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A New Predictive Model for Uniaxial Compressive Strength of Rock Using Machine Learning Method: Artificial Intelligence-Based Age-Layered Population Structure Genetic Programming (ALPS-GP)

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Abstract
Uniaxial compressive strength (UCS) of rocks is the most commonly used parameter in geo-engineering application. However, this parameter is hard for measurement due to a time consuming and requires expensive equipment. Therefore, obtaining this value indirectly using non-destructive testing methods has been a frequently preferred method for a long time. In order to obtain multiple regression models, input parameters need many assumptions. Thus, the estimation of the mechanical properties of rocks using by machine learning methods has been investigated. In this study, UCS values of rocks were estimated by reformulating with artificial intelligence-based age-layered population structure genetic programming (ALPS-GP) which is one of machine learning methods. Artificial neural network (ANN) and ALPS-GP models were performed to predict UCS from porosity, Schmidt hammer hardness and ultrasonic wave velocity test methods. For this purpose, the mentioned three tests (porosity, Schmidt hammer hardness and P-wave velocity) were carried out on ten different stones from Turkey. ANN was performed to evaluate this new technique. Reliability of UCS values determined by models was checked with mean absolute error (MAE), coefficient of determination (R^2), root mean square error (RMSE) and variance account for (VAF) values. These values were calculated as 1.64, 0.98, 2.11 and 99.81 for ANN, and 2.11, 0.98, 2.50 and 97.86 for ALPS-GP, respectively. It was observed that both methods used were quite successful in UCS estimation. The most important advantage of the ALPS-GP model is providing an equation for UCS estimation. In the light of the obtained findings, it has been revealed that this equation derived from ALPS-GP can be used in UCS estimation processes of similar rock types (limestone, dolomite and onyx).

Keywords Artificial intelligence-based age-layered population structure genetic programming (ALPS-GP) · Artificial neural network · Uniaxial compressive strength · P-wave velocities · Schmidt hardness

1 Introduction

The mechanical properties of rocks play an important role in planning and design of construction and mining excavations, including the stability of rocky slopes, underground excavations, tunnels, dams and caves. However, determining these mechanical properties in situ or in laboratory conditions is very difficult, laborious and time consuming. Therefore, non-destructive methods that long since can be used both in situ and in laboratory and cannot damage the sample are more preferred [1]. In mining, construction, geology and geotechnical engineering studies, Schmidt hammer hardness and ultrasonic wave velocity method are frequently preferred techniques for evaluating the mechanical properties of concrete and rocks due to their undamaged, easy-to-apply and reliability [2].

Regression analysis is the statistical modeling performed to estimate dependent variable by using the relationship between two or more variables that have a cause-effect relationship. It is expressed as simple regression analysis if one variable is used as the prediction variable, and as multiple regression analysis if two or more variables are used. Although many researchers have successfully developed and applied simple regression equations to estimate the uniaxial compressive strength of rocks using Schmidt hammer hardness [3–16] and ultrasonic testing methods [17–24], the

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new trend is seen as the usage of machine learning methods rather than regression models. For a long time, it has been seen that machine learning methods are frequently preferred in determining mechanical properties of rocks in geo-engineering application such as civil, construction, mining and geology. Some researchers have determined mechanical properties of rocks using machine learning methods such as fuzzy inference system [25, 26], artificial neural network [27, 28], relevance vector machine [29, 30], support vector machine [30, 31] adaptive neuro-fuzzy inference system [32, 33], particle swarm optimization [34, 35], imperialist competitive algorithm [36, 37], generalized neural feed-forward network [37, 38] and least square support vector machine [39, 40]. Recently, hybrid computing models are replacing such basic methods. Momeni et al. (2015) developed a hybridized intelligence method for uniaxial compressive strength (UCS). They determined that the new technique is more successful in predicting UCS when compared to conventional ANN method and hybridized intelligence method [35]. In a study that a hybridized intelligence method was developed for the UCS and elasticity modulus (E) estimation of rocks, it was observed that the classification error of the hybridized generalized feedforward neural network (ICA-GFFN) for CS and E decreased significantly compared to the generalized feedforward neural network (GFFN) [41]. Similarly, in a study, where a hybridized intelligence method was developed using support vector regression, it was detected that this hybrid method was found to be quite reliable to predict UCS and E [42].

Genetic programming (GP) is technique which enables computers to evaluate and solve problems by generally using genetic algorithms. In GP, computer programs are individuals in population. Thousands of these individuals are genetically breed by using Darwinian principle of survival and reproduction of fittest along with a genetic recombination which is called as crossover. Therefore, combination of Darwinian natural selection and genetic operations plays important role for genetic programming to solve given problems by computers [43]. GP, which is frequently preferred in solving the problems of many disciplines due to its fast, easy and practical features, is structurally divided into three basic groups. The first of these, GP obtained by using individuals made up of chromosomes with a very simple structure. According to this GP, which was discovered by Holland, chromosomes survive according to their characteristics [44]. This GP method has become one of the preferred methods for determining the mechanical properties of rocks. This method was used to estimate dynamic properties of granitic rocks [45] and deformation modulus of rock masses [46]. Second method was discovered by Ferreira, chromosomes belonging to individuals, initially coded in fixed and linear lengths, later turn into branched structures [47]. Chromosomes on branched structures survive depending on the causality principle. This method was used to determine uniaxial compressive strength and tensile strength of limestone [48]. The last method, which was discovered by Koza, consists of individuals with highly complex branched structures and high functionality [43]. In these systems, chromosomes survive due to their own characteristics. This method was used to estimate surface subsidence due to underground mining [49, 50]. Çanakcı et al. (2009) estimated UCS value of basalt samples collected from Gaziantep (Turkey) by means of gene expression programming and artificial neural networks using non-destructive tests like P-wave velocity, dry-saturated density, by weight and bulk density [51]. Ozbek et al. (2013) estimated UCS value of basalt and four ignimbrite (black, yellow, gray, brown) samples by means of GEP using rock properties like water absorption by weight and unit weight and porosity [52]. Dindarloo and Siami-Irdemoosa (2015) predicted UCS value of carbonate rocks by means of GEP, using two parameters of total porosity and P-wave velocity of rocks [53]. Behnia et al. (2017) predicted UCS of rocks by means of GEP using some engineering properties like quartz content, dry density and porosity [54].

Simple and multiple regression models have more meaningful indicators for predicting the dependent variable. But many assumptions need to be met in order to perform multiple regression analysis. The main advantage of machine learning methods is not required such comprehensive assumption. In this study, two machine learning methods, which are known as artificial neural network (ANN) and artificial intelligence-based age-layered population structure genetic programming (ALPS-GP), are used in prediction of UCS. So far, there is no study for prediction of UCS from ALPS-GP. Thus, this new hybrid technique was compared with ANN model. For this purpose, porosity, Schmidt hammer hardness and P-wave velocity were used as inputs for both models and were analyzed to obtain testing and training data. The reliability of estimated UCS determined using models was checked with mean absolute error (MAE), coefficient of determination (significance) (R^2), root mean square error (RMSE) and variance account for (VAF) values. These values were calculated as 1.64, 0.98, 2.11 and 99.81 for ANN, and 2.11, 0.98, 2.50 and 97.86 for ALPS-GP, respectively. If a proposed model result in $R^2 > 0.8$, it is well known that there is a strong correlation between the measured and predicted values. This situation shows that both models used have the ability to make accurate predictions for UCS results. However, the most important advantage of ALPS-GP model over ANN is that it provides an equation for UCS estimation. In addition, ALPS-GP is known to give more successful results in the solution of highly complex structures. Therefore, this study may encourage some researchers to use ALPS-GP in rock mass classifications such as RMR, Q and GSI.

2 Material and Method

2.1 Material

In this study, ten different natural stones (limestone, dolomite and onyx) which obtained from various locations of Turkey were used. The codes, trade names and origins of these rocks used in building and construction in various regions of Turkey are displayed in Table 1. In order to determine the physical and mechanical properties of rocks, cubic samples with 70 mm dimensions were prepared with a marble cutting device. The location map of samples used in experimental study is given in Fig. 1. Images of prepared samples and test devices are given in Fig. 2. The physical and mechanical properties of samples (porosity, Schmidt hammer hardness, P-wave velocity and uniaxial compressive strength) are determined according to ISRM and TS standards [55–58].

Table 1 Sample codes, types and trade names

Code	Trade name	Type
OT	Onix-Travertine	Limestone
SM	Afyon Sugar Marble	Limestone
PE	Pure Emperador	Dolomite
GT	Gray Travertine	Limestone
BE	Bursa Emperador	Dolomite
WO	White Onyx	Onyx
CM	Chipboard Marble	Limestone
PO	Pure Onyx	Onyx
ST	Sivas Travertine	Limestone
WE	White Emperador	Dolomite

2.2 Experimental Studies

2.2.1 Porosity

Porosity is ratio of the void volume formed by grains forming rock to the total volume of rock, which varies depending on shape, size distribution, sequence and cementing degree of grains. Porosity values directly affect uniaxial compressive strength of rocks. Increasing this value negatively affects mechanical strength of rock. Therefore, it is a factor to be taken into account in the indirect estimation of uniaxial compressive strength of rocks [59, 60]. The porosity values of rocks were determined according to TS 699 [55].

2.2.2 Schmidt Hammer Hardness

Schmidt hammer hardness, which was first developed in 1948 to test the concrete hardness non-destructively, was later used to determine rock hardness. This non-destructive test device, which was used in the early 1960s to have an idea about the hardness and strength of rocks, is a quick,

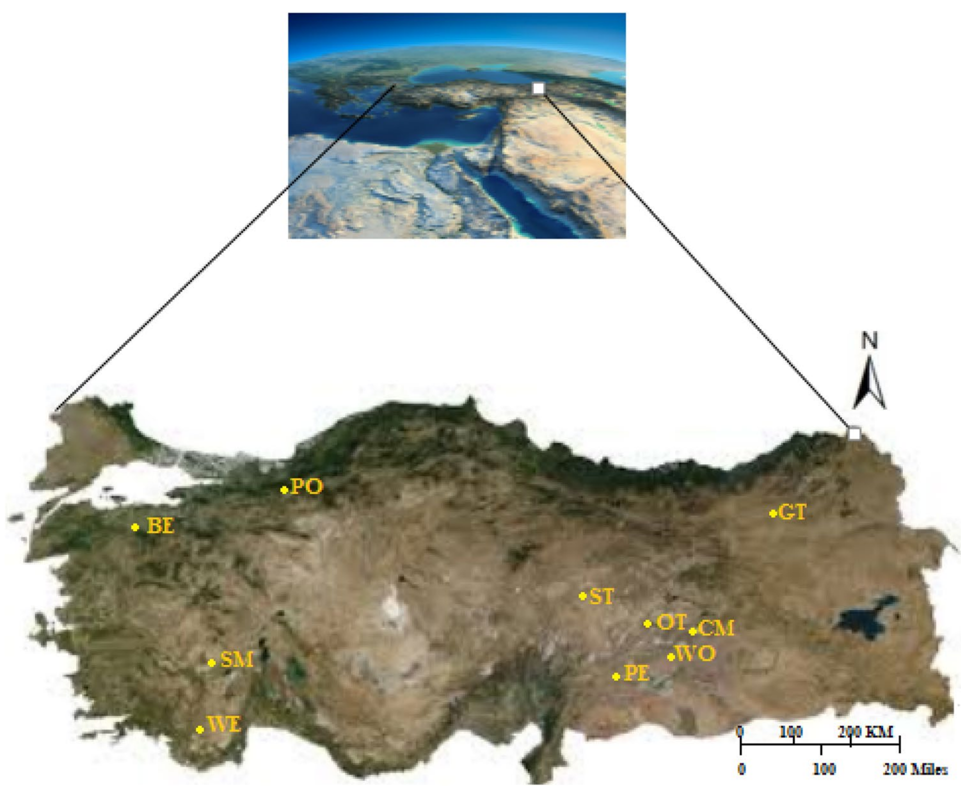

Fig. 1 The locations of samples

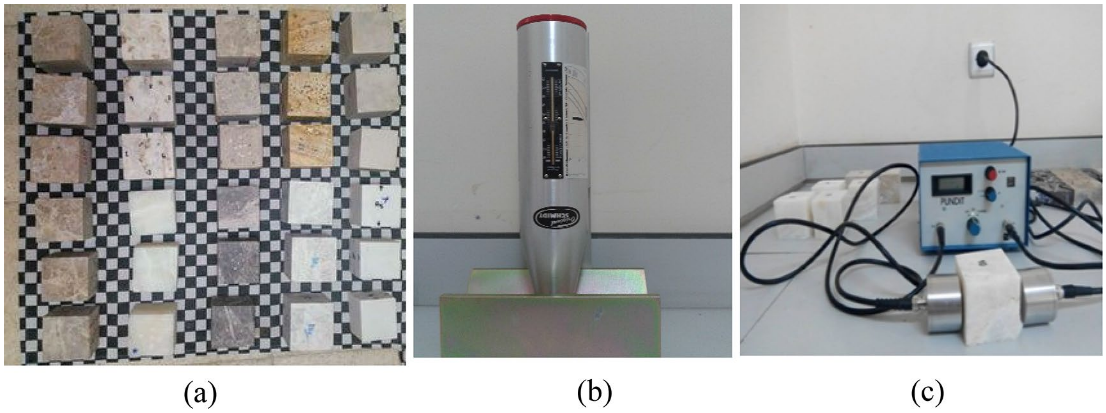

Fig. 2 **a** General view of test samples **b** Schmidt hammer hardness **c** Ultrasonic wave velocity device

portable and simple method. The reliability of test results is directly affected by factors such as hammer type, sample sizes, surface roughness, weakness of sample and moisture content. Schmidt hardness is highly influenced by features such as porosity, dry unit weight and origin of rock [10, 59]. Schmidt hammer hardness values of rocks were determined according to ISRM 1978 [56].

2.2.3 Ultrasonic Wave Velocity

Ultrasonic test methods are techniques used to determine the mechanical properties of rock and concrete samples both in situ and laboratory conditions. Ultrasonic wave propagation has three different waveforms. These are expressed as P-wave (axial-longitudinal), S-wave (shear) and R-wave (Rayleigh) propagation. The fastest-moving waveform is P-wave, the R-wave traveling only along the surface of the material. P and S-wave velocities are most widely used in rock mechanics studies [61]. These wave velocities are affected by parameters such as grain size and shape, density, porosity, anisotropy, moisture content, temperature, filling material [2, 18, 20, 21, 62–65]. P-wave velocity values of rocks were determined according to ISRM 1978 [57].

2.2.4 Uniaxial Compressive Strength

Uniaxial compressive strength is an important parameter used for construction and design purposes in studies related to earth sciences such as mining, construction, geology, geophysical engineering. In rock engineering, it is the most widely used mechanical test in determining the failure properties of rock material and rock mass classifications. However, this mechanical property of rocks is destructive and time-consuming test that requires expensive equipment [66, 67]. UCS of rocks was determined according to method defined by ISRM [58].

2.3 Model Construction

2.3.1 Artificial Neural Network

ANN contains nerve cells neurons just as biological system. These neurons connect to each other in various ways to form a network. These networks have capacity to learn, memorize and reveal the relationship between data. ANN is an effective method that separates complex and nonlinear systems into simple elements. ANN is a data processing that has inputs (xi), connection weights (wi), addition function (Σ), activation function (f) and output (y) (Fig. 3). It consists of three basic layers (i.e., input layer, hidden layer (s) and output layer). The weights of each layer differ from each other. The quality of ANN model determines the selected activation functions. The activation function is used to convert the

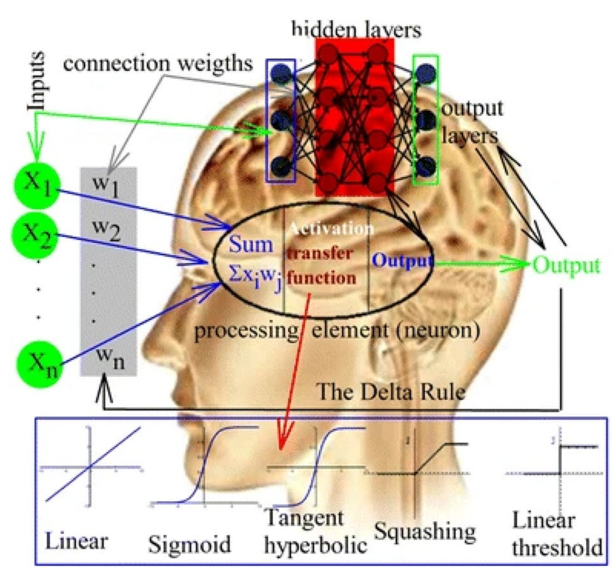

Fig. 3 Basic ANN structure [71]

output to desired ranges. There are many activation functions used by ANN cells. Tangent-hyperbolic, sigmoid and linear functions are generally preferred activation functions due to reliable results. The activation function can be both linear and nonlinear. In this study, tangent-hyperbolic activation function was used. This activation function is a nonlinear that takes values between -1 and 1. For supervised learning of multi-layer ANNs used feedforward backpropagation (BP), which is simple, quite efficient and general algorithm. BP algorithm minimizes the general error by iterating the weight of network. In other words, observed values and predicted output of model were very close [68–70]. ANN model was used to predict UCS from other physico-mechanical tests. MATLAB 14B was used for this model. Porosity, Schmidt hammer hardness and P-wave velocity were used as input parameters in model. R^2, RMSE, VAF and MAE were used to evaluate the performance of model.

2.3.2 Artificial Intelligence-Based Age-Layered Population Structure Genetic Programming (ALPS-GP)

Genetic algorithms are optimization techniques to find the most optimal solutions to any problem. In this new hybrid technique, called ALPS-GP, it is treated as a symbolic expression similar to the group of genes that make up the organism. This symbolic expression is like tree branches containing both symbolic variables and numeric constants. This new hybrid technique was used for the first time in studies on rock mechanics. ALPS-GP is part of evolutionary algorithms (EA). However, it is quite successful compared to EAs in solving more extensive problems. EAs use biology techniques such as mutation, inheritance, crossover and selection. In addition, ALPS controls breeding by defining a new age scale for individuals. ALPS-GP age scale was defined to represent the number of generations. Training procedure of ALPS-GP can be summarized as follows. The algorithm constructs the age layers as a first step and then creates a random population and evaluation. New individuals that are spontaneously formed start with an initial age of 0. When individuals produced from genetic factors such as crossover and mutation are selected as parents, their age increases 1 each time. If a candidate solution is used more than one as a parent, their age increases 1 only once. There is a maximum age limit for each age-layer in the population. Aging scheme given in Table 2 can be used for this age limit. In this study, polynomial aging scheme was used. Individuals were breed in their own layers or from the previous layer. Therefore, for layer i, parents can only be chosen from layers *i* -1 and *i*. When the age of individual exceeds the age limit assigned to this layer, it moves to next upper layer. A new layer is not opened until previous layer is full. Therefore, all layers are filled at the same time [72–76]. In modeling studies latest version HeuristicLab 3.3 package program was used. Porosity, Schmidt hammer hardness, P-wave velocity were used as input parameters in ALPS-GP modeling studies. UCS was defined as the output parameter.

Table 2 Aging scheme distribution examples for ALPS-GP

Aging Scheme	Max age in layer for ALPS-GP				
	0	1	2	3	i
Linear	1	2	3	4	i
Polynomial	1	2	4	9	$(i)^2$
Exponential	1	2	4	8	2^i
Factorial	1	2	6	24	$i!$

ALPS-GP created by HeuristicLab is based on a tree representation. This tree is a symbolic expression of equation obtained by ALPS-GP. ALPS-GP model tree containing both symbolic variables and numeric constants is given in Fig. 4. This tree, which forms the first population of individuals, consists of terminals (porosity, Schmidt hardness, P-wave velocity and constants) and functions (basic mathematical functions). A criterion is used to assess the fitness of each individual in a population. ALPS-GP initially randomly generated 100 population sizes. These programs were developed by genetic operators for next generation. For this purpose, genetic operations such as mutation, crossover and reproduction were used. 50 iterations were made to obtain the best model to be used for UCS prediction. After each iteration, RMSE values were recorded and the best model was established. Convergence procedure of ALPS-GP is given in Fig. 5. Constant coefficients in Eq. 2 are explained in Table 3. General information about training of ALPS-GP model is given in Table 4.

$$UCS = \left(\left(\left(\frac{\left(\frac{\frac{c_0}{((c_1+(c_2-c_3\,\mathrm{Pr}))+c_4)-c_5\,\mathrm{Pr})}}{c_6}+c_7 Vp\right)}{(c_8-c_9\,\mathrm{Pr})}+c_{10}SH\right)+\frac{\frac{\frac{\frac{(c_{11}-c_{12}\,\mathrm{Pr})}{c_{13}\,\mathrm{Pr}}}{c_{14}\,\mathrm{Pr}}}{c_{15}\,\mathrm{Pr}}}{c_{16}\,\mathrm{Pr}}\right)c_{17}+c_{18}\right) \quad (1)$$

3 Results and Discussion

3.1 Experimental Results

Non-destructive tests (porosity, Schmidt hammer hardness and ultrasonic P-wave velocity) and UCS results used in statistical studies are given in Table 5. When Table 6 is examined, it is seen that UCS values increase as Schmidt hammer hardness and P-wave velocity values of rocks increase. It is also seen that UCS value decreases when the porosity value increases. In addition, the increase in porosity value caused the ultrasonic wave to be transmitted late due to

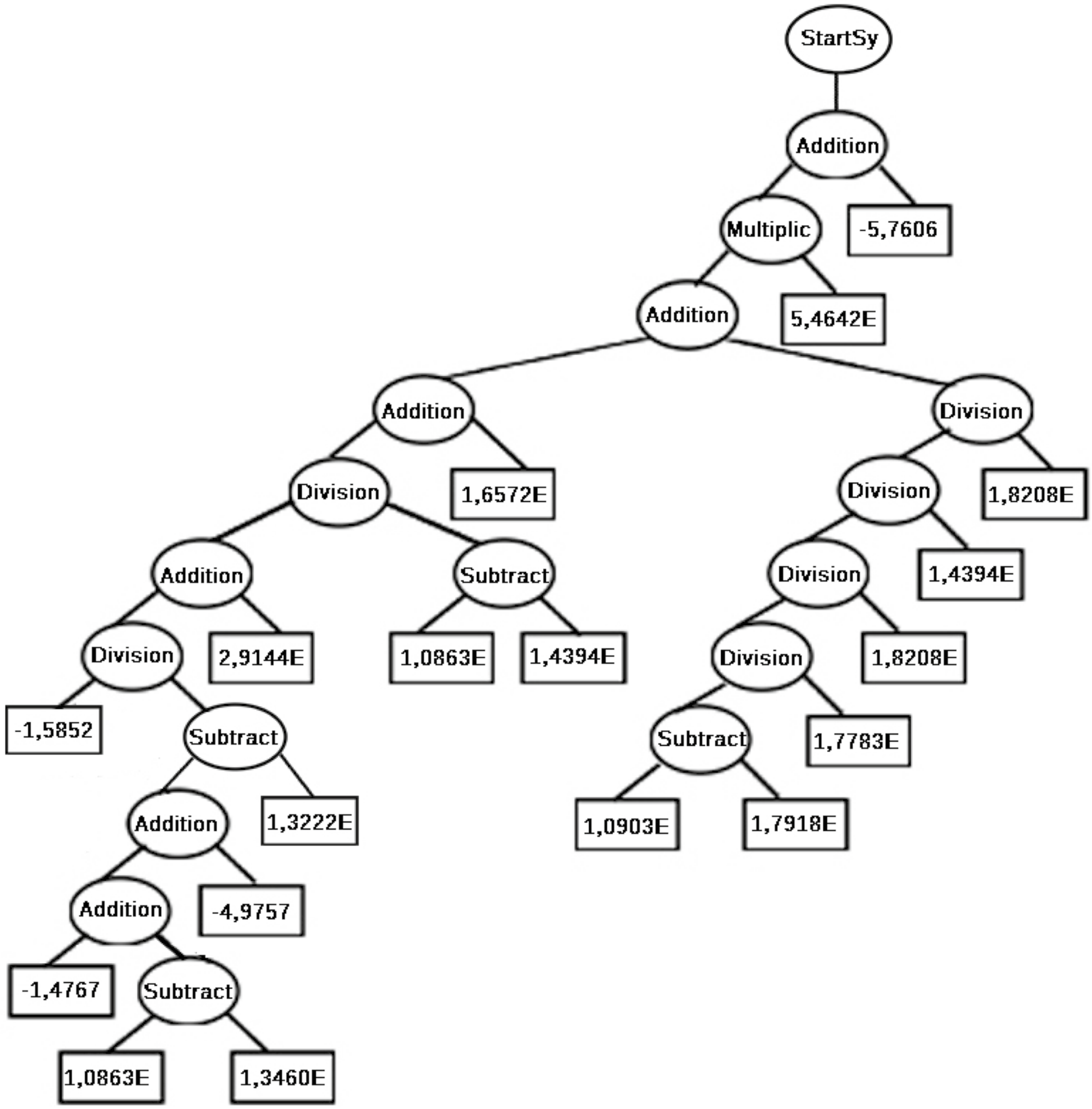

Fig. 4 ALPS-GP model tree

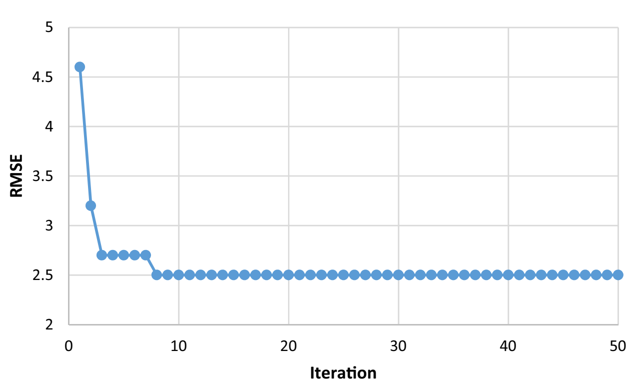

Fig. 5 Convergence procedure of ALPS-GP

the dispersion in space. As a result, it seems that porosity directly affects the physical and mechanical properties of rock.

3.2 Assessment of model performance

UCS data set obtained as a result of experimental studies was divided into two section as testing and training. For the model, 70% of the data was used as training and the remaining 30% as test data. To understand that one model processes properly, there are some certain functions which determine the quality of the estimations. For this purpose, average absolute error (MAE), mean absolute error (MAE), coefficient of determination (R^2), root mean square error

Table 3 Constant coefficients of the model

c_0	−15,852
c_1	−1,4767
c_2	10,863
c_3	1,346
c_4	−4,9717
c_5	1,3222
c_6	−1,4767
c_7	0,29,144
c_8	10,863
c_9	1,4394
c_{10}	1,6572
c_{11}	1,903
c_{12}	1,7918
c_{13}	1,7783
c_{14}	1,8208
c_{15}	1,4394
c_{16}	1,8208
c_{17}	0,54,642
c_{18}	−57,606

Table 4 The ALPS-GP parameters for estimating UCS

ALPS-GP parameters	Values
Terminal set	n, HR, Vp
Functions	+, -, /, ×
Fitness function	RMSE
Maximum iterations	50
Age gap	15
Population size	100
Aging scheme	Polynomial
Genetic operators	Crossover, reproduction, mutation,
Crossover	Subtree swapping crossover
Mutation probability	25%
Selector	Generalized rank selector

(RMSE) and variance account for (VAF) values were calculated in order to compare performance results of obtained by models.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{2}$$

$$R = \frac{\sum_{j=1}^{n}\left(y_j - y_{j,m}\right)\left(\hat{y}_j - \hat{y}_{j,m}\right)}{\sqrt{\sum_{j=1}^{n}(y_j - y_{j,m})^2\sum_{j=1}^{n}\left(\hat{y}_j - \hat{y}_{j,m}\right)^2}} \tag{3}$$

Table 5 Data used in the statistical studies

Sample	Pr	Vp	SH	UCS
OT1	1.88	3545	36.1	41.11
OT2	1.81	3609	37.3	44.89
OT3	1.60	3437	35.6	43.21
SM1	2.29	3133	32.4	38.22
SM2	2.29	3157	32.9	39.53
SM3	2.25	3107	31.1	36.36
PE1	0.88	4920	51.0	70.62
PE2	0.74	5091	52.8	74.34
PE3	0.67	4839	49.2	69.33
GT1	1.11	3842	39.8	45.82
GT2	1.09	4112	42.2	50.35
GT3	1.03	4092	41.8	50.74
BE1	0.97	5394	54.9	85.53
BE2	0.81	5303	53.4	79.42
BE3	0.85	5432	54.1	80.71
WO1	1.18	4275	43.7	57.91
WO2	1.21	4239	43.2	56.52
WO3	1.24	4301	44.5	60.33
CM1	2.38	2858	29.2	29.35
CM2	2.44	2967	30.4	33.04
CM3	2.38	2948	30.1	30.50
PO1	1.85	3678	37.5	41.10
PO2	1.97	3609	36.5	42.46
PO3	2.01	3655	37.3	43.78
ST1	2.14	3101	32.0	36.64
ST2	2.25	3058	31.5	35.91
ST3	2.27	3145	32.4	39.03
WE1	0.89	5152	52.9	75.83
WE2	0.83	5056	51.1	73.21
WE3	0.82	5011	50.7	73.37

Table 6 Performance analysis of models

Model	Data	MAE	R^2	RMSE	VAF
ALPS-GP	Test	2.11	0.98	2.50	97.86
	Train	1.19	0.99	1.61	99.14
ANN	Test	1.64	0.98	2.11	98.43
	Train	0.61	0.99	0.74	99.81

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2} \tag{4}$$

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

Here;

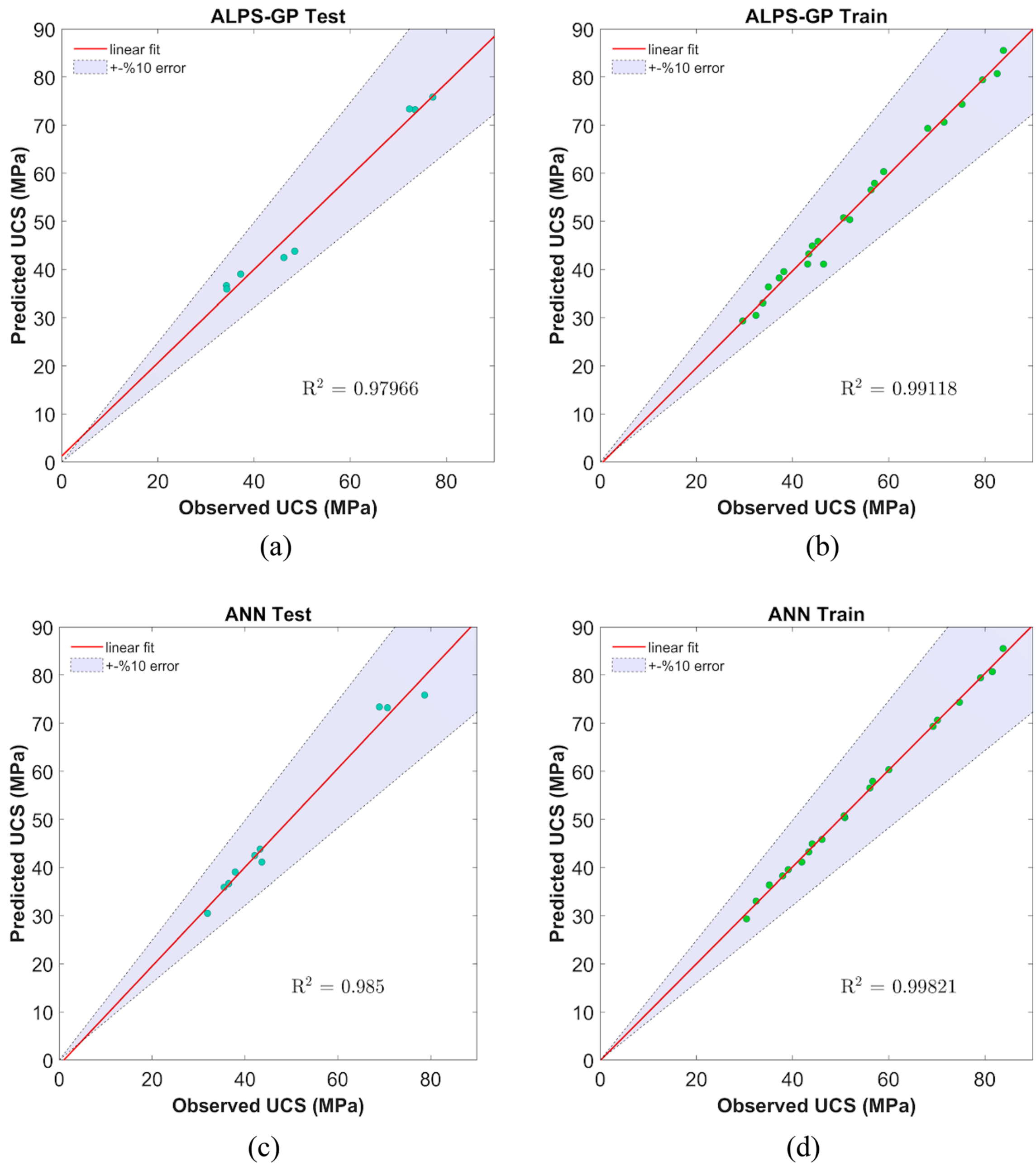

Fig. 6 Testing (**a**, **c**) and training (**b**, **s**) mean relative error obtained from models

y_j = measured UCS value, $\hat{y}_j$ = predicted UCS value and subscript of m indicate mean value.

Performance criteria of models for UCS estimation are given in Table 6, which include the most frequently used criteria to evaluate the performance of models.

The correlation coefficient was determined to decide if there was a linear relationship between the calculated and measured UCS. The value of the correlation coefficient is between 0 and 1 and is the closest to the most optimum 1. R^2 values of the obtained models are seen to be very close to 1. RMSE gives information about the short-term performance of the calculated and measured values. Its results are always positive. As RMSE value approaches zero, it shows that obtained model is strong and meaningful. When RMSE values are examined, it is seen that these values are close to zero. Therefore, it shows that UCS values obtained from models are quite significant. MAE gives average absolute error between measured and experimentally calculated

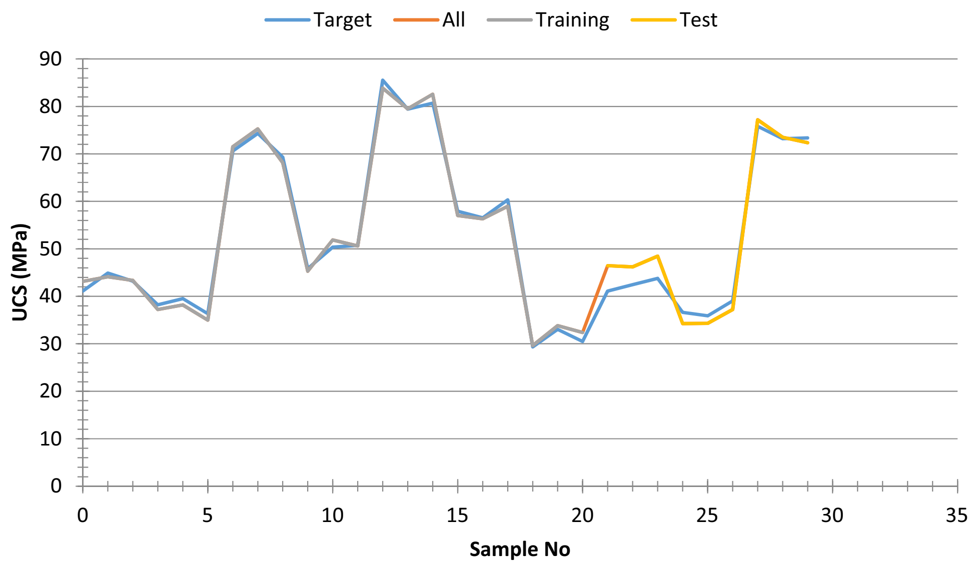

Fig. 7 Predictability level of UCS obtained from ALPS-GP

values. It is widely used in the prediction performance of models. As the MAE value decreases, significance of the model increases. For model to be strong and acceptable, MAE value is required to be less than 10. VAF is a statistical approach used to estimate magnitude and significance of indirect effects relative to total effect. If this value is above 80%, it shows that relationship is quite significant. When VAF values obtained from models are examined, it is seen that UCS estimation is quite successful.

Linear fit graph for training and testing obtained from models is shown in Fig. 6a-d. Mean relative error of models for both data sets is less than 10%. When performance of ALPS-GP and ANN was compared, training and test correlation coefficients were obtained as 0.991–0.985 and 0.998–0.985, respectively. These results show that UCS obtained from models and experiment is compatible with each other. The probability of accurately predicting UCS of rocks using each model is greater than 98%. Although ANN model appears to be stronger compared to ALPS-GP, this new hybrid model can ignore this difference due to presenting an equation. In addition, predictability level for training and testing obtained from ALPS-GP model is shown in Fig. 7. It is necessary to look at predictability level in order to interpret correctly usability of the data obtained from the model. When Fig. 7 is examined, it is obvious that predictability level of model is quite high.

4 Conclusion

UCS is one of the most important and influential parameters used in engineering application. This test is a destructive, expensive and time consuming. Therefore, it is very important to determine this value in a short time with non-destructive test methods. In this study, ANN and new hybrid technique called ALPS-GP were used for predicting UCS from porosity, Schmidt hammer hardness and ultrasonic P-wave velocity. These methods were applied to 30 datasets of porosity, Schmidt hammer hardness and ultrasonic P-wave velocity of ten different stones from Turkey. The reliability of ANN and ALPS-GP models was confirmed with MAE, R^2, RMSE and VAF. These values were calculated as 1.64, 0.98, 2.11 and 99.81 for ANN, and 2.11, 0.98, 2.50 and 97.86 for ALPS-GP, respectively. For UCS prediction, both ANN and ALPS-GP models offered very strong predictions. Although ANN model appears to be stronger compared to ALPS-GP, it is very important that ALPS-GP provides equations like regression analysis. Equation obtained from ALPS-GP model can be used for UCS estimation of similar rock types. In addition, ALPS-GP is known to give more successful results in the solution of highly complex structures. Therefore, this study may encourage some researchers to use ALPS-GP in rock mass classifications such as RMR, Q and GSI.

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