NÖHÜ Müh. Bilim. Derg. / NOHU J. Eng. Sci., 2022; 11(4), 1127-1137

Niğde Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi
Niğde Ömer Halisdemir University Journal of Engineering Sciences

Araştırma makalesi / Research article

www.dergipark.org.tr/tr/pub/ngumuh / www.dergipark.org.tr/en/pub/ngumuh

Predicting compressive strength using the texture coefficient with soft computing techniques for rocks

Kayalar için yapay zekâ hesaplama teknikleri ile doku katsayını kullanarak basınç dayanımını tahmin etme

Ramazan Çomaklı[1,*], Ümit Atıcı[2]

[1, 2] *Niğde Ömer Halisdemir University, Mining Engineering Department, 51240, Niğde, Türkiye*

Abstract

Rock strength plays one of the most dominant roles for mining, geology, and civil engineering in terms of planning, excavation, and safety. Compressive strength (fc), which is the most used strength type, requires time, cost, and standard size specimens are needed to find it in the laboratory. In this study, Regression Analysis (RA), Neural Networks (NNs), Gene-Expression Programming (GEP), and Adaptive Network-based Fuzzy Inference System (ANFIS) were used for predicting using both textural and mechanical properties which are detected with a dimensionless sample or directly in the field. For this purpose, a data set consists of 136 data value (46 magmatic, 77 sedimentary and 13 metamorphic rocks) was used, and three different feature sets were constructed. The comparison of the estimated results with each other was performed by training, testing, and checking of these models. The comparisons and results of the statistical analyses indicate that soft computing techniques represent significantly effective methods to calculate fc even in situations when input and output values are not related to each other, and it is possible to create statistically suitable and valid mathematical models by everyone using GEP.

Keywords: Texture coefficient, Rock compressive strength, Adaptive network-based fuzzy inference system, Neural networks, Gene-expression programming.

Öz

Kaya dayanımı, planlama, kazı ve güvenlik açısından madencilik, jeoloji ve inşaat mühendisliği için en baskın rollerden birini oynar. En çok kullanılan dayanım türü olan basınç dayanımını (*fc*), laboratuvar şartlarında bulmak için zaman, maliyet ve standart boyutlu numunelere ihtiyaç vardır. Bu çalışmada, kayaların şekilsiz numuneler üzerinde veya araziden elde edilen hem doku katsayıları hem de basınç dayanım değerleri regresyon analizi (RA), Sinir Ağları (NN'ler), Gen- ekspresyonu Programlama (GEP) ve Uyarlanabilir Ağ Tabanlı Bulanık Mantık Sistemi (ANFIS) kullanılarak tahmin edilmiştir. Bu amaçla 136 veriden oluşan bir veri seti (46 magmatik, 77 tortul ve 13 metamorfik kayaç) kullanılmış ve üç farklı özellik seti oluşturulmuştur. Tahmin edilen sonuçların birbirleri ile karşılaştırılması bu modellerin eğitimi, test edilmesi ve kontrol edilmesi ile yapılmıştır. İstatistiksel analizlerin karşılaştırmaları ve sonuçları, yapay zekâ hesaplama tekniklerinin, girdi ve çıktı değerlerinin birbiriyle ilişkili olmadığı durumlarda bile *fc*'yi hesaplamak için önemli ölçüde etkili olduğunu ve istatistiksel olarak uygun ve geçerli matematiksel modeller oluşturmanın GEP kullanan herkes tarafından yapılmasının mümkün olduğunu göstermektedir.

Anahtar kelimeler: Doku katsayısı, Kaya basınç dayanımı, Adaptif ağ tabanlı bulanık mantık sistemi, Sinir ağları, Gen ekspresyonu programlama.

1 Introduction

Knowing the strength of rock masses plays the most important role in mining, geological, drilling and tunneling engineering. Planning, design, and cost analysis for businesses require the dominance of these features. Uniaxial compressive strength (*fc*) takes first place among the most significant characteristics of rocks to predict their behaviors, and its importance has been mentioned by many researchers. The International Society for Rock Mechanics ISRM, [1] and the American Society for Testing and Materials [2] are the main standards for the methodology of laboratory testing to determine the *fc* . However, these tests are time-consuming and costly. Therefore, many researchers studied to develop new models to predict *fc*, based on the other physico-mechanical characteristics of rocks that can be obtained with easier test methods [3, 4, 5, 6] .

There are many different parameters that influencing the mechanical properties of rocks. Textural properties, such as the ratio of total grain area to matrix area, the type of cement in the matrix, the degree of cementation, and mineral composition, are all effective parameters on rock strength. There have been several different studies that investigated the effect of textural characteristics on the mechanical properties of rocks since the 1970s, and it has been determined that the mechanical properties of rocks are closely related to their texture [7-13].

Through the statistical gauge, Howarth and Rowlands [14] carried out the development of a texture coefficient (TC), which sums up the main textural parameters of rock and indicates it as a single dimensionless factor. One of the

* Sorumlu yazar / Corresponding author, e-posta / e-mail: rcomakli@ohu.edu.tr (R. Çomaklı)
Geliş / Recieved: 06.08.2022 Kabul / Accepted: 14.09.2022 Yayımlanma / Published: 14.10.2022
doi: 10.28948/ngmuh.1158645

benefits of TC is to utilize thin sections instead of thick, uniform samples and easily comprehend the influence of textural parameters in the mechanical properties of rock. Ersoy and Waller, [15] investigated this influence in drilling performance regarding the strength of limestone, sandstone, and siltstone and the possible relation of these strengths with the texture coefficient of those rocks. The exploration of the link between TC and the quality of the rock was carried out by estimating the uniaxial compression strength of tuff, limestone, and basaltic andesite [16]. A strong relation between TC and *fc* was found for quartzite of the Himalayas by Gupta and Sharma [16]. Ozturk et al. [17] and Ozcelik et al. [18] examined the association between TC and various parameters in marble. Similarly, Atici and Comakli [19] evaluated the physical and mechanical characteristics of plutonic rocks based on TC. However, these studies were based mostly on only one rock type and statistical investigation of data sets.

An invariable-multivariable regression analysis (RA), both linear and non-linear has been used to perform statistical analyses. RA aims at simultaneously determining two or more independent variables explaining alterations in the dependent variable. The benefits of RA are that it does not require software, creates straightforward regression constants, and evaluates the importance level of different input parameters. For a better RA, a robust link between independent and dependent variables is needed, but this is not always feasible. The major deficit of classical modeling methods is that these methods are not human-interpretable models. To deal with these restrictions and challenges, apart from RA, a few alternate soft computing techniques have been developed to give human-like decisions in diverse fields of engineering. Gaining knowledge both empirically and theoretically is among the key features of soft computing. Genetic programming (GP), neural networks, and fuzzy logic are commonly utilized for numerous applications in various engineering fields. Gokceoglu et al. [20] and Singh et al. [21] both carried out researches by utilizing NN and FL to estimate the elastic behavior of rocks, particularly elastic constants. The saturation percentage of soil was assessed by Aali et al. [22] by multiple regression and ANN. Ozbek et al. [6] used GP to estimate the *fc* based on the natural unit weight and water absorption of rocks by taking into account the weight and effective porosity values. The researchers found out that soft computing techniques are a good and flexible option for determining uncertainties in rock characteristics.

Although there have been many previous studies on the prediction of *fc* in the literature, these studies have mostly been obtained by using the mechanical properties of the rocks and it is often necessary to use samples with certain and large dimensions. Since only the mechanical characteristics of the rock were used, a separate model was produced for each rock type. The rock types are determined by using the petrographic properties of the rocks. For example, the degree of crystallization of magmatic rocks, shapes, and dimensions of the rock-forming minerals, and matrix features are determinants in the classification of magmatic rock. Likewise, the presence and severity of foliation in metamorphic rocks are some of the criteria considered in the classification of these rocks. These properties are used in the calculation of texture coefficients. This study, unlike previous studies, aims to develop a single model which can be valid for each rock group by including the mechanical and textural characteristics of rocks in terms of evaluating the compressive strength of the rocks.

The focus in this study is the prediction of *fc* using both mechanical and textural properties which don't require uniformly shaped and relatively large samples. For this purpose, RA, ANN, ANFIS, and GEP were used for the prediction of the *fc* values for diverse rock types. In the sets of the models' Texture Coefficient, Density (ρ), Schmidt hardness (SH), and Ultrasonic P wave velocity (Vp) were included as input variables while the Compression strength (*fc*) values were utilized as outputs.

2 Texture coefficient

It is possible to estimate the mechanical parameters such as *fc*, Brazilian tensile strength (BTS), and so on based on the textural properties of rocks. Therefore, Howarth and Rowlands, [14] carried out the development of TC, which defines the textural properties of rocks. It is known that rock texture plays a role in physical strength against the breaking of the rock under the effect of load. While pressure influences those rocks, causing them to break into pieces, a zone of high stress is generated. As those rocks will be held pressed under strength, strength forces will surpass the rock strength, and the material will crack. Cracks initiation and propagation take place at the surface, and laterally under the material. In the last stage, the breaking of the rock occurs by the arrival of a major fissure at the surface [23].

One of the main methods to evaluate the correlation between geomechanical and textural properties of rocks is to use the TC. Degree of grain packing (AW), grain circularity (FF_0), elongation (N_0, N_1, AR_1), and Orientation (AF_1) are four components in computing the rock texture. The results can be derived from the formula presented below;

$$TC = AW\left[\left(\frac{N_o}{N_o+N_1}x\frac{1}{FF_o}\right)+\left(\frac{N_1}{N_o+N_1}xAR_1xAF_1\right)\right] \qquad [1]$$

Here, AW is the grain packing weighting, N_0 is the number of grains with aspect ratio less than 2.0, and N_1 is the number of grains with AR greater than 2.0. Structure Fig.s (FF_0) are the math average of the structural component for non-elongated grains. Perspective proportion (AR_1) is the mean for lengthened grains' angle proportions. AF_1 is used to quantify those introductions to lengthened grains, as time AW is that grain pressing weighting by Howarth and Rowlands [14].

3 Regression analysis

Regression analysis is utilized for modeling the association between a response variable and one or more predictor variables, and it is expressed in a mathematical model. This association can be linear or non-linear. In case response and a predictor variable are one, this is simple regression. On the other hand, in the case of more than one independent variable, it is called multivariable regression (MVR). For defining at the same time more independent variables justifying alterations in the dependent variables, MVR can be applied. The observed case in a regression model represents a dependent variable, while the observation affecting the case represents a dependent variable and the event affecting the observation represents an independent variable. Regarding the fitted regression model, it is possible to estimate the dependent variable value for any value of the independent variable.

In this study, 136 data sets were utilized in the estimation of *fc* based on the textural coefficient and physical properties such as ρ, SH, and ultrasonic pulse velocity (Vp). The rock blocks consist of sedimentary, magmatic, and metamorphic rock. The relationship between *fc*, TC, ρ and *fc*, SH, Vp is presented in Fig. 1 a,b, respectively, three-dimensionally, and the physico-mechanical properties of rocks are given in Table 1.

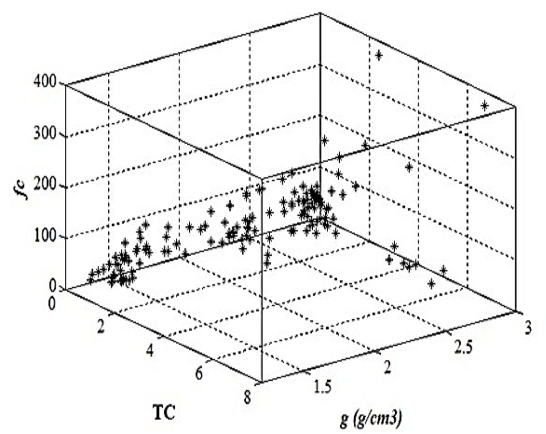

Fig. 1 a The relationship between *fc* and TC, ρ.

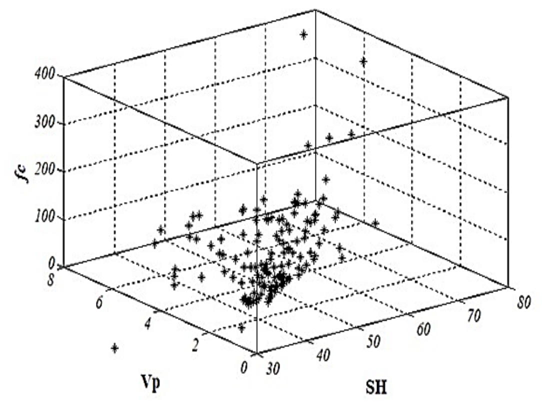

Fig. 1 b The relationship between *fc* and V_p, SH.

Table 1 Physical and mechanical properties of rocks used in experiments.

	Min	Max	Mean	Standard deviation
fc (MPa)	9.80	375.20	72.29	49.20
TC	0.11	6.76	1.39	1.18
ρ (g/cm^3)	1.36	2.99	2.24	0.49
SH	34.00	75.00	50.31	7.40
V_p (km/s.)	1.48	7.44	3.64	1.18

A reliable correlation is needed between dependent and independent variables for better regression analyses. A simple nonlinear and multivariate linear regression analysis has been conducted for the purpose of performing the statistical analyses. As an initial phase of the research, simple regression analyses were carried out. As seen from Table 2, the correlation values (R) of all models are very low, and the standard errors of the estimates are high. This is because the correlation between the *fc* of the rocks and T.C. is low. Howarth and Rowlands [14], Azzoni et al. [24], and Alber and Kahraman [25] found a high correlation in the rocks they studied, unlike Ersoy and Waller [15] because they investigated a single rock type. However, even for different rocks of the same species, different properties can be mentioned.

Table 2 Models developed using simple regression.

Functional form	Model	Correlation Coeff. (r)	Std. Error of the Estimate
Linear	fc =55.06+12.38TC	0.297	47.148
Logarithmic	fc=71.85+25.17Ln(TC)	0.425	44.703
Inverse	fc =87.63-(10.83/TC)	0.319	46.802
Quadric	fc=16.39+62.29TC-9.27(TC)^2	0.551	41.363
Cubic	fc=15.5+64.39TC-10.34TC^2-0.12TC^3	0.551	41.512
Compound	fc =45.62*(1.20^{TC})	0.319	0.639
Power	fc =58.37*TC$^{0.36}$	0.445	0.604
S	Ln(fc)=4.28-(0.159/TC)	0.321	0.638
Growth	Ln(fc)=3.82+0.18$^{(TC)}$	0.319	0.639

In the next step of the analysis, a set of various regression analyses was built. Regression models were developed by using the default method of entering data in the Statistical Package for Social Science software (SPSS). In MRA, the variable selection process is used in which all variables in a block are entered in one step. The statistical analysis was performed at a confidence interval of 95% based on F and t-test values. As a brief explanation of the regression models, the statistical parameters were calculated at a confidence level of 95% since the level in question is usually utilized in statistical analyses. (Table 3). On account of studying the significance level of the variables in the model, a t-test was utilized with a 95% confidence interval. For these models, the t-test showed that the models were not valid, and standardization of the data did not change the results.

4 Artificial neural network

The Nerve Network (NN) exemplifies an artificial intelligence implementation that, nowadays, has been used in a broad spectrum for modeling human activities in various scientific and engineering projects [26]. Neural networks are based on a principle that a system of basic processing elements, biologically similar to the human brain, but in a simplified manner and extremely co-dependent, can absorb the nature of abstruse bonds between independent and dependent variables, which forms the basis of ANNs. NN represents a set of highly parallel structures which may be utilized for solving complex problems through the alliance of significantly interrelated but basic computing elements (or artificial neurons) [26, 27].

Table 3 Statistical summaries for the models of *fc* (at the confidence level of 95%).

Independent variable	Coefficient	t Value	t Sig.	Coefficient R	Coefficient R^2	Adj. R^2	Model Error	F Value	F Sig.
Constant	-219.16	-12.66	0.000						
TC	-2.21	-4.49	0.62						
ρ	12.69	1.85	0.07	0.85	0.72	0.71	26.50	85.97	0.00
SH	5.00	13.73	0.00						
V_p	4.07	0.89	0.38						

As seen in Fig. 2, ANN is a processing system that contains an inlet layer, an outlet layer, and one or more concealed layers interconnected by neurons, all of which are distributed in parallel. Through the function of transfer, a processing element created by a single neuron constitutes an outlet signal by taking one or more outlets. A reference to each link is a weighting that states the influence of a set of inputs or other process elements in the previous layer on current process elements. In the first stage, coincidental values are used for bias and weighting. The subsequent stage is to fix them with the outcomes of training work.

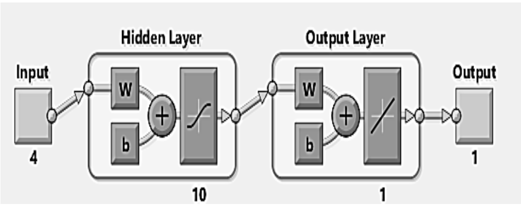

Fig. 2 Typical architecture of a multilayer perception neural network.

A neural network consists of two or three phases that are generally training, testing, and checking. An adjustment of the network is performed per the acquired errors, and processing of the sample data, inputs, and intended outputs, is carried out to optimize the output of the network and therefore minimize deviation. Checking is utilized for measuring the generalization of the network and for stopping training at the moment when generalization stops improving. Testing does not influence training, which therefore ensures an independent measure of the network performance in the course of and after training.

4.1 Structure and parameters of the artificial neural network model

In this study, an ANN model was developed to predict *fc*. TC, ρ, SH and Vp were utilized as input parameters of the ANN model. Herein, 106 data were utilized for the training of the models, 15 data were utilized for testing, and 15 data were used for the checking of the models. In three different stages of the modeling, training, testing, and control, the same datum was used to compare the findings from the RA, ANN, ANFIS, and GEP models.

The ANN toolbox in MATLAB was utilized for performing the required calculations. In a two-layer feed-forward network that was trained using the Levenberg–Marquardt method, a back-propagation training approach was applied. In case if a reasonable fit is not generated and the coefficients are not adequately constrained by the trust-region algorithm, it is necessary to employ the Levenberg–Marquardt algorithm. The back-propagation algorithm, which is one of the most widely used multilayer perception algorithms, is a gradient descent technique that reduces the error for a specific training pattern in which the weighting is always altered by a little amount, to a minimum [28]. In the current investigation, the hidden layer used a nonlinear hyperbolic tangent sigmoid transfer function, while the output layer used a linear transfer function. The momentum rate and learning rate were calculated, and the model was trained using many iterations.

The size of the hidden layer is a challenge that must be solved, and the amount and quality of training samples influence it to some extent. In the hidden layer, there is no principle for selecting the number of neurons. An ANN must have a sufficient number of neurons to accurately model the problem of interest. However, to generalize the network, the number of neurons in the ANN model should be as low as possible. In earlier studies, the number of neurons has been linked to the number of input and output variables, as well as the number of training patterns [29, 30]. Nevertheless, it is not possible to generalize the rules in question [31]. According to some experts, the highest limit for the number of neurons must be more than twice the number of input points. However, the network's generalization is not guaranteed by the above-mentioned rule. The number of neurons in the hidden layer was determined to be 10 in all three models by training a few networks with different quantities of hidden neurons and comparing the predicted results to the intended output. Table 4 contains information on the connection weightings and biases for the model.

5 Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS, which combines ANN and Fuzzy Logic (FL) techniques, is arguably the most widely used hybrid technique in engineering applications. ANFIS was developed by Jang [32] for use when the usage of the traditional approaches fails or is too complex. The ANFIS aims to find a model that will perform the correct simulation of the inputs with the outputs, and spending a lot of effort on system modeling is not required in the ANN during the development of a mathematical model describing the prediction of physical characteristics of the unknown system accurately over an operational range [33]. Since FL is established based on the fuzzy IF-THEN rules, there is no need for the details of the mathematical model.

Table 4 Optimized parameters (weighting and bias) of the neural network models.

Input		Layer 1					Layer 2		Output	
xoffset	gain	Bias	Weight				Bias	Weight	xoffset	gain
0.114	0.301	2,527	-1.968	0.431	0.903	1.102		0.419		
0.487	0.799	-1,750	2.165	-0.0116	2.223	0.584		0.336		
7.401	0.030	-1,951	1.598	-1.290	-1.417	-0.653		0.150		
1.179	0.320	0.760	-1.628	-0.223	-0.197	0.040		0.804		
		0.008	-0.503	0.490	0.089	-2.817	-0.663	-0.170	9.8	0.0055
		-0.524	-0.063	-0.684	3.865	0.562		0.710		
		1.075	1.451	-0.145	1.503	-2.417		-0.517		
		-0.944	-1.219	-0.646	0.940	1.923		-1.123		
		3.271	0.765	1.610	-3.756	-2.143		-1.775		
		2.729	0.433	0.490	-2.525	0.753		0.998		

Furthermore, nonlinearities and uncertainties in systems that are not possible to describe using accurate mathematical models can be sufficiently expressed by FL. Any nonlinear function can be approximated by FL over a compact set [33, 34].

By utilizing the available input/output data set, the toolbox function ANFIS performs the construction of a Fuzzy Inference System (FIS), of which membership function parameters are adjusted by employing a backpropagation algorithm alone or its combination with a least squares type of method. Two certain approaches have been constantly used; The Mamdani and Takagi–Sugeno (TS) models [5, 35]. Linear and constant behavior of output membership functions in the Sugeno model differentiates it greatly from the Mamdani model. Therefore, for more compact and efficient representation it is suitable for employing adaptive techniques in the construction of fuzzy models such as the Sugeno model. These above-mentioned adaptive techniques can also be utilized for customizing the membership functions in such a way that the data are modeled by the fuzzy system in the best way. The mechanism of reasoning for the Sugeno model in question is presented in Fig. 3.

Furthermore, by employing the given data set, the neural training process adaptively develops fuzzy rules and membership functions. Therefore, two methods, such as grid partitioning and subtractive clustering, are used in ANFIS [36].

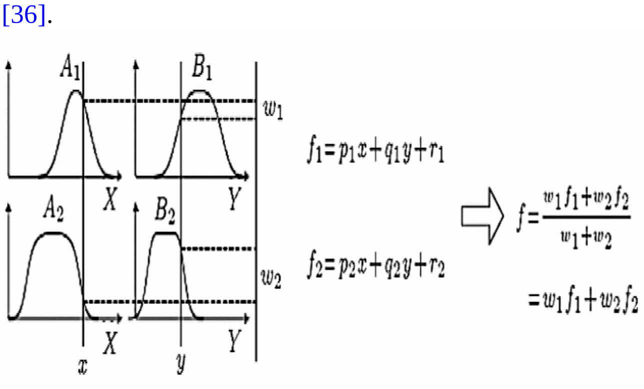

Fig. 3 The reasoning method of the Sugeno model.

The first-order Sugeno-type fuzzy inference system is named after the linear function, while the zero-order Sugeno-type fuzzy inference system is named after the constant function. To keep things simple, we'll assume there are two inputs (x, y) and one output (f), as well as a governing rule based on the two if-then rules of the Takagi and Sugeno types in the ANFIS:

Rule1: If $x=A_1$ and $y=B_1$, then $f_{1(x,y)}=p_1x+q_1y+r_1$.

Rule2: If $x=A_2$ and $y=B_2$, then $f_{2(x,y)}=p_2x+q_2y+r_2$.

Where x (or y) denotes the input node I p, q, and r denote the training-derived consequence parameters, and A and B denote the labels of the fuzzy set providing an appropriate membership function.

The parameters related to the membership functions vary during the process of learning. A gradient vector calculates the parameters in question, or their adjustment, easier. The above-mentioned gradient vector ensures that the fuzzy inference system models the input and output data for a given set of parameters as well as possible. When acquiring the gradient vector, it is possible to apply any of a few optimization routines for adjusting the parameters to decrease some error measures. The difference between the real and predicted results multiplied by the square of the difference generally determines the magnitude of the error in question. Back-propagation or a least-squares estimation with back-propagation and back-propagation for estimating the parameters of the membership function is utilized in the ANFIS. The back-propagation learning algorithm or the hybrid learning algorithm that is well represented by Demuth and Beale Mark, [37] was utilized to update the membership function. In Fig. 4, the basic structure for an ANFIS model is illustrated. As is seen from the Fig., the ANFIS model has five layers in which mathematical calculations are made.

The four essential components of the ANFIS are fuzzification, fuzzy rule basis, fuzzy inference engine, and defuzzification. Furthermore, it is possible to add input and output data. Based on the improvement in one or more membership functions, each item of data in the input is transformed to different levels of membership by fuzzification. The fuzzy rule base has rules containing every potential fuzzy association between input and output data. The above-mentioned rules are presented in the IF-THEN format. All the fuzzy rules in the fuzzy rule base are considered by the fuzzy inference engine, and it learns how a set input can be transformed to the relevant outputs. The resulting fuzzy output data is converted into a number by defuzzification from the fuzzy inference engine [37, 38].

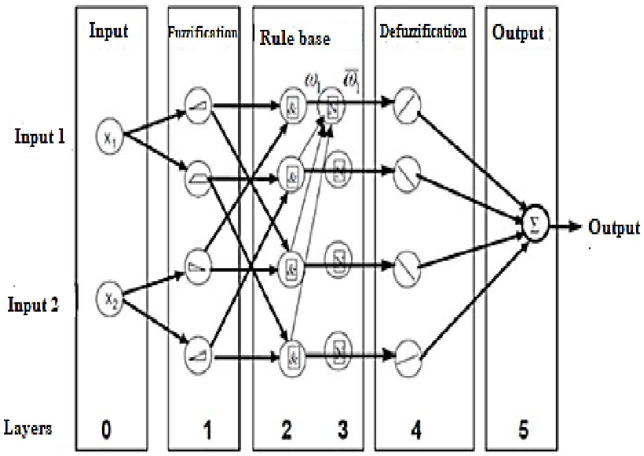

Fig. 4 The architecture of a two-input ANFIS network

5.1 *ANFIS Model structure and parameters*

Fuzzy modeling represents a system recognition task consisting of two main parts called structure definition and parameter estimation. A particular ANFIS type and applicable input data must be selected for the priority of the structure identification. Laterally, the quantity and kind of membership functions and fuzzy rules, as well as their antecedents and consequences are determined [39].

For predicting *fc* by using the textural and physical properties of rocks, the particular datasets were utilized to develop the ANFIS model, and other analysis methods were utilized in these models as well. The developed ANFIS model structure for the evaluation of *fc* is presented in Fig. 5. In this model, gaussian membership relations were utilized together with the Sugeno fuzzy inference models. Input variables plotted as membership function in training are presented in Fig. 6. To train the ANFIS models, 100 epochs are used and the prevention of overfitting is carried out by using the Minimum validation error as a criterion for halting. The ANFIS parameters in this model are summarized in Table 5.

Table 5 Properties of the generated ANFIS models.

	ANFIS Model
Type	sugeno
Number of fuzzy rules	81
NumInputs	4
Number of Input MFs	3 3 3 3
MF Type	Gaussmf
NumOutputs	1
Output	Lineat
Optim. Method	Backpropa
AndMethod	min
OrMethod	max
DefuzzMethod	wtaver

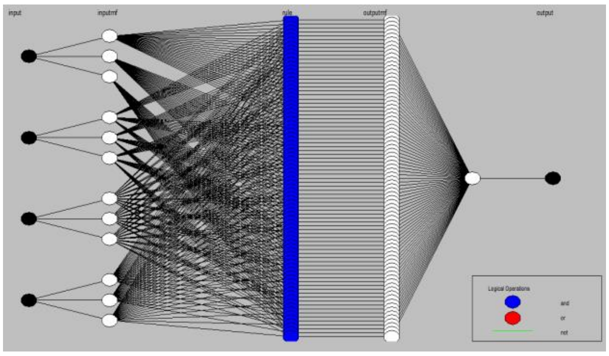

Fig. 5 The structure of the constructed ANFIS model for the prediction of *fc* used for TC, ρ, SH and V_p.

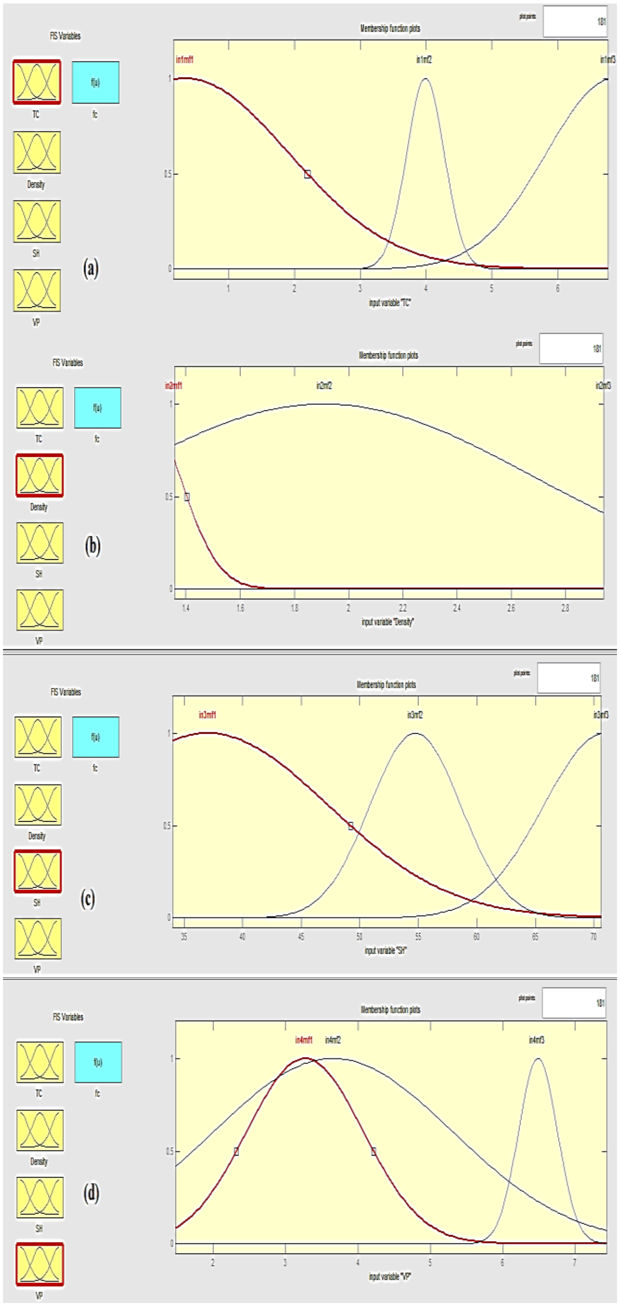

Fig. 6 Membership function plot for input (a) Texture Coefficient (TC); (b) ρ; (c) SH; (d) V_p.

The ANFIS toolbox (anfisedit) in the MATLAB program was utilized for the required calculations. As a result, 81 rules were obtained for *fc* as follows;

IF(TC is TCmfi) and (ρ is ρmfi) and (SH is SHmfi) and (V_p is $V_p$mfi) THEN (*fc* is *fc*mfi) (i=1,2,....81)

The surface graph of two input variables that were used to predict the *fc* is presented in Fig. 7 and Fig. 8. Fig. 7 illustrates that, when ρ increased, *fc* increasing to 1.8, and at higher ρ the *fc* increased slowly, and *fc* increased rapidly while TC decreased rapidly from 4 to 2.

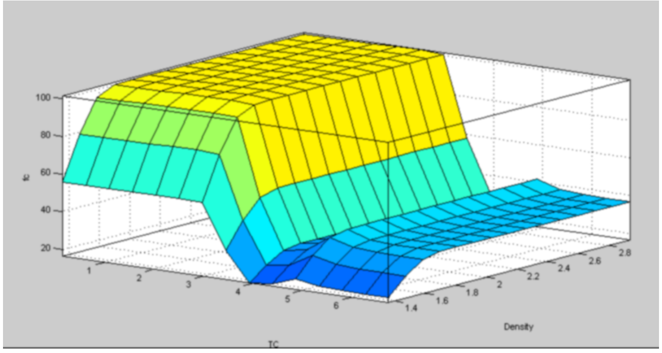

Fig. 7 Surface graph demonstrating the association of *fc* with TC and ρ.

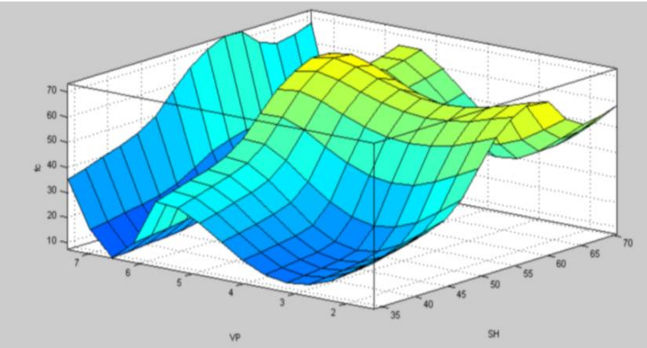

Fig. 8 Surface graph demonstrating the association of *fc* with V_p and SH.

6 Gene-expression programming (GEP)

The major disadvantage of the ANN and ANFIS methods is that they cannot provide mathematical prediction equations. The recommendation of the GP and GEP (a variant of GP) constitutes overcoming this issue. Gene-Expression Programming (GEP) cultivated by Ferreira [12] represents novel progressive artificial intelligence. This algorithm's fixed-length basic linear chromosomes are similar to the chromosomes used in genetic algorithms (GA), and the branched structures of varied sizes and shapes are akin to genetic programming's parse trees (GP). Its assessment system of any kind of information is similar to the biological assessment, and it represents a computer program the coding of which is performed in fixed-length linear chromosomes. The construction of a mathematical function, specified as a polygenetic chromosome, is done by utilizing the available data in the approach in the issue. Even though GEP largely does symbolic regression using the majority of GA and GP's genetic operators, GA, GP, and GEP all have their own set of differences. GA adopts any mathematical expression as fixed-length symbolic chromosomes (strings); these strings are also represented as nonlinear tree entities of various sizes and shapes (parse). However, in GEP, they are encoded as fixed-length simple strings that are consequently expressed as expression trees of various sizes and shapes [36, 40, 42].

The use of GEP approaches revealed a higher degree of nonlinearity between empirical and predicted values, as well as high sensitivity and low error. Because GEP combines the advantages of genetic algorithms (GA) and genetic programming (GP), it has proven to be an excellent modeling method for dealing with complex real-life situations and the complex relationships between the parameters that affect them. Fig. 9 depicts such a gene, its expression tree (ET), and its algebraic expression. Ferreira is a good resource for more information [36, 40-42].

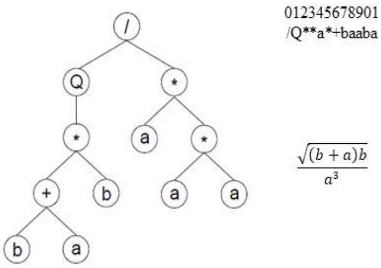

Fig. 9 A general illustration of the GEP expression tree and mathematical equation

6.1 GEP Model structure and parameters

To estimate *fc* using GEP, the model was constructed like ANN, and similar data were used in training, testing, and checking processes. The GeneXproTools software package was used to generate the GEP structure and choose the best prediction model and four main arithmetic operations (+,−, ∗, /) and many primary mathematical functions (3Rt, Avg, Inv, X2, X5, Min, Max, Not, Exp, Tanh, Ln) were used, and as the fitness function, the RMSE parameter was chosen.
The fitness of the output models is significantly affected by the setting parameter values in the GEP. They contain the number of genes, the chromosome number, the ratio of genetic operators, and the head size of the gene. GEP models typically utilized a single gene and two lengths of heads to choose the chromosomal tree, and then increased the number of genes and heads one by one, throughout each run, during testing and training performance of each model.

Following a series of experiments, the models with the greatest outcomes had three numbers of genes and head lengths of 7, 7, and 8, respectively. As a result of the inclusion for the GEP Model, the sub-ETs (genes) were connected.

Finally, as a set of genetic operators, a mix of transposition, mutation, and crossover was utilized. Table 6 lists the parameters utilized in the training model. The best individual generation for *fc* prediction was discovered to be Chromosome 30. The accurate formulation obtained from the constructed models for *fc* is given by;

$$f_c = \left[\sqrt[3]{[(212.204 - 3SH)x(DxSH)x(-0.289]x[D - SH + 48.112]x[\ln(SH)]}\right] + \left[\frac{\left(\frac{1}{D-TC}\right) + [\ln(TC) - (TC + SH - 111.547)]x}{[D + 2(V_p + D)]}\right] + [V_p + [TCx(D - 2.385)^5]x77.48] \quad [4]$$

Table 6 GEP parameters used in the developed model.

Parameter definition	GEP Model
Fitness function	RMSE
Number of chromosomes	30
Gene number	3
Inversion rate	0.00546
Mutation rate	0.00138
Gene recombination rate	0.00277
Gene transposition rate	0.00277
One-point recombination rate	0.00277
Two-point recombination rate	0.00277
Literals	21
Number of generations	2906680
Arithmetic operators	+ - x /
Mathematical function	3Rt, Mul3, Sub4, Ln, Add4, Inv, X^5
Tail Size	25
Head size	8
Gene Size	58
Linking function	Addition

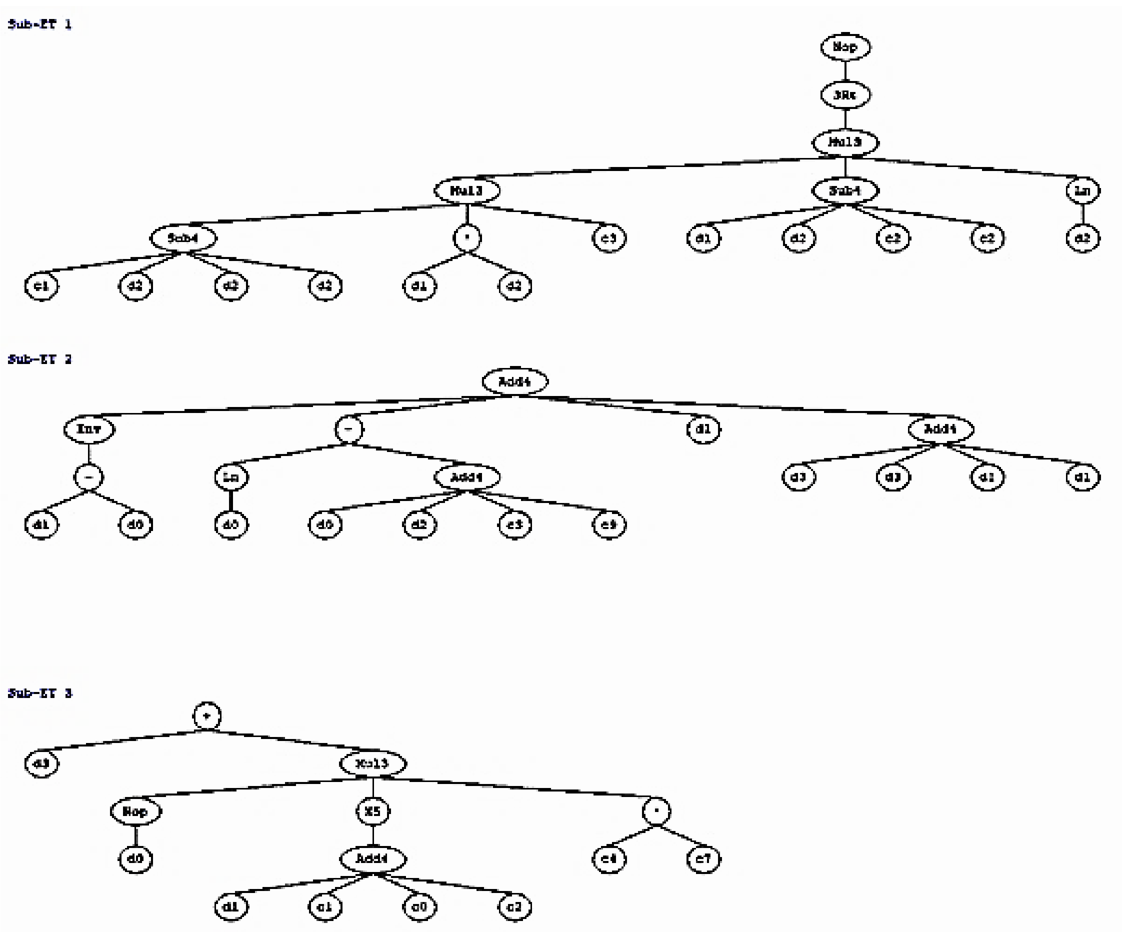

Fig. 10 Expression tree for GEP Model.

The formulation of the GEP model is shown in the expression tree in Fig. 10, where d_0, d_1, d_2, and d_3 refer to TC, ρ, SH and Vp, respectively. Table 7 presents the constants used in the formulation.

Table 7 Constants in the GEP model.

Constant	S-ET1	S-ET2	S-ET3
C_0	-8.32	-4.90	5.64
C_1	212.20	-6.68	-8.30
C_2	-24.06	-8.74	0.28
C_3	-0.29	-9.26	4.02
C_4	7.59	-2.49	7.39
C_5	5.22	-7.31	10.49
C_6	9.86	0.55	9.57
C_7	-1.38	-5.18	10.49
C_8	5.35	0.90	-5.75
C_9	-8.56	-102.29	9.89

7 Result and discussion

The *fc* of the rock was determined by RA and soft computing techniques, which are ANN, ANFIS, and GEP, by using the textural and physicomechanical characteristics of the rock. The subdivision of the database into three sets, being training, testing, and checking, was performed. To control the predictive capacity performance of the empirical models established in this work, the correlation coefficient (R) and root mean square (RMS) error indices were computed. Table 8 shows the statistical success of all of the generated models.

Experimental studies and training, testing, and checking results that were developed by RA, ANN, ANFIS, and GEP are presented in Fig. 11-13. According to the statistical parameter, methods for soft computing (ANN, ANFIS, and GEP) give acceptable compliance considering the statistical assessment criteria contrary to RA. Because ANN, ANFIS, and GEP do not require preliminary knowledge of the functional associations between the variables, the approach in question has been employed for solving inverse problems. Predicting *fc* by using the textural and physical properties of rocks is a very intractable and complex problem. The best outcomes concerning the R and RMSE values were provided by ANFIS (R: 0.95, RMSE: 10.94) from training. The above-mentioned values were found as 0.98 and 6.97 from testing and as 0.97 and 9.53 from checking. However, the other methods gave very close results, and the R and RMSE statistical values from training were found as 0.94 and 12.05 in ANN, and as 0.93 and 12.95 in GEP. Table 8 also shows the statistical values of *fc* calculated as R and RMSE as a result of training, testing, and control in this model. The suggested ANN, ANFIS, and GEP models are appropriate and forecast the *fc* values considerably near to the experimental values, as shown by all statistical values in Table 8. The calculated values had very small, noticeable deviations.

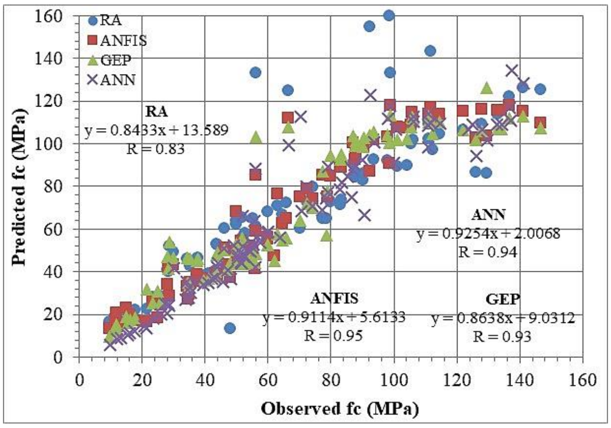

Fig. 11 Comparison between the experimental *fc* and the training outcomes.

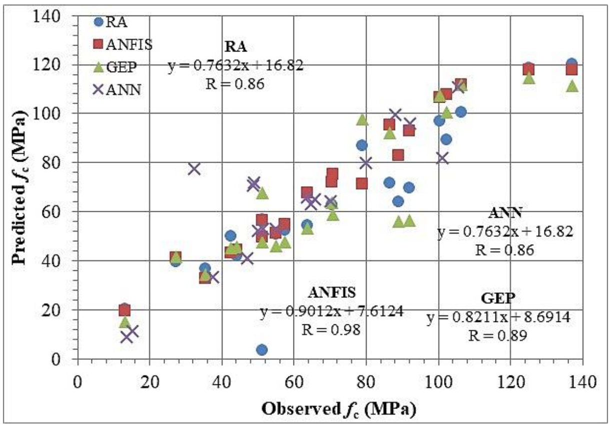

Fig. 12 Comparison between the experimental *fc* and the testing outcomes.

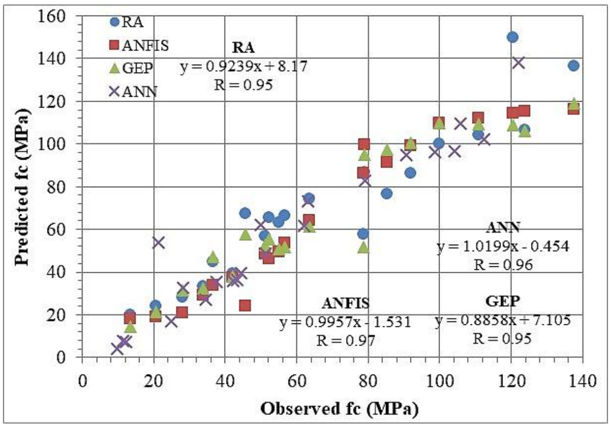

Fig. 13 Comparison between the experimental *fc* and the checking outcomes.

Table 8 The models' performance statistics.

Models	Training		Testing		Checking	
	R	RMSE	R	RMSE	R	RMSE
RA	0.83	22.98	0.86	15.03	0.95	11.78
ANN	0.94	12.05	0.86	9.81	0.96	15.79
ANFIS	0.95	10.94	0.98	6.97	0.97	9.53
GEP	0.93	12.95	0.89	14.76	0.95	10.81

8 Conclusion

In this work, four soft computing approaches, RA, ANN, ANFIS, and GEP, were used to estimate *fc* values using the textural and physical-mechanical characteristics of rocks. These methods are simple to apply and do not require a reference sample to be determine in the laboratory or field. The following was concluded from this study:

The created model exhibited successful performance for all the soft computing techniques used, except for RA, and the best results were found with ANFIS (R: 0.95, RMSE: 10.95 for training, R: 0.98, RMSE: 6.97 for testing, and R: 0.97, RMSE: 9.53 for checking). In addition to this, other methods gave very close results (ANN: R:0.94, RMSE:12.05 for training, R:0.86, RMSE: 9.81 for testing, and R:0.96, RMSE: 15.79 for checking; GEP: R:0.93, RMSE:12.95 for training, R:0.89, RMSE: 14.76 for testing, and R:0.95, RMSE: 10.81 for checking), and RA found them partially suitable (R:0.83, RMSE:22.98 for training, R:0.86, RMSE: 15.03 for testing, and R:0.95, RMSE: 11.78 for checking).

These results show that soft computing techniques, which are ANN, ANFIS, and GEP, are quite suitable and practicable methods for solving inverse and complex problems, such as predicting *fc* for rock materials.

The formulations obtained by GEP could be used easily by everybody, who is not knowledgeable about GEP.

Declaration of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Similarity rate (iThenticate): 18%.

References

[1] ISRM, The Complete ISRM Suggested Methods for Rock Characterization, Testing and Monitoring: 1974–2006, In: R. Ulusay and J. A. Hudson (Eds.), Ankara, Turkey, 2007.

[2] ASTM, Standard test method for unconfined compressive strength of intact rock core specimens. Soil and Rock, Building Stones: Annual Book of ASTM Standards 4.08. Philadelphia, Pennsylvania, ASTM, 1984.

[3] A. Asadi, Application of Artificial Neural Networks in Prediction of Uniaxial Compressive Strength of Rocks using Well Logs and Drilling Data. In Procedia Engineering, 191, 279-286, 2017. https://doi.org/10.1016/j.proeng.2017.05.182

[4] C. Zang and H. Huang, Prediction of rock mechanical parameters and rock mass classification by percussive drilling surveying in a rock tunnel, ISRM SINOROCK, Shanghai, China, June 2013. http://doi.org/10.1201/b14917-28

[5] H. Fattahi, Applying soft computing methods to predict the uniaxial compressive strength of rocks from schmidt hammer rebound values. Computational Geosciences, 21, (4), 665–681, 2017. http://doi.org/10.1007/s10596-017-9642-3

[6] A. Özbek, M. Unsal, and A. Dikec, Estimating uniaxial compressive strength of rocks using genetic expression programming. Journal of Rock Mechanics and Geotechnical Engineering, 5(4), 325–329, 2013. https://doi.org/10.1016/j.jrmge.2013.05.006

[7] U. Åkesson, J. Lindqvist, M. Göransson, and J. Stigh, Relationship between texture and mechanical properties of granites, Central Sweden, by use of image-analysing techniques. Bulletin of Engineering Geology and the Environment, 60(4), 277–284, 2001. http://doi.org/10.1007/s100640100105

[8] K. Gunsallus and F. H. Kulhawy, A comparative evaluation of rock strength measures. International Journal of Rock Mechanics and Mining Sciences , 21(5), 233-248, 1984. https://doi.org/10.1016/0148-9062(84)92680-9

[9] R. Merriam, H. H. Rieke, and Y. C. Kim, Tensile strength related to mineralogy and texture of some granitic rocks. Engineering Geology, 4(2), 155–160, 1970. https://doi.org/10.1016/0013-7952(70)90010-4

[10] T. F. Onodera and H. M. Asoka Kumara, Relation between texture and mechanical properties of crystalline rocks. Bulletin of Association Engineering Geology, 22, 173-177, 1980. https://doi.org/10.1016/j.enggeo.2004.03.009

[11] R. Přikryl, Assessment of rock geomechanical quality by quantitative rock fabric coefficients: Limitations and possible source of misinterpretations. Engineering Geology, 87(3–4), 149–162, 2006. https://doi.org/10.1016/j.enggeo.2006.05.011

[12] A. Tuğrul and I. H. Zarif, Correlation of mineralogical and textural characteristics with engineering properties of selected granitic rocks from Turkey. Engineering Geology, 51(4), 303–317, 1999. https://doi.org/10.1016/S0013-7952(98)00071-4

[13] R. Ulusay, K. Türeli and M. H. Ider, Prediction of engineering properties of a selected litharenite sandstone from its petrographic characteristics using correlation and multivariate statistical techniques. Engineering Geology, 38(1–2), 135–157, 1994. https://doi.org/10.1016/0013-7952(94)90029-9

[14] D. F. Howarth and J. C. Rowlands, Quantitative assessment of rock texture and correlation with drillability and strength properties. Rock Mechanics and Rock Engineering, 20(1), 57–85, 1987.

[15] A. Ersoy and M. D. Waller, Textural characterisation of rocks. Engineering Geology, 39(3–4), 123–136, 1995. https://doi.org/10.1016/0013-7952(95)00005-Z

[16] V. Gupta, and R. Sharma, Relationship between textural, petrophysical and mechanical properties of quartzites: A case study from northwestern Himalaya. Engineering Geology, 135–136, 1–9, 2012. https://doi.org/10.1016/j.enggeo.2012.02.006

[17] C. A. Ozturk, E. Nasuf and S. Kahraman, Estimation of rock strength from quantitative assessment of rock texture. Journal of the Southern African Institute of Mining and Metallurgy, 114(6), 471–480, 2014.

[18] Y. Ozcelik, F. Bayram and N. E. Yasitli, Prediction of engineering properties of rocks from microscopic data. Arabian Journal of Geosciences, 6(10), 3651–3668, 2013. https://doi.org/10.1007/s12517-012-0625-3

[19] U. Atici and R. Comakli, Evaluation of the physico-mechanical properties of plutonic rocks based on texture coefficient. Journal of the Southern African Institute of Mining and Metallurgy, 119(1), 63–69, 2019. https://doi.org/10.17159/2411-9717/2019/v119n1a8
[20] C. Gokceoglu, E. Yesilnacar, H. Sonmez and A. Kayabasi, A neuro-fuzzy model for modulus of deformation of jointed rock masses. Computers and Geotechnics, 31(5), 375–383, 2004. https://doi.org/10.1016/j.compgeo.2004.05.001
[21] R. Singh, A. Kainthola and T. N. Singh, Estimation of elastic constant of rocks using an ANFIS approach. Applied Soft Computing Journal, 12(1), 40–45, 2012. https://doi.org/10.1016/j.asoc.2011.09.010
[22] K. Aali, M. Parsinejad and B. Rahmani, Estimation of Saturation Percentage of Soil Using Multiple Regression, ANN, and ANFIS Techniques. Computer and Information Science, 2(3), 127–136, 2009. https://doi.org/10.5539/cis.v2n3p127
[23] B. Tiryaki and A. C. Dikmen, Effects of rock properties on specific cutting energy in linear cutting of sandstones by picks. Rock Mechanics and Rock Engineering, 2006. https://doi.org/10.1007/s00603-005-0062-7
[24] A. Azzoni, F. Bailo, E. Rondena and A. Zaninetti, Assessment of texture coefficient for different rock types and correlation with uniaxial compressive strength and rock weathering. Rock Mechanics and Rock Engineering, 29(1), 39–46, 1996.
[25] M. Alber and S. Kahraman, Predicting the uniaxial compressive strength and elastic modulus of a fault breccia from texture coefficient. Rock Mechanics and Rock Engineering, 42(1), 117–127, 2009. https://doi.org/10.1007/s00603-008-0167-x
[26] U. Atici, Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network. Expert Systems with Applications, 38(8), 9609-9618, 2011. https://doi.org/10.1016/j.eswa.2011.01.156
[27] M. Sarıdemir, İ.B. Topçu, F. Özcan, and M. H. Severcan, Prediction of long-term effects of GGBFS on compressive strength of concrete by artificial neural networks and fuzzy logic. Construction and Building Materials, 23(3), 1279–1286, 2009. https://doi.org/10.1016/j.conbuildmat.2008.07.021
[28] A. Öztaş, M. Pala, E. Özbay, E. Kanca, N. Çaglar and M. A. Bhatti, Predicting the compressive strength and slump of high strength concrete using neural network. Construction and Building Materials, 20(9), 769–775, 2006. https://doi.org/10.1016/j.conbuildmat.2005.01.054
[29] J. L. Rogers, Simulating Structural Analysis with Neural Network. Journal of Computing in Civil Engineering, 8(2), 252–265, 1994. https://doi.org/10.1061/ (ASCE)0887-3801(1994)8:2(252)
[30] K. Swingler, Applying neural networks a practical guide. London: Academic Press, New York, 1996.
[31] M. M. Alshihri, A. M. Azmy and M. S. El-Bisy, Neural networks for predicting compressive strength of structural light weight concrete. Construction and Building Materials, 23(6), 2214–2219, 2009. https://doi.org/10.1016/j.conbuildmat.2008.12.003
[32] J. S. R. Jang, ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems, Man and Cybernetics, 23(3), 665–685, 1993. https://doi.org/10.1109/21.256541
[33] H. F. Ho, Y. K. Wong, A. B. Rad, and W. L. Lo, State observer based indirect adaptive fuzzy tracking control. Simulation Modelling Practice and Theory, 13(7),646–663, 2005. https://doi.org/10.1016/j.simpat.2005.02.003
[34] C. X. Wong and K. Worden, Generalised NARX shunting neural network modelling of friction. Mechanical Systems and Signal Processing, 21(1), 553–572, 2007. https://doi.org/10.1016/j.ymssp.2005.08.029
[35] T. Takagi and M. Sugeno, Fuzzy identification of systems and its applications to modeling and control. Systems, Man and Cybernetics, IEEE Transactions On, SMC-15(1), 116–132, 1985. https://doi.org/10.1016/B978-1-4832-1450-4.50045-6
[36] C. Kayadelen, O. Günaydin, M. Fener, A. Demir, A. Özvan, Modeling of the angle of shearing resistance of soils using soft computing systems. Expert Systems with Applications, 36(9), 11814–11826, 2009. https://doi.org/10.1016/j.eswa.2009.04.008
[37] H. Demuth and M. Beale, Neural Network Toolbox For Use with MATLAB - User Guide. The MathWorks, 2002.
[38] S. Akkurt, G. Tayfur and S. Can, Fuzzy logic model for the prediction of cement compressive strength. Cement and Concrete Research, 34(8), 1429–1433, 2004. https://doi.org/10.1016/j.cemconres.2004.01.020
[39] İ. B. Topçu and M. Sarıdemir, Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic. Computational Materials Science, 41(3), 305–311, 2008. https://doi.org/10.1016/j.commatsci.2007.04.009
[40] A. Cevik, A new formulation for longitudinally stiffened webs subjected to patch loading. Journal of Constructional Steel Research, 63, 1328–1340, 2007. https://doi.org/10.1016/j.jcsr.2006.12.004
[41] C. Ferreira, Gene Expression Programming : A New Adaptive Algorithm for Solving Problems. Complex Systems, 13(2), 1–22, 2001. https://doi.org/10.48550/arXiv.cs/0102027
[42] D. G. Muñoz, Discovering unknown equations that describe large data sets using genetic programming techniques. Master Thesis, Linköpings Universitet, Linköping, Sweden, 2005.