

Use of Artificial Neural Networks and CPT Data to Assess a Pile Base Influence Zone

presented by

Joshua R. Omer B.Sc. (Hons), M.Sc., Ph.D, R.Eng, GMICE, MDFI

Senior Lecturer in Geotechnical Engineering Kingston University London United Kingdom



INTRODUCTION

Assessing pile load carrying capacity in any soil is a challenge due to the complex mechanisms involved and the effects of soil variability and pile installation process.

As such there is no 100% reliable and accurate method of predicting pile capacity, whether utilising soil lab tests, in-situ tests or full scale pile loading tests.

So it is easy to appreciate why some pile analysis methods can under-estimate or over-estimate pile capacity by as much as 300% or more.

This research focuses on using artificial intelligence (AI) approach to develop a computer based tool for assessing pile capacity with a realistic set of input parameters that can be abstracted a conventional ground investigation report.



The AI tool involves designing an artificial neural network (ANN) which is then "trained" with data from pile load test and cone penetration test (CPT) data.

Also, using the ANN tool, parametric studies are carried out to modify some existing pile analysis methods hence increase their accuracy.

DEVELOPMENT OF THE NEURAL NETWORK METHOD

Artificial neural networks are used in many fields e.g. Finance and Statistics for problem identification, decision-making and prediction.

The success of a neural network relies on:

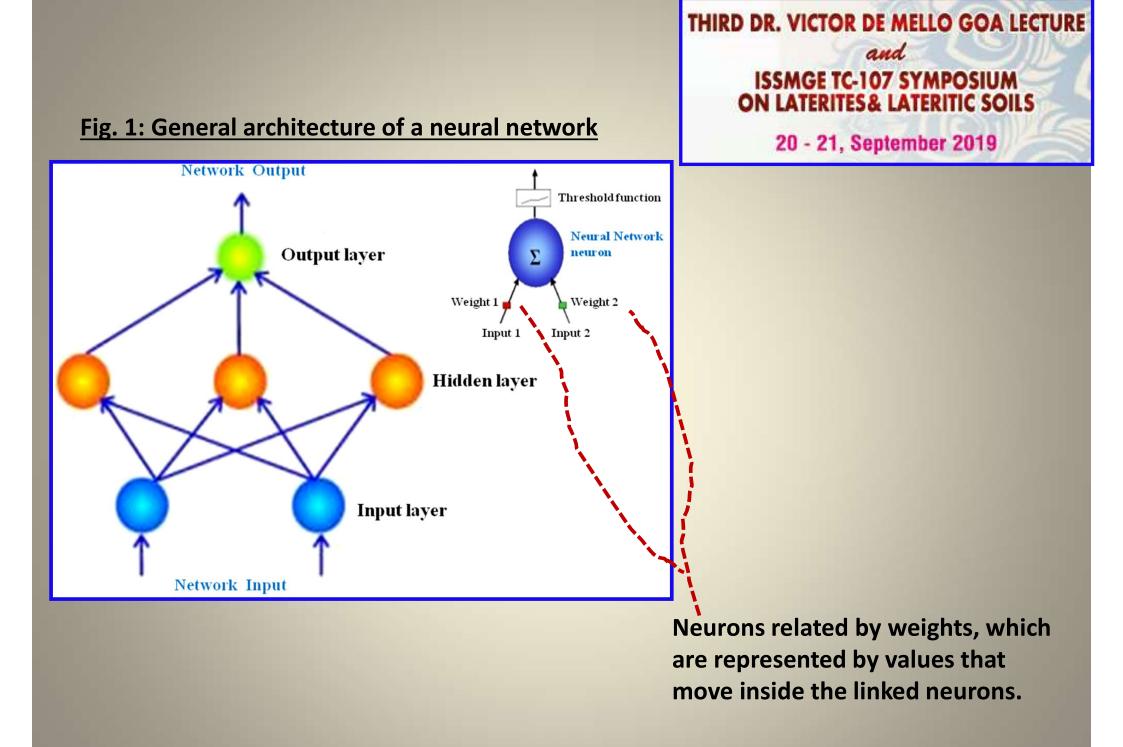
- Identification of the most representative models
- Quality and quantity of the <u>training data sets</u> from which the network can learn models.
- Ability of the network to correctly categorize new models hence make forecasts and predictions.



Here a ANN algorithm is <u>TRAINED</u> by giving it a large number of correct predictions (of pile capacity) from which it can learn underlying relationships between input variables (pile-soil parameters) and outputs (pile capacities).

The basic building block of the neural network is the <u>simulated neuron</u> that generates, classifies, and/or predicts outputs by processing the input data.

Figure 1 shows the general architecture of a neural network.





In this work, using MATLAB software, a Back-Propagation Neural Network (BPNN) is formulated with <u>five inputs</u> comprising:

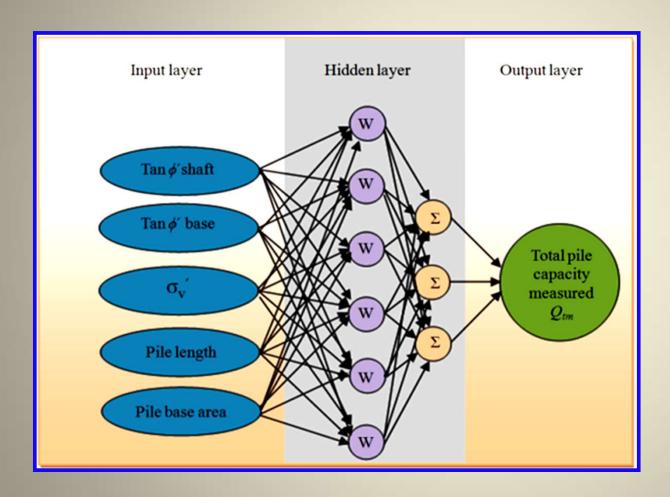
- (i) effective overburden stress σ'_{v} at pile base depth,
- (ii) pile length L,
- (iii) pile cross sectional area A,
- (iv) tangent of the mean angle of soil shear resistance along pile shaft, tan ϕ_{shaft}
- (v) tangent of the mean angle of soil shearing resistance at pile base, tan ϕ_{base}

The target parameter (output) in the network is the true pile head capacity Q_{tm} measured in a pile load test.

Figure 2 shows the design of the network:



Figure 2: Proposed neural network structure



Next, pile test data involving the above parameters are divided into two groups, namely <u>training data</u> and <u>validation data</u>.



The training data included 59 full-scale pile tests [Aziz (2010)], enabling the neurons to learn the association between <u>input</u> and <u>target</u> data.

New data from similar input parameters are then simulated in the new network to obtain output values (predicted pile capacity, Q_{tp}).

APPLICATION OF THE PROPOSED NEURAL NETWORK TO A CASE STUDY OF PILE TESTING IN BELGUIM

The case study analysed here relates to a major research project carried out by the Belgian Building Research Institute (BBRI) and reported in an article by Huybrechts (2001).

The project involved ground investigation and load testing of 32 full-scale piles in sand at a site situated 30 km south of Brussels, see Fig. 3.

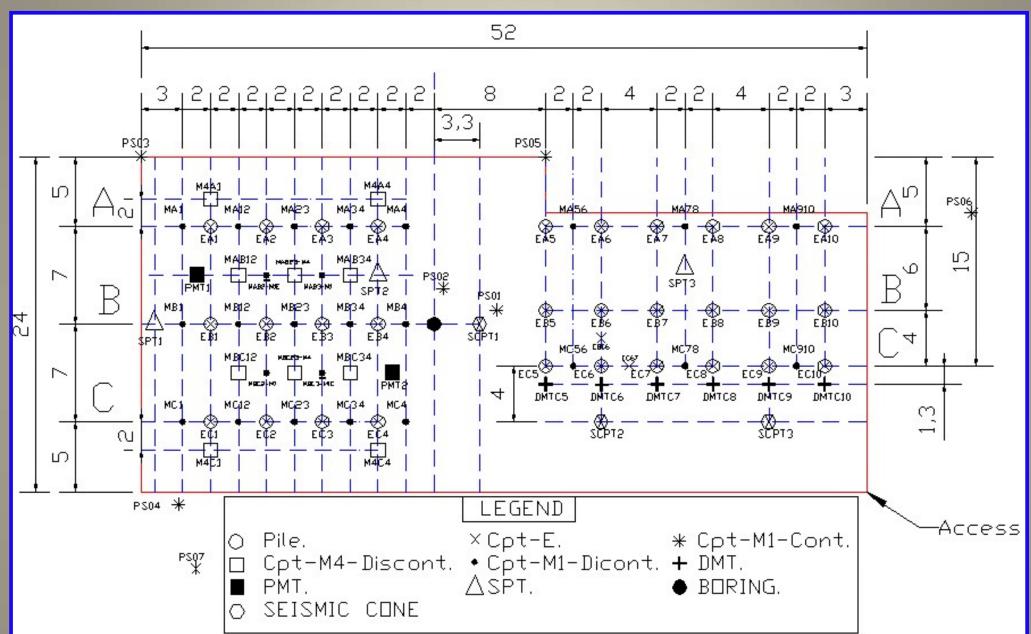


Fig. 3: Case study site (BBRI pile tests, Belgium) [Huybrechts (2001)]

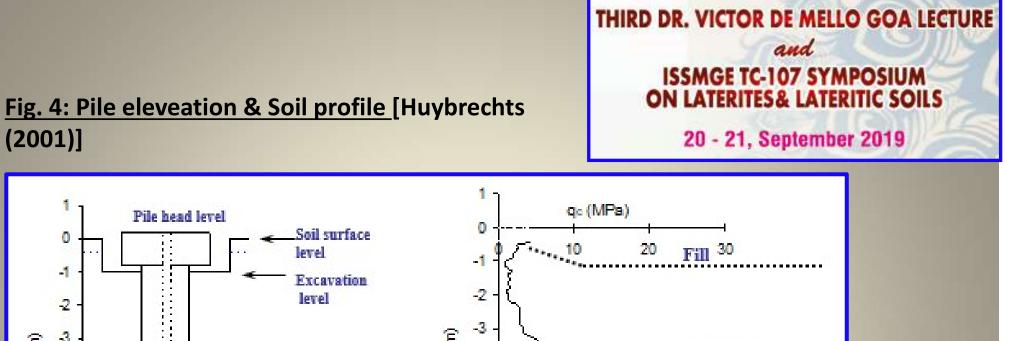
Prior to installing the piles, CPTs (at each predetermined pile location) and other tests (see Fig. 3) were carried out as part of the ground investigation programme.

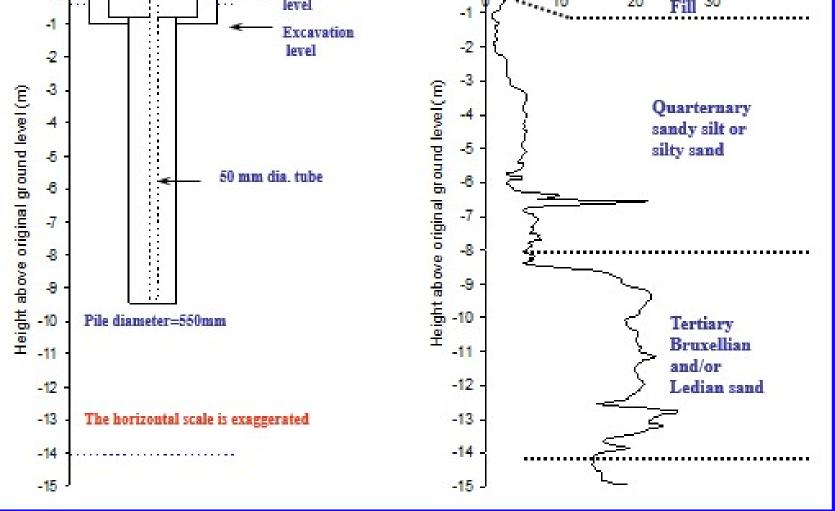


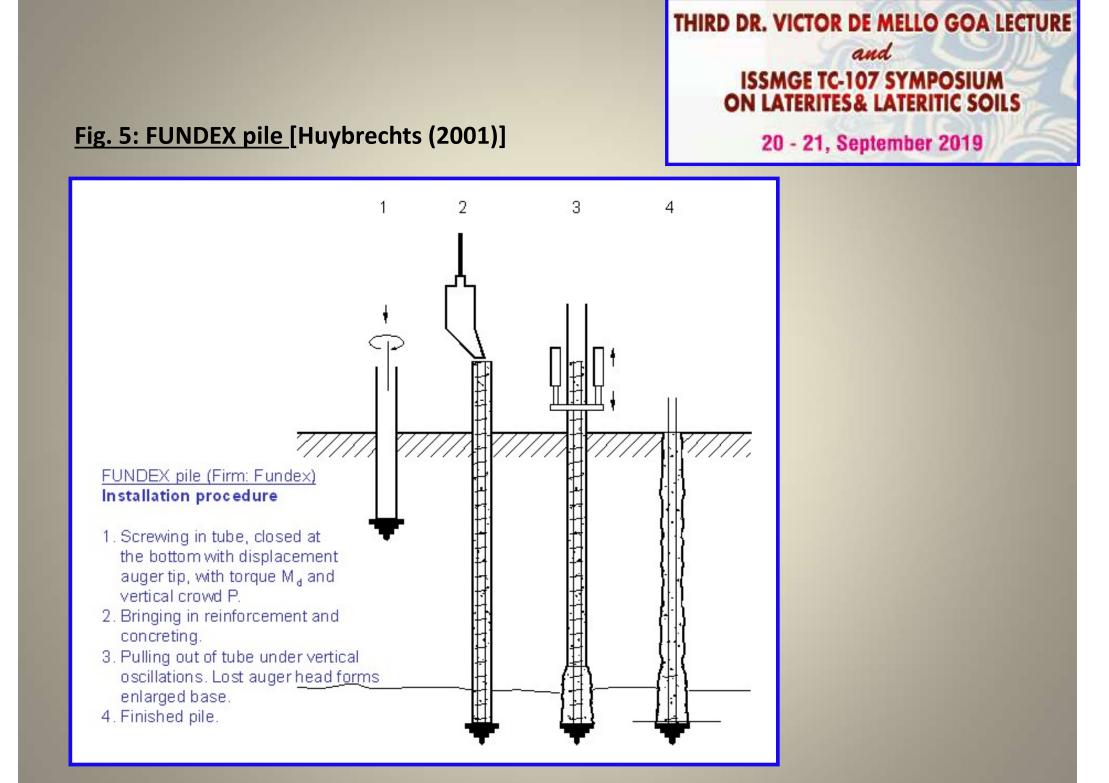
Additionally, boreholes provided soil lab test results. The following 11 piles, of <u>different proprietary types</u> were statically tested to near failure <u>(Table 1)</u>:

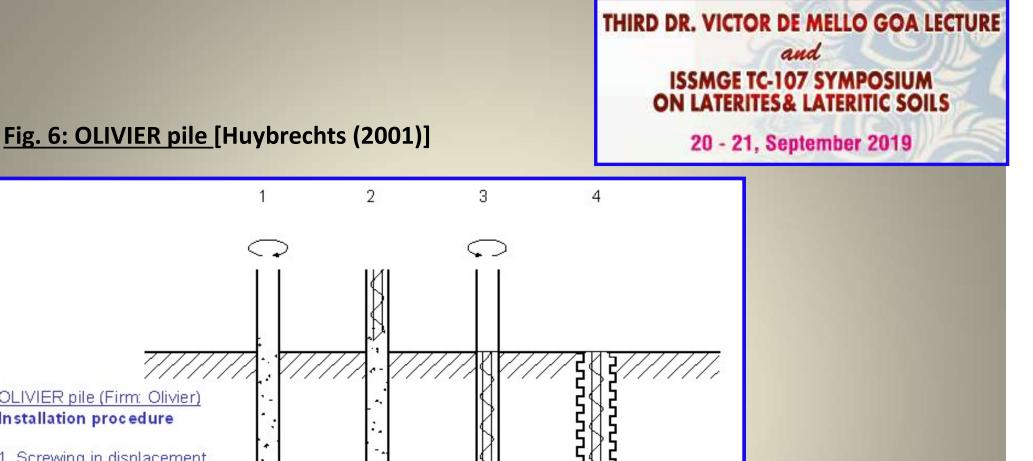
Table 1 – BBRI static pile loading test	(Huybrechts (2001)
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Pile	Date	Pile type &	Shaft	Base dia.	Pile base
No.	installed	nominal	dia. $\phi_{\rm shaft}$	<i>p</i> base	depth (m)***
		diameters	(m)	(m)	
		$\phi_{ m shaft}/\phi_{ m base}$			
Albis	11/06/2001	Fundex 38/45	0.390*	0.450	9.59
A2	12/06/2001	Olivier 36/51	0.550*	0.550*	9.45/9.20**
A3	19/06/2001	Omega 41/41	0.410	0.410	9.45
A4	26/06/2001	De Waal 41/41	0.410	0.410	9.53
B1	20/06/2001	Prefab 35x35	0.446	0.395	9.51
B2	20/06/2001	Prefab 35x35	0.446	0.395	9.57
B 3	29/06/2001	Atlas 36/51	0.510	0.510	9.58/9.43**
B4	29/06/2001	Atlas 36/51	0.510	0.510	9.58/9.43**
C2	12/06/2001	Olivier 36/51	0.550*	0.550*	9.38/9.13**
C3	19/06/2001	Omega 41/41	0.410	0.410	9.45
C4	26/06/2001	De Waal 41/41	0.410	0.410	9.52









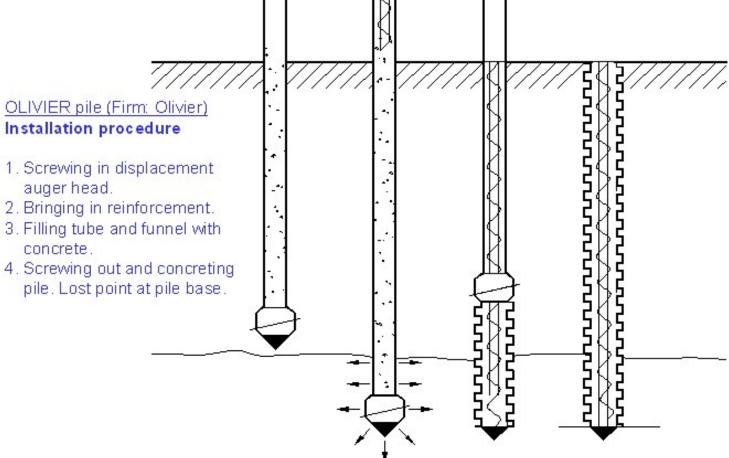


Fig. 7: OMEGA pile [Huybrechts (2001)]

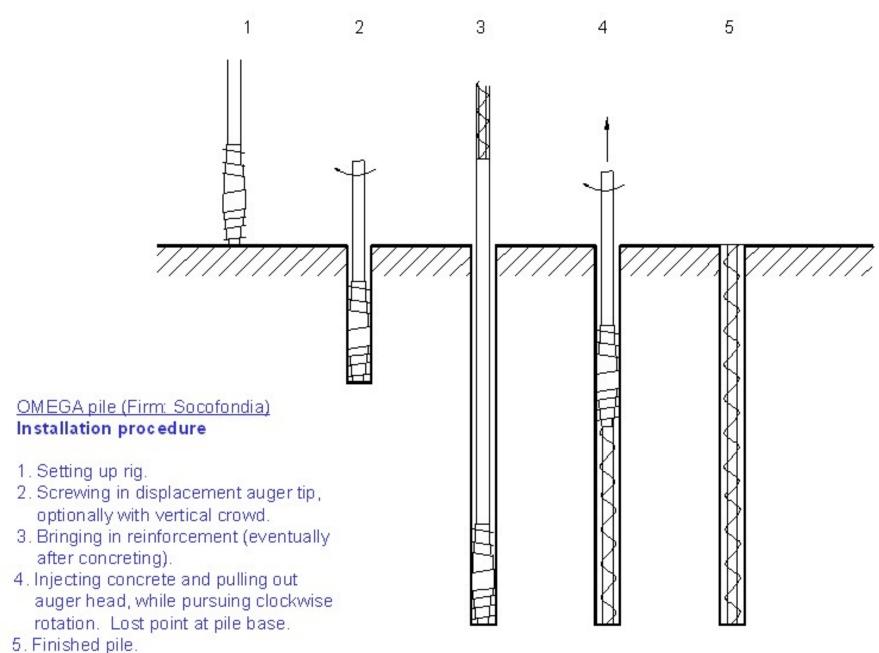
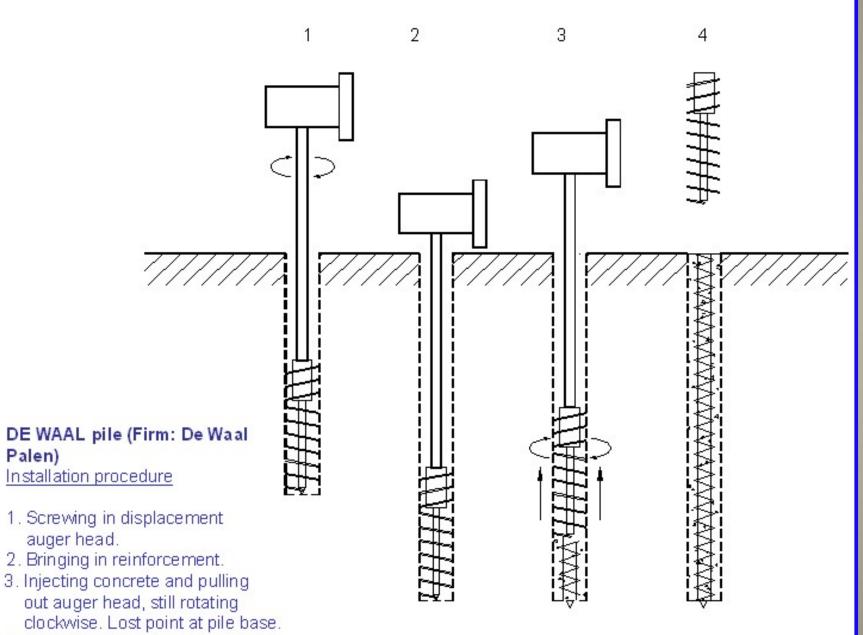
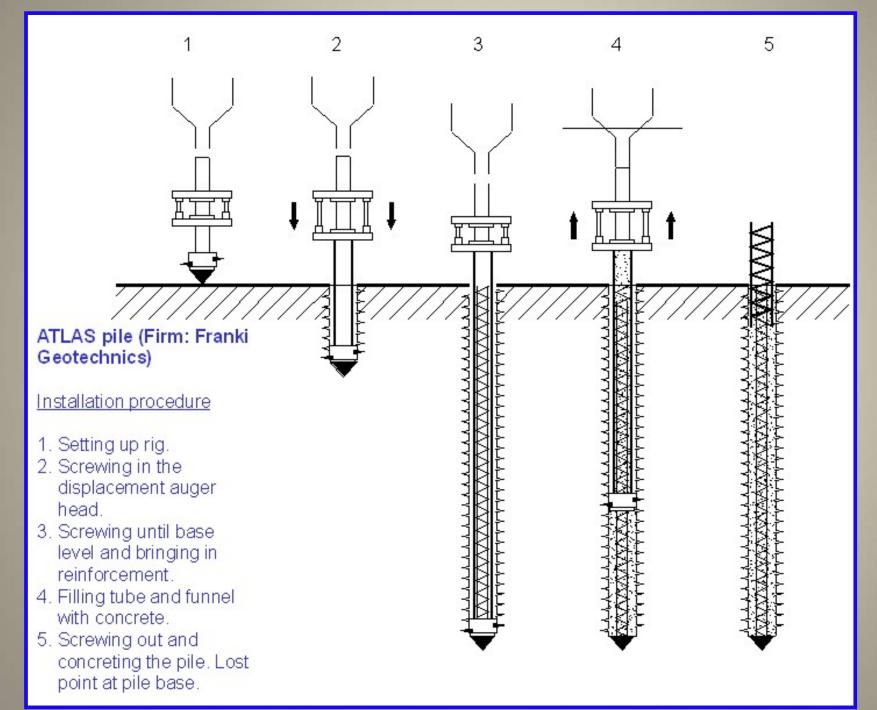


Fig. 8: DE WAAL pile [Huybrechts (2001)]



4. Finished pile.

Fig. 9: ATLAS pile [Huybrechts (2001)]





The author's neural network (BPNN) and 13 other methods were applied to the 11 static test piles (see Table 1) to predict load capacities and draw comparisons.

The 13 methods (Table 2) were programmed by Omer et al. (2006).

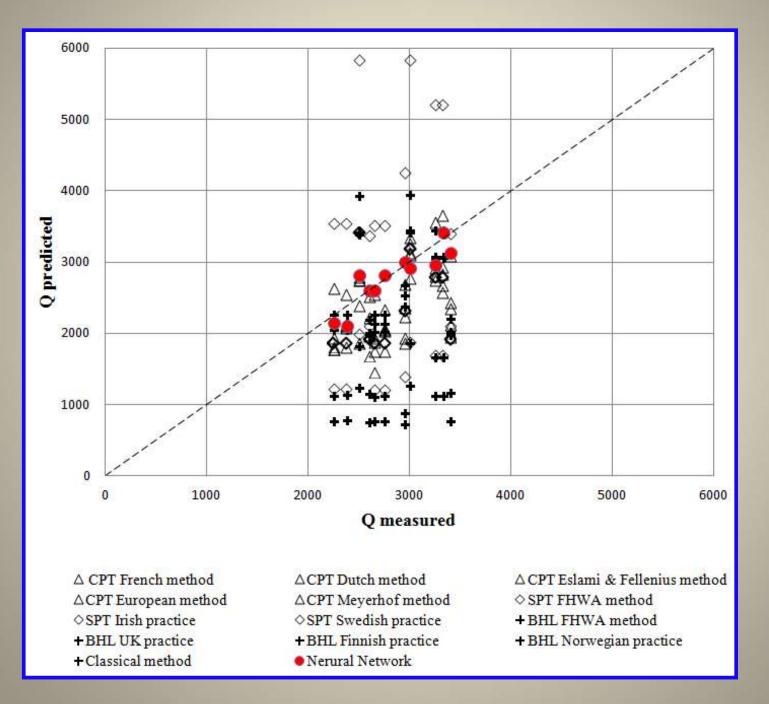
Table 2. Pile calculation methods applied.

Methods based on Cone Penetration Test (CPT) data	Methods based on SPT (Standard Penetration Test) data	Methods based on borehole log data (BHL)	Based on Soil Mechanics theory
 French (Bustamante & Gianeselli, 1982) Dutch Standards (1993) European (De Ruiter & Beringen, 1979) Meyerhof (1976, 1983) Eslami & Fellenius (1997) 	6. Irish* 7. Swedish* 8. FHWA (1998)	9. United Kingdom* 10. Finnish* 11. Norwegian* 12. FHWA (1998)	13. Classical formula (Tomlinson & Woodward, 2008)

* Articles contained in De Cock and Legrand (1997)

Fig. 10 compares the predictive accuracy of the author's BPNN method with the 13 methods, for all 11 piles analysed.

Fig. 10 Predictive accuracy – author's neural network method compared with the 13 methods (data points from 11 piles analysed prior to load testing).





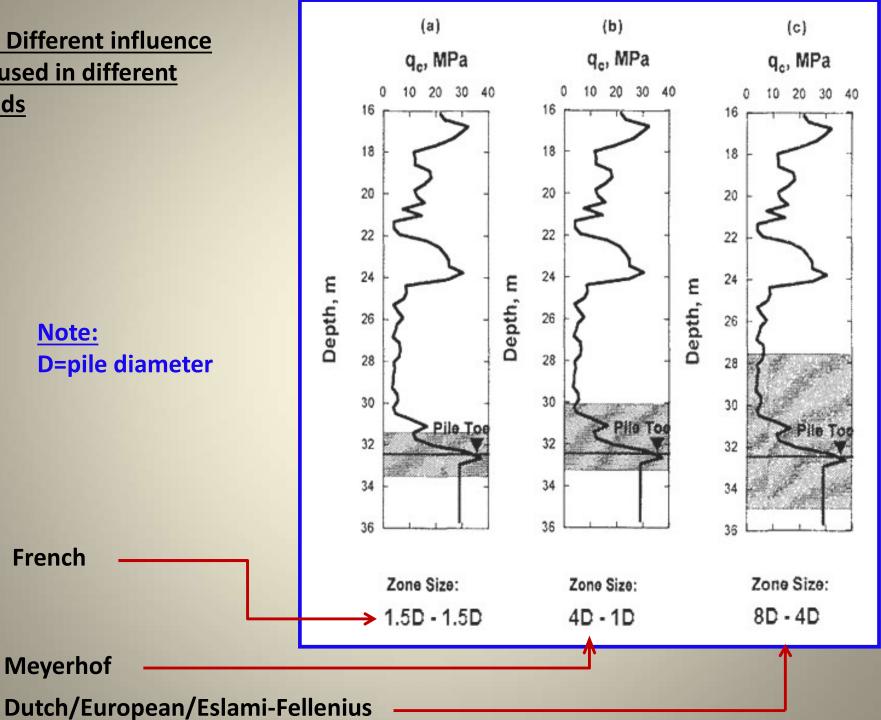
From Fig. 10 it is clear that, for these piles, the author's neural network method is far more accurate than the other 13 methods as its data points are consistently closest to the equality line (y=x).

USING THE NEURAL NETWORK METHOD TO IMPROVE THE ACCURACY OF SOME OF THE EXISTING CPT BASED METHODS

A major reason for the inaccuracy of most of the existing CPT based calculation methods is the uncertainty in the depth range (influence zone) <u>over which cone</u> <u>resistance values should be averaged</u> to compute pile base resistance capacity.

Fig. 10 illustrates the different influence zones adopted by the various methods examined in this work.

Fig. 11 Different influence zones used in different methods



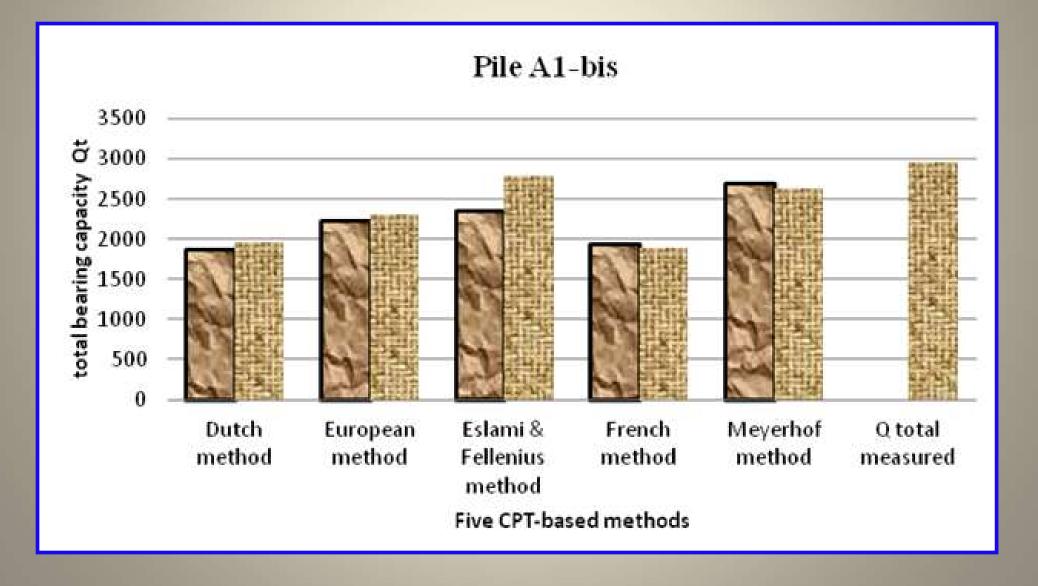


Taking each of the 5 methods (Fig. 10) one at a time, a typical test pile (Pile A1_{bis}) was analysed with the author's BPNN algorithm by inputting many trial influence zones and checking the predicted pile capacity against the measured value.

The large number of trials demonstrated that when the Eslami-Fellenius is modified by taking the influence zone as 6D-3D (i.e 6 pile diameters above pile based to 3 pile diameters below pile base), the predictive accuracy is markedly increased. The comparisons are shown in Fig. 12.



Fig. 12 Effect of modifying the influence zone to 6D-3D





CONCLUSIONS

The proposed neural network BPNN is shown to produce more accurate predictions of pile head capacity than all the other 13 published methods examined.

The present work demonstrates that the assumed extent of the influence zone of soil around a pile base has a significant effect on the calculated pile capacity, when using CPT-based empirical methods.

The accuracy of the Eslami-Fellenius method, which is highly regarded due ability to account for pore pressure (using piezo-cone/CPT_u data) further improved if the influence zone is modified from 8D-4D to 6D-3D. However, there is need to validate this definitively by analysing a large variety of test piles using this modification.



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THANK YOU

Joshua R. Omer

Kingston University London United Kingdom