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Abstract

Uniaxial compressive strength (UCS) is considered to be one of the important parameters in rock engineering projects. In order to determine UCS, direct and indirect techniques are employed. In the direct approach, UCS is determined from the laboratory UCS test. In indirect techniques determine UCS based on the nondestructive test findings which can be easily and quickly performed and require relatively simple or no sample preparation. Indirect techniques are commonly preferred by rock and mining engineers because of their low cost and ease. This study presents the findings of an Artificial Neural Networks (ANN) based model for the prediction of UCS from Schmidt hardness. Schmidt hardness test (SHT) is a nondestructive test method which provides fairly good correlation about the strength of rocks. SHT can be easily and quickly conducted with a portable device known as Schmidt Hammer and it does not require any sample preparation. ANNs have been widely used in solving engineering problems and have emerged as powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more traditional numerical and statistical methods. For this reason, ANNs are used in this study to predict UCS of carbonate rocks from the Schmidt hardness rebound value (N R). A set of 37 test measurements obtained from 37 different carbonate rocks (marble, limestone, and travertine) are used to develop the ANN-based model. The results of the ANN model were also compared against the results of a regression model. The criteria used to evaluate the predictive performances of the models were the coefficient of determination (R 2), root mean square error (RMSE), and variance account for (VAF). The R 2, RMSE, VAF indices were calculated as 0.39, 46.51, 12.45 for the regression model and 0.96, 7.92, 95.84 for the ANN model, respectively. The results show that ANN-based model produces significantly better results than the regression model. It was concluded that the N R value is a useful indicator for the prediction of UCS from the ANN model developed in this study.

Keywords

artificial neural network, carbonate rock, coefficient of determination, Schmidt hammer, Schmidt hardness, carbonation, neural networks, rock mechanics

Disciplines

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A predictive model for uniaxial compressive strength of carbonate rocks from Schmidt hardness

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ABSTRACT: Uniaxial compressive strength (UCS) is considered to be one of the important parameters in rock engineering projects. In order to determine UCS, direct and indirect techniques are employed. In the direct approach, UCS is determined from the laboratory UCS test. In indirect techniques determine UCS based on the nondestructive test findings which can be easily and quickly performed and require relatively simple or no sample preparation. Indirect techniques are commonly preferred by rock and mining engineers because of their low cost and ease. This study presents the findings of an Artificial Neural Networks (ANN) based model for the prediction of UCS from Schmidt hardness. Schmidt hardness test (SHT) is a nondestructive test method which provides fairly good correlation about the strength of rocks. SHT can be easily and quickly conducted with a portable device known as Schmidt Hammer and it does not require any sample preparation. ANNs have been widely used in solving engineering problems and have emerged as powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more traditional numerical and statistical methods. For this reason, ANNs are used in this study to predict UCS of carbonate rocks from the Schmidt hardness rebound value (N_R). A set of 37 test measurements obtained from 37 different carbonate rocks (marble, limestone, and travertine) are used to develop the ANN-based model. The results of the ANN model were also compared against the results of a regression model. The criteria used to evaluate the predictive performances of the models were the coefficient of determination (R^2), root mean square error (RMSE), and variance account for (VAF). The R^2, RMSE, VAF indices were calculated as 0.39, 46.51, 12.45 for the regression model and 0.96, 7.92, 95.84 for the ANN model, respectively. The results show that ANN-based model produces significantly better results than the regression model. It was concluded that the N_R value is a useful indicator for the prediction of UCS from the ANN model developed in this study.

1. INTRODUCTION

Uniaxial compressive strength (UCS) test is widely used for estimating the mechanical properties of rock material in both underground and surface rock engineering projects. UCS is directly determined according to both the American Society for Testing and Materials [1], the International Society for Rock Mechanics [2] and other common standards. Due to the fact that standard experimental test methods based on established standards require costly equipment and that the methods for sample preparation is difficult and time-consuming, indirect methods are more favorable. Indirect methods are relatively simple and generally do not require any sample preparation. In these methods, the UCS value is predicted with a simple mathematical model in a simpler, faster and more economical way.

The Schmidt hammer, which was originally developed for measuring the strength of concrete [3] but nowadays with the developed properties it can be used to predict the strength of rocks. The device consists of spring loaded steel mass that is automatically released against a plunger when the hammer is pressed against the rock surface. The principle of the test is based on the absorption of part of the spring released energy through plastic deformation of rock surface, while the remaining elastic energy causes the actual rebound of the hammer. The distance travelled by the mass, expressed as a percentage of the initial extension of the spring, is called the "*rebound number*" [4].

Several empirical relationships between rocks' physico-mechanical properties and Schmidt hammer hardness values (N_R) have been published in the literature.

Early studies started with Singh and Hassani [5]. They emphasized the importance of laboratory testing of friable coal measure rock for the stability assessment of surface and underground excavations. They obtained strong correlation between UCS and N_R for the sedimentary rocks. Shorey et al. [6] report an investigation to determine whether a correlation exists between the Schmidt hammer rebound and the in situ large-scale strength. The results showed a reasonable correlation between the large-scale in situ crushing strength of 0.3 m cubes of coal and the lower mean of rebound values obtained. Haramy and DeMarco [7] advanced the use of this instrument by testing 10 types of U.S. coals to determine the utility of the Schmidt hammer in designing underground coal mine pillars. Specifically, the tests investigated the correlation of Schmidt hammer rebound index to UCS of laboratory-prepared coal samples. Sachpazis [8] also reported high correlation and regression equations among Schmidt hammer rebound hardness, Tangent Young`s modulus and uniaxial compressive strength. Xu et al. [9] used the same specimens from the weak rocks to determine their corresponding UCS values and establish a correlation between Schmidt hammer rebound value and UCS. Gokceoglu [10] conducted studies on marl and suggested empirical equations between UCS and Schmidt hammer rebound number. Yilmaz and Sendir [11] obtained high correlation between unconfined compressive strength and Schmidt hardness from the samples of gypsum. Yasar and Erdogan [12] investigated the statistical relationship between hardness value and physico-mechanical properties of constructional and cover rocks. They found high correlation values between Schmidt Hammer hardness and uniaxial compressive strength.

A list of the some relationships proposed to predict UCS of rocks in literature is presented in Table 1.

Table 1. Equations between UCS and N_R reported in the literature

Authors	Rock Type	Sample Size	Equation	R
Singh et al.	Sedimentary	30	UCS=2N	0.72
Shorey et al.	Lithological	20	UCS=0.4N-3.6	0.94
Haramy and DeMarco	Lithological	10	UCS=0.99N-0.38	0.70
Sachpazis	Carbonate	29	N=0.24UCS+15.72	0.96
Xu et al.	Mica, gabbro etc.	-	UCS=exp(aN+b)	0.88
Gokceoglu	Marl		$UCS=0.0001N^{3.27}$	0.84
Yilmaz et al.	Gypsum	20	UCS=exp(0.82+0.06N)	0.98

In literature, although there are a number of studies investigating the relationship between UCS and other physico-mechanical properties, fewer studies used the artificial neural networks (ANN) methodology.

The aim of this study is to investigate the relationship between UCS and N_R of the carbonate rocks using ANN.

2. METHODOLOGY

2.1. Sample collection and Preparation

In this study, the selected samples were carbonate rocks merchandised in Turkey and in the World. For this purpose, a total of 37 different natural stones were collected from 19 different natural stone processing plants from different cities of Turkey. Fifteen cubic samples of a size of 70x70x70 mm from each rock were prepared for uniaxial compressive strength tests. For the description of each rock sample, the mineralogical and petrographical properties were determined through laboratory investigation. Thin section samples of the mineralogical and petrographical definitions of the rocks - whose trade names are known - were provided. As for the method of analysis, the modal analysis method was applied, and the rocks were classified according to Folk's (1962) classification [13].

2.2. Test Procedures

Uniaxial compressive strength test

Uniaxial compression tests were performed on cubic samples, which had dimensions of 70 mm. The samples, until constant mass, 70 ± 5 °C were kept in the stove and then the samples are cooled to room temperature. When they are in room temperature, uniaxial compression tests were performed with 0.6 MPa/s constant stress rate. Tests are carried out according to Turkish standard TS EN 1936 [14].

Uniaxial compressive strength values (σ_c) were calculated using the following formula:

$$\sigma_c = \frac{F}{A} \qquad (1)$$

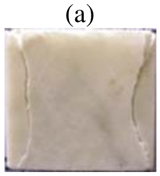
where;

σ_c = Uniaxial compressive strength (MPa)
F = Maximum failure load (N)
A = Section area of specimen (mm^2).

Schmidt hammer hardness

Schmidt Hammer was used to estimate the strength of rocks. For this purpose 20 rebound values were recorded from single impacts separated by at least a plunger diameter on the carbonate rocks blocks, and the average of the upper 10 values was evaluated. Tests are carried out according to ISRM [15]. Schmidt hardness values were obtained from blocks of natural stone. Block dimensions varied between 1.70 x 1.70 x 1.50 m and 2.50 x 1.50 x 1.50 m.

(a)



(b)

Fig. 1. Uniaxial compressive strength test device (a) broken sample (b).

3. ANALYSES OF EXPERIMENTAL DATA

The data obtained in the study were evaluated individually via the ANN models and multiple regression analysis, a traditional statistical method. In order to determine the applicability of the equations obtained, the predictive performances of the results obtained from the ANN and those from traditional statistical methods were compared.

Table 2. Descriptive statistics of data

	UCS	N_R
Minimum	24.50	54
Maximum	192.98	71
Mean	93.47	64.35
Std. Deviation	39.30	4.30
Variance	1544.47	18.46

3.1. Simple Regression

The data obtained in the study were evaluated with the multiple regression analysis, a traditional statistical method. In multiple regression analysis, coefficient of determination (R^2) determines to what extent the model obtained explains the variance of the dependent variable [16]. For a strong predictive model, the value of R^2 is expected to be close to 1.0. A relationship between UCS and N_R is shown in Fig. 2.

The following equation was obtained as a result of the analyses:

$$UCS= 0.0682N_R+57.973 \quad (2)$$

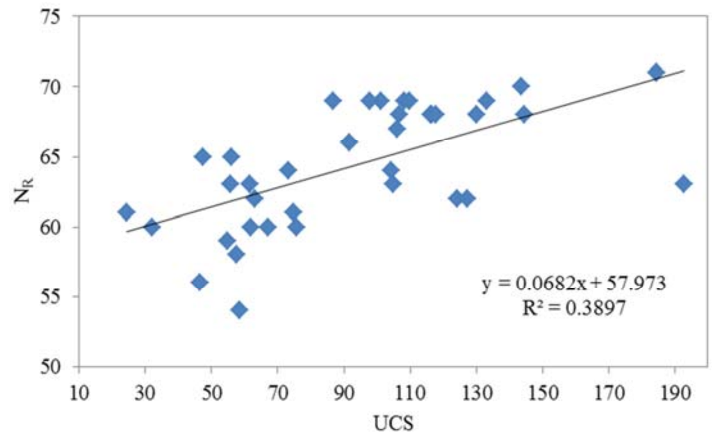


Fig. 2. Correlation graph of regression model between uniaxial compressive strength and Schmidt hammer hardness.

3.2. Artificial Neural Networks

Developments in artificial intelligence and computer sciences enable problems in studies on earth sciences to be modeled with increasing reliability. With the modeling results, evaluation of the forms of behavior observed in the nature strengthened empirical approaches. This caused artificial intelligence applications to become more favorable [17].

ANNs are made up of artificial neural cells called neurons. Artificial neural cells are units including a set of data and processing various inputs from external sources or from other neurons. Neurons are the basic parts of the general architecture used to calculate an output. Figure 3 presents the basic neuron structure with inputs with the number of *m*. Synapses or links are characterized with "weights" [18]. Weights are symbolized with "ω" in artificial neural networks. In defining the weights, indices are used. For instance, with the weight of "ω" and defined with "ω_{kj}"; the first indices (*k*) shows which neuron the weight belongs to, and the second indices (*j*) shows which input the weight belongs to.

In Fig. 3.;

$x_1, x_2,\ldots, x_m$ input signals

$\omega_{k1}, \omega_{k2}, \ldots\ldots\ldots, \omega_{km}$: synaptic weights,

υ_k : input of activation function

b_k : bias value

$\varphi(.)$: activation function

y_k : output signal

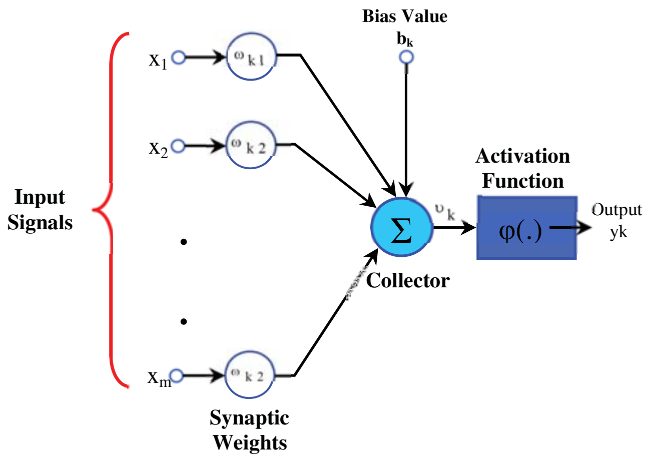


Fig. 3. The neuron model with *m* piece input [19].

The structure in which neurons help each other working in a group is called "*network*". In a network, there are neurons in different numbers depending on the structure of the network or on the configuration that leads to the best solution.

Neurons coming together in the same vertical line form the layers. Neurons are found in layers. Generally, artificial neural networks can have a single layer or multiple layers. Multiple-layer artificial network structures are used for solving nonlinear problems (Fig. 4.)

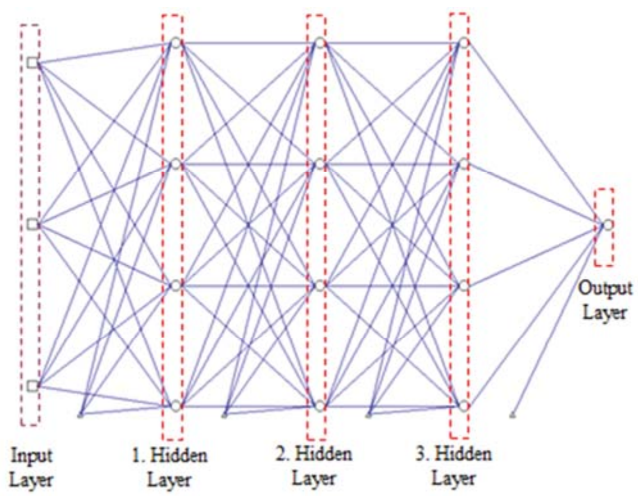


Fig. 4. Simplified view of a multi-layer network.

In general, networks consist of an input layer, one or more hidden layers and an output layer. The number of neurons in the input layer and in the output layer is optimized by the user by trial and error based on the definition of the problem [20, 21].

Transmission from one neuron to another between the layers in artificial neural networks is achieved via synaptic weights. In studies conducted on artificial neural networks, weights are changed for each iteration and in the last iteration for the purpose of determining the weights providing the optimum result. In artificial neural networks, the learning process means adjusting weights based on the number of iteration (Fig. 5).

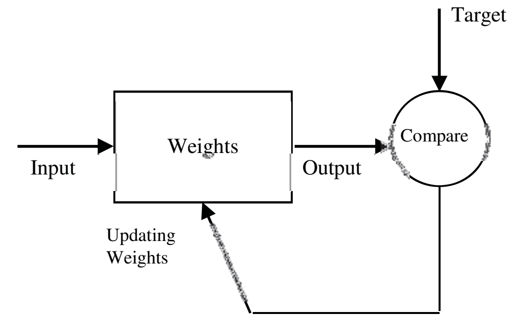


Fig. 5. Change of weights in ANN [22].

The type of neural network used in this study is multi layered perception (MLP). A MLP neural network is shown in Fig. 6. The MLP networks consist of an input layer, one hidden layer and an output layer. For the problem, the network consists of 1 input, 1 output and 1 hidden layer. The number of hidden layer neurons was decided with many trials. Although different configurations are possible, the best results were obtained from 44 neuron configuration.

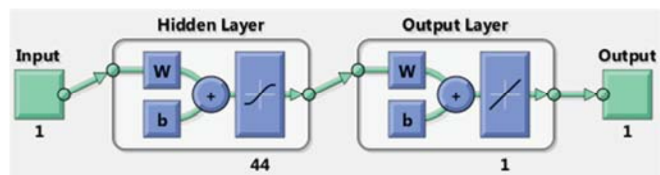


Fig. 6. Architecture of network in this study.

MATLAB (Version 7.12.0 R2011a) was used for ANN modeling. In MATLAB procedure training and testing data is chosen randomly. In this study 70% of data (25 samples) was used for training, 15% of data (6 samples) was used for validation, 15% of data (6 samples) was used for testing. The plot of the predicted UCS values versus actual UCS values for the ANN model is shown in Fig. 7.

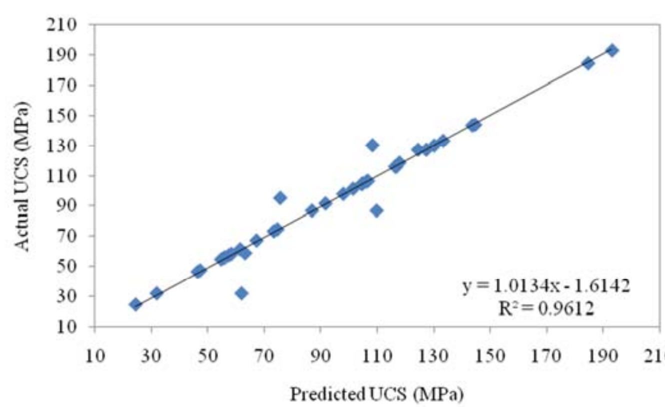


Fig. 7. Relationship between actual and predicted UCS values for the ANN model.

3.3. Comparison of Models

In order to determine the applicability of the equations, the predictive performances of the models were compared. For the purpose of measuring the predictive performances of the models, VAF (Variance Account For) Eq. (3), RMSE (Root Mean Square Error) Eq. (4), coefficient of determination (R^2) Eq. (5) performance indices were used.

$$VAF = \left(1 - \frac{var(y_i - \hat{y})}{var(y_i)} \right) x100 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \quad (4)$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad (5)$$

where;

var: Variance

yi: measured value

$\hat{y}$: predicted value

k: number of parameter

N: number of sample

The performance indices above can be interpreted as follows: if the VAF is higher, then the model performs better. For example, a VAF of 100% shows that the output measured has been predicted precisely. VAF=0 demonstrates that the model performs as poorly as a predictor using simply the mean value of the data. If the RMSE is low, then the model performs better [23]. The best results obtained via the artificial neural networks and the conventional statistics method applied in the present study are shown as Table 3.

Table 3. The comparison of ANN and regression model

	Regression	ANN
VAF	12.45	95.84
RMSE	46.51	7.92
R^2	0.39	0.96

4. CONCLUSIONS

In this study the simple regression analysis and artificial neural networks applications were compared for the prediction of UCS values from the simple laboratory tests. The following results and conclusions can be drawn from the present study:

- The VAF, RMSE, R^2 indices were obtained as 12.45, 46.51, and 0.39 from regression analysis, respectively.
- The VAF, RMSE, R^2 indices were obtained as 95.84, 7.92, and 0.96 from artificial neural networks, respectively.
- The results show that ANN-based model produces significantly better results than the regression model. It was concluded that the N_R value is a useful indicator for the prediction of UCS from the ANN model.
- UCS values are successfully estimated from Schmidt hammer hardness values for carbonate rocks. It provides to practitioner to prediction of the UCS with simple and low costs tests.
- New models can be developed by applying the obtained results not only to carbonate rocks but also to magmatic rocks.

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