J. Civil Eng. Mater.App. 2023 (September); 7(3): 161-168

Journal of Civil Engineering and Materials Application
Journal home page: http://jcema.com

Received: 19 April 2023 • Revised: 13 July 2023 • Accepted: 21 August 2023

Research

doi: 10.22034/jcema.2023.393871.1107

Indirect estimation of uniaxial compressive strength of limestone using rock index tests through computational methods

Asma Hasheminezhad [1], Abbasali Sadeghi [2*]

[1] Department of Civil Engineering, Birjand Branch, Islamic Azad University, Birjand, Iran.
[2] Department of Civil Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran.

*Correspondence should be addressed to Abbasali Sadeghi, Department of Civil Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran. Tel: +9821 73228104; Email: abbasali.sadeghi@mshdiau.ac.ir.

ABSTRACT

Uniaxial compressive strength (UCS) is a critical geomechanical property of rocks that is frequently required during the preliminary stage of civil engineering design. To obtain the UCS value needs a time consuming and costly process of samples collection and preparation. There are alternate methods for determining UCS that can be conducted in situ. In this study, an attempt has been made to predict the UCS of limestone from some simple and inexpensive rock index tests such as block punch index (BPI), ultrasonic wave velocity test (Vp), Schmidt's hammer rebound number (SHR), and point load index tests (I_s50). According to extensive experimental results, a database was established for estimation of the UCS via three computational methods such as support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), and multi layer perceptron (MLP). After developing the models and considering several performance indices including the coefficient of determination R^2, variance account for (VAF), root mean squared error (RMSE), and using simple ranking method, the predictive models were applied to obtain the best model. Consequently, SVM approach predicted the UCS of limestone with higher accuracy in comparison to other studied computational methods.

Keywords: Limestone, Uniaxial compressive strength (UCS), Rock index tests, Computational methods

1. INTRODUCTION

Uniaxial compressive strength (*UCS*) of intact rocks is one of the crucial parameters that is widely underutilized in rock mechanics and engineering. Geomechanical properties of rock allude to the strength characteristics, so many researches have conducted on the simple procedures for obtaining the *UCS* of rock [1-4]. Some methods including regression analysis and artificial neural network have considered to estimation *UCS* [5]. Obtaining the *UCS* value needs a time consuming and costly process of samples collection and preparation [6], to overcome this difficulty used for the nondestructive testing and various predictive models based on index tests to obtain the mechanical characteristics of the rock mass [7-13]. Multi-layer perceptron (*MLP*), statistical techniques, Mamdani fuzzy logic (*MFL*), Sugeno fuzzy logic (*SFL*), adaptive neuro-fuzzy inference system (*ANFIS*) and support vector machine (*SVM*) have been applied to develop *UCS* predictive models in rock engineering [14-15]. Abbaszadeh Shahri et al. (2013) reported better application of multivariate regression analysis for obtaining *UCS* as a function of some simple index tests [16]. Azimian (2016) summarized empirical equations that relate unconfined compressive strength of sedimentary rocks. Multivariate regression introduced assailable tool for predicted *UCS* by Schmidt hammer and P-wave velocity (v_p) [17]. *SVM* is the most appropriate model for prediction *UCS* of travertine rocks proposed by Barzegar et al (2016) [18]. Omar (2016) studied *420* soil samples were located in the *UAE* and were examined including point load test ($I_{s(50)}$) and ultrasonic velocity (*USV*) through its pulse velocity. The results showed that the monographs could predict well the unconfined compressive strength within ± *10%* confidence interval for both $I_{s(50)}$ and *USV* [19]. Shaoqian et al. (2021) used *30* sets of regular cylindrical specimen tests between *PLS* and *UCS* are conducted on limestone mines. The correlation relationship between *PLS* and *UCS* is found by using four basic fitting functions. Then, a prediction model is established by using *SVM* algorithm. Multiple training test data are used to achieve high-precision prediction of *UCS* and the results show it is less different from the actual values. Especially, the R^2 coefficient reached *0.98*. The *SVM* model prediction performance is significantly better than the traditional fitting function [20]. Garrido et al. (2022) heated the limestone samples to *105* (standard conditions), *200*, *300*, *400*, *500*, *600*, *700*, *800* and *900 ºC* and cooled slowly (in air) and quickly (immersed in water). After that, *UCS*, *PLT* and Leeb hardness test (*LHT)* tests were performed to evaluate the changes as temperature increases. Results showed that decreases over *90%* in *UCS*, of between *50* and *70%* in *PLT* index and smaller than *60%* in *LHT* index [21]. Wei et al. (2023) established an artificial neural network (*ANN*) approach to predict the uniaxial compressive strength (*UCS*) in *MPa* of sedimentary rocks using different input parameters; i.e., dry density (ρ_d) in g/cm^3, Brazilian tensile strength (*BTS*) in *MPa*, and wet density (ρ_{wet}) in g/cm^3. The developed *ANN* models, *M1*, *M2*, and *M3*, were divided as follows: the overall dataset, *70%* training dataset and *30%* testing dataset, and *60%* training dataset and *40%* testing dataset, respectively. In addition, multiple linear regression (*MLR*) was performed for comparison to the proposed *ANN* models to verify the accuracy of the predicted values [22]. This study is only the theoretical research to evaluate the performance of artificial intelligence models including Multi-layer perceptron (*MLP*), Adaptive neuro-fuzzy inference system (*ANFIS*) and support vector machine (*SVM*) to estimate the *UCS* values of limestone rocks.

2. MATERIALS AND METHODS

*ANN*s are systems and new computing methods for machine learning, knowledge representation and finally applying knowledge to predict output from complex systems. The main idea of these networks is based on the function of biological nervous system to process data and information in order to learn and create knowledge. This system consists of many processing elements called neurons, that work together to solve a problem. Neural network (*NN*) needs to be trained and process large number of information as input pattern. This feature allows the interpolation great, especially when data is input with the noise and failure (not accurate). *NN*s may be applied as a direct replacement for the correlation, linear regression, multiple regression, trigonometric and statistical analysis techniques. Therefore, the *NN* can act as an expert. Training is done with the release of a network. Since the *1940s*, *ANN*s have been utilized in various applications in engineering. *ANN* general software systems mimic the *NN*s of the human brain. Artificial neural networks can perform generalized learning classification, identification and optimization functions associated with actions. Since the *ANN*s have the ability to work with incomplete data, with fault tolerance, they indicate a gradual convergence. They can easily form models for complex problems. Particularly in the development of semi-structured or unstructured solutions to problems, *ANN* models can provide very successful results. In addition, they are cheaper, faster and more adaptable than conventional methods, and mathematical models based on biological *NN*s. *ANN* processing information using simple interlocking elements is called neurons, which are situated in particular layers of the network [14]. In this research, the *UCS* values of limestone rocks are predicted based on *MLP*, *ANFIS* and *SVM*. In addition, the laboratory data sets and the process of tests are extracted from past studies [23-25]. In the following, some empirical relationships between the *UCS* and mechanical properties are indicated based on Table 1.

2.1. MLP model

MLP model consists of three layers including an input layer, output layer, and intermediate or hidden layers. Therefore, to perform a parametric study, a *MATLAB* code was prepared. Each layer included one or more nodes (neurons) [26]. The lines show the flow of information between the nodes that is transmitted from one node to the next. The study of artificial neural networks composed of four distinct types of layers, an input layer, two hidden layers and an output layer, and the number of neurons in hidden layers *5* and *3*. Data sets such as *BPI* (*MPa*), *SHR*, v_p (m/s), I_{s50} (*MPa*) were divided as input and *UCS* (*MPa*) as the output of education (*70%* of the dataset) and test (*30%* of the data set) subset for the modeling.

2.2. ANFIS model

To develop model *ANFIS*, is used a hybrid algorithm that combines the method of least squares and gradient descent was released to optimize and adjust the parameters of the membership function of Gaussian and coefficients, equations, the linear output [18]. Reduction of fuzzy clustering based on density measurement data points in the feature space, to create a law-based relationship between input and output variables that were used.

2.3. SVM model

Support Vector Machines is a powerful methodology for solving problems in nonlinear classification. Least Squares Support Vector Machines (*LS-SVM*) are reformulations to the standard *SVMs* that lead to solving linear *KKT* systems. In this study, *SVM* model with *RBF* kernel performance tests have shown the best results. The models were created by using *LS-SVMlab Toolbox* [20].

3. RESULTS AND DISDUCCION

In order to achieve the purposes of this study were applied three non-linear methods, namely *MLP*, *ANFIS* and *SVM*. During procedure *MLP* model, were divided datasets such as *BPI* (*MPa*), *SHR*, v_p (*m/s*), I_{s50} (*MPa*) as input and *UCS* (*MPa*) as the output of training (*70%* of the dataset) and test (*30%* of the dataset) subset for the modeling. In Table 2, the obtained values of the performance indices for the proposed *MLP*, *ANFIS* and *SVM* models. The values of R^2, *RMSE* and *VAF* are compared with each other in this research for specifying the best computational method among *MLP*, *ANFIS* and *SVM* for predicting the uniaxial compressive strength of limestone. The supplementary information of the coefficient R^2 calculation is presented in References [27-29]. The coefficient R^2 has been used as a vital quality factor in various engineering applications. *RMSE* measures the deviation of predicted values from the observed values. *RMSE* is used for comparing the accuracy of different models for dataset. *RMSE* is never to be negative, and a value of zero shows a good agreement of a prediction model to the data. In fact, the low values of *RMSE* shows high accuracy in predicting the data [30]. *VAF* is another measure to evaluate the accuracy of prediction models. High *VAF* shows high performance to predict the data [31]. Correlation between the predicting and measured *UCS* for training and testing datasets are shown in Figures 1 to 3. The result of *MLP* model is based on R^2 , *RMSE* and *VAF* value are obtained, respectively, *0.899*, *12.104* and *69.272* for testing step and *0.933*, *9.936* and *80.207* for training step. The ANFIS model in the training step resulted in the R^2 of *0.974*, *RMSE* of *8.729* and *VAF* of *83.538* and for the testing step are *0.949*, *10.456* and *83.494*, respectively in Fig 3, respectively. The result of the developed *SVM* , that created by using *LS- SVMlab* Toolbox, based on R^2, for testing step in Fig 4 is *0.967* and on *RMSE* and

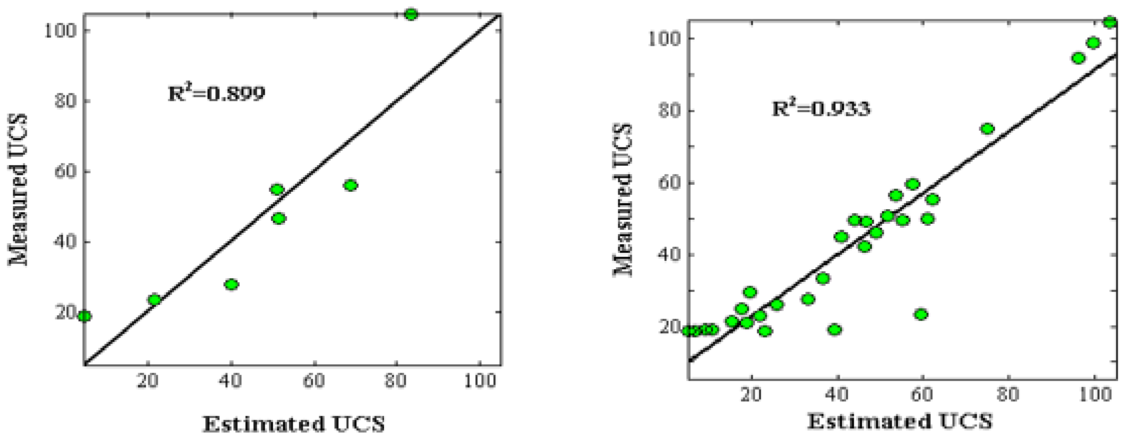
VAF value are *9.439* and *92.122* and for training step are *0.993*, *6.891* and *95.489* , respectively. The relation between predicting *UCS* and measured *UCS*, of models are shown in Figures 4 to 6. The result of *MLP*, *ANFIS* and SVM models is based on R^2 value are obtained *0.902*, *0.951* and *0.991*, respectively. The *SVM* model has higher accuracy than *MLP* and *ANFIS* models, in addition to, Standard deviation and mean, simultaneously are better in this model.

Table 1. Some empirical relationships between the *UCS* and mechanical properties.

Rock property	Rock type	Correlation	Coefficient of determination (R)	Reference
BPI	23 different rocks	UCS=5.5 BPI	0.94	[32]
		$UCS=9.82\ e^{-0.108BPI}$	0.83	
		$UCS = 40.48\ln(BPI) - 13.4$	0.82	
	9 different rocks	$UCS= 6.1\ BPI - 3.3$	0.86	**[33]**
	Marl, mudstone, sandstone, schist	UCS=5.25BPI	0.90	
	23 different rocks	UCS= 5.1 BPI	0.90	**[34]**
	Limestone,travertine,andesite,sandstone ,marl and schist	$UCS = 0.8 \times 2.266 m_i^{0.3824} \times BPI$	0.86	**[35]**
	Limestone,sandstone,mica schist, shale and travertine	$UCS=5.1\times 1.47^{-0.00456\alpha} BPI_\alpha$	-	**[23]**
	Granite,schist,sandstone	$UCS=4.93BPI_c$	0.87	**[36]**
	Granite,schist,sandstone	UCS=5BPI	0.86	**[25]**
SHR	Granite	$UCS=7.45e^{(0.07SHR)}$	0.92	**[37]**
	11 different rock	$UCS=4.24e^{(0.059SHR)}$	0.66	**[38]**
	Shale, anhydrite, dolomite	UCS=3.201SHR-46.59	0.76	**[39]**
	9 different rocks	$UCS=0.0028SHR^{2.584}$	0.92	**[13]**
	Granite	UCS=1.15SHR-15	0.91	**[9]**
	Conglomerates rock	UCS=0.678SHR	0.88	**[40]**
	Granite,schist,sandstone	$UCS=2.33e^{0.065SHR}$	0.87	**[25]**
	47 different rocks	$UCS=0.1383SHR^{1.743}$	0.913	**[41]**
V_p	27 different rocks	$UCS=9.95v_p^{1.21}$	0.83	**[10]**
	Serpentinites	$UCS=0.11v_p - 515.56$	0.81	**[42]**
	12 different rocks	$UCS=0.1333v_p - 227.19$	0.96	**[43]**
	Peridotites	$UCS=0.14v_p - 899.33$	0.83	**[44]**
	Conglomerates rock	$UCS=0.005v_p$	0.94	**[40]**
	13different rocks	$UCS=0.039v_p - 50.01$	0.934	**[45]**
I_{s50}	22 different rocks	$UCS=8.41I_{s50} + 9.51$	0.85	**[10]**
	Coal measure rocks	$UCS=23.62I_{s50} - 2.69$	0.93	
	23 different rocks	$UCS=15.3I_{s50}$	0.83	**[46]**
	9 different rocks	$UCS = 9.08I_s + 39.32$	0.85	**[38]**
	38 different rocks	$UCS=10.22I_{s50} + 24.31$	0.75	**[11]**
	Granite	$UCS=18I_{s50}$	0.97	**[37]**
	11 different rocks	$UCS=100\ln I_{s50} + 13.9$	0.98	**[47]**
	Serpentinites	$UCS=19.79I_{s50}$	0.74	**[42]**

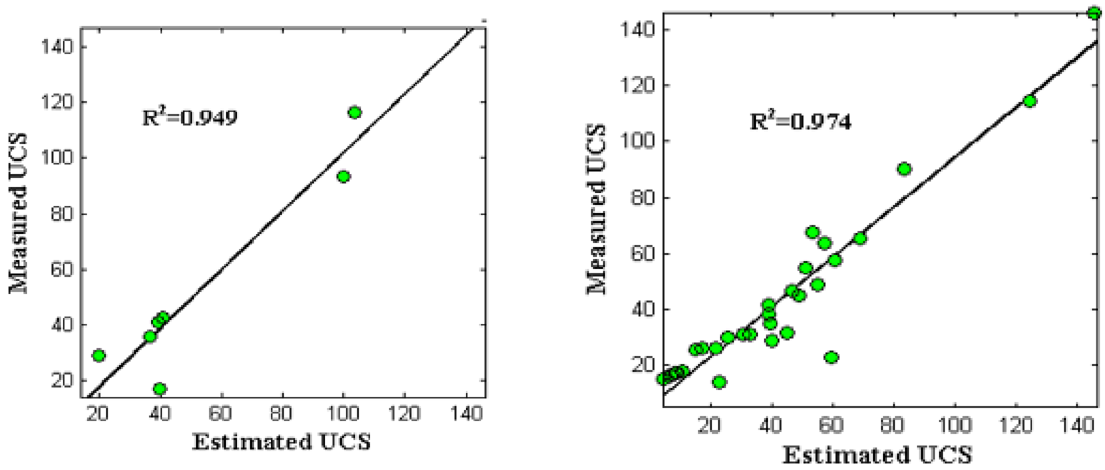
Table 2. Ranking values of the trained and testing steps for predict *UCS*

Model	Training Step			Testing Step		
	R^2	*RMSE*	*VAF*	R^2	*RMSE*	*VAF*
MLP	0.933	9.936	80.207	0.899	12.104	69.272
ANFIS	0.974	8.729	83.538	0.949	10.456	83.494
LS-SVR	0.993	6.891	95.489	0.967	9.439	92.122



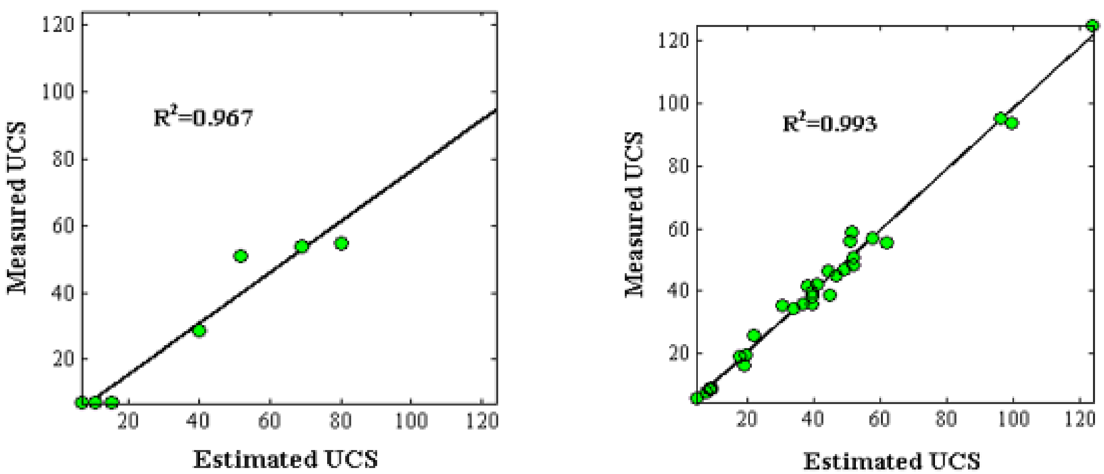
a) b)

Figure 1. Value of R^2 of *MLP* model (a) test (b) train



a) b)

Figure 2. Value of R^2 of *ANFIS* model (a) test (b) train



a) b)

Figure 3. Value of R^2 of *SVM* model (a) test (b) train

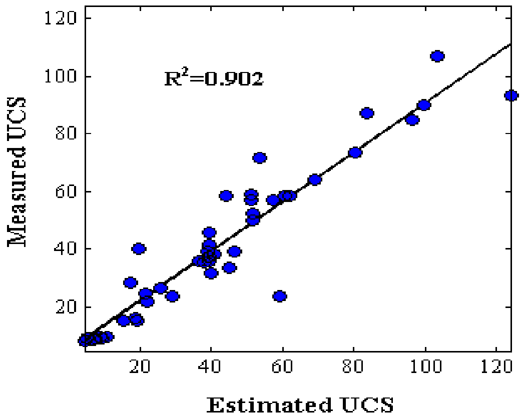


Figure 4. Measured and estimated *UCS* for limestone rocks in *MLP* model

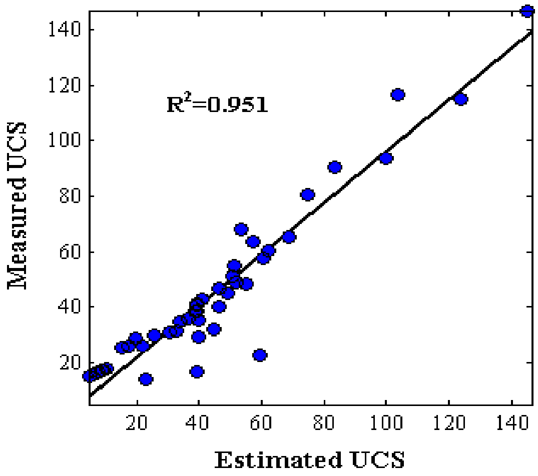


Fig 5. Measured and estimated *UCS* for limestone rocks in *ANFIS* model

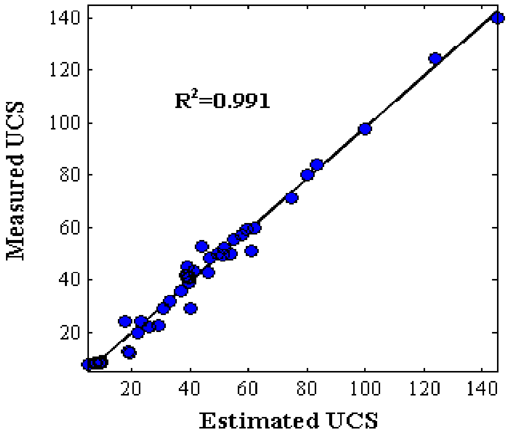


Figure 6. Measured and estimated *UCS* for limestone rocks in *SVM* model

4. CONCLUSION

In this study, three non-linear methods that are the *MLP*, *ANFIS* and *SVM* models were compared. The models were tested using *21* testing samples. All models to predict *UCS* indicated satisfactory results in relation to statistical performance metrics. Thus, the models were passable to predict the *UCS* of limestone. The models examined for prediction, provided relatively lower errors for training data. In comparison *ANFIS* model and *MLP* model, *ANFIS* model gave better performance in prediction of the *UCS* than the *MLP* model. *SVM* model with *LSSVR* function yielded the most appropriate results in the testing step and included the highest R^2=*0.993*, the *RMSE= 9.439 MPa* and *VAF =92.122 MPa*. It was concluded that the *SVM* model was superior to the other developed models that was expected to be bound up with dimensional independence. It is noted that the results of this research are within the scope of modeling and examined samples.

FUNDING/SUPPORT

Not mentioned any Funding/Support by authors.

ACKNOWLEDGMENT

Not mentioned bv authors.

AUTHORS CONTRIBUTION

This work was carried out in collaboration among all authors.

ONFLICT OF INTEREST

The author (s) declared no potential conflicts of interests with respect to the authorship and/or publication of this paper.

5. REFERENCES

[1] Chang C, Zoback MD, Khaksar A. Empirical relations between rock strength and physical properties in sedimentary rocks. Journal of Petroleum Science and Engineering. 2006 May 16;51(3-4):223-37. [View at Google Scholar]; [View at Publisher].

[2] Chary KB, Sarma LP, Lakshmi KP, Vijayakumar NA, Lakshmi VN, Rao MV. Evaluation of engineering properties of rock using ultrasonic pulse velocity and uniaxial compressive strength. InProc. National seminar on Non-destructive evaluation 2006 Dec 7 (pp. 7-9). [View at Google Scholar]; [View at Publisher].

[3] Altindag R. Correlation between P-wave velocity and some mechanical properties for sedimentary rocks. Journal of the Southern African Institute of Mining and Metallurgy. 2012 Mar;112(3):229-37. [View at Google Scholar]; [View at Publisher].

[4] Azimian A, Ajalloeian R. Empirical correlation of physical and mechanical properties of marly rocks with P wave velocity. Arabian Journal of Geosciences. 2015 Apr;8(4):2069-79. [View at Google Scholar]; [View at Publisher].

[5] Dehghan S, Sattari GH, Chelgani SC, Aliabadi MA. Prediction of uniaxial compressive strength and modulus of elasticity for Travertine samples using regression and artificial neural networks. Mining Science and Technology (China). 2010 Jan 1;20(1):41-6. [View at Google Scholar]; [View at Publisher].

[6] Shalabi FI, Cording EJ, Al-Hattamleh OH. Estimation of rock engineering properties using hardness tests. Engineering Geology. 2007 Mar 27;90(3-4):138-47. [View at Google Scholar]; [View at Publisher].

[7] Ceryan N, Okkan U, Kesimal A. Prediction of unconfined compressive strength of carbonate rocks using artificial neural networks. Environmental earth sciences. 2013 Feb;68:807-19. [View at Google Scholar]; [View at Publisher].

[8] Yesiloglu-Gultekin NU, Gokceoglu C, Sezer EA. Prediction of uniaxial compressive strength of granitic rocks by various nonlinear tools and comparison of their performances. International Journal of Rock Mechanics and Mining Sciences. 2013 Sep 1;62:113-22. [View at Google Scholar]; [View at Publisher].

[9] Gupta V, Sharma R. Relationship between textural, petrophysical and mechanical properties of quartzites: a case study from northwestern Himalaya. Engineering Geology. 2012 May 15;135:1-9. [View at Google Scholar]; [View at Publisher].

[10] Kahraman SA. Evaluation of simple methods for assessing the uniaxial compressive strength of rock. International Journal of Rock Mechanics and Mining Sciences. 2001 Oct 1;38(7):981-94. [View at Google Scholar]; [View at Publisher].

[11] Kahraman SA, Gunaydin O, Fener M. The effect of porosity on the relation between uniaxial compressive strength and point load index. International Journal of Rock Mechanics and Mining Sciences. 2005 Jun 1;42(4):584-9. [View at Google Scholar]; [View at Publisher].

[12] Kahraman SA. The determination of uniaxial compressive strength from point load strength for pyroclastic rocks. Engineering Geology. 2014 Feb 20;170:33-42. [View at Google Scholar]; [View at Publisher].

[13] Yagiz S. P-wave velocity test for assessment of geotechnical properties of some rock materials. Bulletin of Materials Science. 2011 Jul;34:947-53. [View at Google Scholar]; [View at Publisher].

[14] Kallu R, Roghanchi P. Correlations between direct and indirect strength test methods. International Journal of Mining Science and Technology. 2015 May 1;25(3):355-60. [View at Google Scholar]; [View at Publisher].

[15] Mishra DA, Basu A. Use of the block punch test to predict the compressive and tensile strengths of rocks. International Journal of Rock Mechanics and Mining Sciences. 2012 Apr 1;51:119-27. [View at Google Scholar]; [View at Publisher].

[16] Abbaszadeh Shahri A, Larsson S, Johansson F. Updated relations for the uniaxial compressive strength of marlstones based on P-wave velocity and point load index test. Innovative Infrastructure Solutions. 2016 Dec;1:1-7. [View at Google Scholar]; [View at Publisher].

[17] Azimian A. Application of statistical methods for predicting uniaxial compressive strength of limestone rocks using nondestructive tests. Acta Geotechnica. 2017 Apr;12:321-33. [View at Google Scholar]; [View at Publisher].

[18] Barzegar R, Sattarpour M, Nikudel MR, Moghaddam AA. Comparative evaluation of artificial intelligence models for prediction of uniaxial compressive strength of travertine rocks, case study: Azarshahr area, NW Iran. Modeling Earth Systems and Environment. 2016 Jun;2:1-3. [View at Google Scholar]; [View at Publisher].

[19] Omar M. Empirical correlations for predicting strength properties of rocks–United Arab Emirates. International Journal of Geotechnical Engineering. 2017 May 27;11(3):248-61. [View at Google Scholar]; [View at Publisher].

[20] Li S, Wang Y, Xie X. Prediction of Uniaxial Compression Strength of Limestone Based on the Point Load Strength and SVM Model. Minerals. 2021 Dec 8;11(12):1387. [View at Google Scholar]; [View at Publisher].

[21] Garrido ME, Petnga FB, Martínez-Ibáñez V, Serón JB, Hidalgo-Signes C, Tomás R. Predicting the uniaxial compressive strength of a limestone exposed to high temperatures by point load and Leeb rebound hardness testing. Rock Mechanics and Rock Engineering. 2022 Jan;55(1):1-7. [View at Google Scholar]; [View at Publisher].

[22] Wei X, Shahani NM, Zheng X. Predictive Modeling of the Uniaxial Compressive Strength of Rocks Using an Artificial Neural Network Approach. Mathematics. 2023 Mar 29;11(7):1650. [View at Google Scholar]; [View at Publisher].

[23] Karakul H, Ulusay R, Isik NS. Empirical models and numerical analysis for assessing strength anisotropy based on block punch index and uniaxial compression tests. International Journal of Rock Mechanics and Mining Sciences. 2010 Jun 1;47(4):657-65. [View at Google Scholar]; [View at Publisher].

[24] Heidari M, Khanlari GR, Torabi Kaveh M, Kargarian S. Predicting the uniaxial compressive and tensile strengths of gypsum rock by point load testing. Rock mechanics and rock engineering. 2012 Mar;45:265-73. [View at Google Scholar]; [View at Publisher].

[25] Mishra DA, Basu A. Estimation of uniaxial compressive strength of rock materials by index tests using regression analysis and fuzzy inference system. Engineering Geology. 2013 Jun 27;160:54-68. [View at Google Scholar]; [View at Publisher].

[26] Jiang W, He G, Long T, Ni Y, Liu H, Peng Y, Lv K, Wang G. Multilayer perceptron neural network for surface water extraction in Landsat 8 OLI satellite images. Remote Sensing. 2018 May 15;10(5):755. [View at Google Scholar]; [View at Publisher].

[27] Ly HB, Le LM, Duong HT, Nguyen TC, Pham TA, Le TT, Le VM, Nguyen-Ngoc L, Pham BT. Hybrid artificial intelligence approaches for predicting critical buckling load of structural members under compression considering the influence of initial geometric imperfections. Applied Sciences. 2019 May 31;9(11):2258. [View at Google Scholar]; [View at Publisher].

[28] Nguyen HQ, Ly HB, Tran VQ, Nguyen TA, Le TT, Pham BT. Optimization of artificial intelligence system by evolutionary algorithm for prediction of axial capacity of rectangular concrete filled steel tubes under compression. Materials. 2020 Mar 7;13(5):1205. [View at Google Scholar]; [View at Publisher].

[29] Pham BT, Nguyen-Thoi T, Ly HB, Nguyen MD, Al-Ansari N, Tran VQ, Le TT. Extreme learning machine based prediction of soil shear strength: a sensitivity analysis using Monte Carlo simulations and feature backward elimination. Sustainability. 2020 Mar 17;12(6):2339. [View at Google Scholar]; [View at Publisher].

[30] Hyndman RJ, Koehler AB. Another look at measures of forecast accuracy. International journal of forecasting. 2006 Oct 1;22(4):679-88. [View at Google Scholar]; [View at Publisher].

[31] Bahaaddini M, Hosseinpour Moghadam E. Evaluation of empirical approaches in estimating the deformation modulus of rock masses. Bulletin of Engineering Geology and the Environment. 2019 Jul 1;78(5):3493-507. [View at Google Scholar]; [View at Publisher].

[32] Ulusay R, Gokceoglu C. The modified block punch index test. Canadian Geotechnical Journal. 1997 Dec 1;34(6):991-1001. [View at Google Scholar]; [View at Publisher].

[33] Gokceoglu C, Aksoy H. New approaches to the characterization of clay-bearing, densely jointed and weak rock masses. Engineering Geology. 2000 Sep 1;58(1):1-23. [View at Google Scholar]; [View at Publisher].

[34] Sulukcu S, Ulusay R. Evaluation of the block punch index test with particular reference to the size effect, failure mechanism and its effectiveness in predicting rock strength. International Journal of Rock Mechanics and Mining Sciences. 2001 Dec 1;38(8):1091-111. [View at Google Scholar]; [View at Publisher].

[35] Sonmez H, Tunusluoglu C. New considerations on the use of block punch index for predicting the uniaxial compressive strength of rock material. International Journal of Rock Mechanics and Mining Sciences. 2008 Sep 1;45(6):1007-14. [View at Google Scholar]; [View at Publisher].

[36] Mishra DA, Basu A. Use of the block punch test to predict the compressive and tensile strengths of rocks. International Journal of Rock Mechanics and Mining Sciences. 2012 Apr 1;51:119-27. [View at Google Scholar]; [View at Publisher].

[37] Aydin A, Basu A. The Schmidt hammer in rock material characterization. Engineering geology. 2005 Sep 1;81(1):1-4. [View at Google Scholar]; [View at Publisher].

[38] Fener MU, Kahraman SA, Bilgil A, Gunaydin O. A comparative evaluation of indirect methods to estimate the compressive strength of rocks. Rock Mechanics and Rock Engineering. 2005 Sep;38:329-43. [View at Google Scholar]; [View at Publisher].

[39] Shalabi FI, Cording EJ, Al-Hattamleh OH. Estimation of rock engineering properties using hardness tests. Engineering Geology. 2007 Mar 27;90(3-4):138-47. [View at Google Scholar]; [View at Publisher].

[40] Minaeian B, Ahangari K. Estimation of uniaxial compressive strength based on P-wave and Schmidt hammer rebound using statistical method. Arabian Journal of Geosciences. 2013 Jun;6:1925-31. [View at Google Scholar]; [View at Publisher].

[41] Karaman K, Kaya A, Kesimal A. Use of the point load index in estimation of the strength rating for the RMR system. Journal of African Earth Sciences. 2015 Jun 1;106:40-9. [View at Google Scholar]; [View at Publisher].

[42] Diamantis K, Gartzos E, Migiros G. Study on uniaxial compressive strength, point load strength index, dynamic and physical properties of serpentinites from Central Greece: test results and empirical relations. Engineering Geology. 2009 Oct 8;108(3-4):199-207. [View at Google Scholar]; [View at Publisher].

[43] Khandelwal M. Correlating P-wave velocity with the physico-mechanical properties of different rocks. Pure and Applied Geophysics. 2013 Apr;170:507-14. [View at Google Scholar]; [View at Publisher].

[44] Diamantis K, Bellas S, Migiros G, Gartzos E. Correlating wave velocities with physical, mechanical properties and petrographic characteristics of peridotites from the central Greece. Geotechnical and Geological Engineering. 2011 Nov;29:1049-62. [View at Google Scholar]; [View at Publisher].

[45] Sarkar K, Vishal V, Singh TN. An empirical correlation of index geomechanical parameters with the compressional wave velocity. Geotechnical and Geological Engineering. 2012 Apr;30:469-79. [View at Google Scholar]; [View at Publisher].

[46] Sulukcu S, Ulusay R. Evaluation of the block punch index test with particular reference to the size effect, failure mechanism and its effectiveness in predicting rock strength. International Journal of Rock Mechanics and Mining Sciences. 2001 Dec 1;38(8):1091-111. [View at Google Scholar]; [View at Publisher].

[47] Kılıç A, Teymen A. Determination of mechanical properties of rocks using simple methods. Bulletin of Engineering Geology and the Environment. 2008 May;67:237-44. [View at Google Scholar]; [View at Publisher].