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Engineering with Computers

Assessing cohesion of the rocks proposing a new intelligent technique namely group method of data handling

--Manuscript Draft--

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Abstract:	In this study, evaluation and prediction of rock cohesion is assessed using multiple regression as well as group method of data handling (GMDH). It is a well-known fact that cohesion is the most crucial rock shear strength parameter, which is a key parameter for the stability evaluation of some geotechnical structures such as rock slope. To fulfill the aim of this study, a database of three model input parameters, i.e., p-wave velocity, uniaxial compressive strength and Brazilian tensile strength and one model output, which is cohesion of limestone samples was prepared and utilized by GMDH. Different GMDH models with neurons and layers and selection pressure were tested and assessed. It was found that GMDH model number 4 (with 8 layers) shows the best performance among all of tested models between the input and output parameters for the prediction and assessment of rock cohesion with coefficient of determination (R2) values of 0.928 and 0.929, root mean square error (RMSE) values of 0.3545 and 0.3154 for training and testing datasets, respectively. Multiple regression analysis was also performed on the same database and R2 values were obtained as 0.8173 and 0.8313 between input and output parameters for the training and testing of the models, respectively. The GMDH technique developed in this study is introduced as a new model in field of rock shear strength parameters.
Response to Reviewers:	Response Letter Ref.: EWCO-D-19-00076 Title: Assessing cohesion of the rocks using a new intelligent technique namely GMDH To: Engineering with Computers

Dear Editor,

I would like to thank you for giving us the opportunity to evaluate our paper with your expert and knowledgeable reviewers. The revised format of our paper is now ready based on the comments and advises of reviewers. In the revised manuscript, the changes are shown using red color. Our responses to the comments of reviewers can be seen in the following lines.

- Response to Reviewer #1
- Response to Reviewer #2

Thank you for your time and kind consideration.
Best regards,
Dieu Tien Bui
Corresponding author

Response to the reviewer #1:
Dear Prof. / Dr.
I would like to appreciate your precise comments. Please consider our explanations and clarifications.

In the above paper, the new model of intelligence methods (GMDH) was used to assess the cohesion. The subject is worth to investigate and the manuscript is well-written in terms of material and methods. Nevertheless, it is suggested to explain below comments and the required information:

Reply: Thank you very much for mentioning these points.

1. Suggest to add some other related AI studies to enhance the quality of your work.
Reply: Thank you for mentioning this point. We have added several related works.

2. Please correct some of your tables.
Reply: Thank you very much. We changed and corrected them.

3. Although, in the introduction section, very good contents are presented, suggest to more focus on this section.
Reply: Thank you for this point and we added several sentences in the revised manuscript to this section.

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It is fairly well written and can be considered for the publication after a double check avoiding typographical errors.
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Best regards,
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Corresponding author

Cover Letter

Date: 26 February 2019

Subject: Submission of a revised manuscript for evaluation and publication

Dear Editor,

I am enclosing herewith a **revised** manuscript entitled "***Assessing cohesion of the rocks proposing a new intelligent technique namely group method of data handling***" for possible evaluation and publication in "***Engineering with Computers"***. The helpful and constructive comments by the reviewer are greatly appreciated. The revised format of our paper is now ready based on the comments and advises of reviewer. As seen in the enclosed documents, the content of the manuscript has been rewritten entirely with better understanding and clearer concept.

It should be mentioned that our response to reviewer's comments can be found as "Response Letter" file and our changes are shown using red color.

Sincerely Yours,

Dieu Tien Bui
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Ton Duc Thang University,
Ho Chi Minh City, Viet Nam.
Email: buitiendieu@tdtu.edu.vn.

Response Letter

Ref.: EWCO-D-19-00076

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To: Engineering with Computers

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Assessing cohesion of the rocks proposing a new intelligent technique namely group method of data handling

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Abstract

In this study, evaluation and prediction of rock cohesion is assessed using multiple regression as well as group method of data handling (GMDH). It is a well-known fact that cohesion is the most crucial rock shear strength parameter, which is a key parameter for the stability evaluation of some geotechnical structures such as rock slope. To fulfill the aim of this study, a database of three model input parameters, i.e., p-wave velocity, uniaxial compressive strength and Brazilian tensile strength and one model output, which is cohesion of limestone samples was prepared and utilized by GMDH. Different GMDH models with neurons and layers and selection pressure were tested and assessed. It was found that GMDH model number 4 (with 8 layers) shows the best performance among all of tested models between the input and output parameters for the prediction and assessment of rock cohesion with coefficient of determination (R^2) values of 0.928 and 0.929, root mean square error (RMSE) values of 0.3545 and 0.3154 for training and testing datasets, respectively. Multiple regression analysis was also performed on the same database and R^2 values were obtained as 0.8173 and 0.8313 between input and output parameters for the training and testing of the models, respectively. The GMDH technique developed in this study is introduced as a new model in field of rock shear strength parameters.

Keywords: GMDH, Rock cohesion, P-wave, Uniaxial compressive strength, Brazilian tensile strength.

1. Introduction

One of the most important aspects of designing underground structures is that the engineer should understand and predict the mechanical behavior of rock under pressure. Rocks under pressure encounter two mechanisms of resistance – (1) Internal friction angle (ϕ) and (2) cohesion (C). For example, a precise estimate of Shear Strength, which will determine to what extent the rock can resist deformation under shear forces, is very important [1]. Shear Strength can be measured directly from lab tests on samples, but there are two problems with it – it is time consuming and expensive; and good quality samples are difficult to obtain particularly in weak and jointed rocks [2]. Hence a method of using rock index tests has been developed [1, 3–6], which makes it easier for assessing shear strength. These tests are faster and cost are lesser than uniaxial or triaxial compressive tests [7, 8]. Scientists carry out such shear strength tests on samples made of mixture rock particles, sand and clay [9–17], and find that increase in the proportion of rock particles increases the shear strength [18]. For weak and highly jointed rocks, a non-linear Mohr-Coulomb strength criterion has shown good results. However, this test has two limitations propounded by Singh and Singh [19]– one is linear strength response and the other is non-consideration of intermediate principal stress on strength behavior. By applying Barton's critical state concept [20], non-linear strength criterion was acquired. Bivariate and multiple regression techniques applied on 45 different mudrock samples by Hajdawrish and Shakoor [21] established a correlation between geological and engineering properties like shear strength. In this manner they determined relationships between mineralogy, clay content, water, adsorption, dry density, Atterberg Limits, void ration, specific gravity, slake durability and shear strength and reported the estimation of ϕ and C in mudrock samples.

A comparison of Mohr-Coulomb and Hoek-Brown criteria [22] as applied to shale was studied by Yazdani [23]. The study showed that using Hoek-Brown criterion to develop a failure envelope gave a better description of the behavior of shale in field. The reason was that the classical Mohr-Coulomb criterion of prediction of rock behavior did not consider inherent discontinuities in the in situ rock masses. In another research, Ghazvinian et al [24] established that under normal stress by external loading, the anisotropic shear behavior in compact rock sample is represented by *ß*, the gradient of schistosity planes. The effective shear strength, which depended on influences of confinement and anisotropy varied from high to low, with variation in *ß*. In a study of mechanical properties of shale, Islam and Skalle [25] computed various properties under different confinement pressures, varying bedding planes, using drained/undrained processes. Lab tests on shale samples showed that the Poisson's ratio had decreased by 40% after drainage, accompanied by a high degree of heterogeneity. This led Barton [26] to conclude that non-linear classical Mohr-Coulomb criterion gave a more reliable forecast of in rock behavior in different conditions – rock fill or rock joints or rock masses.

The Application of artificial intelligence in geotechnical engineering is increasing [27–35]. The group method of data handling (GMDH) which is a type of neural network (NN), can be considered as a potent identification technique without having specific understanding of the processes. It is utilized for model complicated systems, in which unknown relationships exist between the variables. The GMDH algorithm is considered as a self-organizing approach and it can generate complex models, gradually according to their performances [36, 37]. Although GMDH is similar to NN, there are a number of advantages compared to NN. Among them, high speed and using easier mathematical functions which are accessible, can be mentioned for GMDH technique [38].

On the other hand, NN does not have an acceptable performance prediction in implementing and solving complex problems [37].

The application of the GMDH method has been used in various fields for evaluating different issues. This method has been used for issues that require linear and nonlinear computing. Some uses of this method are also used in civil and geotechnical engineering [38–40]. Recently, one of the things that has been discussed in the development of this approach has been by Koopialipoor et al. [41].

As far as authors know, application of GMDH for predicting rock cohesion has not been used/evaluated by the researchers. Therefore, in this study, a GMDH model is proposed to be developed for forecasting rock cohesion. In the first step, 63 data sets were prepared and used to develop a model. In these data sets, the model inputs were - p-wave velocity (*Vp*), uniaxial compressive Strength (UCS) and Brazilian tensile strength (BTS). In the next step, the case study and all applied methods were tested for predicting cohesion of the rock. The results would be discussed and the most suitable model for prediction of rock cohesion would be introduced to the reader.

2. Structure of GMDH

Artificial neural network (ANN) concept is considered as a system of high non-linearity by parallel operation, that is motivated by the complicated structure of the human brain [37]. The group method of data handling (GMDH) is a type of NN which can be recognized as a self-organizing method. It is able to generate complex networks according to their performances estimation on asset of multi-input, single-output data pairs (Xi, yi) (=1, 2, .., M). Generating an analytical function in a feed-forward network (FFN) according to a transfer function is called quadratic node. In this way, function coefficients are achieved using the regression methods in the principle idea of GMDH. The GMDH algorithm is used to display a model consists of a series of neuron layers, where in every layer, through a quadratic polynomial, various pairs are connected, and produce new neurons in the following layer(s). Such characteristic of the model allows mapping inputs to output or outputs.

In Figure 1, the structure of the technique is given. As can be seen, the four input parameters enter the system. In the first layer, different functions are created and then they are selected by the criteria, these functions and entered into the stage or the next layer. Finally, a function is named as the output of the model.

The relation 1 shows the general function of the parameters.

$$\hat{y}_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots x_{in}),\ (i = 2, 3, \ldots M) \tag{1}$$

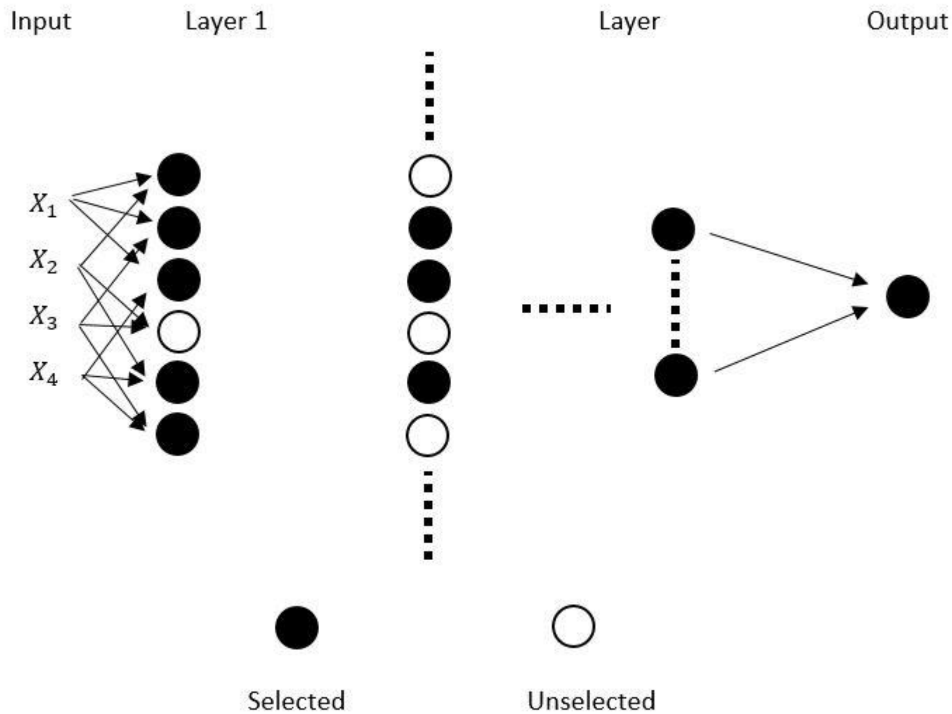

Figure 1 A proposed structure of GMDH model

The general trend of this model is based on the determination of the following function parameters:

$$y = a_o + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ijk} x_i x_i x_k + \ldots \qquad (2)$$

In fact, here, a mathematical relationship between different variables must be solved. Coefficients of ‘a’ are among the most important parameters to be determined. To determine this parameter, different functions are created at each stage and layer. This process is repeated to minimize the following equation:

$$E = \frac{\sum_{i}^{M} = 1(y_i - y(x_i, x_j))^2}{M} \rightarrow \min \tag{3}$$

For more information, refer to recent research [41].

The generated functions are determined on each layer using the neurons that they use. To select these parameters in the layers, the selectionpressure criterion is defined. This criterion acts so that any created function that has the required conditions is sent to the next step, and other functions are deleted. This criterion is defined by the mathematical relation 4. The value of this parameter is between 0 and 1. When the α parameter is given a value of 1, that is, the functions with the lowest error are selected. This causes the number of functions to be selected. When the value is closer to zero, more data is selected for the next step.

$$e_c = \alpha \times RMSE_{min} + (1 - \alpha) \times RMSE_{max} \tag{4}$$

$$RMSE = \sqrt{MSE} \tag{5}$$

The main trend of this model is presented in Figure 2. In this flowchart, all the scenarios used to implement the water model are mentioned. In the end, to check the performance of the models, the regression index of R^2 is also used alongside RMSE.

$$R^2 = \left(1 - \frac{\sum_{q=1}^{Num_{doto}} (Y_q - \hat{Y}_q)^2}{\sum_{q=1}^{NUM_{doto}} (Y_q - \bar{Y})^2} \right) \tag{6}$$

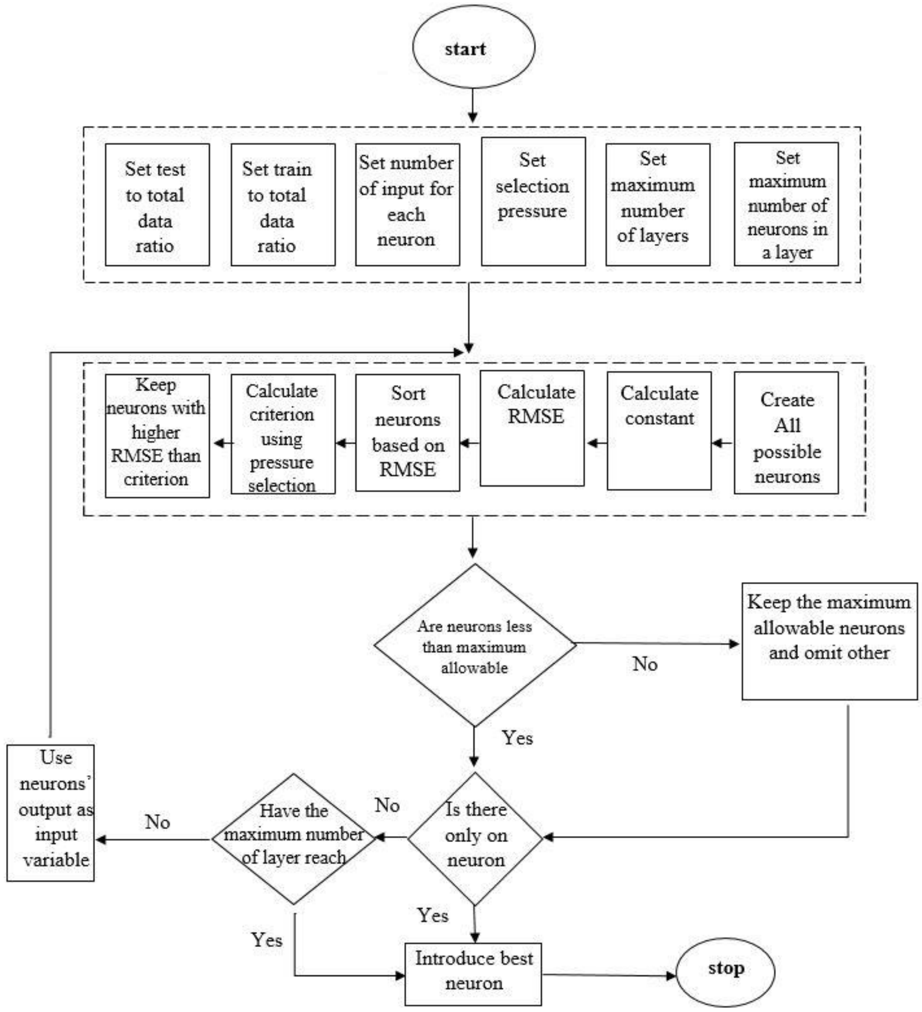

Figure 2 The general trend of implementing a GMDH model

3. Laboratory Investigation

Core drilled rock samples in NX size were collected from the subject rock mass. The ends of core samples were trimmed and cut to standard sizes as per ISRM [42]. The ends were thoroughly smoothened, using a lathe machine, to avoid end-effects, and then various physico-mechanical properties were determined.

3.1 Measurement of *p*-wave Velocity

A PUNDIT (**P**ortable **U**ltrasonic **N**on-destructive **D**igital **I**ndicating **T**ester) was used to determine the *p*-wave velocity of rock samples. As per ISRM [43], a prepared sample is subjected to a mechanical pulse generated by piezo-electric transducers in the PUNDIT. High voltage electric pulses are converted to mechanical pulses - *p*-waves - by piezo-electric transducers. These mechanical pulses applied at one end of the sample and received at the other end enable the instrument to determine the *p*-wave velocity.

3.2 Measurement of Uniaxial Compressive Strength (UCS)

As per ISRM [44], NX Size (54mm diameter) cylindrical core-samples of rock are collected and loaded between the platens of the Universal Testing Machine (UTM). A steady stress rate of 1.0 MPa per sec is applied till the failure occurs. The stress values are plotted and the peak of the curve, where it takes a dip at failure, is noted and that is recorded as the compressive strength of the sample.

3.3 Measurement of Brazilian Tensile Strength:

The Brazilian Test is a popular method of measuring tensile strength, in which a tensile failure is induced along one axis while applying a compressive strength along another axis. The principal of the Brazilian Test is that when subjected to biaxial stress fields, most rocks fail in tensile strength in one axis, when a compressive strength is applied at the other axis. The point to be noted, however, is that the magnitude of the compressive stress should not exceed three times that of the of the tensile stress [45].

3.4 Measurement of Cohesion:

The equipment used for measuring cohesion consists of a hydraulic actuator, hydraulic pressure unit, loadframe, data acquisition and measuring devices and a controller unit. Such equipment is used to carry out triaxial compression tests, using isotropic confining pressures (σ_3). This comes very close to simulating the stresses in a rockmass that is subject to weight of the overburden. In order to do this, a core sample is inserted into a triaxial cell and a hydraulic fluid is used as a medium to apply confining pressure. Keeping the confining pressure or cell pressure at a constant level, the axial load is gradually increased using the hydraulic actuator. Measurements are transmitted into the data logger and analyzed using testing software. A Mohr circle is drawn for each sample.

In this study, the cohesion tests were carried out on a number of similar samples, using different confining pressures. The data was used to draw a number of Mohr circles. Then tangent line drawn through the Mohr circles is the measure of cohesion of rock samples.

4. Statistical Data

Enormous amount of literature available shows that shear strength of rock bodies can be predicted using simple rock indices as inputs. Tests used to assess rock indices are simple and easy to perform.

In this study, to develop a model for assessing shear strength, a series of rock index tests were carried out on limestone samples. 63 samples were tested to generate the database, measuring V_p, UCS, BTS and Trixial Compression Tests. These indices were used as inputs to determine the cohesion (*C*) as output. The values of *C* were used for further analyses. These data, along with other related data comprising of the database are presented in Table1.

Table1 Database with Statistical Information of Rock Test Indices

Data	Abbreviation	Unit	Data type	Min	Max	Var	Mean
P-wave velocity	Vp	m/s	Input	3405.78	4735.10	100789.1	3978.74
Uniaxial compressive strength	UCS	MPa	Input	94.53	137.95	105.76	110.10
Brazilian tensile strength	BTS	MPa	Input	11.68	17.31	1.90	14.07
Cohesion	C	MPa	Output	16.13	21.50	1.80	18.45

The process of developing statistical and GMDH models for predicting cohesion properties using data from the database is described in the following sections.

5. Model Development

For identifying the best method of estimating rock cohesion, multiple regression analysis were used along with GMDH predictive models (Under two different conditions). The objective was to tabulate and compare the performance of each predictive model in assessing rock cohesion, and identify the most effective model.

The following sub-sections contain the process of each of the predictive models studied and compared.

5.1 Developing GMDH

In this section, implementation of the water model is considered. The purpose of this research is to develop a new soil model for prediction of water. As mentioned, the water model is a kind of neural network, which is actually introduced as a new method. To design this model, input and output data were selected from Table 1. After initial data analysis, they were divided into two parts: training and testing. According to the researchers' recommendations, 80% of the data was allocated to the training and other data to the testing [46, 47].

Given that any prediction model is affected by various parameters, in this model, parameters such as the number of neurons, the layer and the selection pressure are effective. In the previous section, explanations were given in these cases. In the following, to develop the model, there are several discussions on these parameters. These parameters are evaluated for effective prediction of rock cohesion.

5.1.1 Numbers of Neuron

One of the parameters that is considered in neural networks is the number of neurons. Choosing this parameter, given the conditions in which each data has in computational space, can has a great importance on the performance of the models. In the GMDH model, the choice of this number varies according to each layer. As mentioned in the previous section, this model has different layers, and each layer can have different number of neurons depending on its previous layer. However, a high limit for the number of neurons should be used to allow the model to run. Some researchers have proposed the maximum number of neurons in the GMDH model from equation $\binom{n}{2} = \frac{n(n-1)}{2}$, where n is the number of inputs. Although, according to conditions it may be possible which the number of neurons receive more neurons than this limit. If more neurons are selected from the limit, the percentage of divergence is usually higher in the results, and the result may not be desirable.

In this section, 12 models with a number of neurons from 2 to 20 were designed. Each model was run several times, and the best conditions were chosen. The two statistical parameters, R^2 and RMSE, were used as indicators to compare the performance of the models [48–50]. The R^2 or

RMSE value is closer to 1 and zero, respectively, the model offer an excellent performance. After the R^2 and RMSE values were assigned to both the training and test sections for 12 models, the scoring method introduced by Zorlu et al. [3] was performed. This method is based on the fact that the higher the R^2 value, the higher the score and vice versa. The lower the RMSE, the higher the score is given. This was done for each row of models, and ultimately they get their points in the end. With this method, the model with the highest score is introduced as the best model that predicts rock cohesion. In Table 2, Model 8 with the highest score (30) is selected as the best model obtained by the neuron changes.

Table 2 Effects of neuron number on GMDH performance

Model No	Number of Neuron	Network Result				Ranking				Total Rank
		Train		Test		Train		Test		
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	2	0.931	0.3663	0.929	0.3631	9	5	6	5	25
2	4	0.925	0.3757	0.901	0.4497	6	2	1	2	11
3	6	0.924	0.3648	0.936	0.3479	5	6	9	8	28
4	8	0.939	0.3608	0.909	0.4498	10	8	2	1	21
5	10	0.931	0.3580	0.916	0.3488	9	9	3	7	28
6	12	0.916	0.3777	0.917	0.4334	3	8	4	3	18
7	14	0.923	0.3616	0.948	0.3606	4	1	10	6	21
8	16	0.929	0.3474	0.935	0.3814	8	10	8	4	30
9	18	0.928	0.3725	0.928	0.3176	7	4	5	9	23
10	20	0.928	0.3729	0.931	0.3038	7	3	7	10	27

5.1.2 Number of layers

The next step to improve the performance of the GMDH model is to check the number of layers. In neural network models such as ANN, researchers usually used 3 layers, the first and last layers are introduced as input and output layers. While the hidden layer is the layer that is checked on the neurons. Unlike other neural models, the GMDH model can have several layers, and each with different neurons can be included. However, selecting the number of optimum layers can be effective in performance and runtime system.

In this section, five models were implemented to evaluate the effect of the number of layers. These models consisted of 2 to 10 layers. In this step, R^2 and RMSE were used to help select the most effective model. In the previous section, the number of Neuron 16 (Model 8) was selected as the best model. In this case, all models were designed with 16 neurons. Scoring is the same as the previous section. In Table 3, the results of this review are presented. As can be seen, Model No. 4 has earned the highest score. The training and testing values of prediction model are for R^2 0.928 and 0.929.

Table 3 Effects of the layer number on GMDH model

Model No	Number of Layer	Network Result				Ranking				Total Rank
		Train		Test		Train		Test		
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	2	0.920	0.3759	0.922	0.3206	1	1	4	4	10
2	4	0.932	0.3605	0.915	0.3711	3	2	3	3	12
3	6	0.934	0.3395	0.893	0.4556	4	4	1	1	10
4	8	0.928	0.3545	0.929	0.3154	2	3	5	5	15
5	10	0.939	0.3222	0.905	0.4367	5	5	2	2	14

5.1.3 Selection pressure

The selection of each function has been introduced as a major factor in the design of the GMDH model by various researchers. This selection is known as the "selection pressure". Using this criterion, a number of data from the previous step, which created the best function in those conditions, are selected and entered the next layer. This process is repeated in the new phase to reach the final layer at the end. Finally, the best function that can really provide this model is chosen as the output of the GMDH model. The method of selecting this criterion is based on the number of data or system error. Some researchers have suggested that better performance can be obtained based on system error. In this research, it is also determined by system error. The more percentage of variations is chosen from the lower values, the more time is spent. Of course, further investigations make it possible to examine different conditions by constructing different functions.

In Table 4, a range of changes in the selection pressure criterion was used for GMDH models. 9 models were developed on this basis. These models were designed and executed based on the best model of the previous stage, which included 16 neurons and 8 layers. Like previous processes, two R2 and RMSE parameters were used to evaluate the models in this section. After obtaining these two values for the training and testing sections, the results were scored and the best model was obtained. According to this method, Model No. 6 was introduced as the best model for predicting rock cohesion. Based on this, in the next section of the final model, which includes 16 neurons, and 8 layers and 60% selection pressure, and the influence of the number of parameters on prediction of rock cohesion is evaluated.

Table 4 Effects of various selection pressure percentages on GMDH performance

Model No	**Selection pressure (%)**	**Network Result**				**Ranking**				**Total Rank**
		Train		**Test**		**Train**		**Test**		
		R^2	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	
1	10	0.929	0.3701	0.880	0.3974	6	3	1	1	11
2	20	0.929	0.3671	0.925	0.3419	6	4	7	5	22
3	30	0.928	0.3613	0.935	0.3489	5	5	8	4	22
4	40	0.936	0.3501	0.883	03809	9	8	2	2	21
5	50	0.929	0.3731	0.902	0.3316	6	2	3	8	19
6	60	0.927	0.3457	0.941	0.3125	4	9	9	9	31
7	70	0.922	0.3920	0.921	0.3348	3	1	6	7	17
8	80	0.931	0.3502	0.920	0.3366	8	7	5	6	26
9	90	0.930	0.3591	0.908	0.3745	7	6	4	3	20

5.2 MR model

In this section, a linear regression (MR) model is developed using the same data as the GMDH model. The MR model is used to check the amount of rock cohesion prediction, and then a comparison is made between its results and the model of developed GMDH in this study. To design this model, the data were divided into two parts: training and test, with percentages of 80 and 20 percent, respectively [51]. This model creates a linear relationship between dependent and independent variables. This modeling is used by various researchers to assess the performance of developed models for initial evaluation [30, 41].

In this study, A ML model was obtained for comparison with the GMDH model results. In Figure 3 and 4, the results of this model are presented for rock cohesion evaluation. As can be seen, the accuracy of this model is less than GMDH models.

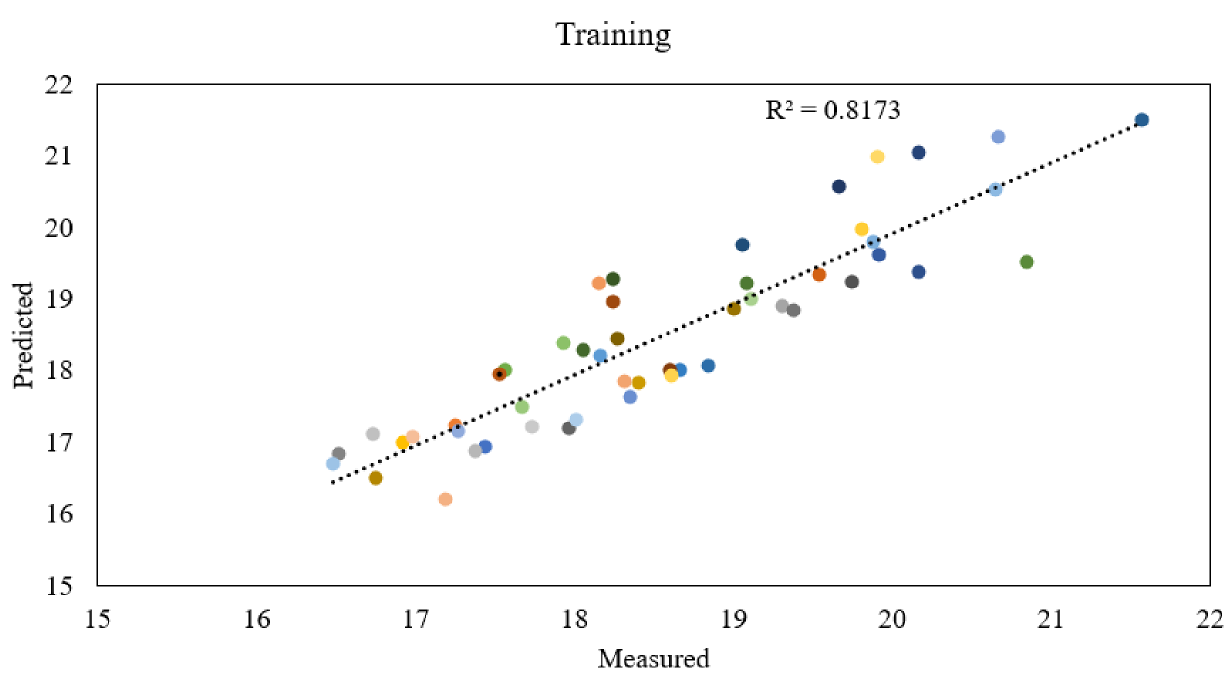

Figure 3 The proposed MR model to estimate rock cohesion

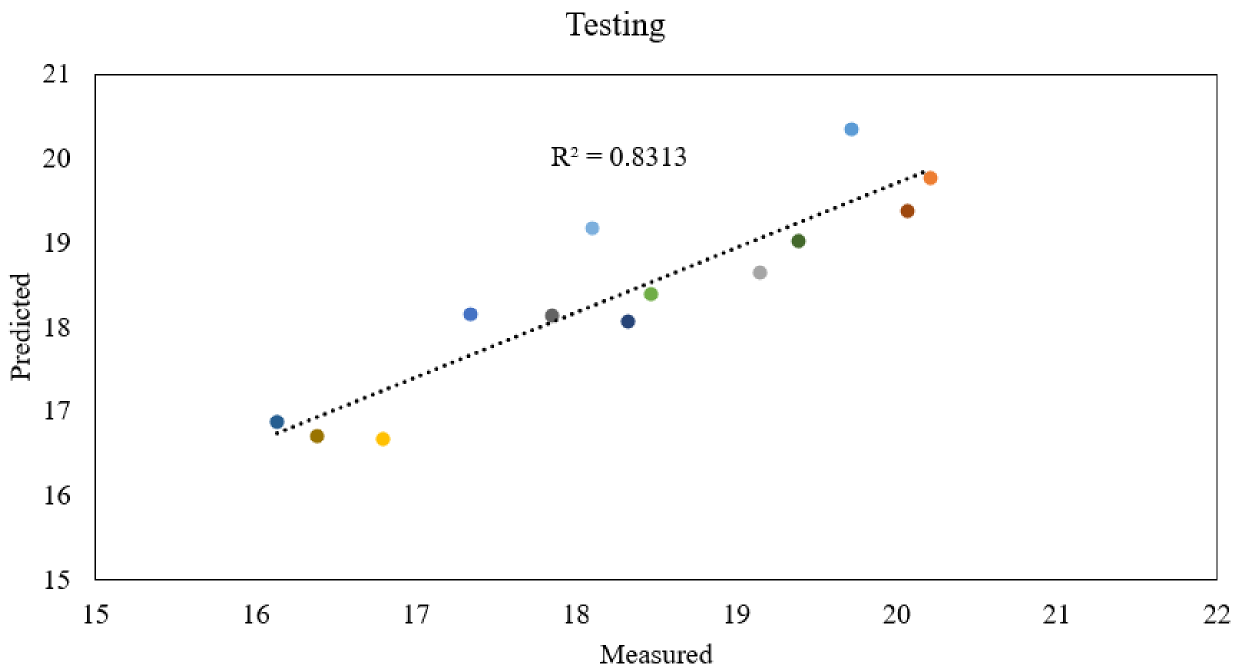

Figure 4 The proposed MR model to estimate rock cohesion

6. Evaluation of input numbers

In order to investigate the effects of input numbers, two models of GMDH1 (2 inputs) and GMDH2 (3inputs) models in predicting rock cohesion were developed. In this section, by comparing these two models, the effect of inputs on the prediction of GMDH is investigated. It should be noted that for GMDH1 model, UCS and BTS and for GMDH2 model, Vp, UCS and BTS were used, respectively. The developed GMDH model was studied with the best conditions obtained from the previous stage (Number of neuron=16, Number of layer=8 and Selection pressure=60%). To evaluate the performance of developed models, two statistics indexes of R2 and RMSE are used [47, 52]. During modeling, various models were made to reduce errors. This way help to check the results carefully. In this study, according to past research, five models were implemented [53, 54].

Table 5 and 6 show the obtained R^2 and RMSE results for all 5 developed models in predicting rock cohesion with 2 and 3 inputs. As stated earlier, the previous method for ranking of R^2 and

RMSE was used. Therefore, based on total rank values, GMDH1 model number 1 with rank = 16 and GMDH2 model number 5 with rank = 16 show the best performance capacity in their class.

The final results (R^2 = 0.834, R^2 = 0.749 for training and testing of GMDH1 and R^2 = 0.943, R^2 = 0.939 for training and testing of GMDH2) indicated that GMDH2 model has a great capacity in comparison with GMDH1 model for prediction of rock cohesion. Additionally, here the influence of the input parameters on the performance of the system can be studied. However, the existence of the third parameter (Vp) can improve up to 10% of the model's performance. Given that the two parameters of UCS and BTS have a great influence on Rock Cohesion, the third parameter can increase the prediction of rock cohesion. Finally, the prediction models for training and testing sections of model GMDH2 are shown in Figures 5 and 6, respectively. Figure 7 shows the values obtained from the two models and the actual values. In this figure it can be concluded that three parameters can improve the performance of the rock cohesion prediction with high accuracy.

Table 5 The result values for the developed model of GMDH1 in predicting rock cohesion with 2 inputs

Model	**Network Result**				**Ranking**				**Total Rank**
	Train		**Test**		**Train**		**Test**		
	R^2	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	
GMDH 1	0.834	0.5222	0.749	0.6837	3	5	5	3	16
GMDH 2	0.849	0.5390	0.691	0.8434	5	4	1	1	11
GMDH 3	0.837	0.5724	0.726	0.5566	4	2	3	5	14
GMDH 4	0.849	0.5431	0.699	0.8032	5	3	2	2	12
GMDH 5	0.807	0.6187	0.729	0.6683	2	1	4	4	11

Table 6 The result values for the developed model of GMDH2 in predicting rock cohesion with 3 input

Model	Network Result				Ranking				Total Rank
	Train		Test		Train		Test		
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
GMDH 1	0.938	0.3017	0.922	0.3059	2	1	1	2	6
GMDH 2	0.940	0.2939	0.938	0.3001	3	3	4	4	14
GMDH 3	0.947	0.2849	0.924	0.3089	5	5	2	1	13
GMDH 4	0.934	0.2899	0.933	0.3042	1	4	3	3	11
GMDH 5	0.943	0.2943	0.939	0.2991	4	2	5	5	16

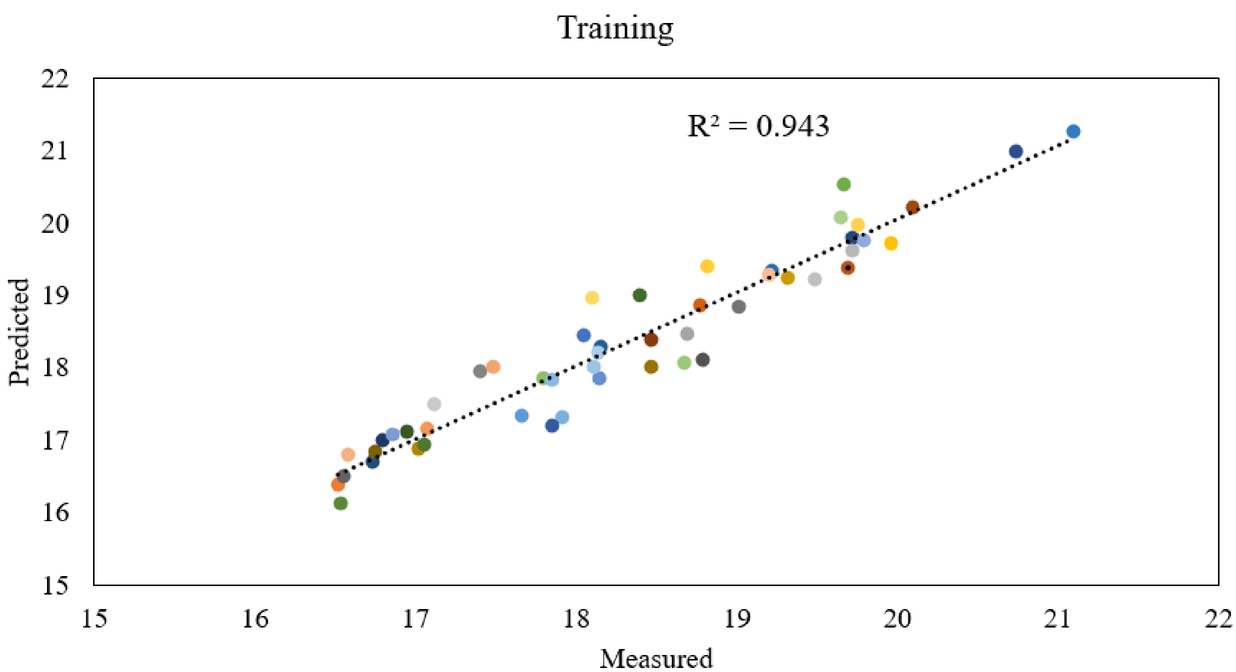

Figure 5 Training rock cohesion values for the best developing GMDH2 model with 3 inputs

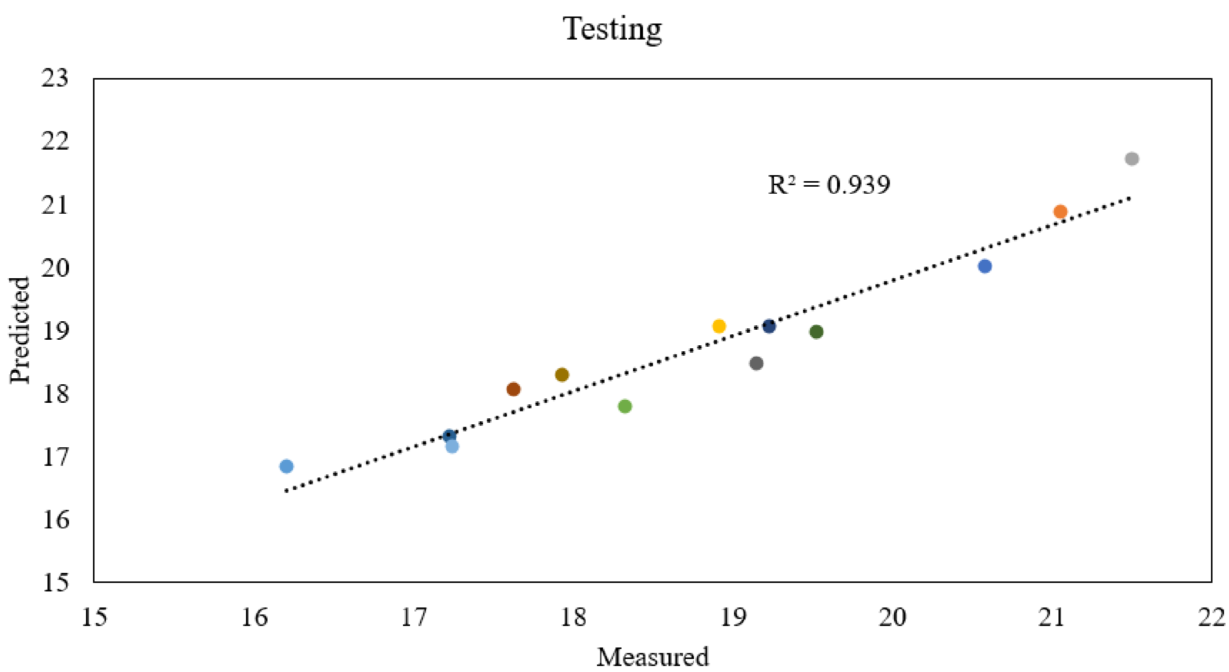

Figure 6 Testing rock cohesion values for the best developing GMDH2 model with 3 inputs

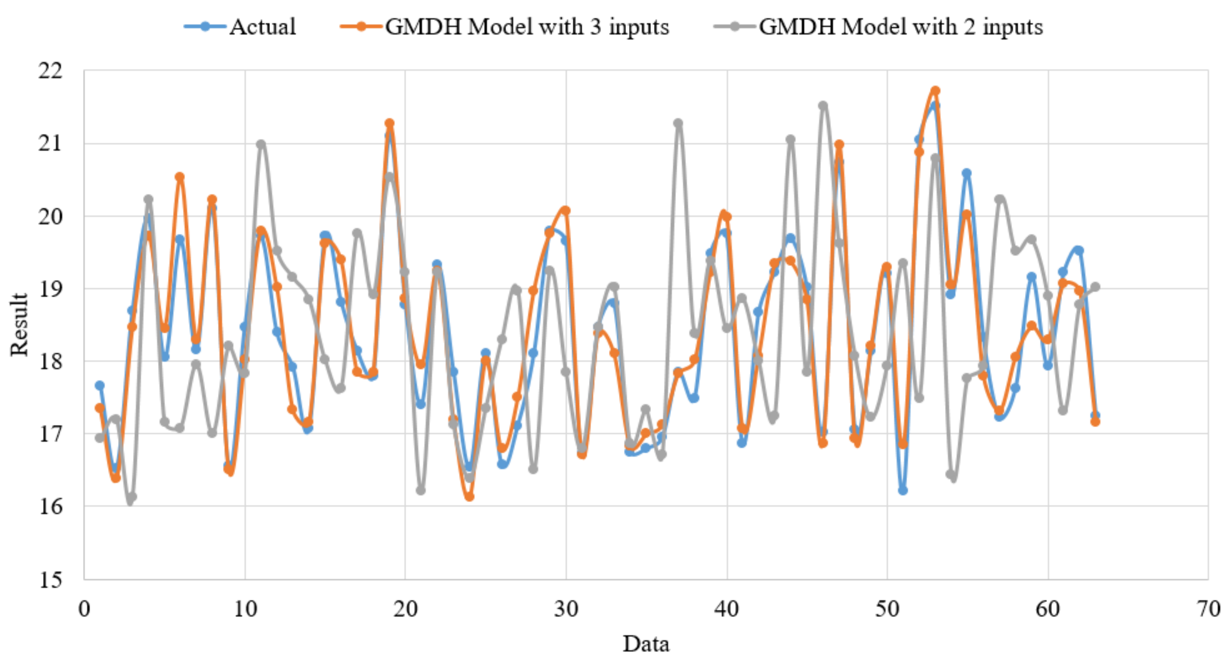

Figure 7 The results of GMDH1 and GMDH2

7. Conclusions

In this paper, an attempt has been done to find models for estimating / predicting cohesion in rocks using a new intelligent method. In the first stage, laboratory tests were measured for 63 samples. Four sets of data were measured including Vp, UCS, BTS and Cohesion. Then, the first three sets were given as inputs to conduct the intelligent model namely GMDH. This method, which is a branch of neural networks, was fully implemented and its prediction performance was investigated. At the end, the best model was selected with regard to two and three input parameters and their impacts. From the comparison between the two models (1 and 2), it can be concluded that the Vp parameter can increase the performance of the model up to 10%. ‘ To investigate performance of the GMDH technique, MR methodology was also considered and constructed. In terms of R^2, values of 0.943 and 0.939 for training and testing of GMDH and 0.817 and 0.831 for training and testing of MR indicate that GMDH technique is a capable method for rock cohesion prediction and it can be used for similar condition.

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