



Estimating bearing capacity of shallow foundations by artificial neural networks

Mustafa Aytekin *

Department of Civil Engineering & Architecture, University of Bahrain, 32038 Isa Town, Kingdom of Bahrain

ABSTRACT

In this study, the Artificial Neural Network, ANN is applied to data extracted from a large set of random data created by using Terzaghi and Meyerhof formulae. By using MS Excel, 3750 sets of data for Terzaghi's equation, 4000 for Meyerhof's equation were generated. A simulated ANN was trained on a subset of bearing capacity data, and the performance was tested on the remaining data. The performances of the ANN models were compared to Terzaghi and Meyerhof results. ANN models were as accurate as the other techniques in estimating the ultimate bearing capacity. The models estimated the ultimate bearing capacity with an average error of around 1% of the value obtained from Terzaghi and Meyerhof equations, and the coefficient of determination (r^2) was almost equal to 1. Their sensitivity and specificity is dependent on the function and the algorithm used in the training process. Validation subset is crucial in preventing the over-fitting of the ANN models to the training data. ANN models are potentially useful technique for estimating the bearing capacity of the soil. Large training data sets are needed to improve the performance of data-derived algorithms, in particular ANN models.

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1. Introduction

Bearing capacity is affected by several parameters and factors such as width and depth of foundation, unit weight of soil, depth of ground water table, friction angle, and cohesion of soil. Due to the complex relationship between the parameters, estimating of ultimate bearing capacity is neither easy nor accurate (Das, 2011; Bowles, 2001). The purpose of this research is to investigate the adequacy of using ANN in estimating ultimate bearing capacity as a new alternative method. The idea was to use a number of field data that are obtained from field tests to develop ANN program that is capable of estimating bearing capacity to avoid the need of field test in the future, but due to lack of field data, Terzaghi and Meyerhof equations have been used to produce data that are used for ANN.

2. Bearing Capacity of Shallow Foundations

Terzaghi expressed well known ultimate bearing capacity of a strip foundation in the form:

$$q_u = cN_c + qN_q + \frac{1}{2}\gamma BN_\gamma \quad (1)$$

The ultimate bearing capacity equation that expressed by Terzaghi did not take into account the shear resistance along the failure surface in soil above the bottom of the foundation. Also, it assumed the load on the foundation is vertical and axial. However, the load may be inclined. To account for all these shortcomings, Meyerhof (1963) suggested the following form of the general bearing capacity equation:

$$q_u = cN_c F_{cs} F_{cd} F_{ci} + qN_q F_{qs} F_{qd} F_{qi} + \frac{1}{2}\gamma BN_\gamma F_{\gamma s} F_{\gamma d} F_{\gamma i} \quad (2)$$

* Corresponding author. Tel.: +973-36936675 ; Fax: +973-17680843 ; E-mail address: maytekin1@gmail.com (M. Aytekin)

Meyerhof introduced more factors for Terzaghi's bearing capacity equation to take into account the various effects that Terzaghi ignored or assumed. Also, tests on laboratory show different results for bearing capacity factors.

3. Artificial Neural Network

The research community started studying the possibility of generating an artificial neural network that is similar to human brain neurons which can be produced through evolutionary algorithms for the last 32 years (Kauffman, 1993). This information processing paradigm is inspired by mimicking the biological nervous systems (Graupe, 2006).

4. Artificial Neural Network Training Program

4.1. Procedure

Due to lack of field data, a set of data were generated using two methods (Terzaghi, and Meyerhof) and bearing capacity was calculated using the equations. By using MS Excel, a set of data were generated (3750 for Terzaghi's equation, 4000 for Meyerhof's equation). The involved parameters were constrained by some limits that Table 1 shows.

Table 1. Limits of bearing capacity parameters.

Parameter	From	To
γ : Unit weight of soil [kN/m ³]	13	21
γ_{sat} : Saturated unit weight of soil [kN/m ³]	13	23
c : Cohesion of soil [kN/m ²]	0	100
D_f : Depth of foundation [m]	0	7
B : Width/Diameter of foundation [m]	0	11
L : Length of foundation [m]	0	40

After generating the input and target data, MATLAB was used to perform ANN training program. Using the ANN main tool "nnstart" seen in Fig. 1, the functions were generated. These functions had simple setups which results in large deviation from the desired values that have been calculated using the theoretical equations, so a need for customized function is required. Due to the complexity of the ANNs and the large amount of parameters involved in the bearing capacity equations, the customized script has to be changed for each case (the three cases of depth of groundwater D_w) and re-trained so that a suitable output is achieved. Then, by creating a customized script the training period started.

In the training period, the script that does the training process had to be changed in terms of number of neurons and hidden layers in a trial and error process. It worth mentioning that the use of a large number of neurons will cause two problems, the first one is that the

ANN tool will over fit the data on the data that has been used for the training and producing perfect results for them but when new data is tested in the function the output will not match the desired target value. Secondly, a large number of arterial neurons will need a long time and huge processing power of the computer which is unfortunately was not available for us.

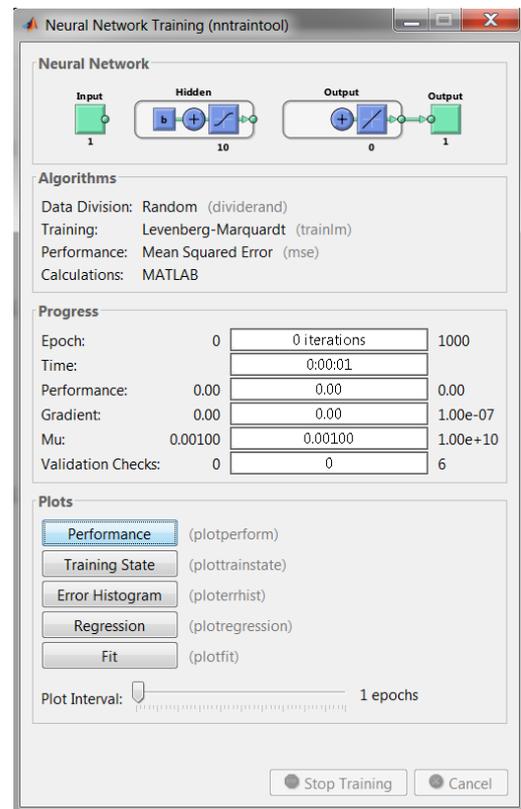


Fig. 1. ANN training progress window.

Thus, as mentioned before a balance between the over-fitting and non-fitting result is required. After finding a suitable number of neurons and hidden layers the retraining process will take place because as the program retained the performance and outputs will get better up to a certain point, after that the program will start to deviate from the intended target.

After finishing the training process, the functions were generated with a small mean squared error values. This conclude the usage of ANN, then a verification of the functions that has been generated using the ANN had been done by using a random set of data to test the functions so the ones with the huge error were excluded and the best were selected. After that, a conclusive data analysis is performed on the functions to find its reliability. The final stage is to use all the functions that has been created and tested to generate a graphical interface that is easy to use and independent of MATLAB and could be used to calculate the ultimate bearing capacity with a high level of confidence.

After performing program training for each case for both equations (Terzaghi and Meyerhof) the generated ANN functions were tested under various conditions and scenarios in order to check the percentage error of the

functions by comparing its results with Terzaghi and Meyerhof equations results before deciding whether the produced function is adequate to be used or not.

The testing process is based on different scenarios. There are three cases according to depth of groundwater D_w . The variation of each parameter involved in bearing capacity equation with the value of ultimate bearing capacity for each case are analyzed by Terzaghi or Meyerhof against ANN. The detailed analyses were performed for strip, square, rectangular and circular foundations of Terzaghi's equations under axial loads while for Meyerhof's equation the analysis have been performed for rectangular/square foundations under axial load as well as under one way eccentricity in x or y directions.

4.2. Analysis of Terzaghi's approach

Fig. 2 shows the results of ultimate bearing capacity comparing the use of the equations against using the ANN model for strip foundation type. It can be noticed from the graph that all points are uniformly distributed on the line indicating that the obtained results from ANN model were excellent. Also, this can be verified numerically as the average percentage error (0.36%) did not exceed 1 with coefficient of determination (r^2) of 1.0.

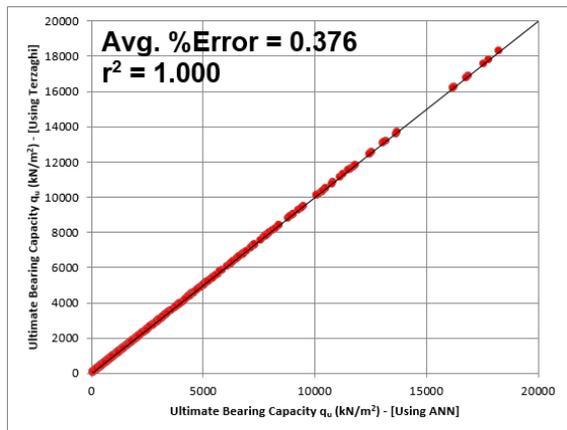


Fig. 2. Comparison between Terzaghi and ANN results for circular foundation.

On the same basis, the results of ANN models for square, rectangular and circular are showed similar behavior. Again, the obtained results were very accurate with average percentage error less than 1% and coefficient of determination (r^2) equal to 1.0.

It is worth mentioning that sometimes the percentage of error jumps dramatically in our analysis but these jumps occur only for very small values of ultimate bearing capacity that is less than 100 kN/m² which is impossible to use in project soil, because of the resultant unpredictability of the soil mentioned. Besides, this high percentage error is logical for small values although the difference between values is numerically small which is statistically insignificant. Table 2 shows the average percentage error and coefficient of determination for each type of Terzaghi foundations.

Table 2. Results comparing for Terzaghi ANN models.

Foundation Type	Avg. %Error	r^2
Strip Foundation	0.356	1.000
Square Foundation	0.332	1.000
Rectangular Foundation	0.362	1.000
Circular Foundation	0.376	1.000

4.3. Analysis of Meyerhof's approach

The analysis continues for Meyerhof ANN models as Fig. 3 shows the variation of ultimate bearing capacity for Meyerhof's equation and ANN models for concentric foundation. Similar results were obtained for eccentrically loaded foundations too. Fig. 3 indicates a good distribution of the points on the 45 degree line which means that the results ANN function models produced are matching Meyerhof's equation. It should be noted that average percentage error for Meyerhof's ANN models are a little bit higher than what is obtained for Terzaghi's ANN models although it is still less than 1%, and that because Meyerhof's equation is much more complicated than what Terzaghi described. Meyerhof's equation contains many factors that are approximations or obtained empirically which made life more complicated for ANN model to follow. Despite that, the ANN model for Meyerhof approach is still excellent to use with coefficient of determination (r^2) equal to 1.0. Table 3 shows the average percentage error and coefficient of determination for each type of Meyerhof foundations.

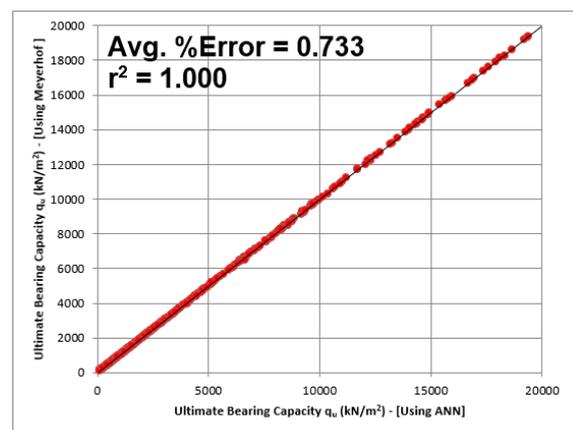


Fig. 3. Comparison between Meyerhof and ANN results for concentric foundation.

Table 3. Results comparing for Meyerhof ANN models.

Foundation Type	Avg. %Error	r^2
Concentric Foundation	0.733	1.000
Eccentric (eB) Foundation	0.622	1.000
Eccentric (eL) Foundation	0.676	1.000

Though in some cases in the detailed analysis the maximum error is large, the coefficient of determination is 1.0 and the average error of all cases is less than 1%, this means that the ultimate bearing capacity computed from the ANN models are following the data calculated from Meyerhof formula and this become obvious when studying the graphs generated from the detailed analysis.

Also from the random data analysis the data are following the 45 degree line meaning that all the values obtained from the theoretical methods and form the ANN models are almost equal. This result in the reinforcement of our findings specifically that the values generated from the ANN models are reliable and accurate enough to be used in estimating the ultimate bearing capacity.

5. Conclusions

This paper proposed a potential solution using an intelligent technique based on ANN to predict the bearing capacities of different types of shallow foundations under various conditions. ANNs were used to simulate the mechanical behavior of soil and more particularly the prediction of the ultimate bearing capacity. The ANNs used were Cascade-forward and Feed-forward neural network were trained with the Bayesian Regularization algorithm.

The performance of the model relies on the training data sets generated. Therefore to have an expert model, a lot of training data sets based on desired results need to be generated. Therefore, a database containing 3750 cases generated through MS-Excel form random generator based on Terzaghi and Meyerhof formulas for ultimate bearing capacity was used for model development and verification. An analysis was carried out to study the relative importance of the factors that affect the ultimate bearing capacity.

The results of the ANN model were compared with the results of the theoretical data which were obtained from the two mentioned traditional methods. The results indicate that the ANN model was capable of accurately simulating the ultimate bearing capacity by using from seven to nine simple parameters as model inputs such as (D_f , B , c , etc.). The results obtained also demonstrate that the ANN method performs as good as the traditional methods with an average percentage error of around 1%

of true value obtained from Terzaghi and Meyerhof equations, and coefficient of determination (r^2) almost equal to 1. The neural network model currently demonstrated for this work can be further applied for other theoretical methods as well as field test derived data with various conditions.

A neural network performance depends mostly on its generalization capacity, which in return depends on the data. The study of ultimate bearing capacity variables before the learning process of an ANN model enabled us to determine the importance of the variables on the phenomena. The merits of the neural network are the ability to detect complex nonlinear relationships between dependent and independent variables and to detect the possible interaction between predictor variables and the training algorithms.

ANNs have the advantage that once the model is trained, it can be used as an accurate and quick tool for estimating the total bearing capacity without the need of using tables or charts. The model currently to be developed would increase the efficiency of geochemical design by avoiding complicated and time consuming input file preparation. Thus, neural networks are valuable tools to the soil engineer. An ANN models have been developed for geochemical engineering applications. Also, independent software was produced to ease the calculation of the ultimate bearing capacity for both Terzaghi and Meyerhof.

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