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Prediction of Free Swell Index for the Expansive Soil Using Artificial Neural Networks

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ABSTRACT

Prediction of the free swell index of the expansive soil using artificial neural network has been presented in this paper. Input parameters for the artificial neural network model were plasticity index and shrinkage index, while the output was the free swell index. Artificial neural network algorithm used a back propagation model. Training of the artificial neural network model was conducted on the data collected from literature, and the weights and biases were obtained which described the relation among the input variables and the output free swell index. Further, the sensitivity analysis was performed, and the parameters affecting the free swell index of the expansive soil were identified. The sensitivity analysis results indicated that the plasticity index (63.97 %) followed by shrinkage index (36.03 %) was affecting the free swell index in this order. The study shows that the prediction accuracy of the free swell index of the expansive soil using artificial neural network model was quite good.

1. Introduction

In India, nearly 20 % portion of the soil is expansive in nature which tends to swell or contract in the presence or absence of moisture leading to damage to the light structures, roadways, airport slabs, pipelines, bridges, piers, earth retaining structures resting on it. Free swell index was generally determined through laboratory test that consumes time of about 24 hours as per [1]. Therefore, a model is required that can predict the data from past observation by learning rather

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making assumption and aid in addressing the problem in hand. In recent years artificial neural networks converted from a theoretical approach to the widely-used technology with successful applications to different problems. In the present study, artificial neural network (ANN) was used for predicting the free swell index of the expansive soil.

2. Background

Experimental studies were required to determine the free swell index of the expansive soils. From the recent two decades, several studies in geotechnical engineering such as prediction of the hydraulic conductivity of clay liners [2], pile driving records reanalyzed [3], pile bearing capacity [4], in situ soil properties at any half-space point at a site [5], uplift capacity of suction caissons [6], modeling soil collapse [7], pre-consolidation pressure [8], cyclic swelling pressure of mudrock [9], Undrained lateral load capacity of piles in clay [10], effective stress parameter of unsaturated soils [11], soil and subsurface sediments distribution in dam [12], stability analyses of slopes [13], swelling pressures of expansive soils [14], compression index of soils [15], strength of reinforced lightweight soil [16], permeability coefficient of soils [17], soil specific surface area [18] deviator stress of sand reinforced with waste plastic strips [19], ultimate bearing capacity of the regular shaped such as circular [20], strip [21,22][23], spread [24] footing resting on sand/clay/rock, bearing capacity and settlement of foundations in different mediums [25–27], Load-settlement behavior modeling of single pile [28], horizontal stress in underground excavations and bearing ratio from index properties of soils [29,30] using artificial neural network have been reported. However, no study has been reported to predict the free swell index of expansive soil in literature. In order to fill this research gap, this paper presents a neural network model to predict the free swell index from the data collected from the literature. The input parameters in the developed neural network models were a plastic index, shrinkage index of the expansive soil and the output was free swell index.

3. Artificial neural network

The methodology used for modeling the prediction of the free swell index of the expansive soil using a neural network has been presented in this section. The process began with the selection of input parameters and the output parameter. The input data used in this investigation were a plastic index (Ip), shrinkage index (Is) of the expansive soil and the output was the free swell index (FSI). Data required for modeling were collected from the literature [31–132]. This collected data were divided in two parts for the training and the testing purpose for developing the ANN model. The range of the input and output parameter of the collected data were presented in Table 1. Based on the thumb rules reported by [133–135], the architecture of the present neural network model was selected as 2-2-1 and was shown in Fig. 1. The various performance measures used at assess the accuracy of the developed neural network model were the coefficient of correlations (r), coefficient of determination (R^2), mean squared error (MSE), relative mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

Table 1
Range of data used for the ANN model.

Parameters	Minimum range	Maximum range
Plasticity index (Ip)	6.25	313.79
Shrinkage index (Is)	0.3	60
Free swell index (FSI)	2.3	860

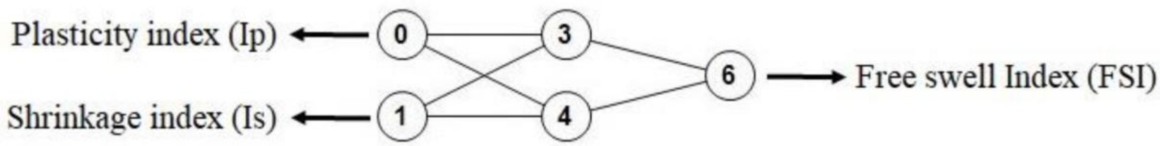

Fig. 1. Neural network representing 2-2-1 architecture.

Trial and error procedure was followed in order to select the optimum no of iterations and the graph was plotted between the MSE and the number of iterations as shown in Fig. 2.

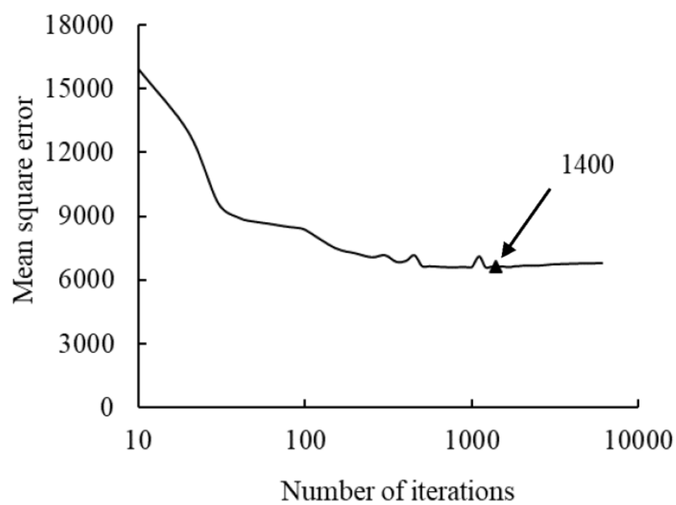

Fig. 2. Mean square error versus number of iterations.

A close examination of Fig. 2 reveals that the optimum no of iterations corresponding to minimum MSE was 1400. The open source software AgielNN which contains 18 different activation functions was used in this study. The next task was to select the learning rate which has been adopted as 0.7 (default value in AgielNN). By trial and error, changing the activation function, the performance measures of each of the model present in AgielNN were calculated and compared with each other. Among the 18 activation functions, the best three activation functions have been obtained and discussed in the upcoming section. Sensitivity analysis was performed using weights and biases obtained from the optimum activation function and the relative importance of the independent parameter with respect to the output free swell index has been found. Finally, a mathematical model has been developed using the weights and biases obtained in the neural network.

3.1. Performance measures

The best three models obtained among the 18 activation functions based on the performance measures were shown in Fig. 3. It was reported by [19] that for deciding an optimized activation function, performance measures such as coefficient of correlation (r) and coefficient of determination (R^2) were initially used and compared. Fig. 3(a) and Fig. 3(b) shows that the 'r' and 'R^2' for the sigmoid, sigmoid stepwise and sigmoid symmetric were close to unity both for the training and testing data. A careful study of Fig. 3(a) and Fig. 3(b) reveals that the sigmoid activation function was showing the r and R^2 closer to the 1 in comparison to the remaining activation functions.

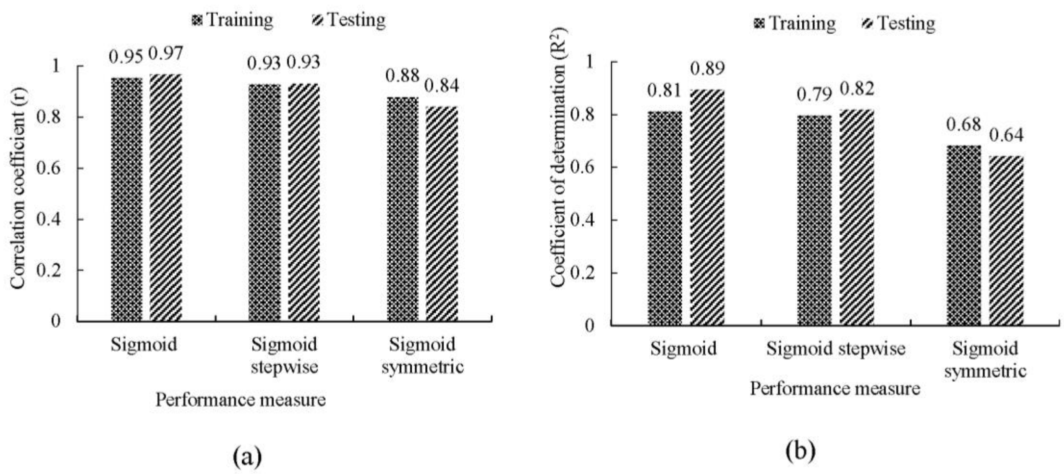

Fig. 3. Performance measure (a) coefficient of correlation (b) coefficient of determination for the training and the testing data.

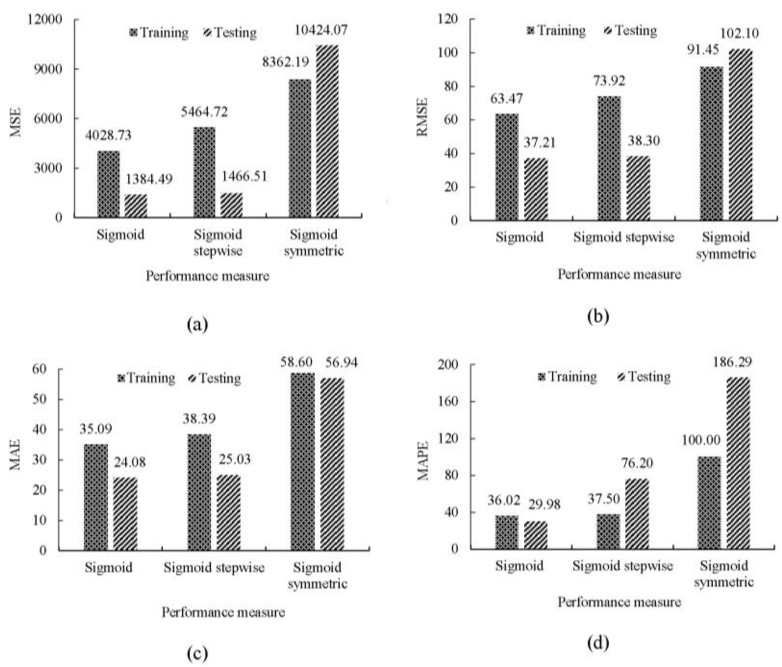

Fig. 4. Performance measures (a) MSE (b) RMSE (c), MAE (d) MAPE.

The other performance measures (MSE, RMSE, MAE, MAPE) for the selected sigmoid, sigmoid stepwise and sigmoid symmetric activation function were represented in the graphical form as shown in Figs. 4 (a) to (d). Figs. 4 (a) to (d) reveals that the sigmoid activation function yields least error indices (MSE, RMSE, MAE, MAPE) in comparison to the other two activation function. Therefore, the sigmoid function was considered as the best optimizing activation function keeping in view the coefficient of correlation, the coefficient of determination, MSE, RMSE, MAE and MAPE.

3.2. Sensitivity analysis

In order to study the influence (relative) of the input parameter on the output free swell index, a sensitivity analysis was carried out. For this purpose, the connection weight approach reported by [136] has been used, and the governing equation (1) was as given below.

$$RI_j = \sum_{k=1}^{h}\left(w_{jk} \times w_k\right) \tag{1}$$

Where w_{jk} is the connection weight between j^{th} input parameter 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, RI_j is the relative importance of the j^{th} neuron of the input layer, and h is the number of neurons in the hidden layer.

The influence (relative) of the individual input parameter affecting the output free swell index using sigmoid activation function based on the 2-2-1 architecture was shown in Fig. 5.

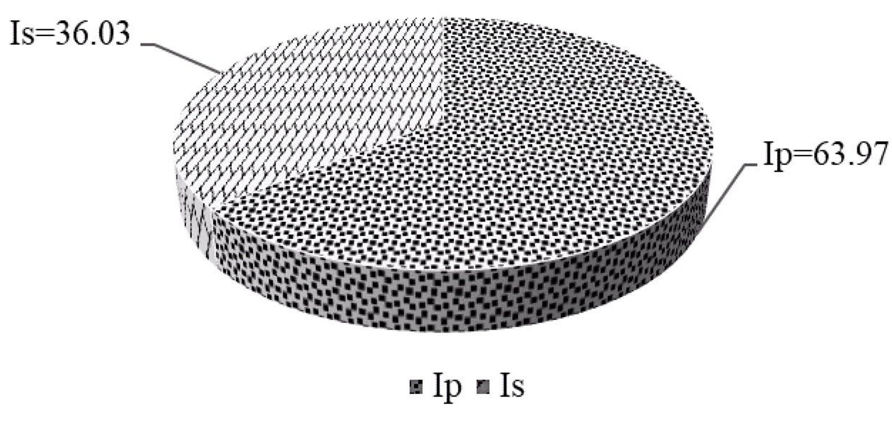

Fig. 5. Influence (relative) of the individual input parameter on the output free swell index.

Fig. 5 reveals that the plasticity index (Ip) was the most important parameter affecting the free swell index of the expansive soil followed by shrinkage index (Is) of the expansive soil.

3.3. Model equation

For the development of the model equation to predict the free swell index of the expansive soil, the obtained hidden weights and the biases between the input and the output parameter were shown in Table 2. The basic output function considered in the neural network model was as given below as equation (2).

$$FSI = f\left\{b_0 + \sum_{k=1}^{h}\left(w_k \times f\left[b_{hk} + \sum_{j=1}^{m}\left(w_{jk} \times X_j\right)\right]\right)\right\} \tag{2}$$

The equation derived for the output free swell index based on the trained weights and biases as shown in Table 2 gave the following equations:

Table 2
Final weights and biases obtained in the ANN model between the input neuron and hidden neuron as well as hidden neuron and the output neuron.

Weights (w)			biases	
Ip	Is	FSI	2	5
-7.03	2.87	-3.00	1.46	1.21
-7.68	-5.01	-5.54	0.50	--

$$A = 1.46 - 7.03 \times Ip + 2.87 \times Is \tag{3}$$

$$B = 0.50 - 7.68 \times Ip - 5.54 \times Is \tag{4}$$

$$E = 1.21 - \frac{3.0}{(1+e^{-A})} - \frac{5.54}{(1+e^{-B})} \tag{5}$$

$$FSI = \frac{1}{(1+e^{-E})} \tag{6}$$

FSI obtained from the above equation will be in the range of [0 to 1] for the sigmoid activation function. The de-normalization of the equation (6) was required in order to obtain the actual free swell index as given below.

$$FSI_{actual} = 0.5(\mathrm{FSI}+1)(\mathrm{FSI}_{\max} - \mathrm{FSI}_{\min}) + FSI_{\min} \tag{7}$$

Where FSI_{max} is the maximum predicted free swell index, FSI_{min} is the minimum predicted free swell index respectively. The plots were drawn for the training and the testing data of the ANN model and were shown in Fig. 6. The R^2 of Fig. 6 reveals that the artificial neural network model was able to predict the free swell index of the expansive soil.

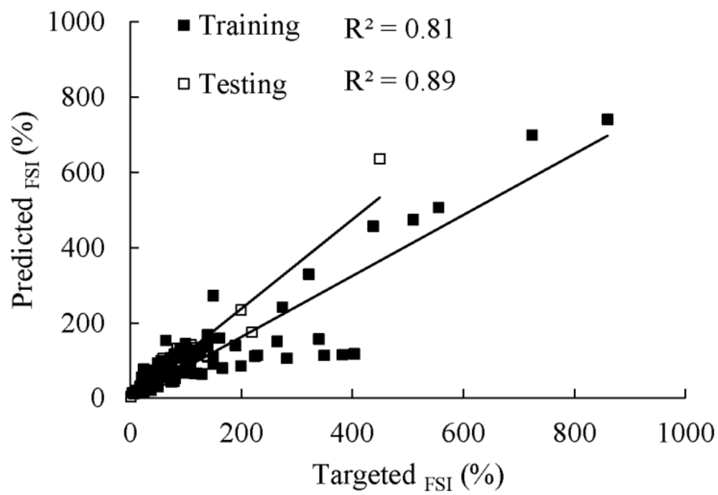

Fig. 6. Plot showing the variation of testing and training data set of the ANN model with respect to coefficient of determination (R^2).

4. Multiple linear regression model

Non-linear multiple regression analysis (MRA) was carried out on the total data set using Datafit 9.0 (trial version) software and the equation obtained from this analysis was shown below as equation (8), and the performance measures obtained for this equation were tabulated in Table 3.

$$FSI_r = 293.76 - 236.31 \times \log(Ip) + 47.95 \times \log(Ip)^2 + 9.88 \times \log(Is) \tag{8}$$

Table 3
Comparison between performance measures of ANN model and regression model.

Performance measures	Prediction model			
	Artificial neural networks		Multiple regression analysis	
	Training	Testing	Training	Testing
r	0.95	0.97	0.89	0.92
R^2	0.81	0.89	0.54	0.53
MSE	4028.73	1384.49	7851.23	4030.52
RMSE	63.47	37.21	88.61	63.49
MAE	35.09	24.08	55.60	41.94
MAPE	36.02	29.98	98.38	145.78

Table 3 shows that the r and R^2 of the regression model were less in comparison to one obtained using neural network model. From the above analysis, it has been found that the ANN model's prediction accuracy was superior to the one obtained using regression modeling. The predicted versus the targeted free swell index of the expansive soil using MRA was shown in Fig. 7. The coefficient of determination (R^2) of Fig. 7 reveals that the model equation obtained from the multiple regression analysis was not able to predict the free swell index of the expansive soils to a fair degree of accuracy.

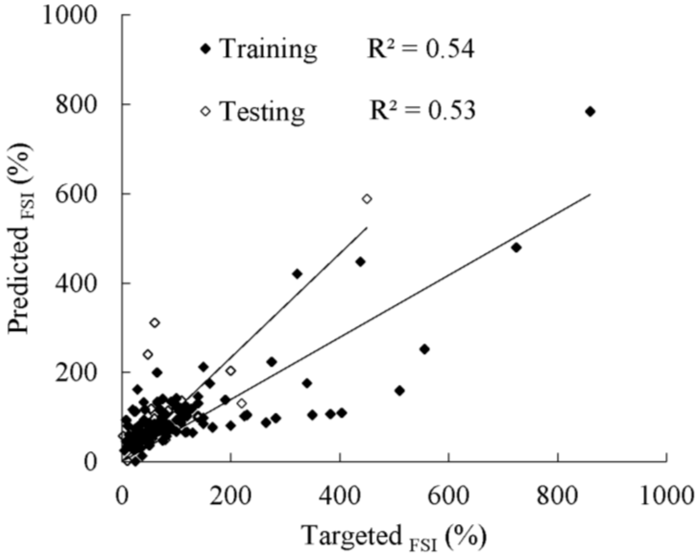

Fig. 7. Plot showing the variation of training and testing data set of the multiple regression analysis model with respect to the coefficient of determination (R^2).

5. Comparison

The developed model equation using weights and biases of the ANN was compared with the free swell index model obtained through MRA, and the results were shown in Fig. 8. The higher coefficient of determination obtained for the ANN model as shown in Fig. 8 reveals its superiority over the multiple regression model. This was attributed to the fact that the regression modeling may not compete well with the non-linear data whereas artificial neural network, on the other hand, was suitable for prediction for the non-linear data. Further, the sigmoid activation function suits the best for the raw experimental data.

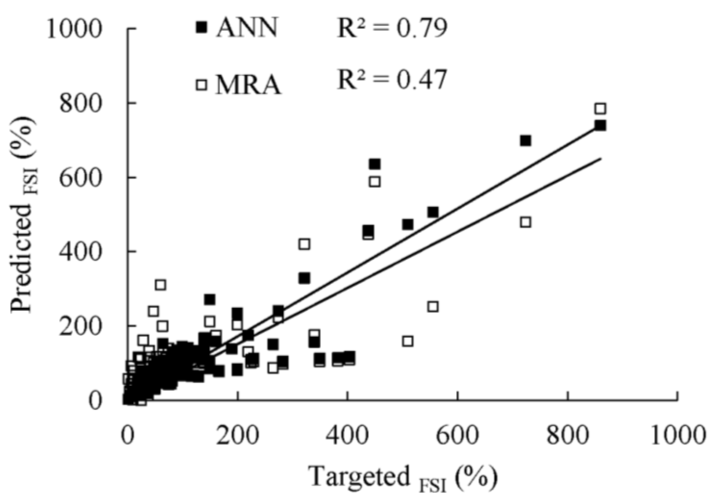

Fig. 8. Plot showing the comparison of MRA and ANN model in the prediction of bearing capacity.

6. Conclusion

Predicting the FSI of the expansive soil was a complex phenomenon. Use of experimental methods for determining the free swell index may turn out to be highly time-consuming. An attempt has been made using ANN in predicting the FSI of the expansive soil. The model equation has been obtained which gave acceptable results and compared with the multiple regression model. The study brings forward the following conclusion.

1. Neural network architecture with 2-2-1 topology has produced fairly accurate results to predict the FSI of the expansive soil.
2. Among the 18 activation functions, the sigmoid activation function gave the best results.
3. Proposed neural network architecture with sigmoid activation function was able to predict closer to the actual FSI of the expansive soil.
4. Sensitivity analysis results indicated that the plasticity index (63.97 %) followed by shrinkage index (36.03 %) was affecting the FSI in this order.
5. The mathematical model equation was proposed for the prediction of the FSI of the expansive soil.
6. The multiple regression analysis was not able to predict the free swell index of the expansive soil to a fair degree of accuracy.
7. Prediction of the FSI using ANN model was more accurate in comparison to the regression model.

Notations

Ip	Plasticity index
Is	Shrinkage index
FSI	Free swell index
MRA	Multiple regression analysis
ANN	Artificial Neural network
b_{hk}	Bias at the k^{th} neuron of the hidden layer
b_o	Bias at the output layer
f	Optimum activation function
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MSE	Mean square error
RMSE	Root mean square error
FSI_{actual}	Actual free swell index
FSI_{max}	Maximum free swell index
FSI_{min}	Minimum free swell index
FSI_r	Regression model free swell index
r	Correlation coefficient
R^2	Coefficient of determination
RI_j	Relative importance of the j^{th}neuron of input layer

W_{jk}	Connection weight between j^{th} input variable and k^{th}neuron of
W_k	Connection weight between k^{th}neuron of hidden layer and the single
Xj	Normalized input variable j in the range [0, 1]

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