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PREDICTING LOAD-SETTLEMENT RELATIONSHIP OF DRIVEN PILES IN SAND AND MIXED SOILS USING ARTIFICIAL NEURAL NETWORKS

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Abstract

An accurate prediction of pile behaviour 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 driven piles in sand and mixed soils, and subjected to axial loads. ANNs have been recently applied to many geotechnical engineering problems and have shown to provide high degree of success. Two models are developed; one for steel piles and the other for concrete piles. The data used for ANN models development are collected from the literature and comprise a series of in-situ driven piles load tests as well as cone penetration test (CPT) results. Predictions from the ANN models are compared with the results of experimental data, and statistical analysis is conducted to verify the performance of ANN models. The results indicate that ANN models perform well and able to predict the pile load-settlement relationship quite accurately.

Keywords: driven piles, artificial neural networks, load-settlement, sand soil, CPT

1. Introduction

It is well known that bearing capacity and settlement are the two main factors that govern the design process of pile foundations so that safety and serviceability requirements are achieved. In order to satisfy these requirements, the load-settlement relationship needs to be accurately identified. The in-situ pile load testing is the most reliable method for this purpose. However, this option is not always available because it is expensive and time consuming. Alternatively, the pile load-settlement relationship can be predicted and used for design. Currently, there are two approaches to estimate the pile load-settlement relationship; empirical or analytical. However these approaches can not provide an accurate and consistent prediction of pile load-settlement relationship because the behaviour of pile in different soil types is complex and not entirely understood. In this respect, artificial neural networks (ANNs) may 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 behaviour 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. 1, 2, 3].

This paper aims to: (i) utilize the ANN technique to simulate the load-settlement relationship of driven piles in sand and mixed soils; (ii) compare the performance of the developed ANN model with experimental results; and (iii) measure the accuracy of the ANN model using statistical analysis.

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 neural network used in this study is the multilayer perceptrons (MLPs) trained with the back-propagation algorithm [4]. Full description of this type of neural networks is beyond the scope of this paper and can be found in many publications [e.g. 5]. The 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 relationship involves 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 [6] and consists of two sets of input units; i.e. 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 [7]. Two ANN models are developed for piles installed in sand and mixed soil; one for steel piles and the other for concrete piles. The data used for ANN model development are collected from the literature and comprise experimental results of 60 load-settlement tests as well as cone penetration test (CPT) results that are reported by Eslami [8]. The piles have different sizes and shapes with equivalent diameters ranging from 250 to 660 mm and lengths from 8 to 36.3 m. The piles 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. [9] and 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 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 equivalent pile diameter, D_{eq}, which is taken as the pile perimeter/π, and pile embedment length, L. The soil properties are represented by the weighted average cone point resistance over the pile tip failure zone, $\bar{q}_{c-tip}$, weighted average cone point resistance over the shaft length, $\bar{q}_{c-shaft}$, and weighted average sleeve friction over the shaft length, $\bar{f}_s$. 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 element 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}.

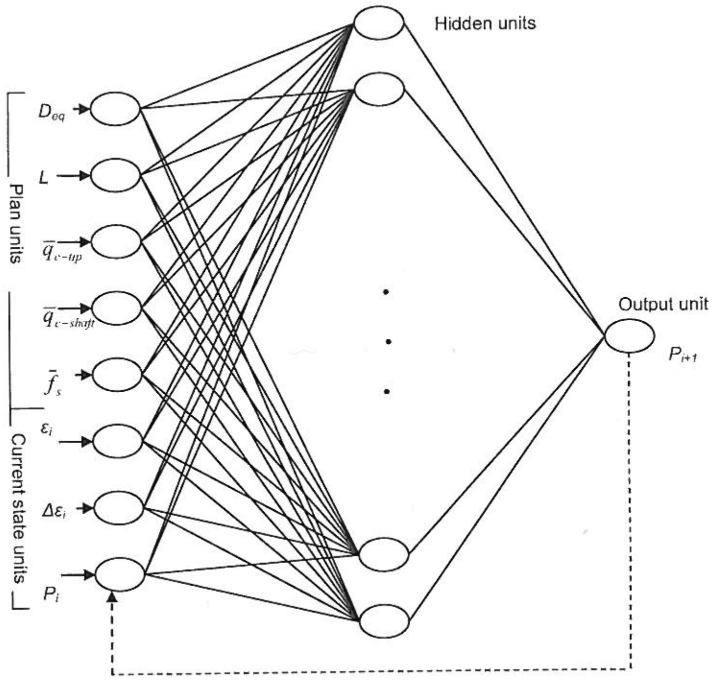

Figure 1. Schematic representation of the structure of ANN models

In this study, the varying normalized settlement increments are chosen as: 0.01, 0.02, 0.03, ..., 0.1, 0.11. As recommended by Penumadu and Zhao [10], 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 40 training patterns was used in representing 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 [8], 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 [11] 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 Mayne [12], 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. For f_s values, the mechanical cone gives higher readings than the electrical cone in all soils and Kulhway and Mayne [12] suggested a ratio of 2 for sand which is adopted in the current study.

The next step in development of the ANN models is the data division. In this work, the data are randomly divided into two statistically consistent sets, as recommended by Masters [13] and detailed by Shahin et al. [14]. This includes a training set for model calibration and an independent validation set for model verification. In total, 26 steel pile case records (84%) of the available 31 cases of steel piles were used for training and 5 cases (16%) for validation. On the other hand, 24 concrete case records (83%) of the available 29 cases of concrete piles were used for training and 5 cases (17%) for validation. The statistics of the data used for the training and validation sets of the steel piles are given in Table 1, which includes the mean, standard deviation, minimum, maximum and range. For brevity, the statistics of the data used for the concrete piles 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 of the steel piles

Model variable and data sets	Statistical parameters				
	Mean	Standard deviation	Minimum	Maximum	Range
Equivalent pile diameter, D_{eq} (mm)					
Training	395.8	101.7	273.0	660.0	387.0
Validation	412.8	123.4	300.0	609.0	309.0
Pile embedment length, L (m)					
Training	17	7.1	8.5	36.3	27.8
Validation	23.8	11.6	11.1	34.3	23.2
Weighted average cone point resistance along pile tip failure zone, $\overline{q}_{c-tip}$ (MPa)					
Training	7.2	8.2	0.0	23.9	23.9
Validation	3.1	3.9	0.0	8.7	8.7
Weighted average cone point resistance along shaft length, $\overline{q}_{c-shaft}$ (MPa)					
Training	9.5	5.6	1.5	17.6	16.1
Validation	8.0	6.9	1.4	15.5	14.1
Weighted average sleeve friction along shaft length, $\overline{f}_s$ (kPa)					
Training	57.2	23.9	18.0	131.0	113.0
Validation	42.4	19.4	19.0	65.0	46.0

The following step in the 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 [15] 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 the network parameters. In the first stage, the number of hidden nodes was determined by assuming the following values of neural network parameters; initial connection weight of 0.3, learning rate of 0.1 and momentum term of 0.1, tanh transfer function in the hidden layer and sigmoidal transfer function in the output layer. Several networks were then trained assuming numbers of hidden nodes of 2, 3, 4, ..., (2*I*+1); where *I* is the number of inputs, as recommended by Caudill [16]. The optimum model parameters is achieved by training the network with different combinations of learning rates (i.e. 0.05, 0.1, 0.15, ..., 0.6) and momentum terms (i.e. 0.05, 0.1, 0.15, ..., 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 driven piles in sand and mixed soil; Model 1 for steel piles and Model 2 for concrete piles. The 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 steel piles is composed of eleven hidden layer nodes, learning rate of 0.3 and momentum term of 0.2. The model that was found to perform best for concrete piles includes eleven hidden layer nodes, learning rate of 0.2 and momentum term of 0.3. The performance of the optimum ANN models, i.e. Models 1 and 2, in the training set and the predictive ability of the models in the validation set are depicted in Figures 2 and 3, respectively. It should be noted the dotted lines in Figures 2 and 3 represent the experimental data and the solid lines are for ANN model predictions. For brevity, only some representative curves are selected and presented in Figures 2 and 3, which show good performance for ANN models.

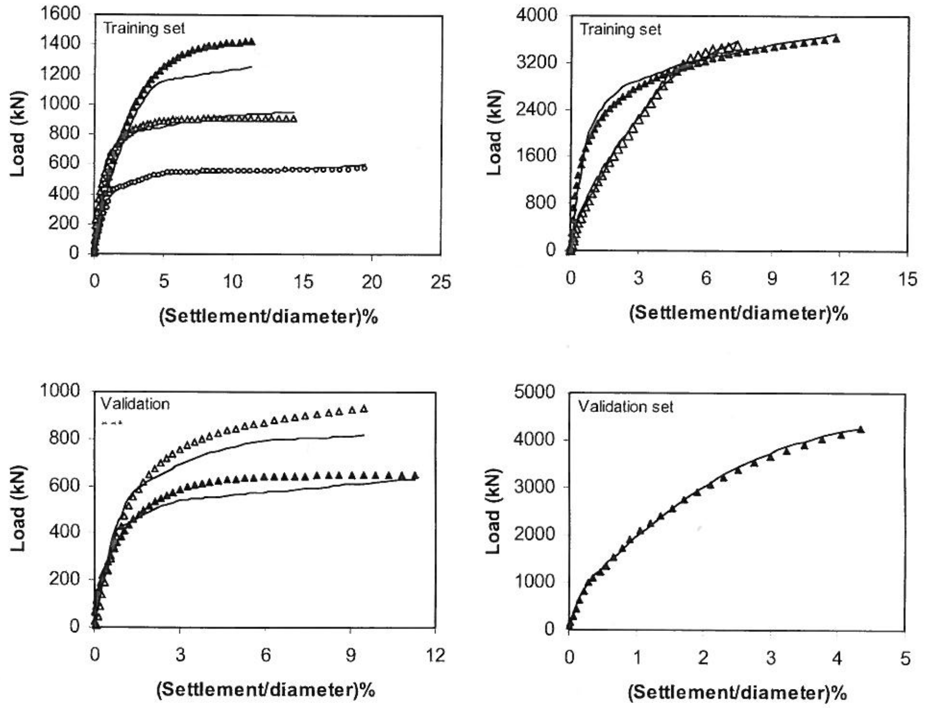

Figure 2. Some simulation results for ANN Model 1 in the training and validation sets

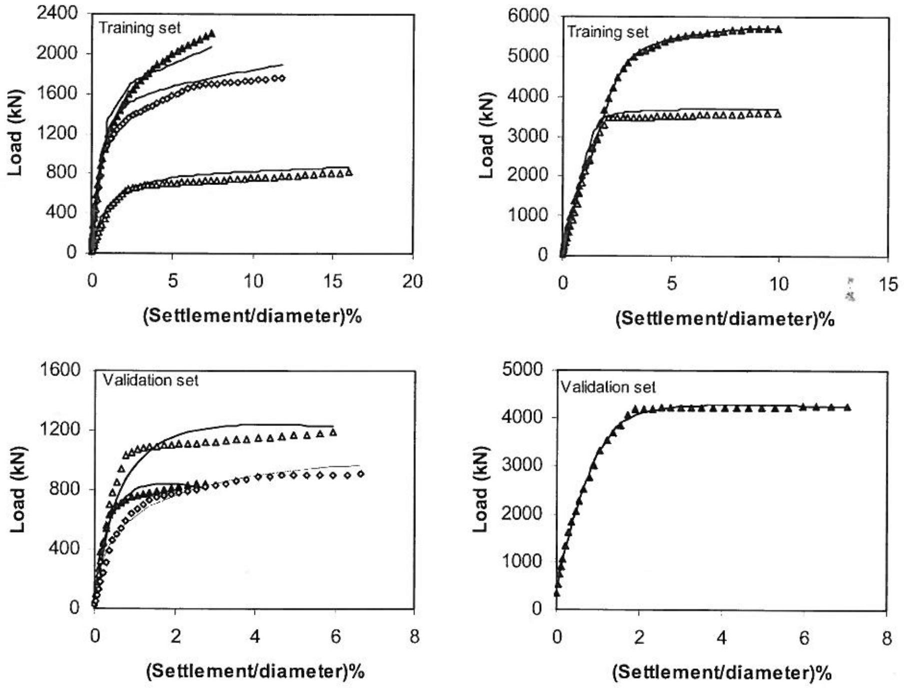

Figure 3. Some simulation results for ANN Model 2 in the training and validation sets

It can be seen from Figures 2 and 3 that the complex nonlinear relationship of the pile load-settlement is well simulated by the ANN models including the strain hardening behaviour. The performance of the developed ANN 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 1 and 2 perform well with high *r* of 0.99 and 1.00 in the training and validation sets, respectively.

The above results demonstrate that the developed ANN models are able to accurately predict the nonlinear behaviour of the pile load-settlement relationship in sand and mixed soils, hence, can be used with confidence for routine design practice.

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

ANN Model	Data set	Correlation coefficient, *r*
Model 1 (steel piles)	Training	0.99
	Validation	1.00
Model 2 (concrete Piles)	Training	0.99
	Validation	1.00

5. Conclusions

This paper proposed an artificial neural network approach for modeling the load-settlement relationship of steel and concrete piles driven in sand and mixed soils. 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 analyses of the coefficient of the correlation indicate high values close to unity for the performance of ANN models in the training and validation sets.

6. References

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