Geopersia 2024, 14(1): 45-62
DOI: 10.22059/GEOPE.2023.360469.648718

RESEARCH PAPER

Estimating the uniaxial compressive strength of Esfandiar limestone strata based on their physical characteristics (Case study: North of Tabas City, Iran)

Zohre Sharifi, Gholamreza Lashkaripour *, Mohammad Khanehbad, Mojtaba Rahimi Shahid

Department of Geology, Faculty of Science, Ferdowsi University of Mashhad, Iran

Received: 07 June 2023, Revised: 29 August 2023, Accepted: 23 September 2023

Abstract
Uniaxial compressive strength is one of the most important properties of rocks, whose determination is important for rock engineering studies in civil engineering and mining projects. Determining the uniaxial compressive strength is time-consuming and expensive. Empirical relations obtained from easier methods can be used to reduce cost and time. In this research, using the artificial neural network method, experimental relationships have been presented to estimate the uniaxial compressive strength of limestones of the Esfandiar formation in the north of Tabas city. In this method, the physical properties of the rock sample include relative specific gravity, specific gravity, percentage of water absorption, and porosity as independent variables, and input parameters that are used to calculate the uniaxial compressive strength as a dependent variable. These relationships consist of a general structure with 4 inputs and 1 output, which was performed using a perceptron multilayer neural network. In this research, the root mean square error (RMSE) was investigated. The results of this research show that the amount of errors caused by testing, and validation is close to zero and these relationships can be used to estimate the uniaxial compressive strength of limestones of the Esfandiar formation. Also, the results of the artificial neural network have been compared with the results of multivariate regression, and the results show that the value of the confidence coefficient obtained from the artificial neural network is more acceptable.

Keywords: Physical Properties, Limestone, Artificial Intelligence, East Of Iran, Uniaxial Compressive Strength.

Introduction

Determining the uniaxial compressive strength of rock is essential in most engineering projects. Uniaxial compressive strength of stone (UCS1) is one of the most useful mechanical parameters of stone, which is used more in design and engineering projects than other parameters of stone (Bieniawsk, 1976). The uniaxial compressive strength test is undoubtedly one of the best and the main pillar in geotechnical science, which is often used in rock mechanics and is often used as a serious and accurate indicator for a wide range of related issues. The uniaxial compressive strength of rock is 9 times more useful than the second most important rock mechanics parameter, the triaxial compressive strength (Cargill & Shakoor,1990). Cylindrical cores with certain dimensions are needed to perform the uniaxial compressive strength test. The device for performing this test is also equipped and non-portable, and to perform this test, it is necessary to

* Corresponding author e-mail: Lashkaripour@um.ac.ir

transport a significant amount of rock blocks from the site to the laboratory; Therefore, to carry out some studies (especially basic studies), there are methods that can be used to evaluate the uniaxial compressive strength indirectly and by using physical and engineering properties that require less time and cost to estimate. Among these methods, we can mention single and multivariate linear and non-linear regression and artificial intelligence methods (neural network).

In recent years, many advances have been made in the rapid processing of information and numerical calculations by means of software. These methods speed up the calculation, reduce the error, and also provide solutions that were not possible with experimental methods. One of these advances and innovations in modeling and calculation through artificial neural networks. The technique of artificial neural networks has been developed with inspiration from the functioning of the human brain and nervous system. Artificial neural networks are actually a small network of artificial neurons that are trained to solve complex problems. In other words, neural networks are parallel distributed processors that have a natural tendency to store empirical knowledge. These networks, like any other system, can be trained and become intelligent in a certain range (Norusis, 1994, Hagan et al, 2014). The most widely used architecture of neural networks is forward-feed multilayer networks, which are called Multi-Layer Perceptron networks, abbreviated as Mlp (Emami & Yathrabi, 2013).

Artificial neural network models are one of the powerful tools of data analysis in many different scientific fields, which have attracted the attention of geotechnical engineers (Pala et al., 2007). In this field, much research has been done to predict the properties of soil and materials by means of neural networks, and different researchers have used neural networks in the topics of geotechnical engineering, engineering geology, structure, and building (Minhaj, 2019). Many studies in the field of rock mechanics have used artificial neural networks to achieve experimental relationships, among which the following studies can be mentioned: (Motahari., 2005; Ajal Luian & Mansouri., 2013;Esmaili et al., 2015; Abdi & Ghasemi Dahnavi., 2018; Aras et al., 2019; Ebdali et al., 2020; Barham et al., 2020; Rastegarnia et al., 2021; Moussas et al., 2021; Jin et al., 2022; Hacıefendioğlu et al., 2022 ; Abedelhedi et al., 2022; Hassan &, Arman., 2022).

In general, one of the important applications of neural networks in rock mechanics is the estimation of expensive and time-consuming tests using less expensive and simpler tests. Due to their spread on the earth's surface and as an important group of sedimentary rocks, limestones are usually observed in most engineering projects. These stones are very important both as building materials and as the bed in which the structure is built. For example, limestone is widely used in various engineering projects as a building stone and in the cement production industry, limestones are also seen as reservoir rocks in oil reservoirs; Therefore, it is important to study and investigate these types of stones and provide empirical relationships. Many studies have been conducted on the engineering characteristics of limestone in Iran, among which the following can be mentioned: (Safari Farrokhed et al., 1398; Rostgarnia et al., 1398; Moradi et al., 1396; Jafaripour et al., 1393;Khalili et al., 1392)

A large part of Tabas county in the east of Iran is covered by Esfandiar formation (containing limestone) and many construction projects and mines have been built or are being built in this formation. Therefore, it is very important to investigate the mechanical properties of limestones of this formation in the region. For this purpose, in this study, using an artificial neural network, uniaxial compressive strength (in dry and saturated states) has been estimated using the physical characteristics of limestone samples prepared from this formation. The physical properties used include relative specific gravity (Gs), porosity (n), dry specific gravity (γdry), saturated specific gravity (γsat), and water absorption capacity (W.A).

Geographical and geological situation of the region

The studied area is located in the north of Tabas city. Tabas City is located in the eastern part of the country and in the northwest of South Khorasan province (Figure 1). The Esfandiar Formation is one of the rock units of Central Iran and the extension of this formation is located in the northeast to the southeast of Tabas city in South Khorasan province which is located between the two blocks of Lut and Tabas. Figure 2 shows a view of the alternating layers of the Esfandiar formation, which is located around Goshen village, 25 km from Tabas city. The age of the Esfandiar Formation, which consists of many fossils, shows the Upper Jurassic based on index fossils such as ammonites, foraminifers, and other skeletal components. The Esfandiar formation consists of limestones with medium to thick beds, which were deposited on a wide and shallow platform with a length of more than 170 km and a width of between 30 ad 40 km and occupies most of the heights of the Shotori mountain range (Fursich et al., 2003). With the predominance of hot and dry weather conditions in the time interval from Calvin to Oxfordian in a large part of the north of the Tabas block, a large lime factory was activated on the platform of the Shotori mountains, which created the Esfandiar formation and a large part of the limestones of Qala Dokhtar. The formation of calcareous sediments in the late Oxfordian in parts of the beginning of the Kimmerian ends with the rise of the water level on a global scale (Hallam, 2001) and the sinking of the Esfandiar platform in the eastern part of the Shotori Mountains. The spread of the Esfandiar formation in the studied area is shown in Figure 1c.

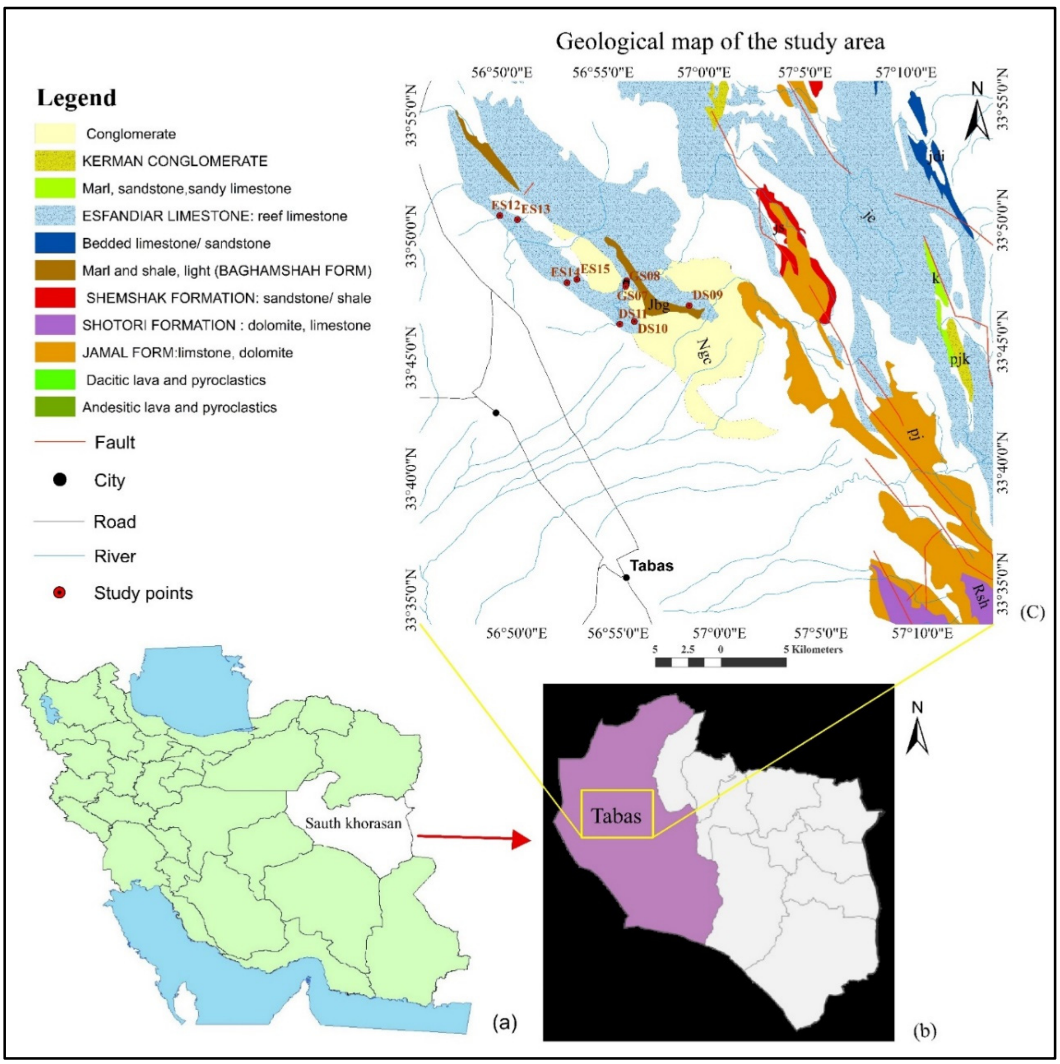

Figure 1. (a) Location of the study area in Iran, (b) Location of the study area in the province, (c) Geological map of the study area (adapted from the 1:250,000 map of Beshravieh)

Figure 2. A view of the alternating layers of the Esfandiar formation - the direction of the image is facing north

Materials and methods

In order to carry out this study, rock blocks were collected from 15 stations of Esfandiar limestone in the north of Tabas city. Figure 1 shows the location of the collected samples. After transferring the blocks from the studied area to the Engineering Geology Laboratory of the Ferdowsi University of Mashhad, the samples were prepared for mechanical tests (Figure 3). To conduct the test, first, cylindrical core samples with a diameter of 54 mm and a length-to-diameter ratio of 2/1 were prepared from 15 rock blocks for uniaxial compressive strength testing. To perform the uniaxial compressive strength test according to the standard of the International Society of Rock Mechanics (ISRM, 2007), dry cylindrical samples were placed in an oven at a temperature of 105°C for 24 hours, and also to perform the test in a saturated state, the samples were saturated in a vacuum. Each sample was subjected to pressure by the compressive concrete breaker jack with a loading rate of about 0.5 MPa/min until the failure. By determining the maximum load on the samples during the test and calculating the effective cross-sectional area of each core, the uniaxial compressive strength of the samples was calculated (Figure 4). Then the necessary tests were performed to determine the physical characteristics of the samples. In order to calculate the physical properties, in the saturation state, the samples were saturated in the vacuum state. Then the weight of the saturated sample with dry surface and submerged weight was measured. Also, in order to perform tests in a dry condition, the samples were placed in an oven at a temperature of 105 degrees Celsius for 24 hours. Finally, the dry weight of the sample was measured and the tests were carried out under normal laboratory conditions. Physical property tests include relative specific gravity (Gs), porosity (n), dry specific gravity (γdry), saturated specific gravity (γsat), water absorption (W.A) according to the standards of the International Society of Rock Mechanics (ISRM, 1981) were determined. Then, a multi-layer perceptron neural network was designed using Matlab software. Finally, using the designed artificial neural network, the uniaxial compressive strength was estimated in both dry and saturated states. Also, the uniaxial compressive strength was calculated from the multivariate linear regression using SPSS software based on the physical characteristics of the rock sample, and then the significance level of the two neural networks and multivariate linear regression methods were compared.

Figure 3. Preparing samples for testing

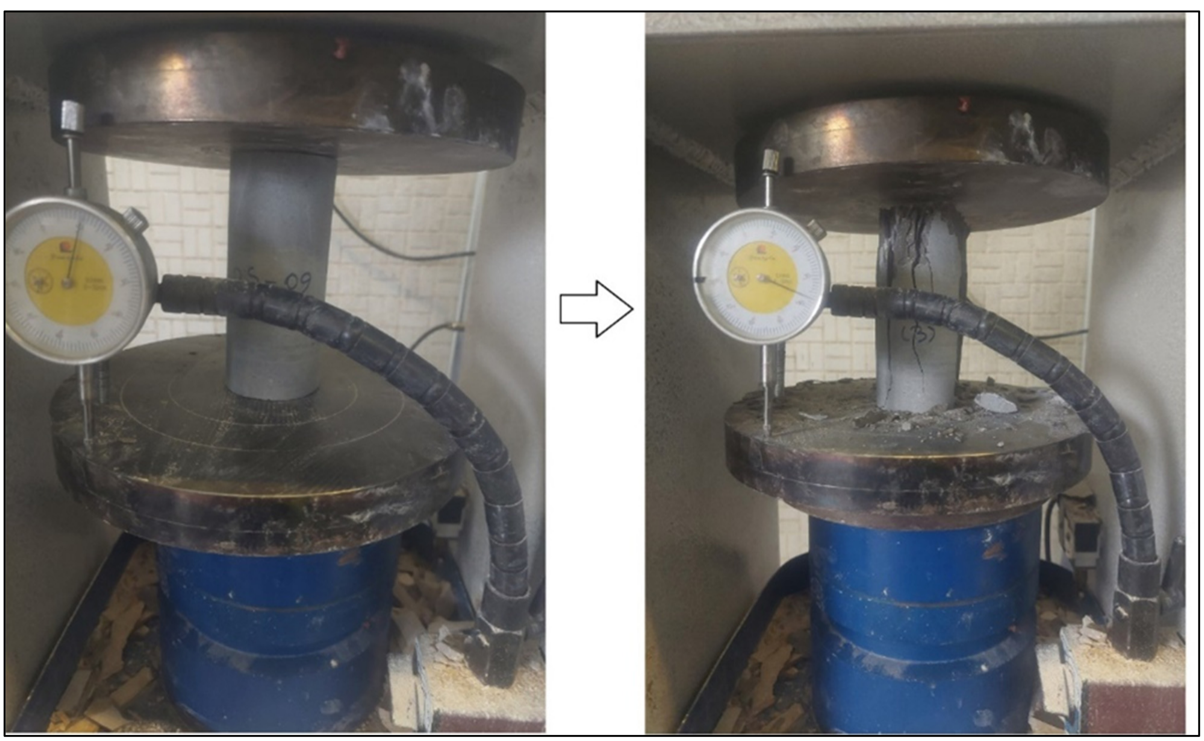

Figure 4. Conducting the uniaxial compressive strength test on the samples prepared by the compressive jack machine

Physical characteristics

In Tables 1 and 2, the average value of standard deviation, maximum and minimum, etc., of each of the physical properties in two sets of dry and saturated states of cylindrical samples are mentioned. Figures 5 and 6 show the frequency diagram and the normal curve of physical characteristics. Figure 5 shows a collection of 25 samples. The maximum abundance in the graph of dry specific gravity (γdry) is between 26.80 and 27 kN/m2. Relative specific gravity (Gs) has a normal curve and its average frequency is equal to 2.49. Porosity (n) has an average of 1.02%. The graph of water absorption (W.A) is not normal and its average is 0.38%. As can be seen in Figure 6, the physical properties of a total of 23 samples have been examined. The saturation specific gravity (γsat) has an average of 26.91 kN/m2 and its highest frequency is around 27 kN/m2, the relative specific gravity graph (Gs) has an average of 2.53 and the highest frequency is between 2.48 and 50. is 2. Porosity (n) has an average of 1.05%. The water absorption graph (W.A) has an average value of 0.39%. In Figure 6, relative specific gravity (Gs), porosity (n), saturation specific gravity (γsat), and water absorption capacity (W.A) do not have a normal curve.

Table 1. Table of descriptive statistics of the results obtained from dry cylindrical samples

	Gs	**γ_{dry} (KN/m3)**	**n (%)**	**W.A. (%)**
N	25	25	25	25
Mean	2.49	26.86	1.02	0.38
Std. Error of Mean	0.007	0.056	0.15	0.06
Median	2.49	26.90	0.60	0.22
Std. Deviation	0.03	0.28	0.76	0.29
Variance	0.001	0.08	0.586	0.084
Range	0.14	1.13	2.15	0.81
Minimum	2.42	26.34	0.19	0.07
Maximum	2.57	27.47	2.34	0.89

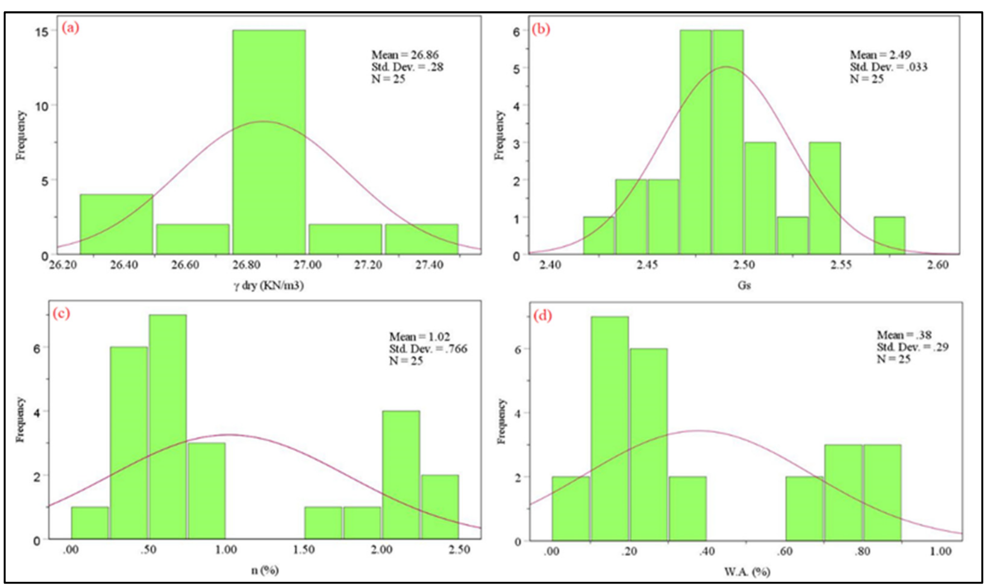

Figure 5. Frequency diagram and normal curve of physical parameters in the dry state of ucs samples: (a) dry specific gravity (kn/m2), (b) relative specific gravity, (c) effective porosity (%), (d) percentage of water absorption (%)

Table 2. Descriptive statistics table of results obtained from cylindrical samples in saturated state

	Gs	n (%)	γ_{sat} (KN/m3)	W.A. (%)
N	23	23	23	23
Mean	2.53	1.054	26.91	0.39
Std. Error of Mean	0.021	0.14	0.042	0.05
Median	2.51	0.76	26.92	0.28
Std. Deviation	0.104	0.705	0.204	0.26
Variance	0.011	0.498	0.042	0.072
Range	0.36	2.18	0.88	0.83
Minimum	2.44	0.15	26.57	0.06
Maximum	2.8	2.34	27.45	0.89

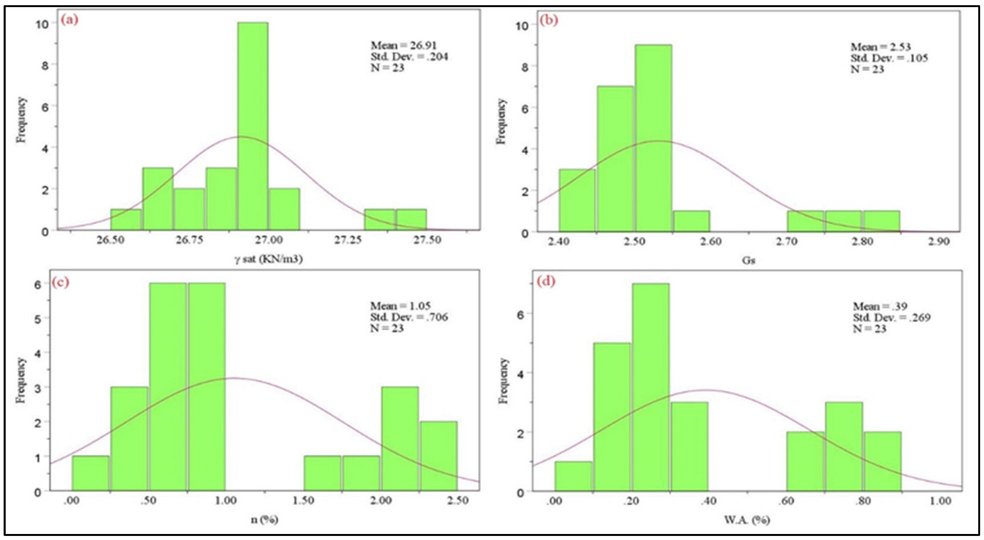

Figure 6. Frequency chart and normal curve of physical parameters in the saturated state of ucs samples: (a) saturated specific gravity (kn/m2), (b) relative specific gravity, (c) effective porosity (%), (d) percentage of water absorption (%).

Uniaxial compressive strength

The uniaxial compressive strength was measured according to the standard (ISRM, 2007). In Figure 7, the results of 23 saturated samples and 25 dry samples are presented in MPa. In fact, the uniaxial compressive strength in the saturated state has decreased by 18.63% compared to the dry state According to Figure 7, the frequency of uniaxial compressive strength in the dry state is between 20 and 80 MPa, and in the saturated state, the frequency is between 10 and 70 MPa. To classify uniaxial compressive strength values, the classification provided by the International Society of Rock Mechanics (Bieniawski, 1979) was used (Table 1), based on this classification of Esfandiar Formation rocks, on average, in dry and Saturation has a relatively low resistance and according to the classification of Dear & Miller (1966), the average resistance of samples in dry and saturated states are in the low category (Table 1).

Artificial neural network

Artificial neural networks are patterns for information processing that are made by imitating human neural networks. Each processor unit in artificial neural networks has an input and output characteristic. The output of each unit is determined according to its internal connections to other units and the possibilities of external inputs. The overall performance of artificial networks is regulated by network topology, characteristics of individual neurons, learning method, and training data. There are two separate steps in artificial neural networks. The learning phase is in which the data is continuously entered into the network and the weights are updated until the desired answer is obtained. The second stage is the test stage, in which the network with final weights is used for new data. An artificial neuron in neural networks is a processing unit that associates the input data with the output variable (Akbari Poursalimi &Nikfar, 2017). This model has the ability to extract hidden relationships between inputs and outputs. This structure consists of a large number of processing elements or neurons that are used to solve complex problems. These networks, like human experience, learn from examples and are organized for specific applications such as pattern recognition or data classification during the learning process, and this is a simple description of an artificial neural network (Amanpour, 2013). There are different types of artificial neural network. One of the neural networks with a wide range of applications is called the multilayer perceptron artificial neural network. This type of artificial neural network consists of three layers: an input layer that is connected to multiple hidden layers, and this layer in turn is connected to the output layer or layers. Figure 8 shows the schematic structure of a multilayer artificial neural network. Neural networks with hidden layers have more ability. However, there are no rules to determine the optimal number of input layers or the number of hidden layers. The total inputs of each neuron after multiplying by the corresponding weights are applied to a function known as the stimulus function, and based on the specific needs of the problem that is to be solved by the neural network, it can be chosen as linear or non-linear. In fact, the stimulus function estimates the relationship between the input and output of nodes and the network (Tan et al., 2014).

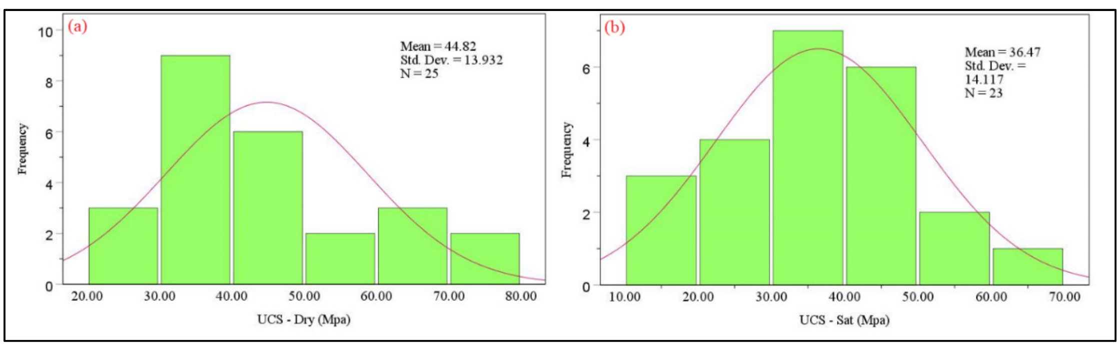

Figure 7. Frequency diagram and normal curve of uniaxial compressive strength (MPa): (a) in dry state, (b) in saturated state

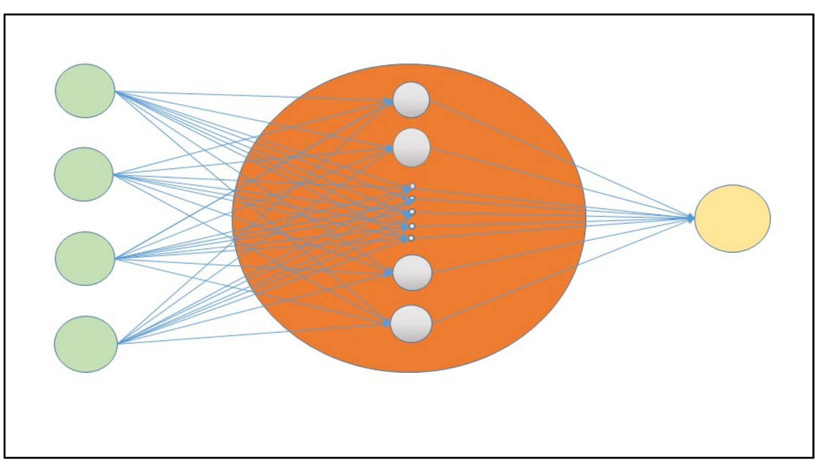

Figure 8. Schematic figure of the structure of a multilayer artificial neural network

Results and discussion

Estimation of uniaxial compressive strength in a dry state

In this research, in order to investigate the capability of artificial neural networks in estimating uniaxial compressive strength, a multilayer perceptron neural network was used. Figure 9 shows an example of the artificial neural network structure in the dry state, where relative specific gravity (Gs), porosity (n), dry specific gravity (γdry), water absorption ability (W.A) are input to the neural network and the first hidden layer has 4 neurons. The second layer has 7 neurons and the third layer has an output as a linear function. The second hidden layer in the form of a sigmoid tangent function has brought the network to the lowest error, and the third layer is in the form of a linear function.

Different modes of training, testing, and validation in two dry and saturated modes are shown in Figure 10-a. In this network, during the twelfth step of the model in the dry state, the best point was determined where the mean square error (MSE) reached its minimum and at this point, the network provided the best model. The desired network model in Figure 10-b shows the performance of the network during training, which is in 18 cycles, and how the neural network training process proceeds from the input data.

In Figure 11, using regression relationships using Matlab software, the correlation coefficient of the values for test data, validation, test, and in general for the neural network in a dry state has been calculated and a 1:1 line graph has been drawn.

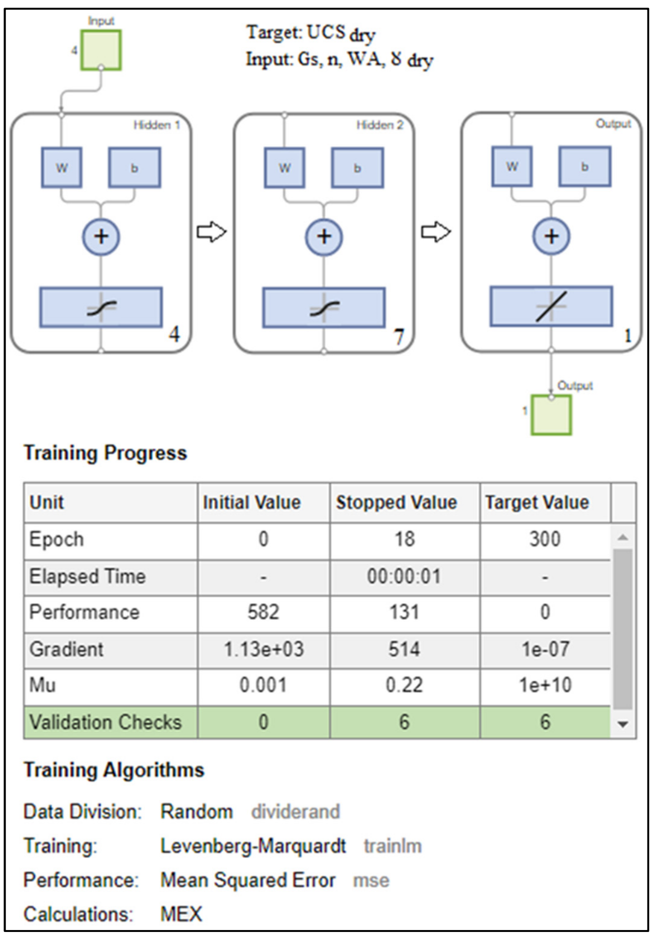

Figure 9. The general structure of multilayer perceptron artificial neural network in this research in dry state

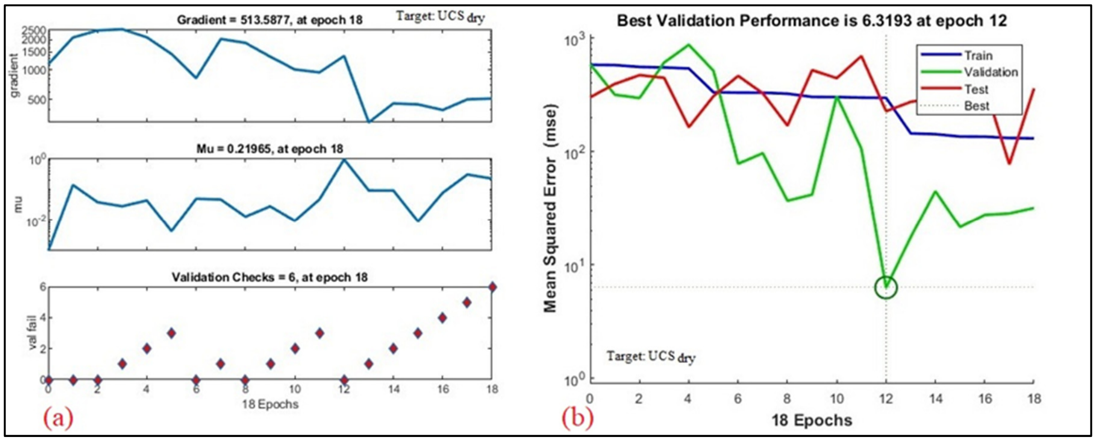

Figure 10. The results of ucs model in dry state (a) network training steps (b) artificial neural network error rate in uniaxial compressive strength estimation and the best point in model selection

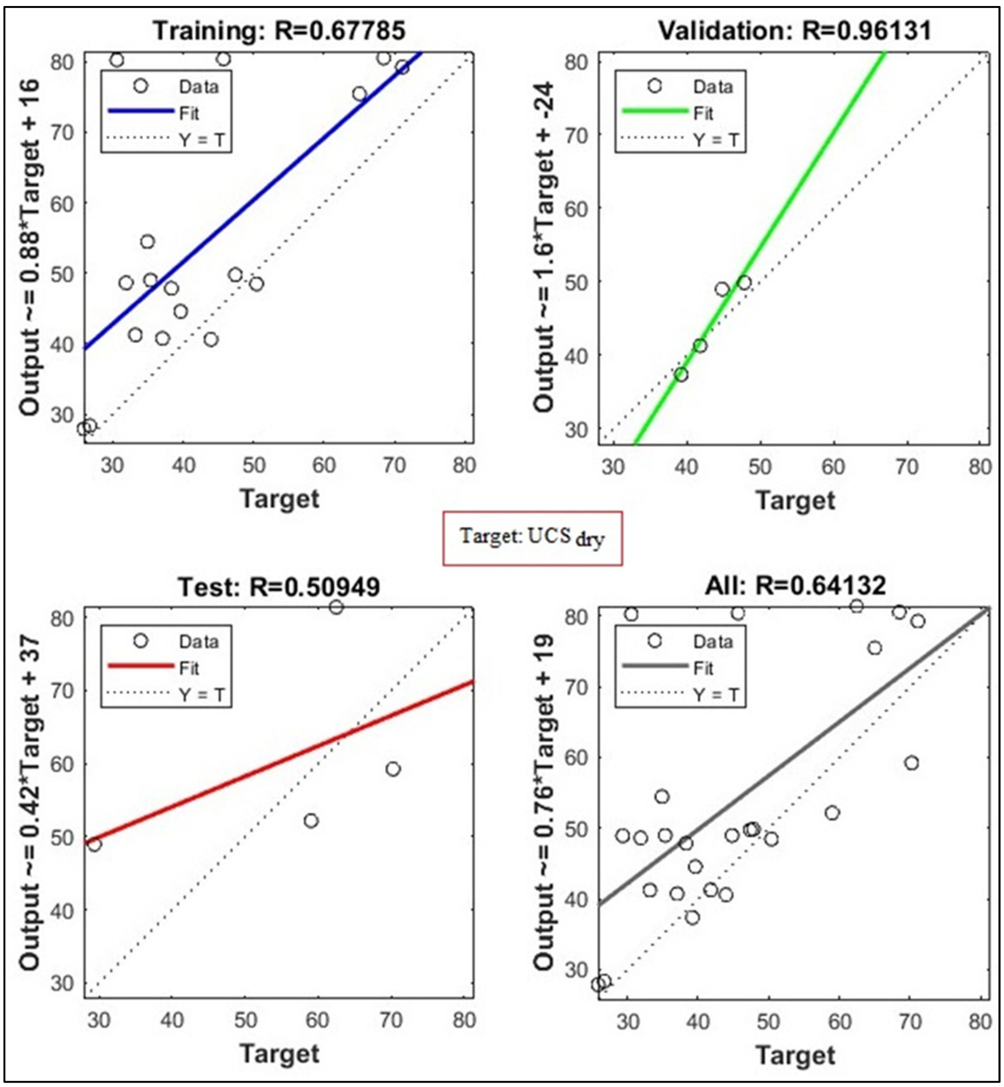

Figure 11. Correlation between the input and output values of the regression equation measured ucs with ucs calculated from the neural network in dry state

In this figure, the value of R in the test mode is equal to 0.67. For validation 0.96, for test

0.50, and in general, for the mentioned neural network model, its coefficient was equal to 0.64%, and the high value of the correlation coefficient in the validation state indicates the appropriate correlation of the model and its acceptable validity.

Figure 11 shows that 17 samples have been considered for training, 4 samples for performance, and 3 samples for testing. In fact, 70% of the samples have been used for training 15% for performance, and another 15% for testing in a dry state.

If the amount of error between the distribution points with the regression line reaches its minimum, the error histogram of the neural network model in the dry state (Figure 12), the amount of error caused by testing, testing and validation has the highest distribution on the zero axis, which shows that this model is suitable.

Estimation of uniaxial compressive strength in a saturated state

The tests of physical properties include solid specific gravity (Gs), porosity (n), saturated specific gravity (γsat), water absorption ability (W.A) (Figure 13) as input layers of the neural network, and uniaxial compressive strength in the saturated state (ucs) as the output is the structure. This network has three layers, the two hidden layers of which each has 6 neurons with a sigmoid tangent activation function. The activator function is used for these hidden layers, and the third layer of this network is its output, which has a single layer with a linear activator function.

Figure 14-a shows the stages of network training in 16 periods. Figure 15-b shows that during the tenth step, the mean square error (MSE) reached its minimum and at this point, the network presented the best model. In this figure, three network diagrams are shown during training, evaluation, and testing.

Using the regression relationship, the correlation coefficient of the values for the test data, validation, test and in general for the neural network in the saturation state has been calculated and the 1:1 line graph has been drawn (Figure 15). In this Figure, the value of R in the test mode is equal to 0.70. For validation 0.96, for test 0.99 and in general for the mentioned neural network model, its coefficient was equal to 0.78%, which indicates the very good correlation of the model and the high value of R in validation shows the high validity of the model.

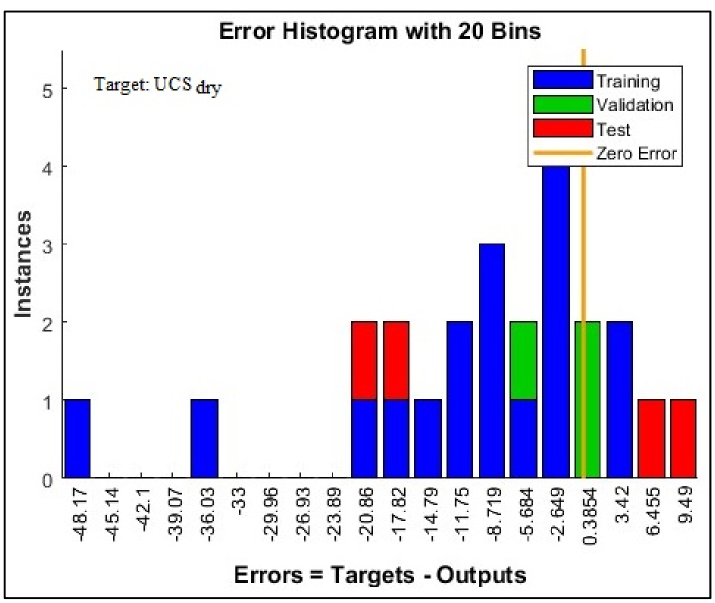

Figure 12. Error histogram of neural network model for estimating uniaxial compressive strength in dry state

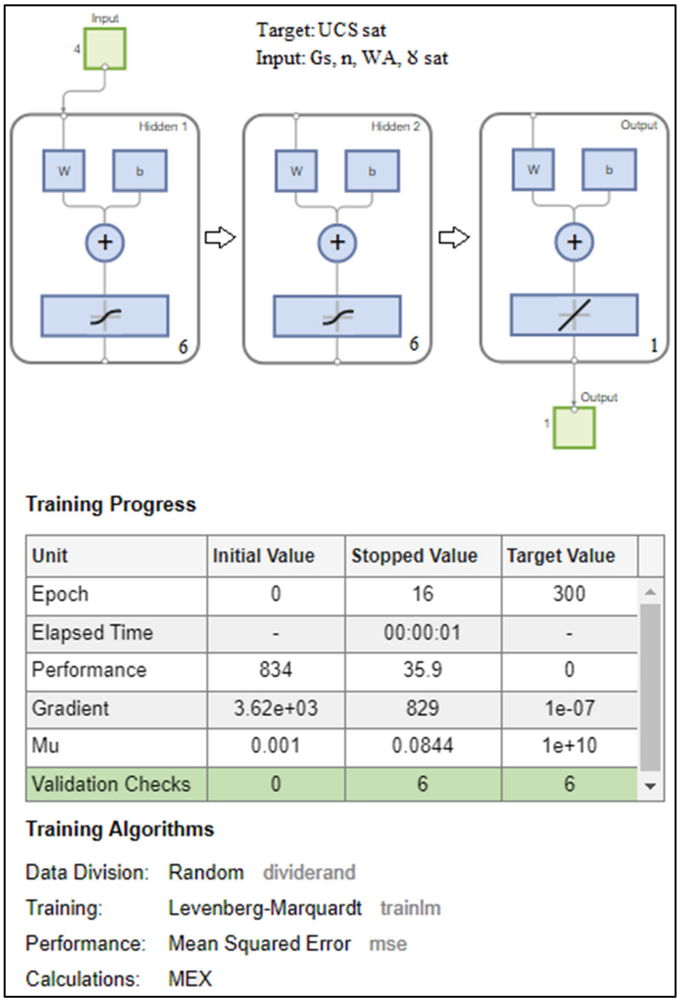

Figure 13. The general structure of multilayer perceptron artificial neural network in this research in saturation mode

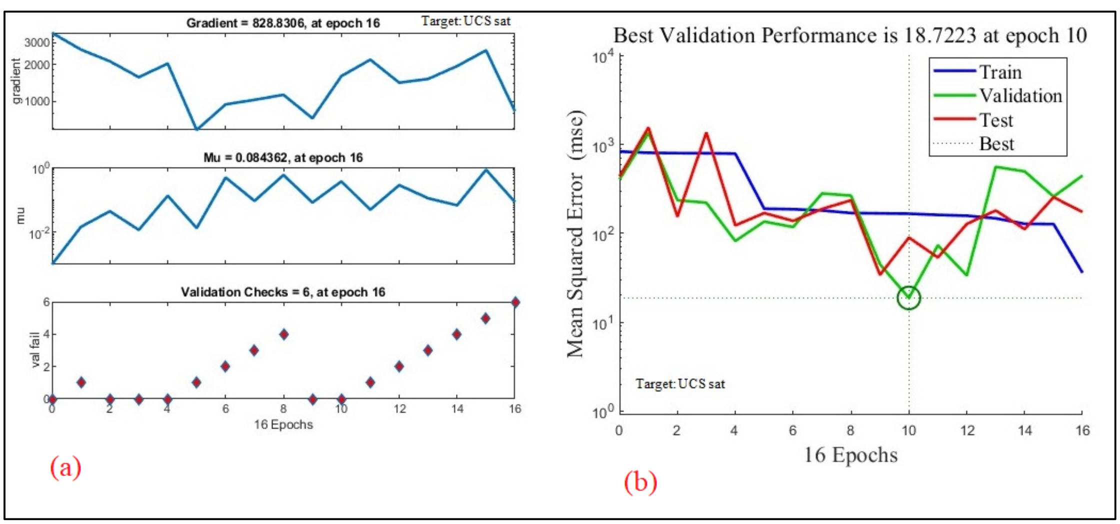

Figure 14. The results of ucs model in saturation (a) network training steps (b) the amount of artificial neural network error in estimating uniaxial compressive strength and the best point in selecting the model in saturation

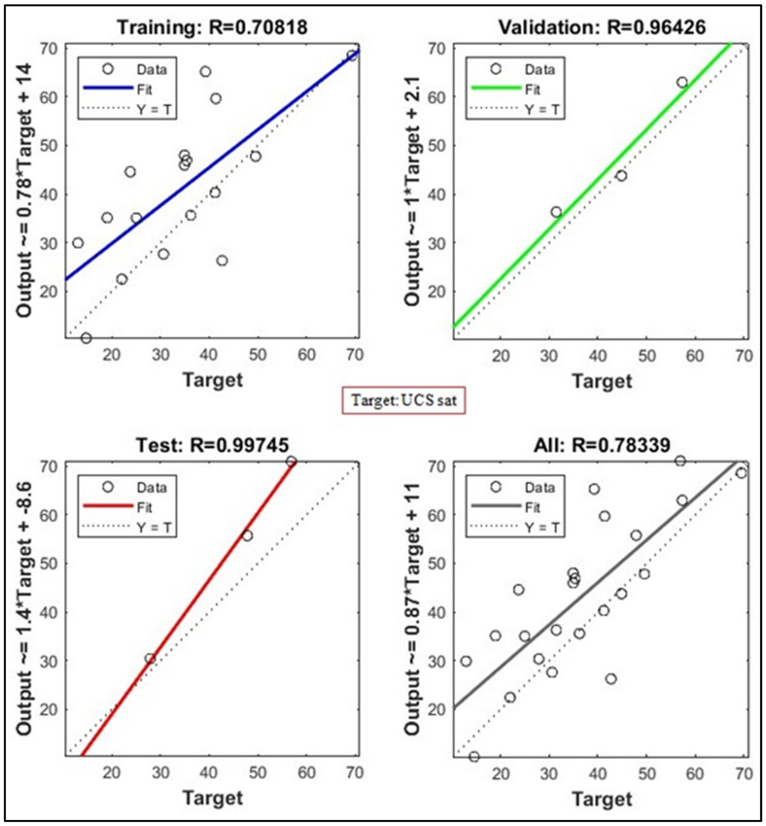

Figure 15. Correlation between the input and output values of the measured ucs regression equation with the ucs calculated from the neural network in saturation mode

The number of samples in saturation state was 23, of which 16 samples were used for training, 3 samples for performance and 4 samples for testing. If the amount of error between the distribution points and the regression line reaches its minimum, the appropriate model is determined. In the error histogram of the neural network model in dry state (Figure 16), the amount of error caused by testing, testing and validation has the highest distribution on the zero axis, which shows that the model has very little error.

Comparing the results of artificial neural network with the results of multivariate regression

In this section, the results of artificial neural network have been compared with the results of multivariate regression. First, in Table 4, the value of R^2 and the equation obtained from the multivariate regression relationships using the physical characteristics of the samples are shown. Then, using the box plot diagram, the average value of the measured uniaxial compressive strength, the estimated uniaxial compressive strength using neural network and the estimated uniaxial compressive strength using multivariate regression have been compared. Also, a comparison has been made between the R value of two multivariate regression methods and an artificial neural network in dry and saturated conditions.

One of the methods of showing the accuracy of the results of experiments, simulators and statistical relationships is the use of confidence interval charts. A box plot is a standard way to display the distribution of data based on five numbers, minimum, first quartile, median, third quartile, and maximum. As seen in figures 17 and 18, the uniaxial compressive strength estimated using multivariate regression data has more outliers than the values estimated using artificial neural network.

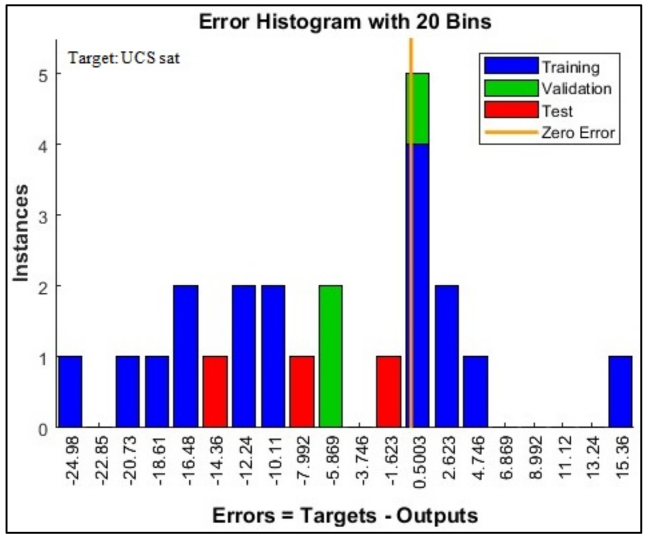

Figure 16. Error histogram of neural network model for estimating uniaxial compressive strength in saturated state

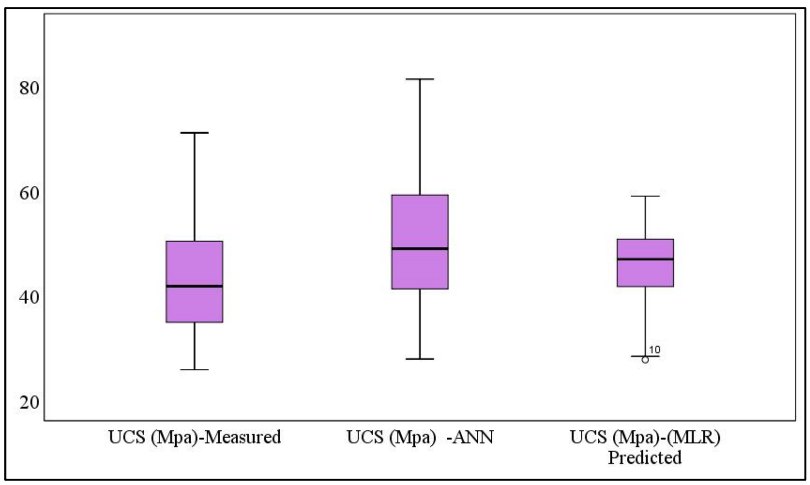

Figure 17. Comparison of the value of uniaxial compressive strength in three methods: measured, artificial neural network, predicted by multivariate regression using box plot in dry state

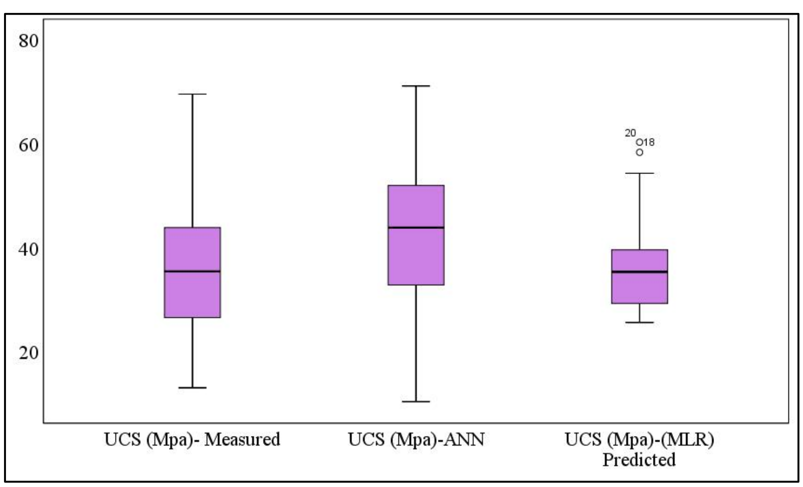

Figure 18. Comparison of the value of uniaxial compressive strength in three methods: measured, artificial neural network, predicted by multivariate regression using box plot in saturation state

It can also be seen that Area_mean in figures 17 and 18 has more variation for UCS obtained from neural network. We also get information about data compression or symmetry from these two forms.

Based on these two ways of using artificial neural network, more reliable results are obtained. In these graphs, the standard deviation of each variable is drawn as lines above and below each graph, based on which it is possible to judge whether the average of groups or variables is equal or different, and to measure the range of each parameter, which in Figure 17 means the dry state of the average. The samples in the three methods are almost close to each other. In Figure 19, we have compared the value of R in two methods of multivariate regression and artificial neural network, which shows that in both dry and saturated conditions, the value obtained from artificial neural network has obtained more acceptable results.

Table 3. Classification of virgin rock based on uniaxial compressive strength in megapascals (Deere and Miller, 1966; Bieniawski, 1979)

Noun	Deere and Miller	Noun	Bieniawski
Very low	28>	Very low	1-5
Low	28-56	Low	5-25
Middle	56-112	Relatively low	25-50
High	112-224	Middle	50-100
Very high	224<	High	100-250
		Very high	250<

Table 4. Statistics of the relationship between uniaxial compressive strength in two dry and saturated states, with physical properties

Regression equation	(R^2)
$\mathrm{UCS_{dry}} = 16.44\ \mathrm{Gs} + 19.46\ \gamma_{\mathrm{dry}} - 11.72\ \mathrm{Log\,W.A} - 0.99\ \mathrm{Log\,n} - 525.37$	0.413
$\mathrm{UCS_{sat}} = 82.02\ \mathrm{Gs} + 210465.7\ \gamma_{\mathrm{sat}} - 1.80\ \mathrm{Log\,W.A} - 6.03\ \mathrm{Log\,n} - 210665.2$	0.480

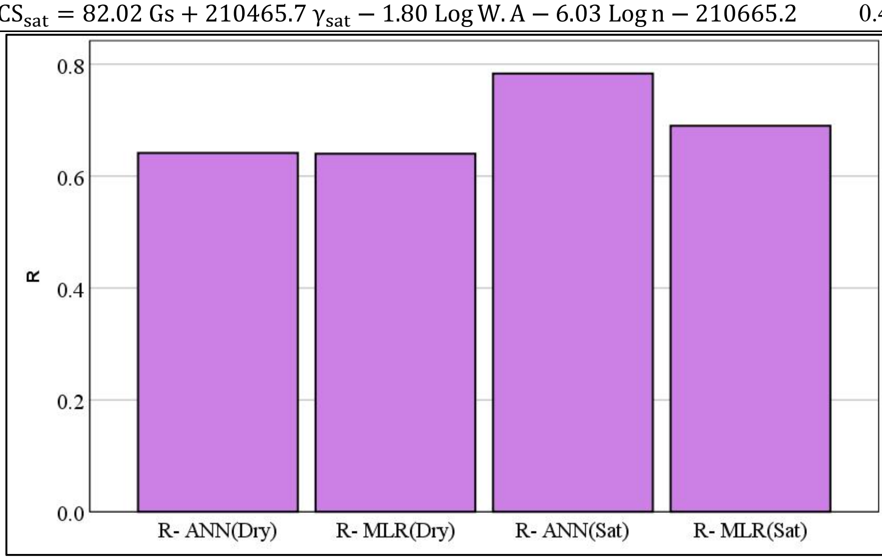

Figure 19. Comparison of R value obtained from two methods of multivariate regression and artificial neural network in two states of dry and saturated sample using histogram chart

Conclusions

In this research, the obtained experimental relationships were used to estimate the uniaxial compressive strength of Esfandiar formation limestones using physical characteristics. For this purpose, physical properties including solid specific gravity (Gs), porosity (n), dry specific gravity (γ_{dry}), saturated specific gravity (γ_{sat}), water absorption ability (W.A) on 25 dry cylindrical core samples and 23 core samples The saturation of the limestones of this formation was evaluated and the range of resistance obtained in the dry state is between 20 and 80 MPa and in the saturated state it is between 10 and 70 MPa. Then, using perceptron multilayer neural network, the effect of these characteristics on uniaxial compressive strength was evaluated in both dry and saturated states.. The coefficient of determination in training mode, performance, test mode and in general mode in the dry state of the sample is equal to 0.67, 0.96, 0.50, 0.64 respectively, and for saturated mode, it is equal to 0.70 respectively, 0.90, 0.99, 0.78. These numbers show that the performance of the neural network has high reliability. The evaluation of mean square error and coefficient of determination of this research showed that the estimation of uniaxial compressive strength using this model is very appropriate. The comparison of the value of uniaxial compressive strength in the two methods of perceptron multilayer neural network and multivariate regression with the experimentally measured value shows that the value of uniaxial compressive strength obtained in the neural network method in the Esfandiar Formation limestone sample is closer to the value measured in the laboratory than the multivariate regression.

Acknowledgments

The authors of this article consider it necessary to express their gratitude to the Department of Geology of Ferdowsi University of Mashhad for providing the necessary facilities to carry out research project number 56873. We would like to thank Mr. Hamid Hafezi Moghadas, the head of the Engineering Geology Laboratory of the Ferdowsi University of Mashhad. They are also grateful to Tabas Geopark for assisting in sampling the required stone blocks.

References

Abdelhedi, M., Jabbar, R., Mnif, T., & Abbes, C., 2020. Prediction of uniaxial compressive strength of carbonate rocks and cement mortar using artificial neural network and multiple linear regressions. Acta Geodynamica et Geomaterialia, 17(3): 367-377.

Abdi, Y., Ghasemi Dehnavi, A., 2018. Prediction of uniaxial compressive strength and elastic modulus of sandstones using artificial neural network and multivariate regression analysis. New Findings of Applied Geology, Volume 13, Number 26: 45-54.

Ajal Luian, R., Mansoori, H., Mohammadi, M., 2013. Prediction of the elastic modulus of limestone using multivariate regression and artificial neural network. Journal of the Iranian Engineering Geological Society, Volume 5, Number 3: 33-38.

Akbari Poursalimi, Sh., Nikfar, Maryam., 2017. Prediction of urban development using sentinel satellite images by neural network method. Technology Quarterly in Air and Space Engineering, Volume 2, Number 3: 13-22.

Amanpour, S., Soleimani Rad, A., Keshtkar, L., Mokhtari Chelche, S., 2013. estimation of Ahvaz city housing price using neural network. scientific-research quarterly of economics and urban management. Volume 3, Number 9: 45-57.

Aras, A., Özşen, H., Dursun, A., 2019. Using Artificial Neural Networks for the Prediction of Bond Work Index from Rock Mechanics Properties. Mineral Processing and Extractive Metallurgy Review, 1–8.

Ashtoklin, Y., Nabavi, M., 1349. Geological map 1:250000 of Beshravieh Quadrangle.

Barham, W., Rababah, S., Aldeeky, H., Hattamleh, O. H., 2020. Mechanical and Physical Based Artificial Neural Network Models for the Prediction of the Unconfined Compressive Strength of Rock. Geotechnical and Geological Engineering, 38(5): 4779-4792.

Bieniawski Z.T., 1974. Estimating the strength of rock materials. Journal of the Southern African

Institute of Mining and Metallurgy. 74: 312-320.
Bieniawski, Z.T., 1976. Rock mass classification in rock engineering. Explor Rock Eng, Proc Symp. 1.97–106.
Cargill, J.S., Shakoor, A., 1990. Evaluation Of Empirical Methods For Measuring The Uniaxial Compressive Strength Of Rock. Int J Rock Mech Min Sci & Geomech Abstr, 27:495-503.
Deere D., Miller R., 1966. Engineering classification and index properties of intact rock.Technical Report No. AFNL-TR.65-116.
Ebdali, M., Khorasani, E., Salehin, S., 2020. A comparative study of various hybrid neural networks and regression analysis to predict unconfined compressive strength of travertine. Innovative Infrastructure Solutions. 5: 1-14.
Emami, M., Yathrabi, S., 2014. Application of artificial neural network in the interpretation of barometric test results. Madras Civil Engineering. Volume 14. Number 20. 11-25.
Esmaili, M., Pashandi, M., Hashemi Esfahanian, Mahmoud., 2016. Estimation of modulus of elasticity of virgin rock using artificial neural network and nonlinear regression. Advanced Applied Geology. Volume 6, Number 3: 10-28.
Ferentinou, M, Fakir, M., 2017. An ANN approach for the prediction of uniaxial compressive strength, of some sedimentary and igneous rocks in Eastern KwaZulu-Natal. International Society for Rock Mechanics and Rock Engineering. Ostrava.
Fursich, F.T., Wilmsen, M., Seyed-Emami, K., Majidfard, M.R., 2003. evidence of Synsedimentary Tectonics in the Northern Tabas Block, East-Central Iran: The Callovian (Middle Jurassic) Sikor Formation-Facies. 48: 151-170.
Ghafoori .M., Rastegarnia .A., Lashkaripour. G.R., 2018. Estimation of static parameters based on dynamical and physical properties in limestone rocks. Journal of African Earth Sciences.1.
Hacıefendioğlu, K., Genc, A. F., Nayır, S., Ayas, S., Altunışık, A. C., 2022. Automatic Estimation of Post-fire Compressive Strength Reduction of Masonry Structures Using Deep Convolutional Neural Network. Fire Technology. 58(5): 2779-2809.
Hagan, M. T., Demuth.H. B., Beale. M. H., Jesús. O. D., 2014. Neural Network Design, (2 edition), 1012 p.
Hallam, A., 2001. A review of the broad pattern of Jurassic sea-level changes and their possible causes in the light of current knowledge, Paleogeography. Paleoclimatology, Paleoecology. 167: 23-37.
Hassan, M. Y., & Arman, H., 2022. Several machine learning techniques comparison for the prediction of the uniaxial compressive strength of carbonate rocks. Scientific Reports, 12(1).20969.
Heydari, M., Rafiei, B., Nouri, M., Khanleri, G., Momeni, A., 2014. Estimation of uniaxial compressive strength and modulus of elasticity of conglomerate samples using regression and artificial neural network. Geotechnical Geology Journal. 1(3): 35-46.
Huang, M., Peng, G., Zhang, J. And Zhang, S., 2006. Application Of Artificial Neural Networks To The Prediction Of Dust Storms In Northwest China. Journal Of Global And Planetary Change .52: 216 – 224.
ISRM, 1981. Rock Characterization, Testing and Monitoring. In: Brown, E.T. (Ed.). ISRM suggested methods. Pergamon Press, Oxford.
ISRM, 2007. The complete ISRM suggested methods for rock characterization, testing and monitoring, In: Ulusay R, Hudson JA (eds). Suggested methods prepared by the commission on testing methods.
Jafaripour,f., Hafizi Moghads, N., Lashkaripour,G R., 2015. engineering geological investigation of limestone decorative stones (case study of Mashhad city). I National Geology and Resource Exploration Conference
Jin, X., Zhao, R., Ma, Y., 2022. Application of a Hybrid Machine Learning Model for the Prediction of Compressive Strength and Elastic Modulus of Rocks, Minerals, 12(12):1506.
Minhaj, M.B., (1379), Computational intelligence, first volume: Basics of neural networks. first edition, Amirkabir University of Technology. Tehran. 502.
Moradi, M., Lashkaripur, GH., Ghafouri, M., 2016. Investigating the effect of durability index on the mechanical properties of Tirgan formation limestones, 5th National Conference of Applied Researches in Civil Engineering, Architecture and Urban Management, Tehran, Khwaja Nasiruddin Tousi University of Technology.
Motahari, M., 1400. Investigating the effect of index parameters on the static properties of limestone in dry and saturated conditions using artificial neural network. New findings of Applied Engineering

Geology. Volume 15 (30): 113-95.

Moussas, V. C., & Diamantis, K., 2021. Predicting uniaxial compressive strength of serpentinites through physical, dynamic and mechanical properties using neural networks. Journal of Rock Mechanics and Geotechnical Engineering. 13(1): 167-175.

Norusis, m.j., 1994. SPSS Advanced Statistics Company. Chicago, Illinois, 606 p.

Pala, M., Erdogan O., Ahmet., O., Ishak Yuce, M., 2007. Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks.Construction and Building Materials 21: 384 –394

Rastegarnia, A., Teshnizi, E. S., Hosseini, S., Shamsi, H. and Etemadifar, M., 2018. Estimation of punch strength index and static properties of sedimentary rocks using neural networks in southwest Iran. Measurement. 128: 464-478.

Safari Farrokhd, S. Lashkaripur, Gh. R. Hafizi-moqds, N., 2018. Evaluation of the brittleness index 20S of limestone and investigation of factors affecting it in dry and saturated state. Journal of the Engineering Geological Society of Iran, volume 12, number 3, pages 21-36Atmospheric Environment. 215-222

Tan, M., Li, X., Xin, L., 2014. Intensity Of Dust Storms In China From 1980 To 2007: A New Definition. Atm ospheric Environment. 215-222