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MODELING LOAD-SETTLEMENT CURVES OF BEHAVIOR OF BORED PILES USING ARTIFICIAL NEURAL NETWORKS

Iyad Alkroosh [1], Mohamed Shahin [2], Hamid Nikraz [3]
[1, 2, 3] Curtin University of Technology, Perth, Western Australia
[1] PhD Candidate, phone: (+618) 92661782, e-mail: iyad.alkroosh@postgrad.curtin.edu.au
[2] Senior Lecturer, phone: (+618) 92661822, e-mail: M.Shahin@curtin.edu.au
[3] Professor, phone: (+618) 92661624, e-mail: H.Nikraz@curtin.edu.au

ABSTRACT: Accurate prediction of pile behavior under axial loads is necessary for safe and cost effective design. This paper presents the development of a new model, based on artificial neural networks (ANNs), to predict the load-settlement relationship of behavior of bored piles subjected to axial compression loads. ANNs have been recently applied to many geotechnical engineering problems and have shown to provide high degree of success. In this paper, two ANN models are developed; one for bored piles installed in sand and mixed soils, and the other for cohesive soils. The data used for ANN model development are collected from the literature and comprise a series of in-situ bored pile load tests as well as cone penetration test (CPT) results. Predictions from the ANN models are compared with those obtained from the experimental tests, and statistical analysis is used to assess the performance of ANN models. The results indicate that ANN models are able to accurately predict the load-settlement relationships of behavior of bored piles with high accuracy.

1. Introduction

Strength and serviceability requirements are two factors that govern the design process of pile foundations and in order to satisfy these requirements, the load-settlement relationships of pile behavior need to be accurately identified. In this respects, the in-situ pile load testing is needed; however, the in-situ load testing is not always available due to its cost and time consumption. Alternatively, the pile load-settlement relationships can be predicted using analytical or numerical methods. However, the behavior of pile load-settlement in different soil types is complex and not yet entirely understood. Consequently, most available methods failed to produce consistent success for predicting the load-settlement behavior of pile foundations. In this regard, ANNs can be used to provide more accurate solution. The modeling advantage of ANNs over traditional methods is the ability of ANNs to capture the nonlinear and complex relationship of pile behavior without the need for a priori formula of what could be this relationship. In recent times, artificial neural networks have been successfully applied to many geotechnical engineering problems (e.g. Penumadu and Zhao, 1999; Banimahd et al., 2005; Shahin and Indraratna, 2006).

This paper aims to: (i) utilize the ANN modeling technique to simulate the load-settlement relationship of behavior of bored piles installed in cohesionless, mixed and cohesive soils; (ii) compare the performance of the developed ANN model with experimental results; and (iii) measure the accuracy of the ANN model using statistical analyses.

2. Overview of artificial neural networks

Artificial neural networks (ANNs) are problem solving technique that tries to mimic the function of the human brain and nervous system. The type of the neural network used in this study is the multilayer perceptrons (MLPs) trained with the back-propagation algorithm (Rumelhart et al., 1986). Full description of this type of neural networks is beyond the scope of this paper and can be found in many publications (e.g. Fausett, 1994). An MLP is usually composed of three layers; an input layer, intermediate hidden layer and output layer. Each layer consists of a number of processing elements, known as nodes or neurons. The processing elements of each layer are fully or partially connected to the nodes of the other layers via weighted connections. The network is trained to gain its knowledge about specific problem by presenting a set of input patterns and the corresponding target patterns. The input patterns are fed to the network to produce predicted output patterns. The output patterns are compared with the target patterns and the summation of the squared error is calculated. The error is then back propagated through the network and a gradient-descent rule is used to modify the connection weights and to minimize the summed squared error. The above process is continued until a stopping criterion is met.

As the pile load-settlement curves involve interdependency between the current and previous states of load-settlement points, the sequential (recurrent) neural network is used. The sequential neural network was first proposed by Jordan (1986) and consists of two sets of input units; plan units and current state units. The role of the current state units is to remember past activity and during training, patterns of input data are presented to the plan units while the current state units are set to zero. At the first training epoch, the output is produced and copied back to the current state units for the next training epoch. This process continues until the end of the training phase. The performance of the trained network is then tested using an independent validation set.

3. Development of ANN Models

In this work, ANN models are developed using the commercial available software package *Neuroshell 2*, release 4.0 (Ward, 2000). Two ANN models are developed in this work; one for bored piles installed in sand and mixed soils, and the other for piles located in cohesive soils. All piles are subjected to slow maintained axial compression loads. The data used for ANN model development are collected from the literature and comprise experimental results of 66 load-settlement tests as well as cone penetration test (CPT) results. The database consists of 58 cases reported by Alsamman (1995), 6 cases reported by Eslami (1996) and 2 cases reported by Milovic (1989). The number of cases for piles in sand and mixed soils is 50, and for piles in cohesive soils is 16. The piles have different sizes and circular shapes with diameters ranging from 320 to 1800 mm, and lengths from 6 to 27 m. Since the piles considered in the current study have a wide range of diameters, they are classified into two categories; small-diameter piles (for pile diameter < 600 mm) and large-diameter piles (for pile diameter > 600 mm). This classification is in accordance with Ng et al. (2004) and is based on the fact that large-diameter piles may behave differently in comparison with small-diameter piles.

In order to accurately predict the pile load-settlement relationship, the significant factors that influence the load-settlement behavior need to be identified and presented to the neural network as input variables. These include the pile geometry and soil properties. The pile geometry is represented by the pile diameter, D, and pile embedment length, L. The soil properties are represented by the weighted average cone point resistance over pile tip failure zone, $q_{c\text{-}tip}$, and weighted average cone point resistance over shaft length, , $q_{c\text{-}shaft}$. These input variables represent the plan units of the neural network, as shown in Figure 1. In simulations of the pile load-settlement curves, the current state of load and settlement governs the next state of load and settlement. Thus, a typical neural network for pile load-settlement modeling includes current state nodes, which as mentioned previously, are processing elements that remember past activity (i.e. memory nodes). At the beginning of the training process, the inputs for the current state of load and/or settlement are set to zero and training proceeds to predict the next expected state of load and/or settlement for an input load or settlement increment. The predicted load and/or settlement are then copied back to the current state nodes for the next pattern of input data. The inputs to the ANN models in the current state units are the current state of load, P_i, current normalized settlement, ε_i (where ε_i = settlement/pile diameter) and normalized settlement increment, $\Delta\varepsilon_i$, as shown in Figure 1. The single output is the next state of load, P_{i+1}.

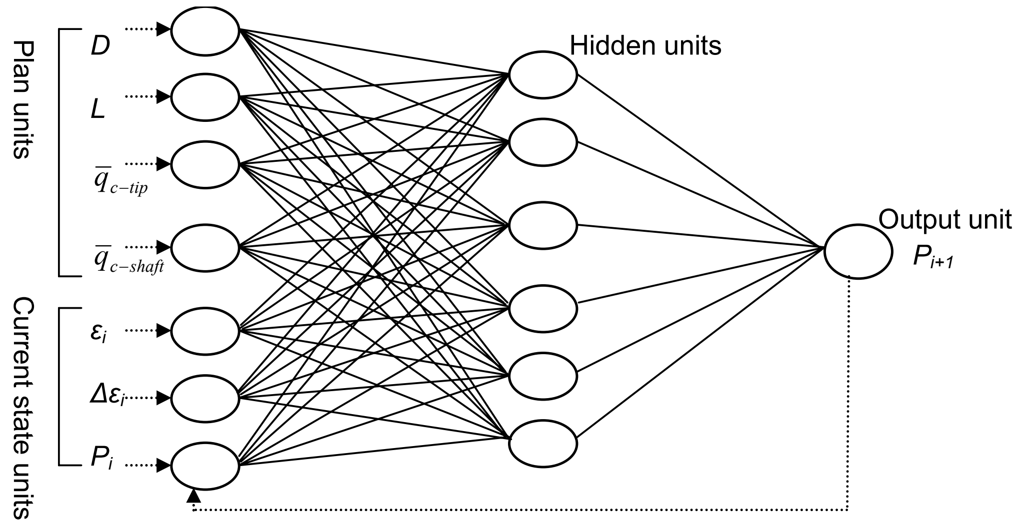

Fig. 1. Schematic representation of the structure of ANN models

In this study, the following varying normalized settlement increments are chosen: 0.01, 0.02, 0.03, …, 0.1, 0.11. As recommended by Penumadu and Zhao (1999), using varying strain increment values results in good modeling capability without the need for a large size of training data. Because the data needed for the ANN models at the above settlement increments were not recorded in the original experiments of the pile load-settlement tests, the curves of the available tests were digitized to obtain the required data. A set of 50 training patterns was used to represent a single load-settlement curve.

It should be noted that for small-diameter piles, the failure zone over which $q_{c\text{-}tip}$ is averaged was taken in accordance with Eslami (1996), in which when the pile tip is located in a homogenous soil, the failure zone extends 4*D* below and above the pile tip, whereas when the pile tip is located in a strong soil layer above which a weak layer exists, the failure zone extend from 4*D* below and 8*D* above the pile tip. On the other hand, when the pile tip is located in a weak layer beneath a dense stratum, the failure zone extends from 4*D* below to 2*D* above the pile tip. For large-diameter piles; however, the failure zone is taken in accordance with Alsamman (1995) to be 1*D* below the pile tip. It should be also noted that several pile load tests include mechanical rather than electric CPT data and thus, it was necessary to transform the mechanical CPT readings into equivalent electric CPT values. This was carried out using the correlation proposed by Kulhawy and Maine (1990), as follows:

$$\left(\frac{q_c}{p_a}\right)_{Electric} = 0.408\left(\frac{q_c}{p_a}\right)^{1.19}_{Mechanical} \qquad (1)$$

where; p_a is the atmospheric pressure, and p_a and q_c are in kPa.

The next step in development of the ANN model is the data division. In this work, the data are randomly divided into two statistically consistent sets, as recommended by Masters (1993) and detailed by Shahin et al. (2004). This includes a training set for model calibration and an independent validation set for model verification. In total, 41 case records (80%) of the available 50 cases of piles installed in sand and mixed soil were used for training and 9 cases (20%) for validation. On the other hand, 13 case records (80%) of the available 16 cases of piles located in cohesive soil were used for training and 3 cases (20%) for validation. The statistics of the data used for the training and validation sets for piles in sand and mixed soil are given in Table 1, which includes the mean, standard deviation, minimum, maximum and range. For brevity, the statistics of the data used for piles in cohesive soils are not shown. It should be noted that, like all empirical models, ANN performs best in interpretation rather than extrapolation, thus, the extreme values of the data used were included in the training set.

Table 1. ANN input and output statistics for piles in sand and mixed soil

Model variables and data sets	Statistical parameters				
	Mean	Standard deviation	Minimum	Maximum	Range
Pile diameter, *D* (mm)					
Training set	591	327	320	1800	1480
Validation set	625	412	320	1500	1180
Pile embedment length, *L* (m)					
Training set	11	5	6	27	21
Validation set	9	4	6	17	11
Weighted average cone point resistance along pile tip failure zone, $\overline{q}_{c-tip}$ (MPa)					
Training set	18	11	2	48	46
Validation set	17	9	6	31	25
Weighted average cone point resistance along shaft length, $\overline{q}_{c-shaft}$ (MPa)					
Training set	9	4	1	20	19
Validation set	9	6	3	19	16

The following step in development of the ANN model is determining the optimal model geometry. A network with one hidden layer is used in this study, as Hormik et al (1989) recommended that one hidden layer can approximate any continuous function provided that sufficient connection weights are used. The trial-and-error approach is used to determine the optimum values of network parameters. In the first stage, the number of hidden nodes was determined by assuming the following neural network parameters: initial connection weights of 0.3, learning rate of 0.1, momentum term of 0.1, tanh transfer function in the hidden layer and sigmoidal transfer function in the output layer. Several neural networks were then trained assuming the following number of hidden nodes; 2, 3, 4, …, ($2I$+1); where I is the number of inputs, as recommended by Caudill (1988). The optimum model parameters is achieved by training the network with different combinations of learning rates (i.e. 0.05, 0.1, 0.15,…, and 0.6) and momentum terms (i.e. 0.05, 0.1, 0.15, …, and 0.6). The mean squared error, MSE, between the actual and predicted values of the pile loads in the validation set was used as stopping criterion to terminate training. Whenever the MSE of the validation set has reached the lowest value with no improvement in performance of the training set, training is stopped and the output is examined.

4. Results and model validation

Two good models were selected for predicting the load-settlement relationship of bored piles; Model 1 for piles installed in sand and mixed soils; and Model 2 for piles located in cohesive soils. These models were selected because they have minimum number of hidden nodes accompanied with high and consistent performance in the training and validation sets. The model that was found to perform best for bored piles installed in sand and mixed soils is composed of six hidden layer nodes, learning rate of 0.08 and momentum term of 0.3. The model that was found to perform best for bored piles located in cohesive soil includes eight hidden layer nodes, learning rate of 0.3 and momentum term of 0.1.

The performance of the optimum ANN models, i.e. Models 1 and 2, in the training sets and the predictive ability of the models in the validation sets are depicted in Figures 2 and 3, respectively. It should be noted that the dotted lines in Figures 2 and 3 represent the experimental data while the solid lines are for the ANN model predictions. For brevity, only some representative curves are selected and presented in Figures 2 and 3, which show good performance of the developed ANN models.

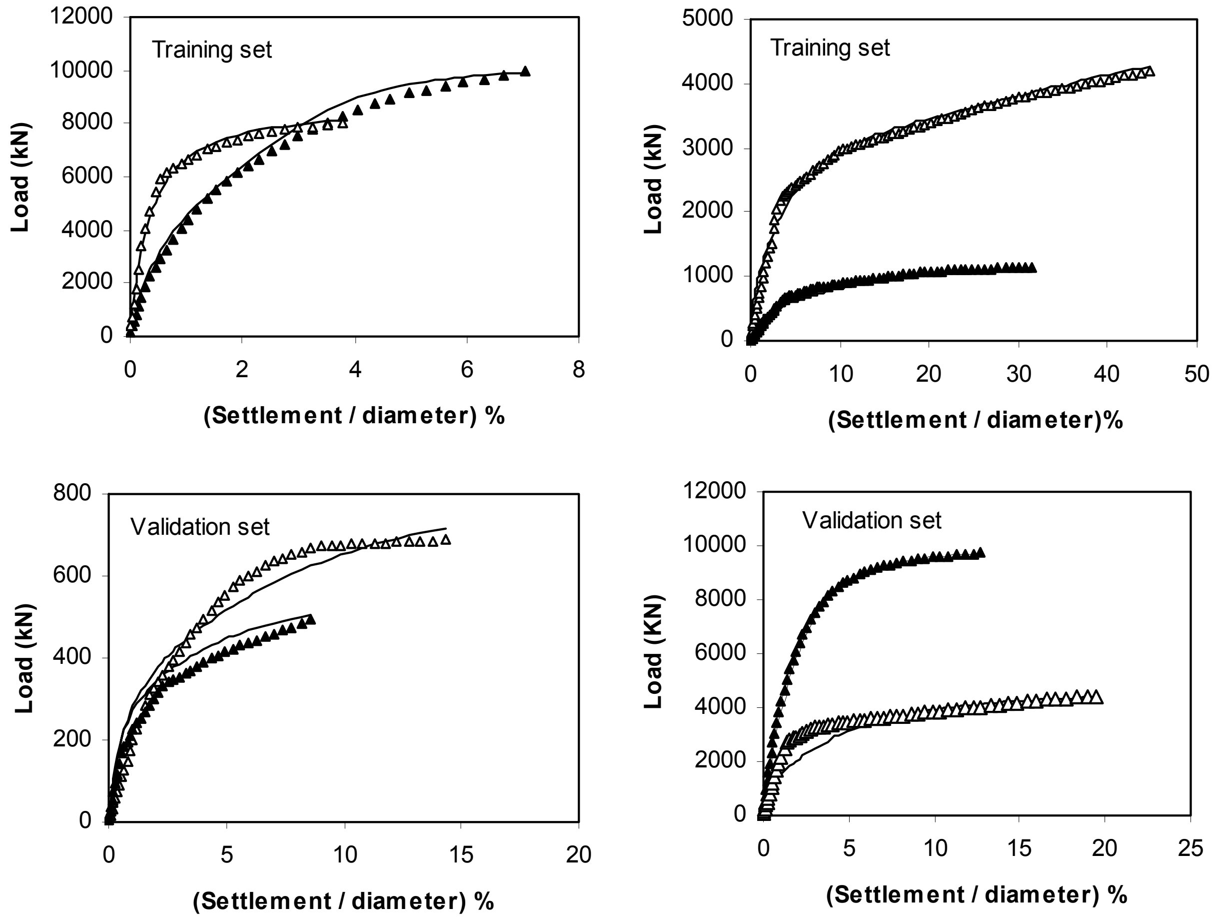

Fig. 2. Some simulation results of the developed ANN Model 1 in training and validation sets

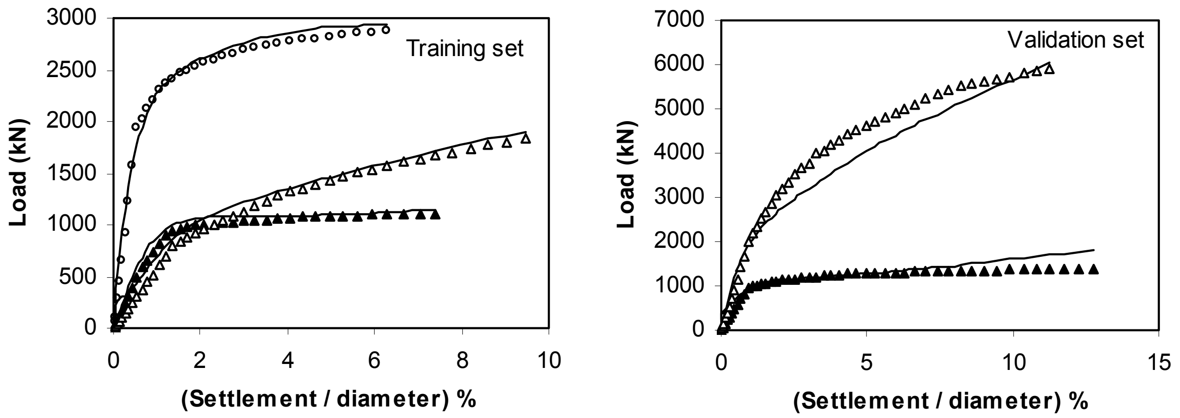

Fig. 3. Some simulation results of the developed ANN Model 2 in training and validation sets

It can be seen from Figures 2 and 3 that the complex nonlinear relationship of pile load-settlement is well simulated by the ANN models including the strain hardening behavior. The performance of the developed models is also measured analytically using the coefficient of correlation, r, in the training and validation sets and the results are given in Table 2. It can be seen that both ANN models perform well with high r of 0.98 and 0.97 in the training and validation sets, respectively, for Model 1, and r = 0.99 and 0.98 in the training and validation sets, respectively, for Model 2. The above results demonstrate that the ANN models are able to accurately predict the nonlinear behavior of pile load-settlement in different soil types, hence, can be used with confidence for routine design practice.

Table 2. Performance of the ANN models in the training and validation sets

Piles group	Data set	Correlation coefficient, *r*
Piles in sand & mixed soil	Training	0.98
	Validation	0.97
Piles in cohesive soil	Training	0.99
	Validation	0.98

5. Conclusions

This paper proposed an artificial neural network approach as a potential alternative to estimate the load-settlement relationship of bored piles subjected to axial compression loads. Two models were developed; one for piles installed in sand and mixed soils and the other for piles located in cohesive soil. The results indicate that the ANN models are capable of accurately predicting the complex nonlinear behavior of pile load-settlement with high degree of accuracy. The statistical analysis of the coefficients of correlation indicate high values close to unity in the training and testing sets used for ANN model development.

6. References

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