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COMBINATION OF ARTIFICIAL NEURAL NETWORKS AND NUMERICAL MODELING FOR PREDICTING DEFORMATION MODULUS OF ROCK MASSES

The deformation modulus of the rock mass as a very important parameter in rock mechanic projects generally is determined by the plate load in-situ tests. While this test is very expensive and time-consuming, so in this study a new method is developed to combin artificial neural networks and numerical modeling for predicting deformation modulus of rock masses. For this aim, firstly, the plate load test was simulated using a Finite Difference numerical model that was verified with actual results of the plate load test in Pirtaghi dam galleries in Iran. Secondly, an artificial neural network is trained with a set of data resulted from numerical simulations to estimate the deformation modulus of the rock mass. The results showed that an ANN with five neurons in the input layer, three hidden layers with 4, 3 and 2 neurons, and one neuron in the output layer had the best accuracy for predicting the deformation modulus of the rock mass.

Keywords: Artificial Neural Networks; Numerical Simulation; Finite Difference Method; Deformation Modulus of Rock Mass; Arch Dam

1. Introduction

One of the most important parameters in designing the concrete arch dam is the rock mass deformation modulus. The deformation modulus of the rock mass can be estimated via several methods such as empirical methods and in situ testing. In situ tests are mostly used to determine the deformation modulus include the plate loading tests, plate jacking tests, radial jacking tests

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(Goodman jack test), flat jack tests; cable jacking tests; dilatometer tests; pressure chamber (Palmström & Singh, 2001). The in situ tests of the deformation modulus are time-consuming and impose notable costs and operational difficulties. Because of this fact, the deformation modulus is often estimated indirectly from classification systems, the experience of the engineering geologist or from literature data (Finley et al., 1999). The relationship between the deformation modulus and rock classification systems has been investigated by some researchers (Bieniawski, 1978; Serafim, 1983; Nicholson & Bieniawski, 1990; Hoek & Brown, 1997; Hoek et al., 2002; Zhang & Einstein, 2004; Hoek & Diederichs, 2006).

Some researchers have used numerical modeling to simulate in situ tests and obtain deformation modulus (Tajduś, 2009, 2010; Ravandi et al., 2013; Alshkane, 2015). Artificial neural networks (ANN) have been applied for solving logical functions in many fields of geomechanics. Roy and Singh are employed ANN for evaluating complex features of rock (Roy & Singh, 2004). The special model of the ANN method is implemented by Maulenkamp and Grima for developing a method of uniaxial compressive strength prediction (Meulenkamp & Grima, 1999). Yang and Zhang have developed an ANN system for point load test process (Yang & Zhang, 1997), and Cai and Zhao used this method for designing underground spaces like tunnels (Cai & Zhao, 1997). In addition, the deformation modulus has been predicted with Neuro-fuzzy or artificial neural network model (Gokceoglu et al., 2004; Sonmez et al., 2006; Gholamnejad et al., 2013). But the combination of ANN and Numerical simulation have not used in previous work in this filed.

In this study, the numerical method and artificial neural network are combined to develop a method for predicting the deformation modulus of the rock mass. To this aim, firstly, the plate load test, which has been performed in the Pirtaghi dam, is simulated by FLAC3D (Fast Lagrangian Analysis of Continua in 3Dimensions). Secondly, the obtained deformation modulus with the numerical method is used to train the Artificial Neural Network. Finally, the results of the artificial neural network are compared with the actual deformation modulus values that are obtained from the plate load test.

2. Pirtaghi dam

The Pirtaghi dam is a double curvature concrete arch dam that will be constructed on the Ghezelozan river in the Ardabil province of Iran. Pirtaghi dam site will be located on the rock masses consisting of andesite, basaltic andesite and rhyolite (belonging to the Oligocene age), which are located discordantly on the tuff, volcanic breccias and tuff breccias (belonging to the Eocene age). The plate load test is used to determine the geomechanical rock mass properties of the Pirtaghi dam abutments. Eight plate load tests are performed in two galleries (LG1 and RG1). The location of these galleries is shown on the geology plan in Fig. 1.

The plate load test, which has wide application in rock engineering practice, involves loading two opposite sides of a test gallery, by stiff or flexible plates, and measuring the corresponding deflections at the surface and depth below the plate.

The main objective of a plate load test is to determine the deformation modulus of the rock mass. This is generally done by interpretation of the measured displacements using the ASTM[1]

[1] American Society for Testing and Materials.

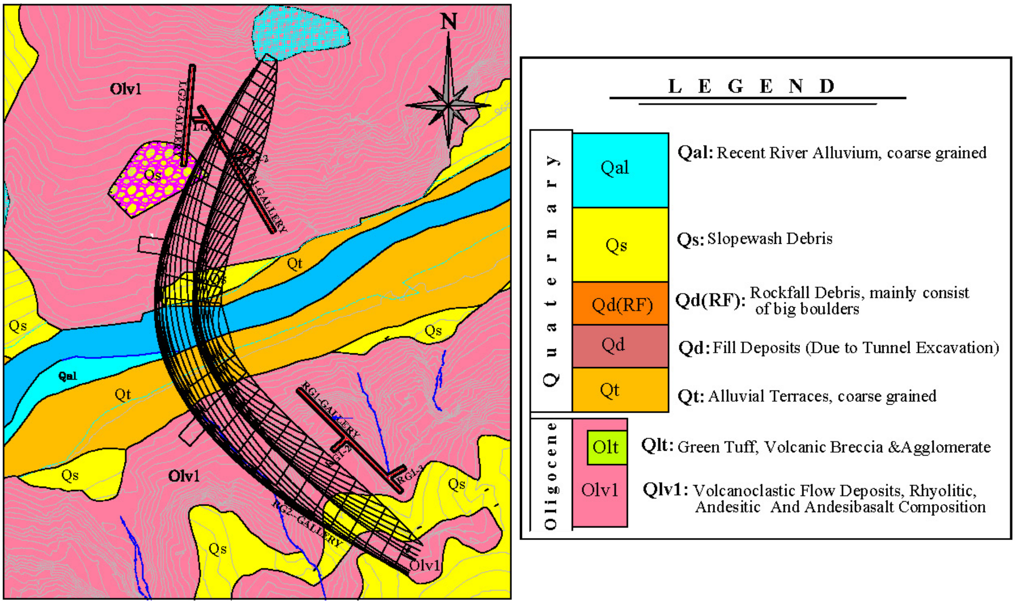

Fig. 1. The geometry plan of the Pirtaghi dam and the location of its galleries

D. 4394-08 Suggested method for "determination of the deformation modulus of the rock mass" as Eq. (1):

$$E = \frac{(1+\upsilon).P.R}{2.w_Z}\left[(2-2\upsilon).\arcsin\left(\frac{R}{\left(R^2+Z^2\right)^{0.5}}\right)-\left(\frac{R.Z}{R^2+Z^2}\right)\right] \tag{1}$$

where w_z is the vertical displacement (m), R is the radius of the loading plate (m), P is the applied stress (MPa), Z is the depth of deformation measurement along the loading plate axis (m), υ is Poisson's ratio and E is the deformation modulus of the rock mass (GPa).

3. Numerical modeling

In this paper, the in situ plate load test is simulated using Finite Difference Methods (FDM) by FLAC3D. The simulations are aimed to generate one set of data for training an artificial neural network to evaluate the deformation modulus of the rock mass. The indentation process is a simulated loading process of the plate load test in an exploratory gallery. The loading steps and measurement points are modeled in real conditions. For a given loading process, the corresponding displacement is extracted for measurement points at different distances from the loading place. The deformation modulus of the rock mass is computed by ASTM suggested formulation (Eq. (1)). The 3D geometry model is presented in Fig. 2.

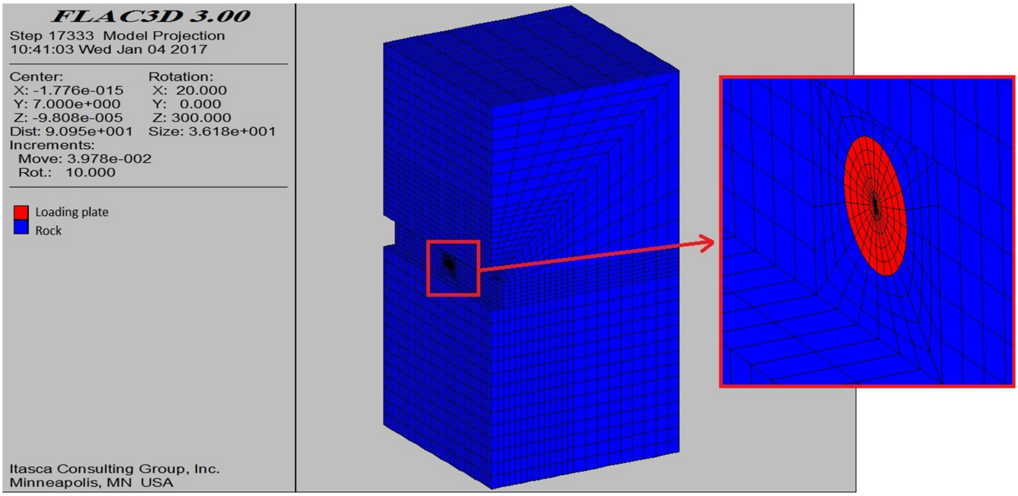

Fig. 2. Geometry model of Pirtaghi dam gallery

After verification of the numerical model using real test data, the simulation process is repeated for different conditions, and the obtained data are collected for the next stage of the solution process. In the next stage, the ANN is trained by the data obtained from the numerical model (Table 1).

4. Artificial neural networks (ANNs)

Artificial neural networks (ANNs) have a powerful ability to model difficult problems where the relationship between the model variables is complex or unknown. ANN is a collection of elementary processing units called neurons. Neurons consist of a set of weighted input connections (ANN learning and training are achieved by this adjustable connection weight (w_{jn})), bias input, state function, transfer function, and output. The neurons are interconnected in a predefined topology called layers (Kishan et al., 1997). Typical network topology consists of the input layer, one or more hidden layers and the output layer (Fig. 3).

The input and output data given in Table 1 are used for training, validation, and testing the model of the neural network. From these, 65% of the data are chosen for training, 15% for validation and 20% for the final test. The input parameters are Poisson's ratio (v), elastic modulus of intact rock (E_i), Rock Mass Rating (RMR), uniaxial compressive strengths of the rock (UCS), and the vertical stress at the centers of the loading plate due to overburden (S_v). In order to determine the mechanical parameters (E_i, UCS, and v), 53 numbers of core samples from drilled boreholes in Pirtaghi dam site were selected for laboratory tests. The Rock Mass Rating (RMR), given by Bieniawski (1989), is calculated based on six field and laboratory parameters that collected in aformentioned site. These parameters were UCS, RQD, Spacing of discontinuities, Conditions of discontinuities, Groundwater conditions and Orientation of discontinuities. The output parameter is the deformation modulus of the rock mass obtained from FLAC3D.

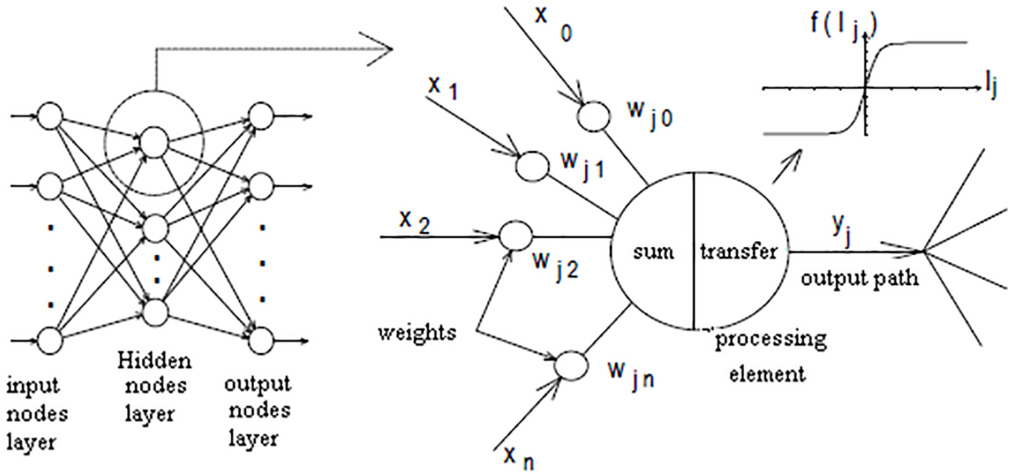

Fig. 3. Flowchart of a typical one-hidden-layer and operation of ANNs (Shahin et al., 2001)

TABLE 1

Rock properties and the measured E_m for Pirtaghi dam

v	E_i (GPa)	UCS (MPa)	RMR	S_v (Pa)	E_m (FDM) (GPa)
1	2	3	4	5	6
0.22	49.52	176.43	66	822960	28.09
0.2	34.61	172.69	65	1294095	19.34
0.21	47.54	179.4	65	656625	26.75
0.19	35.23	185.32	67	464400	19.58
0.2	48.76	175.82	66	883485	27.37
0.18	35.6	144.77	64	1339380	19.59
0.19	46.36	158.15	64	2302020	25.81
0.21	44.17	149.11	61	4607880	24.88
0.19	55.93	187.26	68	560640	31.05
0.24	21.04	112.82	61	1439570	12.1
0.19	23.64	177.66	65	1043200	13.11
0.18	70.4	235.69	68	156000	38.88
0.2	39.34	124.13	65	1831395	21.94
0.19	52.19	187	67	1255170	29.01
0.22	51.83	167.37	67	852810	29.46
0.23	22.82	74.77	61	1270815	12.99
0.19	30.77	102.26	63	2640055	17.06
0.19	54.76	167.69	66	3578400	30.33
0.21	34.97	173.65	67	84150	19.67
0.21	28.36	96.06	61	5485870	15.9
0.23	28.58	162.97	66	660400	16.28
0.19	43.5	169.1	68	2378710	24.13

1	2	3	4	5	6
0.22	31.7	135.7	65	3369310	17.94
0.22	42.2	138.8	65	4004880	24
0.23	37.6	115	64	667500	21.37
0.21	52.33	196.44	66	2254920	29.51
0.21	35.4	120.1	63	841500	19.92
0.24	20.9	72.16	61	850500	12.01
0.21	30.6	117.5	67	1389380	17.22
0.2	29.27	141.9	65	514000	16.4
0.21	37.4	91.5	61	527360	21.06
0.23	28.5	102.3	63	336340	16.27
0.19	52.29	159.01	66	1673280	28.98
0.2	53.67	201.46	68	1218694	30.06
0.26	20.15	75.64	61	915325	11.61
0.23	33.45	171.93	64	624960	19.09
0.21	33.43	125.46	63	488560	18.74
0.22	27.97	104.01	62	720000	15.8
0.23	28.35	89.42	61	427680	16.07
0.22	25.22	96.41	63	2191630	14.17
0.22	30.91	126.73	62	3238500	17.52
0.22	34.12	117.3	63	222270	19.17
0.26	21.92	81.36	61	1590880	12.7
0.21	26.32	122.73	62	2926400	14.75
0.19	43.29	148.55	64	4490240	24.03
0.21	34.53	174.57	67	4853760	19.46
0.21	35.15	174.01	67	5392420	19.76
0.19	52.59	168.5	66	679520	29.09
0.19	52.29	153.01	65	1679920	28.99
0.24	26.56	90.69	62	812910	15.16
0.21	52.33	196.44	68	2254920	29.51
0.21	36.17	166.72	67	4335000	20.36
0.22	34.12	117.3	65	222270	19.17

In this paper, in order to reach an appropriate architecture, several network topologies were examined. The Feed-forward back propagation network was chosen because the back-propagation algorithm is a strong technique of modeling for input/output pattern identification problems (Javad & Narges, 2010; Monjezi et al., 2011).

The target network should produce a minimum error for the training pattern and give a generalized solution that performs well in the testing pattern. The results are presented in this section to demonstrate the performance of the networks. The mean squared error (MSE) and the coefficient of correlation between the predicted and observed values are taken as the performance measures.

Several runs were performed to provide the best results. The best results were obtained by the Levenberg-Marquardt algorithm and the network with architecture 5-4-3-2-1 (five neurons in the input layer, three hidden layers with 4, 3 and 2 neurons, with tangent sigmoid transfer function, and one neuron in the output layer with pure linear transfer function), which had the minimum MSE and maximum correlation coefficient, was considered as the optimum model. The structure of the optimum network is shown in Fig. 4. Validation of the results given in Table 2. The errors obtained for this validation show the satisfactory quality of the analysis.

TABLE 2

Validation of results

Best Networks	Cross-Validation
Run #	2
Epoch #	71
Minimum MSE	2.4133E-05
Final MSE	2.76017E-05

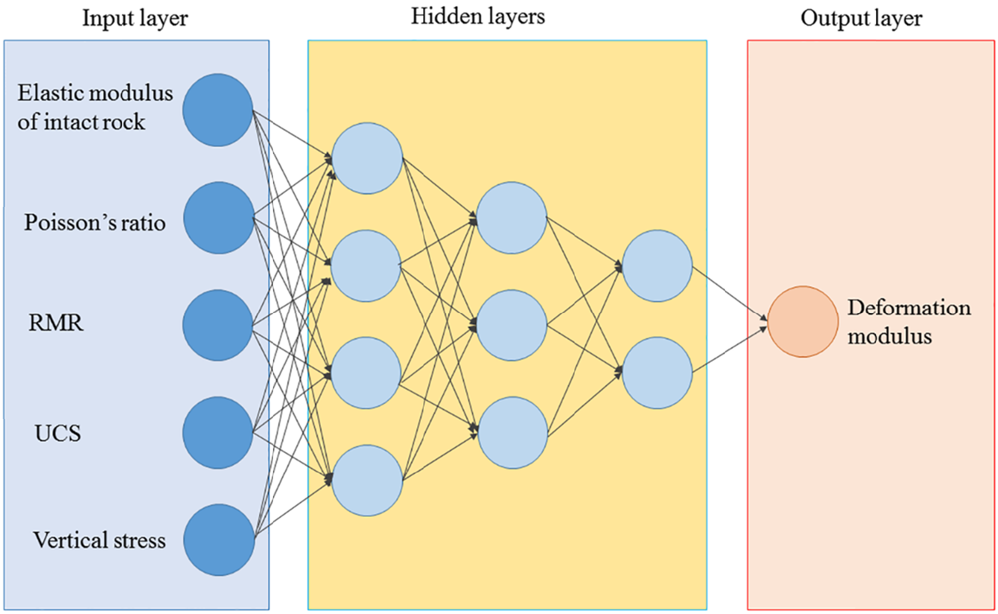

Fig. 4. Suggested ANN for E_m prediction

Fig. 5 illustrates the comparison between the measured deformation modulus with FLAC3D and the predicted deformation modulus by ANN. The obtained MSE is 0.0098 which is a small value.

Finally, the deformation modulus values obtained from the neural network method were compared with the real data obtained from the plate load test. The results presented in Fig. 6 are indicative of a high correlation coefficient between measured and predicted deformation modulus (E_m). Hence, it can be proved that neural network predictions are close to plate load test results.

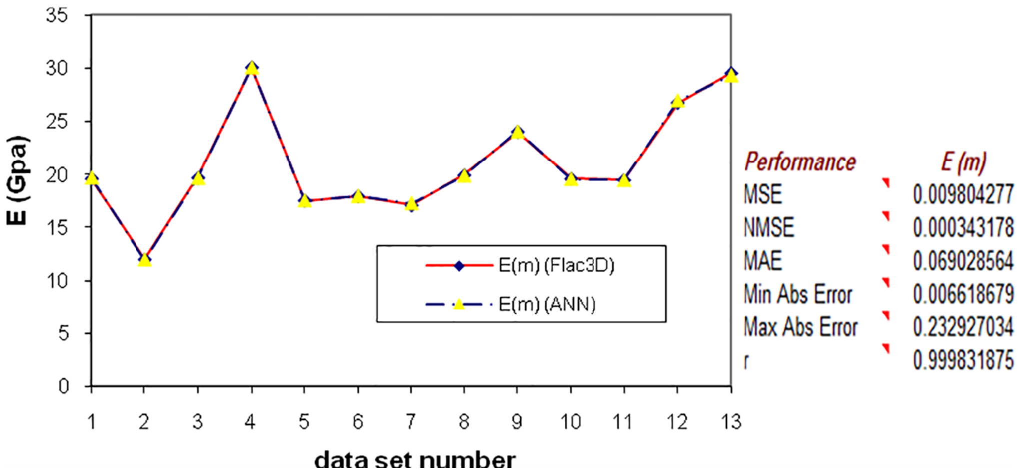

Fig. 5. Comparison of measured vs. predicted values

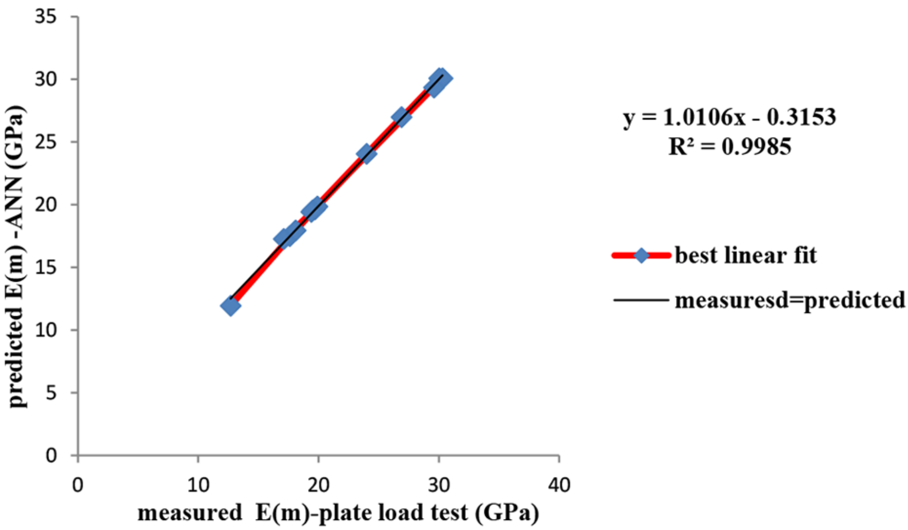

Fig. 6. Correlation between measured and predicted E_m

5. Conclusions

In this study, numerical modeling and artificial neural network were combined to estimate the deformation modulus of the rock mass of the Pirtaghi dam site. For this purpose, the plate load test was simulated by FLAC3D and the accuracy and reliability of the numerical model were verified by field data. Artificial Neural Network has been trained using the data obtained from the FDM analysis. The optimum ANN architecture was found to be five neurons in the input layer, three hidden layers with 4, 3 and 2 neurons, and one neuron in the output layer.

The high correlation coefficient (0.99) and low mean squared error (0.0098) determined for the predicted values by the ANN versus the measured deformation modulus can be demonstrated that the proposed method had an excellent capability for predicting the deformation modulus of the rock mass as well as the plate load. By update datasets of training stage over the time, the suggested optimum neural network structure in this paper can produce results with a higher degree of accuracy, and it could be replaced to expensive plate load test to determine the deformation modulus in other sites.

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