Sand behavior around pile tip: An ANN Approach

Prabhat Ranjan Jena[1], Dr.M.L.Narasimham[2] and A R Routray[3]
[1& 2] Centurion University of Technology and Management, Paralakhemundi
[3]Fakir Mohan University
[1]prjena@rediffmail.com, [2]deanacademic@cutm.ac.in, [3]ashan2r@yahoo.co.in

Abstract

The prediction of the sand behavior around pile tip is of greatest uncertainty in foundation design. Several traditional methods have been developed to overcome the uncertainty in the prediction. Considering the limitations of traditional methods for predicting pile bearing capacity, further research is required to overcome the difficulties associated with the problem. Intelligent computing approaches like artificial neural networks (ANNs), genetic programming (GP), Fuzzy logic, support vector machines will be used to compare different parameters of piles in the coastal regions of Odisha. The work of prediction of the sand behavior around pile tip covers analysis of geotechnical data from different parts of coastal Odisha, evaluation of capacity and load transfer mechanism and analysis using intelligent computing approach with development of an Expert System. The proposed model will be used for more accurate prediction of the sand behavior around pile tip based on experimental, theoretical and intelligent techniques and development of Load Bearing Expert System for Coastal Odisha. The main objective of this study is to propose an ANN-based predictive model of the sand behavior around pile tip using real PDA and site investigation data.

Keywords: Artificial Neural Network, PDA,

1. Introduction

Pile foundations are used to transfer structural loads deep enough into the ground. Proper estimation of the sand behavior around pile tip is of prime importance in designing geotechnical structures. The maximum amount of the load, which can be carried by the pile shaft, determines the type of pile as piles are classified according to their load-transfer mechanism (friction piles and end-bearing piles).

There are numerous methods for the sand behavior around pile tip and its distribution. Although many attempts have been made to develop analytical or empirical methods for pile bearing capacity estimation (e.g. Meyerhof, 1976; Vesic, 1977; Coyle and Castello, 1981), most of these methods rely on empiricism and they are site specific (Randolph, 2003). The most direct way for determining the axial bearing capacity of piles is static load test (SLT). The test is standardized by American standards test methods (ASTM D1143-07). However, conducting SLT is time consuming, expensive and difficult (Likins and Rausche, 2004). High strain dynamic testing (HSDT) of piles is a current approach for predicting the ABC of piles and its distribution. HSDT is based on one dimensional wave propagation theory and is performed by using a pile driving analyzer (PDA).

Utilization of artificial neural network (ANN) in civil engineering has recently drawn considerable attention. It is generally attributed to the ANN power in finding complex relationship between different parameters when the contact nature between them is unknown (Garret, 1994). Although many researchers have attempted to show the superiority of ANN in predicting the bearing capacity problems, most of them focused on the prediction of ultimate bearing capacity of piles rather than its separate shaft and tip resistances (Goh, 1995; Goh, 1996).

2. Artificial neural network

Artificial neural network(ANN) is a tool used in geotechnical engineering for accurate estimation of pile foundation behavior. Artificial neural network is a flexible non-linear function approximation tool that estimates a relationship between given input and output parameters. Simpson (1990) reported that a specific ANN can be defined using three important components: transfer function, network architecture and learning law. More details on ANN structure are addressed elsewhere (e.g. Hecht-Nielsen, 1990; Maren, et al. 1990; Zurada, 1992; Fausett, 1994; Ripley 1996). However, study by Haykin (1999) recommends that the most well-known type of feed-forward ANNs is Multi-Layer Perceptron (MLP). In feedforward ANNs, the neurons are usually combined into layers. Using neuron connections, signals transmit from input layer through the hidden layer(s) to output layer.

In essence, ANNs designed with a set of parallel layers and several interconnected nodes or neurons in hidden layers. There is also a transfer or activation function along each node which transmits signals to either other nodes or output of the network. The activation function in each node is applied to the net input of that node. The net input of the node is obtained by summation of connection weights as well as a threshold value known as bias.

Among different algorithms for training ANNs, Back-propagation (BP) algorithm is recognized as the most common training algorithm (Dreyfus, 2005). Basically, BP algorithm consists of two passes; a forward pass and a backward pass. In the former, using transfer function, the outputs are calculated and the errors at the actual output unit are determined (Demuth et al. 2007). If the obtained error (mean squared difference between the actual and predicted outputs) is more than adequate, then the error is propagated back through the network and updates the individual weights as shown in Fig. 1. This procedure is called backward pass. Forward and backward passes are repeated several times until the error is converged to a level specified by a cost function such as mean square error (MSE) or root mean square error.

3. Rationale of the Study

Using the procedure suggested by ASTM (D4945-08), various PDA tests conducted at various project sites in Balasore and Bhadrak Districts of Odisha. The tested piles are reinforced and pre-stressed concrete piles with different diameters and lengths. Most of the tests are conducted in cohesionless soils.

Method of analysis: Experimental, Use of Computational Tools like MATLAB to implement intelligent method of proposed model.

The first step in a machine learning problem is the database acquisition. The database creation is necessary to allow the ANNs models observe the environment and learn to make reasonable decisions about the categories of the patterns.

The second step involves the definition of entries of ANN model. The choice of input variables is fundamental to assure the model performance. Variable selection is intended to select the best subset of predictors, removing redundant predictors and defying the curse of dimensionality to improve classification performance

4. Laboratory experiments and Data Collection

Piles placed in coastal regions bears indirect loading during settlement. Both pile and soil move downward due to axial load and surcharge. Intital data has been collected from ridge over dubdubi nallah on lunakundi kasafala gahangadia of coastal Balasore region as shown in Figure 1 with consideration of shielded and unshielded piles. The number of real tests was conducted but training the network required huge data, In this work for determining load bearing capacity of vertical piles under axial load, pile load carrying capacity determination tests using various grain sizes of sand were taken using a moderrn load carrying device which was made in soil testing laboratory of Bemonde Associates, Balasore.

Classification of data from geotechnical studies that performed in the coastal region of Balasore, Odisha, grain size in the project location are as follows.

- Silt & Clay in % (0.075mm to0.001mm) Fine Gravel In % (20mm To 10mm)
- Fine Gravel In % (10mm To 4.75mm)
- Coarse Sand In % (4.75mm To 2.00 mm)
- Medium Sand In % (2.0mm To 0.425mm)
- Fine Sand in % (0.425mm to 0.075 mm)

5 . Back Propagation Neural Network in this work

Based on the classification of data, layers of back propagation with number of layers are selected. Input neurons are selected with parameters like soil properties, grain size of sand, internal friction angle, pile diameter (D) and pile length (L) and converted to [-1, 1] interval. Variables were normalized by its linearity to obtain maximum and minimum.

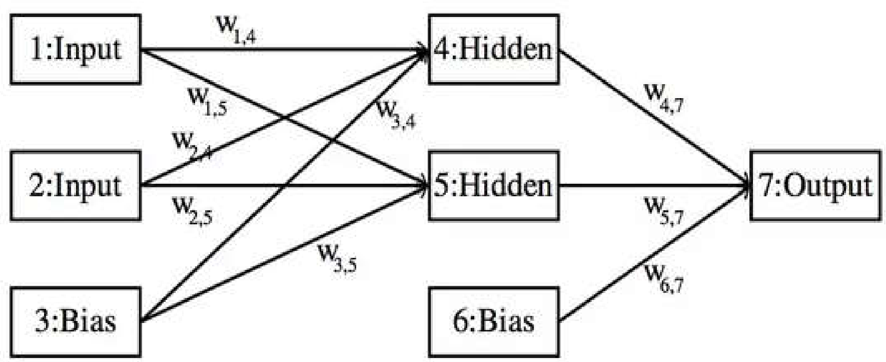

Fig. 1. Model of ANN

Bipolar sigmoid function is selected for activation of each neuron in input, hidden and output layers. Number of hidden layers were used for testing purpose. The networks were compared for training and test data using error parameters. Mean Absolute Error (MAE) and R^2 are considered representing average value of error in training set.

Training and testing networks are performed using neural network toolbox of MATLAB software . The learning rate was calculated and the MAE and R-square is computed by changing number of hidden layers.

In this work, number of hidden layers such as 4, 6, 8 and 10 are tested .

The outputs are back propagated and the weigts of neural network updated during the testing and analysis phase.

Table 1: TESTING ANALYSIS CHART

Location	Depth	Grain size analysis					
		Fine Gravel In % (20mm To 10mm)	Fine Gravel In % (10mm To 4.75mm)	Coarse Sand In % (4.75mm To 2.00 mm)	Medium Sand In % (2.0mm To 0.425mm)	Fine Sand in % (0.425mm to 0.075 mm)	Silt & Clay in % (0.075mm to0.001mm)
BRIDGE OVER DUBDUBI NALLAH ON LUNAKUNDI KASAFALA GAHANGADIA ROAD	0.5MT	0.00	0.00	0.00	0.25	1.41	98.34
	1.5MT	0.00	0.00	0.00	0.17	1.19	98.64
	3.0MT	0.00	0.00	0.00	3.08	13.46	83.46
	4.5MT	0.00	0.00	0.00	2.92	10.52	86.56
	6.0MT	0.00	0.52	0.36	2.48	11.76	84.88
	7.5MT	0.00	0.00	0.37	3.41	6.56	89.66
	9.0MT	0.00	0.00	0.03	7.96	15.57	76.44
	10.5MT	0.00	0.00	0.31	6.91	9.43	83.35
	12.0MT	0.00	0.00	0.25	12.34	22.20	65.21
	13.5MT	7.17	3.40	0.54	13.91	20.94	54.04
	15.0MT	0.00	0.00	0.12	14.30	24.10	61.48
	16.5MT	2.45	2.36	0.79	2.50	9.76	82.14
	18.0MT	0.00	0.00	0.28	8.70	13.57	77.45
	19.5MT	2.58	2.82	0.39	9.28	15.56	69.37

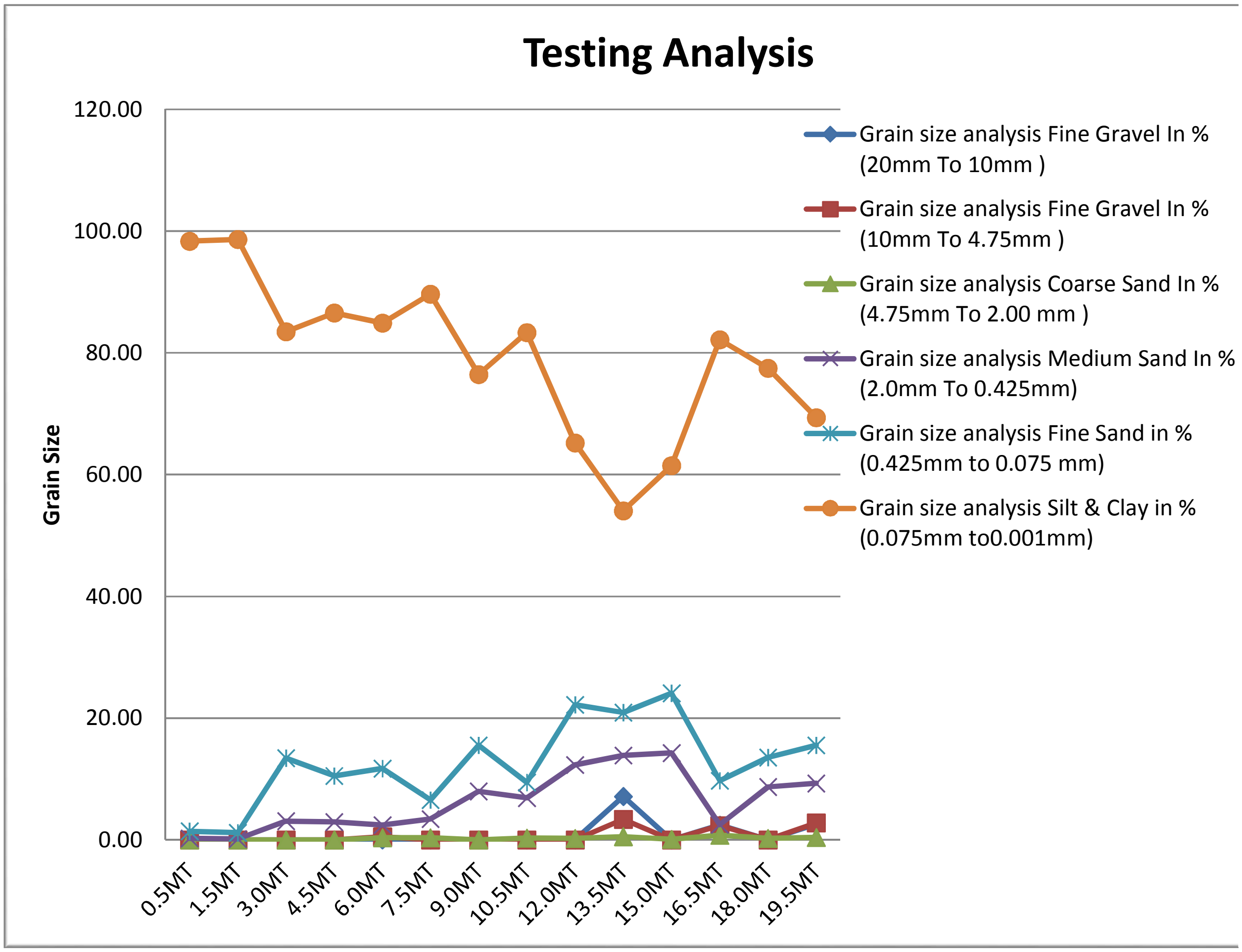

Figure 2: Test Result

The overall prediction performance (for all dataset) of the ANN-based model is summarized in Table. In this table, apart from R^2 and MAE were also used to control the capacity performance of the model.

Output	R2	MAE
QA	0.972	0.098
QB	0.890	0.067
QC	0.910	0.071

Table 2: Performance Metrics

6. Conclusion:

To develop an ANN-based predictive model for the sand behavior around pile tip of piles, 14 testing of depth data like Fine Gravel In % (20mm To 10mm) Fine Gravel In % (10mm To 4.75mm) Coarse Sand In % (4.75mm To 2.00 mm) Medium Sand In % (2.0mm To 0.425mm) Fine Sand in % (0.425mm to 0.075 mm) and Silt & Clay in % (0.075mm to0.001mm)were performed on different concrete piles with various depth values. The tests were mostly performed in cohesionless soils and the results are shown in

Figure 2. For network construction purpose, pile length and cross sectional area, and the average values along the pile shaft and tip were used as inputs while the sand behavior around pile tip and its distribution were set as outputs. Through a trial-and-error procedure, it was found that a network with four hidden nodes in one hidden layer yields the best performance.

References

[1] Predicting pile dynamic capacity via application of an evolutionary algorithm, I. Alkrooshn, H. Nikraz Department of Civil Engineering, Curtin University, Perth, Western Australia, Australia, **Soils and Foundations 2014**;54(2):233–24

[2] Predicting axial capacity of driven piles in cohesive soils using intelligent computing, Iyad Alkroosh, Hamid Nikraz **Engineering Applications of Artificial Intelligence,** Volume 25, Issue 3, April 2012, Pages 618–627, Elsevier

[3] J.E. Bowles **Foundation Analysis and Design** McGraw-Hill, New York (1997)

[4] H. Ardalan, A. Eslami, N. Nariman-Zadeh Piles shaft capacity from CPT and CPTU data by polynomial neural networks and genetic algorithms **Computers and Geotechnics**, 36 (4) (2009), pp. 616–625

[5] M.A. Abu-Kiefa General regression neural networks for driven piles in cohesionless soils **Journal of Geotechnical & Geoenvironmental Engineering**, 124 (12) (1998), pp. 1177–1185

[6] Abu-Kiefa, M. (1998). General regression neural networks for driven piles in cohesionless soils, Journal of Geotechnical and Geoenvironmental Engineering. 124 (12), 1177-1185.

[7] Adarsh, S., Dhanya, R., Krishna, G., Merlin, R. and Tina. J. (2012). Prediction of ultimate bearing capacity of cohesionless soils using soft computing techniques, Artificial Intelligence. doi:10.5402/2012/628496.

[8] Alkroosh, I. and Nikraz, H. (2012). Predicting axial capacity of driven piles in cohesive soils using intelligent computing, Engineering Applications of Artificial Intelligence. 25(3), 618-627.

[9] American Society for Testing and Materials (2010). Standard test methods for deep foundations under static axial compressive load. D 1143-07, Annual Book of ASTM Standards. ASTM, Philadelphia, PA, 4:07.

[10] American Society for Testing and Materials (2010). Standard test method for high-strain dynamic testing of piles, D 4945-08, Annual Book of ASTM Standards. ASTM, Philadelphia, PA, 4, 08.

[11] Ardalan, H., Eslami, A. and Nariman-Zadeh, N. (2009). Piles shaft capacity from CPT and CPTu data by polynomial neural networks and genetic algorithms, Computers and Geotechnics. 36, 616-625.

[12] Benali, A. and Nechnech, A. (2011). Prediction of the pile capacity in purely coherent soils using the approach of the artificial neural networks, International Seminar, Innovation and Valorization in Civil Engineering and Construction Materials, Morocco - Rabat / November 23-25.

[13] Chan, W. T., Chow, Y. K. and Liu, L. F. (1995). Neural network: an alternative to pile driving formulas, Computers and Geotechnics. 17(2), 135-156.