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Investigating Correlation of Physico-Mechanical Parameters and P-Wave Velocity of Rocks: a Comparative Intelligent Study

Hadi Fattahi[1*], Mahdi Hasanipanah[2] and Nastaran Zandy Ilghani[1]

1- Faculty of Earth Sciences Engineering, Arak University of Technology, Iran
2- Department of Mining Engineering, University of Kashan, Iran

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Abstract

The mechanical characteristics of rocks and rock masses are considered as the determining factors in making plans in the mining and civil engineering projects. Two factors that determine how rocks responds in varying stress conditions are P-wave velocity (PWV) and its isotropic properties. Therefore, achieving a high-accurate method to estimate PWV is a very important task. This work investigates the use of different intelligent models such as multivariate adaptive regression splines (MARS), classification and regression tree (CART), group method of data handling (GMDH), and gene expression programming (GEP) for the prediction of PWV. The proposed models are then evaluated using several error statistics, i.e. squared correlation coefficient (R2) and root mean squared error (RMSE). The values of R2 obtained from the CART, MARS, GMDH, and GEP models are 0.983, 0.999, 0.995, and 0.998, respectively. Furthermore, the CART, MARS, GMDH, and GEP models predict PWV with the RMSE values of 0.037, 0.007, 0.023, and 0.020, respectively. According to the aforementioned amounts, the models presented in this work predict PWV with a good performance. Nevertheless, the results obtained reveal that the MARS model yields a better prediction in comparison to the GEP, GMDH, and CART models. Accordingly, MARS can be offered as an accurate model for predicting the aims in other rock mechanics and geotechnical fields.

1 Introduction

Mechanical characteristics of rock masses is significantly effective in petroleum engineering, geological mining, geotechnical studies, etc. [1,2]. These features are considered as a significant indication for planning in the long-term and designing the programs provided for exploring and exploiting natural resources. The anisotropy of rock masses has an adverse effect on the rock strength. The primary wave velocity (PWV) is affected by many variables, i.e. chemical composition, hardness, and density. The dynamic features of rocks are typically determined using the seismic methods. These techniques are incrementally applied at different levels of constructions because they are not damaging, and their implementation is relatively easy [3,4]. Szlavin [5] has conducted a study to find whether a statistically-significant relationship exists amongst different examined properties. His findings showed that a high correlation exists amongst the rock mechanical features.

Determining PWV in the field and laboratory is monotonous. Extracting much information related to the rocks and minerals that are likely to occur in various deeper layer of earth is possible if the field and laboratory geophysical and geological and geochemical data are regarded together. Therefore, estimating the physical features of the rocks and PWV seems appropriate [4]. Many laboratory data related to the mechanical features are required in order to characterize the site. It is not much easy to directly get all the studied parameters considering the discontinuity and anisotropy in the rocks. The analytical or

Corresponding author: h.fattahi@arakut.ac.ir (H. Fattahi).

empirical relationship between different mechanical strength features of the interested materials are applied by the rock engineers [6]. Numerous investigators have suggested that a significant relationship exists between the rock properties and PWV. In order to estimate PWV and the anisotropic characteristics of rocks, some variables such as the uniaxial compressive strength (UCS), density, hardness, and rocks' chemical formation can be used [7,8]. Karakus, Tutmez [9] have used the fuzzy and regression methods in order to assess the intact rock strength on the basis of a point load strength index and sonic velocity. According to their findings, the proposed method had a relatively good flexibility in order to determine the uncertainties in the rock features. An adaptive neuro-fuzzy inference system (ANFIS) has been implemented by Zoveidavianpoor et al. [10] to predict PWV in a carbonate reservoir. Ansari [11] has employed the ANFIS model to predict the porosity, and subsequently, mixed through a power law committee machine. In another study conducted by Golsanami et al. [12], the application of the fuzzy logic (FL), artificial neural network (ANN), and ANFIS models have been investigated to estimate capillary pressure. The studies with the highest similarity with this research work were conducted by some researchers [13-15]; however, they used various input and output parameters. Rajabi *et al*. [13] have predicted PWV, shear and Stoneley wave velocities from conventional well log data through FL, genetic algorithm (GA), and ANFIS models. The aforementioned models were also successfully applied by Asoodeh, Bagheripour [14] to predict the same purpose. In another study, FL, ANN, ANFIS, and support vector regression (SVR) were employed by Labani, Sabzekar [16] to predict the sonic shear and stoneley velocities. With the same purpose, Miah et al. [17] have used a least-squares support vector machine (LSSVM) optimized by a global optimization technique. Their results indicated the effectiveness of the proposed model in this field. A long short term memory (LSTM) recurrent neutral network optimized by particle swarm optimization (PSO) was proposed for predicting the shear wave velocity (SWV) in the study conducted by Wang et al. [18]. They also used the empirical and multiple linear regression models for the comparison aims. Their results obtained showed a satisfactory achievement between the observed and predicted values by the proposed model to predict SWV. An ANFIS optimized with PSO and GA was presented by Anemangely et al. [19] in order to predict SWV. The multivariate regression analysis (MVRA) and empirical models were also used in their study. Based on the results obtained, ANFIS-PSO exhibited a higher performance than the other models in predicting SWV. A LSSVM model implemented by a Cuckoo Optimization Algorithm (COA) was developed to predict SWV using petrophysical logs [20]. They also combined the LSSVM model with PSO and GA, and compared the performance of the proposed models. According to the results obtained, LSSVM-COA was found a superior predictive model in comparison to the LSSVM-PSO and LSSVM-GA models in predicting SWV. Modeling of SWV in limestone was investigated by Behnia et al. [21] using the ANFIS, gene expression programming (GEP), and neuro-genetic models. They revealed that GEP was more accurate than the other models in the studied case and had the capacity to generalize.

The use of machine learning and non-linear methods in different rock mechanics and geotechnical fields have been expanded but its application in the PWV prediction is limited. To this view, the present work develops several practical models in this field. Multivariate adaptive regression splines (MARS) is a powerful method for predicting the aims, and has been used in different fields but its application in the rock mechanic field is limited. In other words, the present research work presents a practical application of MARS to predict PWV. Apart from that, a group method of data handling (GMDH), gene expression programming (GEP), and classification and regression tree (CART) are also employed. To the best of our knowledge, it is the first work that predicts PWV through the MARS model. The rest of this paper is organized as what follows. The background of aforementioned models is briefly explained in part 2. Then the modeling processes are explained in part 3. Finally, the comparison of the models, their results, and the conclusions are presented in parts 4 and 5, respectively.

2. Considered intelligent models

2.1. CART

The CART algorithm is a subset of the decision tree (DT) method, and is one of the data mining techniques [22]. Though the CART algorithm has been developed for measurable variables, it is enforceable to any variable. The CART algorithm does not take into account the initial assumption of the connections between the variables [23]. As stated earlier, when the output is set as real value, tree regression (TR) should be used. Thus considering the output results, TR should be applied. The starting point is known as the root node that covers the data in the recursive partitioning. Thereafter, every node is consequently split into two subsets, and this process is replicated in each node till the leaf and the system can be calculated for the target. For the CART method, several termination criteria can be established, out of which three key criteria include the maximum depth of tree, a minimum observations number in a node split, and the interval number. A comprehensive explanation of the CART algorithm can be found in Breiman et al. [22]. The use of the CART method in different engineering fields has been investigated by many researchers. Ebrahimy et al. [24] have offered the CART method in the field of land subsidence. In another study, Naghibi et al. [25] have evaluated the maps of groundwater using the CART method. In addition, the use of CART method to predict the performance of tunnel boring machine has been examined by Salimi et al. [26]. In the field of mine blasting, Khandelwal et al. [27] have predicted the ground vibration through the CART method. Furthermore, in order to determine heavy-metals pollution, Cheng et al. [28] have used the CART method. The aforementioned studies have confirmed the acceptability of the CART method for the prediction and classification aims.

2.2. MARS

MARS offers a flexible modeling technique for a high-dimensional data [29]. The regression function of the MARS model is defined as:

$$\hat{y} = \hat{f}_M(x) = c_0 + \sum_{m=1}^{M} c_m B_m(x) = c_0 + \sum_{m=1}^{M} c_m \prod_{k=1}^{K_m} b_{km}\left(x_{v(k,m)}\right) \tag{1}$$

where c_0 is a constant, y^ is a variable vector estimated using MARS, and $B_m(x) = \prod_{k=1}^{k_m} b_{km}\left(x_{v(k,m)}\right)$ is the product of splines $b_{km}\left(x_{v(k,m)}\right)$. The splines b_{km} is defined as:

$$b_{km}(x) = [x - t_{km}]_+^q = \begin{cases} (x - t_{km})_+^q, & if\ x > t_{km}, \\ 0 & others \end{cases} \tag{2}$$

and

$$b_{k,m+1}(x) = [t_{km} - x]_+^q = \begin{cases} (t_{km} - x)_+^q, & if\ x < t_{km}, \\ 0 & others \end{cases} \tag{3}$$

The bases functions are selected according to Eq. (1) in the forward process. In the backward process, based on the generalized cross-validation (GCV) criteria, the unsuccessful basis functions are discarded. The GCV criterion is defined as:

$$GCV = \frac{1}{n} \frac{\sum_{m=1}^{n} \left(y_i - \hat{f}_M(x_i)\right)^2}{\left(1 - C(M)/n\right)^2} \tag{4}$$

where n is the object number, and $C(M)$ is described as:

$$C(M) = (M+1) + dM \tag{5}$$

d is the penalty (in this paper, d = 3), and M is the term number in Eq. (2). A comprehensive explanation of the MARS theory can be found in [29]. The MARS method has been widely used in different fields. Zheng et al. [30] have used the MARS method in tunnel displacement. In another research work, Kang et al. [31] have evaluated the behavior of concrete dam by the MARS method. The above researches indicated the effectiveness of the MARS method in the studied fields.

2.3. GMDH

The GMDH neural network was proposed by Ivakhnenko [32]. The GMDH neural network has been employed in a numerous varieties of fields such as rock/soil mechanics for optimization and forecasting [33]. In the GMDH neural network, it is now possible to train the network for any given input vector, $X = (x_{i1}, x_{i2}, x_{i3}, ..., x_{in})$ to estimate the output values ($\hat{y}_i$), that is:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, ..., x_{in})\ i = 1, 2, ..., M \tag{6}$$

It should be possible for the GMDH neural network to decrease the error square between the measured and estimated values:

$$\sum_{i=1}^{M}\left[\hat{f}\left(x_{i1},x_{i2},x_{i3},...,x_{in}\right)-y_i\right]^2 \rightarrow \min \tag{7}$$

It is possible to define the relation between the output and inputs as follows:

$$\begin{aligned} y &= a_0 + \sum_{n}^{1} a_i x_i + \sum_{n}^{1}\sum_{n}^{1} a_{ij} x_i x_j + \\ &+ \sum_{n}^{1}\sum_{n}^{1}\sum_{n}^{1} a_{ijk} x_i x_j x_k + ... \end{aligned} \tag{8}$$

The two variables and the quadratic form are utilized in several applications, as follows:

$$\begin{aligned} \hat{y} = G\left(x_i, x_j\right) &= a_0 + a_1 x_i + a_2 x_j + \\ &+ a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \end{aligned} \tag{9}$$

By the regression methods, a_i in Eq. (9) is determined.
In the GMDH neural network, all neurons are built from n input variables, thus:

$$\binom{n}{2} = \frac{n\left(n-1\right)}{2} \tag{10}$$

The neurons are constructed as follows in the second layer:

$$\left\{\left(y_i, x_{ip}, x_{iq}\right) \middle| \begin{array}{l} i = 1,2,...,M \\ \& \\ p,q \in 1,2,...,M \end{array}\right\} \tag{11}$$

For each M triple row, a form of the function described in Eq. (9) is utilized. These equations can be described as follows:

$$A\,a = Y \tag{12}$$

where A is the unknown coefficient vector of the equation presented in Eq. (9).

$$a = \{a_0, a_1, a_2, a_3, a_4, a_5\} \tag{13}$$

$$Y = \{y_1, y_2, y_3, ..., y_M\}^T \tag{14}$$

The observation vector is the output values, thus:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix} \tag{15}$$

and

$$a = \left(A^T A\right)^{-1} A^T Y \tag{16}$$

A detailed explanations of the GMDH neural network can be found in [34-36]. Many researchers have used the GMDH method in different areas of studies. Koopialipoor et al. [37] have predicted the performance of tunnel boring machine through the GMDH method. In the field of rock mechanic, Chen et al. [38] have offered GMDH for the prediction of the cohesion of rocks. The mentioned studies show the ability of the GMDH method for the prediction aims.

2.4. GEP

GEP is achieved from genetic programming and genetic algorithm improvement proposed by Ferreira [39]. In GEP, the solutions are known as chromosomes like genetic algorithm. However, in the GEP algorithm, the chromosomes are described in the Karva language [40]. In this algorithm, each chromosome consists of two parts, tail and head. There are all terminals and functions for the tails, although there are only constant and input variables for the heads. The GEP algorithm consist of five key components: operator(s), stop condition, fitness function, terminal set, and function set. The main steps and the flow chart of the GEP algorithm is presented in Figure 1. Also a comprehensive explanation of the GEP algorithm can be found in [39]. The application of GEP has been highlighted by some scholars. Faradonbeh et al. [40] have offered the GEP model for the fly-rock estimation in mine blasting. In another study, the performance of road-header in tunneling has been approximated by Faradonbeh et al. [41]. Additionally, İnce et al. [42] have estimated the uniaxial compressive strength of rocks using the GEP model. The aforementioned research works confirmed the reliability of the GEP model in the mining and geotechnical fields.

2.5. Database

In order to construct the predictive models, the required datasets were borrowed from a comprehensive research work carried out by Verma, Singh [43]. In the database used, some variables such as the hardness and porosity were assigned as the input parameters; also PWV was assigned as the output parameter. In total, 36 data samples were applied in the modeling process, and categorized into the training and testing phases. More details regarding the database are mentioned in Table 1.

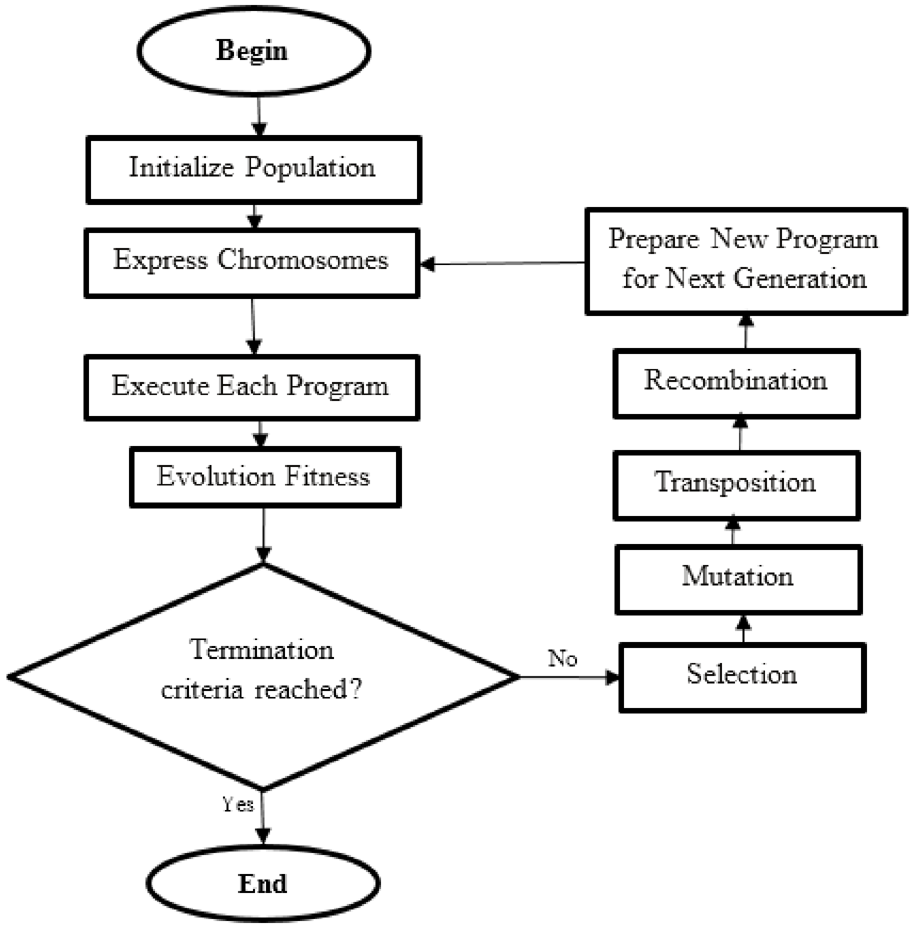

Figure 1. A flow chart of GEP algorithm.

Table 1- Descriptive statistics of the database [43].

Descriptive statistics	Parameters						
	Input						Output
	Hardness	Porosity (%)	Absorption (%)	Compressive strength (MPa)	Density (g/cc)	Fracture roughness coefficient	PWV (cm/s)
Standard error	0.179	0.058	0.014	6.673	0.017	0.170	21.547
Median	5.43	0.91	0.367	177	2.7115	2.244	498.828
Standard deviation	1.079	0.351	0.089	40.039	0.106	1.021	129.287
Kurtosis	-0.983	-0.765	-1.191	-1.310	-0.943	-1.054	-1.074
Skewness	-0.437	0.312	-0.030	0.032	-0.127	-0.129	-0.399
Minimum	3.28	0.43	0.215	104.98	2.51	0.236	239.59
Maximum	6.93	1.81	0.54	244	2.889	3.905	671.094

2.6. Model performance evaluation

In order to improve the stability of the training of the proposed models (CART, GMDH neural network, MARS, and GEP), the data of both the output and inputs should be normalized. In this work, all data was converted into the values between [0, 1] by the following expression:

$$x_M = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{17}$$

where x, x_M, x_{min}, and x_{max} are before being normalized, after being normalized, minimum value, and maximum value, respectively.

Also in order to evaluate the performance of the models, squared correlation coefficient (R^2) and root mean squared error (RMSE) were selected as the error statistics. RMSE and R^2 are formulated [44-52]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2} \quad (18)$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^2 - \frac{\sum_{i=1}^{n}\hat{t}_k^2}{n}} \quad (19)$$

where t_k , $\hat{t}_k$, and n are the actual value, predicted values, and observation numbers, respectively.

3. Results and discussion

About prediction of PWV using CART, the MATLAB software was applied in this work. Using the training data, the CART model aims to learn the relationships between the output and input parameters to obtain a low prediction error. The testing data was also utilized to measure the efficiency of the built method. Firstly, all data was divided randomly into testing (20%) and training (80%). In order to obtain the best CART, the range of interval numbers and maximum depth of tree was chosen [1–9 and 2–9], respectively. Different approaches were tested (based on the trial-and-error) in order to evaluate these two parameters. After numerous trials and errors, five CART models were established. In order to analyze the model performance, R^2 and RMSE were calculated.

Based on the two error statistics (see Table 2), model 5 (with maximum tree depth = 4) was the best model. Figure 2 shows the tree structure that starts with the hardness parameter as the root node, and has 13 nodes.

Table 2- Error statistics for assessment of CART models.

No.	Maximum tree depth	R^2 (Train)	R^2 (Test)	RMSE (Train)	RMSE (Test)
1	5	0.97231	0.91287	0.04845	0.05321
2	6	0.94281	0.92521	0.02372	0.05334
3	7	0.96523	0.93215	0.03924	0.05725
4	6	0.95222	0.93521	0.02452	0.05114
5	**4**	**0.99557**	**0.98387**	**0.01967**	**0.03753**

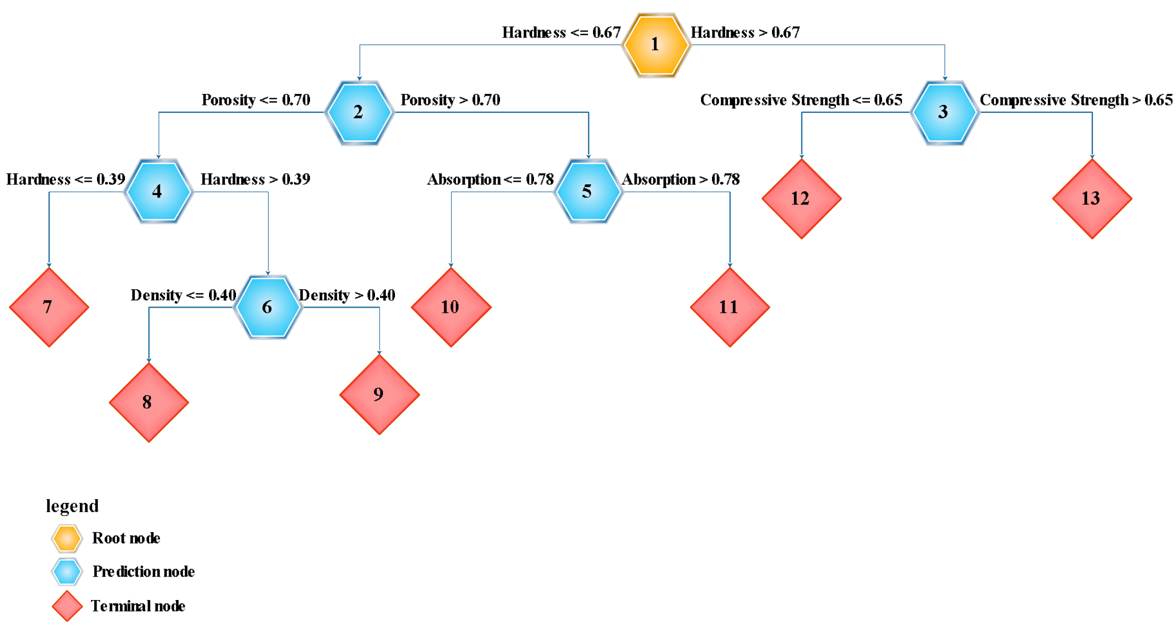

Figure 2. Tree structure of the best CART.

About prediction of PWV using MARS, in this work, the MARS model was constructed by the MATLAB software. Also this work adopts R^2 and RMSE to evaluate the MARS's performance. 15

basic functions were utilized to develop the MARS model. Finally, 6 basis functions were utilized for the optimum MARS model. The optimum equation for estimation of P-wave velocity is given by:

$$P-wave = 0.665 + \sum_{i=1}^{6} a_i B_i \tag{20}$$

The a_i and B_i values are presented Table 3. In addition, the performance of both the training and testing phases is listed in Table 4. The mentioned results in this table show that the developed MARS is a powerful method for the estimation of PWV.

Table 3- The a_i and B_i values of the MARS model.

B_i	Equation	a_i
B_1	Max (0, Hardness - 0.558904)	0.6117
B_2	Max (0, 0.558904 - Hardness)	0.9855-
B_3	Max (0, 0.525248 – Compressive strength)	0.1682
B_4	Max (0, Density - 0.422164)	0.1153
B_5	Max (0, 0.422164 - Density)	0.3247-
B_6	Max (0, Fracture roughness coefficient - 0.51867)	0.6409-

Table 4- Error measurement by MARS model.

MARS model	Train		Test	
	RMSE	R^2	RMSE	R^2
	0.00381	0.99983	0.00798	0.99927

About prediction of PWV using the GMDH neural network, in this work, the professional ANN software was utilized to develop the GMDH neural network, namely GMDH Shell. This software does not require initial data normalization and noticeably reducing processing time. A data collection containing 36 data points was used, while 80% of the data was applied for training (approximate equation), and the remaining data was applied for calculation of the accuracy degree. A schematic presentation of the proposed GMDH neural network is shown in Figure 3. After modeling, the equation given by the GMDH shell program is given in Table 5. Also the error measurement given by the GMDH shell and a comparison of the measured data with the estimated data are presented in Table 6 and Figure 4.

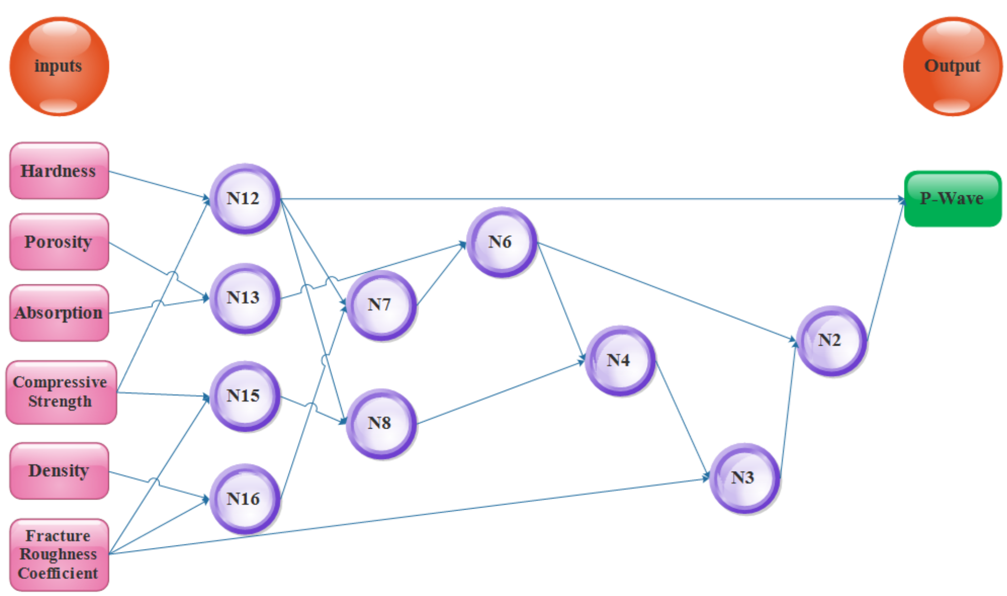

Figure 3. A view of the proposed GMDH.

Table 5- Given equation by software.

Proposed Model: P-wave = 0.000596132 - **N12***0.168554 + **N12**^2*0.0831675 + **N2***1.1666 - **N2**^2*0.0817804	
Nodes	
N2=	2.40644e-05 - N6*0.232669 + N6^2*0.0227659 + N3*1.23259 - N3^2*0.0227148
N3=	0.00230702 - FractureRoughnessCoefficient^2*0.00451408 + N4*1.00179 - N4^2*0.00378364
N4=	-0.000687493 + N8*1.00327 - N8^2*0.741414 + N6^2*0.738464
N6=	-0.00581691 - N13*0.290212 + N13^2*0.199494 + N7*1.30897 - N7^2*0.209071
N7=	-0.147936 + N12*1.37108 - N12^2*0.467611 + N16*0.164835 + N16^2*0.0650832
N8=	0.00217457 + N12*1.01064 + N12^2*0.0452028 - N15^2*0.0654248
N12=	-0.0758137 + Hardness*0.732606 + Hardness^2*0.240665 + CompressiveStrength*0.73875 - CompressiveStrength^2*0.665822
N13=	1.04956 - Porosity*3.03513 + Absorption*1.84419
N15=	-4.80563 + CompressiveStrength*11.0636 - CompressiveStrength^2*5.58128 + FractureRoughnessCoefficient^2*4.23617
N16=	0.417828 + Density*0.820534 - Density^2*0.163054 - FractureRoughnessCoefficient^2*0.394987

Table 6- Error measurement by GMDH neural network model.

	Train		Test	
GMDH neural network model	**RMSE**	**R^2**	**RMSE**	**R^2**
	0.003667	0.999835	0.023325	0.995024

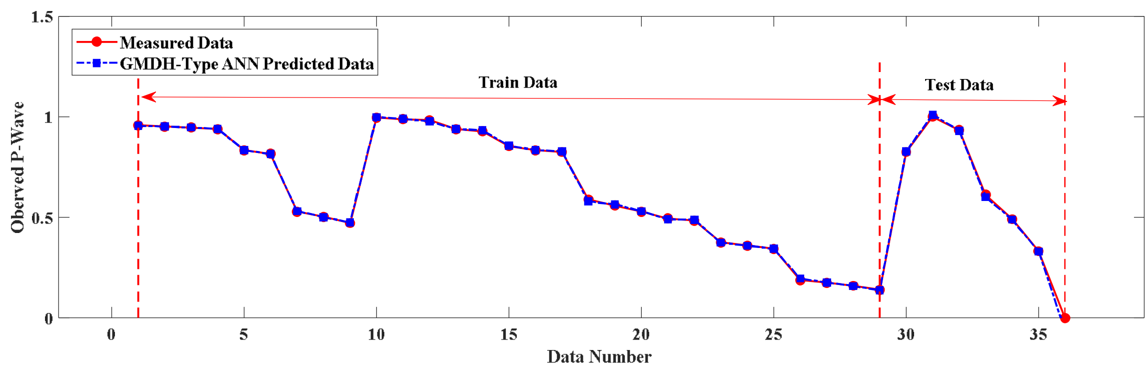

Figure 4. Comparison of measured values with those estimated by GMDH neural network.

About prediction of PWV using the GEP algorithm, this section aims to find a function in the template of *PWV =f(fracture roughness, porosity, absorption, density, compressive strength)* to estimate PWV, where the fracture roughness, porosity, absorption, density, and compressive strength are the independent factors, and PWV is the dependent factor. The GeneXpro Tools 4.0 is a powerful flexible modeling software for the classification, logic synthesis aims, and function finding. Therefore, in this work, GeneXpro Tools 4.0 was selected and utilized. First of all, 80% of the data was applied randomly for training, and 20% of the dataset was applied for testing. Note that since there is no definite procedure to evaluate the general setting values, a trial-and-error method was employed to obtain this aim, and finally, considering Table 7, the best solution was achieved. In addition, the tree structure of the GEP model for predicting the PWV is shown in Figure 5.

Table 7- Parameter values for the developed GEP.

GEP algorithm parameters	Parameter settings
Number of generation	1000
Chromosomes	30
Head size	8
Fitness function	RMSE
Linking function	Addition (+)
Number of genes	3
Mutation rate	0.00138
Inversion rate	0.00546
One-point recombination rate	0.00277
Two-point recombination rate	0.00277
Gene recombination rate	0.00277
Gene transposition rate	0.00277

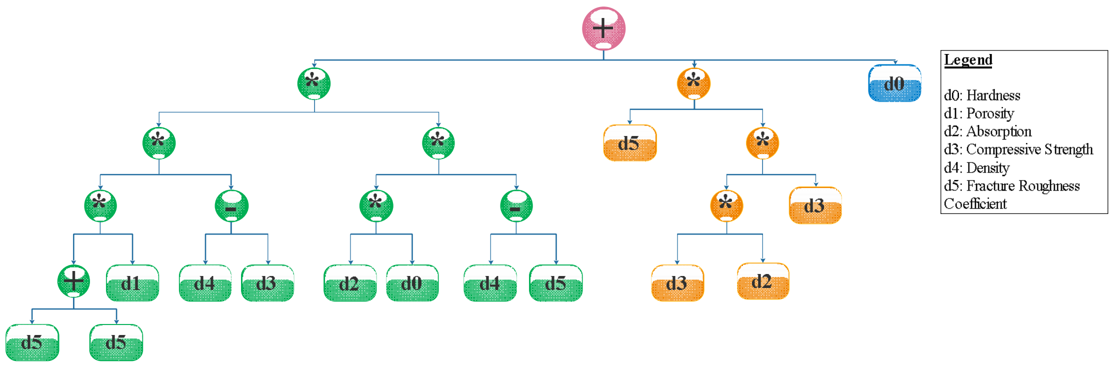

Figure 5. Tree structure of the GEP model for predicting PWV.

In order to determine the GEP model performance, R^2 and RMSE were measured. In the training, the calculated values of 0.008 and 0.999413 were achieved for RMSE and R^2, respectively, while the values of 0.998676 and 0.0204 were achieved for the two performance indices, respectively. The results obtained showed that the GEP model was able to estimate PWV with a good precision. A better view between the estimated and measured PWV by GEP for all data is presented in Figure 6.

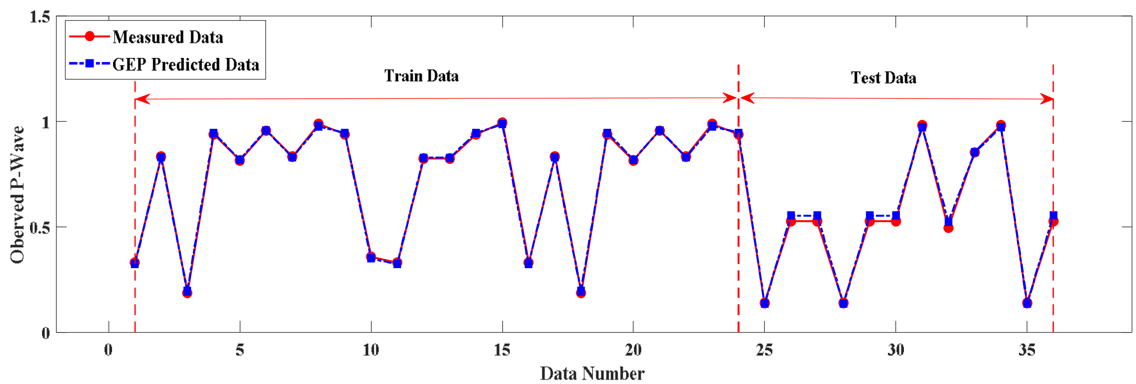

Figure 6. Comparison of measured values with those estimated by GEP model.

At the end, we compared our results of the proposed models (CART, GMDH neural network, MARS, and GEP); this comparison is shown in Figure 7. As it can be seen, all the models offered in the current research work were able to effectively estimate PWV; however, MARS reveals a better accuracy level to other models.

4. Conclusions

The physical and mechanical characteristics of rocks play an important role in the whole operational segments in the activities related to mining and ranges from exploration to dispatch of material. There are two characteristics, i.e. PWV and the rocks' anisotropic behavior, which help us to understand the rock behavior in the conditions of stress. Further, the breakage mechanism of rocks is affected by the two above-noted characteristics. The literature consists of a number of methods used to determine PWV and anisotropy in the *in situ* and laboratory conditions. However, such techniques are burdensome, and take a lot of time. This work employed different artificial intelligence methods including CART, MARS, GMDH, and GEP in order to predict PWV. Then the proposed models were evaluated through statistical functions, i.e. R^2 and RMSE. Some conclusions can be drawn as what follows. (1) Reviewing the results, the proposed models provided good predictions of PWV. The values of the statistical functions (R^2 and RMSE) obtained from the CART, MARS, GMDH, and GEP models were (0.983, 0.037), (0.999, 0.007), (0.995, 0.023), and (0.998, 0.020), respectively. According to the aforementioned results, the MARS model produced better results than the other models. (2) As a conclusion, the ability of the MARS model can be confirmed, and it has the capacity to generalize in other rock mechanic fields

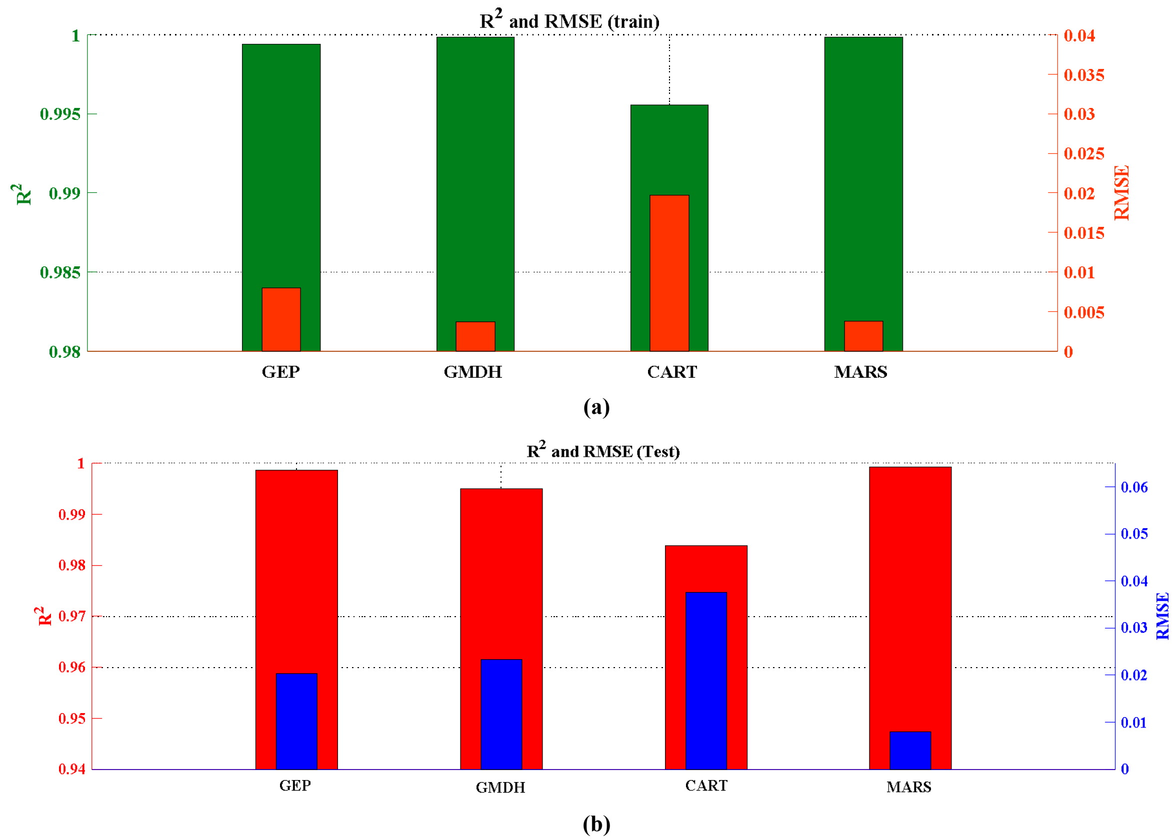

Figure 7. Comparison of performance of the proposed models for a) training, b) testing.

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بررسی همبستگی پارامترهای فیزیکی-مکانیکی و سرعت موج فشاری سنگ‌ها: یک مطالعه مقایسه‌ای هوشمند

هادی فتاحی[1*]، مهدی حسنی پناه[2] و نسترن زندی ایلقانی[1]

۱- دانشکده مهندسی علوم زمین، دانشگاه صنعتی اراک
۲-گروه مهندسی معدن دانشگاه کاشان

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* نویسنده مسئول مکاتبات: h.fattahi@arakut.ac.ir

چکیده:

ویژگی‌های مکانیکی سنگ‌ها و توده‌های سنگی به عنوان عوامل تعیین کننده در طراحی پروژه‌های معدنی و عمرانی در نظر گرفته می‌شوند. دو عامل تعیین کننده نحوه واکنش سنگ‌ها در شرایط مختلف تنش، سرعت موج فشاری (PWV) و خواص ایزوتروپیک آن است. بنابراین، دستیابی به روشی با دقت بالا برای برآورد PWV یک کار بسیار مهم است. در این مقاله استفاده از مدل‌های مختلف هوشمند مانند خطوط رگرسیون تطبیقی چند متغیره (MARS) ، درخت طبقه‌بندی و رگرسیون (CART) ، روش گروهی مدیریت داده‌ها (GMDH) و برنامه ریزی بیان ژن (GEP) برای پیش‌بینی PWV را مورد بررسی قرار گرفته است. پس از مدلسازی، با استفاده از چند شاخص آماری، نظیر ضریب همبستگی مربع (R^2) و مجذور خطای مربع میانگین (RMSE) ارزیابی می‌شوند. مقادیر R^2 بدست آمده از مدل‌های CART، MARS، GMDH و GEP به ترتیب ۰/۹۸۳ ، ۰/۹۹۹ ، ۰/۹۹۵ و ۰/۹۹۸ است. علاوه بر این، مدل های CART، MARS، GMDH و GEP به ترتیب PWV را با مقادیر RMSE ۰/۰۳۷، ۰/۰۰۷ ، ۰/۰۲۳ و ۰/۰۲۰ پیش‌بینی می‌کنند. با توجه به مقادیر شاخص‌های فوق الذکر، مدل‌های ارائه شده در این مقاله PWV را با عملکرد خوبی پیش‌بینی می‌کنند. با این وجود، در نهایت نتایج بدست آمده نشان می‌دهد که مدل MARS در مقایسه با سایر مدل‌های GEP، GMDH و CART پیش‌بینی بهتری دارد. بر این اساس، MARS می‌تواند به عنوان یک مدل دقیق برای پیش‌بینی سایر اهداف در مسائل مختلف مکانیک‌های سنگی مورد استفاده قرار گیرد.

کلمات کلیدی: سرعت موج فشاری، هوش مصنوعی، مدل‌های پیش بینی، خطوط رگرسیون تطبیقی چند متغیره.