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ORIGINAL PAPER

Development of new models for the estimation of deformation moduli in rock masses based on in situ measurements

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Abstract Knowledge of the deformation properties of the rock mass is essential for the stress–strain analysis of structures such as dams, tunnels, slopes, and other underground structures and the most important parameter of the deformability of the rock mass is the deformation modulus. This paper describes statistical models based on multiple linear regression and artificial neural networks. The models are developed using the test results of the deformation modulus obtained during the construction of the Iron Gate 1 dam on the Danube River and correlate these with measurements of the velocities of longitudinal waves and pressures in the rock mass. The parameters used for defining the models were obtained by in situ testing during dam construction, meaning that scale effects were also taken into account. For the analysis, 47 experimental results from in situ testing of the rock mass were obtained; 38 of these were used for modelling and nine were used for testing of the models. The model based on the artificial neural networks showed better performance in comparison to the model based on multiple linear regression.

Keywords Deformation modulus of rock masses · Velocities of longitudinal waves · Rock mass pressures · In situ testing · Multiple linear regression · Artificial neural networks

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Introduction

For the design of structures that are built into rock masses (tunnels, dams, underground structures, etc.), it is necessary to know the mechanical and deformation properties of the rock mass. One of the most significant deformation properties is the deformation modulus of the rock mass. The best methods for determining the deformation modulus are in situ experiments: the plate load test and flat jack test (Hoek and Diederichs 2006) and dilatometer test (Wittke 2014). Also, the Institute for the Development of Water Resources Jaroslav Černi developed two more in situ tests for determining deformation modulus within the rock masses: a hydraulic jack method (Kujundzic 1970, 1977) and radial press method (Kujundzic 1970). These in situ tests are expensive, difficult to conduct, and time consuming (Aksoy et al. 2012). Therefore, in recent years many researchers have developed indirect methods and models for the estimation of deformation modulus. Some authors (Bieniawski 1978; Serafim and Pereira 1983; Nicholson and Bieniawski 1990; Hoek and Brown 1997; Kayabasi et al. 2003; Gokceoglu et al. 2003; Chun et al. 2009; Alemdag et al. 2015b; Ajalloeian and Mohammadi 2014; Nejati et al. 2014; Shen et al. 2012) established indirect equations for determining modulus of deformation. These equations are based on statistical linear regression, using the relation between deformation modulus and geotechnical parameters (such as RMR, GSI, UCS, E_i). These correlations are useful for practical application. Geotechnical parameters (i.e. RMR, GSI, UCS, E_i) are usually determined during field investigations in rock masses and are, therefore, available for the estimation of deformation modulus. However, the classification parameters are subjective indicators of the rock mass, as they are obtained on the basis of geological description and not on exact measurements.

With development of soft computing methods such as fuzzy inference system, artificial neural networks (ANNs) and adaptive neuro–fuzzy inference systems further progress of models for estimation of deformation modulus and other geotechnical parameters was made possible. ANNs have shown to be robust technique for predicting many geotechnical engineering problems (Sonmez et al. 2006; Monjezi and Dehghani 2008; Majdi and Beiki 2010; Banimahd et al. 2005; Nejati et al. 2014; Alemdag et al. 2015a). Available literature suggests that soft computing techniques are superior in establishing predictive models in the area of rock mechanics.

Furthermore, some authors (Pappalardo 2015; Brotons et al. 2014; Khandelwal 2013; Azimian and Ajalloeian 2014) have noticed correlations between the velocity of P-waves and other geotechnical parameters (such as UCS, E_i, density, porosity) based on laboratory tests. These relations are not easily applicable due to scale effects in rock masses. For example, deformation modulus of rock samples can be more than two times higher than deformation modulus of the rock mass (Chun et al. 2009). The velocity of P-waves in rock masses can also be smaller than the ones obtained in tested samples (Shen et al. 2016). Authors (Kujundzic and Grujic 1966; Song et al. 2011; Shen et al. 2016) have noticed the dependence between deformation modulus and velocity of elastic waves based on in situ measurements. Models suggested by these authors have an advantage over the models based on laboratory performed tests due to the scale effect. Some of the correlations mentioned in the works above are given in Table 1.

The aim of the research presented in this paper is to establish new models for the estimation of deformation modulus of rock masses based on correlations between modulus of deformation (D) and velocity of longitudinal waves (V_p) and the pressure in the rock mass (p) obtained from in situ measurements. The input parameters used in this study were measured during the construction of the dam Iron Gate 1 HPP. In order to determine more precise method, this study applied two different methods for estimation of deformation modulus: multiple linear regression (MLR) and artificial neural networks (ANNs).

Dataset

The results used for the estimation of deformation modulus in this paper were obtained from the construction of dam Iron Gate 1 HPP. For the analysis, 47 measurements of deformation modulus, velocity of waves, and pressures in the rock mass were obtained. For the modelling, 38 values were used, and for the testing, nine values of measured parameters were used.

This dam is located on the Danube River at the chainage 943 km of the Danube river flow. The dam construction began in 1964, and the first generator units were commissioned in 1970. The dam was built in accordance with the agreement between the former SFR of Yugoslavia and Romania. Both sides, Yugoslav and Romanian, have six generator units each of the individual installed power 1200 MW.

The dam at the Iron Gate 1 HPP is mainly located in metamorphic rocks, such as: biotite gneiss, chlorite gneiss, granogneiss, and chlorite-sericite schists. For defining the

Table 1 Correlations between deformation modulus and other geotechnical parameters of rock masses

Equation	References
$D = 2\mathrm{RMR} - 100$	Bieniawski (1978)
$D = Ei\left[0.0028\mathrm{RMR}^2 + 0.9e^{\left(\frac{\mathrm{RMR}}{22.921}\right)}\right]$	Nicholson and Bieniawski (1990)
$D = \sqrt{\frac{\mathrm{UCS}}{100}}10^{\frac{\mathrm{GSI}-10}{40}}$	Hoek and Brown (1997)
$D = 4.32 - 3.42\mathrm{WD} + [0.19Ei(1 + (\mathrm{RQD}/100))]$	Kayabasi et al. (2003)
$D = 0.02386V_p^{4.3266}$	Song et al. (2011)
$D = 0.295V_p^{2.387}$ (*Xiangjiaba dam*)	Shen et al. (2012)
$D = 0.100V_p^{3.267}$ (*Baihetan dam*)	
$\frac{E_{\mathrm{dyn}}}{E} = 5.3 - \frac{E_{\mathrm{dyn}}}{200000}$ $\frac{E}{D} = \frac{1550}{645 + \sqrt{D}}$	Kujundzic and Grujic (1966)

D is deformation modulus of rock mass [GPa], E is modulus of elasticity of rock mass [GPa], E_i is modulus of elasticity of intact rock [GPa], *UCS* is uniaxial compressive strength of intact rock [MPa], *WD* is the degree of weathering, *RQD* is rock quality designation, E_{dyn} is dynamic modulus of elasticity of rock mass, V_p is velocity of longitudinal elastic waves

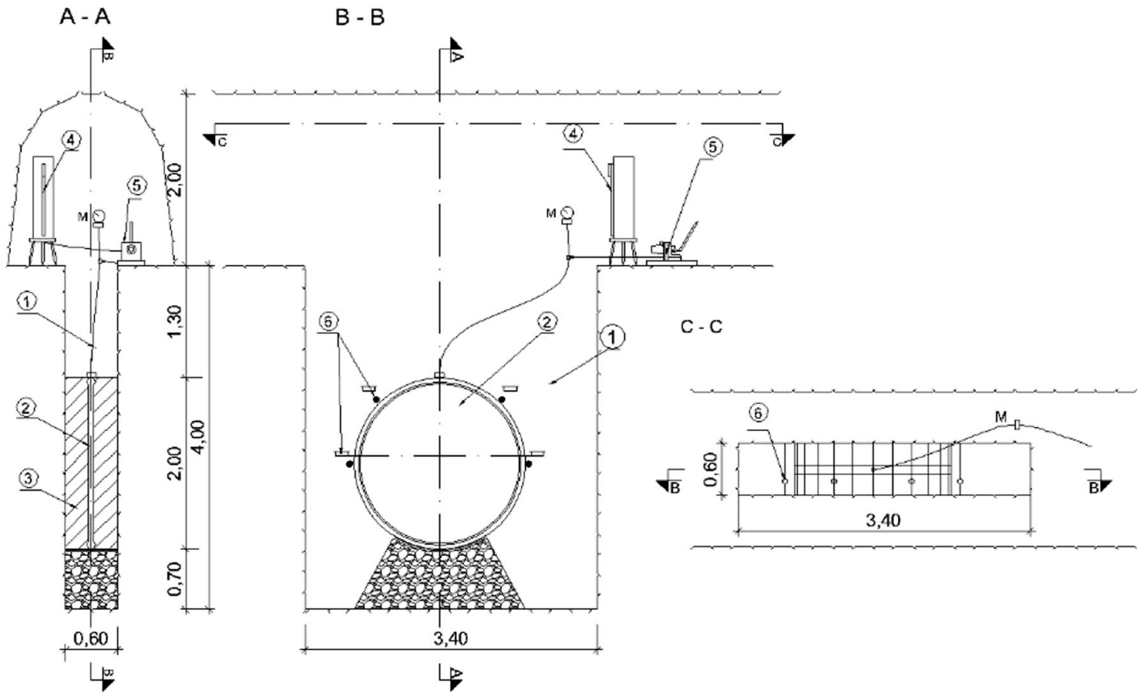

Fig. 1 Hydraulic jack method: *1* slot in the rock mass; *2* flexible flat jack ø 2 m; *3* concrete fill; *4* hydraulic reservoir tube and indicator tube for measurement of average deformations; *5* hydraulic pump; *6* deflection gages for measurement of boundary deformations

deformation properties of the rock masses, in situ tests were conducted using hydraulic jack test (Kujundzic 1970, 1977) which is used for determining the deformation modulus and elasticity modulus of the rock masses. Figure 1 shows the scheme of test site for hydraulic jack with all the elements. Since there is no photo of hydraulic jack test on dam Iron Gate 1, Fig. 2 displays a photo of a sheet metal jack located at the Komarnica Dam, Montenegro. Figure 3 is a photo of a slot in the rock mass where hydraulic jack and a concrete fill were installed, also located at the Komarnica dam. Hydraulic jack tests (Kujundzic 1970, 1977) were conducted in adits on both riverbanks of the Danube.

By applying the pressure in hydraulic jack the deformation in the rock mass is obtained. Mean deformation in rock mass (Kujundzic 1970, 1977) is calculated according to Eq. (1).

$$u_s = \frac{a\Delta h}{2A} - \frac{pd}{2E_c}, \tag{1}$$

where u_s is mean deformation of the rock mass a is a cross sectional area of hydraulic reservoir tube, A is area of sheet metal jack and Δh is difference in levels in the hydraulic reservoir tube, p is the applied pressure in the hydraulic jack, d is the thickness of the concrete infill,

Fig. 2 Sheet metal jack (example from the investigation works at the Komarnica Dam, Montenegro)

Fig. 3 The slot in the rock mass where a hydraulic jack was installed and concrete fill placed (example from the investigation works at the Komarnica Dam, Montenegro)

E_c is modulus of elasticity of the concrete. The first member in the Eq. 1 represents the deformation resulting from the change in volume of the jack and the second member represents a correction due to deformation of the concrete.

The test was repeated with several cycles of loading and unloading, and the typical pressure-deformation diagram in rock masses was obtained and is shown in Fig. 4.

Based on the pressure-deformation diagram, the values of the deformation modulus can be determined in the rock mass for each cycle of loading. The deformation modulus value is calculated according to Eq. (2) (Kujundzic 1970).

$$D_i = 0.54 \frac{A(1 - \nu^2)}{r} \frac{p_i - p_0}{u_i - u_0}, \tag{2}$$

where D_i is deformation modulus of the ith cycle, p_i is pressure at the end of the ith cycle, p_0 is initial pressure, u_0 is initial deformation, u_i is the mean deformation in the rock mass at the end of the ith cycle, A is area of sheet metal jack, r is radius of sheet metal jack and ν is Poisson's ratio of rock mass.

The diagram given in Fig. 5 is the result of measuring of deformations at the measuring point EGD-2 on the right riverbank of Danube.

Loading of the hydraulic jack started with the initial pressure of 0 MPa and it was increased to the determined level, when unloading began down to the pressure p_0(0.2 MPa in this case). Then, the next cycle of loading began at other pressure level and unloaded to the pressure p_0. This procedure was repeated through several cycles of loading and unloading until the required maximum stress was reached or until hydraulic jack had cracked.

Measurement of velocity of longitudinal seismic waves can be conducted at the same place where hydraulic jack

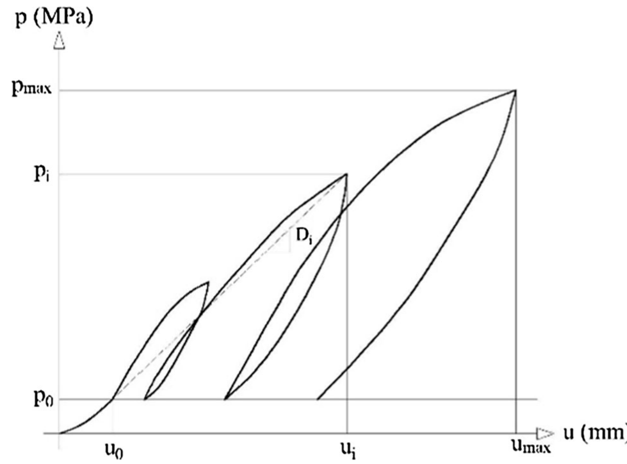

Fig. 4 Typical diagram of pressure-deformation in rock masses

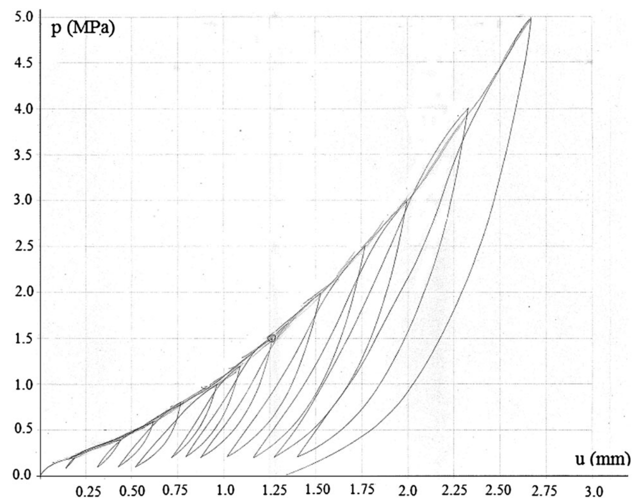

Fig. 5 Diagram pressure-deformation at the measuring point EGD-2

test is performed by applying a polar method (Kujundzic and Grujic 1966; Kujundzic 1970). Figure 6 displays a diagram of a hydraulic jack and the principle of measuring P-wave velocities around the hydraulic jack. In the borehole located at a distance of 4 m from the slot the explosion caused seismic waves. The waves were measured using geophones placed in the slot where the jack was located. Thus, the polar diagram of velocities around the hydraulic jack was obtained. For the analysis of data, a mean value of spreading velocities of seismic longitudinal waves was used. This method is suitable because it is cost effective, easy to perform and does not require special technical support, and most importantly it is applied in the undisturbed rock mass (Kujundzic and Grujic 1966).

Gneisses and schists, the most common rock masses at the site of the dam, can have a very pronounced

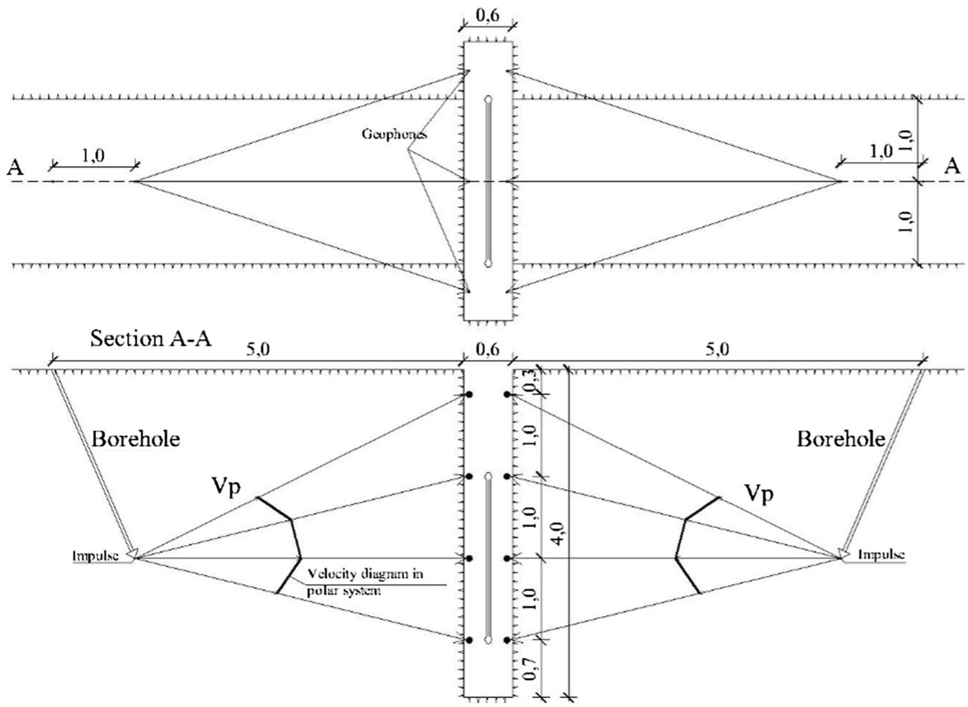

Fig. 6 Microseismic method with polar procedure: *1* slot for hydraulic jack, *2* sheet-metal jack, *3* hole, *4* aftershock, *5* geophones, *6* polar velocity graph

anisotropy; therefore, the level of deformation characteristics of the rock mass will depend on the direction of loading, normal or parallel to schistosity. Pinto da Cunha and Muralha (1990) presented the research results of the deformation modulus obtained using the flat jack test perpendicular to the schistosity and parallel to the direction of schistosity. Pinto da Cunha and Muralha 1990 also gave the results of dynamic modulus in the rock mass, which were calculated based on the measurements of velocity of longitudinal waves around the flat jack. Based on these results it can be concluded that the average deformation modulus parallel to schistosity is about 20% higher than the modulus perpendicular to schistosity and that the mean dynamic modulus parallel to schistosity is 100% higher than the dynamic modulus perpendicular to schistosity.

As far as dam Iron Gate 1 is concerned, tests of the velocity of propagation of longitudinal waves parallel and perpendicular to the schistosity showed that there is no significant difference in the results (velocities parallel to the schistosity are 6–7% higher than the velocities perpendicular to the schistosity) which indicates that anisotropy at the site of the dam is not significantly present.

In this research, values of deformation moduli and velocity of longitudinal seismic waves were determined from eight measuring points: five measuring points were at the exploratory adits on the right bank of the Danube, and three measuring points were at the exploratory adits on the left bank.

Development of a model for prediction of deformation modulus

Multiple regression analysis

Modelling implies making correlations between the deformation modulus and pressure and wave velocity. The analysis showed that Eq. (3) best describes the dependence between the deformation modulus and velocity of elastic waves under various pressures.

$$D = a\ln(Vp) + b. \tag{3}$$

Figure 7 displays the results of the dependence of the deformation modulus from velocity under various pressures applied during the test. There is a good correlation between the deformation modulus and velocity of longitudinal waves. The coefficient of determination is in most cases over 0.75. For the purpose of introducing the influence of pressure during testing into the regression model, variables $a = f(p)$ and $b = f(p)$ were proposed, where a and b are the unknown coefficients in Eq. (3). Equations (4) and (5) are assumed for calculation of the a and b variables:

$$a = a_1 p + a_2 \tag{4}$$

$$b = b_1 p^2 + b_2 p + b_3. \tag{5}$$

When Eq. (4) and Eq. (5) are inserted into Eq. (3), Eq. (6) is obtained.

$$D = a_1 p\ln(V_p) + a_2\ln(V_p) + b_1 p^2 + b_2 p + b_3. \tag{6}$$

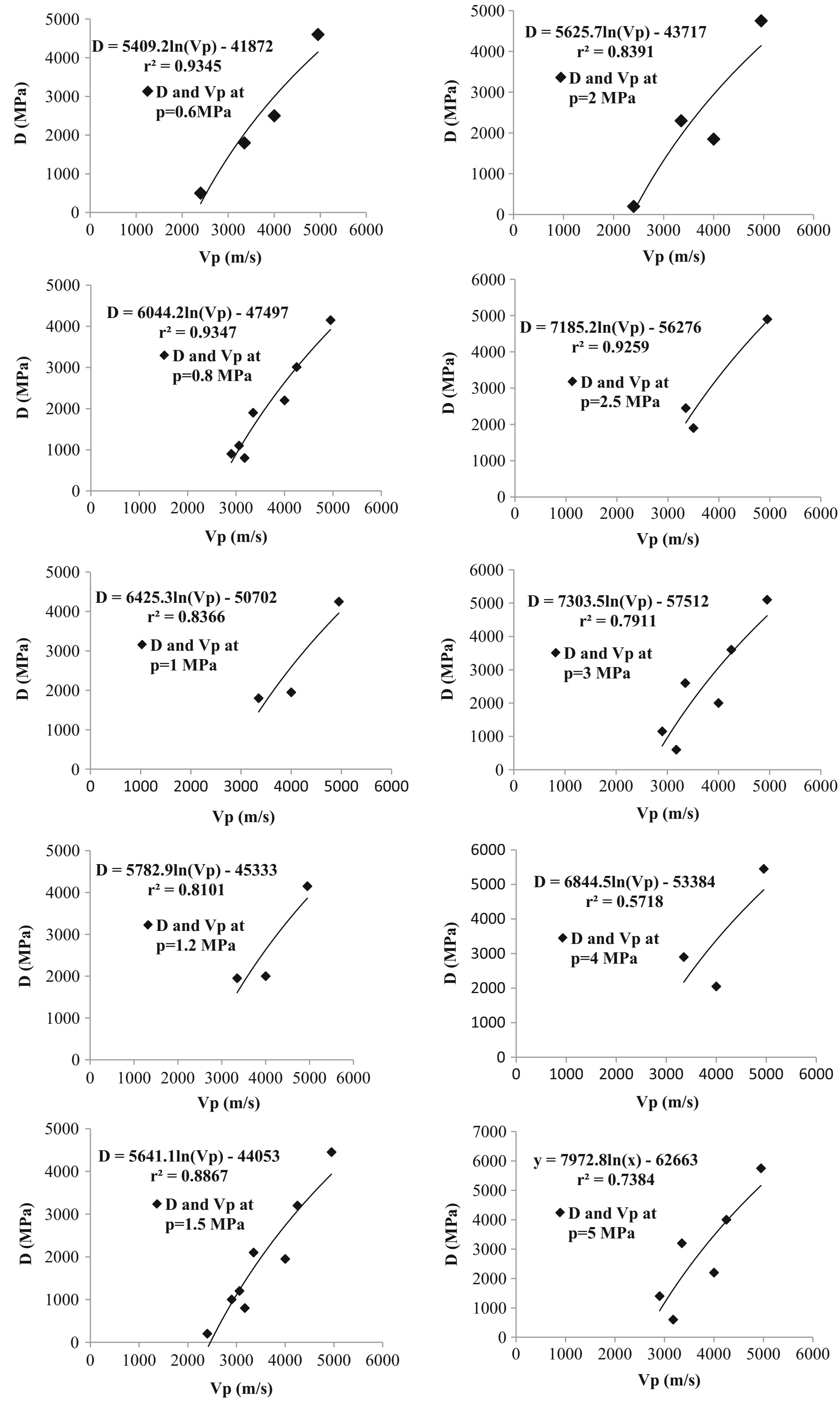

Fig. 7 Relations between the velocity of P-wave and deformation modulus under various pressures in the rock mass

The given equation can be transformed into Eq. (7):

$$D = a_o + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4. \quad (7)$$

The regressive functions are: $x_1 = p\ln(V_p)$, $x_2 = \ln(V_p)$, $x_3 = p^2$ and $x_4 = p$, and the Eq. (7) is a multiple linear regression model (MLR).

The main part of defining the model for prediction of the deformation modulus is determination of the coefficients:a_0, a_1, a_2, a_3, a_4 using regression functions. Determining the coefficients using regressors was conducted in MATLAB software.

The prediction performance of each model is evaluated by calculating the root mean square error (RMSE), mean absolute error (MAE) and the Pearson correlation coefficient (r):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{mi} - y_i)^2} \quad (8)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}|y_{mi} - y_i| \quad (9)$$

$$r = \frac{\sum_{i=1}^{N}(y_{mi} - \bar{y}_m)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(y_{mi} - \bar{y}_m)^2 \sum_{k=4}^{N}(y_i - \bar{y})^2}}, \quad (10)$$

where y_{mi} and y_i denote the measured value and the multi linear regression output, respectively; $\bar{y}_m$ and $\bar{y}$ denote their average values respectively, and N represents the number of available samples.

Based on the Eq. (7) using the MATLAB software package multiple linear regression analysis was conducted and the coefficients were obtained using predictive functions. The Eq. (11) is a prediction model.

$$D = -40194 + 700p\ln(V_p) + 5168\ln(V_p) - 30p^2 - 5765p. \quad (11)$$

The Eq. (11) is valid in cases where the velocity of longitudinal waves is greater than 2500 m/s. The velocity in Eq. (11) is in units of m/s and pressure is in units of MPa. Deformation modulus is obtained in MPa.

Using the regression model given in the Eq. (11), the values for deformation modulus were calculated for the values of pressure and velocities. The Fig. 8 shows the values of the deformation modulus calculated from the proposed model (Eq. 11) and the values of deformation modulus obtained experimentally which were used for modeling.

The Fig. 9 is a scatter diagram of the calculated values of the deformation modulus from the proposed model (Eq. 11) and experimental values of deformation modulus for the dataset which was used for testing.

The Table 2 contains the values of RMSE, MAE, and r for the case of training and testing of multiple linear regression model.

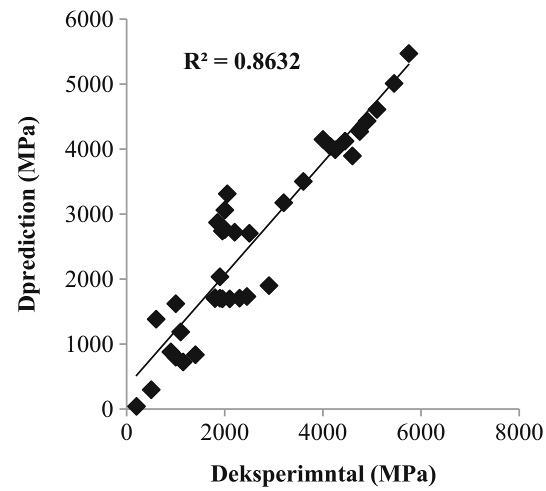

Fig. 8 Comparison of calculated values of deformation modulus on the basis of regression model (Eq. 11) and experimental values of deformation modulus for the dataset which was used for modeling

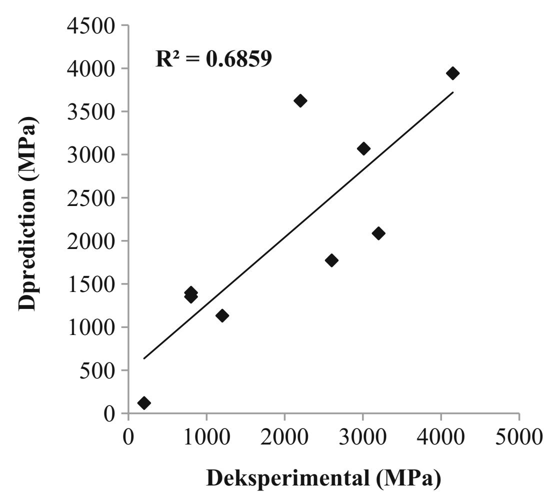

Fig. 9 Comparison of values of deformation modulus calculated on the basis of regression model (Eq. 11) and the values of deformation modulus obtained experimentally for the dataset which was used for testing

Table 2 Values of RMSE, MAE, and r

	RMSE	MAE	r
Training	549.102	443.241	0.929
Testing	720.415	547.637	0.828

Artificial neural network modelling

Neural network used in this study is feedforward neural network (FNN), which is widely used as a soft computing method in statistical models because of its good ability of nonlinear mapping and generalization of the functional relationships between input and output variables.

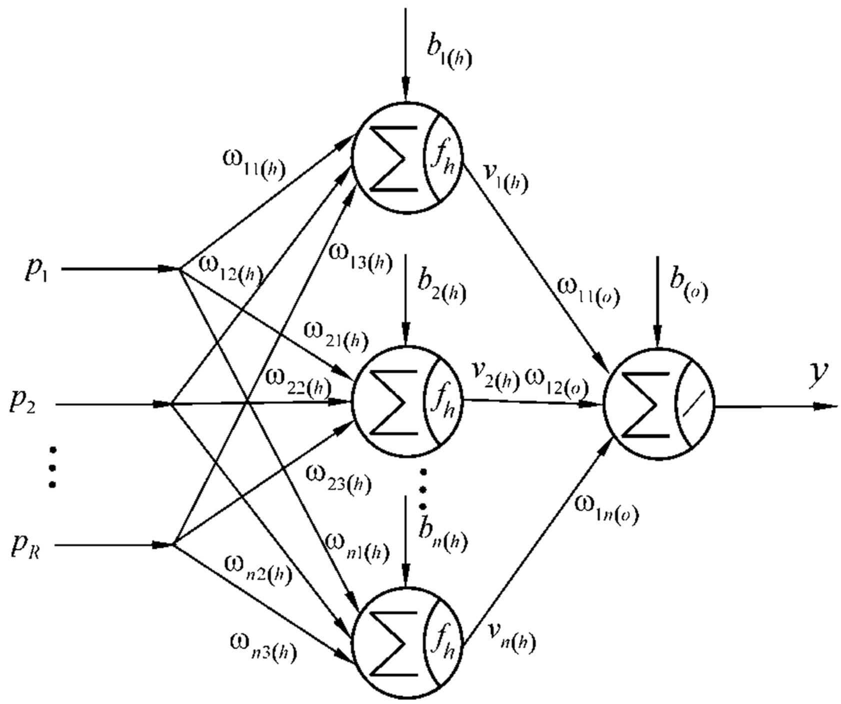

Fig. 10 Feedforward Neural Network with one hidden layer and one neuron in the output layer

FNN has been implemented and designed using Neural Network Toolbox of MATLAB.

An example of a FNN with R input variables, a single hidden layer with n neurons and one output variable is shown in Fig. 10.

The output of the hidden neurons of the FNN can be expressed by Eq. (12).

$$v_{i(h)} = f_h\left(\sum_{j=1}^{R} \omega_{ij(h)} p_j + b_{i(h)}\right), \quad j = 1, 2, \ldots, n, \tag{12}$$

where $v_{i(h)}$ is the output of the ith neuron of the hidden layer, f_h is the activation function of the hidden neurons, $\omega_{ij(h)}$ is the weight value between the ith neuron in the hidden layer and jth input variable in a neural network model, p_j is the jth input variable, $b_{i(h)}$ is the bias value of the ith neurons in the hidden layer, n is the number of the neurons in the hidden layer.

The most commonly used activation functions of the hidden neurons in the neural networks are logistic sigmoid function and hyperbolic tangent sigmoid function, which can be expressed by Eq. (13).

$$f_h(x) = \frac{1}{1 + e^{-x}}. \tag{13}$$

and Eq. (14).

$$f_h(x) = \frac{2}{1 + e^{-2x}} - 1. \tag{14}$$

The output of the neural network when the activation function for the output layer is linear can be obtained according to the Eq. (15).

$$y = \sum_{j=1}^{n} \omega_{1j(o)} v_{j(h)} + b_{(o)} \tag{15}$$

where $\omega_{1j(o)}$ is the weight of the jth neuron in the hidden layer to the output neuron, $b_{(o)}$ is the bias of the output layer.

The most widely used steepest descent algorithm, also known as the backpropagation algorithm (Rumelhart et al. 1986) and the different versions of it can be used to find the optimal values of the network weights and biases (i.e. train the network) in order to minimize an error criterion. Also, the Gauss–Newton algorithm (Osborne 1992) and the Levenberg–Marquardt algorithm (Hagan and Menhaj 1994) are often used. The Levenberg–Marquardt (LM) algorithm essentially combines the steepest descent method and the Gauss–Newton algorithm and is suitable for training small- and medium-sized data modelling problems (Yu and Wilamowski 2011).

There is no general rule for determining the optimum number of neurons in hidden layer and usually it is determined through the trial-and-error method. Different network architectures were developed by varying the number of neurons in the hidden layer and using the logistic sigmoid (logsig) and the hyperbolic tangent sigmoid (tansig) activation functions in the hidden layer.

Table 3 Comparison of different FNN network structure performances

Model	Network topology	Activation function in the hidden layer	Data set	RMSE	MAE	r
FNN 1	2–4–1	Logsig	Training	356.6285	246.3434	0.8896
			Test	569.3589	444.7467	0.8693
FNN 2	2–4–1	Tansig	Training	467.5789	256.6729	0.8867
			Test	574.3748	498.5398	0.8678
FNN 3	2–6–1	Logsig	Training	271.4834	179.3074	0.9334
			Test	464.7465	353.5683	0.9224
FNN 4	2–6–1	Tansig	Training	279.7936	187.435	0.9112
			Test	475.1156	454.7579	0.8913
FNN 5	2–7–1	Logsig	Training	257.7681	170.231	0.9855
			Test	393.9559	355.6572	0.9662
FNN 6	2–7–1	Tansig	Training	269.1745	177.1946	0.9553
			Test	407.2001	365.4291	0.9335
FNN 7	2–8–1	Logsig	Training	274.8943	180.4584	0.9467
			Test	423.9559	371.6572	0.9325
FNN 8	2–8–1	Tansig	Training	303.5639	189.5643	0.9398
			Test	456.7606	374.4201	0.9213

To select the optimal number of neurons in the hidden layer, networks were trained with 4, 6, 7, and 8 hidden neurons. Also, the efficiency of the models developed using the logistic sigmoid (logsig) function and the hyperbolic tangent sigmoid (tansig) activation function has been analysed based on the performance parameters (RMSE, MAE, r), Table 3.

The neural network with the highest r and the lowest MAE and RMSE was chosen (FNN 5 from Table 3). It can be observed that the best FNN contains 7 neurons in the hidden layers.

The weights and biases necessary to implement the adopted optimal FNN are presented in Table 4.

Adopted ANN model has 2 neurons in input layer, 7 neurons u hidden layer and 1 neuron in output layer.

The Fig. 11 is a comparison of values of deformation moduli calculated with selected neural network and experimental values of deformation modulus for the data set which was used for modeling.

The Fig. 12 is a scatter diagram of the calculated values of the deformation modulus with selected neural network and experimental values of deformation modulus for the dataset, which was used for testing.

Prediction of deformation modulus using feedforward neural networks (FNN) shows better results than the multiple linear regression models. The Pearson's ratio is greater when calculated using FNN than using MLR. For the values of RMSE, MAE are smaller for the model based on the FNN than for the one based on MLR. These observations are given in the Tables 2 and 3. Better performance of the dataset for training and testing can also be noticed in the case of FNN based model.

Table 4 The weights and biases necessary to implement the adopted FNN

i	$\omega_{i1(h)}$	$\omega_{i2(h)}$	$\omega_{1i(o)}$	$b_{i(h)}$
1	−4.6589	−1.7713	−2.1367	8.6484
2	−0.2504	−7.9181	−0.8071	3.4288
3	3.7159	−8.4543	−1.6976	6.4826
4	−2.9832	−3.2914	−0.6924	4.187
5	0.69593	−17.5616	5.1944	−3.698
6	−0.0332	11.0947	5.5637	2.4977
7	−2.8405	7.8661	−1.5596	−6.4008
$b_{(o)} = -0.70796$				

Results and discussion

The results obtained in this study were compared with the results obtained by other authors shown in Table 5 since all empirical models depend on the quality and quantity of data.

The values of correlation coefficients in the previously described studies in Table 5 are close to the values obtained from the models described in this paper for both ANN and MLR. In all mentioned research, RMSE values are greater than the value of RMSE in this study. The correlation coefficients between the estimated and

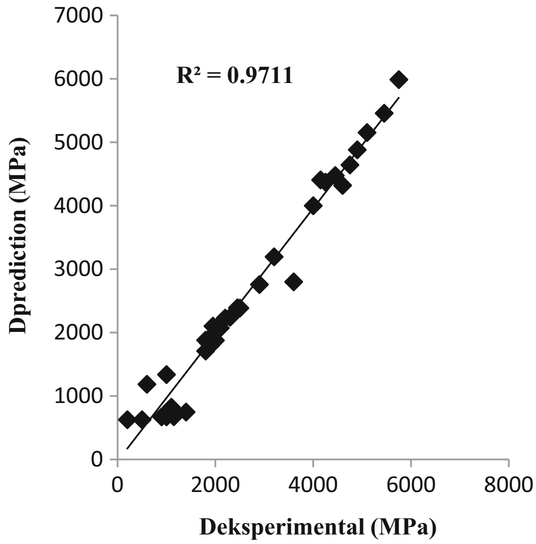

Fig. 11 Comparison of calculated values of deformation modulus obtained on the basis of predictive model using FNN and experimental values of deformation modulus for the dataset, which was used for modeling

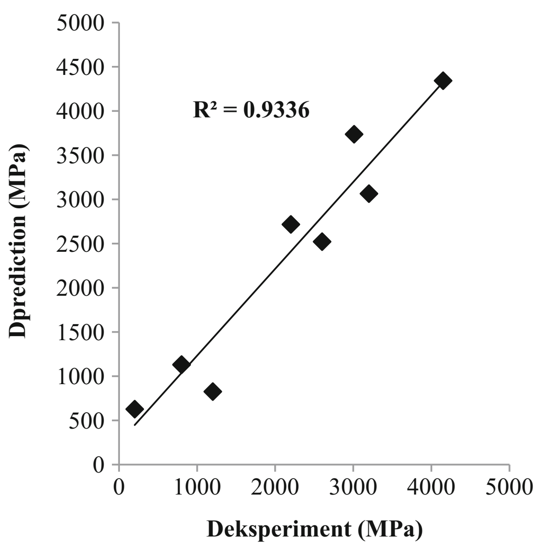

Fig. 12 Comparison of calculated values of deformation modulus obtained on the basis of predictive model using FNN and experimental values of deformation modulus for the dataset, which was used for testing

measured deformation modulus for MLR were 0.93 for training and 0.83 for testing. The correlation coefficients for ANN models were 0.99 for training and 0.97 for testing. The values of RMSE for training and testing for the MLR model were 0.549 and 0.72, respectively. The values of RMSE for training and testing for the ANN model were 0.258 and 0.394, respectively. Presented results prove that the accuracy of the model established in this study is within the range of accuracy of the models published by other authors. Also, it is noted that there is an intensive use of ANN models for deformation modulus estimation and for the estimation of other geotechnical parameters. Application of ANN model shows greater accuracy than the application of MLR model, which is also the case in this study. Number of datasets used for modelling in this study corresponds well to the number of datasets used by other authors.

As for the number of input variables researchers (Nicholson and Bieniawski 1990; Hoek and Brown 1997) had two input variables in the models, (Pappalardo 2015; Azimian and Ajalloeian 2014; Kujundzic and Grujic 1966) used one input variable for estimation of the modulus, while Kayabasi et al. (2003) used 3 input variables and Gokceoglu et al. (2003) used 4 input variables. Number of variables can affect the accuracy of the model. For example Nejati et al. (2014) analysed the correlation between the deformation modulus and RMR, as well as the correlation between the deformation modulus and parameters: UCS ratings, RQD rating, JSR, JCR, GWR. The correlation coefficient in the first case was 0.67 and in the second case was 0.84. Obviously, the reason for deviation is the number of variables.

In this paper, the authors adopted two input variables: velocity of longitudinal waves and the pressure in rock mass. Compared to the works of Kujundzic and Grujic (1966) and Shen et al. (2016) that dealt with similar issues to this study, another input variable was introduced—the pressure in the rock mass. The pressure is important for the estimation of deformation modulus, because the modulus depends on the level of loading in the rock mass. In relation to the works of Kujundzic and Grujic (1966) and Shen et al. (2016) who used only MLR, the authors of this paper performed analysis using ANNs and MLR.

Suggested models have the disadvantage that they cannot be applied for the estimation of deformation modulus for every rock type. The model from this paper can be upgraded in two ways. The first way is expansion of the input data to different types of rock masses and the second way is increasing the number of different input parameters. In this study, the input parameters were P-wave velocity and pressure; other input parameters that can be introduced for example are UCS or degree of cracks in the rock and the effect of anisotropy where applicable. The authors of this paper did not take into account the effect of anisotropy because it is not significantly demonstrated at the site of the dam as described in Sect. 2.

Conclusions

In this paper the models for estimating the modulus of deformation in the rock mass at the site of the Iron Gate 1 HPP are presented. The estimation was based on the

Table 5 Estimation model properties proposed by other authors

References	Input parameters	Method	r	RMSE	Number of data
Kaybasi et al. (2003)	E_i, RQD, WD	MLR	0.74	3.64	57
Gokceoglu et al. (2003)	E_i, UCS, RQD, WD	MLR	0.80	4.49	115
Nejati et al. (2014)	UCS, RQD, JCS, JCR, GWR	ANN/MLR	0.97/0.92	–	52
Ajalloeian and Mohammadi (2014)	RMR, RQD, GSI	MLR	0.73–0.84	4.84–9.36	14
Alemdag et al. (2015a)	E_i, UCS, RQD, RMR	ANN	0.85	–	50
Shen et al. (2016)	V_p	MLR	0.86 and 0.98	2.36 and 1.44	33

JCR is joint condition rating, *JSR* is joint spacing rating, *GWR* is ground water rating

measurements of velocity of longitudinal waves in the same places where hydraulic jack tests were performed. In addition to wave velocities, the values of pressure at which the hydraulic jack tests were executed, were also used. Models described in this study have an acceptable accuracy within the range obtained by other authors in models of a similar type. Models based on the FNN gave better accuracy than the model based on the MLR.

The advantage of the proposed model is primarily that it used in situ measurements of moduli of deformation, velocity of waves and pressures during the experiment. In this way, the effect of scale that exists in the rock masses is taken into account.

Modelling in this study was conducted on a limited number of data. Therefore, this research cannot be generalized for all rock masses, but solely for the area around the dam and the rock masses present in that area.

Measuring deformation modulus in the rock mass is an expensive process, but determining the velocity of waves in boreholes is cheaper, and it is common in geological surveys for construction of dams, tunnels, and other structures. This means that if the speed of longitudinal waves in the relevant cross sections in the rock mass (obtained by geophysical methods) is available, deformation modulus can be estimated based on the developed models for the expected level of stresses in the rock mass.

The polar method used for determining the velocity of elastic waves can be applied with some modifications at measuring points using plate loading test. The plate loading test is a cheaper and simpler test in comparison to the hydraulic jack and it has wider application than hydraulic jack. Hence, using the same principle, the results obtained by plate loading test can be also modelled using relevant measuring of velocity of waves.

The proposed models can be improved and applied on a number of rock masses and they can be used for more general purposes when defining deformation properties of rocks for different structures both during design and construction and during exploitation of structures. Authors have the intention to further the research by adapting the model for application in other rock masses and eventually increasing the number of input parameters.

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References

Ajalloeian R, Mohammadi M (2014) Estimation of limestone rock mass deformation modulus using empirical equations. Bull Eng Geol Environ 73:541–550. doi:10.1007/s10064-013-0530-3

Aksoy CO, Geniş M, Aldaş GU, Özacar V, Özer SC, Yilmaz Ö (2012) A comparative study of the determination of rock mass deformation modulus by using different empirical approaches. Eng Geol 131–132:19–28. doi:10.1016/j.enggeo.2012.01.009

Alemdag S, Gurocak Z, Cevik A, Cabalar AF, Gokceoglu C (2015a) Modelling deformation modulus of a stratified sedimentary rock mass using neural network, fuzzy inference and genetic programming. Eng Geol 203:70–82. doi:10.1016/j.enggeo.2015.12.002

Alemdag S, Gurocak Z, Gokceoglu C (2015b) A simple regression based approach to estimate deformation modulus of rock masses. J Afr Earth Sci 110:75–80

Azimian A, Ajalloeian R (2014) Empirical correlation of physical and mechanical properties of marly rocks with P wave velocity. Arab J Geosci 8:2069–2079. doi:10.1007/s12517-013-1235-4

Banimahd M, Yasrobi S, Woodward P (2005) Artificial neural network for stress-strain behavior of sandy soils: knowledge based verification. Comput Geotech 32:377–386

Bieniawski ZT (1978) Determining rock mass deformability: experience from case histories. Int J Rock Mech Min Sci Geomech Abstr 15:237–247

Brotons V, Tomás R, Ivorra S, Crediaga A (2014) Relationship between static and dynamic elastic modulus of calcarenite heated at different temperatures: the San Julián's stone. Bull Eng Geol Environ 73:791–799. doi:10.1007/s10064-014-0583-y

Chun BS, Ryu WR, Sagong M, Do JN (2009) Indirect estimation of the rock deformation modulus based on polynomial and multiple regression analyses of the RMR system. Int J Rock Mech Min Sci 46:649–658. doi:10.1016/j.ijrmms.2008.10.001

Gokceoglu C, Sonmez H, Kayabasi A (2003) Predicting the deformation moduli of rock masses. Int J Rock Mech Min Sci 40:701–710. doi:10.1016/S1365-1609(03)00062-5

Hagan M, Menhaj M (1994) Training feedforward networks with the Marquardt algorithm. IEEE Trans Neural Netw 5:989–993

Hoek E, Brown E (1997) Practical estimation of rock mass strength. Int J Rock Mech Min Sci 34:1165–1186

Hoek E, Diederichs MS (2006) Empirical estimation of rock mass modulus. Int J Rock Mech Min Sci 43:203–215. doi:10.1016/j.ijrmms.2005.06.005

Kayabasi A, Gokceoglu C, Ercanoglu M (2003) Estimating the deformation modulus of rock masses: a comparative study. Int J Rock Mech Min Sci 40:55–63. doi:10.1016/S1365-1609(02)00112-0

Khandelwal M (2013) Correlating P-wave velocity with the physico-mechanical properties of different rocks. Pure Appl Geophys 170:507–514. doi:10.1007/s00024-012-0556-7

Kujundzic B (1970) Contribution of Yugoslav experts to the development of rock mechanics. In: Proceedings of the second congress of the international society for rock mechanics, pp 169–174

Kujundzic B (1977) Basics of rock mechanics I. Society of Civil Engineers and Technicians of Yugoslavia, Belgrade

Kujundzic B, Grujic N (1966) Correlation between static and dynamic investigations of rock mass in situ. In: Proceedings of the first congress of the international society of rock mechanics, pp 565–571

Majdi A, Beiki M (2010) Evolving neural network using a genetic algorithm for predicting the deformation modulus of rock masses. Int J Rock Mech Min Sci 47:246–253

Monjezi M, Dehghani H (2008) Evaluation of effect of blasting pattern parameters on back break using neural networks. Int J Rock Mech Min Sci 45:1446–1453

Nejati HR, Ghazvinian A, Moosavi SA, Sarfarazi V (2014) On the use of the RMR system for estimation of rock mass deformation modulus. Bull Eng Geol Environ 73:531–540. doi:10.1007/s10064-013-0522-3

Nicholson G, Bieniawski Z (1990) A nonlinear deformation modulus based on rock mass classification. Int J Min Geol Eng 8:181–202. doi:10.1007/BF01554041

Osborne M (1992) Fisher's method of scoring. Int Stat Rev 60:99–117

Pappalardo G (2015) Correlation between P-wave velocity and physical—mechanical properties of intensely jointed dolostones, Peloritani Mounts, NE Sicily. Rock Mech Rock Eng 48:1711–1721. doi:10.1007/s00603-014-0607-8

Pinto da Cunha A, Muralha J (1990) About LNEC experience on scale effects in the deformability of rock masses. In: proceedings of the first international workshop on scale effects in rock masses, Loen, Norway

Rumelhart D, Hinton G, Williams R (1986) Learning representations by back-propagating errors. Nature 323:533–536

Serafim JL, Pereira JP (1983) Considerations on the geomechanical classification of Bienawski. In: Proceedings of the symposium on engineering geology and underground openings 1133–1144

Shen J, Karakus M, Xu C (2012) A comparative study for empirical equations in estimating deformation modulus of rock masses. Tunn Undergr Space Technol 32:245–250

Shen X, Chen M, Lu W, Li L (2016) Using P wave modulus to estimate the mechanical parameters of rock mass. Bull Eng Geol Environ. doi:10.1007/s10064-016-0932-0

Song YH, Ju GH, Sun M (2011) Relationship between wave velocity and deformation modulus of rock masses. Rock soil Mech 32(5):1507–1512 **(in Chinese)**

Sonmez H, Gokceoglu C, Nefeslioglu HA, Kayabasi A (2006) Estimation of rock modulus: for intact rocks with an artificial neural network and for rock masses with a new empirical equation. Int J Rock Mech Min Sci 43:224–235

Wittke W (2014) Rock mechanics based on an anisotropic jointed rock model (AJRM). Ernst & Sohn, Berlin

Yu H, Wilamowski BM (2011) Levenberg–Marquardt training. Ind. Electron. Handbook, vol. 5—IEE Inteligent Systems 12–1 to 12–16. CRC Press 2011, London. doi:10.1201/b10604-15