Rock Brittleness Prediction Using Geomechanical Properties of Hamekasi Limestone: Regression and Artificial Neural Networks Analysis

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Abstract

The cold climate is a favorable parameter for the development of tension cracks and decrease of rock brittleness. Therefore, this paper attempts to investigate the Hamekasi porous limestone in order to predict the brittleness indices during freeze-thaw cycles. The freeze–thaw test was executed for one cycle including 16 h of freezing, and 8 h of thawing. The geo mechanical properties and brittleness indices (B_1, B_2, B_3) of limestones were measured across freeze-thaw cycles from cycle 0 (fresh rock) to cycle 40. Statistical analyses, including simple and multiple regressions, were applied to identify those geomechanical parameters that are most influenced by the progression of freeze-thaw cycles and more appropriate for the brittleness prediction. Based on simple regression, all geomechanical properties including tensile strength (σ_t), uniaxial compressive strength (σ_c), P-wave velocity (Vp), porosity (n), and quick absorption index (QAI) (except dry density (ρ_d)) demonstrated good correlations with brittleness index (B_3). The integrated prediction of brittleness is put forward to develop some models by multiple regression (MR) and artificial neural network (ANN) with some statistic parameters (R, RMSE, VAF and ME), based on all geomechanical properties examined in this research. It is concluded that models based on n, Vp and ρ_d exhibited high performance according to the obtained statistic parameters. In spite of the fact that Vp has good correlation coefficient (R) with freeze-thaw cycles, and B_3 (R^2= 0.74, and 0.55, respectively) in simple regression, it does not have a prominent effect on B_3 in MR models. Also, parameters with low correlation coefficient in simple regression (ρ_d=0.15) cannot improve the model performance in ANN methods.

Keywords: *ANN Models, Brittleness Indices, Freeze–Thaw Cycles, Multiple Regression Models, Porous Limestone.*

Introduction

Brittleness is of vital importance to the rock mechanics projects, and rock industry. It was defined as the ability of a rock material to deform from continuum (intact rock) to discontinuum (fracturing without appreciable deformation under low stress) (Goktan & Yilmaz, 2005; Hajiabdolmajid *et al*., 2002; Kaiser *et al*., 2000). In cold regions, rocks are exposed to freeze-thaw cycles which induce tensile stress in the porous system of rock, and therefore increase rock damage (Bayram, 2012; Chen *et al*., 2004; Hori & Morihiro, 1998). Brittleness and rock damage depend on rock type (lithology), composition, temperature, porosity, and moisture content (Heidari *et al*., 2013), and also in cold regions depend on the number of freeze–thaw cycles as they increase micro-cracks (Chen *et al*., 2004; Takarli *et al*., 2008; Tan *et al*., 2011). Besides, it is evident that rock strength properties such as σ_c and σ_t decrease with an increase in micro-cracks and/or porosity (Al-Harthi *et al*., 1999; Gharahbagh *et al*., 2011; Moh'd, 2009; Palchik & Hatzor, 2004; Rajabzadeh *et al*., 2012). Consequently, the brittleness index is largely a function of rock properties and freeze-thaw cycles in cold regions; therefore, its measurement based on these factors is highly crucial.

Gong and Zhao (2007) divided the brittleness measurements into five groups as follows: (i) Strain based method with only one parameter for estimation (George 1995; Hajiabdolmajid *et al*., 2002; Hucka & Das, 1974); (ii) Reversible energy based method using the areas under the stress–strain diagram (Altindag, 2003; Hucka & Das, 1974; Vihtuk, 1998); (iii) Mohr's envelope based method (Hucka & Das, 1974); (iv) Strength ratio based method using Eqs. 1 to 3 defined later in the paper (Altindag, 2002; Hucka & Das, 1974; Kahraman, 2002); (v) Special test based method, using the percentage of fines formed in the impact test, and the ratio of maximum force to the penetration value gained from punch penetration test (Blindheim and Bruland, 1998; Protodyakonov, 1963; Yagiz, 2009). Furthermore, regarding these classifications, statistical analysis methods such as simple and multiple regressions and fuzzy inference system, using some cheap, simple and time effective tests such as ρ_d (dry density), n (porosity), point load index (Is) shore hardness (SH) instead of σ_c and σ_t, as these two tests need strict requirements for sample preparation (core samples) (Yagiz & Gokceoglu, 2010; Altindag & Guney, 2010; Heidari *et al*., 2013).

The main objectives of this study are to estimate brittleness index based on σ_t and σ_c and to develop some MR, and ANNmodels for estimating brittleness index in the studied area. Several possible models are proposed, using a combination of various physical and mechanical properties including n, ρ_d, G_s, QAI, and Vp. The Hamekasi porous limestone from western Iran is selected as the material of interest with respect to freeze-thaw degradation, and brittleness index.

Study area

The study area is a part of the Sanandaj–Sirjan Zone (SSZ), or Zagros Imbricate Zone of the Zagros Origin (according to Alavi, 1994). The oldest and the most predominant rocks in this zone are the slightly metamorphosed slate, phyllite, and schist rocks of late Triassic– Jurassic age, which are locally accompanied by sedimentary and magmatic rocks (Berberian & Alavi Tehrani, 1977; Sepahi 1999). The study area was a shallow water environment over early Cenozoic time which had come to an end by the deposition of Oligo-Miocene limestone in the Qom Formation. This Formation is formed of stratified and massive limestone, pale green–grey marl and sandstone (Geological and Mineral Survey of Iran, 1979). For the present study, Hamekasi limestone outcrop was investigated (Fig. 1). This limestone, in the northern part of the SSZ in western Iran, is so porous and karstified (Amiri, 2005; Karimi & Taheri, 2010; Khanlari et al., 2012; Zamiran Consulting Engineers, 2003). The climate of the study area is regarded as cold semiarid, with an average precipitation and temperature of about 300 mm and 13.35°C per year, respectively. The average number of freezing days is computed 85 days per year with 150 cm freezing depth (Sabziparvar, 2003).

Thin sections were examined and photomicrographs of these limestones before freeze-thaw test are presented in Figure 2, that are a and b. The microfauna collected from the Qom Formation include Miogypsina sp., Nummulite sp., and Corraline red Algea which confirms its aforementioned age. The thin section analyses of the carbonate rocks in Hamekasi demonstrate packestone structure and sparite cement.

Materials and Methods

Materials

As mentioned, in this study the Hamekasi limestone sample is used to characterize rock brittleness in relation to freeze and thaw cycles.

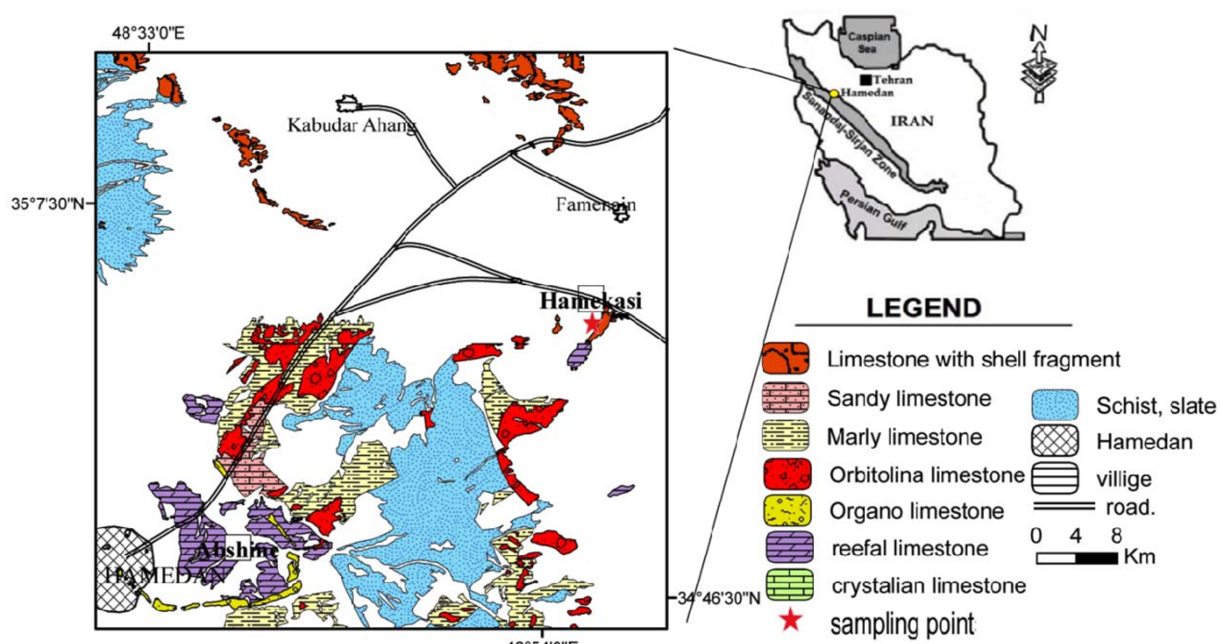

Figure 1. Location of different limestone and sampling points in the study area

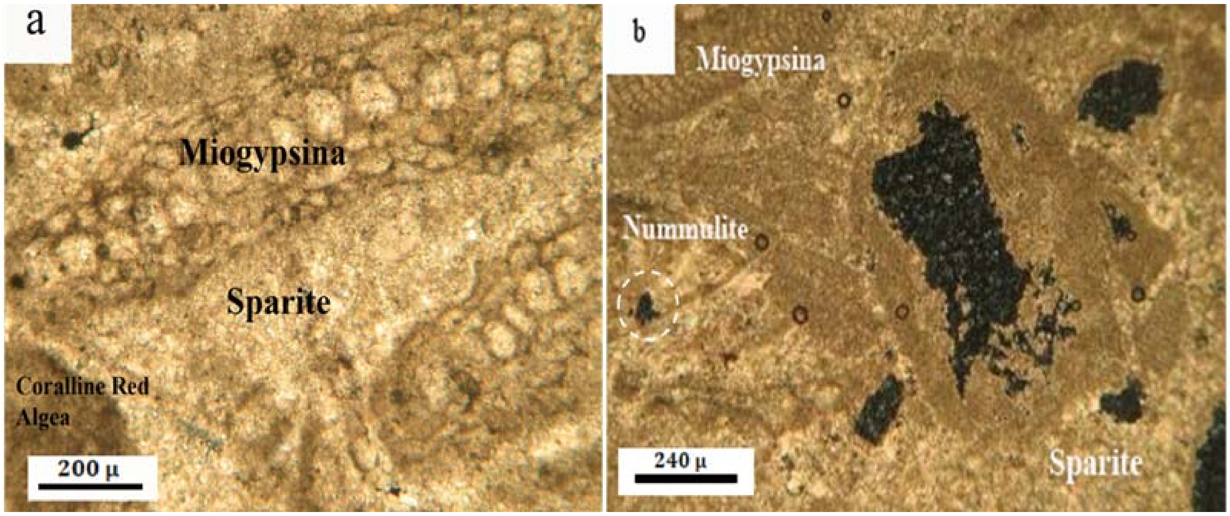

Figure 2. a) Bioclastic packestone with Miogypsina sp., and Corraline red Algea ;b) Bioclastic packestone with Nummulite, and Miogypsina sp.

Samples were collected from Hamekasi village outcrops, and about 10 large blocks were prepared, each of which was capable of providing more than 10 core samples. Samples were executed at the Rock Mechanics Laboratory of the Engineering Geology Department of Bu-Ali Sina University in Hamedan, Iran.

Methods

The two size of samples, according to ISRM 1979 and 1978, were prepared in the laboratory to avoid sample preparation effect during freeze-thaw test (Fig. 3), and to determine their physical and mechanical properties, including: dry density (ρ_d), total porosity (n), quick absorption index (QAI), P-wave velocity (Vp) (ISRM 1981); uniaxial compressive strength (σ_c) (ISRM 1979); Brazilian tensile strength (σ_t) (ISRM 1978).

Brittleness Indices

The determination of brittleness is largely driven by empirical results, but not easily accessible to experiment. Numerous different measurements of rock brittleness were generated based on different approaches. Among the brittleness coefficients, the ones based on σ_c and σ_t are the most widely used concepts for quantification of rock brittleness (Altindag, 2002; Gong & Zhao, 2007; Kahraman, 2002; Yagiz, 2004, 2006). The brittleness indices found by Hucka and Das (1974) (Eqs. 1 and 2) and Altindag (2002) (Eq. 3) which have been calculated in this study are as follows.

$$B_1 = \frac{\sigma_c}{\sigma_t} \tag{1}$$

$$B_2 = \frac{(\sigma_c - \sigma_t)}{(\sigma_c + \sigma_t)} \tag{2}$$

$$B_3 = \frac{(\sigma_c \times \sigma_t)}{2} \tag{3}$$

where B_1, B_2, B_3 are brittleness indices, σ_c is uniaxial compressive strength (MPa), and σ_t is Brazilian tensile strength (MPa). It should be mentioned that only B_3 was used for MR and MLP analyses.

Freeze–thaw test procedure

The physical weathering was simulated in laboratory by freeze and thaw test, following the method suggested by ASTM 5312 (2004). As the average maximum (37.5˚C) and minimum (-19˚C) temperatures of the study area are so close to ASTM, it is supposed to be a proper simulation system for freeze and thaw test. Nevertheless, some modifications had been made such as test numbers, and sample shapes. In this study, the freeze-thaw test had been repeated in 40 cycles. The test was performed on aforementioned three size samples including cores with a diameter of 54 mm, and length to diameter ratio (L/D) of 2.5 for uniaxial compression strength test, and 0.5 (L/D) for σ_t test (Fig. 3). According to these standards 100 samples were prepared for all laboratory tests. Finally, 41 data were measured for each test in all freeze–thaw cycles.

Figure 3. Limestone samples with various dimensions for freeze–thaw test (stage 1, and stage 5)

For the execution of this test, samples were submerged in water solution with 5% isopropyl alcohol. The saturated samples were subjected to freezing temperature of −20°C for 16 h. Upon completing the freezing time, the samples were subjected to thawing at a temperature of 32˚C for 8 h (Fig. 4). Before freeze-thaw test, all geomechanical properties were determined. Then after each 10 freeze–thaw cycles, 30 samples were dried in an oven at 110°C. The percentage loss of weight, and index properties including ρ_d , n , QAI, Vp, σ_c and σ_t and brittleness indices (B_1, B_2, B_3) for limestone samples were measured after each 10 freeze–thaw cycles.

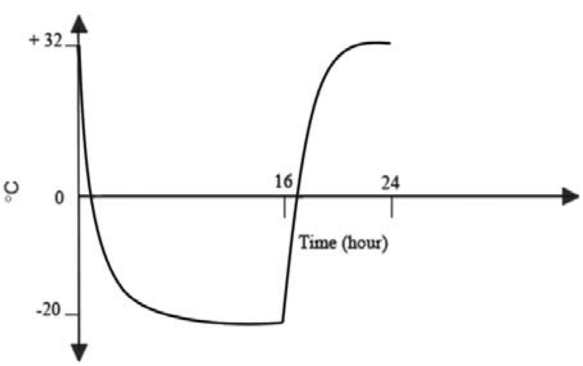

Figure 4. Generalized temperature curve for a freeze–thaw cycle (ASTM 5312, 2004)

Multiple Linear and Non Linear Regressions (MR) Analyses

The multivariate regression technique is employed to combine more than one parameter which affects rock brittleness (Torabi-Kaveh *et al*., 2014). This method can be practical in those cases where complex relations are involved (Karakus *et al*., 2005). Altindag (2010) and Yagiz & Gokceoglu (2010) proposed that the combination of engineering parameters (geomechanical properties) should be considered if a better rock brittleness is to be made. Therefore, this research examined various combinations of independent variables (X) as inputs to the MR models. It was to evaluate the degrees of effect of variables on dependent parameter (Y). Both linear and nonlinear regressions analysis were performed using Datafit statistical software 8.1 for prediction of rock brittleness. Here, MR equations were computed accompanying by some statistics including: the correlation coefficient (R) for the strength of relationship (Eq. 4), root mean square error (RMSE), mean error (ME) and variance accounted for (VAF) for the equation performance, accuracy and comparison of models (Eqs. 5; 6; 7). The best model performance gives the lowest RMSE and ME (close to 0) and the highest R and VAF (close to 100).

$$R = \frac{N\left(\sum y_i \hat{y}_i\right) - \left(\sum y_i\right)\left(\sum \hat{y}_i\right)}{\sqrt{\left[N\sum y_i^2 - \left(\sum y_i\right)^2\right]}\sqrt{N\sum \hat{y}_i^2 - \left(\sum \hat{y}_i\right)^2}} \quad (-1 - 1) \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{1}^{N} (y_i - \hat{y}_i)^2}{N}} \quad (0 - +\infty) \quad (5)$$

$$VAF = \left[1 - \frac{var(y - \hat{y})}{var(y)}\right] \times 100 \quad (0 - 100) \quad (6)$$

$$ME = \frac{\sum_{1}^{N} (y_i - \hat{y}_i)}{N} \quad (-\infty - +\infty) \quad (7)$$

where N is the total number of data, y_i is the measured B_3, $\hat{y}_i$ is the predicted B_3 and $\overline{y}$ is the average of measured B_3. To determine underestimated and overestimated data in the models, ME statistic was used. ME has negative and positive values; therefore, the outliers are indicative of data points that belong to both underestimated and overestimated data.

Artificial Neural Network (ANN)Analysis

ANN consists of simple synchronous processing elements, called neurons, which are inspired by biological nerve system (Malinova and Guo, 2004). It is a popular choice for modeling nonlinear systems and for implementing general-purpose nonlinear controllers. The most particular characteristic of an ANN system is its capability to learn from the data being processed. It can be used to solve problems that are not suitable for conventional statistical methods (Aqil *et al*., 2007). ANN is typically organized in layers. Layers are made up of a number of interconnected 'Neurons' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output. The output layer, on the other hand, uses supervised learning to set its parameters. In supervised learning, Neural network entails learning a mapping between a set of input variables X and an output variable Y and applying this mapping to predict the outputs for unseen data (Fig. 5A).

Multilayer perceptron (MLP) with default scale [0 –1] is the most common type of ANN used for supervised prediction. A MLP is a feed-forward neural network. In this type, network reaction routes always proceed feed-forward, and permit signal to transform only one route that is input to output (Fig. 5B).

After normalizing/standardizing of data, for the development of ANN models, all data should be partitioned into two data sets, training (twothirds of all data), and testing (one-third of all data) (Lawrence, 1991; Zurada, 1992). The training data set is used to make several MLP architectures, with especially different learning conditions for MLP models. Also, the testing data set is separated to verify suitability of trained models. As supervised learning is used for MLP models, the observed values (measured brrittleness) are needed to confirm the results from MLP.

Results and Discussions

Geomechanical and Brittleness Indices during Freeze and Thaw Test

The results of the physical and mechanical tests performed on the limestone samples before freeze–thaw test (cycle '0') and after each 10 cycles (Cycles '10', '20', '30' and '40') are reported in Table 1. The percentage loss in weight, σ_c and σ_t are also presented in Table 1. It can be seen that there is a considerable change after cycle '0' in all geomechanical properties (except ρ_d). This may be related to the first freeze shock of rock that caused some fractures which were developed over other freezing stages. Moreover, Martinez-Martinez *et al*., (2013) stated that after a threshold, microcracks turn into cracks, so it could be the reason for the second sharp changes in some index properties such as n, QAI and Vp in the last stage of freeze-thaw test (cycle '30'). As it was expected, rock deterioration was constantly occurring after cycle '40'; as a result, it was decided not to perform freeze-thaw test more than 40 cycles. ρ_d shows relatively disorder trend during freeze-thaw test (Table 1). This is because each porous rock has a large range of ρ_d.

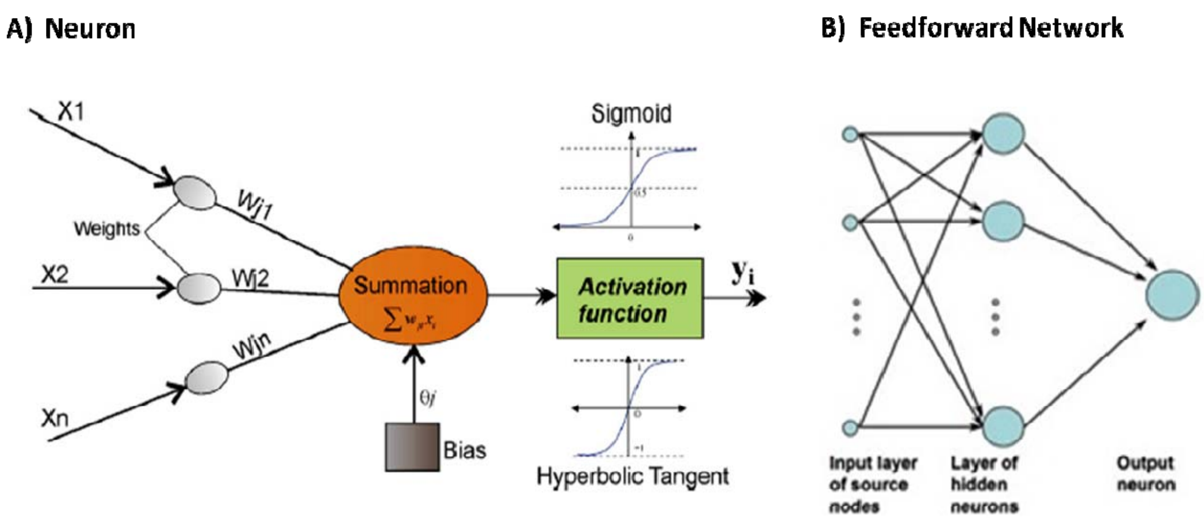

Figure 5. Typical details of a neuron and a feed-forward ANN model

Table 1. Physico-mechanical properties and Brittleness indices of limestone samples before and after freeze and thaw test

Cycle No	ρ_d (g/cm^3)	n (%)	QAI (%)	Vp (m/s)	σ_c (MPa)	σ_t (MPa)	Percentage loss in weight	Percentage loss in σ_c	Percentage loss in σ_t	B_1	B_2	B_3 (MPa)^2
0	1.90	14.97	8.00	3342.38	14.91	4.05	0	0	0	3.68	0.57	30.17
	1.87	13.66	7.21	3573.03	14.24	2.35	0	0	0	6.06	0.72	16.73
	2.08	13.88	5.83	3294.12	12.63	3.24	0	0	0	3.90	0.59	20.45
	2.01	14.50	6.87	3253.67	13.73	3.65	0	0	0	3.76	0.58	25.05
	2.09	14.98	7.43	3532.01	14.64	4.10	0	0	0	3.57	0.56	30.04
	1.97	13.71	7.78	3309.69	13.91	3.82	0	0	0	3.65	0.57	26.54
	1.84	14.20	8.10	3389.02	14.53	4.44	0	0	0	3.27	0.53	32.24
Ave.	1.97	14.27	7.32	3384.85	14.08	3.66	-	-	-	3.99	0.59	25.89
Std.	0.10	0.56	0.79	122.46	0.76	0.69	-	-	-	0.94	0.06	5.63
10	2.10	18.20	8.29	3088.24	12.83	2.58	0	8.88	29.44	4.97	0.66	16.57
	1.96	18.30	9.35	3009.40	12.50	3.81	0.031	11.22	-4.15	3.28	0.53	23.82
	1.86	18.50	9.48	3333.33	12.67	3.56	0.064	10.01	2.79	3.56	0.56	22.54
	1.85	18.00	9.21	3498.92	11.16	2.80	0.074	20.74	23.56	3.99	0.60	15.61
	1.91	18.30	9.80	3244.55	12.42	2.53	0.063	11.77	30.89	4.91	0.66	15.71
	1.97	18.70	9.99	3081.63	11.62	2.94	0.058	17.45	19.67	3.95	0.60	17.09
	2.23	17.56	8.90	3129.41	13.90	2.61	0	1.30	28.66	5.32	0.68	18.14
	2.21	19.00	8.34	3236.02	14.28	3.11	0.109	-1.39	15.02	4.59	0.64	22.20
	1.95	17.30	8.63	3200.38	12.67	2.49	0.209	10.01	32.02	5.09	0.67	15.76
Ave.	2.01	18.21	9.11	3202.43	12.67	2.94	0.07	10.00	19.77	4.41	0.62	18.60
Std.	0.14	0.53	0.61	149.24	0.97	0.47	0.06	6.91	12.96	0.73	0.05	3.31
20	2.00	19.20	10.45	3176.11	10.15	3.23	0.117	27.92	11.72	3.14	0.52	16.40
	2.09	20.00	11.09	3018.79	10.11	3.64	0.043	28.22	0.43	2.77	0.47	18.42
	2.27	17.89	9.10	2992.30	12.47	3.20	0.046	11.47	12.57	3.90	0.59	19.94
	2.09	18.00	11.04	3116.80	11.41	2.02	0.066	18.95	44.71	5.64	0.70	11.55
	2.12	19.91	10.09	3111.89	12.30	2.58	0.000	12.67	29.44	4.76	0.65	15.88
	2.05	18.50	8.60	3225.72	13.43	2.73	0.091	4.59	25.40	4.92	0.66	18.34
	2.12	17.58	9.50	3274.84	11.62	2.04	0.090	17.45	44.18	5.69	0.70	11.87
	1.82	17.87	10.07	3374.74	11.63	2.13	0.028	17.40	41.75	5.45	0.69	12.40
	1.86	18.90	9.61	3276.80	11.65	2.78	0.882	17.26	23.94	4.18	0.61	16.22
Ave.	2.05	18.65	9.95	3174.22	11.64	2.71	0.15	17.32	26.02	4.50	0.62	15.67
Std.	0.14	0.91	0.84	126.47	1.06	0.58	0.28	7.51	15.75	1.07	0.08	3.08
30	1.89	20.99	9.88	3088.24	11.49	2.87	0.104	18.39	21.49	4.00	0.60	16.51
	1.92	19.34	10.31	3178.91	11.51	2.56	0.149	18.25	30.05	4.50	0.64	14.73
	1.97	20.86	10.59	2891.01	11.47	2.10	0.049	18.54	42.62	5.46	0.69	12.04
	1.86	18.10	9.20	3232.00	11.87	2.48	0.016	15.70	32.13	4.78	0.65	14.74
	1.91	19.53	11.14	2983.18	11.20	2.03	0.045	20.45	44.47	5.51	0.69	11.38
	1.96	17.98	8.51	3081.63	11.30	2.35	0.086	19.74	35.82	4.81	0.66	13.27
	2.07	18.00	9.01	3329.41	11.50	2.20	0.028	18.32	39.89	5.23	0.68	12.65
	2.04	19.30	9.39	3236.02	11.60	2.53	0.014	17.61	30.89	4.59	0.64	14.67
Ave.	1.95	19.26	9.75	3127.55	11.49	2.39	0.06	18.38	34.67	4.86	0.66	13.75
Std.	0.07	1.21	0.88	144.67	0.20	0.28	0.05	1.41	7.59	0.52	0.03	1.71
40	1.87	20.93	11.17	2991.10	10.92	1.97	0.145	22.44	46.29	5.55	0.69	10.73
	1.88	21.11	11.24	2730.25	11.32	2.18	0.097	19.60	40.53	5.20	0.68	12.32
	1.85	21.64	11.69	2893.00	11.42	2.41	0.235	18.89	34.10	4.73	0.65	13.77
	1.86	21.20	11.39	2934.20	11.12	1.89	0.052	21.02	48.36	5.88	0.71	10.51
	1.88	21.74	11.56	2781.95	12.09	2.30	0.097	14.16	37.16	5.25	0.68	13.90
	2.04	20.64	10.12	2995.20	10.70	2.38	0.056	24.03	34.95	4.49	0.64	12.73
	2.00	19.32	9.65	2872.73	11.39	1.92	0.103	19.10	47.64	5.94	0.71	10.91
	1.89	20.05	10.58	2622.06	11.36	1.78	0.112	19.32	51.37	6.38	0.73	10.11
Ave.	1.91	20.83	10.92	2852.56	11.29	2.10	0.11	19.82	42.55	5.43	0.69	11.87
Std.	0.07	0.81	0.73	131.65	0.41	0.24	0.06	2.92	6.69	0.64	0.03	1.50

As it can be seen in Table 1, the loss weights are low and only microcracks happen in the first 10 cycles that influence n, QAI and strength properties and have no substantial effect on ρ_d. Overall, the whole geomechanical properties decreased and some of them such as QAI and n increased after 40 freeze and thaw cycles (Figure 6). Among all these properties, n has the highest correlation coefficient (R=0.85) with freeze-thaw cycles. Some other parameters including QAI, V_p, σ_t and σ_c also have acceptable R; 0.77, 0.74, 0.73 and 0.73, respectively. Therefore, the n and QAI are considered to be more sensitive to freeze-thaw test. This is because n and QAI have the most reduction values that make it more sensitive to even small changes in rock properties (Table 1). Among other parameters V_p, in spite of its lower R, seems to be more practical for determination of the changes in n, and the state of fissuring during freeze-thaw test.

The brittleness indices values (B_1, B_2 and B_3) of the studied rock are shown in Table 1. According to previous researchers (Altindag, 2003; Heidari *et al*., 2013; Yagiz, 2009; Yarali & Kahraman, 2011; Yarali & Soyer, 2011), the results of these indices should be decreased by increasing in deterioration of rocks. As shownin Figure 7, brittleness concept (B_3) has a negative relationship with increasing the freeze-thaw cycles, and two others have a positive relationship. The results of B_1 and B_2 are not in agreement with other research papers and both of them should have a negative relationship with increasing n and decreasing rock strength. This reverse trend happened, firstly, because tensile stress and microcrack propagation induced by water crystallization was dominant during freeze-thaw test. Therefore, the σ_t loss percentage is obviously more than the σ_c loss percentage (Table 1). Secondly, in both brittleness formulas (B_1 and B_2), σ_t exists in the denominator of the fractions. Besides, some researchers reported; these two concepts caused some vague definitions for rock brittleness (Heidari *et al*., 2013; Suorineni *et al*., 2009). Therefore, it is postulated that B_3 should be only used in analytical analyses. In addition, B_3 shows the best correlation with the freeze-thaw cycles (Fig. 6).

Statistical Evaluation between the Brittleness Index (B_3) and Geomechanical Properties

In order to establish some predictive models for assessing brittleness based on geomechanical properties under cold condition, some simple analytical analyses were performed by using all 41 data.

The relations between B_3 and other parameters are presented in Figure 7. Some obtained equations are relatively found not to be statistically correlated with brittleness index (B_3) including ρ_d with very low R about 0.15. Also, V_p, n and QAI in comparison to other index parameters can be considered to have fairly good correlations with B_3 values (R> 0.55). The strength parameters (σ_c and σ_t) are shown the better correlation coefficients than other physico-mechanical parameters, as these parameters involved in B_3 formula.

It was reported earlier by Heidari *et al*., (2013) that no meaningful relation could be found between n and brittleness indices, owing to the high mineralogical variety or presence of minerals with plastic behavior. But as mentioned, there is a meaningful relationship between n and B_3 (R=0.69), because mineral composition have never changed and only physical rock deterioration was happened by freeze-thaw test.

The descriptive analyses of the geomechanical properties and B_3 values are presented in Table 2. The V_p parameter, among others, has the highest range from 2622 to 3573(m/s) and the lowest scattering in the results. Due to its higher variation, this parameter can be a good indicator in laboratory for determining B_3 after each freeze-thaw stage as its variation is clearly distinguishable. Although, the percentage loss of this parameter is lower than other parameters.

Assessment of Rock Brittleness Using Multiple Linear and Non Linear Regressions (MR)

As seen in previous section, each engineering parameter may suggest different rock brittleness when used individually.

Owing to that, a multivariate technique (in this case, MR) should be used to simultaneously combine the effects of these different parameters on the rock brittleness.Therefore, 3 equations were generated with 2 to 3 independent variables. The evaluated input combinations for brittleness index (B_3) are shown in Table 3.

The cross-correlations between measured and predicted brittleness index are plotted based on simple indices for all models (Fig. 8).

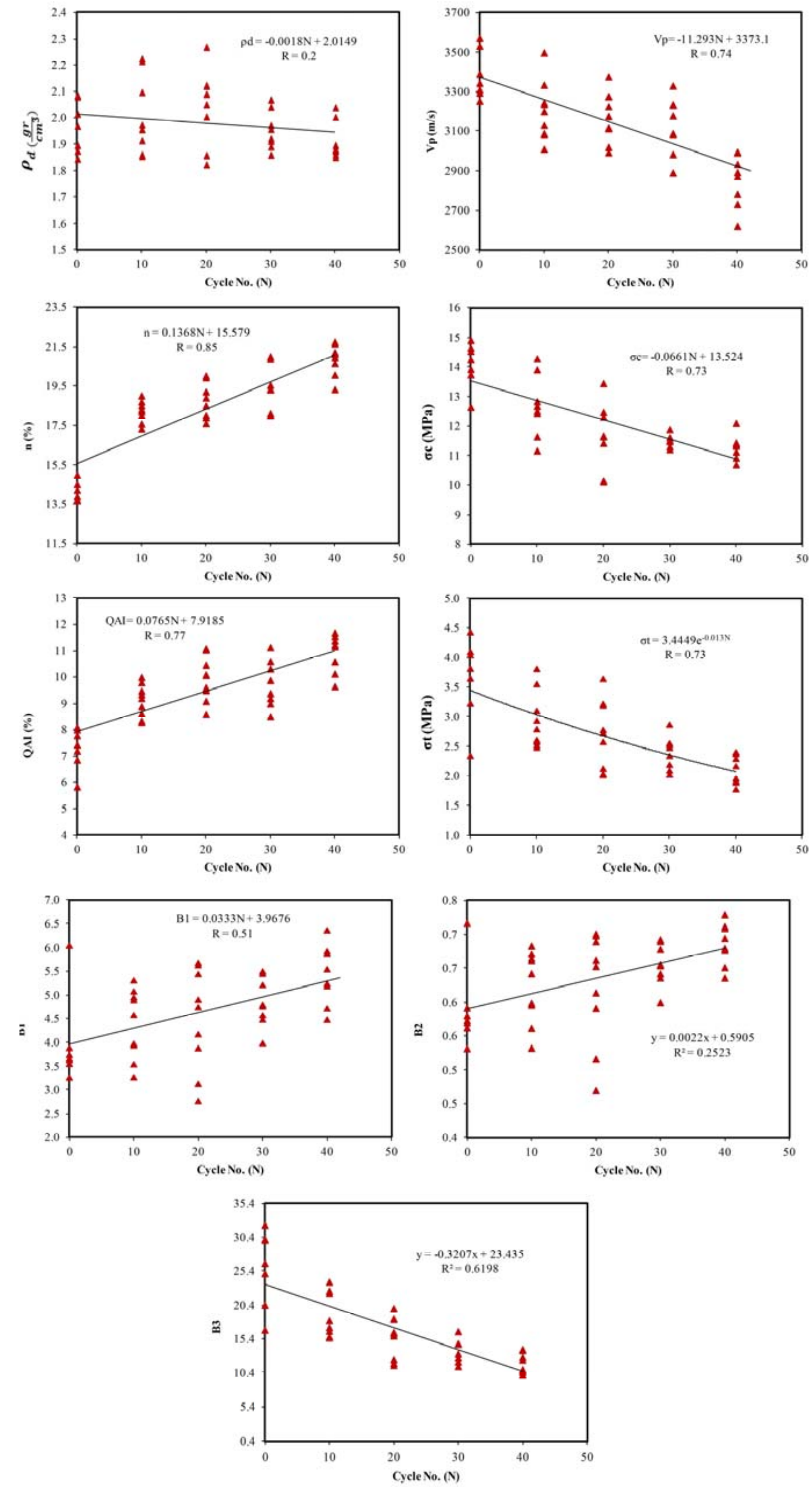

Figure 6. The relationship between geomechanical and brittleness indices and freeze-thaw stages

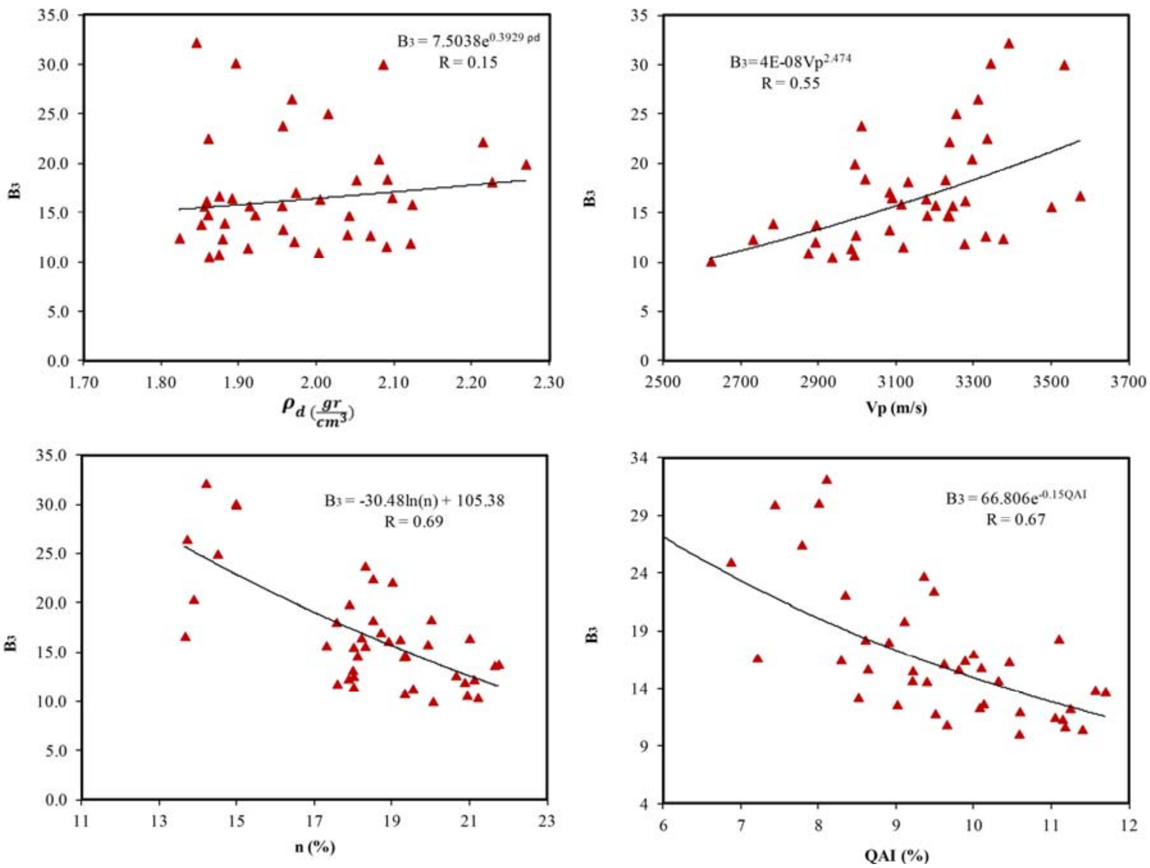

Figure 7. The relationship between geomechanical properties and Brittleness index (B3)

Some engineering parameters such as σ_c and σ_t are widely employed for predicting of rock brittleness, regardless of the difficulties involved in preparing standard core samples (Altindag, 2002; Protodyakonov, 1963). In this study, simple, inexpensive, and non-destructive engineering parameters including physical properties n, V_p and ρ_d were postulated to predict brittleness concept (B_3). Among all models, model 3 appears to be more reliable than others. These parameters were fed to the MR models in three steps based on the best subset method.

As n and QAI parameters provide same information, the n which has the highest R in simple regression analysis considered as constant parameters in all models. Parameters with the highest R in simple regression analyis including n and V_p were put into model 1. It was also decided to put ρ_d in model 2 as it has a lower R in comparison to V_p (Fig. 7). Then, all parameters were fed into the models 3 to prove brittleness prediction.

All three models yield $R < 0.7$, $RMSE \leq 4$, $ME \leq 0$ and $VAF \leq 49.24$ (Table 3). The first multivariate equation (model 1) has good statistic parameters. V_p (model 2) has a relatively good R value in simple regression, and it improved the statistic parameters in multiple regression (R= 0.697, RMSE= 4, ME= 0.00, VAF= 48.6). In spite of the low statistical correlation of ρ_d in simple regression analysis (R=0.15), multivariate equation formed from this parameter appears to be more reliable than the model in simple regression for brittleness prediction (Model 2).

Consequently, the equation forms from simple indices including n, V_p and ρ_d appears to be more precise and reliable than other models for predicting B_3 with higher statistic parameters (Model 3). Although, models (1) and (2) can be considered as good models, because they have very close statistic parameters to model 3 and lower number of variables.

Table 2. Descriptive statistics of training and testing data sets

Variables	Training set					Testing set				
	Range	Mean.	Max.	Min.	Std.	Range	Mean.	Max.	Min.	Std.
n (%)	8.08	18.11	21.74	13.66	2.34	6.22	18.99	21.2	14.98	1.82
QAI (%)	5.86	9.40	11.69	5.83	1.40	3.96	9.64	11.39	7.43	1.34
Vp (m/s)	950.97	3141	3573.03	2622.06	218.18	641	3154.1	3532.01	2891	202.18
ρ_d (g/cm3)	0.43	1.97	2.27	1.84	0.12	0.39	1.99	2.21	1.82	0.12
B_3 $(MPa)^2$	22.13	17.23	32.24	10.11	5.64	19.53	16.16	30.04	10.51	5.88

Table 3. Performance indices (R, RMSE, ME, VAF), and equations for MR models

Model No.	Variables	Equations	R	RMSE $(MPa)^2$	ME $(MPa)^2$	VAF (%)
1	n & V_p	$B_3 = 476.11/n + (2.2\times10^{-3})Vp - 16.37)$	0.697	4	0.00	48.6
2	n,& ρ_d	$B_3 = 514.49/n + 3.61\rho_d - 18.7)$	0.698	3.99	0.00	48.8
3	n, , V_p & ρ_d	$B_3 = \exp(-0.089\ n + (1.12\times10^{-4})\ V_p + 0.19\rho_d + 3.71)$	0.699	3.98	-0.003	49.24

Assessment of Rock Brittleness Using ANN

The multivariate models are more practical than simple models, but they cannot estimate rock brittleness accurately. Therefore, in this paper it is tried to develop more sensible models using MLP, a feed-forward Neural Network to estimate the brittleness index by using geomechanical properties.

In this study MatLab 7.1 software with one layer feed-forward network is programmed, and it is comprised of an input layer (3 units), a hidden layers (10 neurons; with Tangent Hyperbolic activation function), and an output layer (1 neuron and linear activation function) (Fig. 9; Matlab 7.1. 2005). These activation functions were proposed for MLP modelling (Hornik *et al*., 1989; Nourani & Sayyah Fard, 2012). In the analyses, network parameters were adjusted as follows: learning rate parameter: 0.01, momentum parameter: 0.9, number of training epochs: 500 and variable learning rate with momentum (trainLm).

The input variables were put in the MLP models in 3 steps as developed MR models. As mentioned before, for establishing an optimal network, the network should be trained using training data set, and then the accuracy of statistic parameters of the trained neural network should be checked using testing data set. If the statistic parameters are found to be satisfactory, the training process is terminated. The results are represented in Table 4, and Figure 11. In comparison to MR models, all MLP models have higher ME values. As shown in Table 4, model 1 which is based on n and Vp parameters yields good statistic and accuracy values for both training and testing dataset (*i.e.* for training: RMSE= 3.46, VAF= 48.44, ME= 0.02, R= 0.8). Model 2 is based on ρ_d input variable, and it has a dramatic decrease in statistic parameters of testing data set, because this parameter has a negligible correlation coefficient (ρ_d: R=0.15) in simple regression method.

Model 1 and 2 have similar correlation coefficients for training data set (R=0.8), but other statistic parameters differentiate these two models. This implies that it is better to use some statistic and accuracy parameters with correlation coefficient.

As seen earlier in MR models, the statistic parameters have increased fairly well by using all three variables (Model 3), it is also seen this increase in MLP models (R= 0.83, RMSE= 3.24, ME= 0.00, VAF= 43.62).

The MLP models have so obvious changes in statistic parameters for all models in comparison to MR models, and the network has not improved by increasing the number of independent variables.

The Comparison of MR and ANN Models

Residuals between the observed and predicted results for the best MR and ANN models have been shown in Figures 11 and 12. The residuals between the observed and predicted data points which measure mismatch between these points express under and overestimate of each data points, and in other words the value of error. As depictedin Figure 12, MR model mismatchs many of data points. The comparison of the models produced from ANN and MR residuals show that ANN model for the prediction of B_3 is more reliable than the MR model.

Table 4. Performance indices (R, RMSE, ME, AIC) for ANN models

Model No.	Variables	Training set				Testing set			
		R	RMSE (MPa)^2	ME (MPa)^2	VAF (%)	R	RMSE (MPa)^2	ME (MPa)^2	VAF (%)
1	n,& V_p	0.80	3.46	0.02	48.44	0.67	2.05	-0.03	40.2
2	n & ρ_d	0.80	3.3	0.05	46.31	0.56	2.09	-0.08	47.21
3	n, , ρ_d & V_p	0.83	3.24	0.00	43.62	0.67	1.9	-0.01	40.2

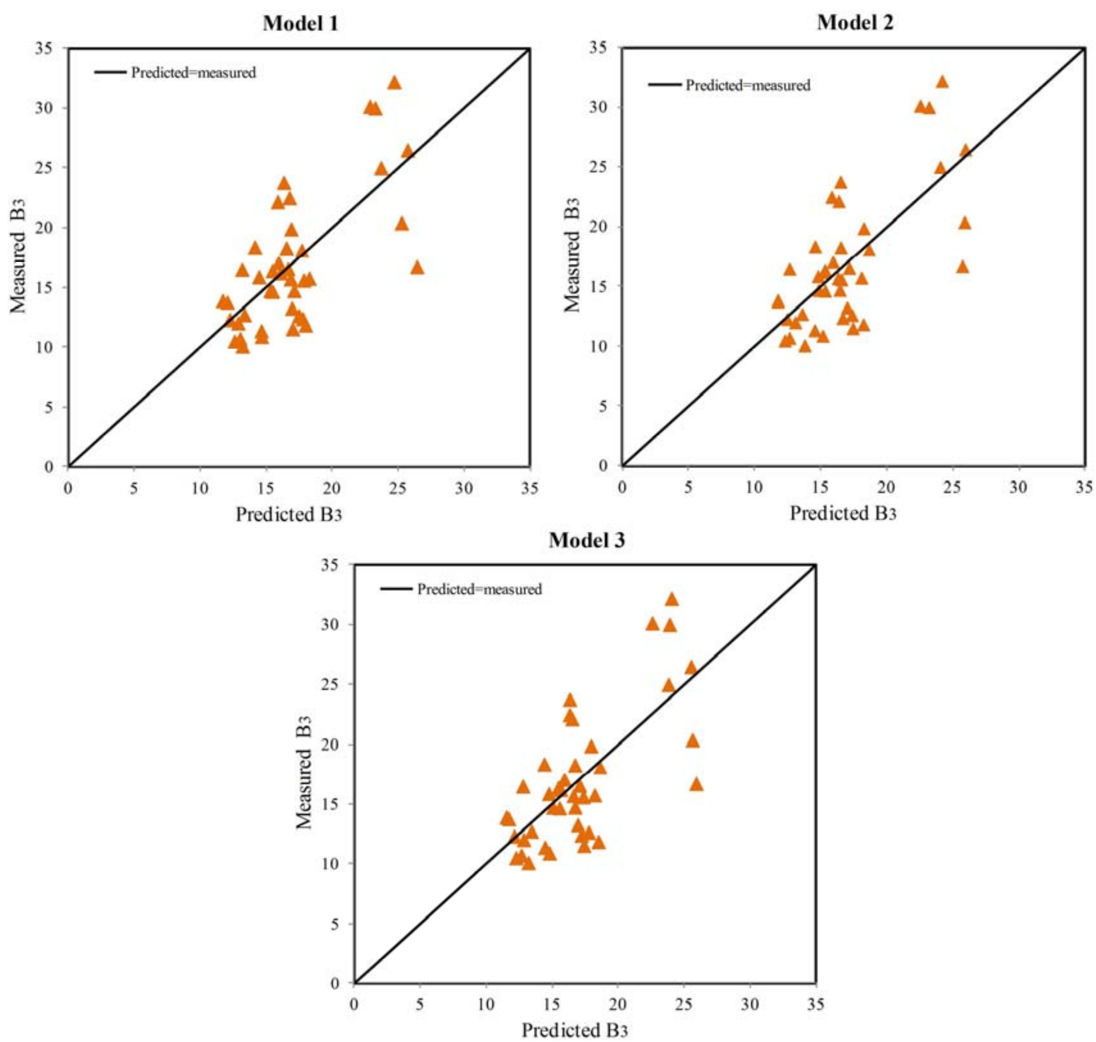

Figure 8. Comparisons between the predicted and the measured brittleness index (B3) in MR models

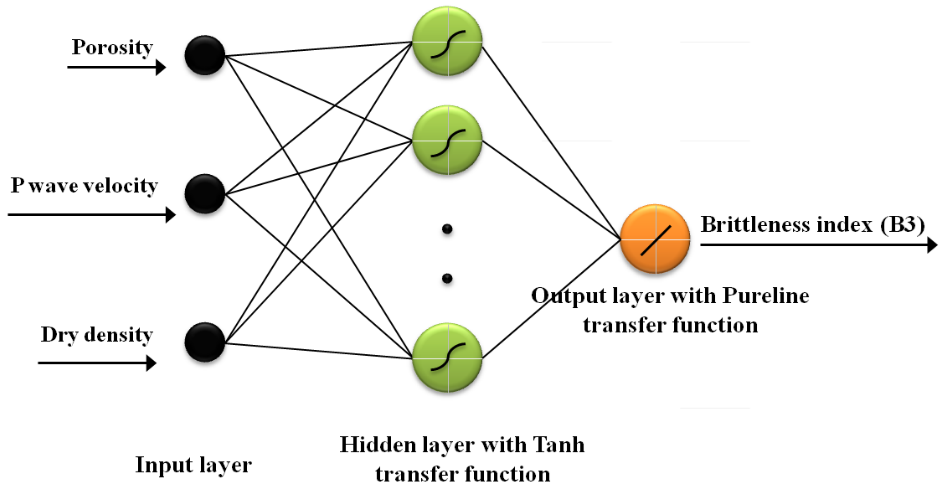

Figure 9. Schematic structure of a feed-forward ANN (MLP) used in this study

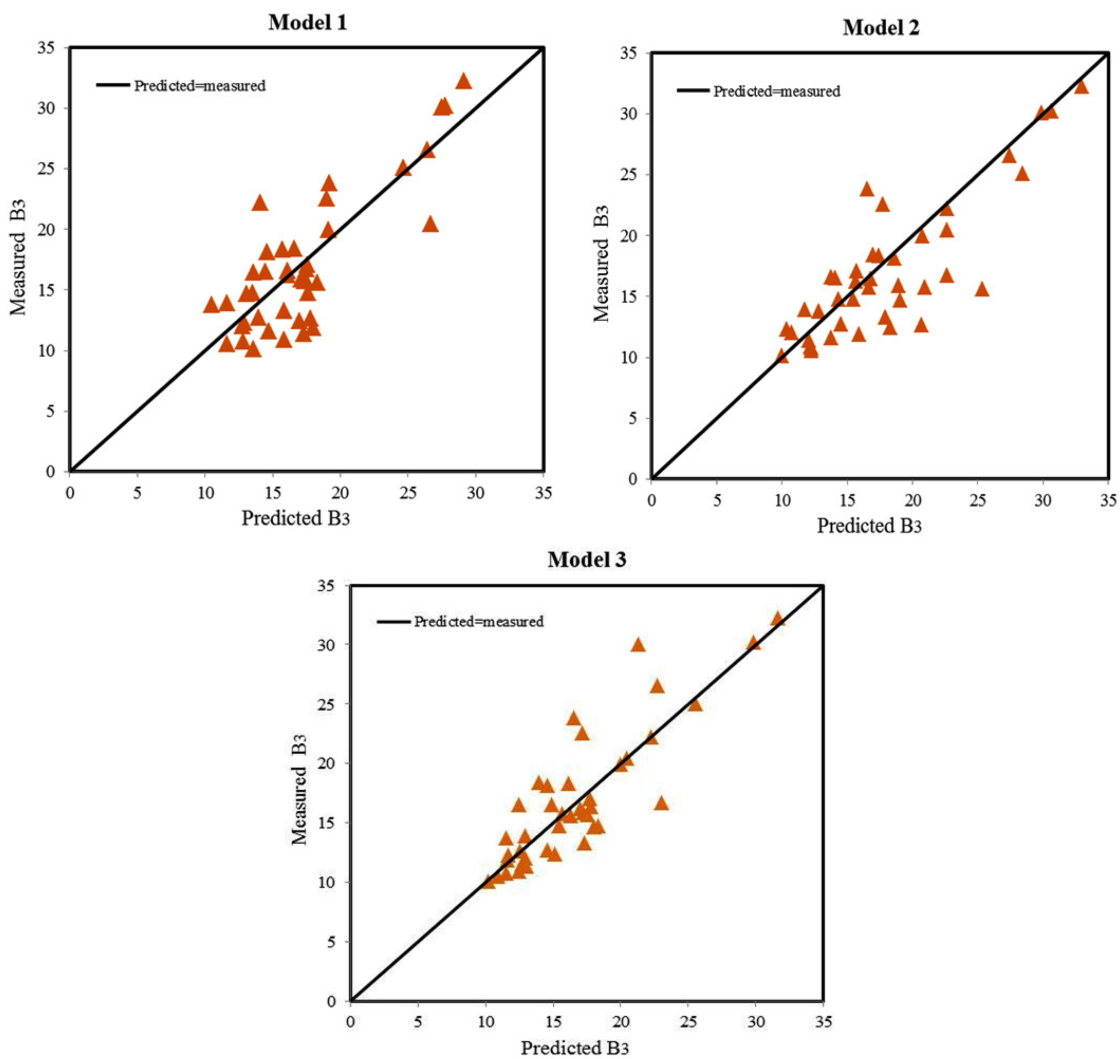

Figure 10. Comparisons between the predicted and the measured brittleness index from ANN

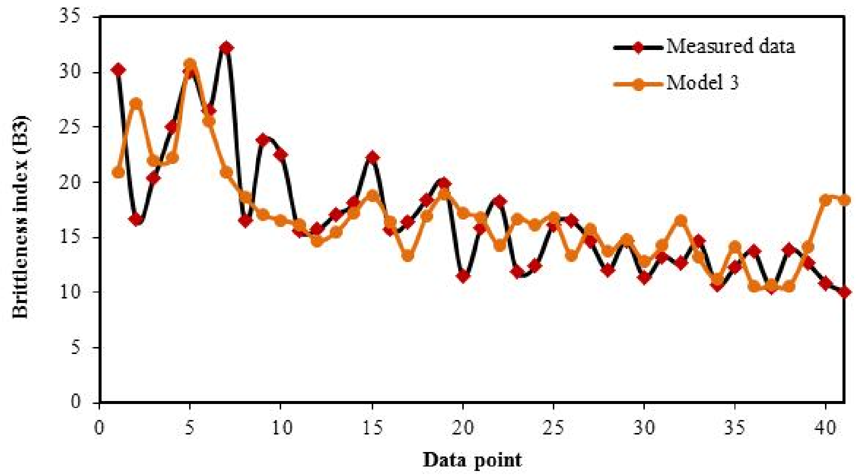

Figure 11. The error distribution for the different MR models and measured data (B_3)

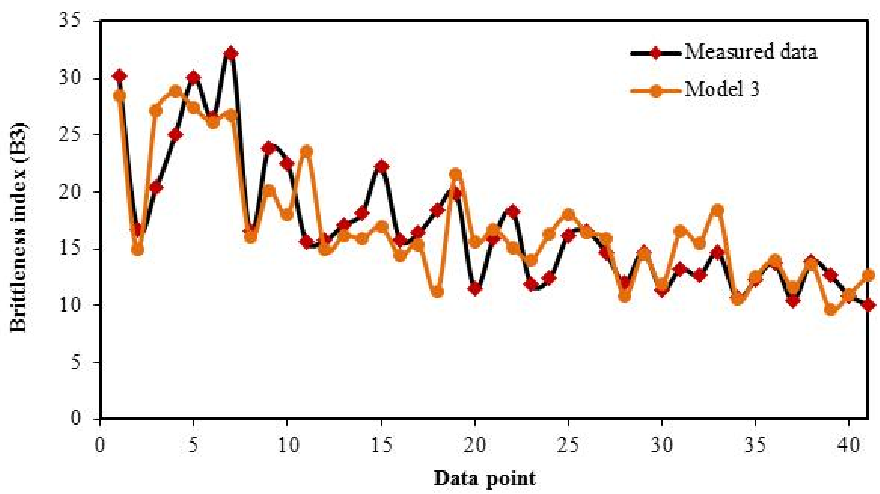

Figure 12. The error distribution for the different ANN model and measured data (B_3)

Conclusions

This paper shows the results of the brittleness of Hamekasi porous limestone during the freeze-thaw test. Overall, the paper presents a comprehensive laboratory test results aimed to establish a model based on geomechanical properties under the freeze-thaw test.

Freeze-thaw cycles cause the development of tension cracks and a decrease in rock brittleness.
In order to investigate the development of tension cracks during freeze-thaw cycles in porous rocks, brittleness index (B_3) is an appropriate parameter.

In the present study, the freeze and thaw test have been performed in 40 cycles. This is because the increase in the number of test cycles turns the microcracks into fractures, and has no other prominent effect on the obtained results.

Contrary to the results have been previously reached by other researchers, it is shown that n and QAI have meaningful relations with brittleness index (B_3).

All MR and MLP models are relatively good for predicting brittleness index and increase in the input variables did not improve models performance. Among all MR and MLP models, model 3 (using n, V_p and ρ_d) can be considered as the best model for predicting B_3.

V_p, which has a relatively good R in comparison to ρ_d, is supposed to increase model statistic parameters, but it does not.

It should be mentioned that using more number of statistic parameters increased the model accuracy.

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