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Modeling uniaxial compressive strength of building stones using non-destructive test results as neural networks input parameters

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HIGHLIGHTS

- The prediction of *UCS* values of natural building stones was aimed.
- 37 Different carbonate rocks were collected from different regions of Turkey.
- Ultrasonic pulse velocity, Schmidt hammers hardness, Shore hardness values were used for *UCS* prediction.
- The *ANNs* approach and conventional multivariate regression analysis were used.
- The *UCS* values for carbonate rocks can be predicted successfully from *ANNs* models.

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ABSTRACT

Uniaxial compressive strength value (*UCS*) is used as a critical input parameter in determining the engineering properties of natural building stones. The purpose of present study was to develop a model to determine the *UCS* of natural building stones via relatively simple and low-cost mechanical tests with the application of artificial neural networks. For this purpose uniaxial compressive strength, ultrasonic pulse velocities, Schmidt hammer hardness, and Shore hardness tests were performed on 37 different specimens of natural building stones collected from various natural stone processing plants in Turkey. The artificial neural networks (*ANNs*) approach was utilized for the development of the model that predicts the *UCS*.

The major goal was to develop a model that makes the best prediction with the fewest number of input parameters. Therefore, analyses for verification of the models started with single input parameter and then combinations of two and three input parameters were used. For that purpose, two separate approaches were utilized with seven different sets of analyses in each method. The results of the *ANNs* models were compared with respect to the results of regression models. 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 results show that the proposed *ANNs* method could be applied effectively for the prediction of *UCS* either from one of the input parameters or from their combinations i.e. ultrasonic pulse velocity, Schmidt hammer hardness and Shore hardness.

1. Introduction

Neural network models provide descriptive and predictive capabilities, therefore, have been applied through a range of rock parameter identification and rock engineering practices [1]. *UCS* values of stones are the most important parameter of rock stones for its mechanical characterization. The most standardized methods in determining the strength properties of rocks require the special sample preparation procedures to obtain high-quality core samples, the experienced test personnel, and the relatively high test costs and times. For practical perspective at design stage, the estimations of *UCS* from simple tests and results with time and cost savings have been investigated as alternatives of standardized laboratory tests [2–5].

The conventional multivariate regression analysis approaches of laboratory test data have been used extensively to establish *UCS* predictive models in engineering geology [4–16].

However, these traditional statistical techniques are inadequate in simulating the process efficiently, since the properties of rock materials are influenced by a multitude of auxilliary factors and the uncertainty involved in the experimental tests. Over the last few years or so, the development of computer hardware and software has inspired new approaches to solve the complex data

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processing and analysis. Among them are artificial intelligent techniques which several researchers have attempted to develop *UCS* predictive models using the given rock material properties.

Meulenkamp and Grima [17] used *ANNs* to estimate the *UCS* from hardness test especially Equitip hardness. A dataset containing 194 rock sample record varying from weak sandstones to very strong granodiorites, was used to train the network with the Levenberg–Marquardt algorithm. Singh et al. [18] used neural networks for the prediction of *UCS*, tensile strength and axial point load strength simultaneously from the mineral composition and textural properties. Statistical analysis was conducted for the prediction of the same strength properties and was compared with the predicted values by neural networks to investigate the authenticity of this approach. A set of data having 112 test results of the four schistose rocks was used to train the network with the back-propagation learning algorithm. Another set of data with 28 test results of the four schistose rocks was used to validate the generalization and prediction capabilities of the network. Yilmaz and Yuksek [19] studied artificial neural networks to predict elasticity modulus and *UCS* on gypsum samples. They first developed prediction models for *UCS* and elasticity modulus through multiple regressions from the values of porosity, slake strength index, and point load strength index. Later, they tried to develop the predictive capabilities with the artificial neural network models that use feed-forward back propagation algorithm. Tiryaki [20] emphasized the importance of determining the static modulus of elasticity and *UCS* in terms of mechanical rock excavation. However, in order to confirm these two properties, it is not always possible to find appropriate samples. For that reason, Tiryaki investigated the prediction of the elasiticity modulus and *UCS* using artificial neural networks, and regression trees technique as well as principle components and factor analyses. Another significant study involving neural network approach was conducted by Zorlu et al. [21]. The main objectives of the study were to investigate the relationships between strength and petrographical properties of sandstones, to construct a database that covers the broadest range possible, to perform a logical parameter selection routine, to discuss the key petrographical parameters governing the *UCS* of sandstones, and to develop a general prediction model for the *UCS* of sandstones. During the analyses, a total of 138 cases including *UCS* and petrographic properties were employed. By employing a large database including 138 cases, two multiple prediction models namely multiple regression and *ANNs* were developed in this study. Kahraman et al. [22], in a more recent study, investigated the predictability of *UCS* and Elasticity (*E*) values of Misis fault breccia (Turkey) from the indirect methods such as density, ultrasonic testing and textural properties by using artificial neural networks. The derived *ANNs* model was also compared with the regression model. Concluding remark was that the Cerchar abrasivity index values could be used for the prediction of *UCS* of Misis Fault Breccia. Another conclusion was that *ANNs* model was more reliable than the regression model.

Literature contains numerous studies that focus on the prediction of uniaxial compressive strength of rocks (Table 1). Previous studies in this area focused mainly on the rock types that were significant in terms of rock mechanics while current study is conducted on the natural building stones that are commercially traded in both domestic and global market.

The objective of this study is to develop a simplified *UCS* predictive model of the some carbonate building stones from their physico-mechanical properties. The artificial neural networks approach and conventional multivariate regression analysis were utilized for the development of the models. For this purpose, prediction of *UCS* of carbonate rocks is investigated with respect to relatively easy to determine physico-mechanical test or tests. Preliminary models with a single entry as well as artificial neural networks and statistical methods have been employed to estimate the *UCS*, followed by the application of double and triple combinations. The significance of the results was tested by statistical methods.

Table 1
Relationships between uniaxial compressive strength and some mechanical properties of rocks in literature.

Author/s	Rock type	Method/s	Inputs	Statistical relationship
Deere and Miller [16]	28 Lithological unit,	Regression	γ, *N*	$R^2 = 0.88$
Beverly et al. [14].	20 Lithological unit	Regression	γ, *N*	–
Haramy and Demarco [12]	10 Lithological unit	Regression	*N*	$R^2 = 0.49$
Sachpazis [4]	33 Different carbonate rocks	Regression	*N*	$R^2 = 0.92$
Gokceoglu [7]	Marl	Regression	*N*	$R^2 = 0.71$
Kahraman [8]	10 Lithological unit	Regression	γ, *N*	$R^2 = 0.86$
Singh et al. [18]	Four different schistose rocks	Regression, *ANN*	*t*, *Q*, *M*, *F*, *Cl*, *G*, A_w, aspect ratio, form factor, orientation	MAPE = 24.5 (reg. model) MAPE = 2.7 (*ANN*)
Meulenkamp and Grima [17]	Granites, granodiorites, granites, limestones, sandstones, dolomites	Regression, *ANN*	*L*, γ, *n*, *G*, *t*	$R^2 = 0.91$ (reg. model) $R^2 = 0.97$ (*ANN*)
Tiryaki [44]	Sandstones, mudstones, limestones	Regression, *ANN*	ρ, *SH*, *CAI*	$R = 0.55$ (reg. model), $R = 0.63$ (*ANN*)
Zorlu et al. [21]	Sandstones	Regression, *ANN*	*PDn*, *CCn*, Q_n:	$r = 0.54$ (reg. model), $r = 0.89$ (*ANN*)
Kahraman et al. [43]	Fault breccias		Set I: *VBP*, ρ, V_s, r, ABD_f Set II: *VBP*, V_s Set III: *VBP*, *d*, V_p, V_s	R^2 = 0.69,063,0.32 (reg. model) R^2 = 0.90,0.80,0.79 (*ANN*)
Kahraman et al. [22]	Fault breccias	Regression, *ANN*	VBP, ρ, Vp, CAI	$R = 0.75$ (reg. model), $R = 0.86$ (*ANN*)
Dehghan et al. [41]	30 Travertine	Regression, *ANN*	*N*, V_p, $I_{s(50)}$, *n*	$R^2 = 0.64$ (reg. model) $R^2 = 0.92$ (*ANN*)
Cevik et al. [42]	Clay bearings rocks	*ANN*, GP	*C*, Id_2, Id_4, *cc*	$R^2 = 0.98$ (*ANN*) *GP* $R^2 = 0.97$

N: Schmidt hardness, γ: unit weight, *t*: rock type, *Q*: % quartz, *M*: % mica, *F*: % feldspar, *Cl*: % clay mineral, *G*: grain size, A_w: area weighting *L*: equotip value, *n*: porosity, *MAPE*: mean absolute percentage error, ρ: density, *SH*: Shore hardness, *CAI*: Cerchar abrasivity index, *PDn*: normalized packing density; *CCn*: normalized concavity-convexity; Q_n: normalized percent quartz index, *VBP*: volumetric block proportion, V_s: S-wave velocity, *r*: roundness of the block, ABD_F:average block diameter factor, V_p: P-wave velocity, $I_{s(50)}$ Point load index, *C*: origin of rocks, Id_2, two-cycle slake durability index; Id_4, four-cycle slake durability index, *cc*: clay content, *GP*: genetic programming, *ANN*: artificial neural network.

Table 2
Rock types used in the study and their descriptive statistics of geotechnical data.

Number of rocks	Rock type	*UCS* (MPa) Min.	Max.	Average	St. deviation	*SH* (MPa) Min.	Max.	Average	St. deviation	N_R Min.	Max.	Average	St. deviation	*SV* (m/s) Min.	Max.	Average	St. deviation
6	Marble	54.74	124.35	72.58	26.44	31.75	46.5	38.29	6.43	59.5	63.1	61.48	1.44	4630	6190	5169	576
4	Fossiliferous limestone (biomicrite)	97.89	127.24	112.37	12.81	55.5	65.8	59.35	4.83	62.9	69.5	67.23	2.95	5230	5964	5654	313
4	Travertine	24.50	73.34	47.90	19.98	31.45	46.15	39.19	6.84	56.20	65.6	61.90	4.11	3235	5283	4602	932
3	Limestone	31.95	67.23		18.21	34.85	36.85		1.13	58.2	60.6		1.36	5011	5292		142
3	Dolomitic limestone	91.60	192.98	133.61	52.87	45.55	54.00	49.85	4.23	63.9	68.3	66.10	2.20	4719	4371	5097	338
2	Dolomite	106.14	184.18	145.31	55.39	47.35	61.15	54.25	9.75	67.5	71.00	69.25	2.47	5021	5727	5374	499
2	Fossiliferous limestone	109.69	144.52	127.11	24.63.	52.40	60.55	56.48	5.76	68.7	69.9	69.30	0.85	5970	6033	6002	45
2	Fossiliferous lacustrine limestone	108.2	130.03	119.12	15.44	54.95	58.90	56.93	2.79	68.8	69.8	69.30	0.71	5879	5928	4964	35
2	Recrystallized limestone	61.43	104.39	82.91	30.38	41.2	47.2	44.2	4.24	63.4	64.5	63.95	0.78	4270	4964	4617	491
2	Intraclastic dolomitic limestone	104.88	143.53	124.21	27.33	55.45	64.7	60.08	6.54	63.6	70.6	67.1	4.95	5531	6225	5878	491
2	Micritic lacustrine limestone	74.63	133.23	103.93	41.44	40.00	60.00	50.00	14.14	61.7	69.7	65.4	6.08	5182	6046	5614	611
1	Micritic limestone	116.61				53.85				68.4				5554			
1	Intraclastic micritic limestone	101.36				60.75				69.1				5615			
1	Breccia	86.84				62.25				69.9				5903			
1	Carbonated ultramafic rock	56.05				41.50				65.10				4899			
1	Ekstraclast limestone	58.33				28.15				54.20				4606			

2. Description of data collection

The data used in this study was obtained from 19 different natural stone processing plants and 16 different locations of Turkey. *UCS*, Shore hardness, ultrasonic pulse velocity and Schmidt hammer tests were applied to a total of 37 different carbonate rock samples. These test methods are selected due to the simplicity of sample preparation and ease of application. In addition, thin cross-sections of rock specimens were subjected to qualitative analysis and were classified according to Folk [23]. A total of 37 different natural building stones are listed under 16 categories based on Folk classification. Sample size, average values and standard deviations for each group are given in Table 2.

2.1. Sampling rock materials

The data used in this study were obtained from the specimens in the shape of standard cubes of 37 different rock samples that were classified under 16 major groups. 25 cube specimens were cut out of each one of the 37 rock samples (37×25 specimens). For instance 10 cube specimens from each sample were used in the determination of the *UCS* values (37×10 specimens).

2.2. Characterization of rock properties

2.2.1. Uniaxial compressive strength test

10 Specimens with the dimensions of $70 \times 70 \times 70$ mm from each 37 rock sample were used to determine the *UCS* values. The 10 cubic specimens were kept in a temperature controlled furnace at an ambient temperature of 70 ± 5 °C until each one reached a constant mass followed by the natural cooling of the specimens to room temperature. Uniaxial compression tests were performed at room temperature at a 0.6 MPa/s constant stress rate. The average of the 10 measurements were used in this study. Tests were carried out according to Turkish standard TS EN 1936 [24].

UCS values (σ_c) were calculated by the following formula:

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

where σ_c is the uniaxial compressive strength (MPa), F is maximum failure load (N), A is the section area of specimen (mm^2).

2.2.2. Ultrasonic pulse (P-wave) velocity

The ultrasonic pulse velocity or sound tests have been gaining popularity in determining dynamic properties of rocks [25].

Test specimens' dimensions are $70 \times 70 \times 70$ mm. Controls UPV E48 test device was used to conduct the tests. The direct transmission method was used. This device has one transmitter and one receiver which are 50 mm in diameter and have a maximum resonant frequency of 54 kHz. Ultrasonic pulse (*P*-wave) velocity was measured on each face of the cube shaped specimens and then the mean of the six measurements from each cube were used in the statistical analysis.

2.2.3. Schmidt hammer hardness

Schmidt hammer rebound tests were applied on the rock blocks having varying dimensions between 2 and 6 m^3. The tests were performed with an *N*-type hammer with impact energy of 2.207 J. The International Society for Rock Mechanics recommendations were applied in the tests for each rock type. ISRM suggested that 20 rebound values from single impacts separated by at least a plunger diameter should be recorded, and the ten highest values were averaged [26].

Table 3
Summary of regression analysis for the prediction of *UCS*.

Analysis	Input/s	R	R^2	Adjusted R^2	F	Sig. level	Standard error of estimate	Equation
A1	*SV*	0.57	0.33	0.31	16.97	0.000	32.71	$=0.037SV - 101.733$
A2	N_R	0.62	0.39	0.37	22.35	0.000	22.35	$=5.710N_R - 273.995$
A3	*SH*	0.70	0.49	0.47	33.23	0.000	28.55	$=2.533SH - 27.857$
A4	*SV*, N_R	0.67	0.45	0.42	14.09	0.000	29.90	$=0.02SV + 4.03N_R - 272.512$
A5	*SH*, N_R	0.70	0.49	0.46	16.40	0.000	28.85	$=2.167SH + 1.092N_R - 80.567$
A6	*SV*, *SH*	0.73	0.53	0.50	19.078	0.000	27.76	$=2.004SH + 0.016SV - 88.276$
A7	*SV*, N_R, *SH*	0.73	0.53	0.49	12.36	0.000	28.17	$=1.908SH + 0.016SV + 0.32N_R - 102.492$

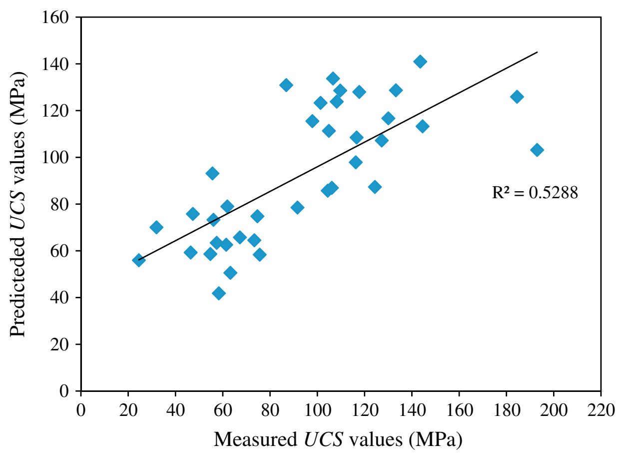

Fig. 1. Comparison of the measured and predicted *UCS* values obtained by analysis *A6*.

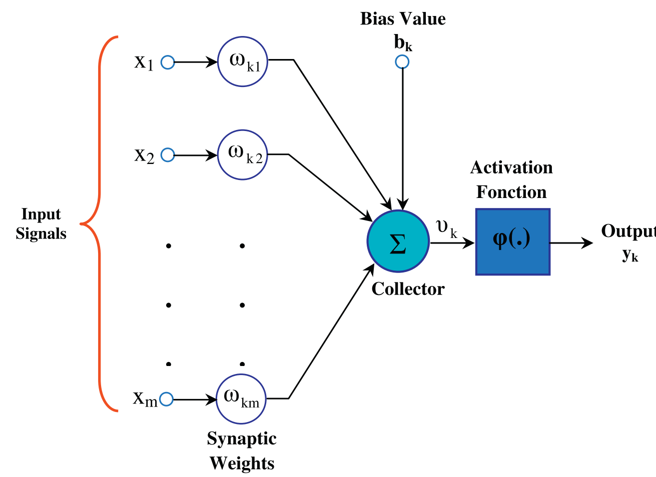

Fig. 3. The neuron model with m number of input parameters [45].

2.2.4. Shore hardness

The C-2 model Shore hardness test device was used in order to determine Shore hardness values of rock samples. The tests were carried out according to the International Society for Rock Mechanics standard [27]. The hardness value was recorded thirty times in a way to have at least 5 mm between the measurement points, and the mean of the hardness values was calculated for each rock sample.

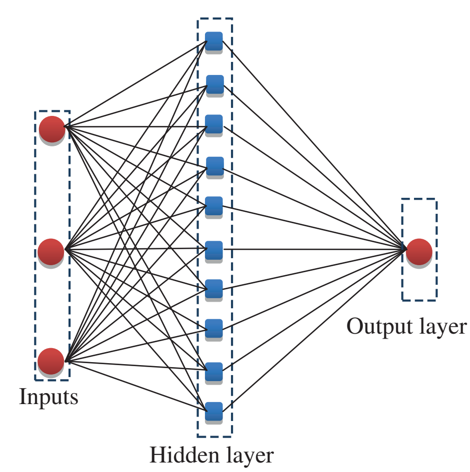

Fig. 4. Simplified view of a multi-layer network with 10 neurons.

3. Development of *UCS* predictive models

The data from this study were evaluated for developing new models with regression analysis and artificial neural networks.

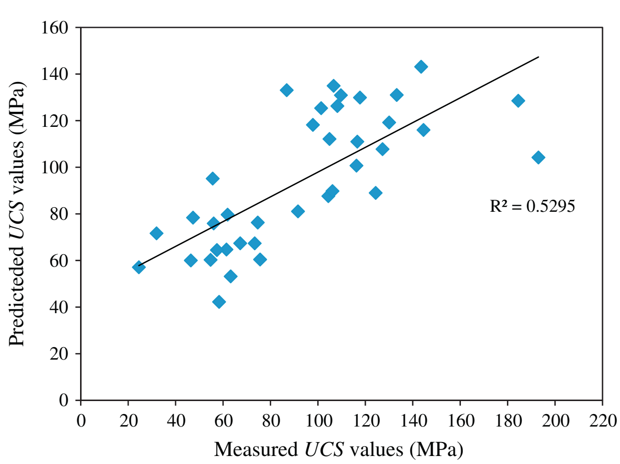

Fig. 2. Comparison of the measured and predicted *UCS* values obtained by analysis *A7*.

The mineralogical–petrographical definitions of rocks and descriptive statistics of data are given in Table 2.

3.1. The regression analysis

The data obtained in this study were evaluated with multiple regression analysis, a classic statistical method. Regression analysis is used to model the relationship between a response variable and one or more predictor variables. In multiple linear regression analyses, coefficient of determination (R^2) represents the extent of the model obtained that explains the variance of the dependent variable [28]. For a powerful predictive model, the value of R^2 is expected to be close to one. However, in regression analysis, the fact that value of R^2 is 1 or close to 1 is not sufficient for the validity of the model developed. In this study, the significance of the parameters chosen and the regression equations obtained were tested at the significance level of 1%.

Three different input parameters which are ultrasonic pulse velocity (*SV*), Schmidt hammer hardness value (N_R), and Shore hardness value (*SH*) were entered into the regression model in single, double and triple combinations in the regression analysis, in order to assess the influence of each variable individually on *UCS*. Furthermore, this was a convenient way for the practitioner to make the most suitable choice for their own application as each test can be time-consuming and costly. The results of regression analysis are given in Table 3.

The best result among the analyses carried out with single-parameter inputs was obtained from the analysis *A*2 in which N_R was used as an input parameter (R^2 = 0.39). In the analyses that used a combination of two input parameters, when used with *SV* and *SH*, a relatively high coefficient of determination was obtained in analysis *A*6 (R^2 = 0.53). The models obtained were significant in the confidence interval of 1% (Sig. level value $\leqslant$0.01).

According to analysis *A*6;

$$UCS = 2.004SH + 0.016SV - 88.276 \tag{2}$$

The regression curve for the measured and predicted *UCS* values and the results obtained in analysis *A*6 are presented in Fig. 1.

The best result of *UCS* values for the analyses carried out with the combination of three input parameters was obtained in analysis *A*7.

According to analysis *A*7;

$$UCS = 1.908SH + 0.016SV + +0.320N_R - 102.49\ 2 \tag{3}$$

where *SH* is the Shore hardness (MPa), N_R is the Schmidt hammer hardness, *SV* is the *p*-wave velocity of rocks (m/s).

The regression curve for the measured and predicted *UCS* values and the results obtained in analysis *A*7 are presented in Fig. 2.

According to results obtained from all regression analyses, relatively low coefficient of determination values were found among some rock mechanical properties which are Schmidt hammer hardness, Shore hardness, ultra sonic pulse velocity values and the *UCS* values.

3.2. Artificial neural networks

Developments in artificial intelligence and computer sciences enable researchers to model the problems in the field of earth sciences with improved reliability. Empirical approaches in parallel with modeling capabilities have evolved to become powerful methods due to the difficulties involved in the modeling of processes observed in the nature. As a result, artificial intelligence applications have been favored more often over conventional methods [29].

ANNs are made up of artificial neural cells called neurons. Artificial neural cells are units consist of sets of data that are processing various inputs from external sources or from other neurons. Neurons are the basic parts of the general architecture used to calculate an output. Fig. 3 presents the basic neuron structure with "*m*" number of inputs. Where; $x_1, x_2, \ldots, x_m$ are the input signals, $\omega_{k1}, \omega_{k2}, \ldots\ldots\ldots\ldots, \omega_{km}$ are the synaptic weights, υ_k is the input value of activation function, b_k is the bias value, $\varphi(.)$ is the activation function, and y_k is the output signal.

Synapses or links are characterized with "*weights*" [30]. *Weights* are designated with "ω" in artificial neural networks. Indices are used defining the weights. For instance, the weight of "ω" that is defined as "ω_{kj}"; the first index (k) shows which neuron the weight belongs to, and the second index (j) shows which input the weight belongs to. The structure in which neurons working together in a group is called "*network*". The number of neurons used in a network may be varied based on the network structure; such that the number and the configuration of neurons that yields the most reliable solution are selected. The layers are formed by the neurons stacked together in the same vertical line. Generally, artificial neural networks may be in the form of a single layer or consist of multiple layers. Single or multilayer artificial neural network structures are used in solving nonlinear problems. In this study multi-layer artificial neural network structures were used (Fig. 4).

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 [31,32].

Transmission from one neuron to another between the layers in artificial neural networks is achieved via synaptic weights. Iterations use a different weight in studies conducted on artificial neural networks, and the weights providing the optimum result are determined in the final iteration. The learning process in artificial neural networks means adjusting weights based on the number of iterations (Fig. 5).

The data from 37 natural building stones samples were used in the *ANNs* analysis. Software called MATLAB (Version 7.12.0 R2011a) was used for *ANNs* modeling. In MATLAB procedure training, testing and validation data are chosen randomly. In this study 70% of data (25 samples) were used for training, 15% of data (6 samples) were used for validation, 15% of data (6 samples) were used for testing of the network.

The training, validation, and testing data sets were randomly selected by the Matlab version used in this study as opposed to the conventional neural networks application software. Training of network stopped in the event that the validation error increased within the selected number of iterations (e.g. the training is stopped if the error increases after 6 iterations). A relatively small final mean-squarre error, a test set error and a validation set error with similar characteristics, and no significant overfitting (where the best validation performance occurs) conditions must be satisfied in order to obtain reliable results [33].

The type of neural network used in this study is multi layered perception (*MLP*). Tangent sigmoid transfer function in hidden layer and linear transfer function in output layer were selected. The *MLP* networks consist of an input layer, one or more hidden layer and an output layer. In the literature, validity of using a single hidden layer was supported by a number of studies [19,20,34–38]. Therefore, one hidden layer was also preferred in this study. Before the analyses, to apply a learning stage independent from magnitude of data and to provide standardization among the inputs and the outputs, all data was normalized using the following equation (Eq. (5)):

$$X_{norm} = (X - X_{min})/(X_{max} - X_{min}) \tag{4}$$

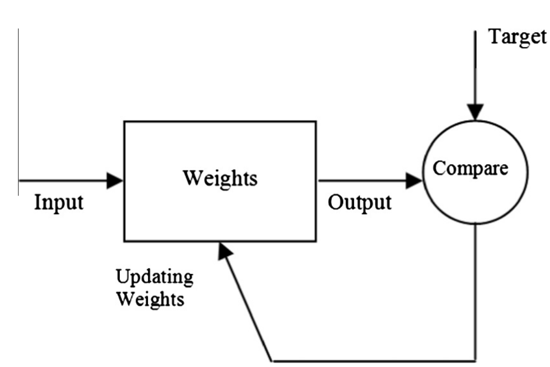

Fig. 5. Change of weights in *ANNs* [33].

where X_{norm} is the normalized value of the input, X is the real value of the input, X_{min} is the minimum value, and X_{max} is the maximum value of the input.

The network consists of one input, one hidden and one output layer. The number of hidden layer neurons was decided based on the results of several analyses. In this study, the architectural analyses with the numbers of neuron such that 5, 10, 20, 30, 40, 45 and 50 were made in order to observe the change in the coefficient of determination depending on the number of neurons. Although different configurations are possible, the best result was obtained from the 20 neuron configuration. Levenberg–Marquardt (*LM*) back propagation learning algorithm was used in this study. *LM* learning algorithm produces significantly faster results compared to other algorithms [33,39].

The most accurate results obtained in the artificial neural network models are usually obtained by the models that define the problem in the most precise way although there is a dependency on the variations on the configurations used in those models. The objective here was to develop the model that made the most accurate prediction for the *UCS* from the physico-mechanical properties of the rock samples by using the fewest number of parameters with the least time consuming and in the most inexpensive way. In this study, *SV*, N_R and *SH* values were used for the prediction of *UCS* values from rock mechanical properties. Subsequently, analyses started with the least number of parameters and then combinations of two and three input parameters were tested. In this section of the present study, seven different series of analysis with seven configurations were used. The results obtained from all *ANNs* models are summarized in Table 4.

The *UCS* predition models were developed by entering the *SV*, N_R, and *SH* values one by one in the single-input parameter models. *SV* values were used as the input parameter in the analysis *N*1. The higher coefficient of determination between the measured and the predicted *UCS* values was found as 0.82 from 45 neuron architecture (Fig. 6) as seen in Table 4. The most accurate result on the single-input parameter models was obtained in the analysis *N*2 that used the N_R values as the input parameter. A higher coefficient of determination value was found as 0.96 in the analysis *N*2. Mea-

Table 4
The results obtained from *ANNs* analyses.

Analysis	Algorithm	Input/s	Output	Number of neuron	*VAF*	*RMSE*	R^2
*N*1	*LM*	*SV*	*UCS*	5	33.34	31.67	0.33
				10	35.84	31.16	0.35
				20	73.92	19.80	0.74
				30	71.05	20.96	0.71
				40	49.08	27.85	0.64
				45	80.66	17.79	**0.82**
				50	64.40	23.26	0.74
*N*2	*LM*	N_R	*UCS*	5	46.57	28.82	0.45
				10	66.23	22.57	0.66
				20	82.53	16.22	0.83
				30	75.77	19.09	0.76
				40	22.05	34.38	0.62
				45	95.77	7.99	**0.96**
				50	95.10	8.78	0.95
*N*3	*LM*	*SH*	*UCS*	5	48.42	28.05	0.48
				10	63.42	23.49	0.63
				20	84.35	15.34	**0.84**
				30	76.86	19.25	0.75
				40	85.16	15.10	**0.86**
				45	84.67	13.31	**0.86**
				50	94.92	8.78	**0.95**
*N*4	*LM*	*SV*, N_R	*UCS*	5	59.70	24.67	0.60
				10	72.89	20.21	0.73
				20	88.53	13.75	**0.89**
				30	84.35	16.18	**0.83**
				40	65.57	23.36	0.74
				45	72.85	20.63	0.78
				50	86.12	14.50	**0.85**
*N*5	*LM*	*SH*, N_R	*UCS*	5	49.70	27.49	0.50
				10	61.98	24.13	0.61
				20	88.62	13.15	**0.89**
				30	82.49	17.48	**0.80**
				40	78.42	18.72	**0.81**
				45	75.69	19.58	0.73
				50	59.15	24.98	0.69
*N*6	*LM*	*SV*, *SH*	*UCS*	5	64.63	23.39	0.64
				10	72.04	20.62	0.72
				20	94.31	9.46	**0.95**
				30	84.11	15.46	**0.84**
				40	81.72	16.64	**0.82**
				45	51.81	28.84	0.70
				50	74.79	19.90	**0.83**
*N*7	*LM*	*SV*, N_R, *SH*	*UCS*	5	72.62	20.29	0.73
				10	72.33	20.40	0.72
				20	96.63	7.21	**0.97**
				30	89.22	12.97	**0.89**
				40	78.49	18.02	**0.82**
				45	84.38	15.45	**0.83**
				50	81.08	17.41	0.79

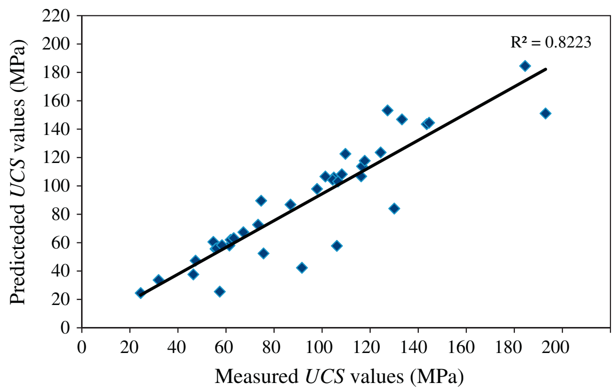

Fig. 6. Measured versus predicted *UCS* values for analysis *N*1, input parameter *SV*.

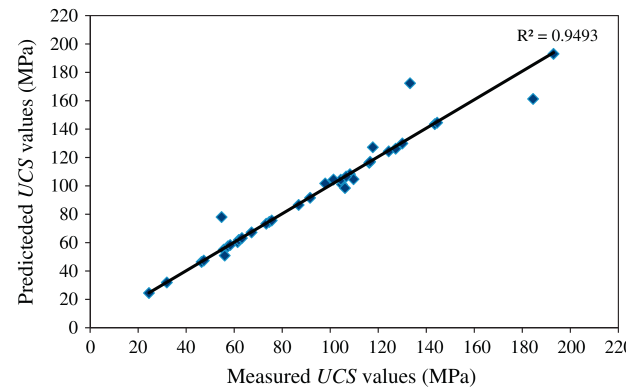

Fig. 8. Measured versus predicted *UCS* values for analysis *N*3, input parameter *SH*.

sured versus predicted *UCS* values for the higher R^2 value in the analysis *N*2 are as shown in Fig. 7.

SH values were used as input parameters in analysis *N*3 and higher R^2 value was calculated as 0.95. The best results in the analysis *N*3 were obtained from 50 neuron architectures. Measured versus predicted *UCS* values for the higher R^2 value in analysis *N*3 are as shown in Fig. 8.

Following the analysis *N*3, among the single-input analyses, we tried the combinations of two input parameters among *SV*, N_R and *SH*. In paired analysis in which the values of *SV* and N_R were used together as input parameters (analysis *N*4), the highest value of R^2 was found as 0.89. Measured versus predicted *UCS* values for the higher R^2 value in the analysis *N*4 are presented in Fig. 9.

SH and N_R values were used as input parameters in the analysis *N*5 and higher R^2 value was found as 0.89 (Fig. 10). The best result out of the analyses carried out on two input parameter combinations was obtained from analysis *N*6 with *SV* and *SH* two-input parameters combination. In this combination R^2 value was found to be 0.95 and it was obtained from 20 neuron architectures (Fig. 11).

We used the all parameters together after completing the analyses with single and double-input parameter calculations. In three-input parameter combination, *SV*, N_R, *SH* values were used as input parameters, and the coefficient of determination was found as 0.97. The best results in the analysis *N*7 were obtained from 20 neuron architectures as shown in Fig. 12. The best result obtained from analysis *N*7 and measured versus predicted *UCS* values are as shown in Fig. 13.

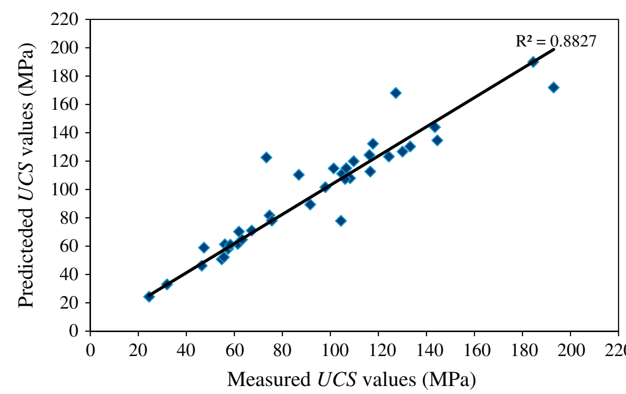

Fig. 9. Measured versus predicted *UCS* values for analysis *N*4, input parameters *SV* and N_R.

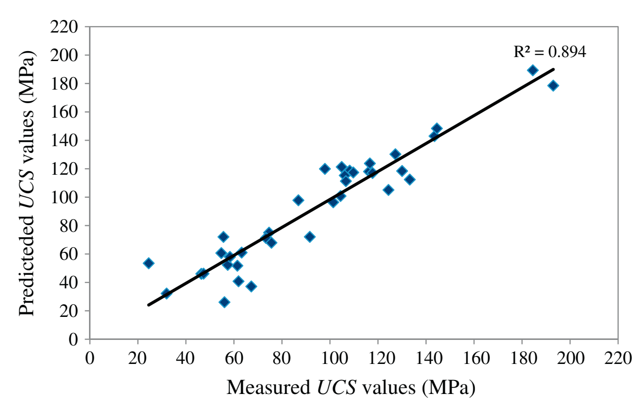

Fig. 10. Measured versus predicted *UCS* values for analysis *N*5, input parameters *SH* and N_R.

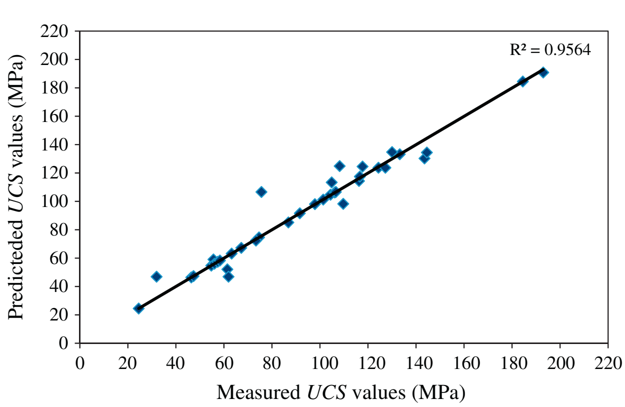

Fig. 7. Measured versus predicted *UCS* values for analysis *N*2, input parameter N_R.

3.3. Regression versus ANNs models: a comparison

The predictive performances of the models were compared in order to determine the applicability of the models developed. Variance Account For (*VAF*) (Eq. (5)), Root Mean Square Error (*RMSE*) (Eq. (6)), and coefficient of determination (R^2) (Eq. (7)) performance indices were used for the purpose of measuring the predictive performances of the models.

$$VAF = \left(1 - \frac{var(y_i - \hat{y})}{var(y_i)}\right) \times 100 \tag{5}$$

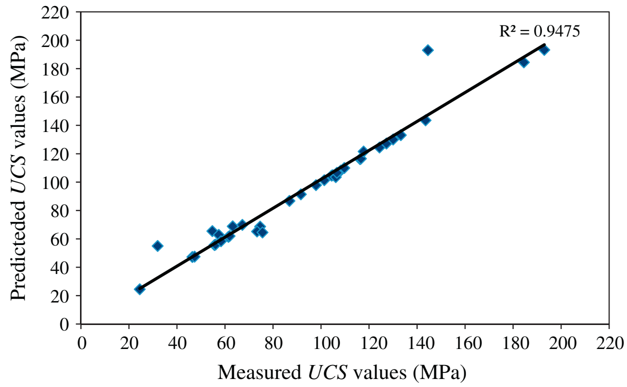

Fig. 11. Measured versus predicted *UCS* values for analysis *N6*, input parameters *SV* and *SH*.

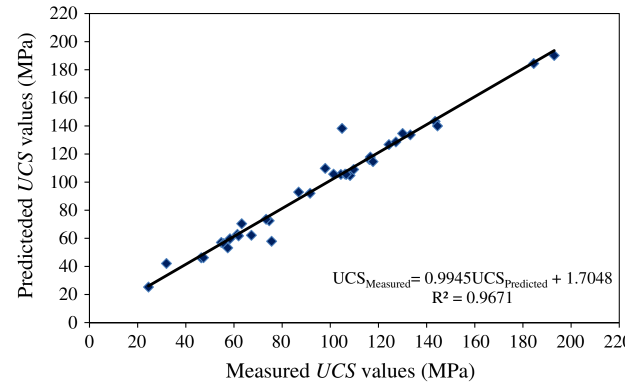

Fig. 13. Measured versus predicted *UCS* values for analysis *N7*, input parameters *SV*, *SH* and N_R.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{6}$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2} \tag{7}$$

where *var* is the variance, y_i is the measured value, $\hat{y}$ is the predicted value, $\bar{y}$ is observed sample mean for variable *y*.

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 (perfect model) *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 [40].

The best results obtained by the *ANNs* and the conventional statistics method applied in the present study are shown in Table 5. According to the results obtained via both methods, the model predicting the value of *UCS* most accurately was obtained by the model of artificial neural networks, in which the values of *SV*, N_R and *SH* were used together as input parameters. It was seen that the highest value obtained via the regression models was 0.53 as the values of R^2 are examined (Table 5).

It was noted in regression models that the results have improved as the number of input parameters is increased. In artificial neural networks, although the best result was obtained via the three-input configuration, high coefficient of determination values were obtained with the single-input and two-input parameter configurations. In general, *ANNs* models also demonstrated that the number of inputs has an important effect on the outcome. The highest value of R^2 in single-input analyses was 0.96, wheras the value of R^2 in three-input analyses was 0.97 at the most in the *ANNs* (Table 5). Considering such factors as time, experienced personnel and cost, single-input configurations are found to be more favorable for practical reasons.

The configuration formed with the use of only the Schmidt hammer hardness value is practically quite useful (R^2 = 0.96, *VAF* = 95.57). It is seen that that the model is also quite successful in predicting the value of *UCS* via the Shore hardness value (R^2 = 0.95, *VAF* = 94.92). The model in which the SV value was used alone as the input parameter produced relatively low coefficient of determination (R^2 = 0.82), the two-input parameter model in which the values of SV and SH were used together produced a

Table 5
The results obtained from all models.

	Regression			ANN		
Input/s	*VAF*	*RMSE*	R^2	*VAF*	*RMSE*	R^2
SV	32.65	31.83	0.33	80.66	17.79	0.82
N_R	40.53	30.01	0.39	95.57	8.20	0.96
SH	48.70	27.76	0.49	94.92	8.78	0.95
SV, N_R	46.38	28.41	0.45	88.53	13.75	0.89
SH, N_R	49.22	27.63	0.49	88.62	13.15	0.89
SV, *SH*	52.88	26.63	0.53	94.31	9.46	0.95
SV, N_R, *SH*	52.95	26.61	0.53	96.63	7.21	0.97

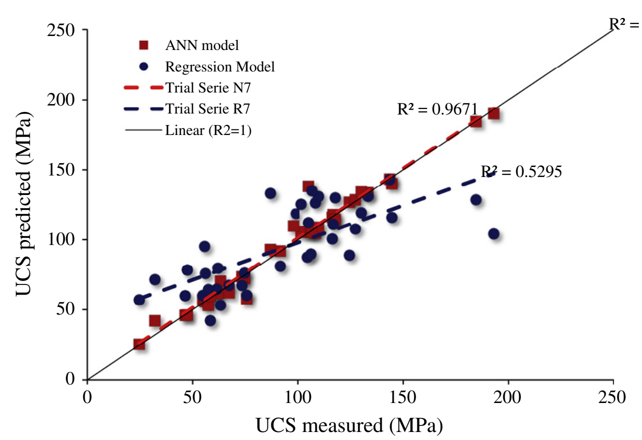

Fig. 14. Measured versus *UCS* predicted values for the whole data.

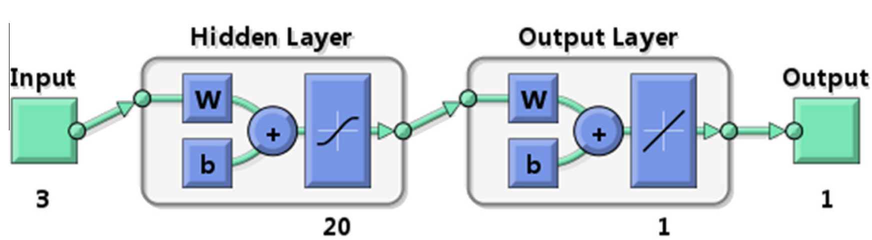

Fig. 12. Network architecture of analysis *N7* with 20 neuron.

higher value of R^2 (R^2 = 0.95, *VAF* = 94.31). The regression curve belonging to the best results obtained in regression and *ANNs* analyses are presented in Fig. 14.

4. Conclusions

Three rock properties in the seven different analyses were used for the prediction of *UCS* values by using conventional statistical method and artificial neural networks. The models developed based on the conventional statistical method produced quite low coefficient of determination values for engineering applications in predicting the *UCS* values, and they have quite low degrees of validity. In *ANNs* analyses, among the three factors, N_R and *SH* are considered as good predictors in single-input parameter analyses. On the other hand, the best predictions were obtained from three-input parameter analyses by using all available parameters. It was presented in this study that the *UCS* value for a natural stone can be reliably (R^2 = 0.96) predicted by using the Schmidt Hardness values obtained from large (2–6 m^3) blocks of natural stones. The results obtained in this study can be considered quite significant compared to the past studies in the same subject especially taking into account that only one input parameter was used (Table 1). It is a costly and time consuming process to determine the uniaxial compressive strength value for natural stones in a laboratory by preparing specimens with specific geometries. Considering the importance of the cost and the amount of time involved, it is quite significant in practice to have the capability to predict a parameter that has great impact on the entirety of the cutting processes for the natural stones by simply using a Schmidt hammer. One other advantage of reliably predicting the *UCS* values from the Schmidt hardness values is that the Schmidt hammer test device does not require any special sample preparation process. It is a remarkably simple to determine this value for the uncut natural stone blocks in practice by using a non destructive testing equipment such as the Schmidt hammer.

On the other hand, the highest R^2 value calculated in this study was obtained from the predictive models that utilized three input parameters. The reliablity of the prediction was found to improve significantly (R^2 = 0.97) as a result of using *SH*, *SV*, N_R as the three input parameters. However, the experiments required to obtained the three input parameters are too costly and time consuming. Furthermore, all other experiments except for the Schmidt hammer require special sample preparation techniques and specific instrumentation. The improvement of 0.02 in the R^2 values with the use of three input parameters may be neglected compared to the advantages of using only one input parameter as it greatly reduces the cost and the time.

The results obtained in the present study exhibit statistical resemblences with the results obtained in the study conducted by Meulenkamp ve Grima [17]. A value of R^2 = 0.97 obtained by Meulenkamp ve Grima [17] by using 5 input parameters (Equatip value, unit weight, porosity, grain size, rock type). Identical result for R^2 value was obtained in our study by using only 3 input parameters (Ultrasonic pulse velocity, Schmidt hardness, Shore hardness). It was appropriate to use the grain size a one of the input parameters in the study carried out by Meulenkamp ve Grima [17] since their samples were collected from magmatic rocks. However, it is tecnically challenging to use the grain size as an input parameter for carbonate rock samples. The main reason behind this is the fact that the carbonate rocks have significantly small grain size in comparison with the magmatic rocks. The input parameters selected for our study consist of parameters that possess built-in indirect effects resulting from minearological properties such as the partical size. Similarly, the determination coefficient was calculated to be 0.98 by Cevik et al. [42], who used 4 input parameters (origin of rock, slake durability index, four cycle durability index, clay content). However, their study reflects findings for clay bearing rock samples. Therefore, our study is distinguished from their study since our study yields with the highest R^2 value by using the least number of input parameters for building stones. Furthermore, a similar study based on *ANN* model approach that reported the prediction of *UCS* results with such high R^2 values as ours was not found in the current literature.

ANNs applications can be successfully evaluated via traditional statistical methods in studies that require impractical data evaluation. Similarly, the *ANNs* models are not commonly used in practice due to the fact that they are dependent on software and equipment and that they do not produce an equation as regression models do and also because of the opaqueness [17,20]. However, today, with the development of computer technologies, the *ANNs* models appear to become commonly used in practical engineering applications. The present study investigated the applicability of artificial neural network models for predicting the value of *UCS*, one of the more significant physico-mechanical features of 37 different natural building stones samples. The significance of the results obtained was tested via statistical methods.

Ultimately, it was demonstrated in this study that the neural network models developed exhibits the most effective prediction capability among the existing methods. Therefore, the approach presented in this study serves as a novel application of the neural networks for modeling the *UCS* of a variety of natural building stones from Turkey. In practice, the *UCS* value that is a significant input parameter used in the industry throughout all stages from the production of natural stone blocks to consumer scale production can be predicted successfully with the simple and low cost tests presented here.

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