PREDICTING LOAD CAPACITY OF PRECAST CONCRETE PILES USING SPT AND ARTIFICIAL NEURAL NETWORK

Juliele N. Jesus[1], Maria do Socorro C. São Mateus[1], Anderson de S. M. Gadéa[1]

[1]*Dept. of Technology, State University of Feira de Santana*
Av. Transnordestina, S/N - University Campus, Department of Technology CEP 44036-900, Feira de Santana, BA, Brazil
njjuliele@gmail.com, socorro@uefs.br, gadea@uefs.br

Abstract. One of the great challenges of foundation engineering is the calculation the bearing capacity of piles because it requires, in theory, the estimation of soil properties, its changes by the execution of the foundation and the knowledge of the soil-pile interaction mechanism. The semi-empirical methods of Aoki-Velloso [1] and Décourt-Quaresma [2] are the most widely used to estimate the bearing capacity of concrete piles in Brazil. However, these methods were developed for a group of soils from a specific region, so it is necessary to adjust them to adequately represent the soil-pile interaction mechanism in soils from regions different from those initially studied. In the geotechnical engineering, Artificial Neural Networks (ANN) have shown potential in determination of the bearing capacity of deep fundations. In this paper, an ANN model is implemented to predict the bearing capacity of precast concrete piles based on data from 126 Standard Penetration Test (SPT) and their respective load tests results, static and dynamic pile testing. Based on the results obtained, the ANN model may represent a promising solution for the design of precast concrete piles.

Keywords: Estimate the bearing capacity; Precast concrete piles; Semi-empirical methods; Artificial Neural Networks (ANN).

1. Introduction

The prediction of the bearing capacity of piles is one of the challenges of foundation engineering as it requires, in theory, the estimation of soil properties, their alterations by the execution of the foundation and the knowledge of the soil-pile interaction mechanism. Faced with the difficulty of reproducing this mechanism analytically and numerically, Brazilian practice uses empirical correlations, directly relating the results of the Standard Penetration Test (SPT) with the performance of the foundation element [3].

Among the semiempirical methods, Aoki-Velloso [1] and Décourt-Quaresma [2] are based on statistical correlations between measurements in the static cone penetration test (CPT), later replaced by SPT, and load tests. However, even though these methods are valuable tools for foundation engineering, it is necessary to recognize that, due to their statistical nature, their validity may be limited to regional constructive practice and the specific conditions of historical cases used in their establishment [4]. Comparative studies between the results estimated by these methods, and those obtained through load tests, such as those found in Dias et al. [5] and Matos et al. [6], for continuous flight auger, and Figueiredo et al. [7], for piles driven and bored drives, showed a great variability in the results obtained [8].

Artificial Neural Networks (ANNs) have demonstrated satisfactory predictive performance in the geotechnical area, as their technique allows generalizations to be made, from a set of data that are properly trained according to the problem to be studied. However, its use is still little explored in the peda of the load capacity of foundations, being the first work found in the literature dated 1995. Chan et al. [9] used ANNs to determine the bearing capacity of driven piles, without considering the type of soil. Recently, in Brazilian research, Delazzeri [8] sought to determine the bearing capacity of precast concrete piles and continuous flight auger, using ANNs, based on data samples of Standard Penetration Test (SPT) and load tests in piles, static and dynamic piles testing, resulting in more efficient mathematical models compared to the semiempirical methods of Aoki-Velloso [1] and Décourt-Quaresma [2]. Jesus [10] applied the ANNs to evaluate bearing piles to compression, seeking to develop a mathematical model capable of predicting the rupture bearing.

In view of the above, this paper seeks to implement an ANN model for predicting the bearing capacity of precast concrete piles, from the database of Lobo [3], which contains data from 126 reports of SPT, and their respective results of static and dynamic load tests. At the end, the model is confronted with other models present in the literature, in order to verify its efficiency.

2. ANN Model Development

For the development of this work, a multilayer feedforward ANN was used, whose typical structure consists of a series of processing elements, the neurons, which are partially or totally connected by synaptic weights. Neurons configure input, intermediate (or hidden) and output layers. For each processing, the input of the processing element of the previous layer (x_i) is multiplied by a synaptic weight (w_{ji}), and the weighted inputs are summed and a bia (b_k) is added or subtracted. Subsequently, the sum of the inputs, with their respective weights and bias, is introduced in a nonlinear activation function 'φ (.)' (e.g., logarithmic function or hyperbolic tangent function) (Fig. 1).

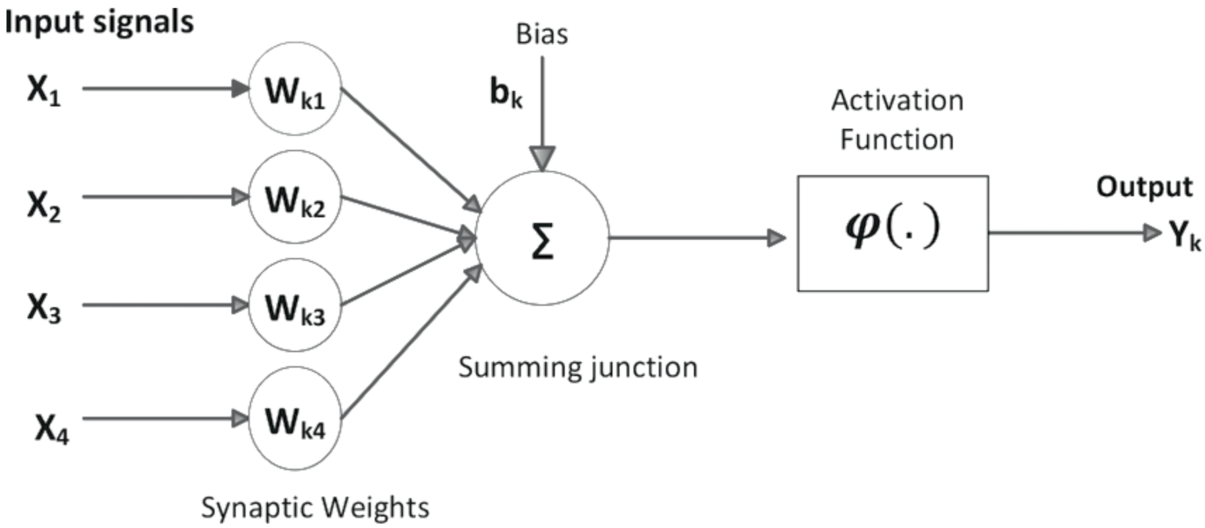


Figure 1. Artificial Neuron Model: McCulloch-Pits [11].

2.1 Neural model

The ANN model, to predict the load capacity of piles, was trained and validated through the data set present in the work of Lobo [3], a population of 126 samples was extracted, containing the SPT reports and their respective results of the load test performed in the piles, in different Brazilian localitions, with different types of soils. For model training, 70% of the data (88 samples) were used and 30% (38 samples) were used for validation.

2.2 Model input and output variables

The input variables for the model were obtained from the methodology proposed by Delazzeri [8], applying the recommendations of the Décourt-Quaresma method [2], according to Tab. 1.

Table 1. Recommendations of the Décourt-Quaresma method [2].

Variables	Conditions
NP	Average N_{spt} value at the base of the pile, obtained from 3 values: the tip, the immediately anterior and the posterior.
NL	Average value of N_{spt} along the pile shaft.
Note: Mean Nspt (NP and NL) were performed with values between 3 and 50. Values below or aboce were replaced by these threshold values.	

As an output variable, there is the pile bearing load capacity (Q_t), the determination criteria were according to the ABNT, NBR 6122 [12]. Na Tab. 2 the variables used for the neuronal model are presented.

Table 2. Input and Output variables for the model.

Input variables			
Variables	Description	Minimum	Maximum
P	Perimeter of the cross section (cm)	60	280
L	Effective length of pile, except tip section (m)	3	40
A	Cross-sectional area (cm²)	225	4900
NL	Average soil N_{SPT} along the pile shaft	1	17
NP	Average N_{SPT} around the pile tip	2	34
Output variables			
Variables	Description	Minimum	Maximum
Q_t	Pile bearing load capacity (kN)	53	5950

2.3 Network topology and choice criteria

In the network architecture, the following parameters were adopted:

- Connection pattern: feedforward.
- Input layer: five neurons (P, L, A, NL, NP).
- Intermediate layer: one layer with the number of neurons ranging from 1 to 5.
- Output layer: one neuron (Q_t).
- Training functions: hyperbolic tangent and logarithmic.
- Learning algorithm: backpropagation associated with the Levenberg-Marquardt update rule.

To choose the most efficient ANN, the following criteria were taken into account:

- Higher values of the coefficients of determination (R^2).
- Distribution of errors in histograms.
- Maximum and minimum errors.
- Network with the lowest number of neurons in the hidden layer, aiming at a model with less robustness.

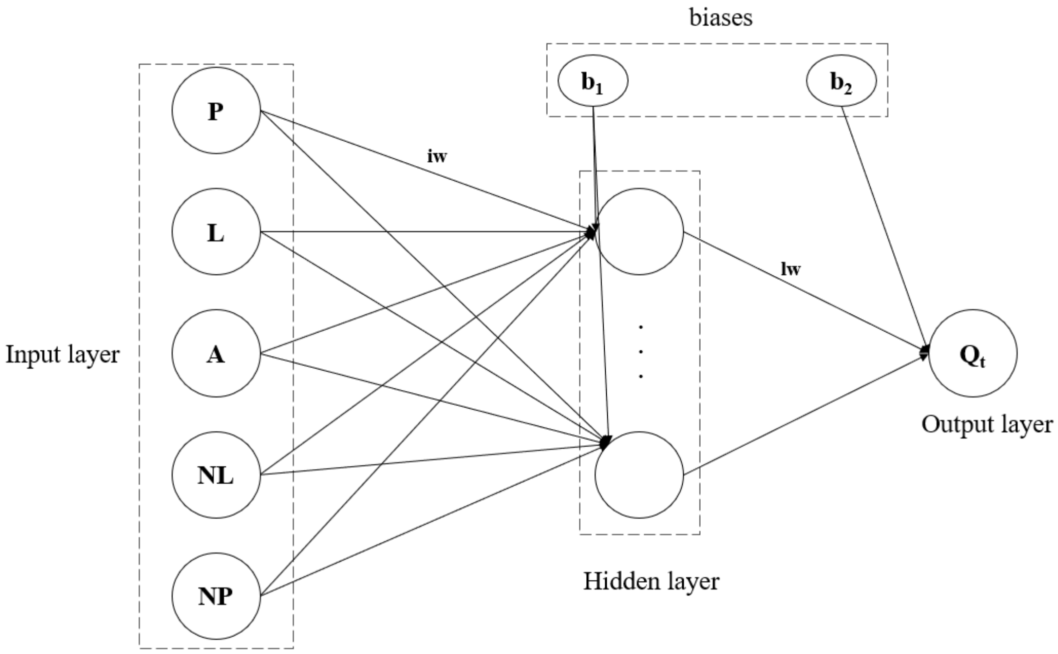


Figure 2. Network architecture.

3. Performance: Model Validation and Robustness

The most efficient ANN model has A:5:2:1 architecture, with 2 neurons in the hidden layer and logarithmic training function. The determination coefficients, shown in Table 3, were 0.916 for training, and 0.967 for validation. The decision to adopt this typology was based on the selection criteria and comparative analyzes, performed among all simulations, of scatter plot and error histograms. It should be noted that, for all test simulations, the logarithmic function presented better results than the hyperbolic tangent function.

Table 3. Variation of the coefficients of determination in the tested ANN.

Number of neurons	Training R^2	Validation R^2	Positive maximum error (%)	Negative maximum error (%)
1	0,906	0,891	98,06	-598,03
2	**0,916**	**0,967**	**74,55**	**-332,22**
3	0,936	0,893	66,49	-494,02
4	0,919	0,908	74,05	-355,57
5	0,923	0,955	63,81	-565,65

For the maximum and minimum errors, the relationship between the load capacity values derived from the load tests (targets) and the values calculated by the ANN (outputs) was found to be 74.55% and -332.22%, respectively. However, as can be observed in the error histogram (Fig. 3), three outliers have minimum error values below -150%. In general, despite the outliers, the curve distribution tends towards normality.

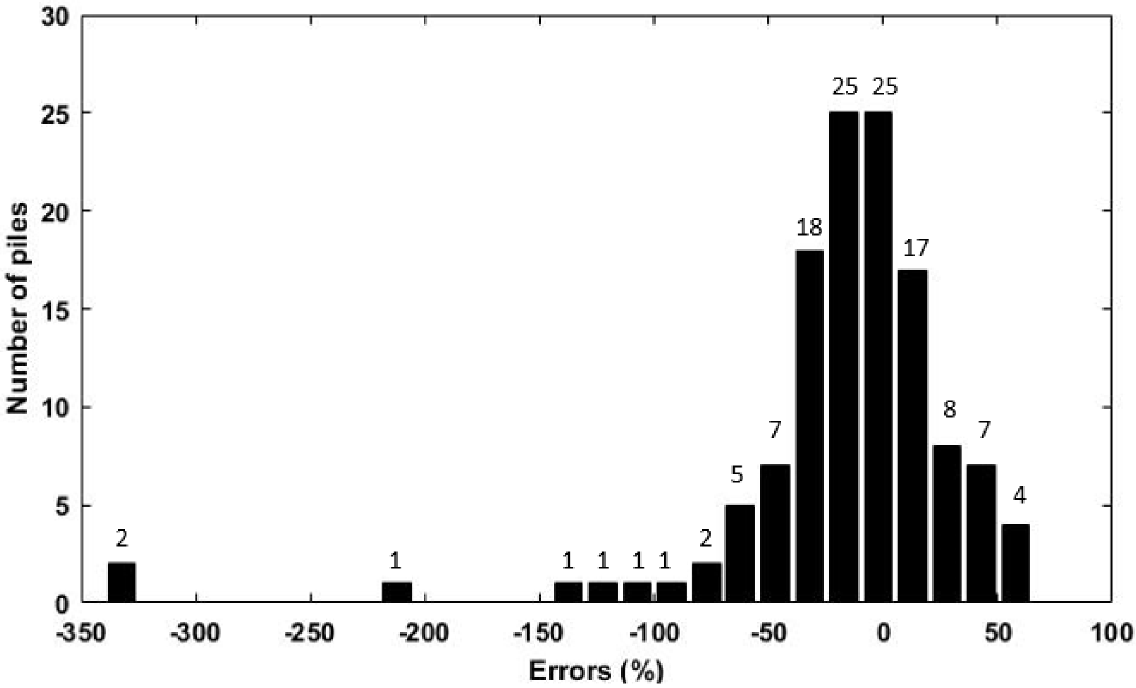
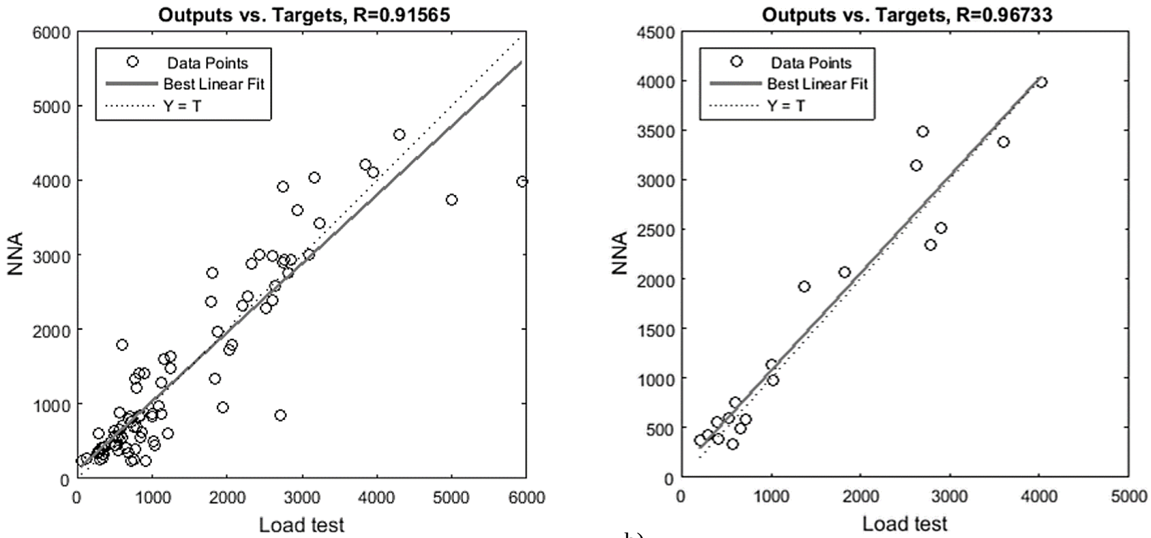


Figure 3. Histogram of errors.

Figure 4 presents the dispersion graphs of the training and validation of the model.



a) b)

Figure 4. NNA coefficients for (a) training and (b) validation.

3.1 Model equation

The equation obtained from the ANN, with two neurons in the intermediate layer and with a logarithmic transfer function, capable of determining the bearing capacity of precast concrete piles, is presented in Equation 1.

$$Qt = \frac{404736}{1319}(e^{a}+1)^{-1} - \frac{1390969}{295}(e^{b})^{-1} + \frac{1807324}{313} \qquad (1.a)$$

$$a = \frac{5709}{153266}P - \frac{20815}{51788}L + \frac{1039}{1029020}A - \frac{86939}{88214}NL + \frac{13772}{171071}NP + \frac{208763}{23283} \qquad (1.b)$$

$$b = \frac{10033}{485596}P + \frac{2554}{307983}L + \frac{241}{1538530}A + \frac{8179}{148202}NL + \frac{4948}{196357}NP - \frac{53705}{9987} \qquad (1.c)$$

Where: P is the perimeter of the cross section (cm); L is the effective length of the pile, except for the tip section (m); A is the cross-sectional area (cm²); NL is the average N_{SPT} of the soil along the bole and NP is the average N_{SPT} at the tip.

3.2 Comparison between models

Delazzeri [8] developed three ANN models to calculate the bearing capacity of precast concrete piles, using the same database as Lobo [3], and subsequently compared them with the semiempirical methods of Aoki-Velloso [1] and Décourt-Quaresma [2]. Table 4 presents the results found by the author, comparing them with the models obtained in the present work.

Table 4. Comparison of models x semiempirical methods: adapted from Delazzeri [8]

Models	Number of neurons	Training R²**/ R²	Validation R²	Maximum positive error (%)	Negative maximum error (%)
ANN – Suggested model	2	0,916	0,967	74,55	-322,22
ANN - Delazzeri [8]	2	0,933	0,877	55,77	-262,15
Aoki-Velloso [1]	*	0,638	*	95,01	-230,06
Décourt-Quaresma [2]	*	0,742	*	74,50	-134,95

*does not apply
** semiempirical methods

As shown in Tab. 4, it can be seen that the ANNs models have an efficient predictive bearing capacity when compared with the results of load tests os piles and semiempirical methods, with correlation coefficients very close to 1. For the maximum error values, there is a convergence of all models, both semiempirical methods and ANNs, although they present discrepant values for the minimum errors. However, when the error histogram is analyzed (Fig.3), it is noticed that most of the piles are concentrated in the error range [-50, 50].

4. Conclusions

From the use of ANN it was possible to elaborate a model to determine the bearing capacity of precast concrete piles, with values of determination coefficients of 0.916 and 0.967, for training and validation, respectively. For the maximum positive and negative errors, the values were 74.55% and -322.22%. When compared with the neuronal model proposed by Delazzeri [8], there is a convergence in the results, indicating the efficiency of the models. In relation to semiempirical methods, the values obtained through the equations are more accurate.

Acknowledgements. We thank the Graduate Program in Civil and Environmental Engineering (PPGECEA) for their support in carrying out the research.

Authorship statement. The authors hereby confirm that they are solely responsible for the authorship of this work, and that all material included herein as part of the present paper is the property (and authorship) of the authors, or has the permission of the owners to be included here.

References

[1] AOKI, N.; VELLOSO, D.A. (1975) An approximate method to estimate the bearing capacity os piles, Panamerican Conference on soil mechanics and foundation engineering, 5, Buenos Aires, 367-376.
[2] DÉCOURT, L.; QUARESMA, A. R.. Capacidade de carga de estacas a partir de valores de SPT, 6° Congresso Brasileiro de Mecânica dos Solos e Engenharia de Fundações, Rio de Janeiro, 1978.
[3] Lobo, B. O (2005). Método de Previsão da Capacidade de Carga de Estacas: Aplicação dos conceitos de energia do ensaio de SPT. 121p. Dissertação (Mestrado)-Escola de Engenharia, UFRS. Porto Alegre.
[4] SCHNAID, F.. Ensaios de Campo e suas aplicações na engenharia de fundações. São Paulo: Oficina de Textos, 2000. 189 p.
[5] DIAS, K.O., CAVALCANTE, E.H., BARBOSA, V.C.S., NETO, O.F., JÚNIOR, C.R.C., JÚNIOR, F.A.P.(2014). Previsão de Capacidade de Carga de Uma Fundação em Estaca Hélice Contínua Apoiada Sobre Solo Mole: Um Estudo de Caso,XVII Congresso Brasileiro de Mecânica dos Solos e Engenharia Geotécnica - COBRAMSEG 2016, Goiânia, Goiás, Brasil, 8p.
[6] MATOS, L.F.S., RÖHDEN, A.B., OLIVEIRA, J.M.(2016). Estudo Comparativo de Métodos de Previsão da Capacidade deCarga de Estacas Tipo HCM – Hélice Contínua Monitorada, XVIII Congresso Brasileiro de Mecânica dos Solos e Engenharia Geotécnica - COBRAMSEG 2016, Belo Horizonte, Minas Gerais, Brasil, 8p.
[7] FIGUEIREDO, L.C., CUNHA, R.P., CONCIANI, W., MARCHEZINI, S.F., BEZERRA, N.M.M. (2016). Análise Comparativa do Método de Previsão de Capacidade de Carga para Estacas de Lobo (2005) com os Métodos Semiempíricos para Solo do Plano Piloto de Brasília, XVIII Congresso Brasileiro de Mecânica dos Solos e Engenharia Geotécnica - COBRAMSEG 2016, Belo Horizonte, Minas Gerais, Brasil, 8p.
[8] DELAZZERI, Marcus Lessandro Costa. Estimativa da capacidade de carga de fundações profundas utilizando rede neural artificial. 2018. 212 f. Dissertação (Mestrado) - Programa de Pós-Graduação em Engenharia Civil e Ambiental, DTEC, Universidade Estadual de Feira de Santana, Feira de Santana - Ba, 2018.
[9] CHAN, W. T.; CHOW, Y. K.; LIU, L. F.. NEURAL NETWORK: AN ALTERNATIVE TO PILE DRIVING FORMULAS. Computers And Geotechnics, Great Britain, n. 17, p. 135-156, 1995.
[10] JESUS, Bruno Vieira de. Experimentos de previsão da carga de ruptura em estacas carregadas axialmente à compressão utilizando Redes Neurais Artificiais (RNA). 2019. 178 f. Dissertação (Mestrado) – Programa de Pós-graduação em Engenharia Civil, Universidade do Estado do Rio de Janeiro, Faculdade de Engenharia, Rio de Janeiro, 2019.
[11] S. A. Seshia, A. Desai, T. Dreossi, D. J. Fremont, S. Ghosh, E. Kim, S. Shivakumar, M. Vazquez-Chanlatte, and X. Yue, "Formal specification for deep neural networks," in International Symposium on Automated Technology for Verification and Analysis. Springer, 2018, pp. 20-34.
[12] ABNT: ASSOCIAÇÃO BRASILEIRA DE NORMAS TÉCNICAS NBR 6122: Projeto e execução de fundações. Rio de Janeiro, 2022, 126 p.