DETERMINATION OF LOAD-BEARING CAPACITY IN DEEP FOUNDATIONS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Knowing the geotechnical characteristics of the construction site is of utmost importance for the engineer when designing a project, regardless it is large, medium, or small in scale. By using SPT-N values, the designer will be capable of determining the load-bearing capacity of the soil. Semi-empirical models have been proposed to calculate the load-bearing capacity in deep foundations. However, these models are developed based mathematical frameworks and approximations, where the calculation is not always accurate. Artificial Neural Networks (ANNs) are considered a mechanism capable of accurately calculating these values because they use more reliable variables. For this reason, the present study aims to propose the use of Multi-Layer Perceptron (MLP) artificial neural networks to determine the load-bearing capacity of deep foundations based on SPT-N values and depth. The database compiled from a series of 68 load tests carried out in the city of Balsas-MA, for which SPT-N values and their respective depths were available. To evaluate the obtained results, the roots of the mean squared errors (RMSE) and Pearson correlation coefficients were calculated. The results indicated that the proposed model is can determine the load-bearing capacity with a small error rate (RMSE) and high correlation with the values calculated using the classical formulas from the literature

KEYWORDS: *Load-Bearing Capacity, Deep Foundations, Artificial Neural Networks & Multi-Layer Perceptron.*

I. INTRODUCTION

Soils, in general, exhibit non-linear characteristics, making their behaviour under loading variable. To find a correlation between loading and soil, foundations were created to support the load applied by the construction to the ground. To determine the type of foundation, it is necessary to know the load-bearing capacity of the soil where the construction will take place. In this context, semi-empirical and theoretical methods were developed to determine this factor in Civil Construction [1].

According to [2], theoretical formulas often fail to achieve satisfactory results in predicting the load-bearing capacity of pile foundations. Therefore, semi-empirical methods are used, as they are based on empirical correlations and in situ results, providing more accurate results. Consequently, numerous semi-empirical methods were developed based on load test results and tests like the Standard Penetration Test (SPT), which is quite common in Brazil [3].

As reported by [1], semi-empirical methods were initially developed to predict settlements in sands due to the difficulty of testing this material in the laboratory. Subsequently, they were applied to clays and, finally, to soils typically used in civil construction, such as silts, clayey sands, and sandy clays.

Thus, the use of semi-empirical methods is crucial for predicting the load-bearing capacity of a foundation, aiding in design and providing reliability to designers and builders, while optimizing execution costs [4]. It is worth noting that despite their extensive use, these methods exhibit high safety coefficient values, thus increasing foundation costs.

In contrast, the use of machine learning models, particularly Artificial Neural Networks (ANNs), has been accepted and shown to be effective in predicting load-bearing capacity values for deep foundations [5].

In this context, this article proposes the use of MLP-type artificial neural networks to determine the load-bearing capacity of deep foundations based on SPT-N values and depth found in the city of Balsas-MA. The methodology of the article was based on a database search to initiate the work. After that, the type of ANN to be used was chosen, as well as the mathematical operations that were utilized to design the algorithm. It is believed that this approach can significantly contribute to optimizing the design and construction processes of civil structures, ensuring greater efficiency and safety in foundations.

II. LOAD-BEARING CAPACITY

Foundations, in general, are responsible for transmitting the forces generated by the construction and are usually classified as shallow and deep foundations. According to [6], deep foundations are characterized as elements capable of supporting the load of the terrain and transmitting this load to the soil through their base and lateral surface, referred to as end-bearing resistance and skin friction, respectively.

Also, according to the standard, this type of foundation must have its end or base supported at a depth greater than eight times its smallest dimension determined in the project and must exceed a minimum of 3 meters. Examples of deep foundations include piles, caissons, and drilled shaft.

The choice of a deep foundation should consider the technical and economic conditions of the construction, where the following terrain characteristics must be known: origin and characteristics of the subsoil, load-bearing capacity to be transmitted to this foundation, limitations of the foundations available on the market, and proximity to neighboring constructions [7]. However, to define the type of foundation, it is necessary to know the load-bearing capacity of the soil where the construction will be done, especially for deep pile foundations [1].

To determine these loads, it is extremely important to carry out a preliminary and complementary geotechnical investigation, based on NBR 6122, where the preliminary investigation can be done through the Standard Penetration Test (SPT), known nationally as the Percussion Drilling Test [8].

According to [9], the SPT is the most widely known geotechnical investigation tool worldwide because it can indicate the consistency of cohesive soils and the compaction of granular soils. Furthermore, the test can determine the groundwater level and the nature of the soil in each penetrated layer, determining the penetration resistance index, known as SPT-N.

According to [10], the SPT equipment consists of a rope, a 65kg hammer, a tripod, a guide, rods, and a standard sampler. The procedure with this equipment essentially involves driving the standard sampler into the soil, penetrating 15cm increments through the free fall of the 65kg hammer from a height of 75cm [11]. After drilling 45cm in all layers, the N_{SPT} value is determined as the sum of the number of blows required to reach the last 30cm that the standard sampler can penetrate [9].

Through the SPT test report, it is possible to define the type of foundation to be used in the soil, as well as the diameter or cross-sectional area of the shaft. Using these variables, along with the length of the pile in each borehole, it is possible to obtain the load-bearing capacity value that the terrain can support [12].

[13] states that the load-bearing capacity is the sum of the end-bearing and skin friction resistances of the studied soil, as shown in Figure 1.

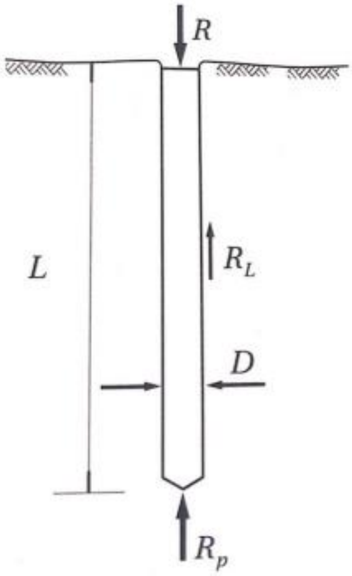

Figure 1. Demonstration of the resistance components for the load-bearing capacity result, [2].

And it can be demonstrated using equation 1.

$$R = R_L + R_P \tag{1}$$

The lateral resistance (R_L) is the product of the perimeter and the sum of the forces obtained from the skin friction resistance along the entire length of the pile, equation 2. In turn, the end-bearing resistance (R_P) is the product of the unit end-bearing stress and the cross-sectional area of the pile base, equation 3.

$$R_L = U * \sum r_L * \Delta_L \tag{2}$$

$$R_P = r_P * A_p \tag{3}$$

The use of these variables, especially the use of the SPT test as a source to define this load, has been present from studies in Egyptian soils to soils with fine and coarse granulation [13]. However, calculating this load-bearing capacity, especially in deep foundations, is declared a major problem for geotechnics. Despite the emergence of semi-empirical models such as those by Aoki and Velloso (1975), Décourt and Quaresma (1978), and Teixeira (1996), the precision of the results is generally inaccurate. This is due to the fact that these models work based on approximations of mathematical models and physical assumptions [14].

III. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANNs) can be classified as a subset of *machine learning*. Their name and structure are inspired by the human brain because they are capable of processing information in a non-linear, parallel, and highly complex manner, as well as identifying and solving patterns [15].

There are different types of artificial neural networks, each designed for specific tasks. The most common types are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Multi-Layer Perceptron (MLP) networks. CNNs are used for image recognition and video processing due to their high capacity for capturing features in spatial dimensions. RNNs are effective in processing sequential data, such as time series, because of their ability to retain information over time. The MLP, on the other hand, is a general-purpose neural network [16].

In analogy to the human brain, ANNs can organize their neurons or nodes to perform tasks quickly, focusing on a specific task. Their components include activation functions, summation, and synaptic weights [8], as illustrated in Figure 2.

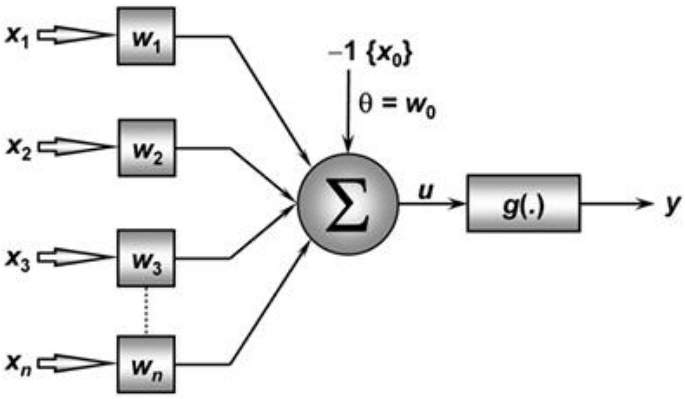

Figure 2. Diagram of an Artificial Neuron, [17].

The input data, represented by x_j, are the starting point of a neuron. They are connected to each synaptic weight in the hidden layers, w_{kj}, which are determined during the training of the ANN. The summation is responsible for the total sum of the products between the input data and the synaptic weights, u_k [8].

According to the author, the activation function, $g(\,)$, determines the output value of a neuron through mathematical functions such as linear, hyperbolic tangent, sigmoid, and threshold functions. The biases, b_k, are applied outside the summation and have the power to adjust the summation response values up or down, allowing the ANN to make corrections after the input data is inserted. Finally, the output, which can be more than one depending on the network model, is determined. Mathematically, the neuron's operation is described by equations 4 and 5.

$$u_k = \sum_{1}^{m} w_{kj} * x_j \tag{4}$$

$$y_k = g(\,u_k + b_k) \tag{5}$$

The units are organized in layers interconnected by synaptic connections, where there are input and output layers as well as hidden layers, which are received by each neuron in the network. The most well-known and simplest artificial neural network technique with this structure is the Multi-Layer Perceptron (MLP) (Figure 3), which operates in two phases: learning and execution. Additionally, it is known for solving function approximation, optimization, and prediction problems [18].

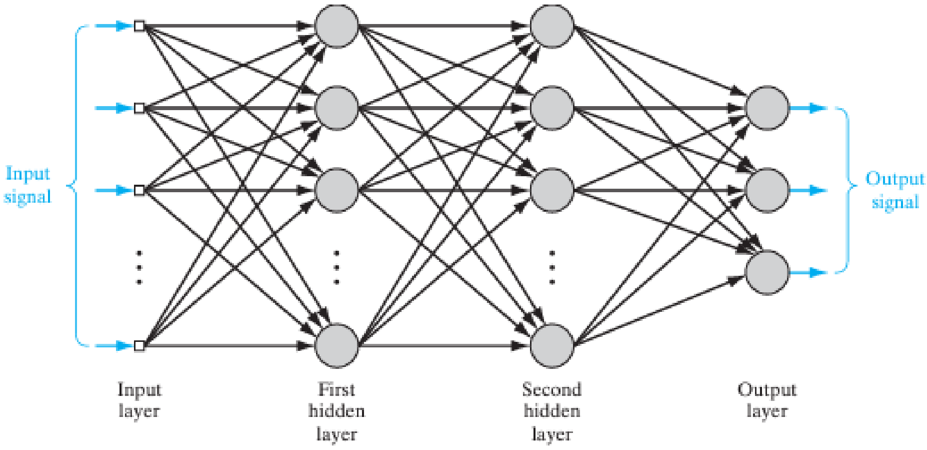

Figure 3. Architecture of a Multi-Layer Perceptron (MLP), [18].

The input layer receives the data that the network will process, where each neuron in this layer corresponds to a feature imposed on the input data by the designer. The hidden layers perform the more complex part of the network, as each neuron in this layer is connected to both the input and output layers, and each of these connections has a weight that is adjusted during the machine's training phase. As the name suggests, the output layer contains the final results of the network, with the number of neurons in this layer corresponding to the number of responses the network is configured to predict [16].

According to [19], the algorithm for updating the synaptic weights of an MLP is *Backpropagation.* This algorithm involves two phases in its implementation: *forward* propagation and *backward* propagation. In *forward* propagation, the input signals remain unchanged as they propagate through all the layers to the network's output, without any change in their weights.

Backward propagation involves propagating the calculation error from the output back to the hidden and input layers through the network. During this propagation, the gradients of the loss function concerning each weight are calculated using the chain rule. The weights are then adjusted in the opposite direction of the gradient using gradient descent, thus reducing the network's error [19].

Once the network is trained, it can perform the tasks programmed in its interface. It is important to note that the neural network's performance will only be beneficial if the network architecture, the implemented algorithm, the dataset used in the training phase, and all its layers and neurons are well-specified and interconnected, thereby producing a minimal sum of errors as the network's function desires [20].

Given this, an ANN can be used to minimize error impacts, particularly in the field of Geotechnics. In a study by [21], artificial neural networks were used to relate the settlement of isolated piles to their geometric properties and the results obtained from SPT tests on soil consistency. Using the QNET 2000 software, the correlation coefficient result was 0.94 in the validation phase.

[22] used ANNs to estimate the load-bearing capacity of continuous flight auger piles and precast concrete piles, comparing the results with those obtained using the semi-empirical methods of Aoki-Veloso and Décourt-Quaresma. He concluded that the network was satisfactory with only four input parameters and a few neurons in the hidden layer.

IV. MATERIALS AND METHOD

4.1. Research method

To determine the load-bearing capacity of a deep foundation, semi-empirical methods based on approximations of mathematical models are used. However, these methods do not always yield accurate results. For this reason, the use of Artificial Neural Networks (ANNs) in geotechnics has been growing, as they provide more precise results that assist in the execution of a foundation.

Based on the discussions proposed by [23], the research conducted in this work can be classified by its methodology as explanatory, regarding its objective, and also quantitative and statistical regarding its approach. For data collection, procedures based on *ex-post facto* were used.

To obtain the results proposed in this work, two types of variables were defined. The first variable was classified as dependent, which is the one where modelling will occur to predict the values it will assume when there is no information about it. In this study, the dependent variable is the load-bearing capacity.

The second variable consists of the characteristics that the model user has available for project development, being independent. In this work, the data for this variable are obtained from SPT-N values and their respective depth.

4.2. Database

The data used as the second variable for the modelling process were obtained from SPT test reports conducted in the city of Balsas, in the state of Maranhão. According to IBGE (2022), the municipality is situated at an altitude of 243 meters and has the following geographic coordinates: latitude: -7º 31' 59'' S and longitude: 46° 2' 6" W. It has a population of 101,767 inhabitants and covers a territorial area of 13,141.637 km². Figure 4 shows the location of the municipality in relation to the State of Maranhão.

Figure 4. Location of the municipal.

The reports were provided by Company Y and the coordinates of the identified points are shown in Figure 5.

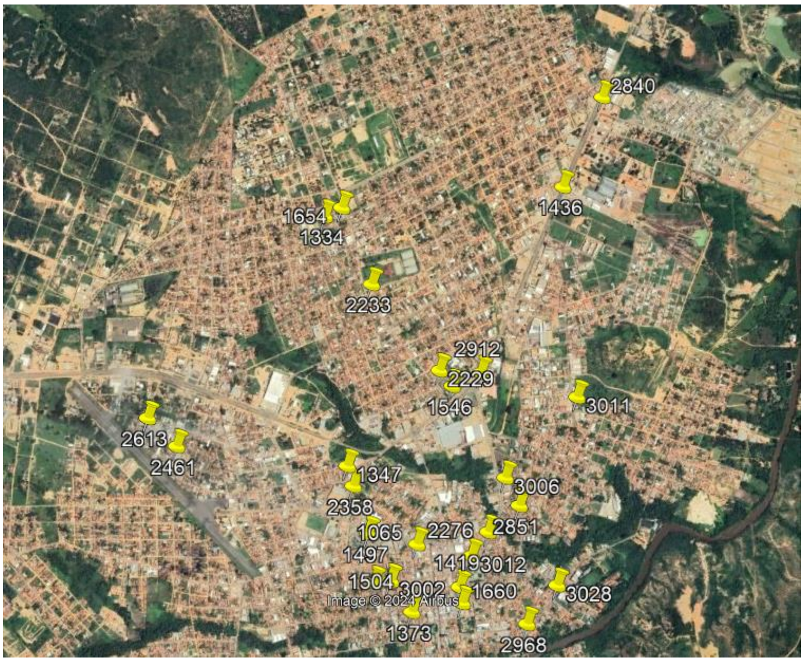

Figure 5. Points where SPT tests were conducted.

Therefore, upon analysing the 26 reports provided by Company Y, it was found that in certain tests, more than one hole was drilled per coordinate, totalling 68 holes. For each drilling depth, an SPT-N value was obtained, and these data were used for modeling the artificial neural network.

4.3. Model used

The model used in the network was implemented in three stages: construction of the algorithm and selection of the type of ANN, training and specifications of the artificial neural networks, and finally, the network testing was performed.

The type of ANN chosen depends on the problem proposed by the designer. In the study in question, the MLP (Multilayer Perceptron) was chosen to determine the load capacity values in deep foundations. The algorithm used in the network was *Backpropagation*, which involves calculating the error through *forward* and *backward* passes.

The variables used for the calculation of load capacity were: two inputs, SPT-N and depth, one hidden layer, varying between 2 to 10 neurons in the hidden layer, and one output corresponding to the load capacity value. Figure 6 shows the network topology and the training phase for determining the load capacity values.

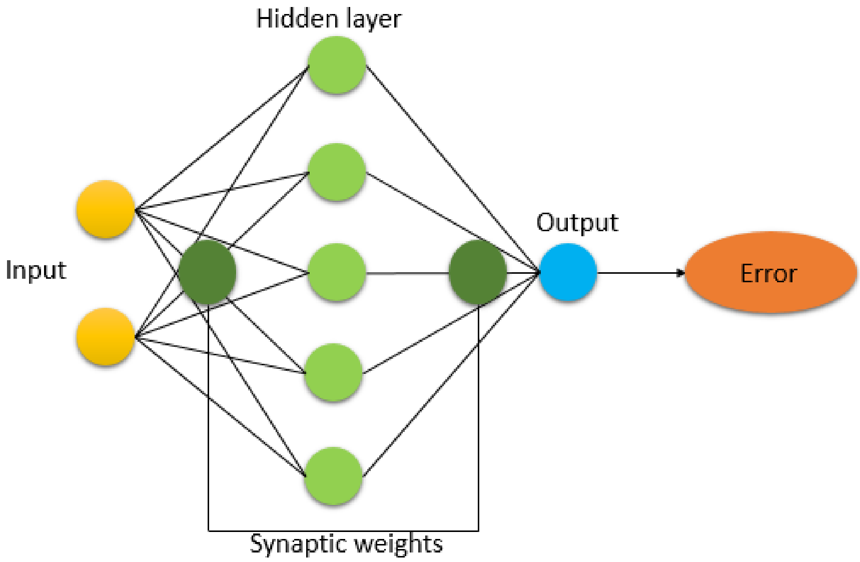

Figure 6. Network topology.

Therefore, the value predicted by the network in each *loop* is then compared with the measured value. As a stopping criterion for the network, it was defined that if the error in one loop is greater than 10^{-7} compared to the error in another *loop*, the network continues updating its synaptic weights if this condition is not met.

4.4. Evaluation Metrics

The model evaluation metrics consist of analyses of statistical characteristics both in the testing phase and in the training phase. These are based on assessments through hypothesis testing, Pearson correlation, and Root Mean Square Error (RMSE).

4.4.1. Root mean squared error

After calculating the values using the artificial neural networks, it was then possible to calculate the Root Mean Square Error (RMSE) based on the results from the output layer and the actual values. RMSE is mathematically defined as shown in equation 6.

$$RMSE = \sqrt{\frac{1}{n} * \sum_{i=1}^{n} (y_i + p_i)^2} \quad (6)$$

Where:

- y_i is the predicted value for the i-th observation;
- p_i is the observed value for the i-th observation;
- n is the total number of observations.

RMSE is one of the essential metrics for evaluating prediction models using ANN, providing a quantitative measure of the accuracy of their predictions. Compared to other metrics, such as Mean Absolute Error (MAE), RMSE can identify and penalize larger errors [25].

4.4.2. Pearson correlation

The Pearson correlation was used to check for the occurrence of linearity between the actual and predicted values. It is responsible for quantifying the strength and direction of the linear relationship between two continuous variables. The formula for calculating the Pearson correlation coefficient (equation 7) is given by:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}} \quad (7)$$

Where:

- n is the number of data pairs;
- x and y are the variables being compared;
- $\sum xy$ is the sum of the products of the data pairs;
- $\sum x \; and \sum y$ are the sums of the individual variables;
- $\sum x^2 \; and \sum y^2$ are the sums of the squares of the individual variables.

According to [26], the correlation ranges between -1 and 1, where the sign indicates its direction and the value indicates its magnitude. If the value is closer to 1, the linear association between the variables is characterized as strong; if it is closer to zero, the association is almost negligible.

V. RESULTS AND DISCUSSION

A computational model based on ANN, designed to calculate load capacity from SPT-N and depth data, was proposed in this article. Data from 68 boreholes were used for each simulation, with each borehole having different depths, totalling 709 load capacity values. Of this total, 68 values (approximately 10%) were randomly reserved for testing, and the remainder was used to train the model.

The network topology used consists of an input layer, an intermediate layer, and an output layer. Simulations were conducted for different numbers of neurons in the intermediate layer and different learning rate values. The training and testing results are presented below in graphs and the previously defined evaluation metrics.

The network topology used is composed of three layers: an input layer, an output layer, and a hidden layer. In the first simulation, 6 neurons were used in the hidden layer with a learning rate of μ=0.01. The results of this simulation are presented in Table 1 and in the graph of Figure 7.

Table 1: Simulation with 6 Neurons.

Metric	Value
RMSE	1,94 kN
Correlation	0,93

In Figure 7, it is possible to see how closely the values estimated by the model match the desired values.

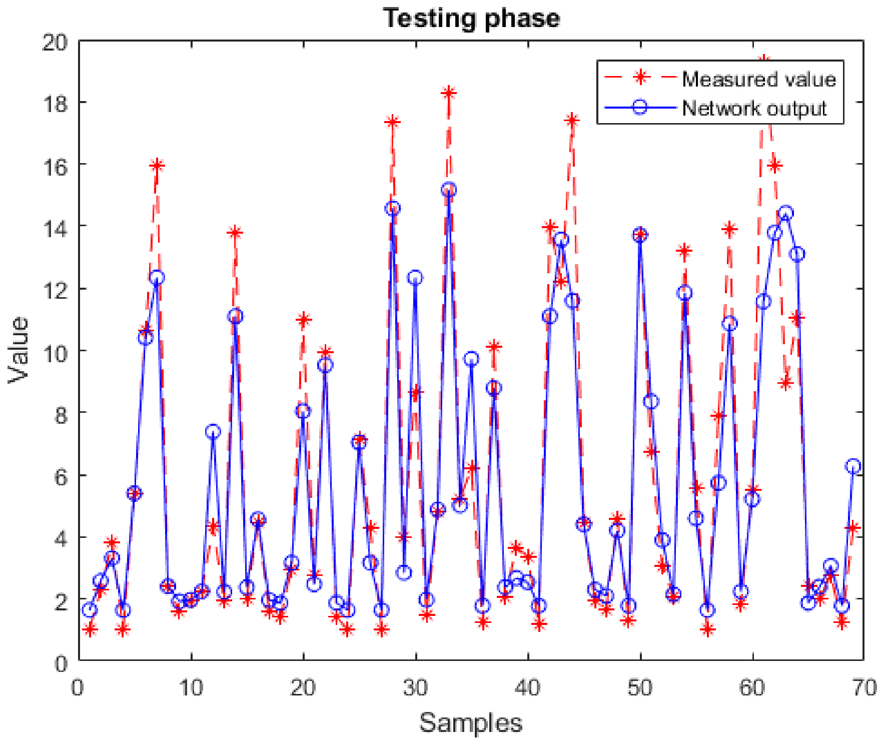

Figure 7: Network testing phase with 6 neurons.

For the second simulation, the number of neurons in the hidden layer was modified, setting it to 8 neurons. Table 2 presents the error and correlation values obtained with this topology.

Table 2: Simulation with 8 Neurons.

Metric	Value
RMSE	2,00 kN
Correlation	0,93

It is noticeable that increasing the number of neurons in the hidden layer resulted in a slight increase in the error value; however, the correlation remained the same. In Figure 8, a comparison between the values obtained by the model and the actual values can be observed.

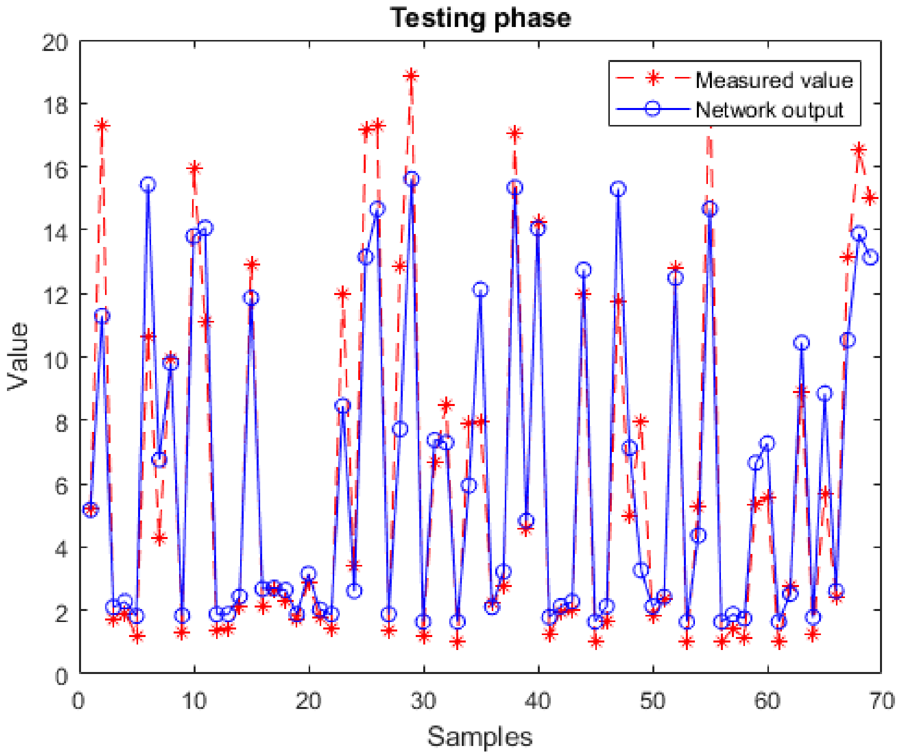

Figure 8: Network Testing Phase with 8 Neurons.

In order to have a broader view of the simulations, Tables 3 to 7 present the simulation values for different learning rates and numbers of neurons in the hidden layer. Initially, 2 neurons were fixed in the hidden layer and the learning rate values were varied. Table 3 shows the results of these simulations.

Table 3: Results of the Network with 2 Neurons.

Number of neurons in the hidden layer	Learning rate	RMSE	Correlation
2	0,1	1,94211931	0,941788378
	0,2	2,09703424	0,904014988
	0,3	2,06777628	0,914820487
	0,4	2,4620696	0,906868907
	0,5	2,2755417	0,92114097
	0,6	2,29602668	0,92062478
	0,7	2,41789689	0,921329994
	0,8	1,91014049	0,955081479
	0,9	**1,81110241**	**0,954929634**
	1	3,33067794	0,913955275

It is noticeable that the best result when the number of neurons was fixed at 2 occurred when the learning rate used was 0.9. Another simulation was conducted by fixing 4 neurons in the hidden layer and varying the learning rate values. The results of this simulation are presented in Table 4.

Table 4: Results of the Network with 4 Neurons.

Number of neurons in the hidden layer	Learning rate	RMSE	Correlation
4	0,1	2,12920883	0,927012651
	0,2	**1,54966102**	**0,950414351**
	0,3	1,99730469	0,943785856
	0,4	1,80576442	0,939042062
	0,5	2,38794901	0,921268879
	0,6	1,88554196	0,933481299
	0,7	3,1582591	0,944415238
	0,8	3,44813794	0,933539309
	0,9	2,60068657	0,915437275
	1	2,40306136	0,899634558

For 4 neurons in the hidden layer, the best result was obtained with a learning rate of 0.2. Following the same methodology of fixing the number of neurons in the hidden layer and varying the learning rate, Table 5 presents the results for 6 neurons in the hidden layer.

Table 5: Results of the Network with 6 Neurons.

Number of neurons in the hidden layer	Learning rate	RMSE	Correlation
6	**0,1**	**1,70121848**	**0,953344514**
	0,2	2,46477456	0,920706435
	0,3	2,06445471	0,9384334
	0,4	2,28858395	0,924912493
	0,5	2,74862754	0,876012368
	0,6	2,03397933	0,913573554
	0,7	2,90541789	0,915521827
	0,8	2,73197701	0,931875275
	0,9	2,25870292	0,930770002
	1	3,99954007	0,90787199

For 6 neurons in the hidden layer, the best result was obtained with a learning rate of 0.1. In the penultimate simulation, eight neurons were fixed in the hidden layer. Table 6 presents the results for this simulation.

Table 6: Results of the Network with 8 Neurons.

Number of neurons in the hidden layer	Learning rate	RMSE	Correlation
8	0,1	2,65040869	0,904444848
	0,2	2,2351627	0,911829876
	0,3	**2,08928934**	**0,93844497**
	0,4	2,17904337	0,924965393
	0,5	2,67351468	0,88643435
	0,6	2,33760268	0,912957167
	0,7	3,75295424	0,894947321
	0,8	2,14574767	0,931255397
	0,9	3,57288427	0,925948839
	1	4,18216093	0,868132723

With 8 neurons in the hidden layer, the best result was achieved with a learning rate of 0.3. Finally, a simulation was conducted with 10 neurons in the hidden layer. The results for this group of simulations are presented in Table 7.

Table 7: Results of the Network with 10 Neurons.

Number of neurons in the hidden layer	Learning rate	RMSE	Correlation
10	0,1	2,47489422	0,91510898
	0,2	4,31178155	0,947399929
	0,3	1,98704772	0,90597883
	0,4	2,30947364	0,898714947
	0,5	**1,89046129**	**0,942592974**
	0,6	2,10081816	0,959191648
	0,7	2,65189015	0,91694354
	0,8	5,59881005	0,89008605
	0,9	5,15250675	0,900390976
	1	3,35600769	0,875248464

With 10 neurons in the hidden layer, the best result was obtained with the learning rate set at 0.5. Overall, among all the simulations presented, the best result was achieved when four neurons were fixed in the hidden layer and the learning rate was set to 0.2 (RMSE = 1.54 and correlation = 0.95), as shown in Table 8.

Table 8: Simulation Results.

Number of neurons in the hidden layer	Learning rate	RMSE	Correlation
2	**0,9**	**1,81110241**	**0,954929634**
4	0,2	1,54966102	0,950414351
6	0,1	1,70121848	0,953344514
8	0,3	2,08928934	0,93844497
10	0,5	1,89046129	0,942592974

VI. CONCLUSIONS

Deep foundations generally depend on good design and precise calculations regarding the load they will support. However, using semi-empirical methods to calculate their load capacity requires numerous variables. On the other hand, for calculating this capacity using ANNs, only two variables are necessary.

To determine the load capacity values for different SPT tests conducted in the city of Balsas-MA, artificial neural networks of the MLP type were used in this work. To present the results, statistical evaluation metrics such as RMSE and Pearson correlation were utilized.

In this context, the neural model underwent various tests with the number of neurons in the hidden layer ranging from 2 to 10. The best result was obtained when four neurons were fixed in the hidden layer and a learning rate of 0.2 was used (RMSE = 1.54 and Pearson correlation = 0.95).

This result demonstrates that using ANNs can aid in determining load capacity values in deep foundations. However, if the database were larger, the study could achieve more effective results, thus improving the model to boost its use in civil construction for this type of calculation.

Furthermore, the study encourages new investigations into the SPT reports provided. Through them, it is possible to use artificial neural network models to calculate the distance between the points under study and also to compare the results obtained by the network with load capacity results calculated using the semi-empirical methods present in the literature.

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