Modelling the Pullout Capacity of Marquee Ground Anchors Using Neurofuzzy Technique

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EXTENDED ABSTRACT

Marquees are temporary light structures that are connected to the ground by tensile anchors to resist forces imposed by wind acting on the structure. Failures of such structures are not rare and have resulted in deaths and tens of thousands of dollars of damage. Consequently, an accurate estimation of the ultimate pullout capacity of ground anchors is essential; however, current methods for estimating the ultimate pullout capacity of marquee ground anchors are inaccurate. This is attributed to the fact that the models used by current methods were originally developed to estimate the axial capacity of a single pile rather than small size anchors. The aim of this paper is to develop a more accurate model for predicting the pullout capacity of marquee ground anchors based on the neurofuzzy technique. The type of neurofuzzy networks used are the B-spline networks that are trained with the adaptive spline modelling of observation data (ASMOD) algorithm. A series of 119 in situ anchor pullout tests, conducted at six different locations in the Adelaide Region, South Australia, are used for the neurofuzzy model calibration and validation. Statistical analyses that compare the actual measured pullout capacity with those predicted by the neurofuzzy model and three existing pile capacity prediction methods are conducted and discussed.

1 INTRODUCTION

Temporary light structures, such as marquees, are almost exclusively connected to the ground using small anchors that resist uplift forces imposed predominantly by wind acting on the structure. The anchors are often installed vertically to transmit the tensile forces from the structure to the surrounding soil. The shear strength of the surrounding soil resists these tensile forces, hence, provides structural stability. Traditionally, these anchors are made of steel rods, less than one metre in length, and have different diameters and shapes. The mechanics of ground anchor behaviour is not well understood (Su and Fragaszy 1988) and available methods for predicting the pullout capacity of ground anchors are inaccurate. Consequently, failures of marquees and other light structures are not rare. As an example of such a failure, in Kapunda, South Australia, an inflatable children's amusement failed, resulting in the death of a young girl (The Advertiser 2001). The inflatable amusement was restrained by ground anchors, and, as a result of a significant wind event, the anchors failed causing the structure to be lifted 10 metres into the air, carrying the child with it (DAIS 2001). In addition, Australian industry sources indicate that when marquees fail, they often need to be repaired or replaced, incurring costs of, sometimes, tens of thousands of dollars (Griggs 2002).

In this paper, an attempt is made to develop a more accurate anchor pullout capacity prediction model using the neurofuzzy technique. The neurofuzzy technique used utilises the B-spline networks that are trained with the adaptive spline modelling of observation data (ASMOD) algorithm. B-spline neurofuzzy networks have been already used successfully by the authors in the field of geotechnical engineering (Shahin *et al.* 2003a; Shahin *et al.* 2003b). B-spline neurofuzzy networks can perform input/output data mappings with the additional benefit of being able to translate the model input/output relationships into a set of fuzzy rules that describe the model in a transparent fashion. In this work, a series of 119 in situ anchor pullout tests that were conducted at six different locations within Adelaide, South Australia, is used to develop and verify the neurofuzzy model. The sites selected for conducting the pullout load tests were chosen so as to cover a variety of soil types and geotechnical conditions. Undisturbed soil samples were taken from sites investigated and laboratory tests were carried out on the samples obtained to quantify the geotechnical properties of the soil at each site. The soil parameters used for developing the neurofuzzy model were derived from a number of cone penetration tests (CPTs) that were conducted at each site. The study focuses on axial loading of rough anchors installed vertically, as these are most commonly used in practice. Three anchor types of different embedment depths, shapes and cross-sectional areas are examined. The actual measured pullout loads from in situ pullout tests are compared with those obtained using the neurofuzzy model as well as three existing methods of pile capacity that use the direct cone penetration test (CPT) data. Statistical analyses to evaluate and rank the performance of the neurofuzzy model and the CPT methods used are conducted and their results are discussed. Details of the field tests and measured data are discussed briefly in Section 3, and in more detail by Shahin and Jaksa (2003).

2 B-SPLINE NEUROFUZZY NETWORKS

B-spline neurofuzzy networks use the fuzzy logic system to store knowledge acquired from a set of input variables (x_1, x_2, …, x_n) and the corresponding output variable (y) in a set of linguistic fuzzy rules that can be easily interpreted, such as: IF (x_1 *is high* AND x_2 *is low*) THEN (y *is high*), c = 0.9, where (c = 0.9) is the *rule confidence*, which indicates the degree to which the above rule has contributed to the output. The concept of fuzzy logic was first introduced by Zadeh (1965). As part of any fuzzy logic system, two main components (i.e. fuzzy sets and fuzzy rules) need to be determined. In order to determine the fuzzy sets, linguistic terms (e.g. small, medium and large) can be interpreted mathematically in the form of membership functions and model variables are *fuzzified* to be partial members of these membership functions in the interval grade (0,1). This means that, for a fuzzy set A, an input variable x is fuzzified to be a partial member of the fuzzy set A by transforming it into a degree of membership of function $u_A(x)$ of interval (0,1). B-spline basis functions are piecewise polynomials of order k that can be used as one form of membership function. For each input variable, the fuzzy sets overlap and cover the necessary range of variation for that variable in the process called *fuzzification*. It should be noted that the model output of a fuzzy set is also fuzzy and, in order to obtain a real-valued output, defuzzification is needed. The *mean of maxima* and *centre of gravity* are the most popular defuzzification algorithms (Brown and Harris 1994).

A typical structure of a neurofuzzy network contains three layers: an input layer; a single hidden layer; and an output layer (Brown and Harris 1994). The input layer normalises the input space in a p-dimensional lattice (Figure 1). Each cell of the lattice represents similar regions of the input space. The hidden layer consists of basis functions, such as B-spline functions, which are defined on the normalised input space. The size, shape and overlap of the basis functions determine the structure and complexity of the network. The output layer sums the weighted outputs from the basis functions to produce the network output using the following equation:

$$y = \sum_{i=1}^{p} a_i w_i \tag{1}$$

where y = model output; a_i = output from the pth basis function; and w_i = connection weight associated with a_i. This output is compared with the actual measured output and a connection error (the mean squared error, MSE, is usually used) is calculated. Using this error and implementing a learning rule, the neurofuzzy network adjusts its weights and determines its fuzzy parameters (i.e. fuzzy sets and rules).

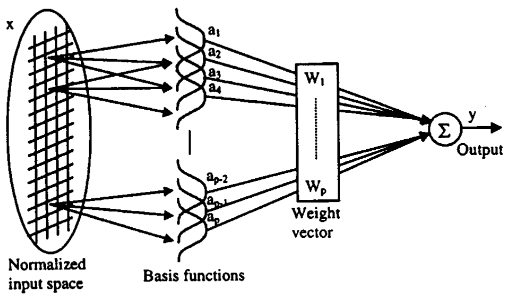

Figure 1. Typical structure of a neurofuzzy network (Brown and Harris 1995)

One major disadvantage of B-spline neurofuzzy networks is the so-called *curse of dimensionality*, in which the number of fuzzy rules is exponentially dependent on the dimension of the input space. This results in a large number of fuzzy rules and consequently impractical model representation. The analysis of variance (ANOVA) representation is one useful approach to overcome this problem (Brown and Harris 1995). ANOVA decomposes an n-dimensional function into a linear combination of a number of separate functions, as follows (Brown and Harris 1995):

$$f(x) = f_0 + \sum_{i=1}^{n} f_i(x_i) + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} f_{i,j}(x_i, x_j) + ... + f_{1,2,...,n}(x) \quad (2)$$

where f_0 represents a constant (the function bias); and the other terms represent the univariate, bivariate and high-order subfunctions. In many situations, the majority of high-order terms are zero or negligible, resulting in a limited number of subfunctions (often called subnetworks) of much lower dimensions that approximate the network input/output mapping. It should be noted that each subnetwork in the ANOVA description represents a neurofuzzy system of its own and the overall model output is produced by summing outputs of all subnetworks.

The adaptive spline modelling of observation data (ASMOD) proposed by Kavli (1993) is an algorithm that can be used to automatically obtain the optimal structure of B-spline neurofuzzy networks and select model inputs that have the most significant impact on outputs. The algorithm starts with a simple model (e.g. only one variable with two membership functions) and iteratively refines the model structure during training so as to gradually increase model capability until some stopping criterion is met. Possible refinements include adding or deleting input variables, forming multi-variate subnetworks using ANOVA, and increasing the number and dimension of an individual subnetwork. For every refinement, the impact of network pruning is evaluated and the network that has the simplest structure with the best performance is chosen. One common stopping criterion is the Bayesian Information Criterion (BIC) given by Brown and Harris (1994), as follows:

$$K = L \ln(MSE) + p \ln(L) \quad (3)$$

where K = performance measure; p = size of current model; MSE = mean square error; and L = number of data pairs used to train the model. The measure, given in Equation 3, balances model complexity, the number of training data, and model error. It should be noted that the BIC stopping criterion requires the data to be divided into two sets; a training set to build the model and an independent validation set to test the predictive ability of the model in real-world situations.

3 DEVELOPMENT OF NEUROFUZZY MODEL

In this work, the neurofuzzy model is developed using the software package *NEUFRAME* Version 4.0 (Neusciences 2000). A series of 119 in situ pullout tests on rough mild steel anchors, given by Shahin and Jaksa (2003), are used to calibrate and validate the neurofuzzy model. The tests were carried out on sites of different soil types and geotechnical conditions. The anchors used have different shapes (i.e. circular, hexagonal and star dropper) and were embedded vertically on the ground at various embedment lengths (i.e. 400, 600 and 800 mm). The anchors were also installed into the ground statically by means of a steady penetration provided by an hydraulic ram associated with a drilling rig or dynamically using a sledge hammer. Details of the tests conducted and the data derived from the tests are given by Shahin and Jaksa (2003). The factors affecting pullout capacity of marquee ground anchors (i.e. anchor equivalent diameter, D_{eq}, embedment length, L, average cone tip resistance over anchor length, $\bar{q}_c$, average sleeve friction over anchor length, $\bar{f}_s$, and installation technique, *InsTech*) are presented to the neurofuzzy model as potential model input variables. The ultimate pullout capacity, Q_u, is the single model output variable. The ASMOD algorithm, described previously, is used to optimise automatically model architecture and selects the input variables that have the most significant impact on model outputs. As mentioned earlier, the ASMOD algorithm also uses stopping criteria (e.g. BIC) that require the data to be divided into two sets; training and validation. In this work, 80% (i.e. 96 case records) of the available data are used for training and 20% (i.e. 23 case records) are used for validation. Once training has been successfully accomplished, the performance of the model is tested and the results are given. It was found that the neurofuzzy model performs well in both the training and validation sets with coefficients of correlation of 0.83 and 0.89 for the training and testing set, respectively. This implies that B-spline neurofuzzy networks are able to predict reasonably well the pullout capacity of marquee ground anchors.

A schematic view of the neurofuzzy model is given in Figure 2. It can be seen that the model uses only 4 out of 5 potential input variables as the most significant inputs. The chosen inputs are the anchor equivalent diameter, D_{eq}, embedment length, L, average sleeve friction, $\bar{f}_s$, and installation technique, *InsTech*. It can also be seen that the model has four 1D subnetworks. In each of the subnetworks obtained, triangular membership functions of order 2 are used for all input variables, as shown in Figure 3. It can be seen from this figure that the membership functions of D_{eq}, L, *InsTech* and Q_u are presented over a two-valued linguistic universe (i.e. small and large for D_{eq}, shallow and deep for L, static and dynamic for *InsTech*, and light and heavy for Q_u). On the other hand, the membership function of the sleeve friction, $\bar{f}_s$, is presented over a three-valued linguistic universe (i.e. light, medium and heavy). As a result, three subnetworks containing two rules are obtained, while only one subnetwork contains three rules, resulting in a model with 9 fuzzy rules, as listed in Table 1. It should be noted that the number between brackets in Table 1 represents the rule confidence described earlier. The fuzzy rules in Table 1 are a valuable source of information from which knowledge can be extracted that governs the relationships between pullout capacity and the factors affecting it. The knowledge that can be derived from Table 1 is as follows:

- *Small* anchor diameters and *shallow* embedment lengths are most likely to result in *light* pullout capacity (Rules 1 and 3) and *Large* anchor diameters and *deep* embedment lengths are most likely to result in *heavy* pullout capacity (Rules 2 and 4);
- *Light* sleeve friction results in *light* pullout capacity (Rule 5) and *Heavy* sleeve friction results in *heavy* pullout capacity (Rule 7). On the other hand, *Medium* sleeve friction is equally likely to result in *light* or *heavy* pullout capacity (Rule 6); and
- *Static* or *dynamic* installation techniques are equally likely to result in *light* or *heavy* pullout out capacity. However, *static* installation is more likely to result in *heavier* pullout capacity than *dynamic* installation (Rules 8 and 9).

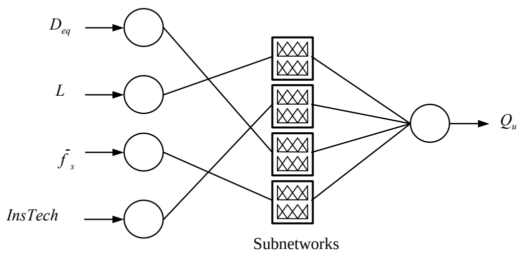

Figure 2. Schematic representation of the neurofuzzy model

It should be noted that the range of applicability of the previous fuzzy rules is constrained by the quality and range of data used in the Neurofuzzy model calibration phase. Consequently, it is unlikely that the fuzzy rules obtained provide a general representation of the relationship between anchor pullout capacity and the factors affecting it. However, in general, the fuzzy rules are in agreement with what one would expect based on the underlying physical understanding of anchors subjected to tension. Interestingly, the rule pertaining to static versus dynamic installation is also as one might expect, as the process of dynamically installing anchors is more likely to reduce adhesion along the shaft of the anchor and, hence, reduce pullout capacity.

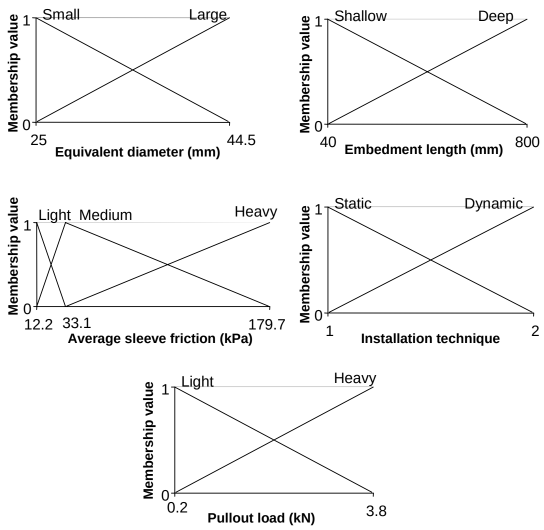

Figure 3. Membership functions of input variables used by the neurofuzzy model

Table 1. Fuzzy Rules Extracted by the Neurofuzzy Model

Subnetwork No.	Rule No.	Rule
1	1	IF "Anchor diameter" is *Small* THEN "Pullout capacity" is *Light* (0.52) OR "Pullout capacity" is *Heavy* (0.48)
	2	IF "Anchor diameter" is *Large* THEN "Pullout capacity" is *Light* (0.33) OR "Pullout capacity" is *Heavy* (0.67)
2	3	IF "Embedment length" is *Shallow* THEN "Pullout capacity" is *Light* (0.64) OR "Pullout capacity" is *Heavy* (0.36)
	4	IF "Embedment length" is *Deep* THEN "Pullout capacity" is *Light* (0.12) OR "Pullout capacity" is *Heavy* (0.88)
3	5	IF "Sleeve friction" is *Light* THEN "Pullout capacity" is *Light* (1.00)
	6	IF "Sleeve friction" is *Medium* THEN "Pullout capacity" is *Light* (0.43) OR "Pullout capacity" is *Heavy* (0.57)
	7	IF "Sleeve friction" is *Heavy* THEN "Pullout capacity" is *Heavy* (1.00)
4	8	IF "Installation technique" is *Static* THEN "Pullout capacity" is *Light* (0.41) OR "Pullout capacity" is *Heavy* (0.59)
	9	IF "Installation technique" is *Dynamic* THEN "Pullout capacity" is *Light* (0.54) OR "Pullout capacity" is *Heavy* (0.46)

4 COMPARISON OF NEUROFUZZY MODEL WITH CURRENT PILE CAPACITY PREDICTION METHODS

In order to examine the accuracy of the neurofuzzy model, it is compared with three pile capacity prediction methods currently used in practice. The methods considered use available data from cone penetration tests (CPTs) and include: Penpile (Clisby et al. 1978); De Ruiter and Beringen (1979); and LCPC (Bustamante and Gianeselli 1982). It should be noted that these methods are normally used to estimate the axial capacity of piles loaded in compression. Whilst marquee anchors are generally much smaller in diameter than piles, these methods should, nonetheless, be applicable to marquee anchors subjected to tensile forces. Furthermore, no other methods are available, other than empirical, that enable the pullout capacity of marquee anchors to be determined.

The ultimate pile/anchor load capacity, Q_u, is composed of the pile/anchor base resistance, Q_b, and the pile/anchor shaft skin friction, Q_s. For pullout load, the base resistance, Q_b, can be assumed to be zero, as it is negligible for piles/anchors in tension, and thus the ultimate load capacity, Q_u, is equal to the shaft skin friction, Q_s, which can be calculated as follows:

$$Q_u = Q_s = f_{ave} C_p L \tag{4}$$

where f_{ave} = average unit skin friction; C_p = pile/anchor cross-section perimeter; and L = pile/anchor embedment length. Several methods are available in the literature for calculating the average unit skin friction, f_{ave} , from measurement of cone tip resistance, q_c, or sleeve friction, f_s. In the present work, the applicability of three different CPT pile capacity methods are assessed in relation to the anchor field testing data, as mentioned above. Details of the average unit skin frictions, f_{ave}, calculated by each method are given elsewhere (Abu-Farsakh and Titi 2004).

To evaluate and rank the performance of the neurofuzzy model and the three CPT methods used, the rank index (*RI*) proposed by Abu-Farsakh and Titi (2004) is used. The rank index is the summation of four ranks (*RI* = *R*1+*R*2+*R*3+*R*4) determined from different statistical criteria and according to this rank index, the performance of a pile capacity method is better for lower *RI*. The rank criteria used (i.e. *R*1, *R*2, *R*3, and *R*4) are described in detail by Abu-Farsakh and Titi (2004), which include: (1) the equation of the best fit of predicted pullout load, Q_p, versus measured pullout load, Q_m, with the corresponding coefficient of correlation, r; (2) the arithmetic mean, μ, and the corresponding standard deviation, σ, of Q_p/Q_m; (3) the 50% and 90% cumulative probabilities (P_{50} and P_{90}) of Q_p/Q_m; and (4) the ±20% accuracy level obtained from the lognormal distribution and histogram of Q_p/Q_m. For each of the methods used in the present work, the abovementioned rank criteria are determined and their results are given in Table 2.

The first criterion is determined by carrying out a regression analysis to obtain the best fit line of Q_p/Q_m of the available 119 anchor tests for each pullout capacity prediction method and the relationship of the best fit line of Q_{fit}/Q_m and the corresponding coefficient of correlation, r, are calculated. According to this criterion, better performance is obtained from the method that has Q_{fit}/Q_m closer to one with r nearer to one. The results of this criterion are shown in Table 2 (columns 2, 3, and 4), for each of the methods used. It can be seen that the neurofuzzy model is given *R*1 = 1 and thus ranks number one. The neurofuzzy model has Q_{fit}/Q_m = 0.95 with r = 0.84, which means that, according to the first criterion, the neurofuzzy model tends to under-predict the measured pullout capacity by an average of 5%. It can also be seen that the method of De Ruiter and Beringen comes last as it ranks number four. This suggests that, according to the first criterion, this method tends to over-predict the measured pullout capacity by an average of 53% as it has Q_{fit}/Q_m = 1.53 with r = 0.48. It can also be seen that the Penpile method and the LCPC method rank second and third and they tend to under-predict the measured pullout capacity by average values of 29 and 43%, respectively.

The second criterion is obtained by calculating the arithmetic mean value, μ, and the corresponding standard deviation, σ, of Q_p/Q_m of the 119 anchor tests for each pullout capacity prediction method. According to this criterion, the performance is better for the method that has μ (Q_p/Q_m) closer to 1 with σ (Q_p/Q_m) nearer to zero. The results of this criterion are given in Table 2 (columns 5, 6, and 7) for each of the methods used. It can be seen that, again, the neurofuzzy model ranks first with μ = 1.05 and σ = 0.34, which means that, according to the second criterion, the neurofuzzy model tends to over-predict the measured pullout capacity by an average of 5%. On the other hand, the method of De Ruiter and Beringen again ranks last with μ = 1.46 and σ =1.43, which suggests that, according to the second criterion, this method tends to over-predict the measured pullout capacity by an average of 46%. It can also be seen that the LCPC method and the Penpile method rank second and third and they tend to under-predict the measured pullout capacity by average values of 23% and 26%, respectively.

The third criterion is determined by sorting, in an ascending order (1, 2, 3, …, *i*, …, *n*), the ratios

Table 2. Performance Evaluation of the Neurofuzzy Model and the CPT Methods used

Method*	Best fit calculations			Arithmetic calculations			Cumulative probability			±20% Accuracy			Overall rank	
	Q_{fit}/Q_m	r	$R1$	M	σ	$R2$	at P_{50}	at P_{90}	$R3$	Log normal	Histo-gram	$R4$	RI	Final rank
1	0.95	0.84	1	1.05	0.34	1	0.98	1.38	1	47.74	67.23	1	4	1
2	0.71	0.77	2	0.74	0.26	3	0.69	1.03	2	26.98	32.77	2	9	2
3	0.57	0.40	3	0.77	0.50	2	0.60	1.50	4	18.14	12.61	4	13	3
4	1.53	0.48	4	1.46	1.43	4	1.36	3.18	3	19.50	1.68	3	14	4

* *1 = Neurofuzzy, 2 = Penpile, 3 = LCPC, 4 = De Ruiter & Beringen.*

r = correlation coefficient, μ = mean, σ = standard deviation, P_{50} = cumulative probability at 50%, P_{90} = cumulative probability at 90%, RI = Rank Index.

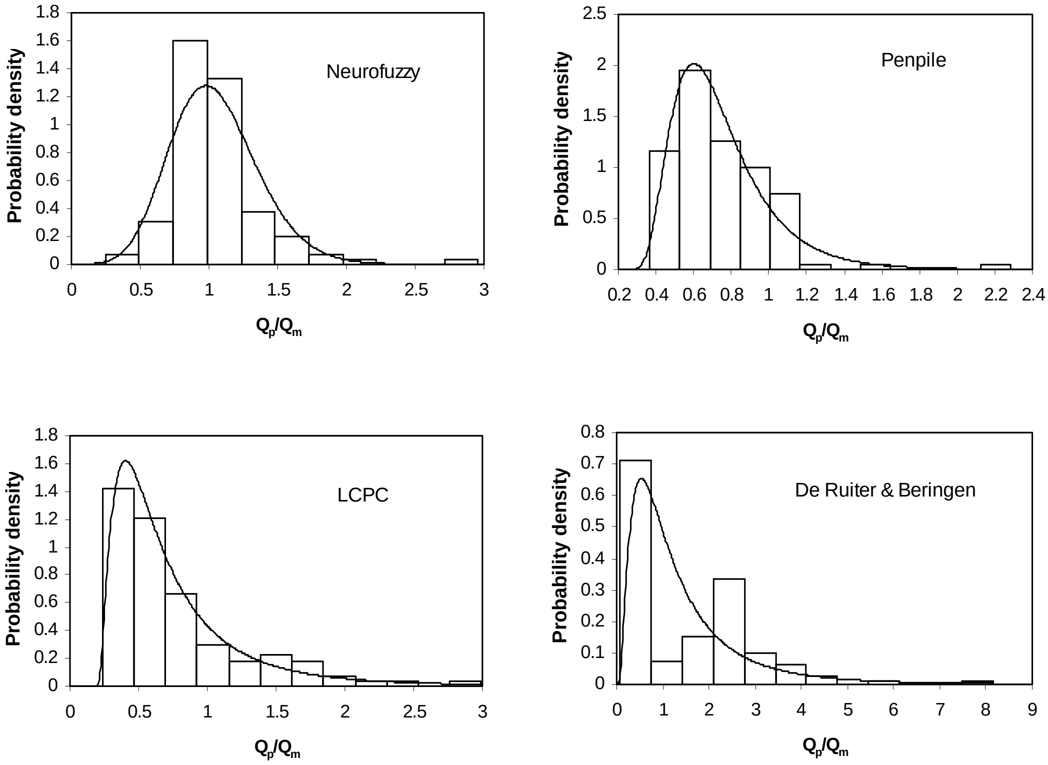

Figure 4. Histogram and lognormal distribution curves of Q_p/Q_m of the pullout capacity methods

Q_p/Q_m of the 119 anchor tests for each of the pile pullout capacity prediction methods used versus the cumulative probability (P) that can be calculated as follows (Long and Wysockey 1999):

$$P = \frac{i}{(n+1)} \tag{5}$$

where i = order number given for the considered ratio; n = number of anchors. The 50% and 90% cumulative probabilities (i.e. P_{50} and P_{90} of Q_p/Q_m) are then obtained and used to measure the tendency of each method to over-predict or under-predict the measured pullout capacity. Based on this criterion, the closer the values of P_{50} and P_{90} are to unity, the better the performance of the method. The results of this criterion, for each of the prediction methods used, are given in Table 2 (columns 8, 9, and 10). It can be seen that the neurofuzzy model again ranks first with P_{50} = 0.98 and P_{90} = 1.38, which means that, according to the third criterion, the neurofuzzy model tends to under-predict the measured pullout capacity by an average of 2%. On the other hand, the LCPC method ranks last with P_{50} = 0.60 and P_{90} = 1.50, which suggests that, according to the third criterion, this method tends to under-predict the measured pullout capacity by an average of 40%. It can also be seen that the Penpile method ranks second and tends to under-predict the measured pullout capacity by an average of 31%, whereas the method of De Ruiter and Beringen ranks third and tends to over-predict the measured pullout capacity by an average of 36%.

The fourth criterion is determined by plotting the histogram and lognormal distribution curves of Q_p/Q_m for the 119 anchor tests of each pullout capacity prediction method and the probability of predicting the pullout capacity within ±20% accuracy is obtained by calculating the area underneath the curves within $0.8Q_m \leq Q_p \leq 1.2Q_m$. Based on this criterion, the higher the probability of ±20% accuracy the better the performance of the method used. The histogram and lognormal distribution curves of the methods used are shown in Figure 4 and the corresponding probabilities and rank of the 20% accuracy are given in Table 2 (columns 11, 12, and 13). It can be seen from Table 2 that the neurofuzzy model again ranks first with the highest lognormal distribution and histogram probability values of 47.74 and 67.23%, respectively. On the other hand, the LCPC method ranks last for this criterion with the lowest lognormal distribution and histogram probability values of 18.14 and 12.61%, respectively. It can also be seen that the Penpile method, and the method of De Ruiter and Beringen, rank second and third, respectively. Finally, the results of the overall rank for the pullout capacity prediction methods used are shown in Table 2 (columns 14 and 15). It can be seen that, according to the evaluation criteria used in this work, the neurofuzzy model outperforms other methods and ranks number one.

5 CONCLUSIONS

The results of this study indicated that the B-spline neurofuzzy model was able to predict well the pullout capacity of marquee ground anchors and significantly outperforms the three traditional pile capacity prediction methods examined. The results of the rank index used as a basis for comparison of the investigated pile capacity prediction methods indicated that the performance of the neurofuzzy model ranked number one over the investigated methods followed by the Penpile method (Clisby et al. 1978) and the LCPC method (Bustamante and Gianeselli 1982). On the other hand, the rank index also showed that the method of De Ruiter and Bringen (1979) ranked last.

6 REFERENCES

Abu-Farsakh, M. Y., and Titi, H. H. (2004), Assessment of direct cone penetration test methods for predicting the ultimate capacity of friction driven piles, *Journal of Geotechnical and Geoenvironmental Engineering*, ASCE, 130(9), 935-944.

Brown, M., and Harris, C. J. (1994), *Neurofuzzy adaptive modelling and control*, Prentice-Hall, Englewood Cliffs, New Jersey.

Brown, M., and Harris, C. J. (1995), A perspective and critique of adaptive neurofuzzy systems used for modelling and control applications, *Int. J. Neural Systems*, 6(2), 197-220.

Bustamante, M., and Gianeselli, L. (1982), Pile bearing capacity prediction by means of static penetrometer CPT, *Proc., 2nd European Symposium on Penetration Testing*, Amsterdam, 493-500.

Clisby, M. B., Scholtes, R. M., Corey, M. W., Cole, H. A., Teng, P., and Webb, J. D. (1978), An evaluation of pile bearing capacities, *Volume 1, Final Report*, Mississippi State Highway Department.

De Ruiter, J., and Beringen, F. L. (1979), Pile foundation for large North Sea structures, *Marine Geotechnology*, 3(3), 267-314.

DAIS (2001), Dept. Administrative & Information Services, Workplace services, *Personal communication*.

Griggs, I. R. (2002), *Personal communication*.

Kavli, T. (1993), ASMOD - An algorithm for adaptive spline modelling of observation data, *Int. J. Control*, 58(4), 947-967.

Long, J. H., and Wysockey, M. H. (1999), Accuracy of methods for predicting axial capacity of deep foundations, *Proc., OTRC '99 Conference: Analysis, Design, Construction, and Testing of Deep Foundations*, Reston, VA, 190-195.

Neusciences. (2000), *Neuframe Version 4.0,* Neusciences Corp., Southampton, Hampshire.

Shahin, M. A., and Jaksa, M. B. (2003), Modelling the pullout capacity of marquee ground anchors, *Research Report No. R174*, School of Civil and Environmental Engineering, The University of Adelaide, Adelaide.

Shahin, M. A., Jaksa, M. B., and Maier, H. R. (2003a), Neurofuzzy networks applied to settlement of shallow foundations on granular soils, *Proc., 9th Int. Conf. on Applications of Statistics and Probability in Civil Eng., ICASP9*, San Francisco, Millpress, Rotterdam, 1379-1383.

Shahin, M. A., Maier, H. R., and Jaksa, M. B. (2003b), Settlement prediction of shallow foundations on granular soils using B-spline neurofuzzy models, *Computers and Geotechnics*, 30(8), 637-647.

Su, W., and Fragaszy, R. J. (1988), Uplift testing of model anchors, *J. Geotech. Eng.*, ASCE, 114(9), 961-983.

The Advertiser (2001), 12 Hurt in Ride Crash, March 12.

Zadeh, L. A. (1965), Fuzzy sets, Information and Control, 8, 338-353.