Performance of ANN Model in Predicting the Bearing Capacity of Shallow Foundations

Mozaher Ul Kabir, Syed Shadman Sakib, Istiakur Rahman and Hossain Md. Shahin

Abstract This study deals with the performance of the artificial neural networks (ANNs) for predicting the ultimate bearing capacity of shallow foundations on cohesionless soil. From cone penetration tests (CPTs), footing dimensions and other soil parameters were considered as the input variables which have the most significant impact on bearing capacity predictions. The application of artificial neural network was carried out through the following steps; at first, we consider a total of 100 sets of data among which we used 89 sets of data for training to determine a relation between input variables and the bearing capacity of the soil. For testing and validation, other 11 data sets were used. The accuracy of the model was evaluated by comparing the results with conventional bearing capacity equations. Also, high coefficients of correlation, low root-mean-squared errors (RMSEs), and low mean absolute errors (MAE) were the indications to confirm that the ANN-based model predicts with much perfection.

Keywords ANNs · Bearing capacity · RMSE · MAE

1 Introduction

Every foundation setup requires satisfying two imperative criteria: ultimate bearing capacity of confinement and limiting settlement of foundations. Between these two criteria, a complete bearing capacity of confinement is managed by shearing nature

M. U. Kabir (✉) · S. S. Sakib · I. Rahman · H. Md. Shahin
Department of Civil Engineering, Islamic University of Technology, Gazipur, Bangladesh
e-mail: mozaher@iut-dhaka.edu

S. S. Sakib
e-mail: shadmansakib@iut-dhaka.edu

I. Rahman
e-mail: istiakur92@iut-dhaka.edu

H. Md.Shahin
e-mail: shahin@iut-dhaka.edu

of the soil and can be evaluated by the theories of Terzaghi (1943), Meyerhof (1963), Vesic (1973), and others. The explanation behind the part of possible theories is the most remote point which adjusted the procedure. In this manner lab results obtained by different researchers were positive. In any case, the trials are generally done on tinier measured models, which are significantly cutback models stood out from real field footings. In this way, various authorities (e.g., (De Beer 1965; Meyerhof 1950)) have prompted that one should be amazingly vigilant while extrapolating disclosures of examinations driven on little footings that have a width of several inches, to the broad evaluated footings. The clarification behind this is credited to the extension in shearing strain along the slip line with the development in width of the foundation and the extent of mean grain size of the soil and the adjust width (Steenfelt 1977). For extensive scale establishments on dense sand, shearing strains demonstrate significant variety along the slip line. The normal assembled point of shearing resistance along the slip line is littler than the greatest estimation of the angle of shearing resistance (φ_{max}) which was obtained via plane strain shear tests.

Henceforth, an ultimate technique is required that gives better gauges of bearing capacity. In the most recent two decades, a few analysts have created successful demonstrating instruments.

One of them is artificial neural networks (ANNs) methodology. In the current past, ANNs have been connected to numerous geotechnical designing issues, including the determination of the bearing capacity of footings, settlement forecasts, liquefaction, and stability of slopes (Shahin et al. 2001). The real preferred standpoint of ANNs is that they reanalyze the old and new information, use the old outline helps or conditions, and additionally propose new conditions (Pande and Shin 2004). This paper shows the relevance of ANN method in building up a compelling nonlinear model for anticipating a definitive bearing capacity of shallow foundations on cohesionless soils. The database, which comprises of load test values of extensive scale footings and smaller estimated demonstrate footings, is utilized to create and check the ANN model. This paper additionally goes for a broad assessment of the ANN model with regression-based models for ultimate bearing capacity using in a total of 100 sets of field data and evaluates their benefits and restrictions. The execution of these models is then occurred to demonstrate the most regularly utilized bearing capacity.

2 Development of Ultimate Bearing Capacity Model

The data used for experimenting and the development of the ANN model were collected from the literatures, which are load test data on real-sized foundations regarding the footing and soil. Among 100 collected field data, 50 are from load tests on large-scale footings and 50 are from small shallow footings. Again from 47 large-scale footing data, 24 were reported by Muhs and Weiß (1971), 11 data by Weiß (1970), 5 of them by Muhs et al. (1969), 2 of them by Muhs and Weiß (1973), 5 of them by Briaud and Gibbens (1999).

One of the challenging initiatives in the model improvement for the prediction of bearing capacity of a shallow foundation is to differentiate parameters those have impact on the bearing capacity, for which a number of the conventional bearing capacity estimation techniques (Terzaghi 1943; Meyerhof 1963; Vesic 1973) are used. In spite of the way that the bearing capacity gotten through these techniques varying abruptly, the fundamental type of condition is the same for every one of the techniques, which is as per the following for establishments in cohesionless soil:

$$q_u = \gamma D N_q S_q d_q + 0.5 \gamma B N_\gamma S_\gamma d_\gamma$$

where *B*—width of footings, *D*—profundity of footings, *c*—unit weight of sand (underneath or more the establishment level), N_q, N_γ—bearing capacity factors, S_q, S_γ—shape factors, and d_q, d_γ—depth factors.

Among the parameters identified with the footings, the principle factors influencing the bearing capacity are its width (minimum horizontal measurement, *B*), footing length (*L*), depth of the foundation (*D*), and shape (square, rectangular and round). The depth of the foundation has the most significant impact on the bearing capacity among all the physical properties of the foundation (Meyerhof GG. The bearing capacity of sand. PhD thesis, University of London 1950).

The fundamental parameters with respect to the soil (sand) are its angle of shearing friction and the unit weights of soil layers adjusted to the water table (if available). There are some different factors, for example, compressibility and thickness of the soil layer underneath the foundation which are responsible for a smaller grade. Among the considerable number of properties of soil, the angle of shearing resistance has most noteworthy impact on the bearing capacity, which decreases with the relative thickness of the soil. The unit weight of the soil is depended on the position of water table and proportional to the bearing capacity.

In light of above discussion, the five input factors used for the model encroachment are width of footing (*B*), depth of footing (*D*), unit weight of sand (*γ*), angle of shearing resistance (*φ*), and ratio of length and width (*L/B*). By using these five factors, the ultimate bearing capacity (q_u) is the final result.

3   ANN Model Development

In this study, feed-forward multilayer perceptron (MLP) is utilized; the portrayal of which can be found in numerous publications (Zurada 2003; Fausett 1994). The data set was arbitrarily separated into two subsets: training and testing. 87% (or 87 cases) of the information was set for training the model, while the remaining 13% (or 13 cases) was utilized for testing or validation the execution of the proposed ANN-based model. A trial-and-error strategy was used to determine the optimum number of hidden layers in the model which was concluded by using ten hidden
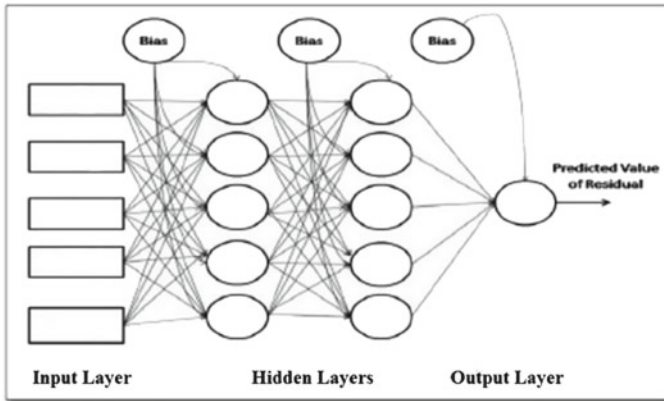
Fig. 1 Architecture of ANN model

layer. Because of five input and one output variable, five nodes were used in the input layer and one in the output layer which is a typical way to deal with problem of overfitting in early stopping (Fig. 1).

This approach includes monitoring the generalization error and stopping training when the minimum validation error is observed. Be that as it may, some care is required when to stop, since the approval mistake surface may have local minima or long flat regions preceding a steep drop-off. To minimize these constraints, Mackay (1991) proposed the use of Bayesian back-propagation neural networks which minimize a combination of squared errors and weights and after that decides the correct combination, in order to create a network which sums up well. This procedure is called Bayesian regularization. In the Bayesian structure, the weights and the biases of the network are assumed to be random variables with indicated appropriation of distribution. The regularization parameters are identified with the unknown variances related to the distribution. These parameters are then evaluated using statistical techniques. In the present investigation, the Levenberg–Marquardt algorithm is utilized under the Bayesian network.

3.1 Multiple-Regression Analysis

To develop a relationship between the single dependent variable, q_u, and one or more independent variables c_i, h_i, and B, multiple-regression is used, and the prediction of q_u is accomplished by the following equation:

$$q_u = w_1c_1 + w_2c_2 + w_3c_3 + w_4c_4 + w_5h_1 + w_6h_2 + w_7h_3 + w_8B + b$$

```
   Source |      SS      df      MS          Number of obs =     89
----------+----------------------------      F( 5,    83) =   41.41
    Model | 19083512.9    5  3816702.58      Prob > F      =  0.0000
 Residual |   7649780    83  92166.0241      R-squared     =  0.7138
----------+----------------------------      Adj R-squared =  0.6966
    Total | 26733292.9   88   303787.42      Root MSE      =  303.59

------------------------------------------------------------------------------
    Bearingpcapc |      Coef.   Std. Err.      t    P>|t|    [95% Conf. Interval]
-----------------+------------------------------------------------------------
           Depth |   1976.073   221.3357     8.93   0.000     1535.845    2416.301
               B |   42.20546   94.93179     0.44   0.658      -146.61     231.021
              LB |  -27.58137   18.34084    -1.50   0.136    -64.06055    8.897819
   angleoffriction|    86.464   10.51894     8.22   0.000     65.54226    107.3857
           unitwt |  -21.22461   14.02371    -1.51   0.134     -49.1172    6.667982
           _cons |   -2833.27   466.6629    -6.07   0.000    -3761.444   -1905.097
------------------------------------------------------------------------------
```

Fig. 2 Output result from StataSE 12 for MLR model

where w_i are the regression weights and are processed in a way that limits the aggregate of the squared deviations. Here, b is the y-axis intercept. Multiple-regression is associated with multiple correlation coefficient, which is the variance of the dependent variable explained collectively by all of the independent variables. A multiple-regression model was obtained using Stata SE 12 (Fig. 2).

The following formulas, using the MLR technique, were found to offer the best fitting:

$$q_u = 1976.073D + 86.464h - 2833.27$$

where q_u (kPa) is the bearing capacity, s (m), and h(deg) is the angle of friction.

4 Performance Evaluations and Results

The performance of the model is being evaluated by assessing the degree to which the values obtained from the simulations match actual output. The assessment was performed in this study with various goodness-of-fit or correlation statistics. The values of the performance indices or measures for the three models are summarized in Table 2. The correlation statistic (R), which evaluates the linear correlation between the actual and predicted ultimate bearing capacity, is good for all the models, for calibration as well as validation data. The model efficiency that evaluates the performance of the model in predicting the ultimate bearing capacity
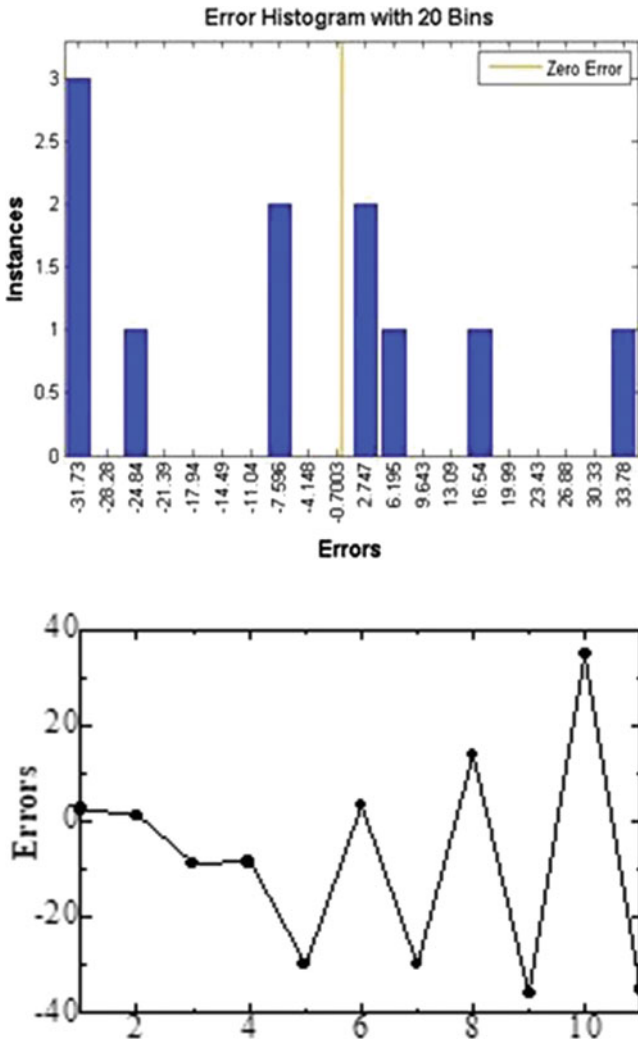
Error Histogram with 20 Bins

Fig. 3 Distribution of prediction error across different error thresholds

values away from the mean is found to be more than 98% for calibration, and validation data for the ANNs model was close to where it was first referenced (Figs. 3 and 4) (Table 1).
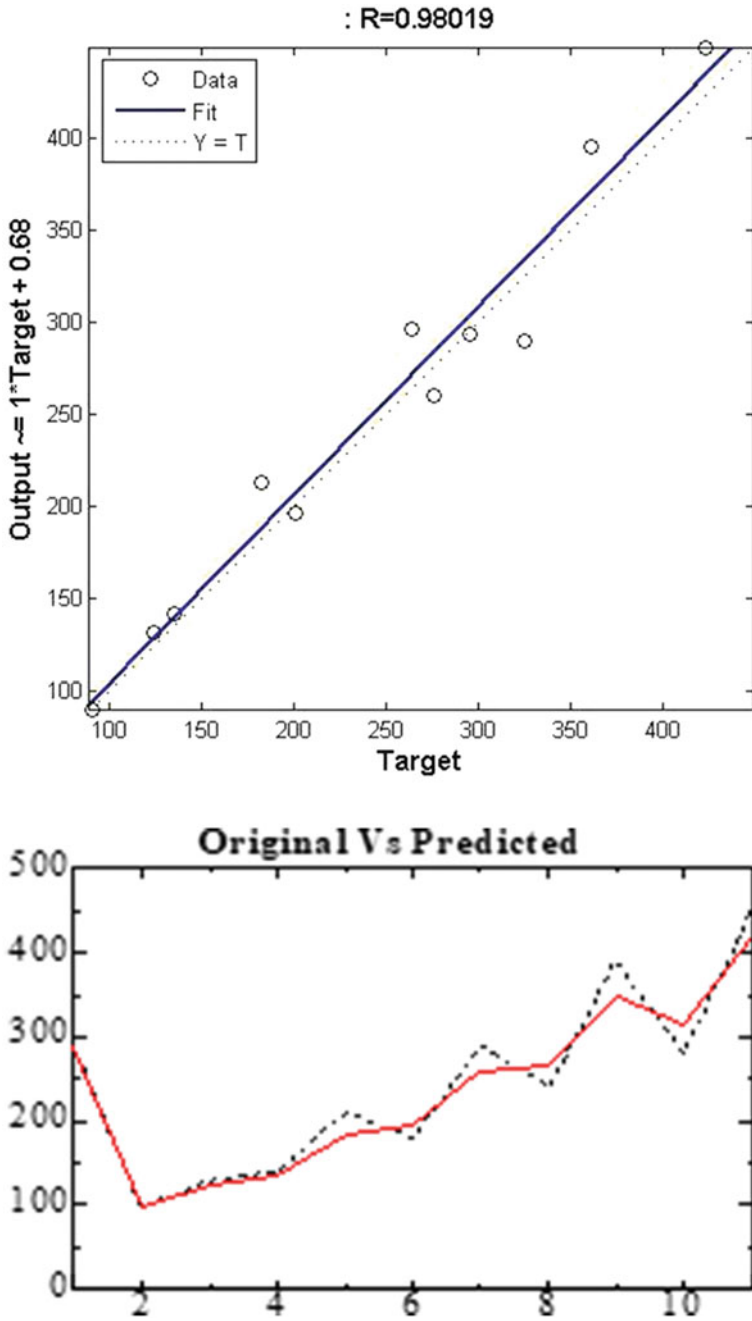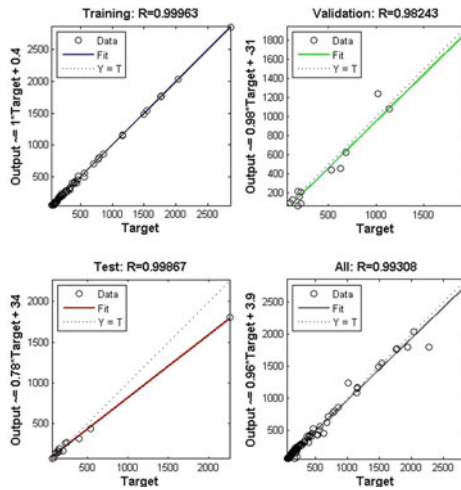
Fig. 4 Measured versus predicted ultimate bearing capacity values

Table 1 Performance evaluation and comparison

Performance index	ANN	MLR	Meyerhof
R^2	0.98019	0.7138	0.648

In this study, artificial neural networks (ANNs) and equation developed by the multilinear regression model (MLR) were used to predict the bearing capacity of circular shallow footings on cohesionless soil. The artificial neural network model serves as a simple and reliable tool for the bearing capacity of shallow foundations in sandy soil. The results produced high coefficients of correlation for the trained and testing data sets, and the values are 0.99,308 and 0.98019, respectively, which have much more higher perfection then MLR model. Nevertheless, this study demonstrates that having some known parameters, we can easily be able to have an idea about the ultimate bearing capacity through the ANN model.

References

Briaud JL, Gibbens R (1999) Behavior of five large spread footings in sand. ASCE J Geotech Geoenviron Eng 125(9):787–796

De Beer EE (1965) The scale effect on the phenomenon of progressive rupture in cohesionless soil. In: Proceedings of the 6th international conference on soil mechanics and foundations engineer, s vol. 2 p 13–7

Fausett LV (1994) Fundamentals of neural networks: architectures, algorithms and applications. Prentice-Hall, Englewood cliff s (NJ)

Mackay DJC (1991) Bayesian methods for adaptive models. PhD thesis, California Institute of Technology

Meyerhof GG (1950) The bearing capacity of sand. PhD thesis, University of London

Meyerhof GG (1963) Some recent research on the bearing capacity of foundations. Can Geotech J 1(1):16–26

Muhs H, Weiß K (1971) Untersuchung von Grenztragfa¨higkeitundSetzungsverhalten flachge-gru¨ndeter Einzelfundamente im ungleichfo¨rmigennichtbindigen Boden. Deutsche Forschungsgesellschaft fu¨ r Bodenmechanik (DEGEBO), Berlin. HEFT 69

Muhs H, Weiß K (1973) Inclined load tests on shallow strip footings. In: Proceedings of the 8th international conference on soil mechanism and foundation engineering. vol II, p 173–9

Muhs H, Elmiger R, Weiß K (1969) Sohlreibung und Grenztragfa¨higkeit unter lotrecht und schra¨g belasteten Einzelfundamenten. Forschungsgesellschaft fu¨r (DEGEBO), Berlin.HEFT 62

Pande GN, Shin H-S (2004) Artificial intelligence v. equations. In: Proc ICE Civil Eng 157(1):43–6

Shahin MA, Maier HR, Jaksa MB (2001) Artificial neural network applications in geotechnical eng. Austr Geomech 36(1):49–62

Steenfelt JS (1977) Scale effect on bearing capacity factor Nc. Proc. of the 9th international conference on soil mechanism and foundation engineering. vol 1, p 749– 52

Terzaghi K (1943) Theoretical soil mechanics. John Wiley & Sons, New York

Vesic AS (1973) Analysis of ultimate loads of shallow foundations. JSMFD, ASCE 99(1):45–73

Weiß K (1970) Der Einfluß der Fundamentform auf die Grenztragfa¨higkeit flachgegru¨nder Fundamente. Deutsche Forschungsgesellschaft fu¨ r Bodenmechanik (DEGEBO), Berlin. HEFT 65

Zurada JM (2003) Introduction to artificial neural systems. Jaico Publishing House