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Evaluating the predicting performance of indirect methods for estimation of rock mass deformation modulus using inductive modelling techniques

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Abstract

The rock mass deformation modulus is an important parameter in numerical modeling for the stability analysis of tunnels and underground excavations. This parameter can be determined by direct and indirect methods. The direct method includes in-situ tests which are costly, timing consuming and the reliability of the result is also questionable. In indirect method different empirical models are used for estimation of rock mass deformation modulus. In this paper Rock Mass Rating (RMR), Geological Strength Index (GSI), Young Modulus of Elasticity and Uniaxial Compressive Strength (UCS) were used as input parameters in empirical models for determination of deformation modulus for rock mass. The Multi Liner Regression (MLR) and Artificial Neural Network (ANN) were used for assessment of the prediction performance of different established empirical models for estimation deformation modulus for rock mass. After analysis and comparison of results obtained from MLR and ANN, it was concluded that, the ANN based model predicting performance is better as compared to MLR model for all five data sets and the performance of both models is much better for those data sets which are collected from empirical equation containing three input variables.

Keywords: Deformation modulus; Multi Liner Regression (MRL); Artificial Neural Network (ANN).

1. Introduction

The rock mass deformation modulus is used as one of the important parameter in numerical modeling and assessment of the pre-failure mechanical behavior of the rock mass (Jiayi Shen et al. (2012); Okay Aksoy et al. (2012); Ebrahim Ghotbi Ravandi et al. (2013); Hoek & Diederichs (2006); Gholamneja et al. (2013). This parameter is determined by direct and indirect methods. In indirect methods various in-situ tests are used, like plate jack, flat jack and load jack, radial jack, load jack etc (Candan Gokceoglu, 2004). For these tests adits or drifts having 2m span and 2.5m height is excavated using drill machine or blast (Okay Aksoy et al. (2012). These tests are time consuming, costly and the results may be questionable (Khabbazi et al. (2013); Sonmeza et al. (2006) due to anisotropic nature, presence of discontinuities, Inhomogeneous and Not-Elastic nature of rock masses (Jing, 2003) availability of expertise, accuracy of instruments, difficult testing procedures used for measuring deformation modulus (Dinc et al., 2011; Candan Gokceoglu (2004); Jiayi Shen et al. (2012) deflection of plates and cracks produced during blasting (Ribacchi 1988; Kayabasi et al., 2003).

In indirect method different established empirical models were used for estimation of rock mass deformation modulus. These models used different input parameters likes rock mass rating (RMR) (Bieniawski, 1973), tunneling quality index (Q-system) (Barton et al., 1974) geological strength index (GSI) (Hoek & Brown, 1997) and mechanical properties of rock masses. In current era of research in the field of rock engineering the researchers gaining more interest in estimation of deformation modulus through different empirical models rather than in situ tests. Because the empirical models are simple, cost effective and required limited input data for estimation of rock mass deformation modulus. Numbers of empirical models developed by different researchers which does not shows that which model give high degree of accuracy in determination of deformation modulus. The predicting and estimation of deformation modulus using inductive modelling techniques, computer programming and fuzzy logic is interesting area for the research (Kayabasi et al., 2003; Grima & Babuska 1999; Singh et al., 2001; Gokceoglu & Zorlu 2004; Gholamneja 2013; Tutmez & Tercan 2007; Tiryaki 2008).

In the present research rock mass along alignment of tunnel was classified into GU1, GU2 and GU3 units using RMR, Q and GSI classification systems. The rock mass deformation modulus was estimated using Nicholson and Bieniawsk (1990), Hoek and Brown (1997), Sonmez et al. (2006), Beiki et al. (2010) and Carvalho. The prediction performance of these empirical models was evaluated using Multi Regression Models and Artificial Neural Network.

2. Rock mass classification and laboratory tests data of project

The capacity of electric generation for golen gole hydropower project is 106 MW. This project is constructing at golen Gole River in district Chitral Khyber Pakhtunkhwa Pakistan. The project includes headrace tunnel and pressure tunnel as major part. Numbers of tests were carried for determination of physical and strength properties of collected representative rock samples from the alignment of tunnel in rock mechanics laboratory of mining engineering department; the average tests values are presented in table 1. The rock mass along alignment of tunnel was classified into three geotechnical units using RMR, Q and GSI and support systems were recommended for each geotechnical unit (Sajjad et al., 2017). The results obtained from rock mass characterization are presented in table 1.

Table 1. Laboratory tests and classification of rock mass results (Sajjad et al., 2017).

Geotechnical unit	Rock Type	UCS MPa	Modulus of elasticity MPa	Poison ratio (υ)	Rock mass classification		
					RMR	Q-system	GSI
1	Granite	125	$3.41e^4$	0.188	71	11	60
2	Quartz Mica schist	54	$3.42e^4$	0.051	59	20	54
3	Calcareous Quartzite	106	$5e^4$	0.277	72	17	67

3. **Estimation of rock mass deformation modulus**

The deformation modulus is playing a vital role in numerical modeling and analysis of pre-failure of mechanical behavior for rock mass. Various empirical models are established for estimation of deformation modulus by different researchers.

Nicholson and Bieniawski developed based on RMR as in put parameter, Sonmez developed empirical model using young modulus of elasticity and RMR as input parameters, Beiki et al. presented empirical model based on GSI and UCS as in put parameters, Hoek and Brown presented an empirical model using UCS and GSI as input parameter, and Carvalho developed an empirical model using young modulus of elasticity and GSI as input parameters for determination of rock mass deformation modulus. In this paper the deformation modulus was estimated using below empirical models as shown in table 2.

4. **Inductive models for rock mass deformation modulus prediction using data collected from empirical equations**

The current paper presents the comparative analysis of multi-linear regression (MLR) and artificial neural network (ANN) for evaluating the predicting performance of different five empirical methods used for estimation of deformation modulus. The models (MLR and ANN) were trained and tested using RMR, GSI, Young modulus of elasticity and UCS. The utility of ANN-based models in prediction of Deformation Modulus for Rock Mass and its comparison with MLR models was investigated in this paper. The input variables were used in ANN and MLR are presented in Table 2.

Table 2. Empirical equations and their results.

S. No	**Equation**	**Researcher**	**Input Parameter**	**Rock Mass deformation modulus (Average value) In GPa**		
				GU-1	**GU-2**	**GU-3**
1	$E_{rm} = 0.01E_i(0.0028RMR^2 + 0.9e^{\frac{RMR}{22.83}}$	Nicholson and Bieniawski (1990)	RMR	12.21	7.91	18.22
2	$E_{rm} = E_i 10^{\left(\frac{(RMR-100)(100-RMR}{4000\exp(-\frac{RMR}{100})}\right)}$	Sonmez et al (2006)	E_i and RMR	13.67	6.91	20.60
3	$E_{rm} = tan\left(\sqrt{1.56 + (\ln(GSI))^2}\right)\sqrt[3]{\sigma_c}$	Beiki et al. (2010)	GSI and UCS	12.21	6.96	14.77
4	$E_{rm} = \sqrt{\frac{\sigma_c}{100}}\left(10^{\left(\frac{GSI-10}{40}\right)}\right)$	Hoek and Brown (1997)	GSI and UCS	23.40	10.55	29.05
5	$E_{rm} = E_i(s)^{\frac{3}{4}}, s = e^{\left(\frac{GSI-100}{9-3D}\right)}$	Carvalho (2004)	E_i, GSI and carvalho	11.83	9.93	20.28

Table 3. Description of input variables for the development of ANN and MLR based models.

S.No	Empirical Models	Input Parameter	
		Symbols	**Description**
1	Nicholson and Bieniawski (1990)	SQ RMR, RMR and Ei	Rock Mass Rating and Young Modulus of Elasticity
2	Sonmez et al (2006)	E_i and RMR	Young Modulus of Elasticity and Rock Mass Rating
3	Beiki et al. (2010)	GSI and UCS	Geological Strength Index and Uniaxial compressive strength
4	Hoek and Brown (1997)	GSI and UCS	Geological Strength Index and Uniaxial compressive strength
5	Carvalho (2004)	E_i and GSI	Geological Strength Index (GSI), Young Modulus of Elasticity

4.1. MLR models

In MLR models the collected data from five different empirical models are used for the development of MLR and ANN models based on 146 data sets for the determination and prediction of Rock mass deformation modulus. The 109 (75% of total data sets) were used for training of both the models while 37(25% of total data sets) were used for validation and testing of models. Since there were three input variables for Nicholson and Bieniawski and Carvalho while two input variables for all the remaining models as described in Table 2, therefore the same were used as input variables for development of inductive models.

Optimal equations were obtained using MLR model for prediction of deformation modulus for five empirical models.

1. MLR equation for Nicholson and Bieniawski data:

$$Output=14.467+0.0105 * RMR^2 - 0.941 * RMR + 0.00034 * E_i \quad (1)$$

2. MLR equation for Sonmez data

$$\text{Output}=45.475+0.6497 * RMR + 0.000385 * E_i \quad (2)$$

3. MLR equation for Beiki et al. data

$$Output=19.669+0.448 * GSI + 0.039 * ucs \quad (3)$$

4. MLR equation for Hoek and Brown data

$$Output=51.247+1.031 * GSI + 0.10 * ucs \quad (4)$$

5. MLR equation for Carvalho data

$$Output=13.365+0.1773 * GSI + 0.000363 * E_i \quad (5)$$

The above five equations were developed based on five mentioned different models. The statistical analysis of each developed equation in term of performance is discussed in later section of the paper. The results obtained from each equation is presented in table 4.

Although MLR models are also giving good results but for more complex phenomena it failed to predict more accurately. To overcome this deficiency, more robust type of Inductive modeling technique called Artificial Neural Network (ANN) is used. The following described the description of ANN, followed by the model development for the above five options and then results and discussion.

4.2. ANN based model

It is a human brain mathematical model that contains interconnected network of neurons. The basic architecture of ANN composed of input, hidden and output layer containing neurons. The ANN models are adjusted through training and testing process for model calibration (Zurada, 1992; Rahmannejad et al., 2010). ANN models are "black box models" as they are not very efficient in describing cause and effect relationship and the expression for the output is cumbersome and very long. These models require a lot of data for predicting output from the given input variables. The ANN models were developed in Neuro sort software (NSS) (Lingireddy et al., 2003). The basic operational procedure of ANN is given in Figure 2.

The optimal outputs for five empirical models were achieved using number of neurons equal to the input variables. Similarly, the hidden layer neurons were kept equal to the number of neurons in the input layers. The sigmoidal activation function was used for modeling the transformation of values across the layers.

The prediction performance of both inductive models (MLR and ANN) were evaluated based on Root Mean Square error (RMSE), Average Absolute error (AAE) and coefficient of determination (R^2). The results are presented in table 4.

5. Results and discussions

The value for Rock Mass Deformation Modulus was predicted using different established empirical models based on the available data. In this study the results obtained from the above mentioned five empirical models were used in the development of inductive models (ANN and MLR). The results for both models in term of RMSE, AAE and R^2 were then compared for evaluating the predicting performance of each model. The results obtained from MLR and ANN based models for the data obtained from all the five empirical models are shown in Table 4 below.

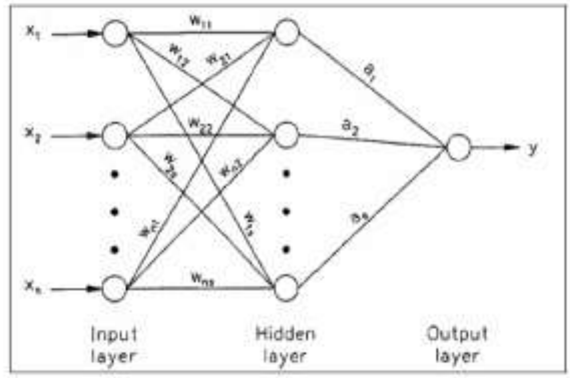

Fig. 1. Process of ANN model for prediction (Jeng DS, 2006).

The results shown in table 4 were compared for the data obtained from five different types of empirical equations using both MLR and ANN. This table revealed that Nicholson & Bieniawski and Carvalho models shows better prediction performed better using the data obtained from. The Carvalho empirical model shows better prediction of deformation modulus for proposed rock mass environment as compared to other empirical models. Similarly, on comparing the performance of MLR with ANN it is clear that ANN performed much better than MLR in term of R^2 (Performance measure), RMSE and AAE. The performance of ANN was noted better to the MLR models. The same trend is shown for both training and testing data sets.

The scattered plots for each model based on ANN and MLR for training and testing data sets are plotted for comparative analysis and evaluating the performance of MLR and ANN models.

5.1.Scattered plots for MLR based models

The plots were drawn for each MLR-based model using data sets (1-5), including training and testing sets of data are shown in Figures 2-5:

Table 4. Statistical analysis of five empirical models.

S.No	Data	Model	Training			Testing		
			AAE	RMSE	R^2	AAE	RMSE	R^2
1	Nicholson and Bieniawski	ANN	**0.293**	**0.340**	**0.996**	**0.437**	**0.260**	**0.990**
		MLR	0.457	0.587	0.987	0.431	0.272	0.999
2	Sonmez	ANN	**0.391**	**0.466**	**0.996**	**0.806**	**0.849**	**0.985**
		MLR	1.263	1.550	0.954	1.925	4.599	0.957
3	Beiki et al.	ANN	**0.280**	**0.345**	**0.995**	**0.426**	**0.318**	**0.978**
		MLR	0.854	1.015	0.954	0.952	1.206	0.971
4	Hoek and Brown	ANN	**0.567**	**0.726**	**0.996**	**0.867**	**1.228**	**0.983**
		MLR	2.328	2.712	0.940	2.307	6.668	0.970
5	Carvalho	ANN	**0.059**	**0.082**	**1.000**	**0.069**	**0.010**	**1.000**
		MLR	0.290	0.414	0.993	0.289	0.130	0.989

1. Scattered Plots for Nicholson and Bieniawski (1990) using MLR:

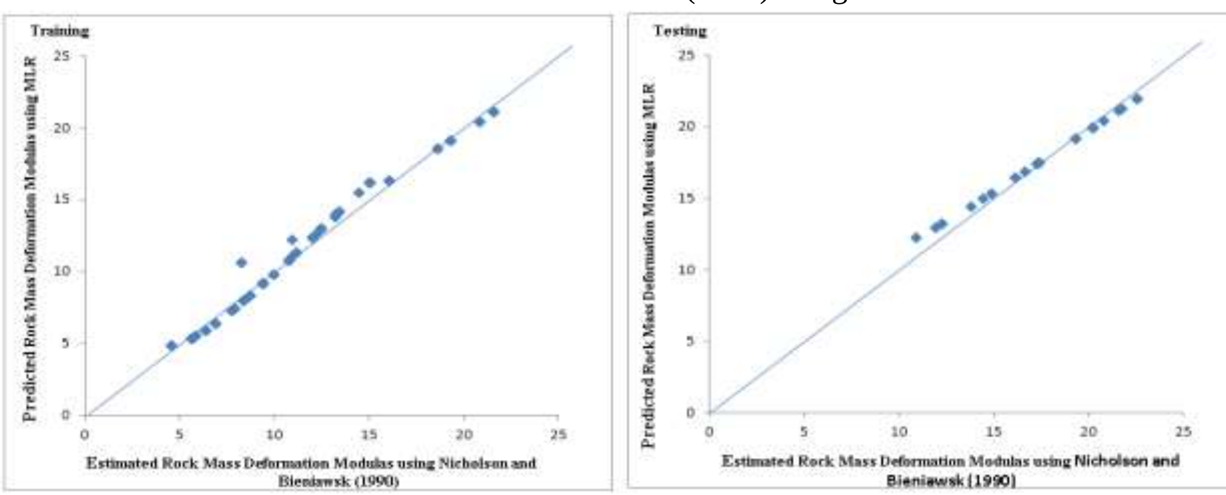

Fig. 2. Scattered plots drawn of MLR based model using Nicholson and Bieniawski (1990) data set.

2. Scattered Plots for Sonmez (2006) using MLR

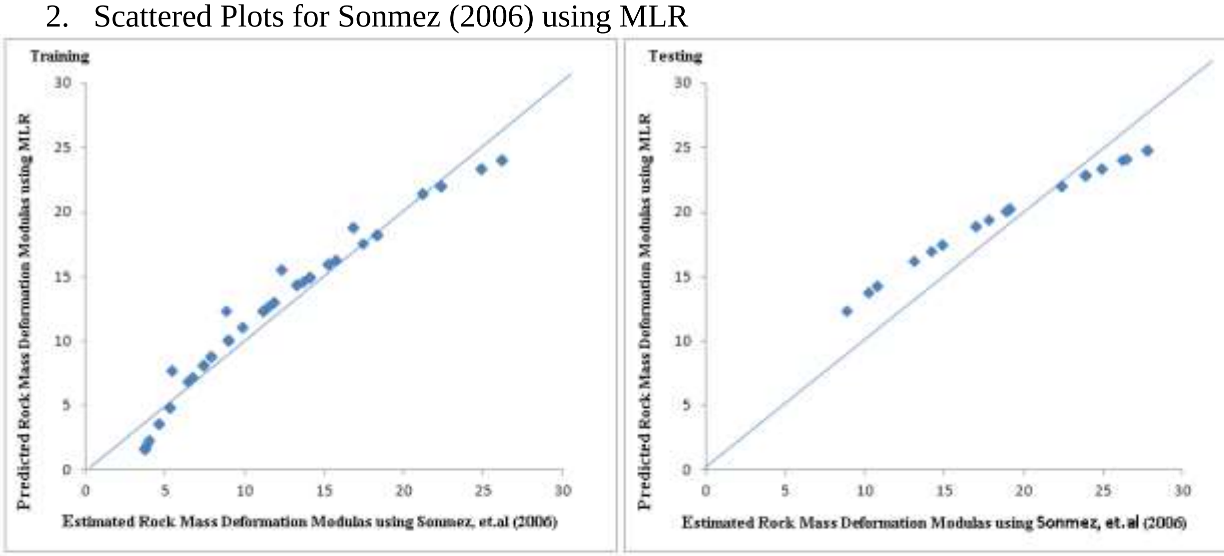

Fig. 3. Scattered plots drawn of MLR based model using Sonmez (2006) data set.

3. Scattered Plots for Beiki et al. (2010) using MLR

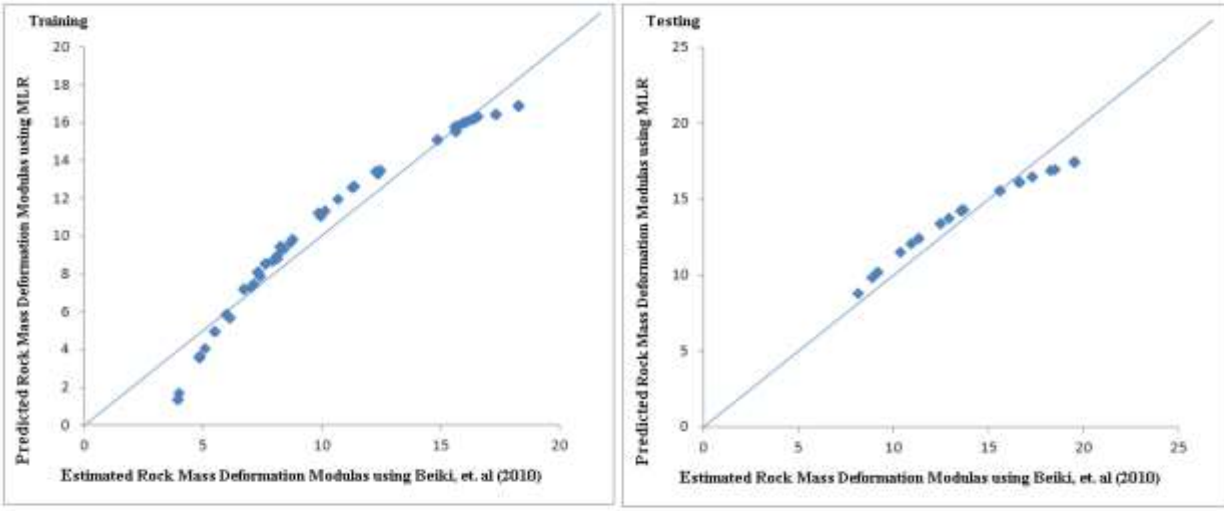

Fig. 4. Scattered plots drawn of MLR based model using Beiki et al (2010) data set.

4. Scattered Plots for Hoek and Brown (1997) using MLR

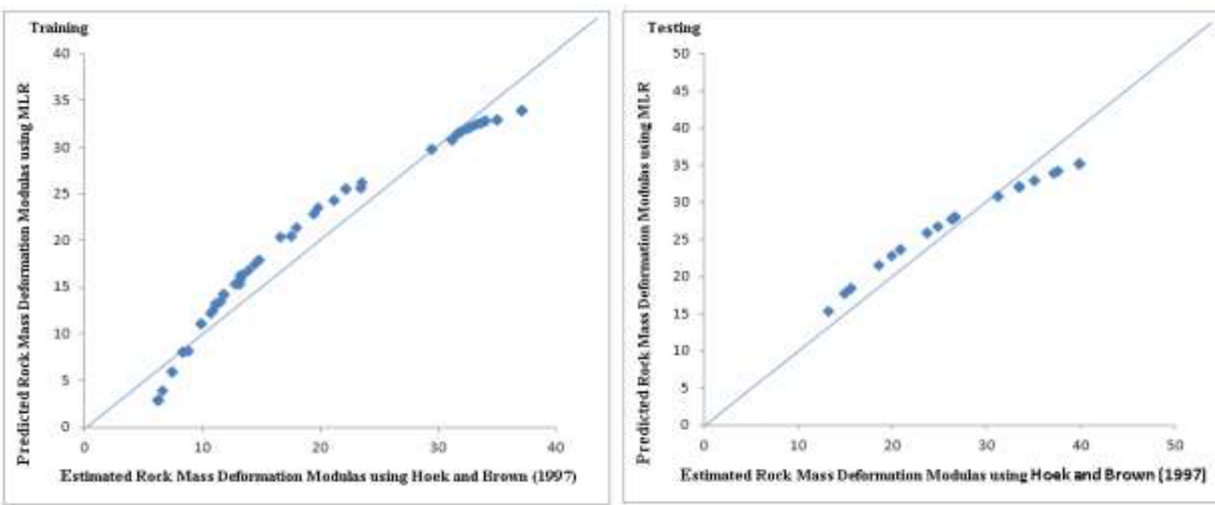

Fig. 5. Scattered plots drawn of MLR based model using Hoek and Brown (1997) data set.

5. Scattered Plots for Carvalho using MLR

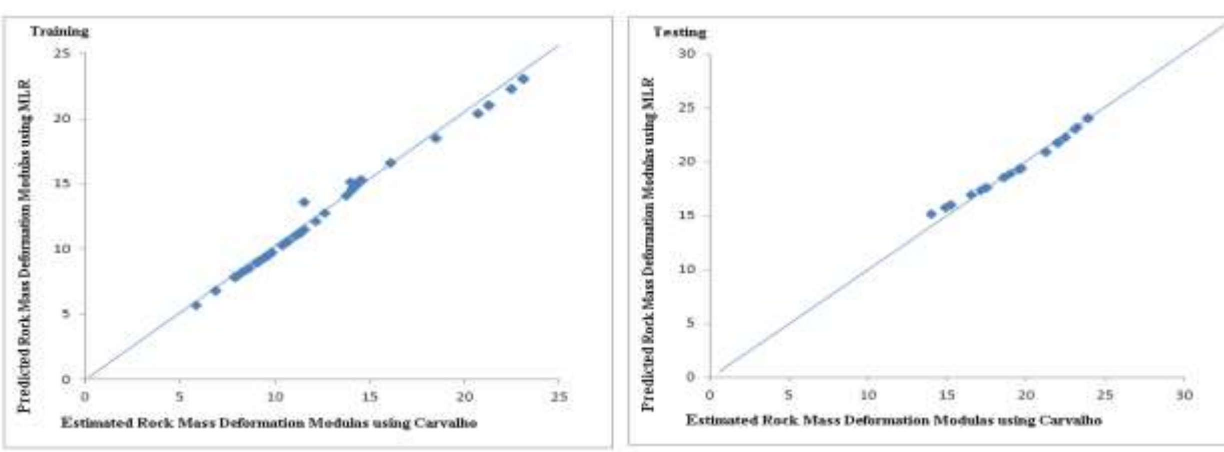

Fig. 6. Scattered plots drawn of MLR based model using Carvalho data set.

5.2. Scattered plots for ANN based models

The plots drawn for each ANN-based model using data sets (1-5) including training and testing sets of data are shown in Figures (7-11) below.

1. Scattered Plots for Nicholson and Bieniawski (1990) using ANN:

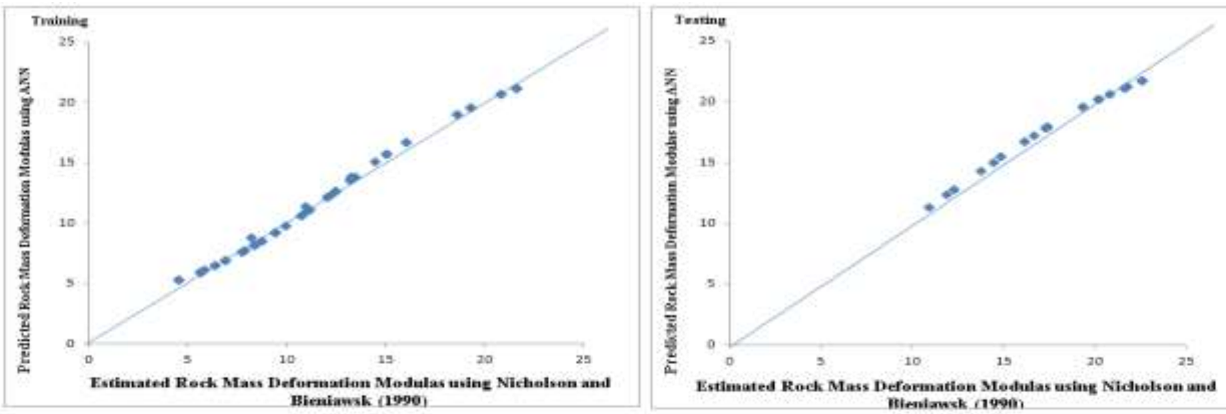

Fig. 7. Scattered plots drawn of ANN based model using Nicholson and Bieniawski (1990) data set.

2. Scattered Plots for Sonmez (2006) using ANN:

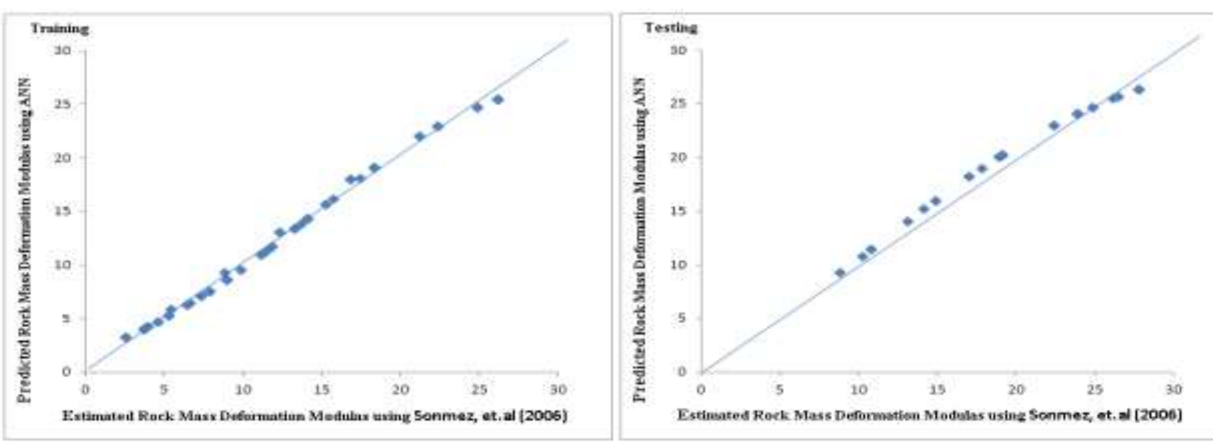

Fig. 8. Scattered plots drawn of ANN based model using Sonmez, et. al (2006) data set.

3. Scattered Plots for Beiki et al. (2010) using ANN:

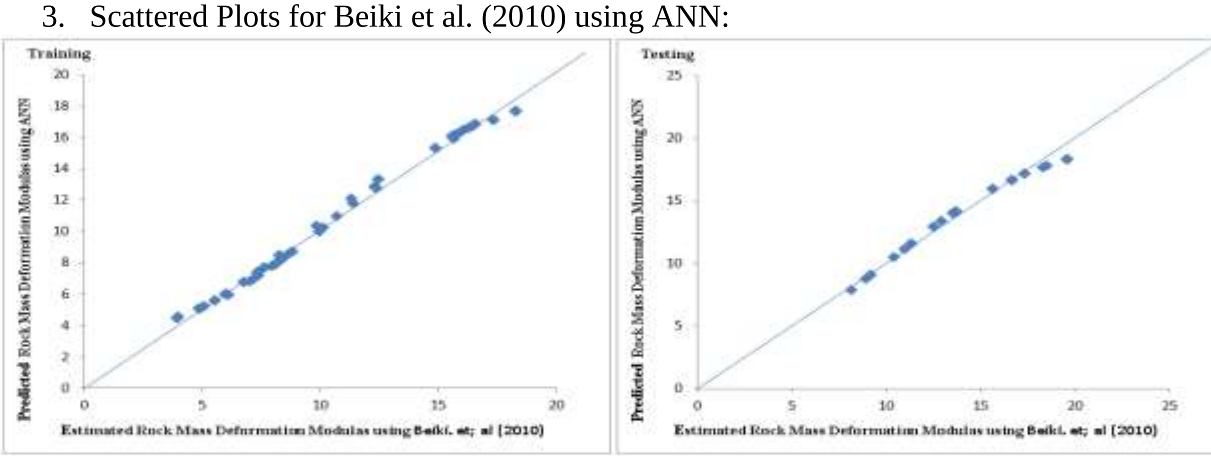

Fig. 9. Scattered plots drawn of ANN based model using Beiki, et. al (2010) data set.

4. Scattered Plots for Hoek and Brown (1997) using ANN:

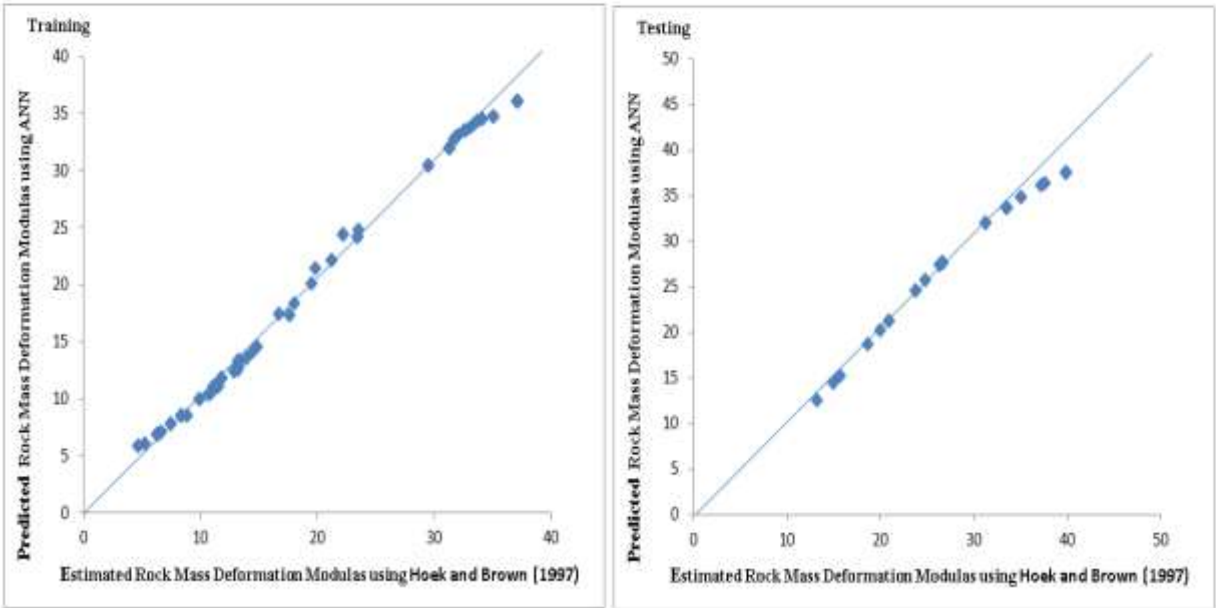

Fig.10. Scattered plots drawn of ANN based model for training and testing data sets using Hoek and Brown (1997) data set.

5. Scattered Plots for Carvalho using ANN:

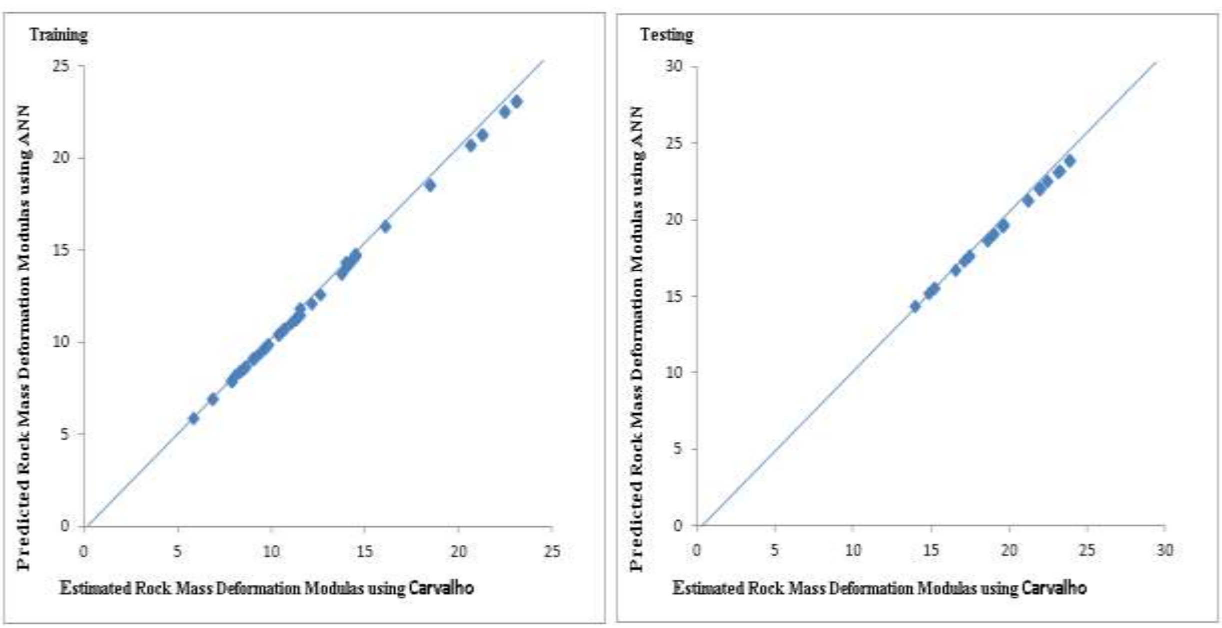

Fig. 11. Scattered plots drawn of ANN based model using Carvalho data set.

5.3. Comparison the performance MLR and ANN based models

The scattered plots were drawn for all five available data sets including training and testing individually. The performance of ANN and MLR models were compared and evaluated. The results in term of performance of both models are shown in Figures (12-16).

1. Scattered Plots for Nicholson and Bieniawski (1990) showing Comparison of ANN and MLR:

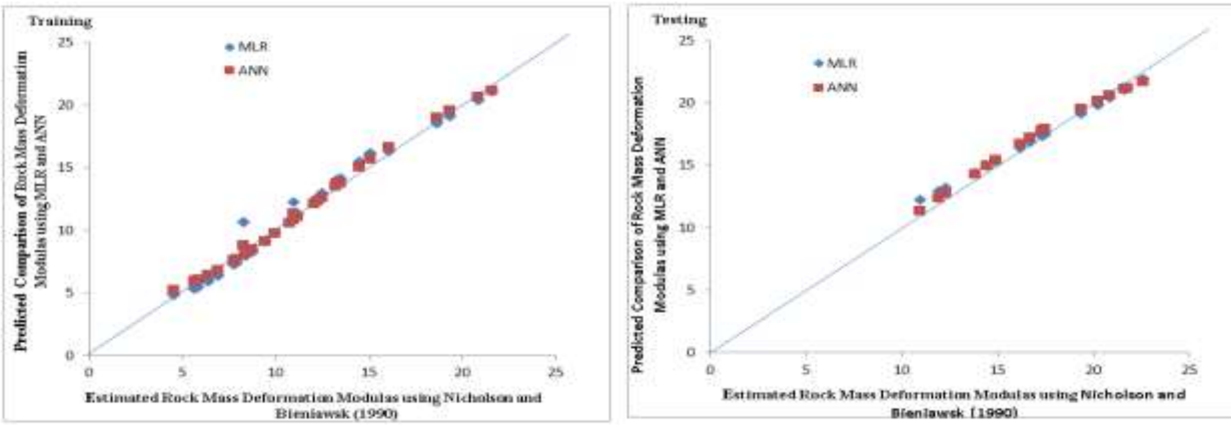

Fig.12. Scattered plots drawn Comparing model performance of ANN and MLR based models using Nicholson and Bieniawski (1990) data set.

2. Scattered Plots for Sonmez (2006) showing Comparison of ANN and MLR:

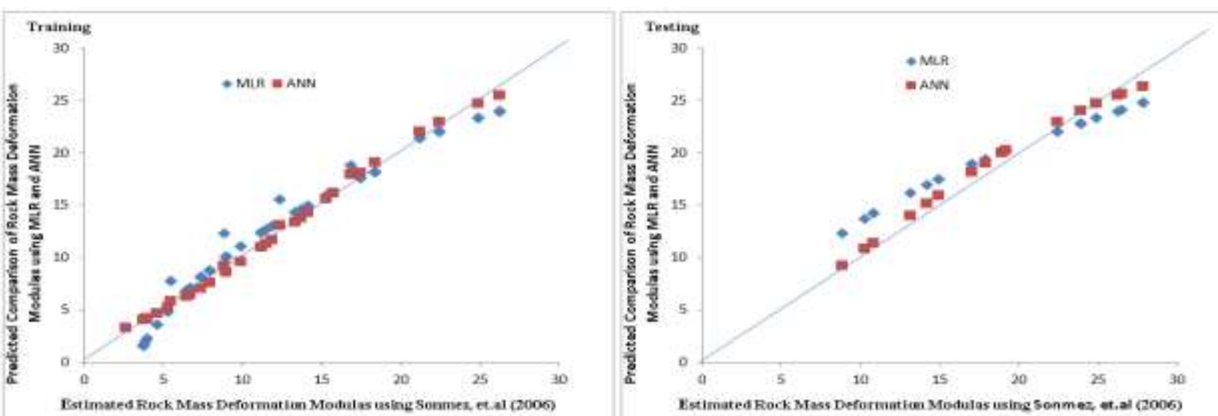

Fig. 13. Scattered plots drawn Comparing model performance of ANN and MLR based models using Sonmez, et. al (2006) data set.

3. Scattered Plots for Beiki et al. (2010) showing Comparison of ANN and MLR:

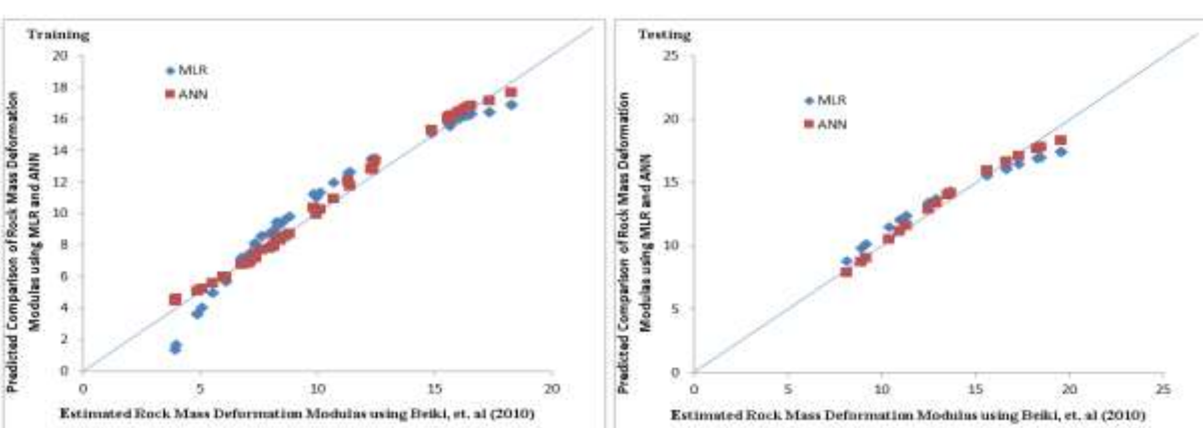

Fig. 14. Scattered plots drawn Comparing model performance of ANN and MLR based models using Beiki, et. al (2010) data set.

4. Scattered Plots for Hoek and Brown (1997) showing Comparison of ANN and MLR:

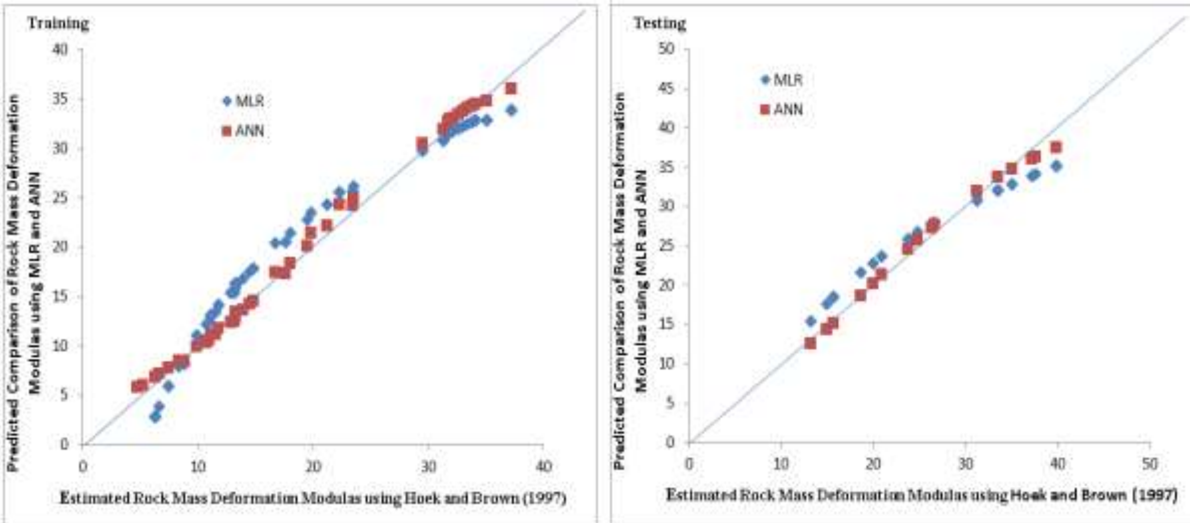

Fig.15. Scattered plots drawn Comparing model performance of ANN and MLR based models using Hoek and Brown (1997) data set.

5. Scattered Plots for Carvalho showing comparison of MLR and ANN:

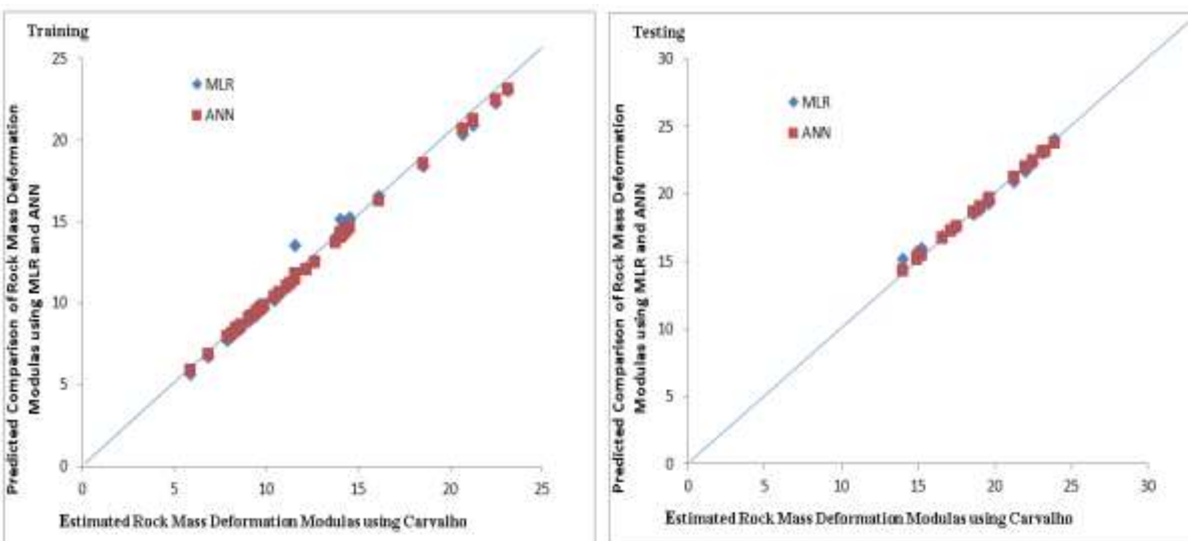

Fig. 16. Scattered plots drawn Comparing model performance of ANN and MLR based models using Carvalho data set.

Scattered plots are drawn for MLR, ANN based models and also for comparison. The individual as well as the combined plots showed that ANN based models performance is better as compared to MLR based model because the points for earlier are located close to the 45 degree line as compared to the later one. Thus it supplements the result that we obtained from the tables.

6. Conclusions

The performance of empirical models used for predicting the deformation modulus should be verified by inductive modelling techniques because, accurate prediction of deformation modulus for any rock mass environment is very essential for accurate numerical analysis of stability and pre-failure mechanical behaviour of rock masses. This paper investigates the predicting performance of empirical models using MLR and ANN based on collected field data from tunnel site. The MLR and ANN based models were developed using data collected from five different empirical equations. The results of the models were presented in tabular form showing the values of error measure RMSE and AAE and performance measures R^2 and graphical form showing the scattered plots between the observed and predicted values. Form all these results it can be concluded that the performance of both models are good for the data sets which were collected from empirical equation containing three variables as compared to the data sets containing two variables. Secondly, on comparing the inductive models within itself, it was concluded that for all the data sets the performance of ANN based models was better to the MLR based models resulting in high values of R^2 and smaller values if RMSE and AAE. So at the end it is concluded that ANN is very effective in predicting the rock mass deformation modulus and can be applied for better prediction in future. It is also concluded that the prediction performance of MLR and ANN models based on Carvalho empirical model was better as compared to other empirical models for rock mass of proposed site.

Authors' Contribution

Sajjad Hussain, proposed the main idea and performed laboratory test works, literature review, paper writing and interpretation of results from inductive modeling. Mujahid Khan, contributed in Applying ANN and MLR, and interpretation of results. Zahid Ur Rehman, contributed in literature review and paper writing. Noor Mohammad, contributed in literature review and paper writing and technical evaluation of paper. Salim Raza, contributed in literature review and paper writing and technical evaluation of paper. Muhammad Tahir, contributed in tests work and evaluate paper. Ishaq Ahmad, contributed in tests work and evaluate paper. Saira Sher, contributed in tests work and evaluation of paper. Naseer Muhammad Khan, contributed in tests work and evaluation of paper.

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