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Prediction of the moment capacity of pier foundations in clay using neural networks

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ABSTRACT

Short piers rely heavily on passive soil resistance and are consequently often referred to as side-bearing foundations. Methods based on a combination of limit state analyses, small-scale modelling or field observations have been used in design. Relatively little centrifuge modelling work at the appropriate stress levels has been reported on the moment capacity problem. The work presented herein describes the use of artificial neural networks (ANNs) for prediction of moment carrying capacity of short pier foundations in clay. The data used in the running of network models have been obtained from an extensive series of centrifuge model tests. The results indicate that the ANN model serves as a simple and reliable tool to predict the moment carrying capacity of pier foundations in saturated clay.

Keywords: Centrifuge modelling; clay; foundation; model tests; neural network

INTRODUCTION

Pier foundations are widely used for railway electrification masts, tall rail and road gantries, towers, large road hoardings and other elevated commercial signs and similar structures in which moment carrying capacity is the dominant design requirement.

The techniques for the analysis of these foundations are not as advanced or as well understood as those for foundations subjected to vertical compressive loads, although the closely related problem of the laterally loaded pile has received considerable attention. One of the earliest attempts to develop design formulae for short rigid pier foundations was derived by UIC/ORE (1957). Alternative design formulae have been developed by Czerniak (1957), Broms (1964b), Brinch-Hansen (1961), McCorkle (1969), Reese & Welch (1975) and, Balfour Beatty Construction Ltd. (1986).

It is very important in soil mechanics and foundation engineering to be able to make realistic predictions of the behaviour of a prototype by using a small-scale laboratory model. However, in order to make accurate predictions, models must be tested at identical stress levels to those in the field. Centrifugal modelling is one convenient method to achieve this requirement. The main purpose of using a centrifuge is to raise the overall level of stresses in the soil to that appropriate in a field situation. The Centrifuge model testing method has been widely accepted and has received widespread attention over the past two decades. The first publication in mainstream geotechnical literature was by Pokrovsky & Fedorov (1936) at the First International Conference on Soil Mechanics and Foundation Engineering in 1936. In the U.K., the method was introduced by Schofield in the early 1960's, and the first specialist geotechnical centrifuge was constructed at the University of Manchester Institute of Science and Technology (UMIST) in 1969 (Bassett & Craig 1988).

Recently, the results of centrifuge model studies of the moment carrying capacity of piers in sand have been reported by Nazir (1994) and Dickin & Nazir (1994b, 1999) and of piers in clay by Laman (1995) and King & Laman (1995).

In this study, an artificial neural networks (ANNs) theory is used to predict the moment carrying capacity of short square piers founded in saturated clay. To the best of the authors' knowledge, no attempts so far have been made to apply ANNs theory to determine the laterally loaded pier foundations in clay. The data set used to define the problem to ANNs theory were obtained from Laman (1995).

OVERVIEW OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are massively parallel distributed processors that have the natural propensity for storing experiential knowledge and making it available for use. The method resembles the brain in two respects: knowledge is acquired by the network through a learning process, and interneuron connection weights, known as synaptic weights, are used to store the knowledge (Haykin 1994).

ANNs have the ability to relate between the input data and corresponding output data which can be defined depending on single or multiple parameters for solving linear or nonlinear problems. Consequently, ANNs do not require any prior knowledge or a physical model of the problem to solve it. The nature of the relationship between the input and output parameters are captured by means of learning samples in the data set (Juang *et al.* 2001, Shahin *et al.* 2001). ANNs can be applied successfully for the solution of the problems which have no specific solutions and are too complex to be modelled by the mathematical and traditional methods (Thirumalaiah & Deo 1998, Adeli 2001).

In recent years, the use of ANNs has increased in geotechnical engineering.

ANNs have been applied to many geotechnical engineering problems successfully such as pile capacity, the settlement of foundations, soil properties and behaviour, liquefaction, earth retaining structures, slope stability, tunnels and underground openings. Comprehensive information about the applications mentioned above can be found in the literature (Nawari *et al.* 1999, Juang *et al.* 2001, Shahin *et al.* 2001).

An ANN is a combination of the processing elements linked to each other with connection weights. The processing elements called neurons are arranged in layers and constitute the network architecture. Multilayer network models are classified as feedforward networks. The basic structure of a multilayer feedforward network model can be determined as consist of an input layer, one or more hidden layers and an output layer. The input layer neurons receive input values from the external environment and pass them on to the first hidden layer neurons. In this layer, data processing is not carried out. Input values distributed from each of the input layer neurons are multiplied by each of the adjustable connection weights linking the input layer neurons to hidden layer neurons. At each neuron in the hidden layer, weighted input values are summed and a bias value is added. Then combined input value is passed through nonlinear transfer functions, like sigmoid or hyperbolic tangent, to obtain the output value of the neuron. This output value is an input for the neurons situated in the following layer.

The objective of the learning is to capture the relationship between the input and output parameters. For this purpose, network models are trained by using a learning algorithm. The great majority of civil engineering applications of neural networks is based on the use of the back-propagation (BP) algorithm primarily because of its simplicity (Adeli 2001). In the BP algorithm, training is supervised because the network connection weights are adjusted according to the sum of the squares of differences between the actual and target outputs. The goal of the training is to reduce the error function iteratively, defined in the form of the sum of the squares of the errors between actual outputs and target outputs. Global error, E, can be defined as:

$$E = \frac{1}{p}\sum_{p=1}^{p} E_p, \tag{1}$$

Where p is the total number of training samples and E_p is the error for training sample p.

E_p is calculated by the following equation;

$$E_p = \frac{1}{2}\sum_{i=1}^{N} (o_i - t_i)^2. \tag{2}$$

In Equation 2, N is the total number of output neurons, o_i is the network output at the i^{th} output neuron and t_i is the target output at the i^{th} output neuron.

In the present study, an attempt is made to reduce the global error by adjusting the weights and biases utilizing the Levenberg-Marquardt (LM) learning algorithm. The LM algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares, then the Hessian matrix can be approximated as:

$$H = J^T J \tag{3}$$

and the gradient can be computed as:

$$g = J^T e, \tag{4}$$

Where J is the Jacobian matrix, which contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard BP technique that is much less complex than computing the Hessian matrix. The LM algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e. \tag{5}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ gis large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm. The application of the LM algorithm for training of feedforward neural networks is presented in Hagan & Menhaj (1994).

CENTRIFUGE MODEL STUDIES OF SHORT PIER FOUNDATIONS IN CLAY

In the centrifuge, a model of the prototype at a scale of 1/n is subjected to a gravity field of n times the earth's gravity, g, in order to achieve identical stresses at geometrically similar points in the ground. The centrifugal model tests were carried out in the Liverpool University geotechnical centrifuge. A centrifugal acceleration of 40g was employed so that stresses due to self-weight of soil would be modelled correctly at $1/40^{th}$ scale. Details of the centrifuge which is shown in Figure 1 have been given by King *et al.*(1984).

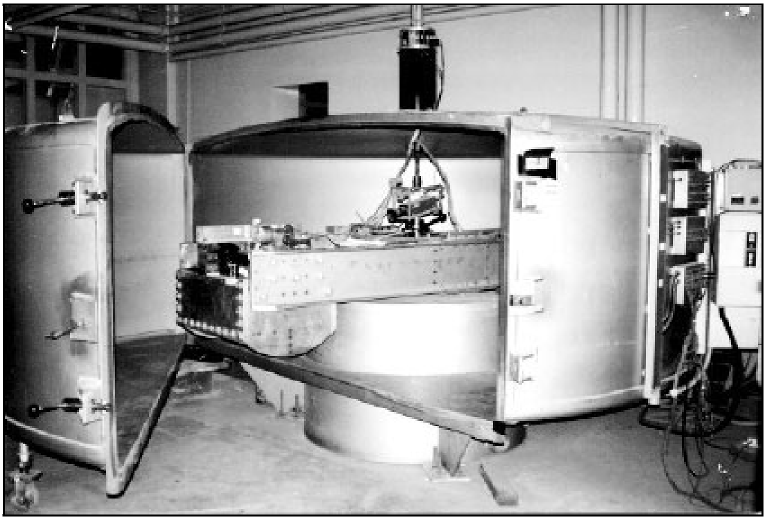

Figure 1. Details of the centrifuge

Details of the Model Piers and Clay Used

The tests were carried out to simulate prototype square piers of 0.80 m, 1.20 m, 1.60 m, 2.00 m and 2.40 m breadth (B) and 0.80 m, 1.20 m, 1.60 m, 2.00 m and 2.40 m depth (D). The dimensions of the piers at model and prototype scale are as listed in Table 1. The piers were made from mild steel with a bulk unit weight of 77 kN/m^3 and modulus of elasticity 207×10^6 kN/m^2. The soil used in the experiments was a remoulded inorganic silty clay of medium plasticity. The main physical properties of the clay are given in Table 2. The degree of saturation in the clay was found to be between 97.50% and 100%. Due to this high level of saturation, undrained shear was observed to occur with $\phi_u = 0$. From a series of undrained triaxial tests the variation of apparent cohesion with moisture content was found to be

$$\mathrm{Log}_{10}c = 4.4344 - 0.1484w \tag{6}$$

in which c is the cohesion of clay (in kN/m^2); and w is the moisture content of clay (%).

Table 1. Dimensions of the model piers with their equivalent prototype sizes

Model (mm)	Breadth	20	30	40	50	60
	Depth	20	30	40	50	60
Prototype (m)	Breadth	0.80	1.20	1.60	2.00	2.40
	Depth	0.80	1.20	1.60	2.00	2.40

Table 2. Main physical properties of the Moreton clay

Moreton clay	
Liquid limit, LL	42%
Plastic limit, PL	15%
Plasticity index, PI	27%
Specific gravity, S_G	2.67
Coefficient of consolidation, C_v	0.465 m^2/year
Range of moisture contents, m	15-18%

Initial Preparation of the Soil and Bin

The clay was cut into small pieces and placed into the bin in layers of approximately 40 mm thickness. Each layer was compacted using steel tampers with a circular base, 150 mm in diameter. Another steel tamper with a rectangular base of 20x20 mm in cross section was also used to compact the clay at the corners and edges of the bin. The tampers were approximately 2 kg in weight and were allowed to fall from a height of 300 mm. Each layer was given 100 tamps. This compaction procedure was used throughout the testing program in order to obtain a reasonably homogeneous soil.

Test Procedure and Experimental Program

Lateral loads were applied at appreciable heights which resulted in large overturning moments. In the tests, the pulling rods were employed to pull the pier laterally via the pulling cable. The rate of displacement of the pulling rod at the connection point (150 mm above the clay surface) was approximately 1.074 mm/min. A pulling cable which was made of stainless steel was used to connect the load cell and the vertical rod. The output from the load cell to the data logger was by means of slip rings.

The lateral displacements of the pulling rods were measured via three conductive potentiometers which were capable of monitoring displacements up to 25 mm. The signal from the transducers to the data logger was by aid of the slip rings. The tests were carried out until the pier rotation reached about 5 degrees. Each test took 13 to 18 minutes depending upon the pier geometry and moisture content of the clay. At the end of the test, a small sample of clay was taken from in front of the pier and used to determine the moisture content of the clay. Since the relationships between moment and rotation were nonlinear and did not exhibit any peak values, arbitrary rotations of 0.5°, 1.0° and 1.5° were considered as alternative limiting working conditions. The following empirical relationship was obtained by moment carrying capacity and geometry:

$$M = c.B.D(\alpha_1 + \alpha_2 B), \tag{7}$$

Where M is the moment (kNm), c is the cohesion of clay (kN/m^2), B is the breadth of the pier (m) and D is the depth of the pier (m). The values of parameters α_1 and α_2 obtained for each rotation limit are listed in Table 3.

Table 3. Values of parameters α_1 and α_2

Parameter	Rotation of pier from vertical axis		
	0.5°	**1.0°**	**1.5°**
α_1	0.91865	1.24476	1.44832
α_2	0.02345	0.07641	0.11948

The results of moment-rotation behaviour of pier foundations observed in centrifugal model tests have been compared with those predicted by a three dimensional nonlinear finite element program, PIER3DNL. In addition, some of the existing design formulae that are frequently used in the literature for predicting the behaviour of single pile and rigid pier foundations subjected to lateral loads and moments are examined. From the comparisons Laman (1995) obtained that the results of the centrifuge model tests were in good agreement with three-dimensional non-linear computer analyses for pier rotations in the range of 0 to 2.5 degrees. Existing analytical solutions for predicting the behavior of laterally loaded pile and pier foundations were also considered. The methods of Brinch-Hansen and UIC/ORE have been applied to the model pier foundations. Brinch-Hansen's method underestimated the results of tests observed in this study, and the rotation values obtained from the intersection of the results varied from the 2.20° to 3.40° (an average value of 2.80°).

ARTIFICIAL NEURAL NETWORK APPLICATION

In this study, ANNs were utilized to estimate the moment carrying capacity of rigid pier foundations in saturated clay soil. For this purpose, multilayer feedforward network models have been trained using the LM learning algorithm. The data used in running of the network models have been obtained from the centrifugal model tests performed by Laman (1995). Details of the centrifugal model tests are given in Section 3.

As in any prediction problem, the selection of input variables is very important. ANN have the ability to determine which input variables are critical. The selection of model input variables and the number of the input variables have significant effect on the model performance. Presenting a large number of input variables both increases the network size and decreases the processing speed. Also, a large number of input variables increases the amount of data required to estimate the connection weights efficiently. For that reason, only the essential variables which have the significant effects on the behavior should be selected. The approach that is generally used for the geotechnical engineering problems is that appropriate input variables can be selected based on a priori knowledge about the problem (Juang *et al.* 1999, Maier&Dandy 2000, Kung *et al.* 2007, Uncuoglu *et al.* 2008).

The problem is proposed to network models by means of five input parameters representing the depth of the pier (D), the breadth of the pier (B), the moisture content of clay (w), the cohesion of clay (c), pier rotation (R) and one output parameter representing moment carrying capacity (M). The moment/cohesion values versus pier rotations of 0.5°, 1.0° and 1.5° for varies pier depths and breadths were used in this study.

Seventy-five data samples obtained from the experimental studies were used in the training, testing and validation of the network models. The available data set was divided into three groups as training, testing and validation data sets which consisted of 50, 15 and 10 data samples, respectively. Data samples were selected randomly from the available data set to constitute mentioned data sets. The statistical properties and range of the parameters are shown in Table 4 and Table 5, respectively.

To develop the best network model, given the available data set, the training data set should contain all representative samples that are present in the available data set (Shahin *et al.* 2004). As seen in Table 4, the data sets represent the same problem domain because the statistical properties of the data sets are consistent with each other. In any model development process, familiarity with the available data is of the utmost importance. Generally, different variables span different ranges. In order to ensure that all variables receive equal attention during the training process, they should be standardized (Maier & Dandy 2000).

Preprocessing of the data is usually required before presenting the data samples to the network model when the neurons have a transfer function with bounded range. The reasons for the scaling of the data samples can be described as to initially equalize the importance of variables and to improve interpretability of network weights (Masters 1993, Goh 1995). In this study, data samples were scaled in the range of 0 and 1 using by the following equation:

$$X_n = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})}, \tag{8}$$

where $X_{\min}$, $X_{\max}$ and X_n denote the minimum, maximum and scaled values of the X data sample, respectively.

Table 4. Statistical properties of data sets

Training data set					
	$\mathbf{X}_{min}$	$\mathbf{X}_{max}$	$\mathbf{X}_{mean}$	$\mathbf{S}_x^*$	$\mathbf{C}_{sx}^*$
D (m.)	0.800	2.400	1.632	0.559	-0.101
B (m.)	0.800	2.400	1.616	0.582	-0.031
w (%)	16.155	17.440	16.786	0.332	-0.073
c (kN/m^2)	70.700	111.235	88.722	10.130	0.320
R (°)	0.500	1.500	0.960	0.426	0.157
M (kNm)	58.655	638.562	275.657	135.116	0.705
Test data set					
	X_{min}	X_{max}	X_{mean}	S_x^*	C_{sx}^*
D (m.)	0.800	2.400	1.520	0.608	0.247
B (m.)	0.800	2.400	1.600	0.585	-3.8E-16
w (%)	16.155	17.440	16.726	0.384	0.452
c (kN/m^2)	70.700	111.235	90.668	11.807	-0.121
R (°)	0.500	1.500	1.100	0.338	-0.256
M (kNm)	85.389	564.155	282.060	168.425	0.554
Validation data set					
	X_{min}	X_{max}	X_{mean}	S_x^*	C_{sx}^*
D (m.)	0.800	2.400	1.560	0.610	0.207
B (m.)	0.800	2.400	1.520	0.526	0.087
w (%)	16.155	17.330	16.719	0.340	0.295
c (kN/m^2)	72.940	111.235	90.656	10.861	0.197
R (°)	0.500	1.500	1.050	0.438	-0.223
M (kNm)	85.032	554.344	267.168	144.303	0.754

*S_x ; Standard Deviation

*C_{sx} ; Skewness Coefficient

Table 5. Ranges of the parameters

Model variables	Minimum value	Maximum value	Range
Pier depth, D (m.)	0.800	2.400	1.600
Pier breadth, B (m.)	0.800	2.400	1.600
Moisture content, w (%)	16.155	17.440	1.285
Cohesion, c (kN/m^2)	70.700	111.235	40.535
Rotation, R (°)	0.500	1.500	1.000
Moment, M (kNm)	58.655	638.562	579.907

Determining an appropriate architecture of a neural network for a particular problem is an important issue, since the network topology directly affects its computational complexity and its generalization capability (Kisi & Uncuoglu 2005). Multilayer feedforward network models with one hidden layer can approximate any complex nonlinear function provided many sufficiently hidden layer neurons are available (Hornik 1989). Therefore, in this study, multilayer feedforward network models containing one hidden layer were used.

Determination of the optimum number of hidden layer neurons is very important in order to predict accurately a parameter using ANNs. But there is no theory how many hidden layer neuron need to be used for a particular problem. For that reason, generally, numbers of hidden layer neurons have been determined by trial and error methods.

A common strategy for finding the optimum number of hidden layer neurons is to start with a few numbers of neurons and then increasing the number of neurons while monitoring the performance criteria until no significant improvement is observed (Goh 1995, Nawari *et al.* 1999).

In this study, the performance of various network models with different hidden layer neuron numbers was examined in order to choose an appropriate number of hidden layer neurons. Hence, 2 neurons were used in the hidden layer at the beginning of the process then the neuron number was increased step-by-step adding 1 neuron until no significant improvement was noted. The network models tried were compared according to the mean absolute relative error (MARE) and the mean square error (MSE) criteria. These criteria are defined as:

$$MARE = \frac{1}{N}\sum_{i=1}^{N} \frac{\left| M_{i_{measured}} - M_{i_{predicted}} \right|}{M_{i_{measured}}} * 100, \tag{9}$$

$$MSE = \frac{\sum_{i=1}^{N}\left(M_{i_{measured}} - M_{i_{predicted}}\right)^2}{N} \quad . \tag{10}$$

In these equations N and M denote the total number of the data samples and moment carrying capacity, respectively.

At the end of these processes, the best performance was obtained from the ANN model which has 7 neurons in the hidden layer. The chosen model architecture is shown in Figure 2. Training of the network models is carried out by presenting a training data set involving input-output data pairs. The connection weights are adjusted during the training phase according to the differences between the target output ($M_{measured}$) and the actual output ($M_{predicted}$).

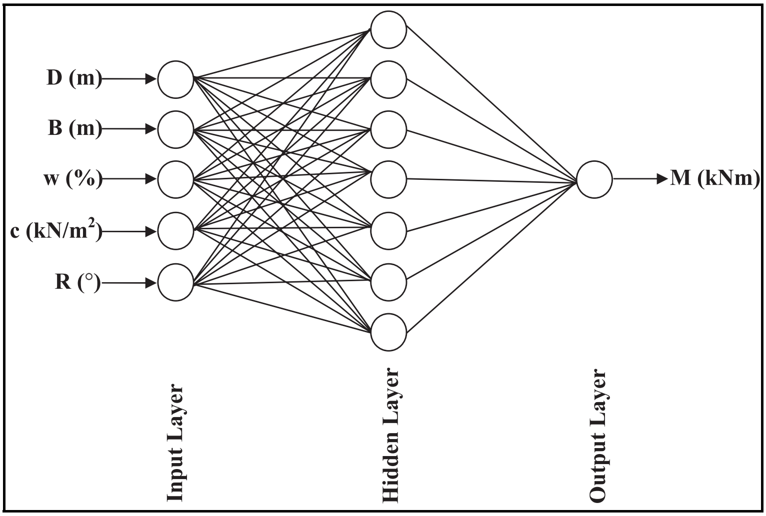

Figure 2. Chosen model architecture

The adjustment of the connection weights are continued until the mean square error over all the training samples falls below a given value or the maximum number of epoch is reached. In the training phase, the performance of the network models is monitored at each epoch using the test data set. Overfitting of the network model is prevented this way. When the training phase was over, the weights were saved for using in the test and validation phases. Once the training was over, the performance of the trained network had to be validated through the validation data set to show whether the network model chosen was reliable or not. The saved weights and biases values used by the chosen network model with 7 hidden layer neurons are presented in Table 6, Table 7 and Table 8, respectively.

Table 6. Saved weights from input layer to hidden layer

Neuron number	I_1	I_2	I_3	I_4	I_5
H_1	-2.5023	3.7278	0.9954	-1.3774	0.4467
H_2	-5.1815	-1.0717	0.4401	1.2498	-3.0556
H_3	-1.0102	-1.0326	2.7013	2.4497	-0.2783
H_4	3.7157	-2.9595	-0.0857	2.7465	2.7248
H_5	-2.4353	2.4652	-0.0704	-0.3972	0.1518
H_6	-2.1015	-2.0743	0.6452	-1.0434	4.2605
H_7	-2.7462	-1.6974	1.7100	1.1441	-0.8816

Table 7. Saved weights from hidden layer to output layer

Neuron number	H_1	H_2	H_3	H_4	H_5	H_6	H_7
O_1	-0.0198	-0.0148	-1.0406	2.3978	0.0949	0.1258	-0.0633

Table 8. Saved biases values

Neuron number	Bias values
H_1	1.2850
H_2	4.3394
H_3	-0.2387
H_4	3.2735
H_5	-1.3050
H_6	3.3004
H_7	0.2725
O_1	-1.3504

To compare the results obtained from the network model with the experimental results, predicted values were transformed back to their original values and then MARE and MSE were computed. The tangent sigmoid, logarithmic sigmoid and pure linear transfer functions were tried as activation functions for hidden and output layer neurons to determine the best network model. The most appropriate results have been obtained from the chosen network model in which tangent sigmoid and pure linear functions used as activation functions for the hidden and output layer neurons, respectively. The program used in running the network models was written in Matlab language code.

Table 9. Results obtained from the chosen network model

Train MSE (kN^2m^2)	263.600
Test MSE (kN^2m^2)	1161.700
Validation MSE (kN^2m^2)	2732.600
Train MARE	6.035
Test MARE	10.917
Validation MARE	12.100
R^2_{train}	0.985
R^2_{test}	0.971
$R^2_{validation}$	0.902
Epoch number	8
Hidden layer neurons	7

The results obtained from the most appropriate network model to estimate the moment carrying capacity of short pier foundations are summarized in Table 9. The comparison of the measured and predicted moment carrying capacities versus data samples are shown in Figures 3, 4 and 5 for training, testing and validation stages, respectively. Figures 6, 7 and 8 present the measured moment carrying capacities versus predicted moment carrying capacities by the network model with R^2 coefficients for training, testing and validation phases, respectively. The results produced high coefficients of correlation for the training, testing and validation data of 0.985, 0.971 and 0.902, respectively. This indicates that the neural network is able to successfully model the moment carrying capacity of short pier foundations in clay.

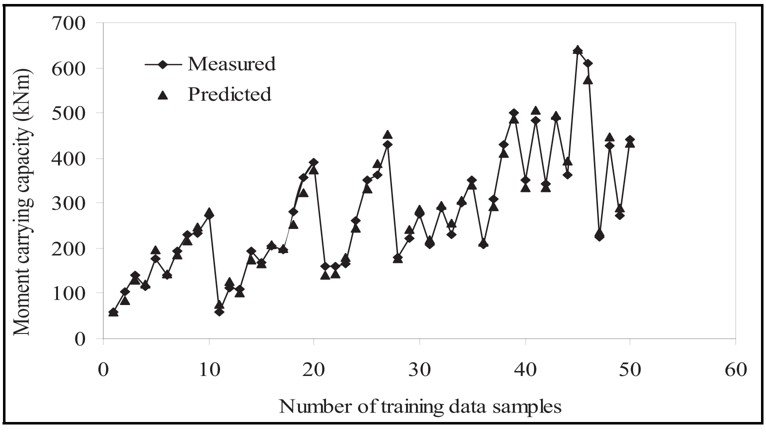

Figure 3. Comparison of the measured and predicted moment carrying capacities in the training phase

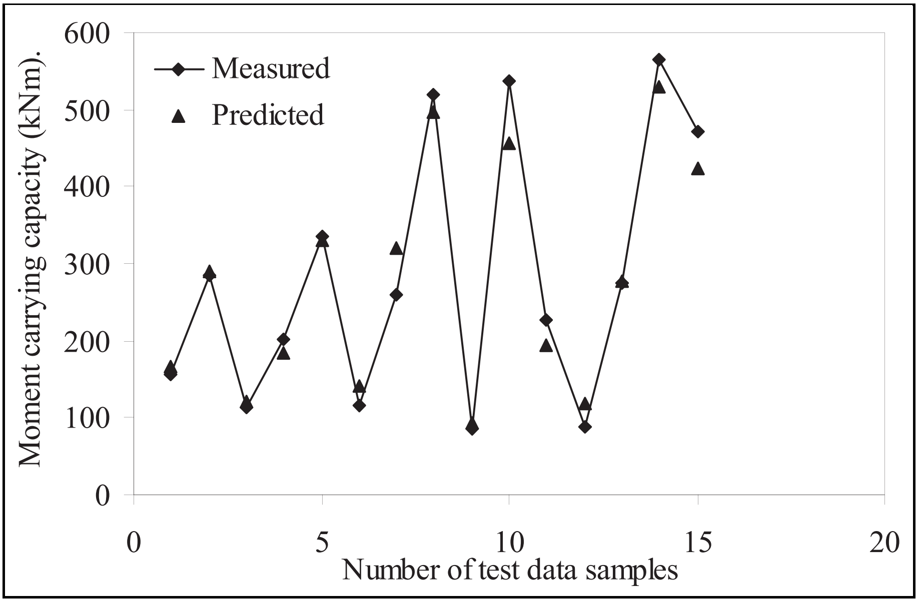

Figure 4. Comparison of the measured and predicted moment carrying capacities in the testing phase

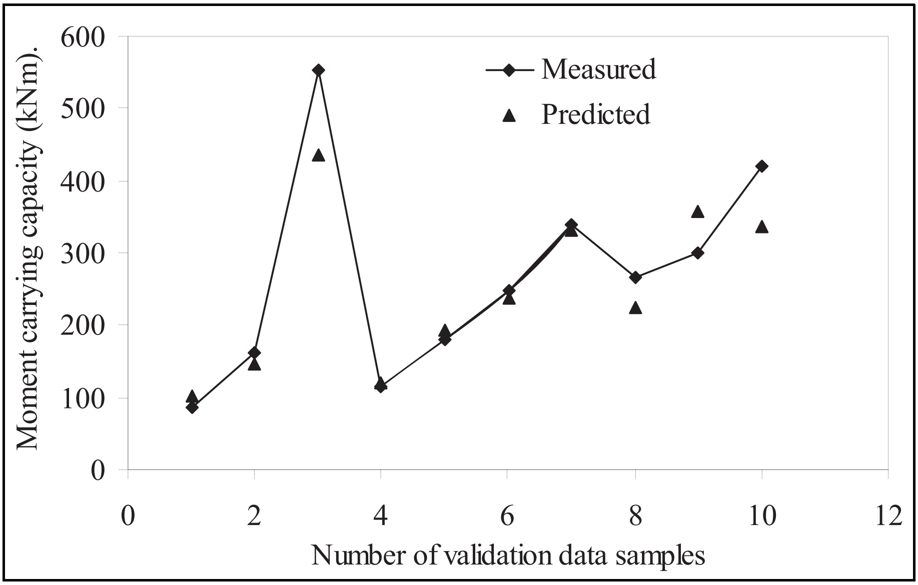

Figure 5. Comparison of the measured and predicted moment carrying capacities in the validation phase

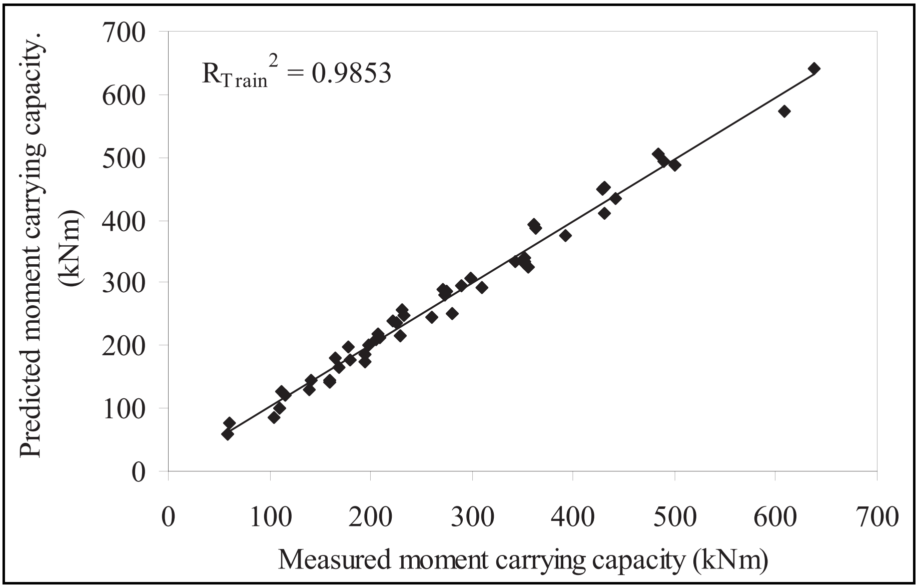

Figure 6. Correlation between the measured and predicted moment carrying capacities in the training phase

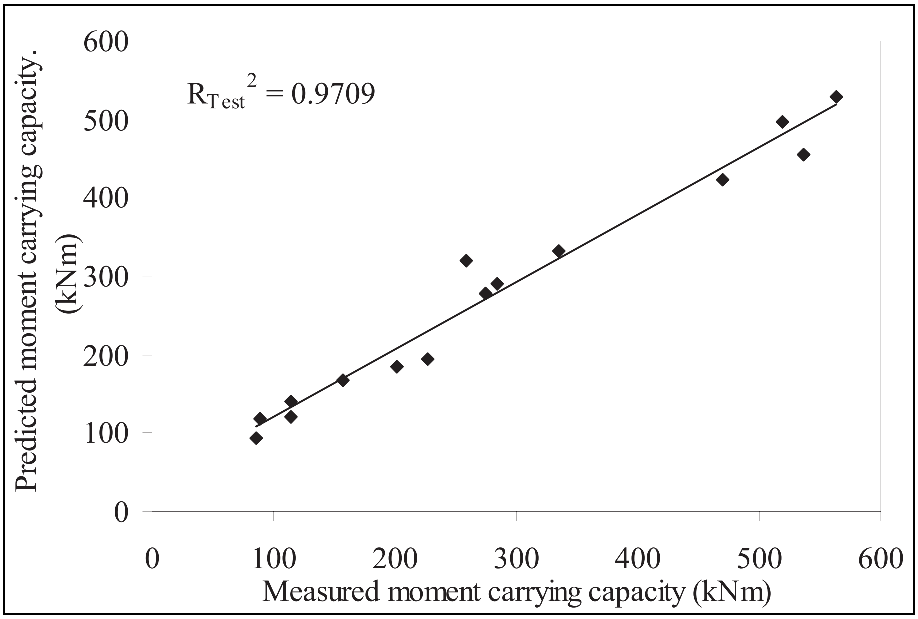

Figure 7. Correlation between the measured and predicted moment carrying capacities in the test phase

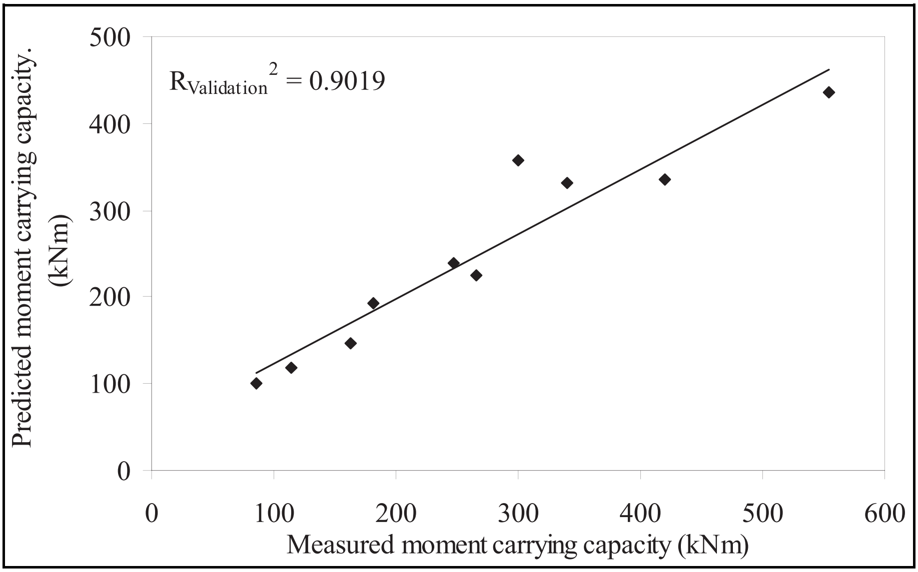

Figure 8. Correlation between the measured and predicted moment carrying capacities in the validation phase

SENSITIVITY ANALYSIS

Sensitivity analysis was carried out on the trained network model which was the most suitable for the problem of estimating the moment carrying capacity of the rigid pier foundations in clay according to Garson's method outlined by Shahin *et al.* (2002). The purpose of the analysis is defining the relative importance of the input parameters on the output parameter. First, sensitivity analysis was performed using the weights given in Table 6 and Table 7. Then the analysis was repeated for the different initial random weights to test the robustness of the network model. The results obtained are presented in Table 10. As seen, the most important input parameter affecting the moment carrying capacity is the depth of the foundation with relative importance equal to 31.02%. The results indicate that the breadth of the foundation also has a significant effect with relative importance equal to 24.98%. R, c and w have moderate effects on the moment carrying capacity with relative importance equal to 16.33, 16.20 and 11.49%, respectively.

Table 10. Relative importance of the input parameters (%) on the output parameter

D	*B*	*w*	*c*	*R*
31.018	24.979	11.487	16.186	16.330

Since ANNs theory generally provided a good match with the observed behaviour for the pier geometries investigated in the centrifuge, further analyses were carried out for different pier geometries not studied experimentally. For example, the predicted moment carrying capacities for the short pier foundations with different values of the input parameters not used in the present work are given in Table 11.

Table 11. Predicted moment values for the short pier foundations

D (m)	B (m)	w (%)	c (kN/m^2)	R (°)	ANN
1.50	1.40	16.85	100.00	1.00	96.33
1.40	1.50	16.85	100.00	1.00	95.73
2.10	1.30	16.85	100.00	0.75	133.64
1.25	1.75	16.85	100.00	0.50	71.20
1.25	2.25	16.85	100.00	0.50	109.23
1.90	1.60	16.85	100.00	0.90	139.76
1.90	0.90	16.85	100.00	0.90	109.24
1.70	1.00	16.85	100.00	1.20	106.55
1.95	1.00	16.85	100.00	1.20	135.23
1.00	1.00	16.85	100.00	1.20	49.19
1.00	1.00	16.85	100.00	0.60	39.69

CONCLUSIONS

The moment carrying capacity of rectangular piers on clay was investigated using an artificial neural networks theory, and by physical modelling in a geotechnical centrifuge. The following main conclusions can be drawn from the work presented herein:

1 - From extensive series of centrifuge model tests on short rigid piers in saturated clay, an empirical equation has been derived between moment carrying capacity and pier geometry for limiting rotations of 0.5°, 1.0° and 1.5°.

2 - A neural network model has been also developed for this problem. Input parameters to assess the moment carrying capacity of short pier foundations by ANNs are: the depth of the pier (D), the breadth of the pier (B), the moisture content of clay (w), the cohesion of clay (c) and pier rotation (R). The output of the neural network is the predicted moment carrying capacity of the short pier foundation in saturated clay.

3 - The ANN models have the ability to predict the moment carrying capacity of short pier foundations in clay.

4 - Sensitivity analysis showed that the most important input parameters affecting the moment carrying capacity are depth and breadth of the foundations.

5 - It is suggested that the model might serve more generally as a guide for the design of moment carrying short square piers in clay soil. In order to make the model more accurate and reliable, some more data would be included for different clay soil conditions.

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التنبأ بقدرة عزم جزء الجدار بين الأساسات في الطين باستخدام الشبكات العصبية

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خلاصة

تعتمد الدعامات القصيرة اعتمادا جليا على المقاومة السلبية للتربة لها، وهي بالتالي تمثل الحامل لجوانب القواعد الأساسية. لقد تم استخدام الطرق المعتمدة على الجمع بين تحاليل حالة محددة، ونمذجة مقياس صغير أو الملاحظات الحقلية في تصميم القواعد. كما تم إنجاز تقرير عن عمل نموذج النابذة القليلة تحت مستويات ضغط مناسبة عن حجم المشكلة. تشرح هذه الورقة فائدة الشبكات العصبية الصناعية للتنبأ بسعة أساس الدعامة الصغيرة المحمولة في الطين. لقد تم الحصول على المعلومات المستخدمة في نماذج الشبكات العصبية من المجموعة الشاملة لاختبارات نموذج النابذة. لقد دلت النتائج على أن نموذج الشبكات العصبية الصناعية يستخدم كأداة بسيطة ومعتمدة للتنبأ على قدرة عزم الجدار بين الأساسات في الطين المشبع.