International Journal of Advanced Science and Research
ISSN: 2455-4227, Impact Factor: RJIF 5.12
www.allsciencejournal.com
Volume 2; Issue 4; July 2017; Page No. 87-91

Improved prediction of load carrying capacity of bored piles by artificial neural network model

Gurdeepak Singh

Department of Civil Engineering, Guru Nanak Dev Engineering College, Ludhiana, Punjab, India

Abstract

In this paper, artificial neural networks (ANNs) have been trained for the prediction of unit shaft friction and unit tip bearing capacity by using two parameters namely soil type and cone penetration resistance value. Thirty five pile loading case histories have been compiled with known soil types and Cone Penetration Test (CPT) results. For all of the 35 piles under the study, the unit skin friction acting around circumferential area of pile has been calculated for every soil layer with which the piles interact. For each pile, the unit end bearing capacity of soil layer in which an individual pile rest has also been calculated. The developed ANNs have been expressed in the form of two sets of equations. The load carrying capacity of all piles under study have been calculated from these equations and compared with load carrying capacity predicted by direct CPT methods. From this study, it has be concluded that the proposed model gives enhanced performance than conventional direct CPT methods. The proposed equations can predict ultimate load carrying capacity of bored piles in axial compression with improved accuracy.

Keywords: pile load capacity, artificial intelligence, CPT data, artificial neural network

1. Introduction

The large civil engineering projects cannot be reliably founded on shallow foundations for the transfer of load without exceeding safe bearing capacity. Therefore, pile foundations are used for transferring heavy loads of superstructures from the soft shallow layers to the deep underground firm layers. The piles can be driven or bored. The bored piles are preferred to avoid high vibrations produced by driving operation; to avoid disturbance/remolding of surrounding soil; to avoid overstressing caused by driving operation and in non-availability of equipments required for driving piles. The rigorous analysis of pile foundation is a complex problem which is not fully explored. For the use of pile foundation, the soft computing techniques like artificial neural networks are very suitable which can map outputs parameters with input parameters without going for details of phenomenon of load transfer. ANN are non-mechanistic models [1] based on the observed experimental data as compared to the conventional methods such as elastic approximation [2, 3, 4], FE analysis [5], hyperbolic models [6, 7]. ANN can explore correlations from imprecise data, therefore it is increasingly being applied to various fields of science and technology [8-21] and geotechnical engineering [22-24]. Several researchers had examined the use of pile driving data for the prediction of the load capacity of driven piles by ANN [25-29]. The applications of neural networks in soil mechanics have been reviewed by Shahin *et al* [30]. The artificial neural networks (ANN) can be used to calculate pile load capacity with some degree of success, if all the input parameters like length, diameter, depth, thickness and soil type of all layers with cone resistance along the pile length and below the bottom are provided. But with more input parameters, ANN becomes more complex and less precise. The approach followed in the this study is to reduce the no. of inputs to ANN, so that an efficient and more accurate network can be trained. Hence unit skin friction and unit tip bearing capacity have been calculated from two input parameters i.e. soil type and cone penetration resistance value.

2. Finite Element Modeling

The entire dataset has been compiled from the literature (mainly soil profile, cone penetraton test results and pile loading tests), which have been reported by Alsamman [31] and Eslami [32]. All 35 piles have been analyzed with Finite Element Modeling (FEM). The purpose of using FEM was to calculate unit skin friction for all soil layers encountered in strata and unit tip bearing capacity for all the piles under the study. The major soil types considered are clay, silt, sand-silt, fine sand, coarse sand and gravels. The soil parameters used in FEM are calculated from cone penetration resistance values and soil types using the relations given in the literature [33-35]. The unit skin friction and unit tip bearing capacity calculated by FEM are corrected by comparing pile load capacity calculated by FEM and pile loading tests. The relationships between soil parameters/soil type, cone penetration resistance and unit skin resistance/unit tip bearing capacity have been established. The relationships between soil type, cone penetration resistance and unit skin resistance/unit tip bearing capacity have been modeled by ANN in the presented work.

3. Architecture of the ANN Model

Modeling in ANN is analogous to human neural system computation. In neural networks correlations are found between the inputs and corresponding outputs obtained from experimentation or simulation. ANN is a great computational tool for predicting the correlations between input /output parameters. ANN models have been used by many researchers for predicting pile load capacity [25, 36, 37]. In this study, two ANN models have been trained. The first ANN model calculates unit skin friction and second ANN model calculates unit tip bearing capacity from two input parameters namely soil types and cone penetration resistance values. ANN models developed in the study are trained with a back-propagation algorithm [38, 39] by using feed-forward multi-layer architecture. The feed-forward multilayer neural network consists of one input layer, one hidden layers and one output layer. The neurons in each layer connect to the elements of the previous or subsequent layers with certain multiplying coefficients called weights and additive coefficients called bias. A ''tansig'' function as activation function.

The neural network models consisting of one hidden layer containing 4 neurons were found to be the best suited architecture. In the present study, input data is divided randomly into three sets, namely training set, validation set and testing set in ratio of 60:20:20. The input and output variables used for training of the neural network model are given in Table 1. The soil types have been coded as per Table 2. For soils existing in between two soil types, the fractional values can be used. The coefficient of determination (R^2) values of both artificial neural networks obtained during the training, validation and testing phases are given in Table 3.

Table 1: Artificial neural network statistical input parameters

S. No.	Input and output variables	Minimum	Maximum	Mean	Standard Deviation
1	Soil Type	1	6	3.5	1.71
2	Cone resistance (MN/m^2)	0.25	35	16.62	10.8
3	Unit skin friction (KN/m^2)	6.1	345.8	134.2	75.7
4	Unit tip bearing capacity (KN/m^2)	171	945.1	499.4	175.8

Table 2: Coding of soil types for artificial neural network

Soil type	Clay	Silt	Sand-Silt	Fine Sand	Coarse Sand	Gravel
Input Value	1	2	3	4	5	6

Table 3: The coefficient of determination (R^2) values of both artificial neural networks during training, validation and testing phases

S. No.	ANN output parameter	Coefficient of determination (R^2)		
		Training	Validation	Testing
1	Unit skin friction	0.8495	0.84948	0.84907
2	Unit tip bearing capacity	0.8483	0.84801	0.84726

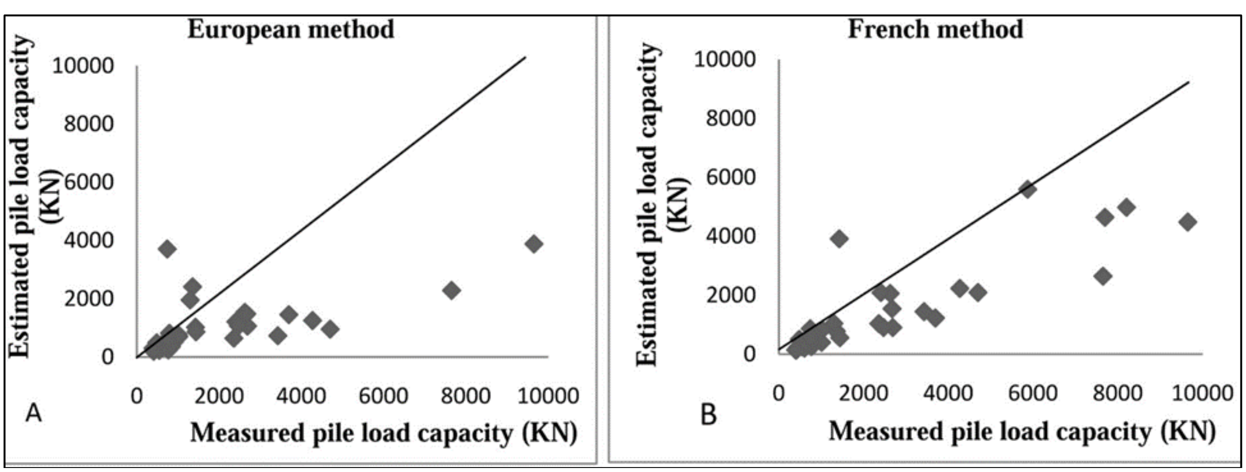
4. Comparison of the proposed ANN method with direct CPT methods

For investigating the performance of the trained ANNs, comparison has been made with direct cone penetration test methods such as de Ruiter and Beringen (European method) [40], Bustamante and Gianeselli Method (LCPC/LCP Method) [41], Aoki and De Alencar Method [42]. The results of this comparison are given in Table 4. The ultimate pile load capacity (Q_u) values are calculated for all methods under comparison using a database of 35 piles under study. The predicted values of ultimate pile load capacity (Q_u) given by direct cone penetration test methods are compared with the pile load test values.

Table 4: Statistical parameters of ratio of predicted to measured ultimate pile load capacity by various direct CPT methods and proposed method.

Statistical parameters	European method	French method	Aoki method	Proposed method
Mean of (*Qu(p)/ Qu(m)*)	0.924876	0.628212	0.369476	0.991909
Std. dev. of (*Qu(p)/ Qu(m)*)	1.056597	0.424989	0.238732	0.192546

Where *Qu(p)* is predicted ultimate load carrying capacity of pile and *Qu(m)* is measured ultimate load carrying capacity of pile from pile loading test.



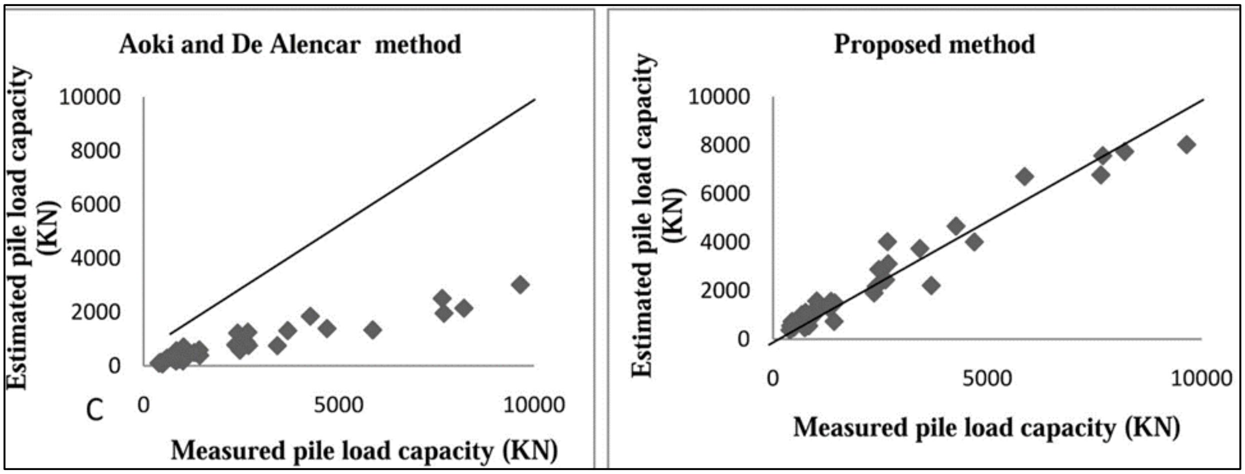


Fig 1: Predicted versus measured ultimate pile load capacity by various CPT direct methods and proposed method.

The comparison demonstrates that the cone penetration test direct methods, namely European method, French method and Aoki method with the average values of 0.92, 0.62, and 0.36 respectively gives piles load capacity on lower side. Of all the methods, the proposed method using ANNs gives the best mean value of 0.99. Hence the proposed method provides best prediction of pile load bearing capacity. The ANN method gives the std. deviation value equal to 0.19. While, the direct cone penetration test methods give the std. deviation values in the range of 0.23 to 1.05. The standard deviation of the proposed method is least, hence providing more realistic values of pile load carrying capacity.

5. ANN model equations for unit skin resistance and unit tip bearing capacity

These equations have been developed from basic mathematic model of ANN using weights and bias obtained after the training of ANNs. The set of equations for unit skin friction are as follows:

$A1=6.2222\ S_t+0.92914\ q_c-5.9986$
$A3= -0.13945\ S_t-0.24322\ q_c+0.67964$
$B1= 0.19755 \times (e^{A1}-e^{-A1})/(e^{A1}+e^{-A1})$
$B3= -3.0135 \times (e^{A3}-e^{-A3})/(e^{A3}+e^{-A3})$
$f_n=0.44164+ B1 + B2 + B3 + B4$

$A2= -0.34838\ S_t+2.0855\ q_c+3.0211$
$A4= -0.72298\ S_t+2.6835\ q_c-2.1845$
$B2= 1.2308 \times (e^{A2}-e^{-A2})/(e^{A2}+e^{-A2})$
$B4= -0.1103 \times (e^{A4}-e^{-A4})/(e^{A4}+e^{-A4})$

The set of equations for unit tip bearing capacity are as follows:

$A1= 0.66968\ S_t+ 0.33034\ QC -1.9904$
$A3= -0.31377\ S_t+ 1.3758\ QC+ 3.1281$
$B1= 4.4309 \times (e^{A1}-e^{-A1})/(e^{A1}+e^{-A1})$
$B3= 10.8732 \times (e^{A3}-e^{-A3})/(e^{A3}+e^{-A3})$
$q_{tn}= -6.6973+ B1 + B2 + B3 + B4$

$A2 =17.7169\ S_t +2.3622\ QC -1.2835$
$A4= 12.7263\ S_t +0.29427\ QC +7.9198$
$B2= 0.15735 \times (e^{A2}-e^{-A2})/(e^{A2}+e^{-A2})$
$B4= 0.060645 \times (e^{A4}-e^{-A4})/(e^{A4}+e^{-A4})$

$q_t=(q_{max}-q_{min})-(q_{max}-q_{min}) \times (1-q_{tn})/2$

Where q_c is normalized cone resistance, S_t is normalized soil type of soil layer, f_n is normalized unit skin friction, q_{tn} is normalizes unit tip bearing capacity considered in range from -1 to 1. Where f is unit skin friction, q_t is unit tip bearing capacity, f_{max} is maximum unit skin friction, f_{min} is minimum unit skin friction, q_{max} is maximum unit tip bearing capacity and q_{min} is minimum unit tip bearing capacity given in Table 1.

The ultimate pile load capacity (Q) of a bored pile foundation is calculated from:

$$\mathrm{Q} = \mathrm{Q_s} + \mathrm{Q_p} = \sum_{i=1}^{n} (\mathrm{f_i}.\pi.\mathrm{d}.\mathrm{z_i}) + (\mathrm{q_t}.\pi.\mathrm{d}^2)/4$$

Where Q_s = total skin friction, Q_p = tip bearing capacity, f_i = unit skin resistance at i^{th} soil layer, z_i = thickness of i^{th} soil layer, q_t = unit tip bearing capacity, d = diameter of pile and n = number of soil strata layers.

6. Conclusions

The predicting prowess of ANNs has been explored to get the models for the prediction of unit skin friction and unit tip bearing capacity of bored pile foundation. Statistical approach was applied to database of all 35 case histories to check the performance of the ANNs and the other direct cone penetration test methods. The comparison demonstrates that the proposed ANN method is significantly superior to the conventional direct CPT methods. This improvement in the results is due to the inferring capabilities of the artificial neural networks. This comparison also validates FEM used in analysis. The artificial neural network models are presented in the form of equations which can be used by practicing engineers for predicting load carrying capacity of bored piles.

7. References

1. Jaksa MB, Maier H, Shahin MA. Future challenges for artificial neural network modeling. The 12th International Conference of International Association for Computer Methods and Advances in Geomechanics. 2008, 1710-1719.

2. Vesic AS. Design of pile foundations. National Cooperative Highway Research Program. Synthesis of Practice No.42, Transportation Research Board, Washington, DC, 1977.
3. Poulos HG, Davis EH. Pile Foundation Analysis and Design, Wiley, 1980.
4. Randolph MF, Wroth CP. Analysis of deformation of vertically loaded piles. Journal of Geotechnical Engineering. 1978; 104:1465-1488.
5. Desai CS. Numerical design analysis for piles in sands. Journal of Geotechnical Engineering Division ASCE. 1974; 100(6):613-635.
6. Chin FK. Estimation of the ultimate load of piles from tests not carried to failure. Proceedings of the Second SE Asian Conference on Soil Engineering, Singapore. 1970, 81-92.
7. Fleming W. A new method of single pile settlement and analysis. Geotechnique. 1992; 42(3):411-425.
8. Hadap AM, Laxaman G. Neural Network Based Characterizing Parameters of Coplanar Waveguides. Indian Journal of Science and Technology. 2010; 3(3):243-247.
9. Latha A, Reddy KK, Rao JCS, Raju AVSR. Performance Analysis on Modeling of Loop Heat Pipes Using Artificial Neural Networks. Indian Journal of Science and Technology. 2010; 3(4):463-467.
10. Ashok V, Singh SR, Nirmalkumar A. Determination of Blood Glucose Concentration by Back Propagation Neural Network. Indian Journal of Science and Technology. 2010; 3(8):916-918.
11. Khodadoust S. Application of Artificial Neural Network for Prediction of Retention Time for some Pesticides in Liquid Chromatography. Indian Journal of Science and Technology. 2012; 5(2):2001-2008.
12. Sefat MY, Borgaee AM, Beheshti B, Bakhoda H. Application of Artificial Neural Network (ANN) for Modelling the Economic Efficiency of Broiler Production Units. Indian Journal of Science and Technology. 2014; 7(11):1820-1826.
13. Kia A, Sensoy S. Assessment the Effective Ground Motion Parameters on Seismic Performance of R/C Buildings Using Artificial Neural Network. Indian Journal of Science and Technology. 2014; 7(12):2076-2082.
14. Zebardast B, Maleki I, Maroufi A. A Novel Multilayer Perceptron Artificial Neural Network based Recognition for Kurdish Manuscript. Indian Journal of Science and Technology. 2014; 7(3):343-351.
15. Subramanian JV, Sadiq MAK. Implementation of Artificial Neural Network for Mobile Movement Prediction. Indian Journal of Science and Technology. 2014; 7(6):858-863.
16. Jayaramappa N, Krishna A, Annpurna BP, Kiran T. Prediction of Base Shear for Three Dimensional RC Frame Subjected to Lateral Load using Artificial Neural Network. Indian Journal of Science and Technology. 2014; 7(6):729-733.
17. Dineshkumar R, Suganthi J. Sanskrit Character Recognition System Using Neural Network. Indian Journal of Science and Technology. 2015; 8(1): 65-69.
18. Abinaya R, Kamakshi S. Improving QOS using Artificial Neural Networks in Wireless Sensor Networks. Indian Journal of Science and Technology. 2015; 8(12):63283.
19. Ashaary NA, Ishak WHW, Ku-Mahamud KR. Neural Network Application in the Change of Reservoir Water Level Stage Forecasting. Indian Journal of Science and Technology. 2015; 8(13):70634.
20. Shekar MS, Krishna PM, Venkatesan M. Artificial Neural Network based Prediction of Pressure Drop in Heat Exchangers. Indian Journal of Science and Technology. 2015; 8(9):87-92.
21. Ramakanth M, Balachandar C, Venkatesan M. Prediction of Channel Diameter to Reduce Flow Mal Distribution in Radiators using ANN. Indian Journal of Science and Technology. 2015; 8(9):341-346.
22. Yang Y, Rosenbaum MS. The artificial neural network as a tool for assessing geotechnical properties. Geotech Eng J. 2002; 20(2):149-168.
23. Goh AT. Probabilistic neural network for evaluating seismic liquefaction potential. Can Geotech J. 2002; 39(1):219-232.
24. Ferentinou MD, Sakellariou MG. Computational intelligence tools for the prediction of slope performance. Comput Geotech. 2007; 34(5):362-384.
25. Lee IM, Lee JH. Prediction of pile bearing capacity using artificial neural networks. J Comput Geotech. 1996; 18(3):189-200.
26. Teh CI, Wong KS, Goh ATC, Jaritngam S. Prediction of pile capacity using neural networks. J Comput Civ Engg, ASCE. 1997; 11(2):129-138.
27. Abu-Kiefa MA. General regression neural networks for driven piles in cohesionless soils. J Geotech Geoenviron Eng, ASCE. 1998; 124(12):1177-1185.
28. Maizir H. Kassim KA. Neural network application in prediction of axial bearing capacity of driven piles. Proceedings of the International Multi-Conference of Engineers and Computer Scientists, Hong Kong. 2013; 1:51-55.
29. Azizkandi AS, Kashkooli A, Baziar MH. Prediction of Uplift Pile Displacement Based on Cone Penetration Tests (CPT). J Geotech Geol Eng. 2014; 32:1043-1052.
30. Shahin MA, Jaksa MB, Maier HR. Artificial neural network application in geotechnical engineering. Aust Geomech. 2001, 49-62.
31. Alsamman O. The Use of CPT for Calculating Axial Capacity of Drilled Shaft. PhD Thesis, University of Illinois, Urbana, 1995.
32. Eslami A. Bearing Capacity of Piles from Cone Penetration Data, PhD Thesis, University of Ottawa, Ottawa, Ontario, 1996.
33. Olsen RS, Farr JV. Site characterization using the cone penetration test. Proc. ASCE Special Conference - In Situ '86: Use of In Situ Tests in Geotechnical Engineering, Blacksburg. 1986, 854-868.
34. Lambe TW, Whitman RV. Soil Mechanics, Wiley, New York. 1969, 160.
35. Robertson PK, Campanella RG. Interpretation of cone penetration tests, Part 1: Sand. Canadian Geotechnical Journal. 1983; 20(4):718-733.
36. Chan WT, Chow YK, Liu LF. Neural network: an alternative to pile driving formulae. Comput Geotech. 1995; 17(2):135-156.
37. Goh ATC. Back-propagation neural networks for modeling complex systems. Artif Intell Eng. 1995;

9(3):143-151.
38. Baziar MH, Nilipour N. Evaluation of liquefaction potential using neural networks and CPT results. J Soil Dyn Earthq Engg. 2003, 23.
39. Baziar MH, Ghorbani A. Evaluation of lateral spreading using artificial neural networks. Soil Dyn Earthq Eng. 2005; 25(1):1-9.
40. De-Ruiter J, Beringen FL. Pile Foundations for Large North Sea Structures. Marine Geotechnology. 1979; 3(3):267-314.
41. Bustamante M, Gianeeselli L. Pile Bearing Capacity Predictions by Means of Static Penetrometer CPT. Proceedings of the 2nd European Symposium on Penetration Testing, ESOPT-II, Amsterdam. 1982; 2:493-500.
42. Aoki N, de-Alencar D. An Approximate Method to Estimate the Bearing Capacity of Piles. Proceedings, the 5th Pan-American Conference of Soil Mechanics and Foundation Engineering, Buenos Aires. 1975; 1:367-376.