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Soft Computing Based Prediction of Support Pressure in Tunnels

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Abstract*: *Prediction of Tunnel support pressure up to an accurate and reliable degree is difficult, but of utmost importance. Empirical models are available with different set of parameters, mostly are based on the rock classification parameters. A feed forward neural network based predictive models from the data collected from literature for the Himalayan tunnels have been developed. The input variables in the developed neural network models were depth of over burden, radius of tunnel, normalised closure. The fourth input variable was rock mass quality or rock mass number or rock mass rating. The output was a support pressure. Sensitivity analysis relating the variables affecting the support pressure has been performed. The developed neural network models were compared with models developed based on the multiple linear regression analysis as well as with empirical models already available in literature. Finally, model equations have been presented based on the connection weight.

Keywords: Tunnel support pressure; ANN; MVLRA; Sensitivity Analysis; Rock classification parameters.

I. INTRODUCTION

Support pressure in tunnels governs the design of support system to be provided. Therefore, its prediction is of utmost importance. Various theoretical and empirical models (Goel et al. [1]) are available in literature to compute the support pressure in tunnels in squeezing and non-squeezing ground conditions. These models were developed based on certain assumptions. Unlike the theoretical and empirical models, artificial neural network model do not use any prior assumptions due to its capability to learn from the experience and to understand inherent relationship among the variables, which makes artificial neural network a better choice for predicting the support pressure in tunnels. Researchers (Alipour et al. [2]; Mohamed et al. [3]; Yeh [4]) have shown that artificial neural network were efficient in predicting the complex rock behavior and provided the solutions to problems related to various tunneling operation. With the above in view, in the present study, a feed forward neural network based predictive models from the data collected from literature for the Himalayan tunnels have been developed. The input variables in the developed neural network models were depth of over burden (D), radius of tunnel (R), normalised closure (u). The fourth input variable was rock mass quality (Q) or rock mass number (N) or rock mass rating (RMR). The output was a support pressure. Sensitivity analysis relating the variables affecting the support pressure has been performed. A comparison of the developed neural network models is made with the already available models in literature. Finally, model equations have been presented based on the connection weight.

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II. DATA USED

The data reported by Goel et al. [1] for the development of the artificial neural network model were used consisting of data from 25 tunnel sections in squeezing and non-squeezing ground conditions with width varying from 2 m to 14 m. For training the artificial neural network, data from 18 tunnels sections were chosen randomly, and the remaining data were used for the testing purpose. For tunnel sections in non-squeezing ground conditions, the normalized closure was taken as 0. The data used for the training and testing purposes are presented separately in the Table 1 and Table 2 respectively.

Table 1 Data Sets Used For Training Of Various Models

Sr. No.	Name of tunnel	Q	N	RMR	R(m)	D(m)	u(%)	P_{ob} (MPa)
1	Chhibro-Khodri	0.05	0.38	14.00	1.50	280.00	2.80	0.31
2	Giri-Bata	0.12	0.60	20.00	2.30	240.00	5.50	0.17
3	Maneri Stage-II	0.80	4.00	35.00	1.25	480.00	2.50	0.17
4	Maneri Stage-III	0.18	0.90	24.00	3.50	410.00	3.00	0.29
5	Chhibro-Khodri	0.05	0.50	14.00	4.50	680.00	6.00	1.08
6	Chhibro-Khodri	0.02	0.11	13.00	4.50	280.00	2.00	1.15
7	Maneri Stage-I	3.60	9.00	51.00	2.90	225.00	0.00	0.06
8	Maneri Stage-I	4.50	12.00	55.00	2.90	550.00	0.00	0.08
9	Maneri Stage-I	0.40	2.00	35.00	2.90	300.00	0.00	0.15
10	Khara	0.40	2.00	35.00	3.00	150.00	0.00	0.11
11	Khara	0.40	2.00	30.00	3.00	200.0	0.00	0.15
12	Lakhwar	8.50	21.25	61.00	3.00	250.00	0.00	0.05
13	Maneri Stage-II	0.84	4.20	40.00	3.50	175.00	0.00	0.08
14	Maneri Stage-II	2.71	7.00	50.00	3.50	250.00	0.00	0.07
15	Salal	1.10	3.00	41.00	6.00	150.00	0.00	0.11
16	Tehri	0.80	3.50	42.00	6.00	220.00	0.00	0.13
17	Upper Krishna	15.00	75.00	68.00	6.50	34.00	0.00	0.02
18	Lakhwar	8.50	21.25	61.00	7.00	250.00	0.00	0.05

Table 2 Data Sets Used For Testing Of Various Models

Sr. No.	Name of tunnel	Q	N	RMR	R(m)	D(m)	u(%)	P_{ob} (MPa)
1	Chhibro-Khodri	0.02	0.11	13.00	1.50	280.00	4.50	0.32
2	Giri-Bata	0.51	2.55	35.00	2.30	380.00	7.60	0.20
3	Loktak	0.02	0.17	15.00	2.30	300.00	7.00	0.54

4	Maneri Stage-I	0.50	3.75	40.00	2.90	350.00	7.90	0.20
5	Maneri Stage-II	0.57	2.50	38.00	3.50	200.00	0.00	0.10
6	Tehri	6.00	15.00	59.00	6.00	300.00	0.00	0.06
7	Upper Krishna	15.00	37.50	65.00	6.50	52.00	0.00	0.03

III. NEURAL NETWORK MODEL

In order to develop three alternate neural network models, and to compare the relative importance of three parameters Q, N and RMR, three separate input variable data sets were chosen. The first data set contains four parameters such as Q, depth of overburden (D), radius of tunnel (R), and normalized closure (u). The second and third data set also contains four parameters. Only Q and RMR was replaced with N keeping other parameters same. These three models are designated as Q-model, N-model and RMR-model in the text of this paper. Support pressure was the output in all the three models.

Optimal Neural Network Models Selection

The architecture of a multi-layer feed-forward neural network model affects the output, and therefore some specific number of hidden nodes and hidden layers are to be designed. Boger and Guterman [5] have suggested that as a thumb rule number of hidden layer neurons can be taken as 2/3 (70%) of the number of the input variables in input layer. Blum [6] have suggested that the number should be between the input layer size and output size. Keeping the above in view, using the thumb rule given by Boger and Guterman [5] 2/3 of 4 inputs, i.e. 3 number of hidden neurons were selected. A similar approach has also been adopted by other researchers (Dutta et al. [7]; Kurkoya [8] ; Ito [9]). With single hidden layer and 3 hidden neurons, initial random weights in the range -1 to 1 were assigned. The next job is to identify the optimum number of epochs for each model. As the insufficiently trained model is inaccurate and heavily trained model creates noise (Dutta et al. [7]) with trial and error the optimum number of epochs were found. Optimality was checked by calculating the mean squared error (MSE) between the actual and the predicted support pressure. An overfitting effect is observed when training was done beyond the optimal point (Dutta et al . [7], Sarle [10]). Therefore training was stopped beyond the optimal point in all the three models. Based on the calculated mean squared error, with a topology of 4-3-1 for each neural network model corresponding to 600, 4000 and 600 number of epochs was selected for Q-model, N-model and RMR-model respectively.

Activation Function Selection

The aim of this work is to select the best activation functions for hidden and output layer neurons of the neural network. This was done using Agiel Neural Network, an open source software. It supports various activation functions such as linear, Threshold, Threshold symmetric, Sigmoid, Sigmoid stepwise, Sigmoid symmetric, Gaussian, Gaussian symmetric, Elliot, Elliot symmetric, Linear piece, Linear piece symmetric, Sin symmetric, Cos symmetric, Sin, and Cos. Activation function governs the output of a neuron corresponding to a given input, it scales the output into a proper range and introduces nonlinearity. With an initial random weight of -1 to 1, maximum error of 0.0001, TRAIN_RPROP as the learning algorithm, and default activation steepness of 0.5 for activation functions of hidden and output neurons, all three models were tested for the above-mentioned activation functions with their respective optimal epochs. Selection of a function was be made using the mean squared error as the performance measure. Lesser value of mean squared error indicates better prediction. Based on the mean squared error, it was found that all three models gave best results with Elliot function. Therefore Elliot function was selected as an activation function for both hidden neurons and output neurons.

Performance Measures for Artificial Neural Network Models

Considering 'Accuracy' as the best performance measure, along with corfficient of correlation (r) and coefficient of determination (R^2), mean square error (MSE) , root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were calculated to calculate the magnitude of the errors. Higher values of MSE, RMSE, MAE and MAPE show less accurate predictions, while the higher values of r and R^2 show more accurate predictions. In general practice, only r and R^2 are used to predict the accuracy of a model, but for a better comparison all the performance measures should be compared. RMSE will always remain less or equal to MAE. Further, when RMSE equals MAE (both can vary from 0 to ∞), then all errors would have the same magnitude. Table 3 presents the mathematical expressions used to calculate these performance measures. The performance measures for the training of the three models are shown in Table 4.

Table 3 Various Statistical Parameters And Error Models

Statistical parameter	Mathematical expression
Correlation coefficient (r)	$r = \frac{\sum Pt_i Pp_i - n\overline{Pt}\,\overline{Pp}}{(n-1)S_{Pt}S_{Pp}}$
Coefficient of determination (R^2)	$R^2 = 1 - \frac{\sum_i (Pp_i - Pt_i)^2}{\sum_i (Pp_i - \overline{Pp})^2}$
Mean square error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(Pt_i - Pp_i)^2$
Root mean square error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Pt_i - Pp_i)^2}$
Mean absolute error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert Pt_i - Pp_i\rvert$
Mean absolute percentage error (MAPE)	$MAPE = \left[\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{Pt_i - Pp_i}{Pt_i}\right\rvert\right]*100$

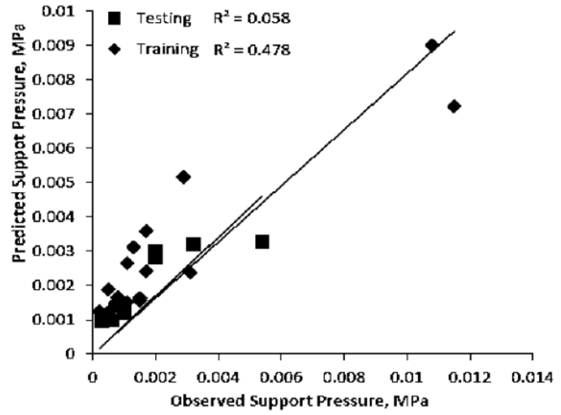
Note: Pt, Pp : target and predicted tunnel support pressure respectively, $\overline{Pt}$, $\overline{Pp}$: mean of the target and predicted tunnel support pressure respectively, S_{Pt}, S_{Pp} : standard deviation of the target and predicted tunnel support pressure respectively, n : number of observations

Table 4 Statistical Values For Training And Testing Data Sets For Three ANN Models With Elliot Activation Function

Neural Network Model	Statistical values for the	r	R^2	MSE	RMSE	MAE	MAPE
Q-Model	training data	0.924	0.478	0.024	0.154	0.121	110.369
N-Model		0.986	0.937	0.005	0.068	0.052	48.041
RMR-model		0.992	0.894	0.007	0.081	0.063	76.377
Q-Model	testing	0.832	0.058	0.010	0.098	0.074	61.761

N-Model	data	0.990	0.932	0.001	0.035	0.024	28.829
RMR-model		0.940	0.745	0.004	0.063	0.050	49.772

Study of this table reveal that best predictions were made by the N-Model having MSE of 0.0046. RMR-model gave the second best predictions with MSE of 0.0065 and the Q-model gave the MSE of 0.0238 and was at number three. Further, models should also be tested for their predictability with the testing data. For this, testing was done using the data of the remaining tunnel sections. Results of the training and testing are shown in Fig. 1(a)., Fig. 1(b)., and Fig. 1(c). for Q-model, N-Model and RMR-Model respectively.



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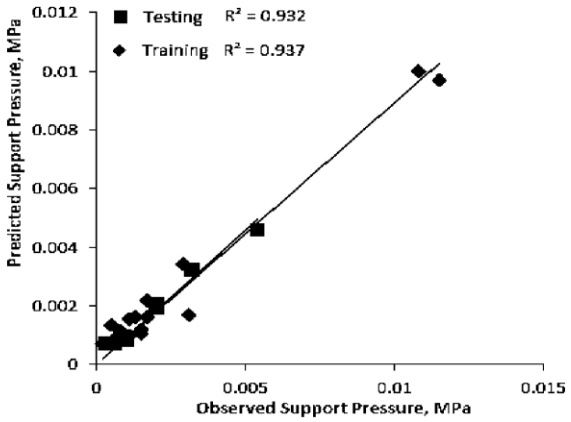

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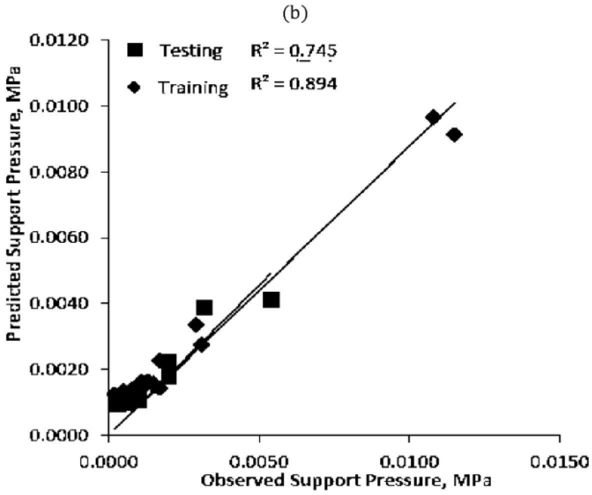


(c)

Fig. 1 Training and Testing of (a) Q-model with Elliot function (b) N-model with Elliot function (c) RMR-model with Elliot function

Sensitivity Analysis

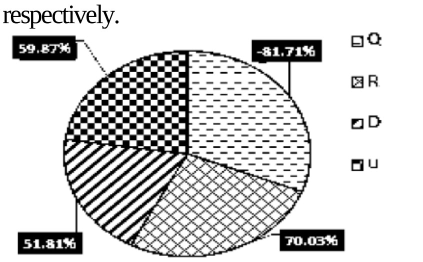
In past many studies, researcher (Goel et al. [1]) has expressed difference of opinion on the effect of parameter such as the size of the tunnel and depth of overburden on the support pressure. Keeping this aspect in view, sensitivity analysis was performed to determine the relative importance (RI) of the input variables
affecting the output. For the sensitivity analysis, methods reported by Garson [11] and Olden and Jackson [12] are available in literauture. Former method is based upon the weights configuration, but it measures the absolute values of the weights, and latter suggests the improvements to overcome these limitation. Therefore, following the procedure given by the latter method, the sum of the product of the final weights of the connection of the input neurons to the hidden neurons with the connection wight of the hidden neurons to the output neurons for all input neurons was calculated individualy for each model. The equation (1) used for performing the sensitivity analysis is given below.

$$RI_j = \sum_{k=1}^{h} w_{jk} * w_k \quad (1)$$

Where,

RI_j is the relative importance of the *jth* neuron of input layer; h is the number of neurons in the hidden layer; w_{jk} is the connection weight between j^{th} input variable and k^{th} *neuron* of the hidden layer; w_k is the connection weight between k^{th} neuron of hidden layer and the single output neuron.

The connection weights between the input neurons and hidden neurons and those of the hidden neurons to the output neurons are given in the Table 5, Table 6, and Table 7 for Q-model, N-model, and RMR-model respectively.



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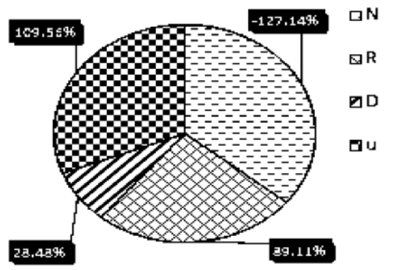

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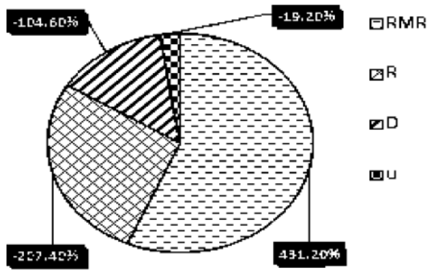

(c)

Fig. 2 Relative importance of various input parameters of (a) Q-Model (b) N-Model (c) RMR-Model

Table 5 Final connection weights for Q-model

Neuron	Weights (w_{jk})					Biases	
	Q	R(m)	D(m)	u(%)	P	b_{hk}	b_0
Hidden neuron 1 (k=1)	3.078	-2.115	-1.911	-3.054	-5.591	2.037	4.975
Hidden neuron 2 (k=2)	2.760	-3.206	-1.820	-0.626	-4.872	2.093	-
Hidden neuron 3 (k=3)	2.947	-2.304	-1.846	-2.603	-5.274	1.964	-

Table 6 Final connection weights for N-Model

Neuron	Weights (w_{jk})					Biases	
	N	R(m)	D(m)	u(%)	P	b_{hk}	b_0
Hidden neuron 1 (k=1)	8.047	-15.362	0.475	0.675	-17.713	6.433	13.589
Hidden neuron 2 (k=2)	6.632	1.982	-3.067	-10.816	-13.074	-0.033	-
Hidden neuron 3 (k=3)	6.379	2.161	-2.954	-10.779	-12.893	-0.168	-

Table 7 Final Connection Weights For RMR-Model

Neuron	Weights (w_{jk})					Biases	
	RMR	R(m)	D(m)	u(%)	P	b_{hk}	b_0
Hidden neuron 1 (k=1)	6.770	-3.376	-1.530	-0.020	-7.983	1.008	8.750
Hidden neuron 2 (k=2)	5.299	-2.178	-1.506	-0.890	-5.893	0.519	-
Hidden neuron 3 (k=3)	6.281	-3.190	-1.468	-0.056	-7.224	0.981	-

When relative importance is positive it signifies that the support pressure increases with the increase in the value of input parameter, if negative, means it decreases with the decrease in the value of the input parameter, when near to zero means that any variation in the input has less effect on the output (Dutta et al. [7]; Kim et al. [13]). The obtained relative importance (RI) of the parameters of the respective models are shown in the Fig. 2. It can be inferred from these results that support pressure (P) is directly proportional to R, D and u for the Q-model and N-model, while inversly proportional to the value of Q and N. Given to the physical meaning of the rock classification parameters Q and N, it can be said that support pressure decrease with the increase in the value of these parameters. Therefore, these results match with physical meaning of the support pressure and its various parameters. Also, support pressure increases when depth of the overburden and size of the tunnel are increased. For the RMR-model, support pressure is directly proportional to RMR, but inversely proportional to R, D and u. These results are in disagreement with the empirical equations reported by researchers (Unal [14]; Goel et al. [1]; Goel and Jethwa [15]). The empirical models presented by the researchers (Unal [14]; Goel et al. [1]; Goel and Jethwa [15]) have shown that the support pressure is directly proportional to the size of the tunnel and depth of the overburden whereas in the RMR-model, the relative importance of the size of the tunnel and depth of the overburden is negative signifying that these parameters are inversly proportional. Further, the relative importance of the RMR was 431.207, which signifies that support pressure increases when RMR is increased. It is contrary to the physical meaning of the rock classification parameter –RMR and the available empirical models, in which support pressure decrease with the increase in the RMR, because higher RMR signifies a good rock. Further, results of the sensitivity analysis also depend upon the accuracy of the available data, therefore an important parameter could show lower relative importance if the data is not correct.

The comparison of the relative dependance of the accuracy of the models on the rock classification parameters, can easily be unerstood by comparing the performance measures of the corresponding artifical neural network models. From Table 4, it can be seen that N-model performs better than the other two models. It has the coefficients of determinations of 0.938 and 0.932 for the training and testing data. The correspoding values for the Q-model and RMR-model are 0.478 & 0.058 and 0.894 and 0.745 respectively. Other performance measures such as MSE, RMSE, MAE and MAPE, also reveal that for both training and testing data, N-model performed better than the other two models. Therefore, it can be said that the relative dependance of support pressure on the respective three parameters of rock classification is similar in order that was reported by Goel et al. [1].

IV. MULTIPLE VARIABLES LINEAR REGRESION ANALYSIS (MVLRA) MODELS

Multiple linear regression analysis is another alternativ to model the complex mathematical relationships. All the input variable of all three models were used separately to create three different regression models. The obtained regression models for the training data sets can be defined by the following equations for the respective models:

$$P_Q = -0.0237*Q + 0.0777*R + 0.0005*D + 0.0754*u - 0.2435 \quad (2)$$

$$P_N = -0.0043*N + 0.072*R + 0.0004*D + 0.0844*u - 0.2397 \quad (3)$$

$$P_{RMR} = -0.0142*RMR + 0.0895*R + 0.0007*D - 0.0016*u + 0.22 \quad (4)$$

Where,

P_Q, P_N, and P_{RMR} are the predicted support pressure by the regression models containing Q, N and RMR parameters respectively. Table 8 shows the calculated values of various performance measures for the MVLRA models.

Table 8 Statistical values of MVLRA models

MVLRA Model	Statistical values for the	r	R^2	MSE	RMSE	MAE	MAPE
Q-Model	training data	0.730	0.124	0.048	0.219	0.148	121.017
N-Model		0.714	0.041	0.050	0.224	0.147	116.639
RMR-model		0.841	0.588	0.030	0.173	0.133	142.921
Q-Model	testing data	0.605	0.054	0.089	0.298	0.215	173.968
N-Model		0.605	0.093	0.103	0.322	0.234	184.898
RMR-model		0.895	0.938	0.560	0.748	0.634	1057.406

Comparison with MVLRA models

MVLRA models were trained and tested using the same data. Table 8 shows the various performance measures. When compared with the performance measures given for the corresponding artifical neural network models given in the Table 4, they performed poorly. The N-model has r and R^2 as 0.986 and 0.938 whereas these values for the MVLRA based N-model were 0.714 and 0.041. Similar results were obtained for the other two models.

Comparison with available Empirical Models

Comparison with the available empirical models can be easily made by looking at the predictions made by the empirical models and those by the artifical neural network models.

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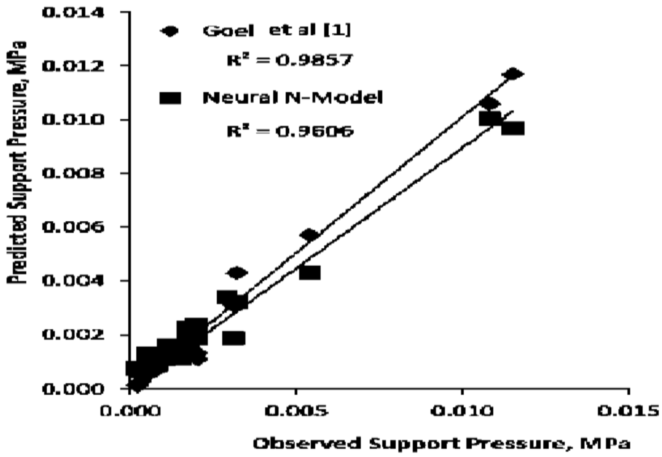

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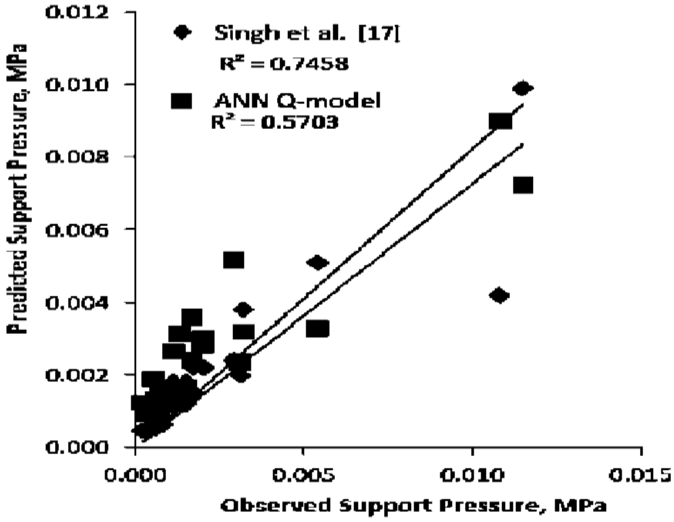

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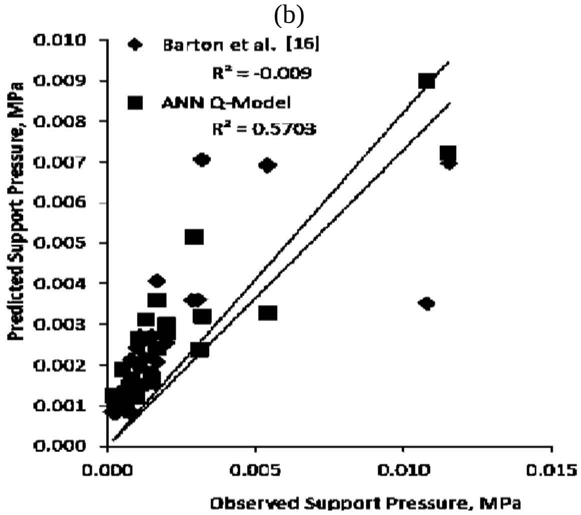

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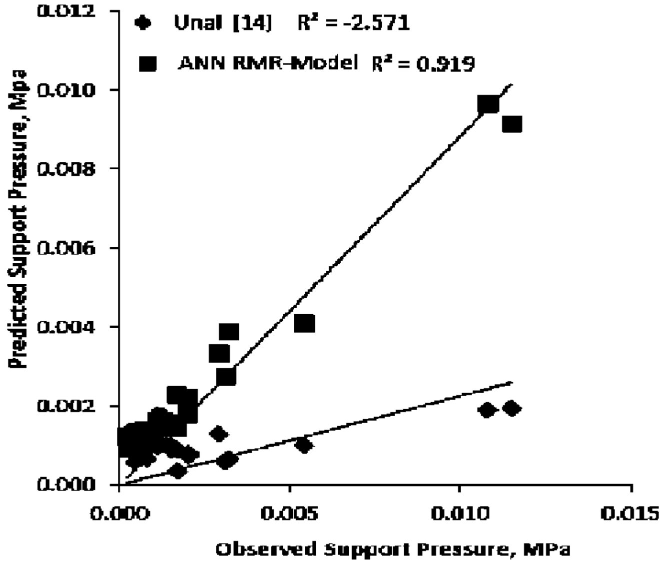

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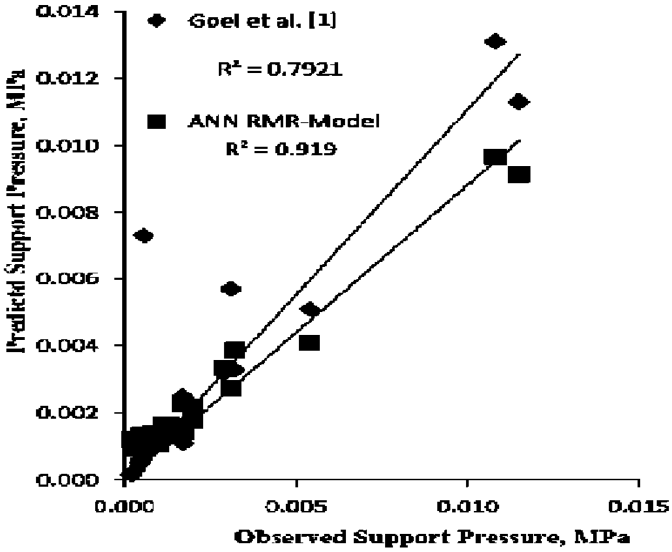

(e)

Fig. 3 (a) Goel et al, [1] vs. ANNs based N-model (b) Singh et al, [17] vs. ANNs based Q-model (c) Bartan et al, [16] vs. ANNs based Q-model (d) Unal [14] vs. ANNs based RMR-model (e) Goel et al, [1] vs. ANNs based RMR-model

Fig. 3 shows the predictions made by various empirical models and their counterpart artifical neural network models. It should be reminded that the same data were used for the determination of the performance measures. It is evident that the predictions of artifical neural network N-Model and the empirical model reported by Goel et al. [1] are comparable. Predictions made by the artifical neural network Q-Model were found to be inferior and superior to the empirical model reported by Singh et al. [17] and Barton et al. [16] respectively. The coefficient of determination for the RMR-Model was 0.919 and it was compared with the predictions made by the empirical models reported by Unal [14] and Goel et al. [1]. This model outperforms both of them.

V. PROPOSED MODEL EQUATIONS

In order to represent the three neural network models for the prediction of PQ, PN and PRMR, base upon their respective input variables, following fundamental equation is used:

$$P_{pn} = f\{ b_o + \sum_{k=1}^{h}[w_k * f(b_{hk} + \sum_{j=1}^{m} w_{jk} * X_j)] \} \quad (5)$$

Where,

Ppn is the normalised value of the predicted support pressure, varies from -1 to +1.

bo is the bias at the output layer;

wk is the connection weight between kth neuron of hidden layer and the single output neuron;

bhk is the bias at the kth neuron of hidden layer; h is the number of neurons in the hidden layer;

m is the number of neurons in the input layer; wjk is the connection weight between jth input variable and kth neuron of hidden layer; Xj is the normalized input variable j in the range [-1, 1] and f is the activation function..

Q-Model with Elliot Function

Based upon the connection weights given in Table 5 following equations are derived:

A =2.037+3.078*Q -2.115*R -1.911*D -3.054*u (6)

B =2.093+2.760*Q -3.206*R -1.820*D -0.626*u (7)

C =1.964+2.947*Q -2.304*R -1.846*D -2.603*u (8)

$$D=4.975-5.591*[\frac{A*0.25}{1+|A*0.5|}+0.5]-4.872*[\frac{B*0.25}{1+|B*0.5|}+0.5]-5.274*[\frac{C*0.25}{1+|C*0.5|}+0.5] \quad (9)$$

$$P_{Qn} = \frac{D*0.25}{1+|D*0.5|} +0.5 \quad (10)$$

N-Model with Elliot Function

Based upon the connection weights given in Table 6 following equations are derived:

A=6.433+8.047*N-15.362*R+0.475*D+0.675*u (11)

B=-0.033+6.632*N+1.982*R-3.067*D+0.547*u (12)

C=-0.168+6.379*N+2.161*R-2.954*D-10.779*u (13)

$$D=13.589-17.713*[\frac{A*0.25}{1+|A*0.5|}+0.5]-13.074*[\frac{B*0.25}{1+|B*0.5|}+0.5]-12.893*[\frac{B*0.25}{1+|B*0.5|}+0.5] \quad (14)$$

$$P_{Nn} = \frac{D*0.25}{1+|D*0.5|} +0.5 \quad (15)$$

RMR-Model with Elliot Function

Based upon the connection weights given in Table 7 following equations are derived:

A = 1.008+6.770*RMR -3.376*R -1.530*D -0.020*u (16)

B = 0.519+5.299*RMR -2.178*R -1.506*D -0.890*u (17)

C = 0.981+6.281*RMR -3.190*R -1.468*D -0.056*u (18)

$$D=8.750-7.983*[\frac{A*0.25}{1+|A*0.5|}+0.5]-5.893*[\frac{B*0.25}{1+|B*0.5|}+0.5]-7.224*[\frac{C*0.25}{1+|C*0.5|}+0.5] \quad (19)$$

$$P_{RMRn} = \frac{D*0.25}{1+|D*0.5|} +0.5 \quad (20)$$

The values of P_{Qn}, P_{Nn} and P_{RMRn} obtained from Eq.10, Eq.15 and Eq.20 respectively vary in the range [-1, 1] and need to be de-normalized using the following formula:

$$P = 0.5.(P_n + 1).(P_{max} - P_{min}) + P_{min} \quad (21)$$

Where, P_n is the normalised value of support pressure (P_{Qn}, P_{Nn} and P_{RMRn}), and the P_{max} and P_{min} are the maximum and the minimum values of predicted support pressure, respectively.

VI. CONCLUSIONS

Modelling of the support pressure is a complex phenomenon. For this, an alternative approach using neural network is adopted to overcome this complexity. Over the past couple of years, applications of neural networks in rock engineering are being explored globally. In this paper, an application of neural network for the modeling of the support pressure based on experimental data reported in literature is presented. The model is developed for the data of 25 records of support pressure. The following conclusions are drawn.

VI. NOTATIONS

1. The results indicate that the 4-3-1 topology of the neural network architecture is fairly capable of predicting the support pressure with acceptable accuracy.
2. The proposed neural network models have been evaluated on a comprehensive performance measures. From the performance measure analysis, it was evident that the proposed neural network models predicted the support pressure closer to the one reported in literature with acceptable accuracy.
3. The three alternate neural network models for the prediction of the support pressure in tunnels based on the rock classification parameters Q, N and RMR perform either comparable or better than the empirical models available in literature.
4. All the ANN based models performed better than the multiple variable linear regressions analysis models.
5. Model equations are presented based on trained weights in the neural network.

Further, more studies are required to be conducted to validate the results obtained using other variants of neural network models. In general, the neural network models have the limitation in giving explanations and reasoning behind the model so obtained. In future, suitability of alternative techniques such as support vector machines, particle swarm optimization or genetic programming, may also be explored.

Q	Rock Mass Quality
N	Rock Mass Number
RMR	Rock Mass Rating
D	Depth
R	Radius
u	Normalized closure
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
R^2	Coefficient Of Determination
r	Correlation Coefficient
RI_j	Relative importance of the j^{th} neuron of input
h	number of neurons in the hidden layer
w_{jk}	connection weight between j^{th} input variable and k^{th} *neuron* of the hidden layer
W_k	connection weight between k^{th} neuron of hidden layer and the single output neuron
b_o	bias at the output layer
m	number of neurons in the input layer
X_j	normalized input variable j in the range [-1 to +1]
f	activation function
P_{Qn}	Normalized value of the support pressure Predicted by ANN Q-model equation
P_{Nn}	Normalized value of the support pressure Predicted by ANN N-model equation
P_{RMRn}	Normalized value of the support pressure Predicted by ANN RMR-model equation

REFERENCES

1. R.K. Goel, J. L., Jethwa and A.G. Paithankar. "Indian experiences with Q and RMR," Tunnelling and Underground Space Technology, 10(1), 97-109, 1995.
2. Alipour, A. Jafari and S.M.F. Hossaini. "Application of ANN and MVLRA for estimation of specific charge in small tunnel," International journal of Geomechanics, 12(2), 189-192, 2012.
3. A.S. Mohamed, B.J. Mark and R.M. Holger, "Artificial Neural Network Applications in Civil Engineering," Australian Geomechanics, 49-62, 2001.
4. I.C. Yeh, "Application of neural networks to automatic soil pressure balance control for shield tunneling," Automation in Construction, 5, 421-426, 1997.
5. Z. Boger and H. Guterman, "Knowledge extraction from artificial neural network models," IEEE Int. Conf. Comput. Cybem. Simul. 4:3030-3035, 1997.
   Blum, "Neural Network in C++", Wiley, New York, 1992.
6. R.K. Dutta, K. Dutta and S. Jeevanandham, "Prediction of deviator stress of sand reinforced with waste plastic strips using neural network," International Journal of Geosynthetics and Ground Engineering, 1(2), 1-12, 2015.
7. V. Kurkova, "Kolmogorov's Theorem and Multilayer Neural Networks,".Neural Networks 5:501-506, 1992.
8. Y. Ito, "Approximation capabilities of layered neural networks with sigmoid unit on two layers," Neural comput., 6:1233-1243, 1994.
9. W. Sarle,"Stopped training and other remedies for overfitting," 27th Symposium on the Interface Computing Science and Statistics, Pittsburgh, 1995.
10. G. D. Garson, "Interpreting neural network connection weights," AI Expert 6(4): 47-51, 1991.
11. J. D. Olden and D. A., Jackson, "Illuminating the 'black box': a randomization approach for understanding variable contributions in artificial neural networks," Ecol. Model., 154: 135-150, 2002.
12. C.Y. Kim, G.J. Bae, S.W. Hong, C.H. Park, H.K. Moon, and H.S. Shin, "Neural network based prediction of ground surface settlements due to tunneling,"Computers and Geotechnics, 28, 517-547, 2001.
13. E. Unal, "Design Guidelines and Roof control Standards for Coal Mine Roofs," Ph. D. Thesis, Pennsylvania State University (Refer to Bieniawski, Z. T. (1984). Rock Mechanics in Mining and Tunneling, p. 113, Rotterdam: A. A. Balkema), 1983.
14. R.K. Goel and J. L. Jethwa, "Prediction of Support Pressure using RMR classification," Proc. Indian Geotechnical Conf. Surat, India, December, 1991.
15. N. Barton, R. Lien and J. Lunde, "Analysis of Rock Mass Quality and Support Practice in Tunnelling, and a guide for Estimating support pressure requirements." Report by Norwegian Geotechnical Institute, 1974.
16. Singh, J.L. Jethwa and A.K. Dube, "Correlation between observed support pressure and rock mass quality," Tunnelling and Underground Space Technology, 7(1), 59-74, 1992.

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