to emulate the human process of expert decision-making reasonably. In traditional NNs, only weight values change during learning, thus the learning ability of NNs is combined with the inference mechanism of the FL for a neuro-fuzzy decision-making system (Lin and Lee, 1991).

An adaptive neural network is a network structure consisting of several nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Once the fuzzy inference system (FIS) is initialized, NN algorithms can be utilized to determine the unknown parameters (premise and consequent parameters of the rules) minimizing the error measure, as conventionally defined for each variable of the system. Due to this optimization procedure the system is called adaptive (Jang, 1993). Figure 1 shows ANFIS architecture for two-input.

The architecture of ANFIS consists of five layers (Fig. 1), and a brief introduction of the model is as follows.

Layer 1: each node i in this layer generates a membership grades of a linguistic label. For instance, the node function of the i^{th} node that is defined as shown in Equation (1),

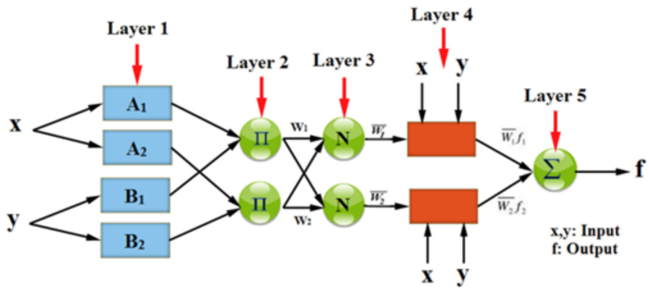

Fig. 1. ANFIS architecture for two-input (after Jang, 1993).

$$Q_i^1 = \mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-v_i}{\sigma_i}\right)^2\right]^{b_i}}, \qquad (1)$$

where, x is the input to node i, and Ai is the linguistic label (small, large, …) associated with this node; and $\{\sigma_i, V_i, b_i\}$, is the parameter set that changes the shapes of the membership function (MF). Parameters in this layer are referred to as the "premise parameters".

Layer 2: Each node in this layer calculates the "firing strength" of each rule via multiplication (Eq. 2).

$$Q_i^2 = W_i = \mu_{Ai}(x)\cdot\mu_{Bi}(y), \quad i = 1,2. \qquad (2)$$

Layer 3: The i^{th} node of this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths that is defined as shown in Equation (3).

$$Q_i^3 = \overline{W}_i = \frac{w_i}{\sum_{j=1}^{2} w_j}, \; i = 1,2. \qquad (3)$$

For convenience, outputs of this layer will be called "normalized firing" strengths.

Layer 4: Every node i in this layer is a node function which is defined as shown in Equation (4),

$$Q_i^4 = \overline{W}_i f_i = \overline{W}_i(p_i x + q_i y + r_i), \qquad (4)$$

where, $\overline{W}_i$ is the output of layer 3. Parameters in this layer will be referred to as "consequent parameters".

Layer 5: The single node in this layer is a circle node labeled R that computes the "overall output" as the summation of all incoming signals that is defined as shown in Equation (5).

$$Q_i^5 = Overall\ Output = \sum \overline{W}_i f_i = \frac{\sum \overline{W}_i f_i}{\sum w_i}. \qquad (5)$$

For a given data set, different ANFIS models can be constructed, using different identification methods. GP, SCM and FCM are three methods utilized in this study to identify the antecedent MFs.

2.1. Grid Partitioning of the Antecedent Variables

This approach proposes independent partitions of each antecedent variable (Jang, 1993). The expert developing the model can define the MFs of all antecedent variables using prior knowledge and experience. They are designed to represent the meaning of the linguistic terms in a given context. However, for many systems no specific knowledge is available on these partitions. In that case, the domains of the antecedent variables can simply be partitioned into a number of equally spaced and equally shaped MFs. Thus, in the GP approach, the domain of each antecedent variable is partitioned into equidistant and identically shaped MFs. Using the available input-output data, the parameters of the MFs can be optimized.

2.2. Subtractive Clustering Method

The mountain clustering method is simple and effective. However, its computation grows exponentially with the dimension of the problem. An alternative approach is subtractive clustering introduced by Chiu (1994) in which data points are considered as the candidates for center of clusters. The algorithm continues as follow,

Step 1: Consider a collection of n data points $\{X_1, X_2, X_3,..., X_n\}$, in an M-dimensional space. Since each data point is a candidate for cluster center, a density measure at data point X_i that is defined as shown in Equation (6),

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\|x_i - x_j\|^2}{\left(\frac{r_a}{2}\right)}\right), \qquad (6)$$

where, r_a is a positive constant. Therefore, a data point will have a high density value if it has many neighboring data points. The radius r_a defines a neighborhood; data points outside this radius contribute only slightly to the density measure.

Step 2: After the density measure of each data point has been calculated, the data point with the highest density measure is selected as the first cluster center. Let X_{c1}, be the point selected and D_{c1} its density measure. Next, the density measure for each data point x_i is revised as Equation (7),

$$D_i = D_i - D_{ci}\exp\left(-\frac{\|x_i - x_j\|^2}{\left(\frac{r_a}{2}\right)^2}\right), \qquad (7)$$

where, r_b is a positive constant.

Step 3: After the density calculation for each data point is revised, the next cluster center X_{c2} is selected and all of the density calculations for data points are revised again. This process is repeated until a sufficient number of cluster centers are generated.

The SCM is an attractive approach to the synthesis of ANFIS networks, which estimates the cluster number and its cluster location automatically. In subtractive clustering algorithm, each sample point is seen as a potential cluster center. By using this approach computation time becomes linearly proportional to data size, but independent of the dimension problem under consideration (Chopra et al., 2006; Smuda et al., 2007). By using the SCM, the cluster center of all data was found out. Then the numbers of subtractive centers were utilized to generate automatic MFs and rule base, as well as the location of MF within dimensions.

2.3. Fuzzy C-Means Clustering Method

The FCM is a data clustering algorithm in which each data point belongs to a cluster to a degree specified by a membership grade. Bezdek introduced this algorithm in 1973 (Bezdek, 1973). The FCM partitions a collection of n vector X_i, i = 1,2,...,n, into c fuzzy groups, and finds a cluster center in each group such that a cost function of dissimilarity measure is minimized. The steps of FCM algorithm are therefore, first described in brief.

Step 1: Chose the cluster centers c_i, i = 1,2,...,c, randomly from the n points $\{X_1, X_2, X_3,..., X_n\}$.

Step 2: Compute the membership matrix U using the Equation (8),

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/m-1}}, \tag{8}$$

where, $d_{ij} = \|c_i - x_j\|$, is the Euclidean distance between i^{th} cluster center and j^{th} data point, and m is the fuzziness index.

Step 3: Compute the cost function according to the Equation (9). Stop the process if it is below a certain threshold.

$$J(U, c_1, \ldots, c_2) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} \mu_{ij}^m d_{ij}^2. \tag{9}$$

Step 4: Compute new c fuzzy cluster centers c_i, i = 1,2,...,c, using the Equation (10).

$$c_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m}. \tag{10}$$

Go to step 2.

3. DATABASE INFORMATION

The main scope of this work is to implement the above methodology in the problem of deformation modulus of an in situ rock mass estimation. Dataset applied in this study for determining the relationship among the set of input and output variables are gathered from open source literature (Chun et al., 2009). The collected data sets used to construct the database are from road and railway construction sites in Korea. A total of 60 data sets were collected. Each data set contains the parameters of the RMR system, Depth, UCS, E_i and the measured deformation modulus. The deformation modulus values were measured using pressuremeter tests in most cases. Partial dataset used in this study are presents in Table 1. Also, descriptive statistics of the all data sets are shown in Table 2.

4. INDIRECT ESTIMATION OF DEFORMATION MODULUS USING ANFIS MODEL

In this paper, ANFIS was utilized to build a prediction model for indirect estimation of deformation modulus from available data, using MATLAB environment. Three ANFIS

Table 2. Statistical description of dataset utilized for construction of the ANFIS models

Parameter	Min	Max	Average
RMR	21.00	92.00	62.23
UCS (MPa)	12.10	254.80	138.09
Depth (m)	4.00	166.00	35.11
E_i (GPa)	17.10	60.70	49.95
E_m (GPa)	3.92	45.62	14.59

Table 1. Partial dataset used for constructing the ANFIS models (Chun et al., 2009)

Case No.	Parameters of the RMR system						Input parameters				Output parameter
	UCS	RQD	Discontinuity density	Discontinuity condition	Groundwater condition	Discontinuity orientation adjustment	RMR	UCS (Mpa)	Depth (m)	E_i (GPa)	E_m (GPa)
1	4	5	6	9	7	–10	21	28.4	5	20.8	3.92
2	12	3	6.4	10	7	–5	33	148.9	8.5	54.5	5.01
3	2	8	6.4	12	7	–5	30	12.1	9.5	17.1	4.76
4	7	17	8.6	24	10	–5	62	82.9	20.4	42.7	7.93
5	9	6.3	9.5	12	10	–5	42	109.9	8.5	49.1	5.32
6	62	17.2	8.5	20	7	–5	54	70	17.5	39.1	11.08
7	9.7	19.2	13	27	7	–5	71	119.9	31	50.8	17.65
8	15	16.4	10.8	17	10	–10	59	213.9	8.5	59.6	19.81
9	15	20	16.9	27	7	–10	76	219.9	17	59.6	27.26
10	12.4	20	12.2	25	7	–15	62	159.9	24	55.5	19.81
11	15	19.6	20	22	7	–2	82	219.2	18	59.6	29.81
12	6	10	7	14	9	–5	41	49	5	30.5	9.18
13	9	15	13	23	10	–5	65	93.1	6	45.6	7.64
14	4	7	6	14	7	–5	33	30.9	15	22.1	4.34
15	11	17	11	25	10	–10	64	125.4	29	51.5	9.25

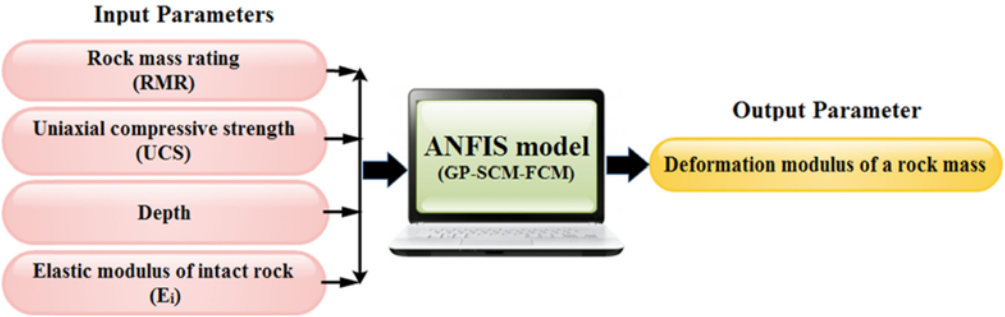

Fig. 2. Architecture of the ANFIS based on the GP, SCM and FCM.

models were implemented, GP, SCM and FCM. Figure 2 shows the fuzzy architecture of the ANFIS. A dataset that includes 60 data points was employed in current study, while 48 data points (80%) were utilized for constructing the model and the remainder data points (12 data points) were utilized for assessment of degree of accuracy and robustness.

4.1. Pre-processing of Data

In data-driven system modeling methods, some pre-processing steps are commonly implemented prior to any calculations, to eliminate any outliers, missing values or bad data. This step ensures that the raw data retrieved from database is perfectly suitable for modeling. In order to softening the training procedure and improving the accuracy of prediction, all data samples are normalized to adapt to the interval [–1, 1] according to the following linear mapping function (Eq. 1),

$$x_M = 2\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) - 1\,, \tag{11}$$

where, x is the original value from the dataset, x_M is the mapped value, and x_{min} (x_{max}) denotes the minimum (maximum) raw input values, respectively. It is to be noted that model outputs will be remapped to their corresponding real values by the inverse mapping function ahead of calculating any performance criterion.

4.2. Performance Criteria

To evaluate the performances of the ANFIS models, root-mean-squared-error (RMSE), mean squared error (MSE) and squared correlation coefficient (R^2) were chosen to be the measure of accuracy. N is the number of samples, y and y' are the measured and predicted values, respectively. RMSE, MSE and R^2 could be defined, respectively, as follows,

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - y')^2}\,, \tag{12}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y - y')^2\,, \tag{13}$$

$$R^2 = \frac{\left(\sum_{k=1}^{N} y_k y'_k - N\mu_y\mu_{y'}\right)^2}{\left(\sum_{k=1}^{N} y_k'^2 - N\mu_y^2\right)^2\left(\sum_{k=1}^{N} y_k'^2 - N\mu_{y'}^2\right)^2}\,, \tag{14}$$

where, μ_y ($\mu_{y'}$) denotes the mean value of the y(y'), $k = 1,...,N$, respectively.

5. RESULTS

The training and testing procedures of three ANFIS models (GP, SCM, FCM) were conducted from scratch for the mentioned five datasets. The obtained RMSE, MSE and R^2 val-

Table 3. Characterizations of the ANFIS models

ANFIS parameter	ANFIS-GP	ANFIS-SCM	ANFIS-FCM
MF type	Gaussian	Gaussian	Gaussian
Output MF	Linear	Linear	Linear
Number of nodes	1402	427	57
Number of linear parameters	4108	210	25
Number of nonlinear parameters	36	336	40
Total number of parameters	3214	546	65
Number of training data pairs	48	48	48
Number of testing data pairs	12	12	12
Number of fuzzy rules	625	42	5

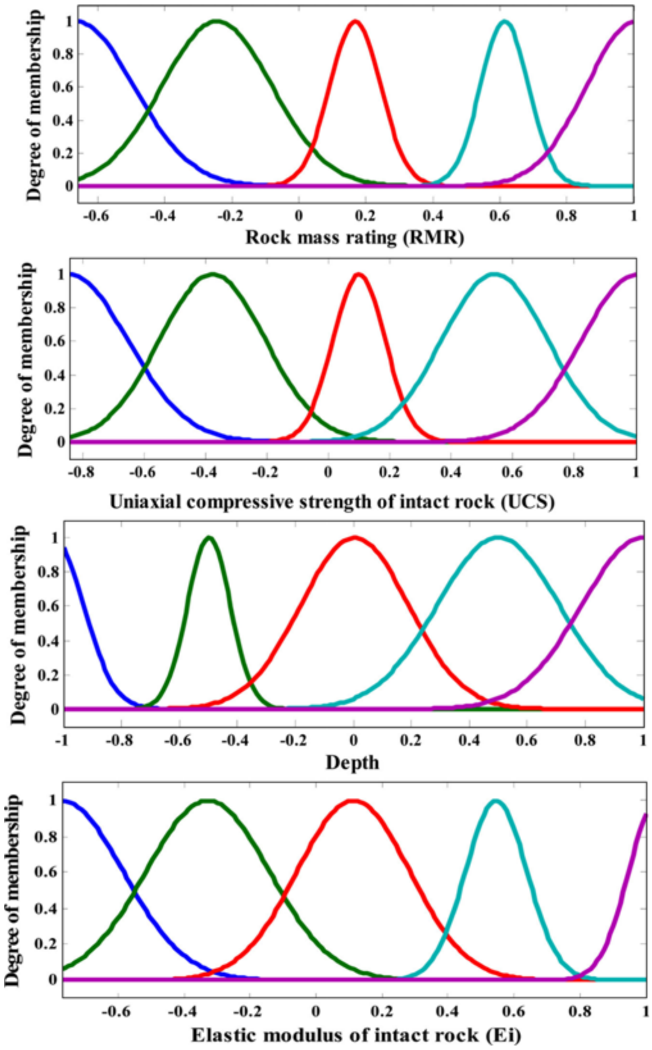

Fig. 3. MFs obtained by ANFIS-GP model.

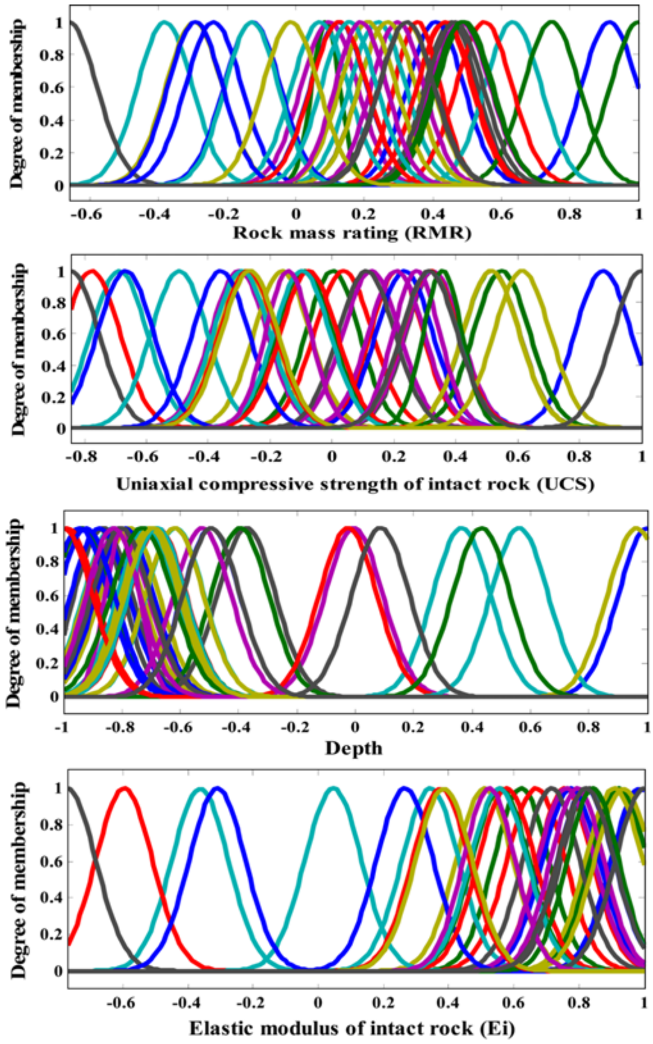

Fig. 4. MFs obtained by ANFIS-SCM model.

Table 4. A comparison between the results of three models for testing datasets

ANFIS model	RMSE	MSE	R^2
ANFIS-GP	0.303	0.092	0.52
ANFIS-SCM	0.278	0.077	0.88
ANFIS-FCM	0.284	0.081	0.77

Table 5. A comparison between the results of three models for training datasets

ANFIS model	RMSE	MSE	R^2
ANFIS-GP	0.061	0.0037	0.98
ANFIS-SCM	0.043	0.0018	0.99
ANFIS-FCM	0.102	0.0103	0.94

ues for training datasets indicate the capability of learning the structure of data samples, whereas the results of testing dataset reveal the generalization potential and the robustness of the system modeling methods. The characterizations of the ANFIS models are revealed in Table 3.

The number of rules obtained for the GP, SCM and FCM models are 625, 42 and 5 respectively. The MFs of the input parameters for different models are shown in Figures 3 to 5.

A comparison between the results of three models for testing datasets is shown in Table 4. As it can be observed from this table, the ANFIS-SCM model with RMSE = 0.278, MSE = 0.077 and $R^2 = 0.88$ for testing datasets performs better than the other two models for indirect estimation of deformation modulus of an in situ rock mass. Also, performance analysis of three models for training datasets is shown in Table 5.

The performance indices obtained in Tables 4 and 5 indicate the high performance of the ANFIS-SCM model that can be utilized successfully for the indirect estimation of deformation modulus of an in situ rock mass. Furthermore, correlations between measured and predicted values of deformation modulus for testing and training phases are shown in Figures 6 to 8.

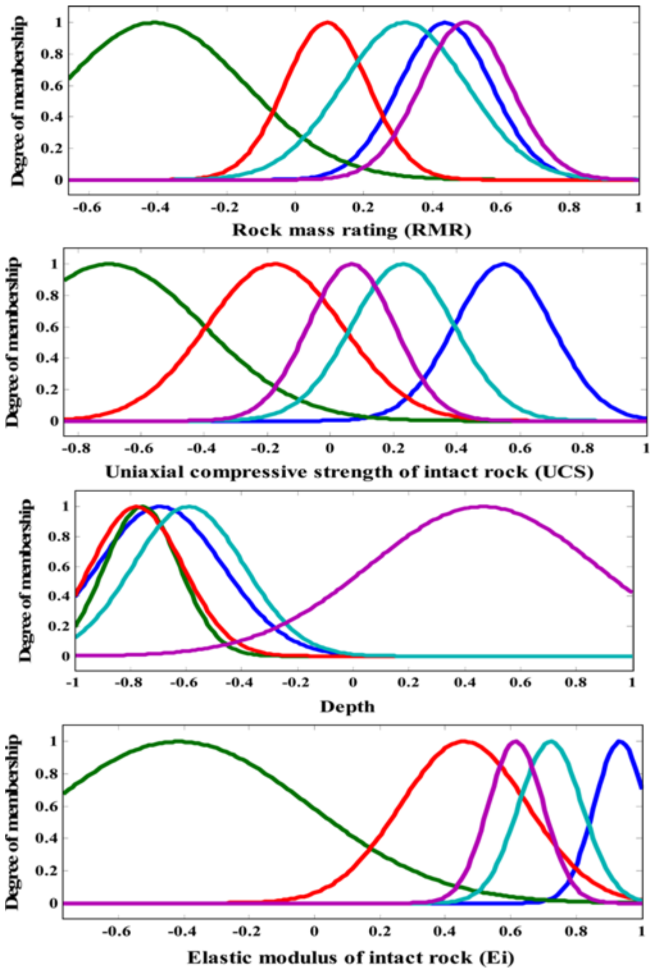

Fig. 5. MFs obtained by ANFIS-FCM model.

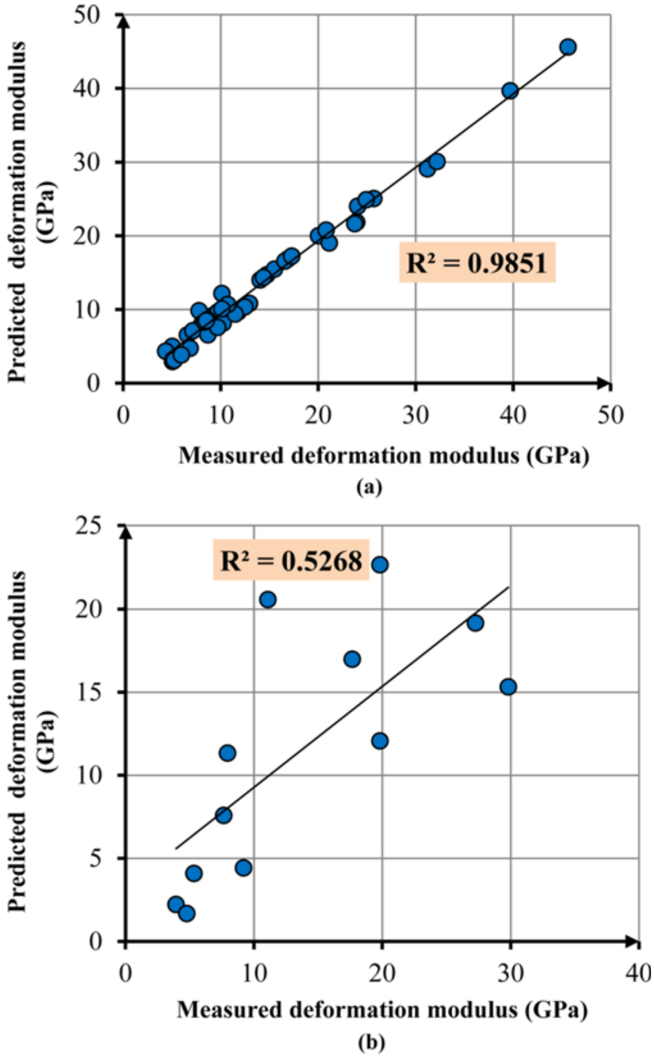

Fig. 6. Correlation between measured and predicted values of deformation modulus by ANFIS-GP model (a) training data, (b) testing data.

A comparison between predicted values of deformation modulus by the ANFIS models and measured values for data sets at testing phases is shown in Figure 9. Also, the error distribution for testing data sets is shown in Figure 10. As shown in Figures 9 and 10, the results of the ANFIS-SCM model in comparison with actual data show a good precision of the ANFIS-SCM model.

6. DISCUSSION AND CONCLUSION

In a conventional fuzzy inference system, the number of rules is decided by an expert who is familiar with the target system to be modeled. In ANFIS simulation, however, no expert is available and the number of MFs assigned to each input variable is chosen empirically, that is, by plotting the data sets and examining them visually, or simply by trial and error. For data sets with more than three inputs and two outputs, visualization techniques are not very effective and most of the time trial and error must be relied on. Generally, it becomes very difficult to describe the rules manually in order to reach the precision needed with the minimized number of MFs, when the number of rules are larger than 3. The better performance of ANFIS than the other intelligent methods is because of FL and ANN combination. The path which a input would covered is like that the input fuzzy inference system convey coordinates of sample to input MFs then it pass through the MF and changes, after that its results go to the rules which according to available rules, its category would be determined and it would have a value, next, rules to a set of output characteristics, output characteristics to output MFs, and the output MF to a single-valued output or a decision associated with the output. One of the most important steps in hybrid neuro-fuzzy modeling is the fuzzy membership values definition. In a conventional FIS, the number of rules is decided by an expert who is aware with the target system to be modeled. In ANFIS simulation, however, no expert is available and the number of MFs assigned to each input variable is chosen empirically, that is, by plotting the data sets

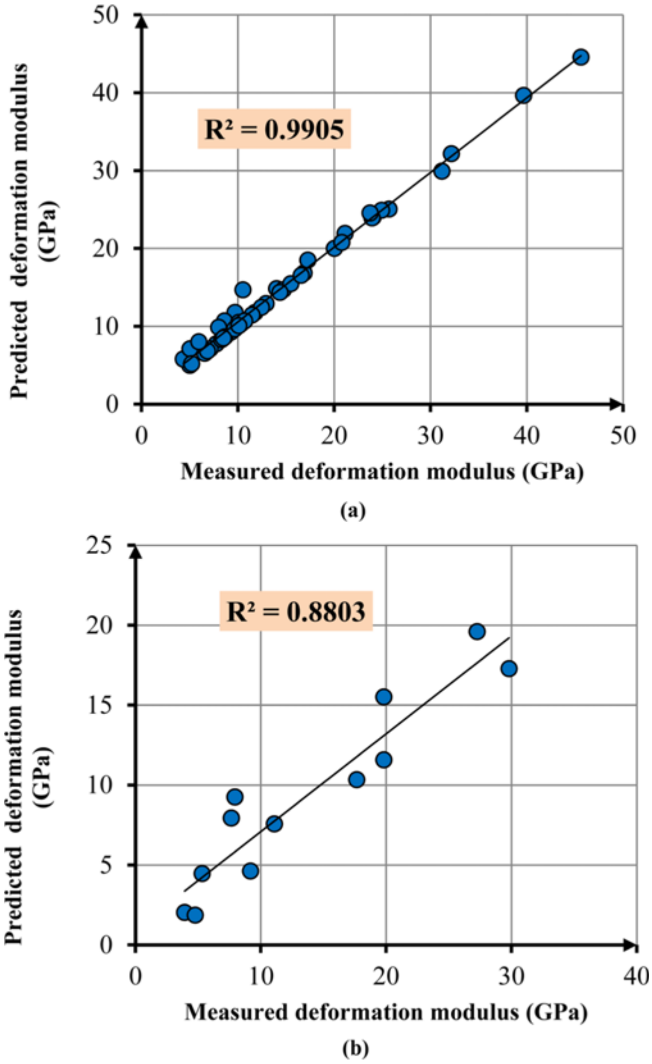

Fig. 7. Correlation between measured and predicted values of deformation modulus by ANFIS-SCM model (a) training data, (b) testing data.

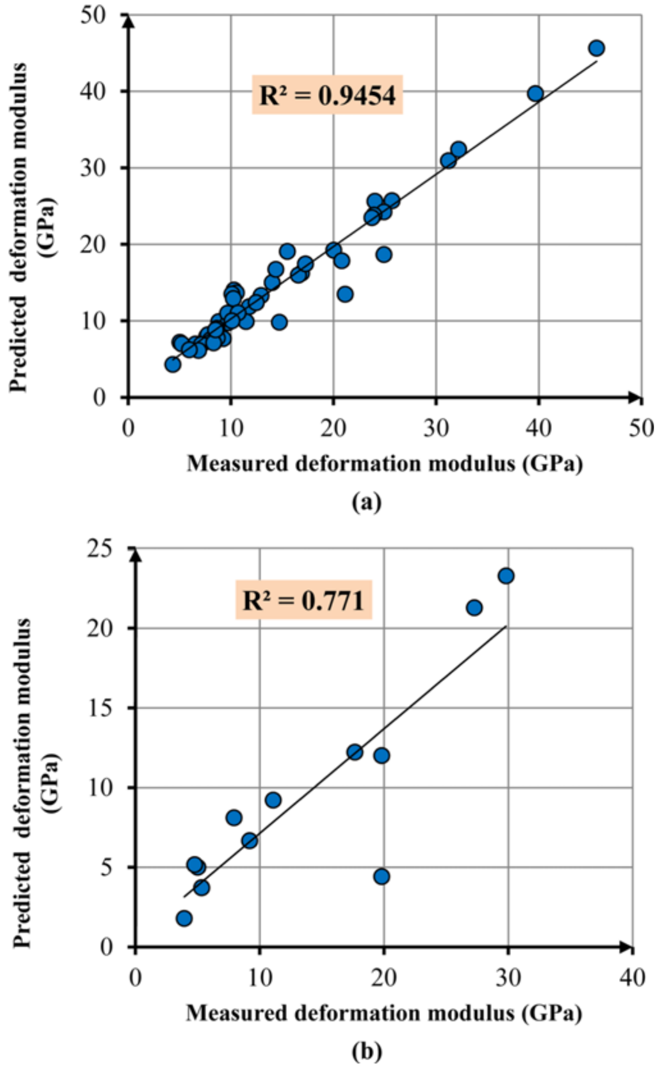

Fig. 8. Correlation between measured and predicted values of deformation modulus by ANFIS-FCM model (a) training data, (b) testing data.

and examining them visually, or simply by trial and error. For data sets with more than three inputs and two outputs, visualization techniques are not very effective and most of the time it must be relied on trial and error. Usually, it becomes very difficult to describe the rules manually in order to reach the precision required with the minimized number of MFs, when the number of rules are larger than 3. The generalized Gaussian MFs were used in the present model. MFs have been tested and it is important to mention that the used rules generally are based on the model and variables that are depended on user experience and trial and error methods. Furthermore, the shape of MFs depends on parameters, and changing these parameters will change the shape of the MF.

In this paper, the analysis for indirect estimation of deformation modulus of rock masses was investigated using three ANFIS models (GP, SCM and FCM) and the following conclusions can be drawn:

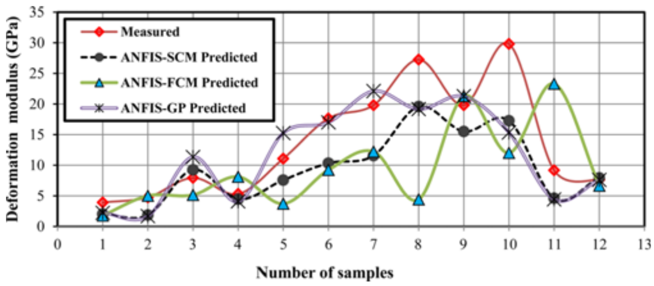

Fig. 9. Comparison between measured and predicted deformation modulus by the ANFIS models for testing datasets.

• RMR, UCS, E_i and depth are incorporated in order to indirect estimate deformation modulus of rock masses. RMR reflects the discontinuities situation within rock masses and UCS and E_i reflects the intact rock properties and also rock type.

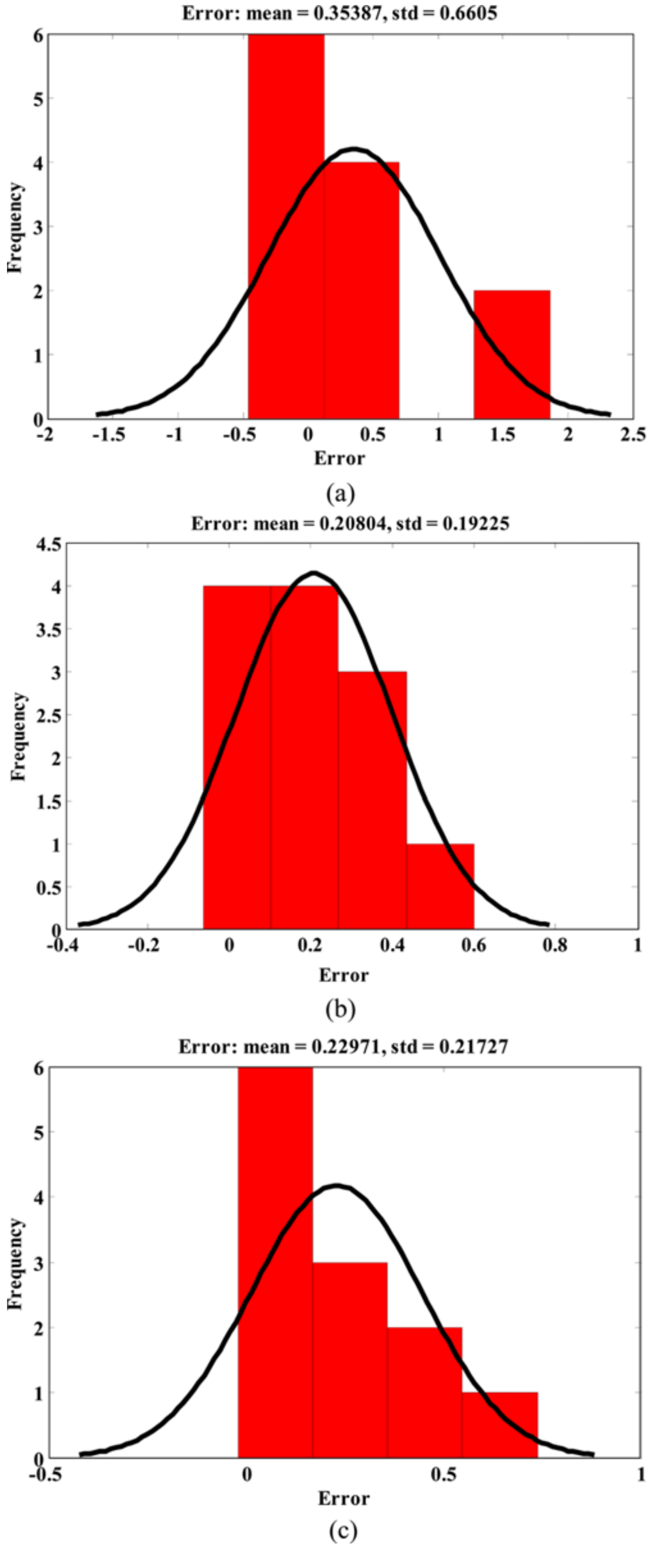

Fig. 10. The error distribution for testing datasets by the ANFIS models (a) ANFIS-GP, (b) ANFIS-SCM, (c) ANFIS-FCM.

• A comparison was made between three ANFIS models, GP, SCM and FCM, using 60 data samples, and based upon the performance indices; RMSE, MSE and R^2, ANFIS-SCM with RMSE = 0.278, MSE = 0.077 and R^2 = 0.88 was selected as the best predictive model.

• Consequently, it may conclude that ANFIS-SCM is a reliable system modeling technique for predicting deformation modulus of rock masses with highly acceptable degree of accuracy and robustness.

• This study shows that the ANFIS approach can be applied as a powerful tool for modeling of some problems involved in engineering geology.

REFERENCES

Barton, N., 2002, Some new Q value correlations to assist in site characterization and tunnel design. International Journal of Rock Mechanics and Mining Sciences, 39, 185–216.

Bezdek, J.C., 1973, Fuzzy mathematics in pattern classification. Ph.D. Thesis, Cornell University, Ithaca, 311 p.

Bieniawski, Z., 1973, Engineering classification of rock masses. Transactions of the South African Institution of Civil Engineers, 15, 335–344.

Chiu, S.L., 1994, Fuzzy model identification based on cluster estimation. Journal of Intelligent and Fuzzy Systems, 2, 267–278.

Chopra, S., Mitra, R., and Kumar, V., 2006, Reduction of fuzzy rules and membership functions and its application to fuzzy PI and PD type controllers. International Journal of Control, Automation and Systems, 4, 438.

Chun, B.-S., Ryu, W.R., Sagong, M., and Do, J.-N., 2009, Indirect estimation of the rock deformation modulus based on polynomial and multiple regression analyses of the RMR system. International Journal of Rock Mechanics and Mining Sciences, 46, 649–658.

Fattahi, H., Shojaee, S., and Farsangi, M.E., 2013, Application of Adaptive Neuro–Fuzzy Inference System for the Assessment of Damaged Zone around Underground Spaces. International Journal of Optimization in Civil Engineering, 3, 673–693.

Gholamnejad, J., Bahaaddini, H., and Rastegar, M., 2013, Prediction of the deformation modulus of rock masses using Artificial Neural Networks and Regression methods. Journal of Mining and Environment, 4, 35–43.

Gokceoglu, C., Sonmez, H., and Kayabasi, A., 2003, Predicting the deformation moduli of rock masses. International Journal of Rock Mechanics and Mining Sciences, 40, 701–710.

Grima, M.A., Bruines, P., and Verhoef, P., 2000, Modeling tunnel boring machine performance by neuro-fuzzy methods. Tunnelling and Underground Space Technology, 15, 259–269.

Hoek, E. and Brown, E., 1997, Practical estimates of rock mass strength. International Journal of Rock Mechanics and Mining Sciences, 34, 1165–1186.

Hoek, E. and Diederichs, M., 2006, Empirical estimation of rock mass modulus. International Journal of Rock Mechanics and Mining Sciences, 43, 203–215.

Iphar, M., Yavuz, M., and Ak, H., 2008, Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system. Environmental Geology, 56, 97–107.

Jalalifar, H., Mojedifar, S., Sahebi, A., and Nezamabadi-Pour, H., 2011, Application of the adaptive neuro-fuzzy inference system for prediction of a rock engineering classification system. Computers and Geotechnics, 38, 783–790.

Jang, J.S.R., 1993, ANFIS: Adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man and Cybernetics, 23, 665–685.

Kalkan, E., Akbulut, S., Tortum, A., and Celik, S., 2009, Prediction of the unconfined compressive strength of compacted granular soils by using inference systems. Environmental Geology, 58, 1429–1440.

Kayabasi, A., Gokceoglu, C., and Ercanoglu, M., 2003, Estimating the deformation modulus of rock masses: a comparative study. International Journal of Rock Mechanics and Mining Sciences, 40, 55–63.

Kayadelen, C., Taşkıran, T., Günaydın, O., and Fener, M., 2009, Adaptive neuro-fuzzy modeling for the swelling potential of compacted soils. Environmental Earth Sciences, 59, 109–115.

Lin, C.T. and Lee, C.S.G., 1991, Neural-network-based fuzzy logic control and decision system. IEEE Transactions on Computers, 40, 1320–1336.

Luis Rangel, J., Iturrarán-Viveros, U., Gustavo Ayala, A., and Cervantes, F., 2005, Tunnel stability analysis during construction using a neuro-fuzzy system. International Journal for Numerical and Analytical Methods in Geomechanics, 29, 1433–1456.

Mitri, H., Edrissi, R., and Henning, J., 1995, Finite-element modeling of cable-bolted stopes in hard-rock underground mines. Transactions-Society for Mining Metallurgy and Exploration Incorporated, 298, 1897–1902.

Nicholson, G. and Bieniawski, Z., 1990, A nonlinear deformation modulus based on rock mass classification. International Journal of Mining and Geological Engineering, 8, 181–202.

Palmström, A. and Singh, R., 2001, The deformation modulus of rock masses—comparisons between in situ tests and indirect estimates. Tunnelling and Underground Space Technology, 16, 115–131.

Pradhan, B., Sezer, E.A., Gokceoglu, C., and Buchroithner, M.F., 2010, Landslide susceptibility mapping by neuro-fuzzy approach in a landslide-prone area (Cameron Highlands, Malaysia). IEEE Transactions on Geoscience and Remote Sensing, 48, 4164–4177.

Serafim, J.L. and Pereira, J., 1983, Considerations on the geomechanical classification of Beniawski. International symposium on engineering geology and underground construction, Lisbon, Sep. 12–15, p. II.33–II.42.

Sezer, A., Göktepe, A., and Altun, S., 2010, Adaptive neuro-fuzzy approach for sand permeability estimation. Environmental Engineering and Management Journal, 9, 231–238.

Singh, R., Vishal, V., Singh, T., and Ranjith, P., 2013, A comparative study of generalized regression neural network approach and adaptive neuro-fuzzy inference systems for prediction of unconfined compressive strength of rocks. Neural Computing and Applications, 23, 499–506.

Smuda, J., Dold, B., Friese, K., Morgenstern, P., and Glaesser, W., 2007, Mineralogical and geochemical study of element mobility at the sulfide-rich Excelsior waste rock dump from the polymetallic Zn-Pb-(Ag-Bi-Cu) deposit, Cerro de Pasco, Peru. Journal of Geochemical Exploration, 92, 97–110.

Sonmez, H., Gokceoglu, C., Nefeslioglu, H., and Kayabasi, A., 2006, Estimation of rock modulus: for intact rocks with an artificial neural network and for rock masses with a new empirical equation. International Journal of Rock Mechanics and Mining Sciences, 43, 224–235.

Sonmez, H., Ulusay, R., and Gokceoglu, C., 2004, Indirect determination of the modulus of deformation of rock masses based on the GSI system. International Journal of Rock Mechanics and Mining Sciences, 849–857.

Zhang, L. and Einstein, H., 2004, Using RQD to estimate the deformation modulus of rock masses. International Journal of Rock Mechanics and Mining Sciences, 41, 337–341.

Manuscript received August 7, 2015
Manuscript accepted October 20, 2015