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Estimative of shaft and tip bearing capacities of single piles using multilayer perceptrons

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Article

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Multilayer perceptrons
Pile shaft bearing capacity
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Abstract

There are an increasing number of studies that use the artificial neural networks (ANN) as a prediction tool in the field of foundations with satisfactory results. In this paper, multilayer perceptrons are used to develop prediction models for the shaft and tip bearing capacities of single piles based on a supervised training using the error back propagation algorithm. Results from static load tests carried out on 95 instrumented single piles executed in different regions of Brazil were used in the ANN modelling. The prediction models of shaft and tip bearing capacities of single piles were obtained portraying indicated in the validation phase determination coefficients equal to 95% and 99%, respectively. To demonstrate their applicability and efficiency, such models were used to estimate the bearing capacity of single piles unused in the models' development, as well as groups of two and three piles. The results demonstrated that the neuron models were much closer to the values of the bearing capacities measured in single pile tests and groups of piles, than the estimated results using semi-empirical methods. As a result of overestimating the predicted bearing capacities in relation to the results of the load tests, it is recommended to use models applying reduction factors of 0.88 for single piles, and 0.75 for groups of up to three piles.

1. Introduction

Pile foundations are responsible for transmitting loads from the superstructure to the ground, so that deformations do not affect the usage of the project. This transmission occurs through two mechanisms: friction (between the side of the pile and the ground) and reaction of the pile tip.

The bearing capacity of single pile (Q_r) is defined by Cintra & Aoki (2010) as the sum of the maximum loads that can be supported by shaft and tip resistance. According to Fellenius (2016, 2021), a pile design based on "the bearing capacity is with a factor of safety of two or better, so we will have no settlement" is an inadequate, because the bothersome settlement is that caused by other factors than the pile loads, such as, fills, groundwater table lowering, neighboring structures, regional subsidence, etc.

The value of Q_r can be determined based on parameters taken from field and laboratory testing, by means of theoretical and or semi-empirical methods. Given the problems in obtaining the ground strength to adopt theoretical methods, the designer often resorts to semi-empirical methods which use Standard Penetration Test (*SPT*) results to estimate the bearing capacity of different types of deep foundations, also taking into account the particular executive methods of each pile. Amann (2010) criticizes the indiscriminate use of such formulations without taking due care to the adjustments referring to the characteristics of the geotechnical profile on the development site of a specific design.

Studies developed by Maya et al. (2013), Probst et al. (2018), Amann et al. (2018), Carvalho & Santos (2019), Pereira et al. (2020), Silva (2020) indicate that there is high dispersion between the values of pile bearing capacity assessed by traditional semi-empirical methods and those ones obtained in dynamic and static load tests.

The static load test is an efficient way to check the bearing capacity of single piles assessed by using semi-empirical methods and, when in instrumented piles, it allows to analyze the load transfer mechanism from the pile to the surrounding soil. In the last decade several researchers have discussed the results of instrumentation performed on different types of piles (Tran et al., 2012; Seo et al., 2013; Haque et al., 2014; Musarra & Massad, 2015; Bohn et al., 2017; Bersan et al., 2018; Narsavage, 2019 and Akl & Mossaad, 2021).

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Quite an alternative used to improve the prediction process of deep foundation behavior has been to apply Artificial Neural Networks (ANN). Moayedi et al. (2020) reviewed the literature in which they found a total of 121 articles about the applicability of ANN in pile bearing capacity (lateral and axial). Pham et al. (2020), Chen et al. (2020), Kardani et al. (2020), Zhang et al. (2020), Benali et al. (2018), Maizir (2017) and Momeni et al. (2014, 2015) applied of ANN when predicting the piles bearing capacity. Most ANN models developed in the studies estimate the bearing capacity of piles or the shaft bearing capacity or tip bearing capacity and, in most cases, for the same soil profile.

There are different types of artificial neural networks for solving problems in geotechnical engineering being the multilayer perceptrons the most used (Tizpa et al., 2015; Kiran et al., 2016; Dantas Neto et al., 2017; Ebtehaj et al., 2018; Zhang et al., 2019; Darbor et al., 2019; De Granrut et al., 2019). What makes this neural network attractive is the presence of hidden layers and the high degree of connectivity which allows it to be capable of understanding the complex behavior of several multivariable phenomenon in geotechnical engineering.

Given the applicability of multilayer perceptrons and the scarcity of neuron models to predict the pile shaft bearing capacity depending on the depth and the pile tip bearing capacity of different types of piles and various geotechnical profiles, and in order to mitigate the restrictions found in semi-empirical methods, the purpose of this article is to propose neuron models that are able to estimate the shaft and tip bearing capacities of single piles and even analyze the applicability of such models in predicting the failure load for groups of piles.

2. Materials and methods

2.1 Data collection

The first step of modeling with artificial neural networks is to define the variable that could influence the studied phenomenon, in this case the load transfer mechanism from the pile to the ground. This phenomenon is influenced by several factors, such as, for example: the pile's geometry, type of pile, installation process, initial stress status of ground and the loading background undergone by the pile (Bohn et al., 2017; Cooke et al., 1979).

Studies such as those by Benali et al. (2018), Maizir (2017) and Momeni et al. (2014, 2015) who used the artificial neural networks to predict the pile bearing capacity were developed by addressing between 35 and 260 field tests (Standard Penetration Test, Cone Penetration Test, Pile Driving Analyzer, Static Load Test), the used variables being related only to the pile's geometry and data take from those tests.

In this article, it was decided to use as input and output variables of the neuron models, developed to estimate shaft and tip bearing capacities of single piles, the information gained from results of static load tests piles, under axial compression effort, instrumented along the length and *SPT* boreholes. A database includes 95 single piles installed in different regions of Brazilian territory, as shown in Figure 1.

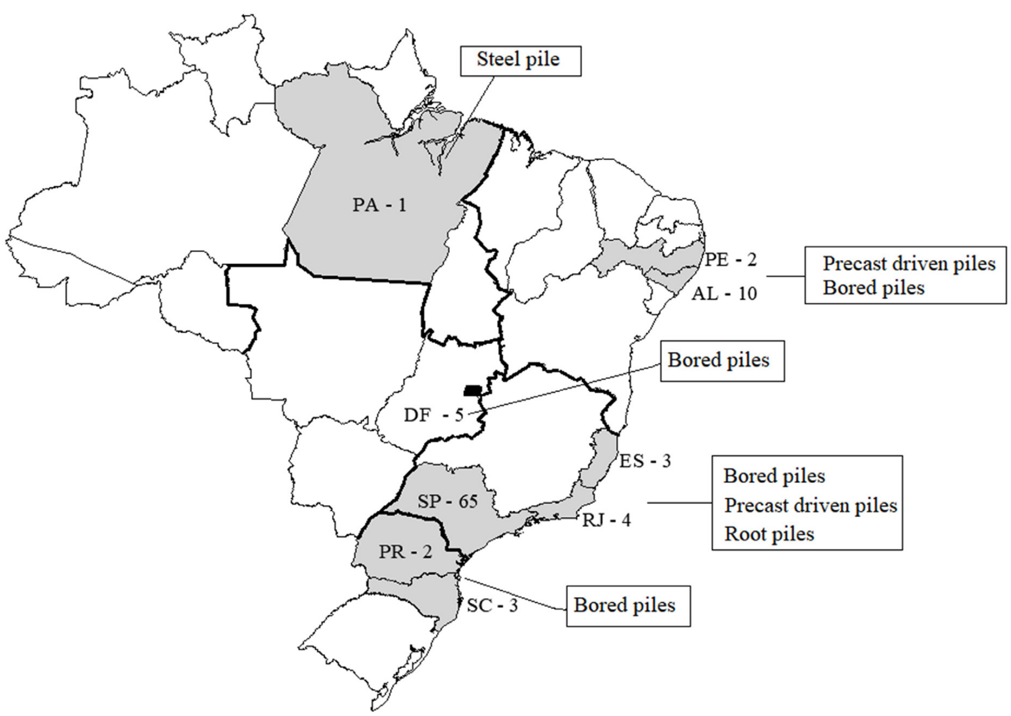


Figure 1. Distribution used instrumented piles on the Brazilian territory.

It is noted that, of the five Brazilian regions in question, the Southeast region concentrated the majority (72 piles), while the North, Midwest and South regions have the smallest quantities, that is, one, five and five piles, respectively.

It should be mentioned that the use of a database with information from different regions in Brazil and, consequently, installed in different geological conditions, gives the proposed neuron models more applicability and representativeness from a practical viewpoint.

2.2 Definition of neuron model variables

In this article, the output variables are the shaft and tip bearing capacities of single piles. To discover the input variables, the available information that influences the ground-pile interaction was fond in the database (Pham et al., 2020; Chen et al., 2020; Benali et al., 2018; Maizir, 2017 and Momeni et al., 2014, 2015), and consequently, is responsible for mobilizing the shaft and tip bearing capacities of piles, namely: pile geometry (diameter and length); pile type; soil type; *SPT* test rate and type of loading applied to the static load test. All procedures and criteria used to define the input and output variables considered are described below.

2.2.1 Shaft and tip bearing capacities of pile

The shaft (Q_s) and tip (Q_p) bearing capacities of piles are provided by the instrumentation of the piles undergoing static load tests. It is important to emphasize that all piles were instrumented, 97% with strain gauges installed at different levels. In addition, the maximum loads applied to the piles are higher than the failure load defined by the Brazilian Standard (ABNT, 2019).

Only in cases where the piles were not instrumented at the tip or had problems at this instrumented level while applying the loads, it was decided to extrapolate the last segment of the pile until reaching the tip, as shown in Figure 2. It is noteworthy that the extrapolations correspond to less than 12% of the total length of the piles.

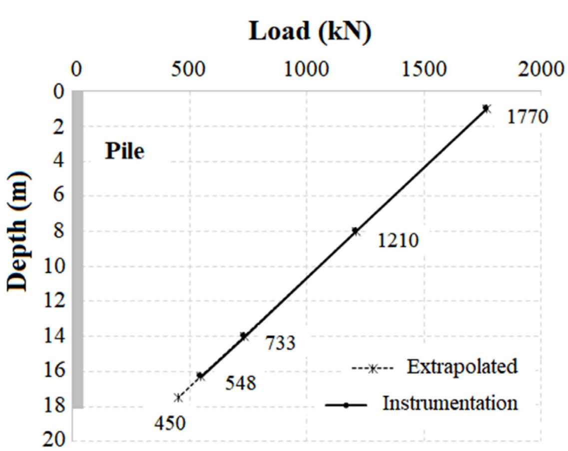


Figure 2. Load distributions in instrumented pile.

It should be stressed that, since this is an analysis in terms of bearing capacity, the only results of interest are those corresponding to the ultimate load applied in the static load test.

2.2.2 Pile type

The input variable, when considering the pile type, was included in the models developed in two ways: the first, *PT1*, based on the classification by Velloso & Lopes (2010); and the second, *PT2*, corresponding to a proposal of the study herein, in which it was decided to separate pile types by their material (precast driven, steel and concrete piles), including piles with similar modeling methodologies, as in the case of micro-piles and root piles.

Tables 1 and 2 provided the values adopted for variables *PT1* and *PT2*, respectively, used to develop the neuron models in this study. It was found from the analyses in these tables that the models proposed for predicting the shaft and tip bearing capacities of single piles include a large variety of pile types, considering the main pile construction methods currently adopted in Brazil and abroad (Velloso & Lopes, 2010; Van Impe, 2003).

2.2.3 Pile geometry

In this study, pile geometry was represented by the diameter (D) and embedded length (L_e), which directly influence the prediction process of the shaft and tip bearing capacities of piles. The diameter values of the piles used in developing the neuron models range from 88.9 mm to 1200 mm, while the embedded lengths vary from 3.5 m to 51 m. For piles with rectangular or square sections and for steel piles the diameter was calculated based on the circumscribed area.

Table 1. Adopted values for *PT1*.

Pile type	Value
Major displacement	1
Minor displacement	2
Substitution	3
Without displacement	4

Table 2. Adopted values for *PT2*.

Pile type	Value
Precast concrete	1
Steel	2
Injected	3
Bored with displacement	4
Continuous flight auger	5
Bored	6
Bored with stabilizer	7

2.2.4 Soil type

In the models estimating the shaft and tip bearing capacities of piles, the three variables adopted to represent the soil type were as follows: $\%Sand_{ac}$; $\%Silt_{ac}$ and $\%Clay_{ac}$. The definitions for such variables were based on those proposed by Araújo et al. (2016), who used the artificial neural networks to predict settlements in single piles, as described in Equations 1, 2 and 3.

$$\%Sand_{ac} = \sum_{1}^{n} \frac{\Delta L_{sand}}{\Delta L_e} \tag{1}$$

$$\%Silt_{ac} = \sum_{1}^{n} \frac{\Delta L_{silt}}{\Delta L_e} \tag{2}$$

$$\%Clay_{ac} = \sum_{1}^{n} \frac{\Delta L_{clay}}{\Delta L_e} \tag{3}$$

where, n is the number of pile sections; $\%Sand_{ac}$, $\%Silt_{ac}$ and $\%Clay_{ac}$ are the factors representing the occurrence of accumulated layers of sand, silt and clay, respectively; ΔL_e is the length in meters of the pile section; and ΔL_{sand}, ΔL_{silt} and ΔL_{clay} are the lengths in meters of the sections occurring sand, silt and clay, respectively.

Some geotechnical profiles contain layers with marine clay or organic clay, and in such cases, they were considered as clay. Stony soils were not to be found and are, therefore, not considered in the neuron models developed.

For prediction models of shaft and tip bearing capacity of single piles, two alternatives were evaluated, as follows:

(a) Percentage values for of sandy, silty and clayey fractions

Three input variables were proposed to represent the soil type in the models that estimate shaft and tip bearing capacities of piles: *Gsand*; *Gsilt* and *Gclay*. Table 3 provided the values to be adopted for each one of the three variables according of the prevailing material type at the depth of the single pile tip.

(b) Values tabulated for each soil type (S)

The soil types adopted are the same proposed in the semi-empirical method of Aoki & Velloso (1975) and the values are displayed in Table 4.

For piles supported on silty organic clay the variable soil type was simplified as silty clay. As there were no stony soils present along the depth of the piles, no soil type was found at the tip, and for this reason it was not included in the developed neuron models.

It is also important to stress that no pile analyzed is supported or embedded in weathered or unaltered rock and in such cases, the models proposed herein do not apply.

Table 3. Combinations for percentage values representing soil types in the models developed for estimating the tip bearing capacity.

Soil	G_{sand} (%)	G_{silt} (%)	G_{clay} (%)
Sand	100	0	0
Silty sand	60	40	0
Clayey sand	60	0	40
Clayey-silty sand	60	20	20
Silty-clay sand	60	20	20
Silt	0	100	0
Clayey silt	0	60	40
Sandy silt	40	60	0
Sandy clay silt	20	60	20
Clayey sandy silt	20	60	20
Clay	0	0	100
Sandy clay	40	0	60
Silty clay	0	40	60
Silty sandy clay	20	20	60
Sandy silt clay	20	20	60

Table 4. Adopted values for *S*.

Soil type	Value
Sand	1
Silty sand	2
Clay-silt sand	3
Clay sand	4
Silty-clay sand	5
Silt	6
Sandy silt	7
Clay sand silt	8
Clayey silt	9
Sandy clay silt	10
Clay	11
Sandy clay	12
Silty sand clay	13
Silty clay	14
Sandy silt clay	15

2.2.5 Soil resistance index

By being aware that the shaft bearing capacity is a value accumulated along the length of the pile, it is understood that the resistance index used in models that estimate the value of this load must also be accumulated. As a result, the variable is known as NF_{ac} and obtained through Equation 4.

$$NF_{ac} = \left(N \times \Delta L_e\right) \tag{4}$$

where, N is the number of blow counts/last 30 cm of penetration in a typical *SPT* test.

In relation to the tip bearing capacity, it was decided to assess three different variables, *NP1*, *NP2* and *NP3* calculated according to the values of the *SPT* (*N*) index. *NP1* is equal to the *N* value corresponding to a layer immediately 1m below the tip of the pile. *NP2* is the arithmetic mean of three (3) *N* values corresponding to the layer 1 m before the tip, the pile tip layer, and the layer 1 m below the tip. *NP3* is the average value of *N* in the interval between four (4) diameters above the tip and one diameter below. It is worth mentioning that these definitions come from already established semi-empirical methods (Aoki & Velloso, 1975; Décourt & Quaresma, 1978; Teixeira, 1996).

2.2.6 Water Level (*WL*)

Teixeira & Albiero (1994) confirmed that saturation increases by around 30% the settlements and reduces the bored pile bearing capacity, evidencing that the variation in moisture alters the load transfer mechanism, and this is the reason why the water level was included in the neuron models as being the accumulated value of depth of the water level, based on the elevation detected in the geotechnical profile.

2.2.7 Loading Type (*LT*)

The instrumented piles belonging to the database underwent a static load test with slow loading (*SML* - Slow Maintained Load) and or quick (*QML* - Quick Maintained Load). The value of 1 was adopted to represent the *SML* loading and 2 for the *QML* loading, both in the models developed to estimate the shaft and tip bearing capacities of piles. Of the 95 piles studied, 56 were carried out in slow maintained conditions whereas 39 in quick conditions.

3. Development of the prediction model

The QNET2000 program (Vesta Services, 2000) was used to develop the neuron models proposed herein. This is a multilayer perceptron computer code that uses the error back propagation algorithm to correct the synaptic weights still in the training phase, with the artificial neurons being able to activate using four types of trigger functions: sigmoid, hyperbolic tangent, hyperbolic secant and gaussian.

It is very common when solving geotechnical problems to use the sigmoid or hyperbolic tangent functions, as can be confirmed in the studies by Dantas Neto et al. (2014), Araújo et al. (2015), Santiago (2018), Maizir et al. (2015), Momeni et al. (2015) and Nejad & Jaksa (2017). In this study, the neurons of all neural network layers were triggered using the sigmoid function (Haykin, 2008). After choosing the trigger function, the following must be defined: the input variables of each neuron model proposed; data handling, training, testing and validation of different architectures and, based on established criteria, the configuration with the best performance.

3.1 Combinations of variables

Nine (9) input variables were adopted for neuron models that estimate the shaft bearing capacity: *D*, NF_{ac}, *WL*, *PT1*, *PT2*, $\%Sand_{ac}$, $\%Silt_{ac}$, $\%Clay_{ac}$ and *LT*. The combinations with those input variables are:

- MQS1: $Q_S = f\left(D,\ NF_{ac},\ WL\right)$
- MQS2: $Q_S = f\left(D,\ NF_{ac},\ WL,\ PT1\right)$
- MQS3: $Q_S = f\left(D,\ NF_{ac},\ WL,\ PT2\right)$
- MQS4: $Q_S = f\left(D,\ NF_{ac},\ WL,\ PT2, \%Sand_{ac}, \%Silt_{ac}, \%Clay_{ac}\right)$
- MQS5: $Q_S = f\left(D,\ NF_{ac},\ WL,\ PT2, \%Sand_{ac}, \%Silt_{ac}, \%Clay_{ac},\ LT\right)$

It is noticeable that the construction of these models began in the simplest manner (MQS1) with only three (3) variables, gradually adding more input variables until reaching the more complex models containing eight (8) input variables (MQS5). It was therefore possible to separately assess the influence of each input variable in the obtained results.

In the neuron models that estimate the tip bearing capacity, the input variables are: *D*, *PT1*, *PT2*, G_{sand}, G_{silt}, G_{clay}, *S*, *NP1*, *NP2*, *NP3*, *WL* and *LT*. The combinations with these input variables are:

- MQP1: $Q_P = f\left(D,\ NP1\right)$
- MQP2: $Q_P = f\left(D,\ NP2\right)$
- MQP3: $Q_P = f\left(D,\ NP3\right)$
- MQP4: $Q_P = f\left(D,\ NP1,\ PT1\right)$
- MQP5: $Q_P = f\left(D,\ NP1,\ PT2\right)$
- MQP6: $Q_P = f\left(D,\ NP1,\ PT2,\ S\right)$
- MQP7: $Q_P = f\left(D,\ NP1,\ PT2,\ G_{sand},\ G_{silt},\ G_{clay}\right)$
- MQP8: $Q_P = f\left(D,\ NP1,\ PT2,\ WL\right)$
- MQP9: $Q_P = f\left(D,\ NP1,\ PT2,\ LT\right)$

The models were created in the same way as the neuron models developed to estimate the shaft bearing capacity.

3.2 Data handling

The sigmoid function, chosen as a trigger function for the developed models, has the benefits of being continuous and distinguishable through its domain, enabling the application of the generalized delta rule (Widrow & Hoff, 1960) to modify synaptic weights. However, its use requires standardizing the values of output variables in an interval belonging to its image set, in this case, the interval (0.1).

Therefore, both output and input variables were standardized by linear interpolation between the values 0.15 and 0.85 and the maximum and minimum values of each of these variables.

3.3 Training, testing and validation

The purpose of the *RNA* training phase is to adjust in the best possible way the values of the synaptic weights, so that the output values estimated by the *RNA* are as close as possible to their actual corresponding values, but without losing generalizing capacity (Haykin, 2008).

To start training, two adjustment parameters must be chosen to adjust the synaptic weights: η (learning rate), which influences the convergence of the error back algorithm propagation; and the factor α (momentum), which minimizes the algorithm's instability during this convergence, as applied by Dantas Neto et al. (2014, 2017) and Araújo et al. (2015) who used QNET2000 in their studies, by adopting $\alpha = 0.8$ and $0.01 \leq \eta \leq 0.30$.

Unlike those authors, this choice was to include the "test" stage in all developed models, this being a stage that occurs simultaneously with training using data not included in the set adopted in that training.

During training the so-called overfitting may occur, meaning that the neural network stored the peculiarities and noise levels, but lost the generalizing capacity (Haykin, 2008). To detect overfitting, as recommended by Nejad & Jaksa (2011, 2017), the early stopping technique was used, that is, the training process is interrupted when the error in the test stage increases even when the number of iterations increases.

In the validation phase, output neurons are calculated with the synaptic weights obtained during the training phase, but using information as yet unknown by the artificial neural network, which is why it is possible to assess the generalizing capacity (Haykin, 2008) of the tested neural network at this stage.

There are no explicit rules to determine the quantity of data used at each of these stages (training, testing and validation), but it was decided to use the same proportion between training, testing and validation adopted by Maizir (2017), Kordjazi et al. (2015) and Tarawneh (2013), i.e., 70%, 15% and 15%, respectively. In this work the examples are randomly separated.

3.4 Criterion for definition of the ANN architecture

The architecture of an artificial neural network is related to how the neurons are structured. The performance of the architectures tested in this study is assessed by the values of root mean square error (Equation 5), *RMSE*, and coefficient of determination (Equation 6), R^2, obtained in the validation phase. These measurements were used in several works (Pham et al., 2020; Chen et al., 2020; Benali et al., 2018; Maizir, 2017 and Momeni et al., 2014, 2015).

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y_i - \overline{y_i}\right)^2} \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}\left(y_i - \overline{y_i}\right)^2}{\sum_{i=1}^{m}(y_i - \overline{y})^2} \tag{6}$$

where m inferred the number of examples, y_i and $\overline{y_i}$ were the actual and predicted outputs, respectively, and $\overline{y}$ was the average value of the y_i.

Considering these concepts, the architectures with correlations closest to 1.0 were selected, totaling 14 models, five of which are to the predictions of the shaft bearing capacity and nine tip bearing capacity, the results of which will be presented and discussed below.

4. Results and discussions

The architectures, iteration numbers and coefficient of determination values obtained in the validation phase, referring of the models developed to prediction of the shaft and tip bearing capacities of single piles are presented in Tables 5 and 6, respectively.

In Table 5 it is apparent that an increase in the quantity of input variables requires more hidden layers and, consequently, more neurons in these layers to achieve the same correlations as the simpler models. In relation to the iterations, it is noticeable that for more complex architectures more iterations are required, the only exception being model MQS3, which differs only in the input variable *PT* of MQS2. However, the number of iterations between them differs by approximately 50%, in contrast to the expected behavior that would be an increase in iterations, since the *PT1* variable assumes only four values while *PT2* variable has seven possibilities.

Table 5. Performance indices obtained in the validation phase for neuron models developed to estimate the shaft bearing capacity.

Model	Input variables	Architecture	Iteration	R^2	*RMSE*
MQS1	$Q_S = f\left(D, NF_{ac}, WL\right)$	3:2:1	800	0.86	0.235
MQS2	$Q_S = f\left(D, NF_{ac}, WL, PT1\right)$	4:4:1	15000	0.91	0.227
MQS3	$Q_S = f\left(D, NF_{ac}, WL, PT2\right)$	4:4:1	7600	0.93	0.184
MQS4	$Q_S = f\left(D, NF_{ac}, WL, PT2, \%Sand_{ac}, \%Silt_{ac}, \%Clay_{ac}\right)$	7:4:2:1	26000	0.94	0.175
MQS5	$Q_S = f\left(D, NF_{ac}, WL, PT2, \%Sand_{ac}, \%Silt_{ac}, \%Clay_{ac}, LT\right)$	8:4:2:1	20000	0.95	0.158

Table 6. Performance indices obtained in the validation phase for the neuron models developed to estimate the tip bearing capacity of piles.

Model	Input variables	Architecture	Iteration	R^2	*RMSE*
MQP1	$Q_P = f\left(D, NP1\right)$	2:2:1	200	0.89	0.102
MQP2	$Q_P = f\left(D, NP2\right)$	2:3:1	1700	0.50	0.175
MQP3	$Q_P = f\left(D, NP3\right)$	2:1:1	1400	0.88	0.161
MQP4	$Q_P = f\left(D, NP1, PT1\right)$	3:4:1	30000	0.77	0.064
MQP5	$Q_P = f\left(D, NP1, PT2\right)$	3:6:1	90000	0.99	0.177
MQP6	$Q_P = f\left(D, NP1, PT2, S\right)$	4:2:1	3000	0.86	0.095
MQP7	$Q_P = f\left(D, NP1, PT2, G_{sand}, G_{silt}, G_{clay}\right)$	6:4:1	78000	0.90	0.094
MQP8	$Q_P = f\left(D, NP1, PT2, WL\right)$	4:3:1	37300	0.87	0.170
MQP9	$Q_P = f\left(D, NP1, PT2, LT\right)$	4:3:1	30300	0.86	0.057

The analysis of the coefficient of determination in Table 5 show that model MQS1, even with few input variables, has already achieved satisfactory results, i.e., a coefficient of determination of 0.86. This affirmation is based on the conclusions reported by Pham et al. (2020), Chen et al. (2020), Benali et al. (2018), Maizir (2017) and Momeni et al. (2014, 2015).

Nevertheless, when including the input variables *PT1* and *PT2* there was an increase in the coefficient of determination from 0.86 to 0.91 and 0.93, the largest being for variable *PT2*. This means that the idea to separate the pile types, both by constructive methodology and their material, is close to the models' responses for the desired value. There is also an increase, albeit smaller, in the coefficient of determination, when adding the input variables that represent the soil type ($\%Sand_{ac}$, $\%Silt_{ac}$ and $\%Clay_{ac}$) and loading type (*LT*), arriving at a coefficient of determination equal to 0.95. Thus, the MQS5 model is proposed herein to estimate the shaft bearing capacity.

Regarding the root mean square error, the values shown in Table 5 are acceptable when compared to the results found by Pham et al. (2020) and Chen et al. (2020) who applied artificial neural networks to estimate the bearing capacity of single piles. The MQS5 model has the lowest root mean square error.

Table 6 shows that, even when increasing the quantity of input variables, it was possible to achieve good results with only one hidden layer. The models with the highest number of iterations are the models MQP5 and MQP7 that have the largest quantity of neurons in the hidden layer and input layer, respectively. No relation was detected between the quantity of neurons of the hidden layer and the number of iterations.

On analyzing the coefficient of determination values in Table 6, it is apparent that the first three models were evaluated to predict the tip bearing capacity of piles, MQP1, MQP2 and MQP3 in which only the input variable is modified with regard to the soil index. The lowest value belongs to model MQP2 and the highest to model MQP1, which means that variable *NP1* better represents the soil index in the developed neuron models for the tip load.

Including variable PT1 in model MQP1 there was a decrease in the coefficient of determination from 0.89 to 0.77, and by repeating the procedure for input variable PT2 it increased to 0.99. As in the case of the model proposed to predict the shaft bearing capacity of piles, pile type PT2 provides answers closer to the desired value also for the tip load. Other input variables were added to model MQP5, but there was no increase in the coefficient of determination value, so model MQP5 is proposed herein to estimate the tip bearing capacity of piles.

The root means square error values obtained in the models developed to estimate the tip bearing capacity, shown in Table 6, are also acceptable. Model MQP9 has the smallest root mean square error and was not chosen because the coefficient of determination is only 0.88.

Figure 3a demonstrates the evolution of the coefficient of determination in function of the iterations for model MQS5, in which the convergence of the curves is noticeable, referring to training and testing performed in the training phase. Figure 3b illustrates the coefficient of determination for model MQS5 in the validation phase for 20000 iterations.

Figure 3c shows the evolution of the coefficient of determination as a result of the iterations for model MQP5, in which a similarity is noticeable of the curves referring to training and testing during the training phase. Figure 3d

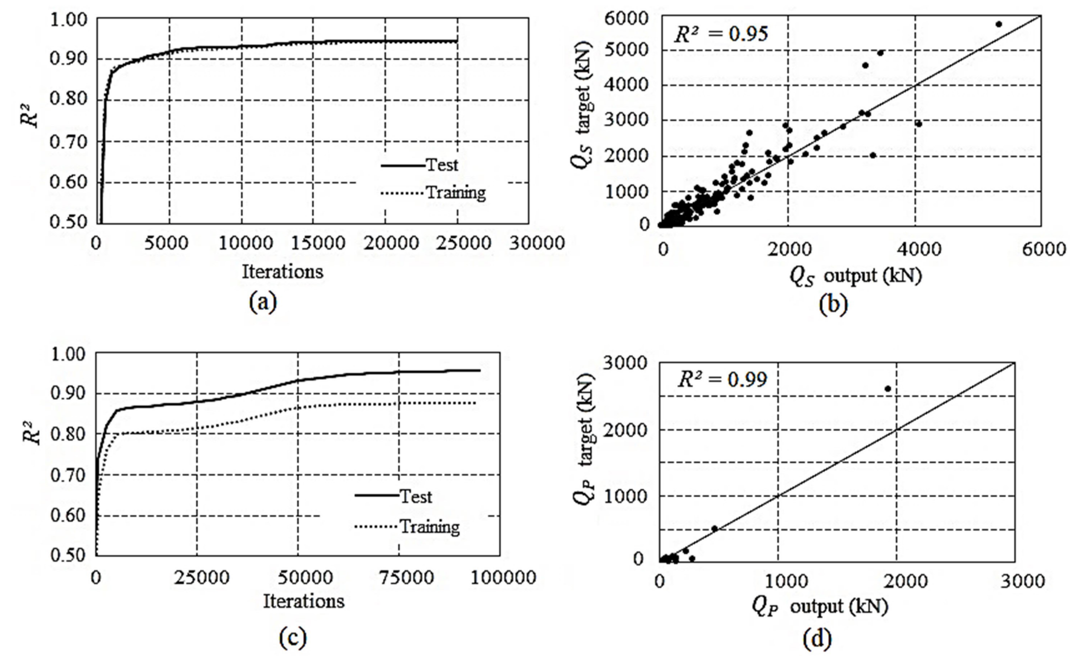


Figure 3. Coefficient of determination for models proposed.

illustrates the coefficient of determination for model MQP5 in the validation phase.

5. Model application

The models proposed in this article were used to estimate the bearing capacity of three (3) single piles (two bored and one continuous flight auger type) as well as in groups of up to three piles implemented in the Experimental Research Site of foundations and in situ testing of the University of Brasilia (Figure 4).

The geotechnical profile and pile characteristics are provided in Figure 5 and were compiled in the study by Anjos (2006). This is a geotechnical profile consisting of three layers: the first, from 0 to 3.5 m, has porous clayey sand; the second, between 3.5 and 8.5 m, provides sandy clay, and from 8.5 m the soil has a siltier texture (Mota, 2003).

The two bored piles (single) were tested until there was a 10% displacement in diameter. One of them placed on only a slightly resistant material with a view to assessing only the shaft bearing capacity. And two consecutive tests were performed on the pile supported on soil (in which it was possible to assess the shaft bearing capacity and tip bearing capacity), the first being a slow maintained load test (*SML*) and the second a quick maintained load (*QML*).

In relation to continuous flight auger piles, Anjos (2006) installed one single pile, a group with two and another with three piles, all subject to slow loading (*SML*). The spacing between the piles in groups was three times the diameter with a rigid crown block in no contact with the ground.

Figure 6 shows the shaft bearing capacity-depth curves corresponding to the semi-empirical methods of Aoki & Velloso (1975) and Décourt & Quaresma (1978) and model proposed in this works. Figure 6a refers to the bored pile E1 and Figure 6b to the continuous flight auger pile E3.

Note that the shaft bearing capacity calculated by the proposed models are higher than those obtained by the semi-empirical methods. Knowing that the semi-empirical methods usually underestimate the shaft bearing capacity, it is possible to infer that the proposed model provides more realistic values.

Figure 7 shows the comparison between the values found in the load test and semi-empirical methods (Aoki & Velloso, 1975; Décourt & Quaresma, 1978) and those obtained from the models proposed in this study. The bearing capacity of the pile groups was considered equal to multiplying between the quantity of piles and the single pile bearing capacity (Cintra & Aoki, 2010).

It is found that for bored single piles the proposed models overestimate the bearing capacity obtained in the static load test, but the difference in percentage terms between the values for the proposed methods and the load test value varies between 3% and 30%, while the method by Aoki & Velloso (1975) shows that this difference ranges from 59% to 83%, and between 38% and 64% for the method by Décourt & Quaresma (1978).

For the single continuous flight auger pile the result achieved with the proposed neuron models can be considered very close to the load test value, since the values calculated by the methods of Aoki & Velloso (1975) and Décourt &

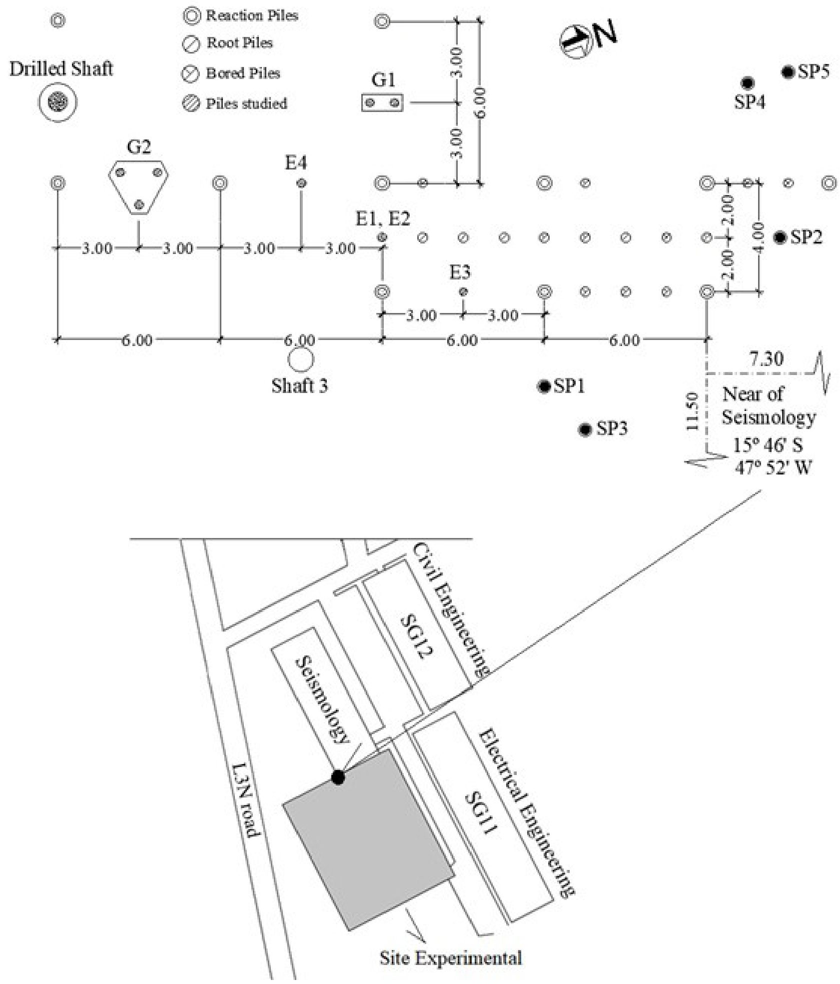
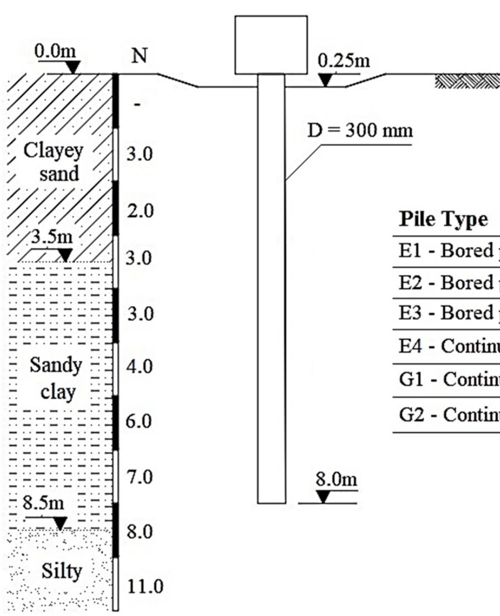


Figure 4. Location map of the site experimental and the piles studied.



Pile Type	LT
E1 - Bored pile (RL + RB)	SML
E2 - Bored pile (RL + RB)	QML
E3 - Bored pile (RL)	SML
E4 - Continuous flight auger pile (single)	SML
G1 - Continuous flight auger pile (group 2)	SML
G2 - Continuous flight auger pile (group 3)	SML

Figure 5. Geotechnical profile for single piles and in groups. Adapted from Mota (2003).

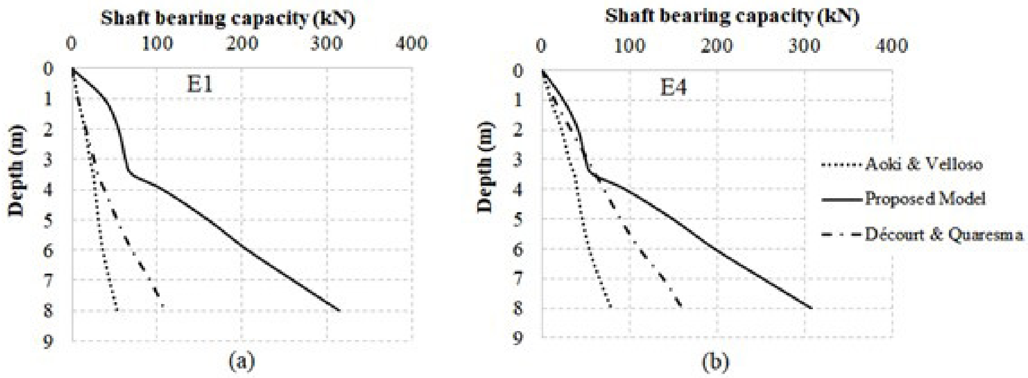


Figure 6. Comparison between the shaft bearing capacity estimated by the proposed models and the values obtained from semi-empirical methods.

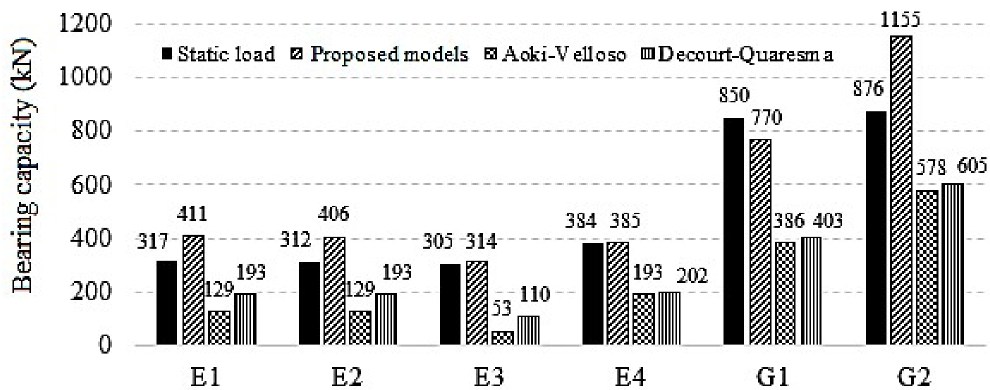


Figure 7. Comparison between the bearing capacity estimated by the proposed models and the values obtained from load testing and semi-empirical methods.

Quaresma (1978) are approximately 50% lower than the desired value.

With regard to the groups consisting of two and three continuous flight auger piles, it is apparent that the proposed neuron models underestimate by only 9% and overestimate by 32% the values obtained from the static load tests on those groups, respectively. However, for the semi-empirical methods of Aoki & Velloso (1975) and Décourt & Quaresma (1978), this same difference is around 55% for the group with two piles and 33% for the three-pile group.

Accordingly, it can be said that the proposed models reproduce more satisfactorily the bearing capacity both for single piles and groups than the semi-empirical models considered. The difference between the values found for the proposed methods and the load test value varies between 9% and 32%, while for the method by Aoki & Velloso (1975) this interval is between 34% and 83% and for the Décourt & Quaresma method (1978) it is between 31% and 64%.

6. Conclusions

According to the results, it can be concluded that the multilayer perceptron is a tool that can estimate the shaft bearing capacity and tip bearing capacity of single piles, based on variables relating to pile geometry and soil type (information collected from boreholes), with a relatively simple architecture.

The neural model proposed to estimate the shaft bearing capacity has eight (8) input variables (D, NF_{ac}, WL, $PT2$, $\%Sand_{ac}$, $\%Silt_{ac}$, $\%Clay_{ac}$, LT) and provided a coefficient of determination equal to 95% between the desired value and the calculated value. On the other hand, the model that estimates the tip bearing capacity has only three input variables (D, $NP1$, $PT2$) with 99% coefficient of determination.

The coefficient of determination obtained from the neuron models that estimate the shaft bearing capacity and tip bearing capacity of single piles range from 0.8 to 0.99, an interval of coefficient of determination similar as those obtained by authors when assessing the applicability of artificial neural networks in the ability to predict the pile bearing capacity. However, the neuron models proposed proved to help the calculation of the shaft bearing capacity according to depth and not only the total value of bearing capacity. Moreover, have the potential to be applicable to seven types of piles and different geotechnical profiles.

When analyzing the results from the neuron models for single piles and groups of piles, it was observed that the proposed methods are more efficient than the semi-empirical methods applied in Brazilian foundation engineering practice, since the dispersion in the results is less when the results achieved are compared to the static load test values.

In general, the proposed models overestimate the bearing capacity, which can be explained by the fact that the models were based on the ultimate load applied during the static load test. Therefore, the recommendation is to use correction factors of around 0.88 for single piles and approximately 0.75 for groups. To improve these values, it is recommended an improved analysis with more data and distinct geotechnical conditions.

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Declaration of interest

The authors have no conflicts of interest to declare. All co-authors have observed and affirmed the contents of the paper and there is no financial interest to report.

Authors' contributions

Luciana Barbosa Amâncio: conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing – original draft. Silvrano Adonias Dantas Neto: conceptualization, data curation, supervision, validation, writing – review & editing. Renato Pinto da Cunha: conceptualization, methodology, supervision, validation, writing – review & editing.

List of symbols

m	Number of examples
n	Number of pile sections
$\underline{y_i}$	Actual outputs
y_i	Predicted outputs
$\overline{y}$	Average value of the y_i.
ANN	Artificial Neural Networks
D	Pile dDiameter
$Gsand$	Percentage values for of sandy fractions
$Gsilt$	Percentage values for of silty fractions
$Gclay$	Percentage values for of clayey fractions
L_e	Embedded length
LT	Loading Type
N	Number of blow counts/last 30 cm of penetration in SPT test
NF_{ac}	Soil resistance index along the shaft
$NP1$	Soil resistance index at tip 1
$NP2$	Soil resistance index at tip 2
$NP3$	Soil resistance index at tip 3
$PT1$	Pile type 1
$PT2$	Pile type 2
QML	Quick Maintained Load
Q_r	Bearing capacity
Q_s	Shaft bearing capacity
Q_p	Tip bearing capacity
S	Soil type
SML	Slow Maintained Load
SPT	Standard Penetration Test
R^2	Coefficient of determination
$RMSE$	Root mean square error
WL	Water Level
$\%Sand_{ac}$	Factor representing the occurrence of accumulated layers of sand
$\%Silt_{ac}$	Factor representing the occurrence of accumulated layers of silt
$\%Clay_{ac}$	Factor representing the occurrence of accumulated layers of clay
α	Momentum
η	Learning rate
ΔL_{clay}	Length of the section occurring clay
ΔL_e	Length of the section
ΔL_{sand}	Length of the section occurring sand
ΔL_{silt}	Length of the section occurring silt

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