ORIGINAL PAPER

PREDICTION OF UNIAXIAL COMPRESSIVE STRENGTH OF CARBONATE ROCKS AND CEMENT MORTAR USING ARTIFICIAL NEURAL NETWORK AND MULTIPLE LINEAR REGRESSIONS

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ARTICLE INFO	ABSTRACT
	Uniaxial compressive strength (UCS) represents one of the key mechanical properties used to characterize rocks along with the other important properties of porosity and density. While several studies have proved the accuracy of artificial intelligence in modeling UCS, some authors believe that the use of artificial intelligence is not practical in predicting. The present paper highlights the ability of an artificial neural network (ANN) as an accurate and revolutionary method with regression models, as a conventional statistical analysis, to predict UCS within carbonate rocks and mortar. Thus, ANN and multiple linear regressions (MLR) were applied to estimate the UCS values of the tested samples. For experimentation we carried out ultrasonic measurements on cubic samples before testing uniaxial compressive strength perpendicularly to the stress direction. The models were performed to correlate effective porosity, density and ultrasonic velocity to the UCS measurements. The resulting models would allow the prediction of carbonate rocks and mortar's UCS values usually determined by laborious experiments. Although the results demonstrate the usefulness of the MLP method as a simple, practical and economical model, the ANN model is more accurate.

1. INTRODUCTION

Building materials attract some significant interest worldwide. Being scarce in several regions and having high cost when imported, creates the need to develop new technologies to facilitate the exploration of these materials and therefore the estimation of physical and mechanical parameters that control geomaterial quality (Wang et al., 2012; Bahadori and Khalili, 2019). In fact, determining physical and mechanical properties of heterogeneous materials is important to judge their usefulness (Maghouset al., 2009; Zhang et al., 2019). Mechanical, physical and geotechnical characteristics of rocks (uniaxial compressive strength UCS, porosity, density, Micro-Deval test and Los Angeles abrasion test etc.) are determined in the laboratory using testing machines.

Uniaxial compressive strength (UCS) is an important parameter in determining a material's quality for mining, geological and geotechnical applications (Bieniawski, 1974; Abdelhedi et al., 2017; Kurtulus et al., 2012). In fact, determining UCS is essential in rock mechanics, for tunnels and dam designs, rock blasting, mechanical rock excavation, slope stability studies and other applications. The UCS essay, adopting classical laboratory methods is laborious, time consuming and expensive. For this reason, the elaboration of prediction models as an indirect method for the estimation of such

parameters is a research field of a great importance (Yagiz et al., 2012; Ferentinou and Fakir, 2017). Consequently, predictive models targeting specific parameters are emerging as an effective alternative method in all areas of scientific research. To determine the *UCS*, two methods are available. First, the direct method tests the specimens in the laboratory. Second, there is the use of predictive models (indirect methods) (Baykasoğlu et al., 2008; Vavro et al., 2019), recommended by many researchers for UCS predictions (Mohamad et al., 2015).

Artificial intelligence applies in several areas such as transportation systems (Jabbar et al., 2018), health (Said et al., 2018) and in the financial sector (Nweke et al., 2018), as well as other areas.

ANN is inspired from the brain and the human nervous system (Ghaboussi et al., 1991), and it represents an algorithm training to find the best relationship between output and input variables. Whenever this relationship is non-linear and complex, this technique becomes very useful (Mohamad et al., 2015; Dehghan et al., 2010). Recently, ANN was used by several studies to predict geo-mechanical parameters (Erdem, 2017; Kong et al., 2016; Shahrbanouzadeh et al., 2015; Meulenkamp, 1997; Singh et al., 2001; Meulenkamp and Grima, 1999; Rabbani et al., 2012; Kahraman and Alber, 2006;
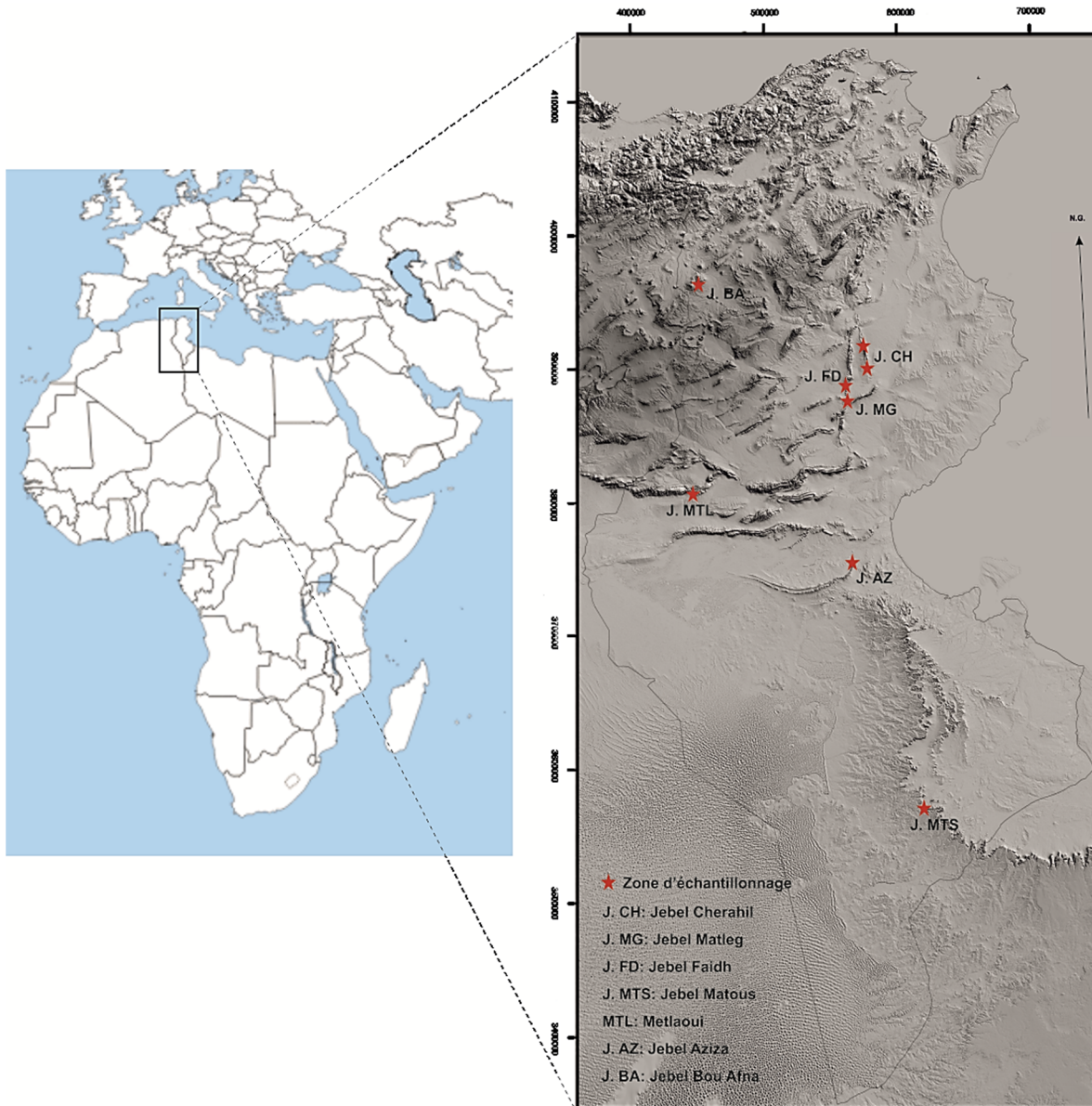
Fig. 1   Sampling locations.

Sarkar et al., 2010; Baykasoğlu et al., 2008; Yagiz et al., 2012; Yılmaz and Yuksek, 2008). Momeni et al. have developed UCS prediction models in carbonate and granitic samples employing different optimization modes of ANN. However, they did not compare neural network modeling with other types of modeling (Momeni et al., 2015). Atici produced UCS prediction models with good coefficients of determination. Nevertheless, the number of samples (28 samples) used in his study was small (Atici, 2011). Yagiz (2012) created many UCS prediction models with 54 carbonate rock samples, nonetheless the coefficients of determination were low (less than 0.5) (Yagizet al., 2012).

The purpose of this study is to develop and evaluate two predictive models, built with ANN and multiple regressions for the estimation of the UCS within geomaterials and evaluate them.

2.   EXPERIMENTAL PROCEDURE

2.1.   PREPARATION OF SAMPLES

In the present work, 66 carbonate rocks samples were collected from 8 geological ages and shaped to cubes of 10 cm on each side according to BS-EN-12390-1standard (Fig. 1, Fig. 2 and Table 1).

Forty mortar specimens were prepared from 1.350 g of normalized sand, water, and Portland cement. The latter was used as a cementitious material with a 32.5 MPa strength grade, in accordance with the EN 196-1 norm (2005). The normalized sand was prepared according to the EN 196-1 norm formulations. This standard relates the steps needed to make normalized sand and its granular fractions. In order to vary the w/c (water/cement) ratio from 0.3 to 1.28 (Table 2), water and cement weights have been varied.

Fig. 2   Mortar and carbonate rocks samples.

Table 1 Locations and geological characteristics of carbonate rock samples.

Samples	Location	Petrographic descriptions
1-5	Sidi-Bouzid	Dolomite with algal laminations
6-10	Jebel Matous	Bioclastic, fine-grained limestones
10-22	Metlaoui (Kef Eddour)	Light-gray limestone with many oysters
23-29	Jebel Aziza Elhamma	Darker red dolomite at the millimeter scale
30-35	Jebel Matleg (Regueb)	Dolomitized limestone rich in rudists
36-42	Kabbara (Nasrallah)	Conglomeratic limestone
43-53	Jebel Cherahil	Bioclastic limestone
54-66	Thala	Beige, hard and compact limestone

Table 2 W/C ratios for (a) dry and (b) saturated mortar samples used in this study.

(a)										
Designation	1	2	3	4	5	6	7	8	9	10
W/C	1.28	1	0.857	0.642	0.5	0.5	0.5	0.4	0.3	0.3
(b)										
Designation	11	12	13	14	15					
W/C	1.28	1	0.857	0.642	0.4					

Mechanical mixing was executed by a programmable mortar mixer as described in the EN 196-1 (2005) standard. The specimen was placed in metallic molds ($10 \times 10 \times 10$ cm³) at ambient temperature for 28 days to dry. To determine the effective porosity, five specimens were subsequently placed in water for 24 hours.

2.2. ULTRASONIC TESTING

The pulse transmission method was utilized to determine the "P" longitudinal wave velocities. The transmitter and the receiver ultrasonic transducers were placed perpendicularly to the load axis (Fig. 3). The pulse velocities V (m/s) were calculated from the resulting travel times according to the equation

$$V = \frac{L}{T} \qquad (1)$$

where L is the length of the straight-wave-path through the specimen, which corresponds to the distance between transducers faces, (i.e. 100 mm), and T is the transit time (s) determined by the ultrasonic device.

The recorded ultrasonic velocities range between 2264 m/s and 6800 m/s in carbonate rocks samples with an average value of 4747.85 m/s. The Ultrasonic velocities vary between the different samples dependently on the density and the heterogeneity of the rock (high velocities for Thala samples and low velocities for Kef Eddour samples). Within mortar samples, velocities range from 2630 m/s to 3953 m/s with an average of 3427 m/s. In mortar samples, which are more homogeneous than carbonate rocks, the variation of ultrasonic velocities is smaller.

2.3. UNIAXIAL COMPRESSIVE STRENGTH TESTS

The steps done in this test were carried out according to the EN 12390-3standard.

The specimen's UCS (uniaxial compressive strength) was calculated by dividing the compressive stress applied by the testing machine by the loaded surface area (MPa) (Fig. 3).

The UCS values were between 15.42 MPa and 124.29 MPa with an average value of 64.62 MPa in

Fig. 3 Uniaxial compression apparatus with ultrasonic transducers.

carbonate rocks samples. They range between 33.49 MPa and 5.29 MPa in mortar samples with an average value equal to 18.51 MPa. The UCS values are higher for carbonate rocks samples than that of mortar samples probably because carbonate rocks densities are higher.

2.4. EFFECTIVE POROSITY AND DENSITY TESTS

The effective porosity represents the volume occupied by the water flow (Lafhaj and Goueygou, 2009). Thus, the specimens were saturated with water to determine the effective porosity (P_e), defined as

$$P_e = \frac{V_{pi}}{V_t} \tag{2}$$

where: V_{pi} and V_t represent the connected pores volume and the volume of the sample, respectively. (Peng and Zhang, 2007).

Rock density is the mass of the sample contained in a given volume unit. It is usually expressed in kN/m^3 or in kg/m^3 (Peng and Zhang, 2007; Abdelhedi et al., 2018).

Measuring results are shown in appendix A and appendix B.

Density values were high within carbonate samples (between 2059 kg/m^3 and 3180 kg/m^3) compared to those of mortar samples (between 1941 kg/m^3 and 2241 kg/m^3). While carbonates effective porosities (from 1.05 % to 19.35 %) were lower than P_e of mortar samples (from 4.74 % to 22,65 %).

2.5. MULTIPLE REGRESSION MODELING

The relationship between several parameters is defined by multiple regression. The analysis of this relationship gives an equation that represents a parameter as a function of several variables. Overall,

the purpose of this method is the prediction of the output parameters according to the input parameters. The LMR models were constructed using Microsoft Office Excel 2007.

2.6. ARTIFICIAL NEURAL NETWORK

Several authors have confirmed that back propagation (BP) is the most efficient training method for artificial neural networks, prediction and decision support systems (Tawadrous and Katsabanis, 2007). Therefore, hyperbolic tangent sigmoid transfer function and back-propagation (TRAINLM) learning were applied in this study. The multiplication of the entries x_n by the weights (w_i) and the addition of the constant bias (Q_i), represents the activation function "y". The hyperbolic tangent function and the output of node "i" are described by the equations

$$f(x) = \tan h(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

and

$$Yi = f(\sum_{j=1}^{k} w_{ik} x_j + Qi) \tag{4}$$

respectively.

An MLP network is formed when connecting the nodes in series and in parallel (Yılmaz and Yuksek, 2008). In this work, "Matlab" was employed in a neural network analysis with a three-layered ANN network using a back-propagation algorithm. One input layer formed by 3 neurons, one hidden layer with 2 neurons and one output layer were used (Fig. 4). Each layer may contain more than one node (Yılmaz and Yuksek, 2008). The network training function and the activation function used in ANN were Levenberg-Marquardt back-propagation (trainlm) and tansig, respectively.

3. RESULTS AND DISCUSSION

Two types of modeling were used to elaborate predictive models linking uniaxial compressive strength with effective porosity, density, and ultrasonic velocity. The relationships between inputs and outputs allowed the establishment of a predictive model for the uniaxial compressive strength (UCS), using three predictor variables: Vp (m/s) P wave velocity, P (%) effective porosity, and "d" density.

Physical and mechanical parameters measurements of carbonate rocks and cement mortar samples and their statistical parameters are shown in appendix A, B and C.

Several authors have emphasized the added value of ANN in the prediction of many parameters in geomaterials (Atici, 2011; Eskandari-Naddaf and Kazemi, 2017; Khademi et al., 2017). Usually, when establishing a relationship between several input variables with a single output variable, multiple linear regressions are generally applied (Tripathy et al., 2015).
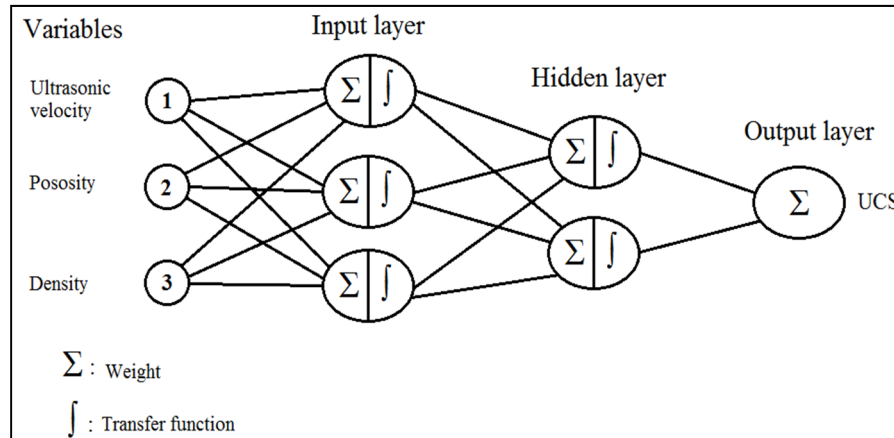
Fig. 4   Structure of the *ANN* model.

Table 3   Recent works on *UCS* Prediction using artificial intelligence techniques.

References	Method	R²	Description	Input parameters
Tonnizam et al., 2018	PSO-ANN	0.91	38 sandstone samples	ρ, Mc, Vp, Is (50), Id
Dehghan et al., 2010	ANN	0.86	30 travertine samples	Vp, Is (50), SRn, n
Yagiz et al., 2012	ANN	0.50	54 carbonate rock samples	Vp, n, SRn, Id,γd
Armaghani et al., 2015	ANFIS	0.98	45 granite samples	Vp, ρ, PSV
Ceryan et al., 2013	ANN	0.88	55 Carbonate rock samples	n, Id, Vm, ne, PSV
Momeni et al., 2015	PSO-ANN	0.95	66 limestone and granite core samples	SRn, Vp, Is (50), ρ
Mishra and Basu, 2013	FIS	0.98	60 granite, schist and sandstone samples	Vp, Is (50), BPI, SRn
Eskandari-Naddaf and Kazemi, 2017	ANN	0.94	54 cement mortar samples	Age of specimen (day), w/c, S/C, CSC, HRWR
Khademi et al., 2017	ANN	0.92	173 concrete samples	W/C, MSA, AG, AC, AS ¾, AS 3/8, MS
Tonnizam et al., 2015	PSO-ANN	0.97	40 shale, old alluvium and Iron pan samples	BD, Is (50), BTS, and Vp
Atici, 2011	*ANN*	0.95	28 concrete samples	*PCR, BS, Age, SRn, and Vp*
Çelik, 2019	*LS-SVM*	0.86	90 carbonate rocks samples	*Vp, SRn* and cubic sample sizes

Is(50): point load index; Vp: P-wave velocity; ρ:density; Mc: Moisture content; Id: Slake durability index; SRn: Schmidt hammer rebound number; n: porosity; ne: effective porosity; γd: (dry unit weight); PSV: petrography study values; Vm: P-wave velocity in solid part of the sample; BPI: block punch index; W/C:water/cement ; S/C: sand/cement; HRWR: volume of super plasticizer; MSA: the maximum size of aggregate; AG: the amount of gravel; AC: the amount of cement; AS¾: the amount of sand ¾; AS 3/8: the amount of sand 3/8; MS: the fineness modulus of sand; CSC: Cement strength class; PCR: Portland cement resistance; BS: Blast-furnace slag.

Table 3 illustrates numerous previous works that used artificial intelligence methods for establishing uniaxial compressive strength prediction models.

3.1. PREDICTION OF UNIAXIAL COMPRESSIVE STRENGTH WITHIN CARBONATE ROCKS WITH MULTIPLE LINEAR REGRESSIONS (MLP)

A multiple regression analysis was created using Excel 2007 as a conventional tool. Figure 5 shows the correlation between the expected uniaxial compressive strength (UCS) and the measured values. The coefficient of determination ($R^2 = 0.83$) proves that the elaborated model was acceptable even if not optimal.

The corresponding equation is:

$$UCS = (0{,}02 \times Vp) - (33.29 \times D) - (2.81 \times P) + 75.71 \quad (5)$$

Where:
Vp = Ultrasonic P-wave velocity (m/s).
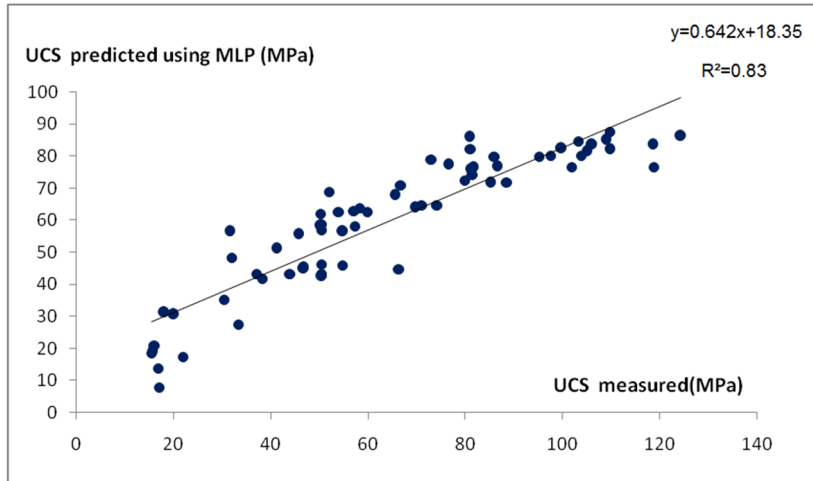UCS = Uniaxial compressive strength (MPa).

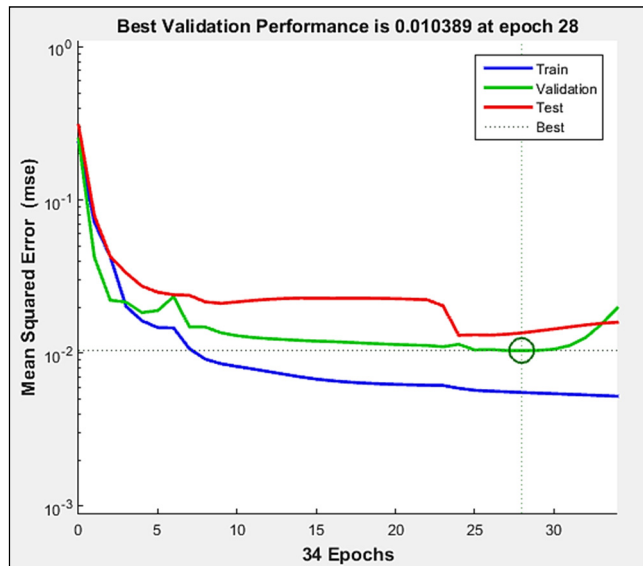**Fig. 5**   Correlation of measured and predicted UCS of carbonate rocks using MLP.

Fig. 6   Validation plot of ANN analysis (For UCS prediction of carbonate rocks).

P = Effective porosity (%).
D = Density(kg/m³).

3.2. PREDICTION OF UCS WITHIN CARBONATE ROCKS USING ANN

The ANN was applied to produce UCS's predictive model. Therefore, ultrasonic velocity, effective porosity and density values previously determined were analyzed.70 % of data (46 samples) were used for training the model, 15 % (10 samples) for testing and 15 % (10 samples) for the validation. One hidden layer containing 2 neurons was used to establish this model (Fig. 4). The number of neurons in the hidden layer was determined according to Vujicic 2016. The input parameters were: ultrasonic velocities, effective porosity and density. Figure 6 illustrates the validation curves.

The curves show that, as the epochs increase, the root mean squared error (*MSE*) of the training curve

decreases. The figure shows the performances achieved throughout training. The best validation performance was equal to 0.01 and was reached at epoch 28 (Fig.6). Figure 7 shows the regression plot for the validation, testing and training of the model.

Very high coefficients of determination (R^2=0.9) linking predicted and measured uniaxial compressive strength values proves the efficiency of the model and its accuracy in the prediction of UCS (Fig. 8). This model is more accurate than the one created with MLP.

In anterior researches, other parameters were used as inputs in order to produce prediction models for the UCS. Tariq et al. (2017) established an *ANN* model to predict UCS in carbonate rocks using density, shear waves and compression wave velocities. The coefficients of determination were 0.84. Ferentinou and Fakir (2017) used the point load index, the weight γ, the tensile strength (σt) and the lithology as input parameters to elaborate predictive models for UCS
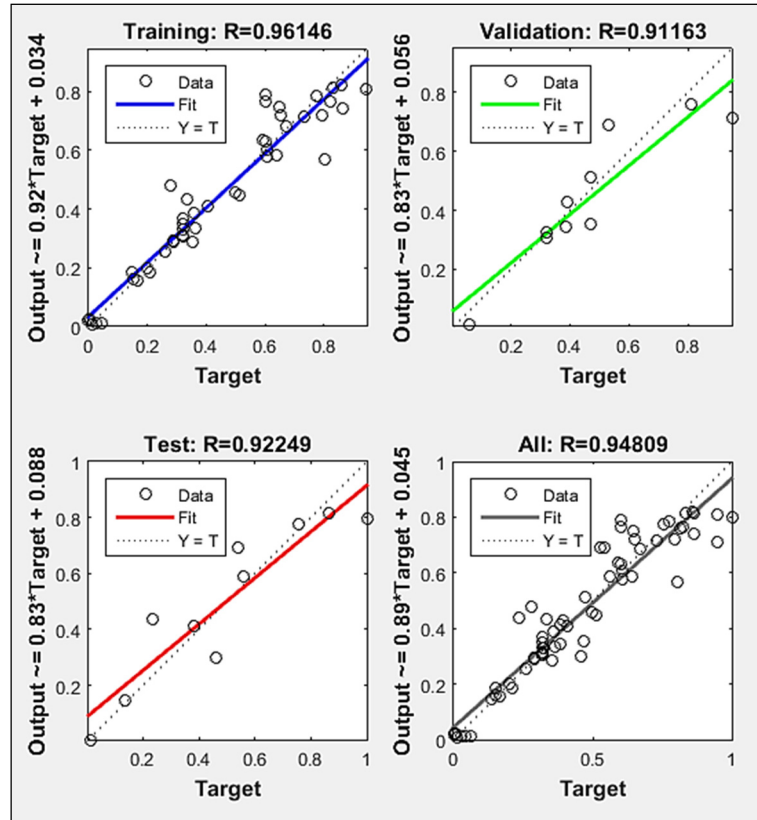
Fig. 7   Regression plot from *ANN* analysis (For UCS prediction of carbonate rocks).
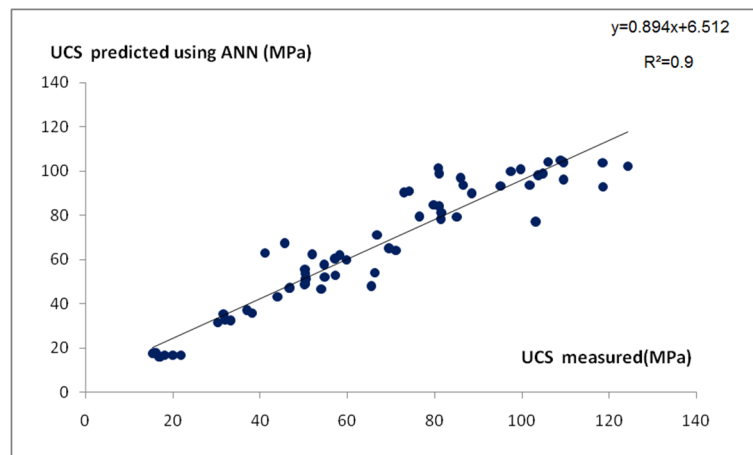

Fig. 8   Relationship between predicted and measured UCS of carbonate rocks using ANN.

within many varieties of rocks in KwaZulu-Natal. The coefficients of determination were 0.99 and 0.92 for training and testing, respectively.

3.3. PREDICTION OF UCS OF MORTAR SAMPLES USING MULTIPLE LINEAR REGRESSIONS (MLP)

Multiple linear regressions were used using Excel to predict UCS values within mortar samples. This model consists of 3 input variables (ultrasonic velocity, density, and effective porosity). Figure 9 shows the correlation between measured and predicted values of UCS.

The figure shows a good relationship between measured and predicted *UCS* within mortar samples. A coefficient of determination R^2 of 0.79 validates the model.

The elaborated equation is:

$$UCS = (2.13xVp) + (19.20xD) + (155.94xPe) - {} - 9166.36 \qquad (6)$$

Where:
Vp = Ultrasonic pulse velocity (m/s),
UCS = Uniaxial compressive strength (MPa),
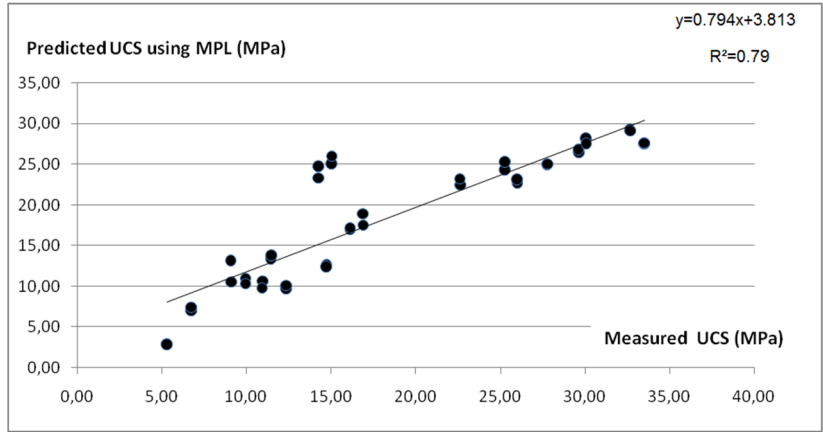P = Effective Porosity (%),
D= Density (kg/m^3).

Fig. 9 Relationship between predicted and measured UCS of mortar samples using MLP.
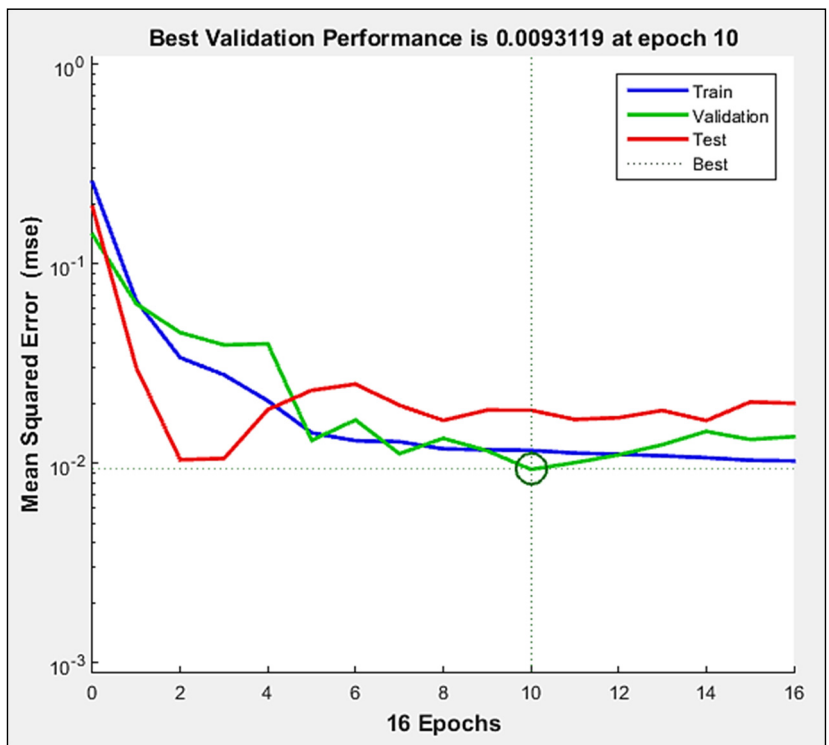

Fig. 10 Validation plot of ANN analysis (For UCS prediction of mortar samples).

3.4. *PREDICTION OF UCS OF MORTAR SAMPLES USING ANN*

An ANN model was created for the prediction of UCS in mortar samples. 70 % of data (28 samples) were used for training, 15 % (6 samples) for testing and 15 % (6 samples) for the validation. The input parameters were ultrasonic velocity, density and effective porosity (three neurons) which were already determined.

The validation line follows the test curve (Fig.10).

The root means squared error (MSE) of the training curve decreases progressively with increasing epochs. The best validation performance was equal to 0.009, it was reached at epoch 10 (Fig.10). Figure 11

shows the regression plot for the testing, the validation, and the training of the model.

The correlation between predicted and measured UCS is quite acceptable (R^2=0.87), which proves the validity of this model (Fig. 12).

Eskandari-Naddaf and Kazemi (2017) established ANN models to predict the UCS of the mortar. These models indicated good precision in predicting the UCS using 5 input parameters: the high range water reducing (HRWR), the W/C ratio, the age of the specimen, the S/C ratio and the cement strength class.

Such models represent an accurate method for rock and mortar quality estimation. The need for fast and accurate methods emerges from the fact that
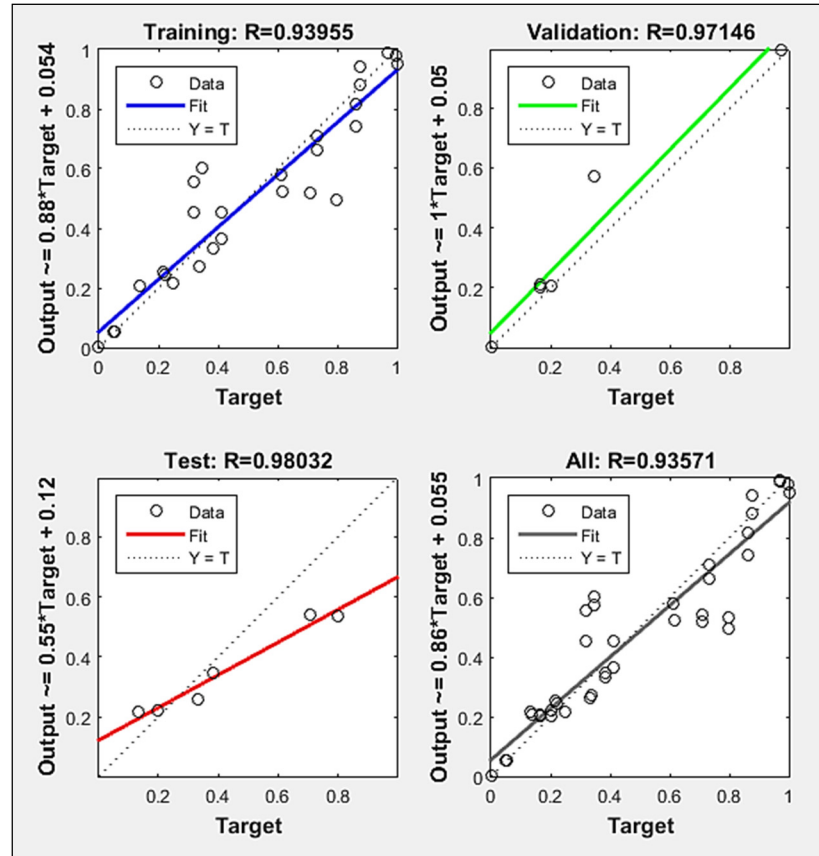
Fig. 11   Regression plot from ANN analysis (For UCS prediction of mortar samples).
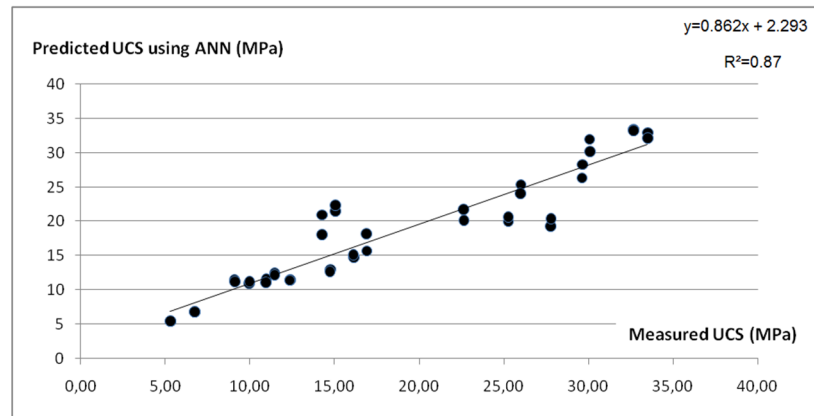

Fig. 12   Correlation of measured and predicted UCS of mortar samples.

standard methods are time consuming and laborious. In the current model, strong relationships with good correlations were recognized to predict the UCS. Models created with ANN showed good prediction accuracy compared to those built with MLP.

4.   CONCLUSIONS

The Geomaterial prospecting involves several domains (civil, geotechnical, geological or mining engineering). The exploitation depends on the quality and the physical, chemical and mechanical characteristics of the said Geomaterials. UCS is one of the most important parameters for geomaterial evaluation. The major outcome of the present work is the comparison between ANN and multiple regressions used to develop prediction models. The latter could be used as a non-destructive and economical method for the prediction of mechanical properties, namely the uniaxial compressive strength of geomaterials. This paper succeeded in confirming the efficiency of ANN to generate accurate models compared to MLP in carbonate rocks and mortar. Such correlations provide good predictions of uniaxial

compressive strength (UCS) within carbonate rocks and mortar. Therefore, this could avoid time-consuming and tedious lab test methods. The determination of ultrasonic velocity, effective porosity, and density is simple, non-destructive and fast. As a result, these models are expected to be useful as a practical approach for the depiction of mechanical properties of geomaterials. The findings of the present work contribute to the artificial intelligence scientific revolution in the scope of the prediction models.

ACKNOWLEDGEMENT

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