Journal of Soft Computing in Civil Engineering 5-4 (2021) 74-89

Contents lists available at **SCCE**

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Application of Machine Learning Techniques in Predicting the Bearing Capacity of E-shaped Footing on Layered Sand

Safeena Nazeer[1*], **Rakesh Kumar Dutta**[2]

1. M.Tech. Student, Faculty of Civil Engineering, National Institute of Technology, Hamirpur, India
2. Professor, Faculty of Civil Engineering, National Institute of Technology, Hamirpur, India

Corresponding author: *19m109@nith.ac.in*

https://doi.org/10.22115/SCCE.2021.303113.1360

ARTICLE INFO

Article history:
Received: 04 September 2021
Revised: 19 November 2021
Accepted: 22 November 2021

Keywords:
Bearing capacity;
E-shaped footing;
Error metrics;
Multi-layer perceptron;
Multi-linear regression;
Model equation.

ABSTRACT

The paper presents the prediction of bearing capacity equation of E-shaped footing subjected to a vertical concentric load and resting on layered sand using machine learning techniques and the data used in the analysis has been extracted from finite element modelling of the same footing. The input variables used in the developed neural network model were the bearing capacity of square footing, thickness ratio, friction angle ratio and the output were the bearing capacity of E-shaped footing on layered sand. Multiple layer perceptron (MLP) and multiple linear regression (MLR) prediction models were used for the determination of error metrics and the ultimate bearing capacity of E-shaped footing resting on layered sand. Finally, for the ANN model development, a model equation was developed with the assistance of weights and biases, based on the MLP and MLR model using open-source WEKA and Anaconda software respectively. Sensitivity analysis has been performed on the data sets which correlates the various input variables with the output variable of both the models. The coefficient of determination (R^2) comes out to be 0.99 and 0.98 for the MLP and MLR models respectively indicating that both the models were able to predict the bearing capacity for the E shaped footing with acceptable accuracy.

How to cite this article: Nazeer S, Dutta RK. Application of machine learning techniques in predicting the bearing capacity of e-shaped footing on layered sand. J Soft Comput Civ Eng 2021;5(4):74–89. https://doi.org/10.22115/scce.2021.303113.1360

1. Introduction

Due to rapid urbanization and scarcity of land, footings with unconventional geometry are required sometimes due to economic and architectural reasons. These types of footings are known as multi-edge footings. Various experimental and numerical studies have been reported in literature [1–10] for the multi-edge footings resting on single and layered soil. A numerical study was conducted by [1] on the bearing capacity of E-shaped footing resting on layered sand subjected to vertical loading using ABACUS. The study reported that the ultimate bearing capacity was higher in case of E-shaped footing as compared to the conventional square shaped footing having similar properties and external dimensions. Study reported by [2–5] concluded that the plus, H, Double box and hexagonal multi-edge footing have shown an improved bearing capacity compared to the square skirted footing. The behaviour of multi-edge footings resting on loose and dense sand was reported by [6]. The authors concluded that the multi-edge footings performed better (in terms of bearing capacity) than the square footing of the same width. The load-settlement behaviour of the plus and H shaped multi-edge footing resting on sand was reported in literature [7]. For this purpose, three-dimensional finite element analyses using FLAC 3D was carried out. The authors concluded that the ultimate bearing capacity of the multi-edge footing was higher than that of the square shaped footing and of the same width. Experimental studies were conducted by [8] to study the behaviour of multi-edge footings resting on loose and dense sand reinforced with geogrid. The parameters varied in this study were shapes of the footing, first reinforcement depth, vertical spacing of reinforcement, number of reinforcement layer and the covering area of the reinforcement layer. It was reported by [9] that the ultimate bearing capacity of multi-edge footings on reinforced sand is equal to square shape footing of the same width. The pressure-relative settlement behaviour of the square and the rectangular footing resting on sand and subjected to a vertical load through a laboratory study was reported by [10] . Estimation of bearing capacity of footing requires the use of bearing capacity equations. These types of equations are available in literature for the regular (circular, square and rectangular) shaped footings. Past studies [11–19] have demonstrated that the neural network-based prediction models can be used in predicting the soil properties or behaviour. In addition to this, equations were proposed using neural-network models for the computation of stresses in the soil. Such equations are not available for the computation of bearing capacity of multi-edge footings in the literature. The study reported by [20] used a back propagation model and predicts the accuracy of the ultimate bearing capacity of different regular shaped skirted footing resting on sand using multiple regression analysis. Researchers [21–23] utilizes different soft computing techniques like artificial neural network, particle swarm optimization and adaptive neuro-fuzzy inference system and have validated the efficacy of soft computing techniques in the prediction of the ultimate bearing capacity. Study conducted by [24] to develop a motivation for the replacement of the tedious operation of conducting the practical laboratory tests with efficient machine learning models for predicting the California bearing ratio (CBR) based on the experimental database. The proposed model was superior in comparison to the classical analytical model in terms of faster convergence rate and higher accuracy. In a study carried out by [25], a meta-heuristic-based algorithm was used to propose an ELM model and thus, was implemented to predict the permeability of the tight carbonates. The authors further reported that the results obtained by the proposed model, was found to be significantly better than those obtained with the particle swarm optimization, genetic algorithm, and slime mould algorithm. This study further illustrates that the proposed model outperforms the other significant models such as back propagation neural networks, regression models, forest random technique and other group methods of data handling for the prediction of permeability of the tight carbonates. Another study conducted by [26] using 257 data sets of saturated soils to determine the thermal conductivity of the unsaturated soils by the implementation of two meta-heuristic optimization techniques viz. firefly algorithm, improved firefly algorithm and three conventional machine learning techniques viz. ELM, adaptive neuro fuzzy interface system (ANFIS) and artificial neural network (ANN). It was reported that the developed model can be employed in the initial stages of any engineering projects for the speedy determination of thermal conductivity. A study was carried out by [27] for the prediction of photovoltaic power that plays a significant role in the future development of the micro grid projects by the implementation of swarm intelligence techniques and fuzzy interference system. The model used various prediction indices to assess the performance of the predictive model and it was reported that the study paved the way for a new alternative to assist engineers for the predicting the photovoltaic power of the solar system at short and long horizons. The current paper will thus, provide a bearing capacity equation of E-shaped footing in terms of the thickness ratio (H/B), friction ratio (ϕ_1/ϕ_2) and the ultimate bearing capacity of the square footing resting on the layered soil subjected to vertical loading. Thus, keeping in view the above, a feed forward neural network using 10-fold cross validation technique, was used to develop a neural network with 3-2-1 topology and a multi-linear regression analysis was done on the same model for the prediction of bearing capacity of E-shaped footing on layered sand subjected to vertical loading by using Weka and Anaconda software respectively. A data generated through the numerical study reported by [1] on the bearing capacity of E-shaped footing on layered sand subjected to vertical loading was used for modelling of the bearing capacity equation and in the calculation of error metrics.This paper will thus, present the application of machine learning techniques in the field of geotechnical engineering. The developed equation for predicting the bearing capacity of a multi edge E-shaped footing on layered sand in terms of square shaped footing will be useful for the architects designing similar shaped footings.

2. Research methodology

2.1. Machine learning softwares

The following two machine learning techniques were used in this study for the prediction of bearing capacity equation of multi-edge E-shaped footing resting on layered sand that was subjected to only vertical loading.

2.1.1. Multi-Layer Perceptron

MLP stands for multi-layer perceptron and is a feed forward neural network. It has at least three layers, including an input layer, an output layer, and a hidden layer. The input layer is where the data to be processed is received. The output layer is responsible for tasks such as prediction and categorization. The true computational engine of the MLP is an arbitrary number of hidden layers inserted between the input and output layers. Hidden layers are layers of mathematical functions that are commonly used in modelling to generate a desired result. It divides the neural function into discrete data slots. Each concealed layer has a unique function for achieving the desired result. The number of hidden layers that should be used is determined by the number of input parameters in the model. It should be two-thirds of the input variables and no larger than two times the input layers' size. Hidden layers are offered to arrive at the best fit for the model, but there is no change in the desired output beyond an ideal value. That is, increasing the number of hidden layers will not improve the output layer accuracy. In most cases, a maximum of two hidden layers is sufficient to solve difficult problems. As a result, it is preferable to train the model with the smallest number of hidden layers possible, as it would be far more difficult to do so with a larger number of hidden layers, especially if the difference is insignificant.The data flows in the forward direction from input to output layer in MLP just like in the case of feed forward network. The neurons in the MLP are trained with the back propagation learning algorithm. MLPs are designed to approximate any continuous function and can solve problems which are not linearly separable. The MLP model is usually used for the pattern classification, recognition, prediction, and approximation. The common activation functions used in MLP model are both sigmoids and can be represented as:

$$y(x) = \tanh(x) \tag{1}$$

$$y(x) = (1 + e^{-x}) \tag{2}$$

Where, 'y(x)' is the activation function for the independent variable 'x' to obtain the desired dependent output variable.

2.1.2. Multiple Linear Regression

Regression analysis enables you to clearly identify which elements are most important, which may be ignored, and how these factors interact. It shows how one or more independent variables are related to the dependent outcome. The regression coefficient might be negative, positive, or zero, indicating that the input and output variables have a negative correlation (inverse relationship), a positive correlation (direct relationship), or no correlation (no relationship). To obtain the intended outcome, this multiple linear regression (MLR) model was trained in Anaconda, a machine learning software, and the matching set of codes were implemented in the Python programming language. The general equation governing the MLR can be written as follows:

$$y = b_1x_1 + b_2x_2 + b_3x_3 + \dots\dots\dots\dots\dots + b_nx_n + c \tag{3}$$

Where,
b_i= regression coefficients,
n= number of variables,
x_i=independent variables,
c = the y-intercept (value of y when all the other parameters are set to zero).

2.2. Data collection

The data sets for both the MLP and MLR modelling were extracted from the study [1] on the ultimate bearing capacity of E-shaped footing resting on layered sand subjected to vertical concentric loading. The input parameters were taken as thickness ratio (*H/B*), where *'H'* is the thickness of the upper loose sand layer and *'B'* is the width of the E-shaped footing, friction angle ratio (ϕ_1/ϕ_2), where 'ϕ_1' and 'ϕ_2' are the friction angles of the upper loose and lower dense layers of sand, and the numerically obtained ultimate bearing capacity of square footing(q_u^S). Only one output parameter was taken as the ultimate bearing capacity of E-shaped footing (q_u^E) as shown in Table 1.

Table 1
Data set used for modelling.

Input Parameters			Output Parameter
q_u^S (kPa)	H/B	ϕ_1/ϕ_2	q_u^E (kPa)
292.75	0.5	0.71	675.02
381.08	0.5	0.68	841.85
476.66	0.5	0.65	1003.45
305.81	0.5	0.76	771.38
420.09	0.5	0.73	975.57
552.13	0.5	0.7	1155.91
318.14	0.5	0.81	771.35
451.53	0.5	0.77	999.77
602.02	0.5	0.74	1307.26
97.43	2	0.71	137.5
98.67	2	0.68	141.95
99.68	2	0.65	153.5
125.64	2	0.76	155
126.45	2	0.73	162.8
127.2	2	0.7	163.85
156.3	2	0.81	160.78
157.54	2	0.77	163.02
163.33	2	0.74	205.47
85.1	4	0.71	89.88
85.2	4	0.68	92.68
85.66	4	0.65	112.55
110.47	4	0.76	92.86
110.59	4	0.73	102.5
110.64	4	0.7	113.76
144.45	4	0.81	150.55
143.99	4	0.77	155.19
143.84	4	0.74	190.32

3. Results and discussion

3.1. Ultimate bearing capacity equation using MLP model

The ultimate bearing capacity equation and the model evaluation metrics for the E-shaped footing in terms of the ultimate bearing capacity of square shaped footing was derived from the MLP model because the latter is readily available in the past literatures. The data was trained in WEKA software under the multi-layer perceptron model. WEKA has a Graphical user interface which let the user to model the neural network. A total of 21 functions were used for the prediction of the ultimate bearing capacity of E-shaped footing on layered soil following a trial-and-error technique. This study thus, revealed that the multi-layer perceptron (MLP) was the best for the prediction of the ultimate bearing capacity of the multi-edge E-shaped footing resting on layered sand. The MLP model uses a sigmoidal function $(f(\sum w_i))$ and it utilizes a supervised learning with a back propagation technique for training of the data. A total of 27 numerical data reported by [1] were taken as an input in the WEKA software to predict the error metrics of E-shaped footing resting on layered sand and subjected to vertical loading. By analyzing the weights obtained from the MLP model it was found that the various parameters that were varied in the numerical study were found to affect the ultimate bearing capacity of the multi-edge E-shaped footing.

A total of three (3) input parameters were used along with the two hidden layers followed by only one output parameter as the ultimate bearing capacity of E-shaped footing. In this study, 10-fold cross validation technique were used to select the most important training and testing data sets. In this cross-validation technique, the partitioning of the sample was done randomly so as to divide the whole data set into 10 equal subsets. Thus, a single subset was selected as the testing data set while the remaining subsets were used as the training data sets. This cross-validation technique was employed to construct the model more efficiently so that the highest prediction accuracy could be achieved in the validation phase as reported by [24]. The WEKA supplicate the learning algorithm eleven times with this 10-fold cross-validation technique, once for each fold of the validation and once for the entire data set. The data in the input sets was normalised in the classification tab before to the commencement of the modelling to make the input and the desired anticipated output comparable. The dot product of each input with the estimated weights generated during the modelling process between the input layers and the hidden layers pushes these inputs forward. Since, the model used a supervised learning technique, the maximum and minimum and the normalised data range used in this model is tabulated in Table 2 and Table 3 as follows:

Table 2
Range of parameters used for modelling for the MLP model.

Input Parameters	Minimum	Maximum	Mean	Standard Deviation
$\boldsymbol{q_u^S}$	85.1	602.02	221.2	158.509
H/B	0.5	4	2.167	0.102
Φ_1/Φ_2	0.65	0.81	0.728	0.047
$\boldsymbol{q_u^E}$	89.88	1307.26	409.101	402.77

Table 3
Range of normalised values of parameters used for the MLP model.

Input Parameters	Minimum	Maximum	Mean	Standard Deviation
q_u^S	0	1	0.584	0.304
H/B	0	1	0.102	0.28
Φ_1/ Φ_2	0	1	0.455	0.266
q_u^E	89.88	1307.26	409.101	402.77

As a result, the MLP model was used to forecast the ultimate bearing capacity of an E-shaped footing in terms of square footing and other dependent variables as stated previously, as shown in Table 4.

Table 4
Weights obtained using MLP model.

Input Parameters	Weight (w_1)	Weight (w_2)
Threshold	-1.103	1.209
Bearing capacity of square footing	1.464	-1.349
H/B	-0.162	1.138
ϕ_1/ ϕ_2	-0.185	-0.324

From Table 4, following calculations were made to obtain the ultimate bearing capacity of E-shaped footing. For a MLP model using sigmoidal function, the general equation between the input parameters, weights obtained, and the hidden neurons can be written as follows:

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} \tag{4}$$

Where,
w_{ij} is the weights of input parameters obtained from MLP model
x_n is the various input parameters given to the MLP neural model
h_n is the hidden layer of the nth element

Substituting the values of all the variables from Table 4 to equation (4), we have

$$\begin{bmatrix} 1.464 & -1.349 \\ -0.162 & 1.138 \\ -0.185 & -0.324 \end{bmatrix} \begin{bmatrix} {q_u}^S \\ \frac{H}{B} \\ \frac{\varphi_1}{\varphi_2} \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} \tag{5}$$

Solving equation (5), we get

$$h_1 = 1.464 q_u{}^s - 0.162 \frac{H}{B} - 0.185 \frac{\varphi_1}{\varphi_2} - 1.103 \tag{6}$$

$$h_2 = -1.349 q_u{}^s + 1.138 \frac{H}{B} - 0.324 \frac{\varphi_1}{\varphi_2} + 1.209 \tag{7}$$

Thus, Activation function, $z = \frac{-1.103}{1+(1+e^{-h_1})} - \frac{1.209}{1+(1+e^{-h_2})}$ (8)

$$q_{ult} = \frac{1}{1+(1+e^{-z})} \tag{9}$$

$'q_{ult}'$ obtained from the above equation will be in a range of [0 to 1] as the function used in the MLP was sigmoidal in nature. To obtain the actual ultimate bearing capacity of E-shaped footing resting on layered sand, the de-normalization of the above equation has to be carried out as given below:

$$q_u{}^E = 0.5\,(q_{ult} + 1)(q_{ultmax} - q_{ultmin}) + q_{ultmin} \tag{10}$$

Where, q_{ultmax} and q_{ultmin} is the maximum and predicted ultimate bearing capacity of E-shaped footing resting on layered sand respectively.
Moreover, the sketch of the neural network is shown in Figure 1.

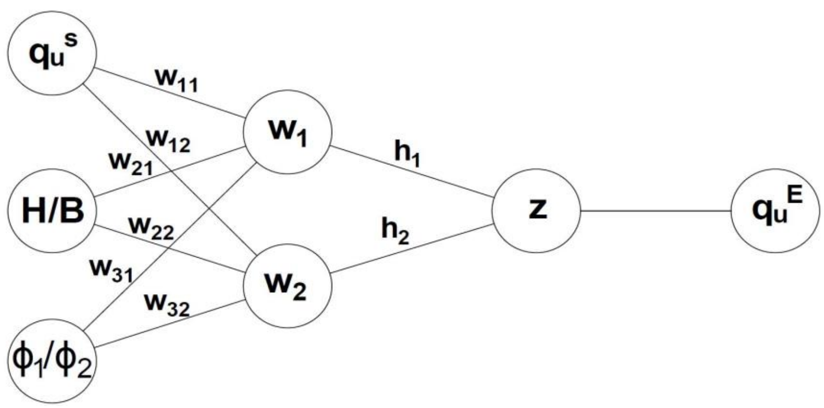


Fig. 1. Neural network with two hidden layers.

3.2. Ultimate bearing capacity Equation using MLR model

For the prediction of the evaluation error metrics and the ultimate bearing capacity equation of E-shaped footing resting on loose over dense sand subjected to vertical loading, the MLR model was used in a software known as Anaconda. This model provided the best prediction equation with directly providing the coefficients and accuracy rate of the equation. However, a set of codes and the software library is used for the prediction analysis to be carried out with less time and more computational accuracy. Three independent variables were used namely the bearing capacity of the square footing, thickness ratio, friction angle ratio and the corresponding regression coefficients were obtained as b_1, b_2, b_3 respectively. The y-intercept (c) for the same independent variables comes out to be 2.29, -31.26, -239.22 and 144.58, respectively.

However, a general flow chart of the training and prediction process is shown in Figure 2.

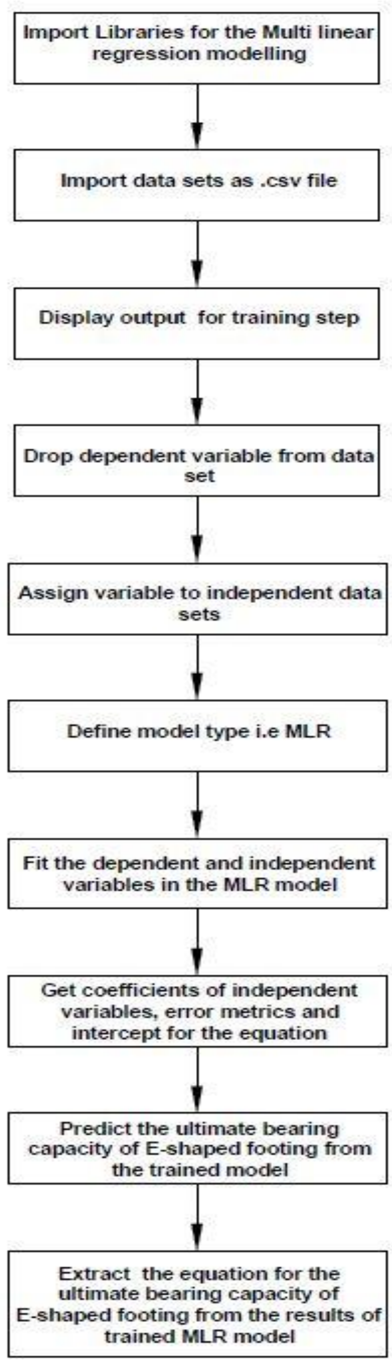


Fig. 2. Flow chart of MLR training model.

Thus, the general equation for E-shaped footing obtained from the MLR model using anaconda software, can be written as follows:

$$q_u^E = 2.29 * q_u^S - 31.26 * \frac{H}{B} - 239.22\frac{\varphi_1}{\varphi_2} + 144.58 \tag{8}$$

From this equation, one can predict the output to any set of independent variables with least cost function (mean square error).

3.2.1. Sensitivity analysis

The open-source machine learning software allows the user to obtain the correlation coefficients (r) between the independent and dependent variables. Thus, in the above MLR model, one more code was introduced to get the correlation coefficients as tabulated in the Table 5.

Table 5
Correlation coefficient between Input and output variables from MLR model.

Correlation Coefficient with respect to q_u^E (kPa)	
Input Parameters	**r**
q_u^S	0.988
H/B	-0.81
$\phi_1/\ \phi_2$	-0.01

Table 5 clearly reveals that there is a strong positive relation between the ultimate bearing capacity of square footing and the ultimate bearing capacity of E-shaped footing resting on the layered sand. It implies that with the increase in the ultimate bearing capacity of square footing, the ultimate bearing capacity of E-shaped footing will also increase under the concentric vertical loading conditions. Also, it was found that a strong but negative correlation exists between the thickness ratio (*H/B)* and the ultimate bearing capacity of E-shaped footing resting on loose over dense sand which implies that with the increase in the thickness of the upper loose sand layer, the ultimate bearing capacity of E-shaped footing will decrease. Moreover, the strong negative correlation between the *(H/B)* and ultimate bearing capacity of E-shaped footing also reveals that with the increase in the width of the footing, the ultimate bearing capacity of E-shaped footing will increase. Both conclusions from the correlation between H/B and ultimate bearing capacity of E-shaped footing proves the authenticity of the results as these are also concluded in [1]. Further examination of Table 5 reveals that there is a weak but negative correlation between the friction angle ratio ($\phi_1/\ \phi_2$) and the ultimate bearing capacity of E-shaped footing which implies that there is not much contribution to the latter because of the friction angle ratio. However, it is well established that with the increase in the friction angles of upper loose(ϕ_1) and lower dense(ϕ_2) sand layer, the ultimate bearing capacity of E-shaped footing will increase.

3.3. Model performance evaluation

To assess the performance of the developed models, widely used performance indices known as the error prediction metrics were used viz. Determination coefficient (R^2), Mean absolute error (MAE), Mean absolute percentage error (MAPE) and Root mean squared error (RMSE) were determined as reported by [24,27–33]. The mathematical expressions of the above-mentioned indices are given as:

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_{avg})^2 - \sum_{i=1}^{n}(y_i - \tilde{y})^2}{\sum_{i=1}^{n}(y_i - y_{avg})^2}$$

y_i = experimental value
y_i = predicted value
n = number of samples in a data set i.e. number of test results under consideration.
y_{avg} = mean of the actual values.
R^2 is used to measure the trend of the predictive models.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(\tilde{y}_i - y_i)|$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \tilde{y}|}{|y_i|} * 100$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y})^2}$$

These prediction error metrics were used to assess the performance of the MLP & MLR models developed from taking into consideration the various factors affecting the bearing capacity of E-shaped footing viz. thickness ratio, friction angle ratio and the bearing capacity of square footing. For a predictive MLP & MLR model having 100% accuracy, ideal values will be obtained as shown in Table 6.

Table 6
Idealized values of prediction error metrics.

Parameters	Ideal value
R^2	1
MAE	0
MAPE	0
RMSE	0

Usually, a ±10% error is normally acceptable while making the predictions in the field of geotechnical engineering as reported by [24].

3.3.1. Comparison between MLP and MLR

The various prediction metrics obtained for the MLP and MLR model are shown in Table 7 and a graph has been plotted for comparison as shown in Figure 3. Figure 3 clearly reveals that the model used for the formulation of both the bearing capacity equations of E-shaped footing is a best fit and the data obtained in this current numerical study is also reliable for the reference purposes. However, due to slight high coefficient of determination in case of MLP model in comparison to MLR model, the former can be considered more reliable for the prediction of ultimate bearing capacity of E-shaped footing than the latter one.

Table 7
Various predicted error metrics obtained from MLP and MLR model.

Prediction Metrics	MLP model	MLR model
R^2	0.99	0.98
MAE	0.38	0.29
RMSE	0.49	0.38
MAPE	0.10	0.78
MSE	0.12	0.92

The numerically obtained ultimate bearing capacity extracted from study [1], ultimate bearing capacity obtained from MLP and MLR model has been tabulated in Table 8. Table 8 reveals that the predictive values of ultimate bearing capacity of E-shaped footing resting on layered sand subjected to vertical loading showed the deviation from the numerically obtained values under the acceptable limits as clearly revealed from the Figure 4(a) and (b).

Table 8
Ultimate bearing capacity from numerical analysis, MLP and MLR model.

Input Parameters			**Output Parameter q_u^E (kPa)**		
q_u^S (kPa)	**H/B**	**ϕ_1/ϕ_2**	**Numerically Obtained from [1]**	**From MLP model**	**From MLR model**
292.75	0.5	0.71	675.02	670.99	629.24
381.08	0.5	0.68	841.85	839.62	838.61
476.66	0.5	0.65	1003.45	1010.24	1064.59
305.81	0.5	0.76	771.38	705.39	647.17
420.09	0.5	0.73	975.57	965.45	915.95
552.13	0.5	0.7	1155.91	1203.5	1225.38
318.14	0.5	0.81	771.35	740.6	663.44
451.53	0.5	0.77	999.77	980.63	978.35
602.02	0.5	0.74	1307.26	1286.3	1330.02
97.43	2	0.71	137.5	129.51	135.24
98.67	2	0.68	141.95	143.5	145.25
99.68	2	0.65	153.5	150.69	154.74
125.64	2	0.76	155	160.32	187.85
126.45	2	0.73	162.8	172.9	196.88
127.2	2	0.7	163.85	175.86	205.78
156.3	2	0.81	160.78	190.63	246.08
157.54	2	0.77	163.02	198.57	258.48
163.33	2	0.74	205.47	250.35	278.92
85.1	4	0.71	89.88	70.65	44.49
85.2	4	0.68	92.68	99.76	51.89
85.66	4	0.65	112.55	110.85	60.13
110.47	4	0.76	92.86	90.64	90.61
110.59	4	0.73	102.5	100.42	98.06
110.64	4	0.7	113.76	110.97	105.35
144.45	4	0.81	150.55	160.89	156.43
143.99	4	0.77	155.19	165.36	164.95
143.84	4	0.74	190.32	200.27	171.78

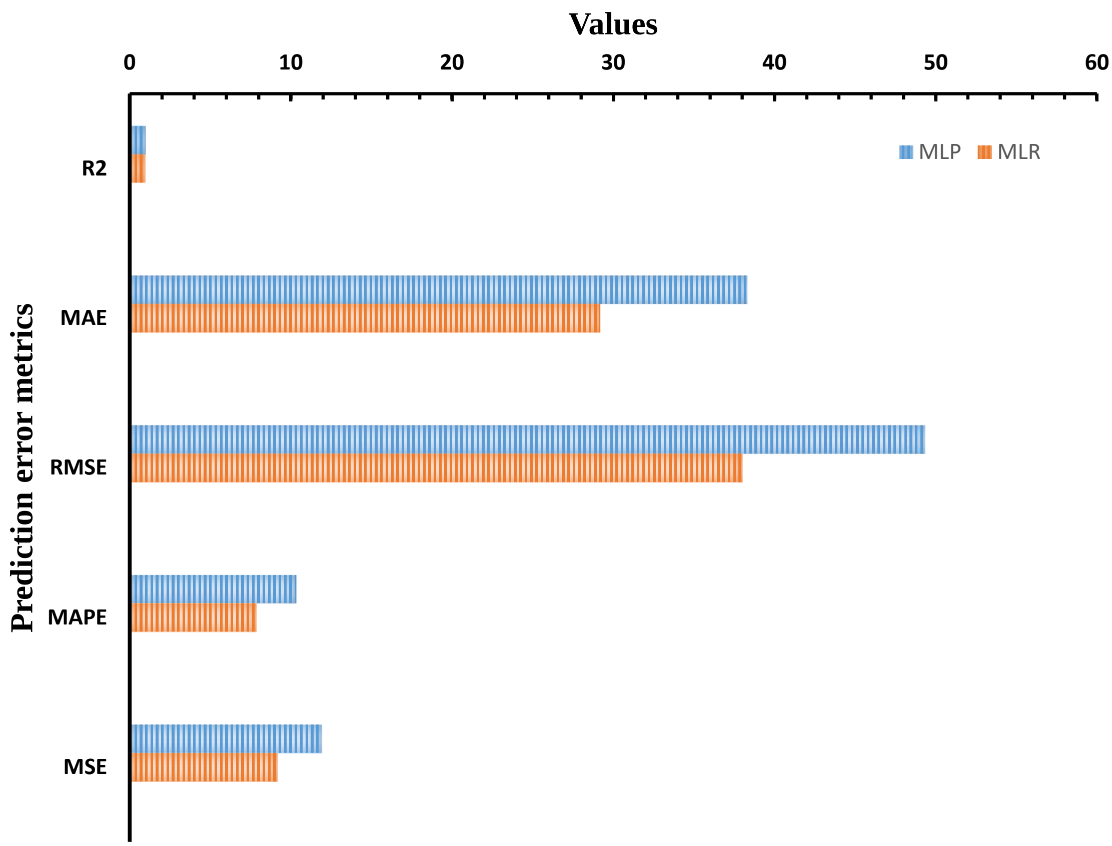
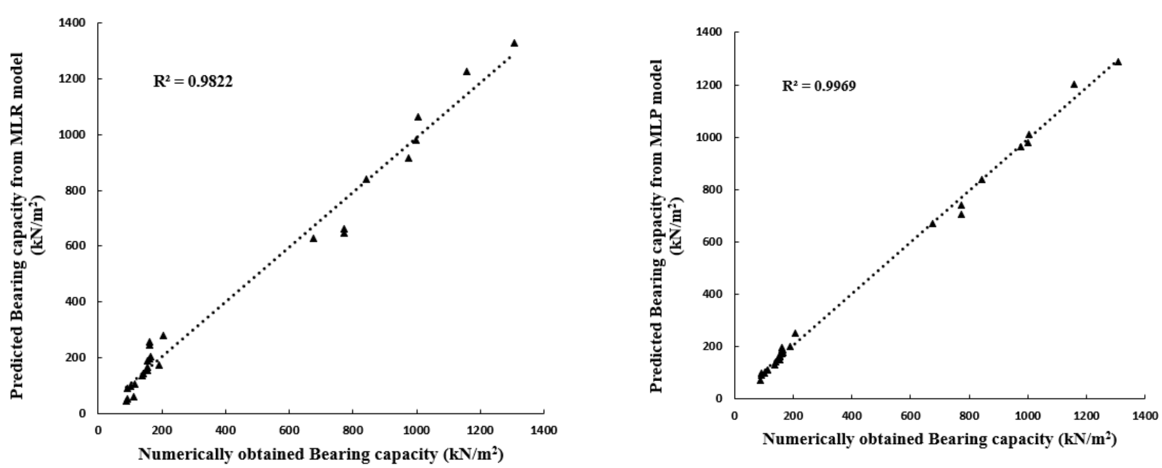


Fig. 3. Comparison of error metrics for the MLR and MLP models.



(a) (b)

Fig. 4. Determination coefficient for (a) MLR model (b) MLP model.

4. Conclusions

A total of 27 data sets were taken from [1] to evaluate the prediction error metrics from MLP and MLR models using WEKA and Anaconda software and to predict the bearing capacity equation of E-shaped footing in terms of regular square shaped footing these models. Following important conclusions were drawn from the analysis:

1. MLR model was found to be cost and time effective as compared to the experimental methods of determining the ultimate bearing equation of footings.
2. Sigmoid activation function was found to be the best fit function for the MLP model among the 21 activation functions and was able to determine the model evaluation metrics for the E-shaped footing resting on layered sand.
3. The coefficient of determination comes out to be 0.99 and 0.98 for the MLP and MLR model respectively which implies that both the models are best fit for the prediction of bearing capacity of E-shaped footing.
4. From the MLP model, the coefficient of correlation, mean absolute error, root mean squared error, relative absolute error and root relative squared error comes out to be 0.99, 0.38, 0.49, 0.10 and 0.12 respectively. It implies that the data obtained from the numerical analysis of [1] is accurate and thus validates the previously used Abacus software for the bearing capacity analysis of E-shaped footing resting on layered sand subjected to vertical loading.
5. The developed MLR model predicts the ultimate bearing capacity E-shaped footing resting on layered sand with ease as the developed equation was quite simple and the prediction was likely to be accurate in both the models.
6. However, due to slight high coefficient of determination in case of MLP model in comparison to MLR model, the former can be considered more reliable for the prediction of ultimate bearing capacity of E-shaped footing than the latter one.
7. From the sensitivity analysis, there was found a positive and strong correlation of 0.98 between the ultimate bearing capacity of square footing and ultimate bearing capacity of E-shaped footing. However, a strong but negative correlation of -0.81 was found to exist between the thickness ratio and the ultimate bearing capacity of E-shaped footing resting on layered sand. Moreover, it was further revealed that a weak negative correlation exists between the friction angle and the ultimate bearing capacity of E-shaped footing.

Funding

This research received no external funding.

Conflicts of Interest

The authors have no conflict of interest with anyone related to the material presented in the paper.

References

[1] Nazeer S, Dutta RK. Bearing capacity of E-shaped footing on layered sand. J Achiev Mater Manuf Eng 2021;2:49–60. https://doi.org/10.5604/01.3001.0015.0517.

[2] Thakur A, Dutta RK. Experimental and numerical studies of skirted hexagonal footings on three sands. SN Appl Sci 2020;2:487. https://doi.org/10.1007/s42452-020-2239-9.

[3] Gnananandarao T, Khatri VN, Dutta RK. Performance of Multi-Edge Skirted Footings Resting on Sand. Indian Geotech J 2018;48:510–9. https://doi.org/10.1007/s40098-017-0270-6.

[4] Gnananandarao T, Khatri VN, Dutta RK. Pressure settlement ratio behavior of plus shaped skirted footing on sand. J Civ Eng 2018;46:161–70.

[5] Gnananandarao T, Dutta RK, Khatri VN. Model studies of plus and double box shaped skirted footings resting on sand. Int J Geo-Engineering 2020;11:2. https://doi.org/10.1186/s40703-020-00109-0.

[6] Davarci B, Ornek M, Turedi Y. Model studies of multi-edge footings on geogrid-reinforced sand. Eur J Environ Civ Eng 2014;18:190–205. https://doi.org/10.1080/19648189.2013.854726.

[7] Davarci B, Ornek M, Turedi Y. Analyses of multi-edge footings rested on loose on loose and dense sand. Period Polytech Civ Eng 2014;58:355–70. https://doi.org/10.3311/PPci.2101.

[8] Ghazavi M, Mokhtari S. Numerical investigation of load-settlement characteristics of multi-edge shallow foundations. 12th Int. Conf. Int. Assoc. Comput. Methods Adv. Geomech. (IACMAG), Goa, India, 2008.

[9] Ghazavi M, Mirzaeifar H. Bearing capacity of multi-edge shallow foundations on geogrid-reinforced sand. Proc. 4th Int. Conf. Geotech. Eng. Soil Mech., 2010, p. 1–9.

[10] Khatri VN, Debbarma SP, Dutta RK, Mohanty B. Pressure-settlement behavior of square and rectangular skirted footings resting on sand. Geomech Eng 2017;12:689–705. https://doi.org/10.12989/gae.2017.12.4.689.

[11] Dutta RK, Dutta K, Jeevanandham S. Prediction of Deviator Stress of Sand Reinforced with Waste Plastic Strips Using Neural Network. Int J Geosynth Gr Eng 2015;1:11. https://doi.org/10.1007/s40891-015-0013-7.

[12] Boger Z, Guterman H. Knowledge extraction from artificial neural network models. 1997 IEEE Int. Conf. Syst. Man, Cybern. Comput. Cybern. Simul., vol. 4, IEEE; 1997, p. 3030–5.

[13] Duan K, Cao S, Li J, Xu C. Prediction of Neutralization Depth of R.C. Bridges Using Machine Learning Methods. Crystals 2021;11:210. https://doi.org/10.3390/cryst11020210.

[14] Das SK. Artificial Neural Networks in Geotechnical Engineering. Metaheuristics Water, Geotech. Transp. Eng., Elsevier; 2013, p. 231–70. https://doi.org/10.1016/B978-0-12-398296-4.00010-6.

[15] Banimahd M, Yasrobi SS, P.K.Woodward. Artificial neural network for stress–strain behavior of sandy soils: Knowledge based verification. Comput Geotech 2005;32:377–86. https://doi.org/10.1016/j.compgeo.2005.06.002.

[16] Ikizler SB, Vekli M, Dogan E, Aytekin M, Kocabas F. Prediction of swelling pressures of expansive soils using soft computing methods. Neural Comput Appl 2014;24:473–85. https://doi.org/10.1007/s00521-012-1254-1.

[17] Yilmaz I, Kaynar O. Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. Expert Syst Appl 2011;38:5958–66. https://doi.org/10.1016/j.eswa.2010.11.027.

[18] Ahangar-Asr A, Faramarzi A, Mottaghifard N, Javadi AA. Modeling of permeability and compaction characteristics of soils using evolutionary polynomial regression. Comput Geosci 2011;37:1860–9. https://doi.org/10.1016/j.cageo.2011.04.015.

[19] Ito Y. Approximation Capability of Layered Neural Networks with Sigmoid Units on Two Layers. Neural Comput 1994;6:1233–43. https://doi.org/10.1162/neco.1994.6.6.1233.

[20] Dutta RK, Rani R, Rao TG. Prediction of ultimate bearing capacity of skirted footing resting on sand using artificial neural networks. J Soft Comput Civ Eng 2018;2:34–46.

[21] Rezaei H, Nazir R, Momeni E. Bearing capacity of thin-walled shallow foundations: an experimental and artificial intelligence-based study. J Zhejiang Univ A 2016;17:273–85. https://doi.org/10.1631/jzus.A1500033.

[22] Nazir R, Momeni E, Marsono K. Prediction of bearing capacity for thin-wall spread foundations using ICA-ANN predictive model. Proc. Int. Conf. Civil, Struct. Transp. Eng. Ottawa, Ontario, 2015.

[23] Momeni E, Armaghani DJ, Fatemi SA, Nazir R. Prediction of bearing capacity of thin-walled foundation: a simulation approach. Eng Comput 2018;34:319–27.

[24] Bardhan A, Samui P, Ghosh K, Gandomi AH, Bhattacharyya S. ELM-based adaptive neuro swarm intelligence techniques for predicting the California bearing ratio of soils in soaked conditions. Appl Soft Comput 2021;110:107595. https://doi.org/10.1016/j.asoc.2021.107595.

[25] Kardani N, Bardhan A, Roy B, Samui P, Nazem M, Armaghani DJ, et al. A novel improved Harris Hawks optimization algorithm coupled with ELM for predicting permeability of tight carbonates. Eng Comput 2021. https://doi.org/10.1007/s00366-021-01466-9.

[26] Kardani N, Bardhan A, Samui P, Nazem M, Zhou A, Armaghani DJ. A novel technique based on the improved firefly algorithm coupled with extreme learning machine (ELM-IFF) for predicting the thermal conductivity of soil. Eng Comput 2021. https://doi.org/10.1007/s00366-021-01329-3.

[27] Kaloop MR, Bardhan A, Kardani N, Samui P, Hu JW, Ramzy A. Novel application of adaptive swarm intelligence techniques coupled with adaptive network-based fuzzy inference system in predicting photovoltaic power. Renew Sustain Energy Rev 2021;148:111315. https://doi.org/10.1016/j.rser.2021.111315.

[28] Salahudeen AB, Ijimdiya TS, Eberemu AO, Osinubi KJ. Artificial neural networks prediction of compaction characteristics of black cotton soil stabilized with cement kiln dust. Soft Comput Civ Eng 2018;2:50–71. https://doi.org/10.22115/SCCE.2018.128634.1059.

[29] Kardani N, Bardhan A, Kim D, Samui P, Zhou A. Modelling the energy performance of residential buildings using advanced computational frameworks based on RVM, GMDH, ANFIS-BBO and ANFIS-IPSO. J Build Eng 2021;35:102105. https://doi.org/10.1016/j.jobe.2020.102105.

[30] Kumar M, Bardhan A, Samui P, Hu JW, Kaloop MR. Reliability Analysis of Pile Foundation Using Soft Computing Techniques: A Comparative Study. Processes 2021;9:486. https://doi.org/10.3390/pr9030486.

[31] Zarei F, Baghban A. Phase behavior modelling of asphaltene precipitation utilizing MLP-ANN approach. Pet Sci Technol 2017;35:2009–15. https://doi.org/10.1080/10916466.2017.1377233.

[32] GHANI S, KUMARI S, BARDHAN A. A novel liquefaction study for fine-grained soil using PCA-based hybrid soft computing models. Sādhanā 2021;46:113. https://doi.org/10.1007/s12046-021-01640-1.

[33] Kumar R, Singh MP, Roy B, Shahid AH. A Comparative Assessment of Metaheuristic Optimized Extreme Learning Machine and Deep Neural Network in Multi-Step-Ahead Long-term Rainfall Prediction for All-Indian Regions. Water Resour Manag 2021;35:1927–60. https://doi.org/10.1007/s11269-021-02822-6.