Study of Pile Cap Lateral Resistance using Artificial Neural Networks

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ABSTRACT

The lateral resistance provided by pile caps is often significant, and that in many cases the cap resistance is as large as the lateral resistance provided by the piles themselves. An artificial neural network (*ANN*) model has been developed to study the pile cap resistance under lateral load. The model test facility was developed and the data generated from this facility were used for both training and testing of the *ANN* model. The observed agreement between the findings from the experimentation and the predictions indicate that the model is capable of effectively capturing the phenomenon. From the results of few full scale tests, model test and analytical studies demonstrate about the pile cap lateral resistance. This developed *ANN* model can be effectively used to study the influences of the different parameter on lateral resistance of pile cap.

Key words: lateral resistance, neural network, experimentation.

1. INTRODUCTION

The deep foundations consist of groups of piles coupled together by concrete pile caps. The pile caps, which are often massive and deeply buried, would be expected to provide significant resistance to lateral loads. However, practical procedures for computing the resistance of pile caps to lateral loads have not been developed and for this reason, cap resistance is usually ignored. Neglecting cap resistance results in estimates of pile group deflections and bending moments under load that may exceed the actual deflections and bending moments by 100 % or more. Advances could be realized in the design of economical pile-supported foundations, and their behaviour more accurately predicted, if the cap resistance can be accurately assessed.

Few study of pile cap resistance against lateral load was found in the literature and the findings from these few previous studies indicate that the lateral load resistance provided by pile caps can be very significant, and that in some cases the cap resistance is as large as the resistance provided by the piles themselves. Mokwa (1999) concluded that the pile caps provide significant resistance to lateral load and it was approximately 50 percent of the overall lateral resistance of the pile group foundations. It was found in the literature that the initial study of this phenomenon was carried out by Beatty (1970). He tested two 6 pile groups of step tapered piles and determined that approximately 50 percent of the applied lateral load was resisted by passive pressure on the pile cap. Mokwa (1999) and Mokwa and Duncan (2001) investigated about influence of pile cap under lateral load. He performed full-scale lateral load tests on single piles, pile groups, and pile caps embedded in natural soil and backfilled with granular soil. The pile caps that he tested in his study provided approximately 50 % of the overall lateral resistance of the pile group foundations. The lateral resistance provided by a pile group/pile cap foundation depends on many interacting factors, which were isolated during his study to evaluate their significance. Full-scale testing by Kim et al. (1979) on three different 2 x 3 pile groups indicated that pile cap deflections were "nearly double" for the same lateral loads with the pile cap base friction component removed. Rollins et al. (2001) and Rollins and Sparks (2002) tested a full-scale 3 x 3 pile group under static and dynamic loads and found that passive resistance and base friction provided 40 and 15% of the total resistance, respectively. McVay, et al. (2007) performed a series of lateral load tests on 3 x 3 and 4 x 4 pile groups in loose and medium-dense sands in the centrifuge with their caps located at variable heights to the ground surface. El-Garhy, et al. (2009) presents the results of experimental study on model piles to show the effect of pile cap elevation below the ground surface and pile spacing on lateral resistance of single pile and pile groups driven in sand. The results of the tests show that the lateral carrying capacity of single pile and pile groups increase as the pile cap depth below the ground surface, D_f, increases and as the spacing between piles in the group increases.

Artificial Neural Network (ANN) can be used to deal with the problems involving in complete information. Several authors (Gunaratnam and Gero, 1994; Hajela and Berke, 1991) have used ANN in structural engineering. The study of Neural Networks (NNs) was inspired by biological NNs and was founded by a semi-empirical base to model the behaviour of the biological nerve cell structure. The processing elements (neurons) in a NN simulate the function of nerve cells in human brain that contains billions of interconnected neurons. These neurons are the fundamental elements of the central nervous system and determine any action that is taken.

The objective of the paper is to study of the influences of different parameter in lateral resistance of pile cap using neural network.

2. EXPERIMENTAL STUDY

A laboratory test facility was developed to perform model pile lateral load tests on pile groups and pile caps embedded in natural soil collected from the river bed. The facility was designed specifically for this study to evaluate the lateral resistance provided by pile caps. Two different materials , aluminium and steel are considered for two different diameter of each. The pile lengths are fixed on the basis of the guidelines available in the literature as flexible piles. Two pile lengths are considered. All total nine pile configuration are considered for experimentation. Influences of variation of spacing were also observed by selecting two spacing *3D* and *9D*. A total of two hundred eighty eight experiments were performed at the facility using developed experimental set up.

3. NEURAL NETWORKS (NN) MODEL

Artificial Neural Networks, also referred as Neural Networks (NN), neuro-computers, connectionist networks, parallel-distributed processors etc are intelligent systems inspired by biological neuron systems. ANN is being used to tackle wide gamut of problems in pattern recognition, clustering, function approximation, forecasting/prediction, optimization etc. ANN as models to perform function approximation has been found successful in various engineering problems and is being widely applied in Traffic Engineering problems. A typical Multi Forward Neural Network (MFNN) has three layers: the input layer, the hidden layer, and the output layer. Since NN has the capability of learning (Lee and Lee, 2003).The most popular and successful learning algorithm used to train MFNNs in areas such as pattern recognition, function fitting speech and natural language processing and system modelling is the Back Propagation (BP) algorithm. Standard back propagation is a gradient descent algorithm, in which the network weights are moved along the negative of the gradient of the performance function. Properly trained back propagation networks tend to give reasonable answers when presented with inputs that they have never seen. A typical NN architecture has been shown in Figure 1.

The number of input neurons is determined from the variables that influence concrete strength because there are too many variables. In present problem only six input parameters namely (i) number of pile, (ii) pile lengths, (iii) pile diameter, (iv) pile and cap material, (v) pile cap position and (vi) spacing are considered.

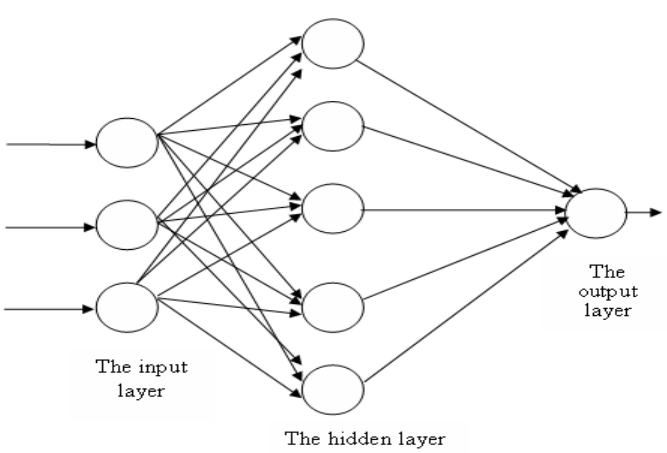

Figure 1: The typical NN Architecture

MATLAB is a mathematical computing software having ANN toolbox which has inbuilt NN architectures, learning, training functions. MATLAB is widely accepted because of its matrix/vector notations and graphics, and has a convenient environment to experiment with ANN. A MATLAB programming has been done using inbuilt functions to develop a Feed Forward Neural Network model with error back propagation learning rule (Rafiq. et al., 2001; Wang and Ni, 1999; Seung, 2002). The following parameters are to be decided for use of ANN algorithm using MATLAB:

- Network Type.
- Number of layers.
- Number of neurons.
- Input Ranges.
- Transfer function.
- Adaptation learning rule.
- Training Function.
- Performance function

3.1. Training and Testing Set Preparation

Data has been collected from developed experimental facility. Total 288 data set is considered to study about the application of NN in lateral resistance of pile cap. It is varying in different range. So, to make database acceptable to the neural network, it has been used to carry out normalization process. The transformation function, which will convert original data range to come between 0.10 to 0.90, is given as:

$$X = \frac{0.8x}{(b-a)} + \frac{(0.1b - 0.9a)}{(b-a)}$$

Where,

x = value of a variable in the original data range,

X = value of same variable in the range of 0.10 to 0.90.

a = minimum value of variable in the original range

b = maximum value of same variable in the original range.

Similarly, while calculating the error values between the observed and predicted outputs, the converted range should be back converted to lie in the original range through a Back-transformation function. This back-transformation is given as below:

$$x = \frac{X(b-a)}{0.8} + \frac{(0.9a - 0.1b)}{0.8}$$

Now, after normalization, database is divided in two subsets namely (i) Training Set, and (2) Testing set.

3.2. Training Set

Out of 288 data available , 66 % data set is selected randomly for the training. This training set is considered to have knowledge representation to make the neural network learn efficiently.

3.3. Testing Set

The testing set comprises of 33% data samples, which are other than that chosen while forming the training set. This testing set is used to evaluate the predictive capability of neural network after training it with the training set. The testing set is also a random representation of data points from the original database.

4. EXPERIMENTATION

The effects of pile lengths, pile diameter, position of pile cap, spacing of pile in group and pile material (viz. aluminium and steel) in lateral cap resistance is observed in the laboratory. Few results of 4 x 1 pile group only are shown in Figures 2 to 5.

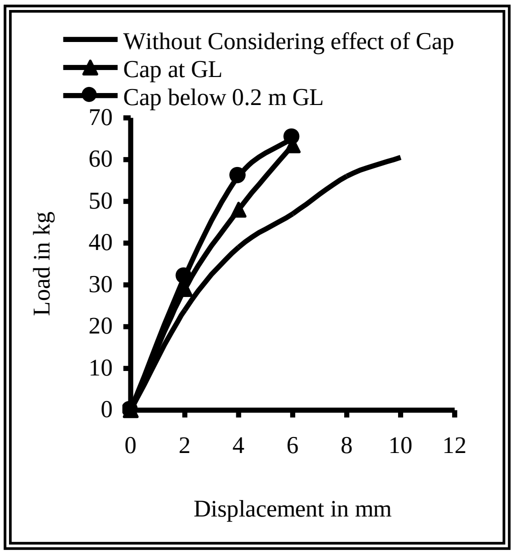

Figure 2: 3*D* Spacing & model pile length=775 mm (At GL-34.98% , Below 0.2m GL-38.94%)

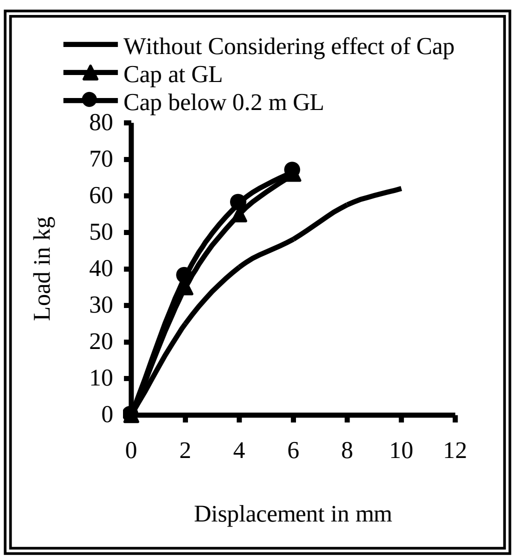

Figure 3: 3*D* Spacing & model pile length=900 mm (At GL-36.93% , Below 0.2m GL-38.59%)

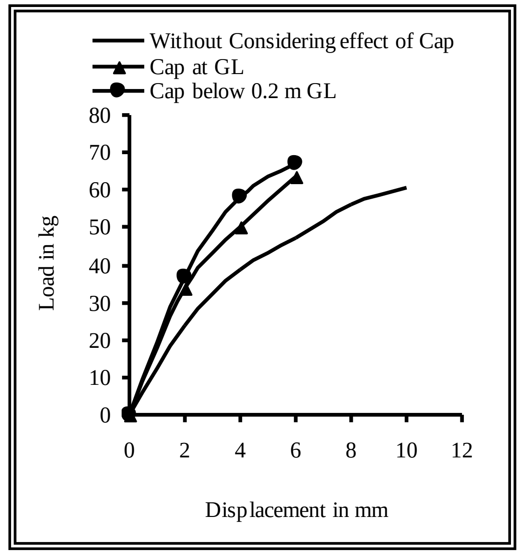

Figure 4: 9*D* Spacing & model pile length=775 mm (At GL-35.74% , Below 0.2m GL-42.34%)

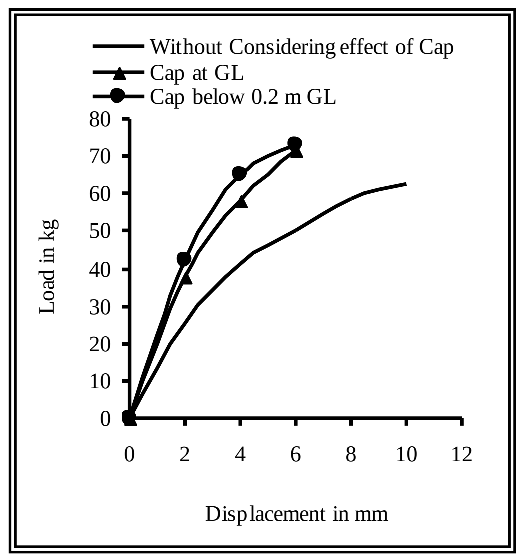

Figure 5: 9*D* Spacing & model pile length=900 mm (At GL-43.20% , Below 0.2m GL-45.90%)

It is observed that all the considered parameters influences on lateral resistance of pile cap. The lateral resistance of pile cap increases as increases of pile diameter, pile lengths , pile spacing and position of pile cap. The most influencing parameters is position of pile cap, as increasing the depth of pile cap from the ground level the pile cap lateral resistance also increases. This can be attributed that the passive restack of soil increases as increasing of pile cap depth from the ground level. Next to this spacing also plays a vital role on the issue. This is obvious as at higher spacing because of pile soil pile interaction the lateral resistance of cap increases.

5. IMPLEMENTATION PROCESS AND RESULTS

A multi-layer feed forward network of three layers has been used having one input and output layer each. The input layer has six neurons each representing an input variable of the problem. The output layer has only single neuron, which has the concrete strength. The hidden number of layer is chosen to be one and number of neurons present in this layer is determined by trial and error approach to give the mean square error of training and testing samples as minimum (Haykin, 1999; Lee and Lee, 2003).

The parameter used for ANN Algorithm is tabulated in Table 1.

Table 1. ANN Algorithm for Parameters Used

Network Type	Feed Forward Back propagation (NEWFF)
Transfer Function	Tansig, purelin
Network Training Function	Trainlm
Network Performance Function	Msereg

5.1. Training and Testing of NN

To train the data in MATLAB programming, Levenberg-Marquardt algorithm is used because it appears to be the fastest method for training moderate-sized feed forward neural networks. It also has a very efficient MATLAB implementation, since the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB setting.

6. RESULTS FROM THE NN

The Figure 6 shows the lateral pile cap resistance observed from the experimentation and the predicted values by NN for testing data set. The observed errors are (i) correlation coefficient =0.923, (ii) mean absolute error = 0.033911743, (iii) mean squared error = 3.18786635, (iv) normalised mean square error = 0.150584761 and (v) total number of instances = 100.

Thus it is obvious that the NN deliberately deal with the phenomenon and thus able to predict about the pile cap lateral resistance preciously.

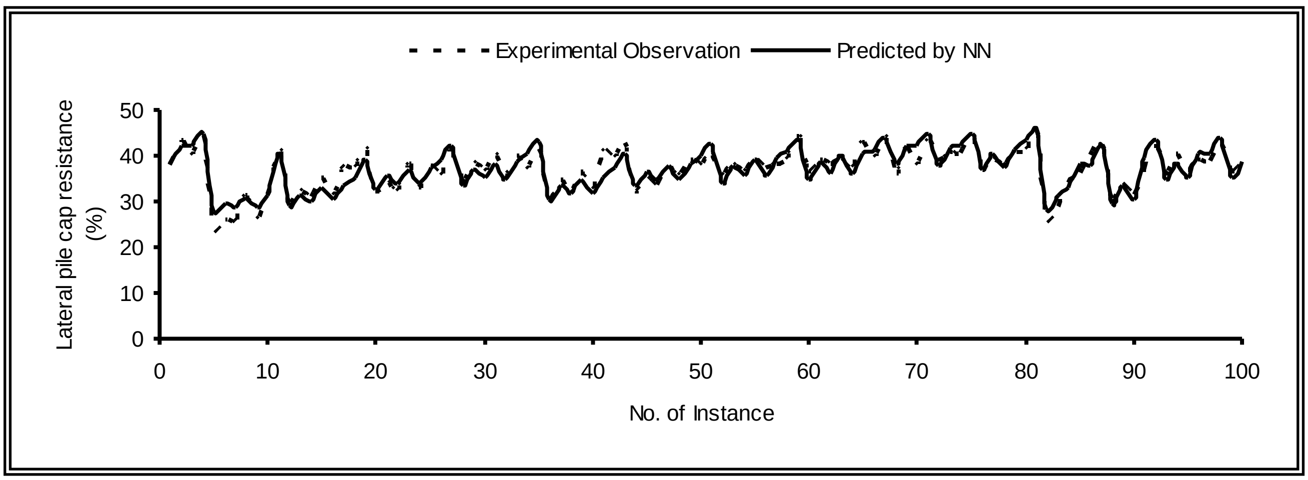

Figure 6: Comparative results of pile cap lateral resistance by experimentation and neural network

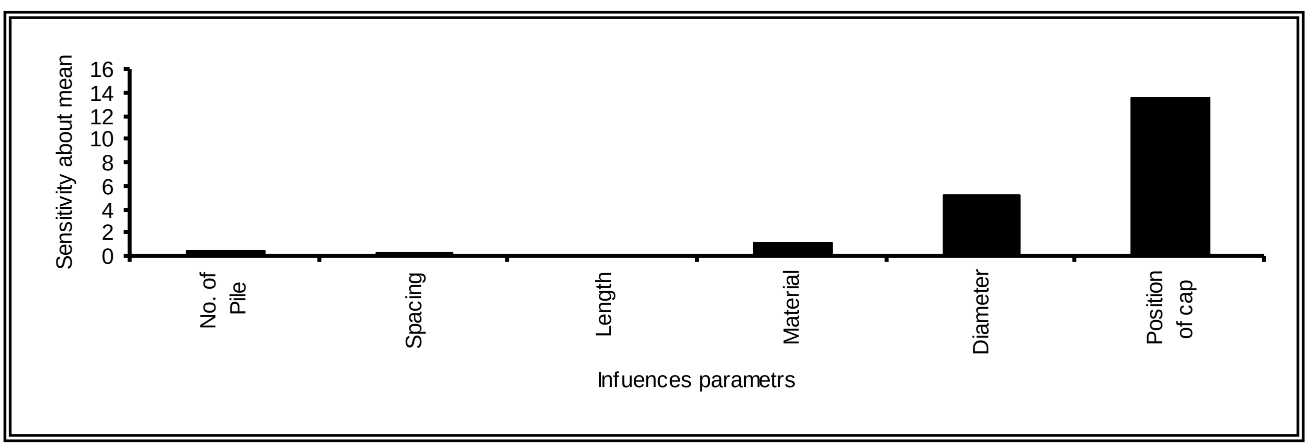

Figure 7: Sensitivity about the mean by neural network

The sensitivity of predicted lateral resistance of pile cap by NN about the mean is shown in Figure 7. It is obvious from the Figure 7 that the position of pile cap is the most influencing parameter of lateral resistance of pile cap.

6.1. Influences of Parameter on Pile cap Lateral Resistance

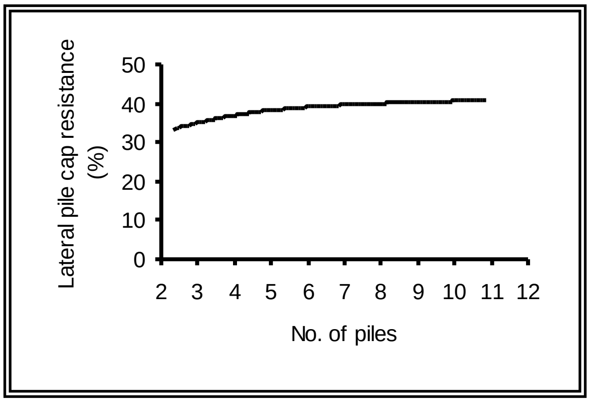

Figure 8: No. of pile vs. pile cap resistance

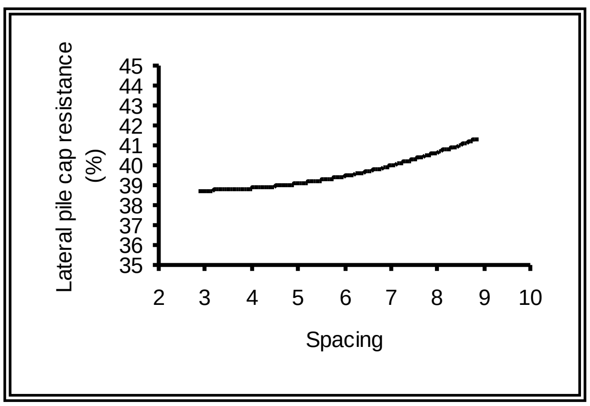

Figure 9: Spacing of pile vs. pile cap resistance

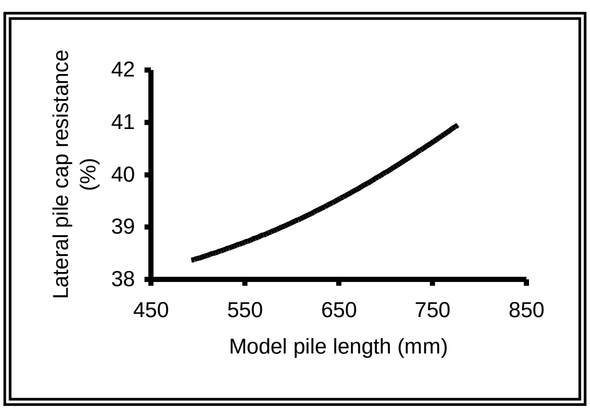

Figure 10: Pile length vs. pile cap resistance

The standard deviation from the mean for number of pile, spacing of pile, pile length, pile diameter and position of pile cap are 2.005578, 0.781968, 0.764933, 1.208065 and 1.365047 respectively. The influencing pattern of the different parameter on the predicted output by NN is shown in Figures 8 to 12. Thus it is obvious from these figures also the position of pile cap plays the important role on pile cap lateral resistance.

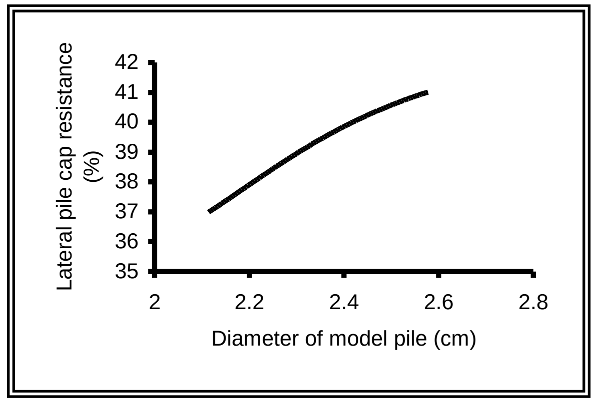

Figure 11: Pile Diameter vs. pile cap resistance

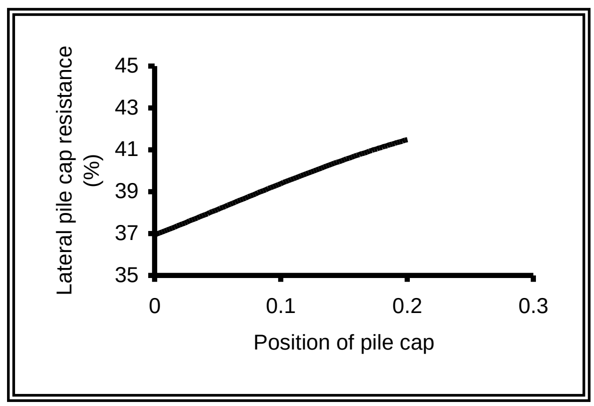

Figure 12: Position of pile cap vs. pile cap resistance

7. CONCLUSION

This study highlighted few important point of lateral resistance of pile cap. The sensitivity analysis from the mean implies that the all the parameters influence the lateral resistance of pile cap. But these variation are different for the different factor. With high correlation coefficient, lesser MAE, MSE and NMSE, the neural network is found to work well for this data set for predicting pile cap lateral resistance. Result with the data set suggests that neural network can effectively be used in this type of complex problem of civil engineering.

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