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ARTIFICIAL NEURAL NETWORKS IN SOIL SHEAR STRENGTH PREDICTION

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Abstract. The estimation of soil shear strength parameters has been of much relevance in Geotechnical Engineering since the early stages, leading to the creation of many correlations based on in situ tests. However, Das and Basudhar (2008), Goktepe (2008) and Shooshpasha, Amiri and MolaAbasi (2014) stated that these existing correlations have limited use and low generalization capacity when compared to the neural models they proposed from index properties of soils. On behalf of that, this work was carried on prediction of cohesion and friction angle of soils in the natural state by the use of backpropagation multi-layer perceptrons built from easy-to-collected in situ input, N_{SPT}, σ_{V0}' and soil type. The architecture chosen, A:3-5-3-2, used hyperbolic tangent activation function, being trained and tested by 38 soil samples, having reached correlations up to 0,94 for training, attesting its efficiency.

Keywords: multi-layer perceptron, shear strength, soil

1 Introduction

In predicting the effective friction angle, most models have focused on the use of N_{SPT} in nonlinear correlations, although there is no consensus on equation modeling. However, some authors understood that this parameter alone was unable to represent the mechanical behavior of the soil and therefore applied corrections taking into account the influence of characteristics such as confining stress (σ_{v0}') (Hatanaka & Uchida, 1996) [1] and standardization of the SPT assay application energy (Dunham,1954 [2]; Decourt, 1989 [3]; Hatanaka & Uchida, 1996 [1]). On the other hand, the correlations for c_u prediction proposed in literature are very similar to each other, with expressive results when the CPT results are used as input to the model. In these models, the parameter N_k has changed values according to the studies performed (Remai, 2013 [4]; Zein, 2017 [5]; Otoko *et al.*, 2019 [6]).

However, such models were generally proposed for purely cohesive or frictional materials, thus lacking the ability to predict both strength parameters simultaneously. In addition, these models simplify the mechanical behavior of mixed materials such as clayey sands, disregarding the portion of effective cohesion (c') or effective friction angle (ϕ') and are unable to predict the effective cohesion of the soil.

In order to mitigate problems of similar complexity, the use of artificial neural networks (ANN) has been widespread in several areas due to its high generalization capacity, which can be verified in the literature review by Schmidhuber (2015) [7]. Reviews on the use of ANN in Geotechnical Engineering can be verified in the works of Shahin *et al.* (2001) [8], Das (2012) [9] and Juwaied (2018) [10], showing the modeling of complex problems such as prediction of mechanical behavior of rock discontinuities. The efficiency of this technique in predicting mechanical behavior of soils can also be verified in the studies by Goktepe *et al.* (2008) [11] and Das & Basudhar (2008) [12].

The aim of this paper is to present and compare the existing models of soil cohesion and friction angle prediction with artificial neural networks modeled from simple and easily collected input variables. The proposed RNA used as input N_{SPT}, initial effective overburden stresss (σ_{v0}') and soil type, which are characteristics whose correlation with shear strength is already proven. The proposed network was trained and tested with a vast database that gathered worldwide data, comparing the results of each model based on the correlation coefficient values. The calculated *versus* measured graphs were plotted to verify the generalization capacity of models, attesting their efficiency. Finally, the research limitations are presented.

2 Literature Review

2.1 Shear resistance of soils

In Geotechnics, mechanical behavior of soils governs how the structures will respond to loads applied in the mass and so the shear strength parameters are vastly used in designing. The most common uses of these parameters in designing are in limit equilibrium analysis or theoretical constitutive models such as the Morh-Coulomb criterion, which results in precise and practical modelling. Morh-Coulomb criterion defines soil mechanical behavior as a result of a cohesive and a frictional part, as shown in Eq. (1). The shear resistance envelope given by τ_s presents a cohesive part called effective cohesion (c'), which is defined by the sum of electrical forces among particles, being present in a more relevant way for fine-grained soils due to size of particles. The frictional part is dependent on effective normal stress (σ') lays on effective friction angle (ϕ'), which tend to govern coarse-grained soil's mechanical behavior by particle-to-particle contact. However, it is not unlikely to observe true cohesion in coarse-grained soils, since cementing of contacts might occur for particles subjected to weathering during long periods, which is observed in sandstone. Furthermore, there are several characteristics that affect shear strength behavior, such as soil composition, structure, particle size and presence of water, (Lambe & Whitman, 1969 [13]).

$$\tau_s = c' + \sigma' \tan(\phi') \tag{1}$$

However, obtaining c’ and ϕ’ in laboratory tests may be unfeasible in many situations due to difficulties of extracting undisturbed soil samples. That said, authors have proposed and attested the efficiency of correlations base on field easy-to-collect input such a number of blow counts from SPT (N_{SPT}) and CPT penetration resistance. A correlation for friction angle prediction based on N_{SPT} is shown in Eq. (2) proposed by Hatanaka & Uchida (1996) [1]. Furthermore, a correction on N_{SPT} value by overburden stress (σ_{v0}’), given in kPa, is shown in Eq. (3), since it is known that number of blow counts alone is incapable of representing shear strength behavior of soils.

$$\phi' = (20\ N_l)^{0.5} + 20°. \tag{2}$$

$$N_l = N_{SPT} / (\sigma'_{v0} / 98)^{0.5}. \tag{3}$$

In cohesion prediction, correlations were proposed only on estimating undrained cohesion (c_u). This simplification of the models is made in order to consider the most adverse situation to which it may be subjected, although it is unfavorable to cost optimization and does not take in consideration the frictional part of shear resistance for soil mixtures. However, correlations such as the ones shown in Eq. (4) proposed by and Decourt (1989) [3] and show good agreement when fine-grained soils are subjected to undrained load conditions.

$$c_u = 12.5\ N_{SPT}. \tag{4}$$

2.2 Artificial Neural Networks

Artificial neural networks (ANN) are processors based on the functioning of the human brain which operates as a parallel association of several simpler units, called artificial neurons, that are separated into layers and are interconnected. The background history of ANN development, from the conception of the first artificial neuron proposed by McCulloch and Pitts (1948) [14] to the most modern unsupervised learning techniques, can be found in Haykin (2001) [15].

Similar to the nervous system cell, these units are interconnected, collecting and summing information proportionally to synaptic weights until an activation potential, also called bias, is reached and the stimulus propagated. The mathematical process that occurs in each processing unit generating the response to stimuli is governed by Eq. (5) and (6).

$$v_k = \Sigma\ w_{kj}\ x_j + b_k = \{w\}^T\{x\}. \tag{5}$$

$$y_k = \varphi\ (v_k) = \varphi\ (\{w\}^T\{x\}). \tag{6}$$

Where, v_k is the induced local field; $\{w\}^T = [b_k, w_{k1}, w_{k2},...w_{km}]$ is the vector of biases and weights of neuron k;$\{x\}^T = [1, x_1, x_2, x_3,... x_m]$ is the input signal vector; b_k is the bias of neuron k; φ is the activation function; and y_k is the output of neuron k.

The activation function is responsible for ensuring that mathematical process is differentiable, so a cost reduction algorithm can be used for an efficient training. Haykin (2001) [15] stated that the most commonly used activation functions are Sigmoid, Hyperbolic Tangent, Hyperbolic Secant and Gaussian.

In Geotechnical Engineering, Dantas Neto *et al.* (2017) [16] stated that multilayer perceptron is the most used type of ANN due to its versatility and simplicity. These neural networks are of feedforward type and may be characterized by the presence of three or more layers, the first of which is responsible for receiving external stimuli. One or more hidden layers follow the input layer, being responsible for the interpretation and generalization of the behavior of the studied phenomenon. At last, an output layer gives the output for the model.

The training of the network is then carried by an error correction algorithm acting during iterations. Mostly, multi-layer perceptrons are trained by a teacher using a backpropagation algorithm, proposed by Rumelhart *et al.* (1986) [17], meaning that weight vector adjustment occurs when the error signal obtained from the difference between desired and calculated output is backpropagated throughout layers (Haykin, 2001) [15]. Therefore, this step aims to minimize a cost function, seeking to maximize the generalization capacity without resulting in overtraining.

2.3 Applications of ANN in Geotechnics

Applications of artificial intelligence in order to develop more efficient machines have been the object of study for some time. Schmidhuber (2015) [7] shows that the first uses of neural networks, in the way they are used today, date from at least the 1960s with the use of nonlinear layers of neurons. However, deep learning was only reached in 1991 when pre-processing data with help of unsupervised learning networks, and the term "deep learning" was first used in 2006.

In the meantime, the studies focused on building programs and machines capable of replicating human behavior, such as visual, writing and audio recognition. Although, in order to do so, various techniques were used in the training of ANN such as: GMDH (Group Method Data Handling), backpropagation and Max-pooling. All those techniques were then combined in different ways so that a neural network could be made that would overcome the main barrier of deep learning: backpropagation training. Schmidhuber (2015) [7] quotes several works of little and great relevance on the development of these neural networks.

In Geotechnical Engineering, the use of artificial intelligence (AI) has been used for many purposes. Shahin, Jaksa & Maier (2001) [8], Das (2012) [9] and, more recently, Juwaied (2018) [10] have explained the state of art and the uses of ANN that have been applied in Geotechnical Engineering. According to those authors, the use of ANN in this field has had a successful performance in the prediction of soil parameters and understanding of phenomena.

Some works in pile bearing capacity were developed by Goh (1995) [18], Abu-Kiefa (1998) [19], Das & Basudhar (2006) [20], Momeni *et al.* (2015) [21] and Maizir *et al.* (2015) [22] on driven piles for sandy and clayey soils, considering lateral load capacity and axial capacity. Studies developed by Lee & Lee (1996) [23] were focused on behavior of piles considering, stress-wave measurements using CAPWAP for ANN training, meanwhile Teh *et al.* (1997) [24], Shahin (2010) [25], Park & Cho (2010) [26] and Wardani, Surjandari & Jajaputra *et al.* (2013) [27] focused on prediction of bearing capacity based on geometry of piles and field responses to SPT (Standard Penetration Test) and CPT (Cone Penetration Test).

Prediction of pile settlement was object of study by some other authors. Sivakugan, Eckersley & Li (1998) [28] proposed an ANN based on N_{SPT} net applied pressure, width of foundation, shape of foundation and depth, obtaining outstanding correlations with measured results. Shahin, Jaksa & Maier (2000) [29] carried studies on prediction of settlement of shallow foundations in cohesionless soils, taking in consideration soil and structure characteristics, using multi-layer perceptrons with standard back propagation algorithm.

Other works on ANN implementation in Geotechnics were carried by Gangopadhya *et al.* (1999) [30] on aquifer characterization; Rizzo & Dougherty (1996) [31] on subsurface contamination; Monjezi & Dehghani (2008) [32], Sayadi *et al.* (2013) [33] and Dantas Neto *et al.* (2017) [16], on rock fragmentation and shear strength of discontinuities. Tunnelling was also object of ANN modelling by Lee & Sterling (1992) [34], Shi, Ortigao & Bai (1998) [35], Yoo & Kim (2007) [36] and Hajihassani *et al.* (2011) [37] on prediction of tunnel settlement, designing and failure prediction.

Nevertheless, even though ANN application covers several areas in Geotechnical Engineering, many of the relevant studies have focused on predictions and behavior of piles probably because data collection and field evaluation of structures is more easily made.

3 Materials and Methods

3.1 Database and treatment

A database was built from the works of Dias (1987) [38], Coutinho *et al.* (2000) [39], Lima (2002) [40], Gomes (2003) [41], Lafayette (2006) [42], Marques (2006) [43], Santos (2007) [44], Silva (2007) [45], Ribeiro *et al.* (2012) [46], Souza (2012) [47], Magalhães (2013) [48] and Souza (2014) [49]. The information collected consisted of N_{SPT}, σ_{vo}', soil type, c' e ϕ'. Soil distribution is shown in Fig. 1, in which a simplified classification of soils was chosen in order to understand the influence of this variable on the output.

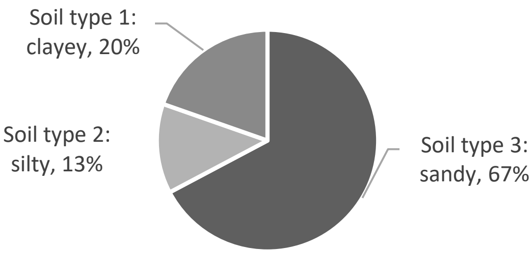

Figure 1. Soil type distribution

Collected data was then normalized between the limits 0.85 and 0.15, as shown in Eq. (7), following the recommendations of some authors (Dantas Neto *et al.*, 2017 [16], Araujo *et al.*, 2016 [50]). The maximum and minimum values used on normalization of each variable is shown in Table 1.

$$(x_{norm} - x_{norm,min})/\ (x_{norm,max} - x_{norm,min}) = (x - x_{min})/\ (x_{max} - x_{min}) \tag{7}$$

Where, x_{norm} representes the variable after normalization; $x_{norm,min}$, the minimum limiting value of normalization; $x_{norm,max}$, the maximum limiting value of normalization; x, the input variable; x_{min} e x_{max}, the minimum and maximum values for each variable in the training database, respectively.

Table 1. Maximum and minimum values used during ANN normalization

	c' (kPa)	ϕ' (º)	σ_{v0}' (kPa)	NSPT
Min	0.00	5.31	8.15	2.00
Max	112.30	54.46	420.00	90.00

3.2 Definition of input variables

In order to propose variables that could simply represent the mechanical behavior of soils in situations in which undisturbed samples extraction and field resistance tests were not feasible, the following input variables for ANN were chosen:

- x_1: N_{SPT};
- x_2: σ_{v0}';
- x_3: soil type.

The choice of the N_{SPT} value as the input variable was based on the possibility of its measurement at great depths. Also, its use on prediction of shear strength parameters had already been validated by existing correlations, such as the one proposed by Decourt (1989) [3]. Shooshpasha, Amir & MolaAbasi (2015) [51] also showed the efficiency of such a variable in an ANN model for prediction of ϕ'.

In turn, σ_{v0}' was chosen because it has a direct influence on soil shear strength (Lambe & Whitman, 1969) [13]. This fact may be noticed in direct shear and triaxial compression tests, in which there is a direct interdependence between the confining stress and soil shear strength. Moreover, the efficiency of using this variable in predicting c' and ϕ' can be verified in the work of Shooshpasha, Amiri & MolaAbasi (2015) [51].

Unlike other studies, soil type was introduced in the proposed model as an input variable considering the differences in soil shear strength mechanism due to this characteristic. According to Morh-Coulomb criterion, the mechanical behavior of soils is governed by a cohesive portion, characteristic of fine soils, and another frictional one, which is quite noticeable in granular soils, thus evidencing the influence of soil type on soil shear strength prediction.

It is noteworthy that, although the variables have a good correlation with the predicted parameters, none of them alone can follow the trend of soil resistance behavior. Thus, the neural network proposed in this paper follows the simplified formulation shown in Eq. (8), in which the function *h* generally represents the architecture, synaptic weights and bias of all neurons.

$$c', \phi' = h\ (N_{SPT}, \sigma_{v0}', \text{soil type}) \tag{8}$$

3.3 Training and testing

In order to develop an ANN with good generalization capacity in the prediction of soil shear strength parameters, some network architectures were proposed. The networks were then trained and tested from the collected database, considering soil types with a quantitative input ranging from 1 to 3, according to the classification shown in Fig. 1.

The collected data were randomly divided into training and testing groups so that 80 samples were used for training and testing, of which 68 for the first stage and 12 for the second stage. This division was based on the works of Tizpa *et al.* (2015) [52], in which 85% of the database was used for training and 15 % for ANN test.

The proposed networks were then modeled with the aid of QNET 2000 software as multi-layer perceptrons using the standard feedforward backpropagation algorithm. Network training occurred up to one million iterations, during which the software default settings were used: learning rate (α) equal to $0.001 \leq \alpha \leq 0.300$ and momentum $\eta = 0.8$, as proposed by Dantas Neto *et al.* (2017) [16].

For the conception of the ANN hyperbolic tangent activation function was used, shown in Eq. (9), which provides more stability during network learning. By doing this, the learning process becomes differentiable and the local gradient can be calculated to allow the calculation and backpropagation of the error signal during training.

$$(\tanh + 1)/2 \tag{9}$$

Concomitantly, the test step was carried, performing the first neural network check by calculating the values of c' and ϕ', as well as the errors for a group of samples also randomly selected and not used to define synaptic and bias weights. Thus, it was possible to verify the occurrence of “overtraining”, which consists in the loss of generalization capacity of the model due to over-adaptation to the training data. This phenomenon may be verified when the root mean square (RMS) value continues to decrease during training and increases for the test. Thus, the ideal network will be the one with the lowest number of iterations for which the lowest RMS value is obtained for both steps (Haykin, 2001) [15].

4 Results and discussion

The proposed artificial neural networks had the training and testing steps performed up to 1,000,000 iterations, as shown in Fig. 2, in which the correlation and RMS curves *versus* number of iterations were plotted. To present the proposed neural networks the nomenclature used was A: X-Y-Z, where X represents the input signals of the model; Y, the neurons in the hidden layer; Z, neurons in the output layer.

For the choice of optimal ANN, it was observed the convergence of maximum correlation for training and testing at a minimum amount of iterations without overtraining (Dantas Neto *et al.*, 2017) [16] . With this in mind, analyzing Fig. 2 shows that there is a growing trend of correlations during training, although in the test stage this statement is not true for all proposed ANN.

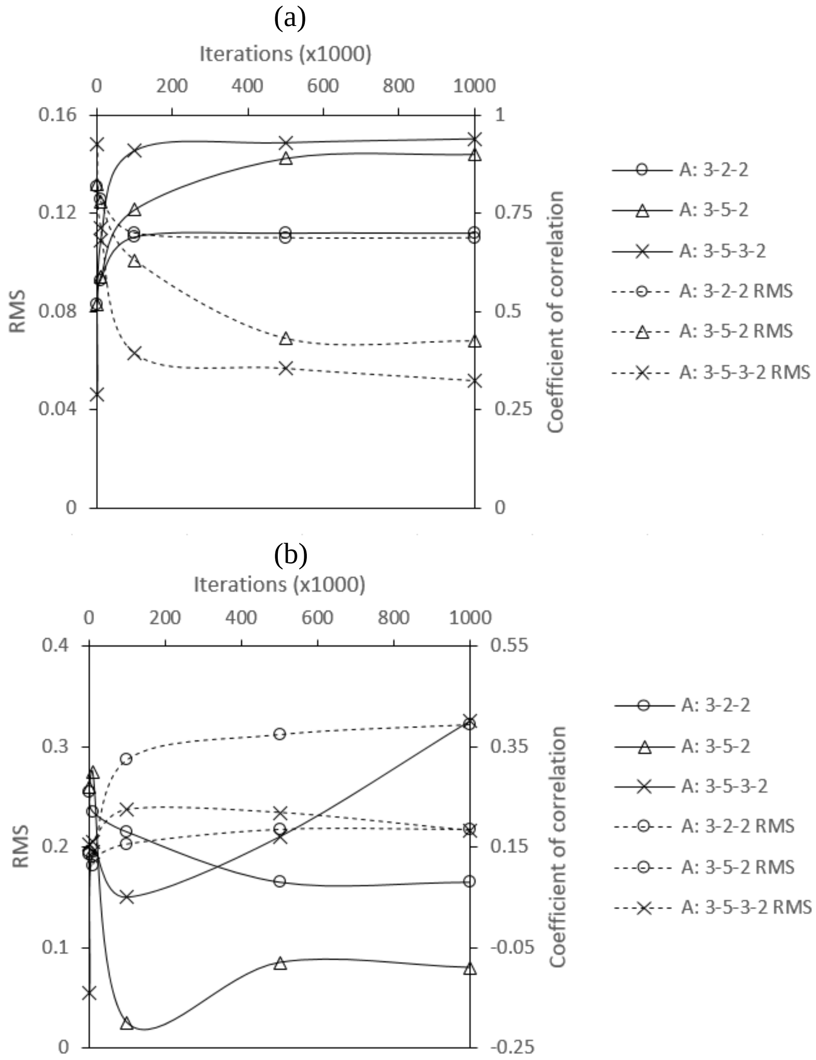

Figure 2. Correlation history: (a) training; (b) test

Table 2 presents the architectures and number of iterations considered optimized for each ANN. The ANN defined by A: 3-5-3-2, shown in Fig. 3, presented the best results, with the highest correlation values during both phases with a simple architecture, thus being selected as the ideal network to predict the parameters of soil resistance. However, correlations during testing phase reached low values, meaning that models might have failed during generalization. This is due to the various mechanisms that interfere in soil natural shear strength behavior such as suction and moisture content, which were not taken in account in this study.

Table 2. Correlations and iterations for optimized ANN

Architecture	Coefficient of correlation		Iterations at convergence
	Traning	Testing	
A: 3-2-2	0.69	0.18	100,000
A: 3-5-2	0.89	0.08	500,000
A: 3-5-3-2	0.94	0.40	1,000,000

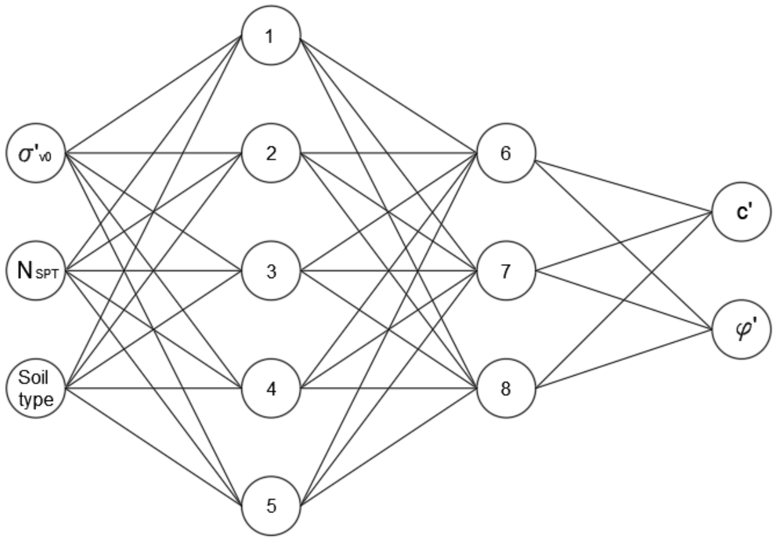

Figure 3. Network architecture of model A:3-5-3-2

The outputs of the model were then plotted on a scatterplot of measured *versus* calculated, presented in Fig. 4, showing that although correlations during test phase were not so high, the results had a good adjustment to the x = y line. It may be observed that both cohesion and friction angle prediction presented a good agreement throughout the whole range of training, meaning that the model actually had fair generalization capacity.

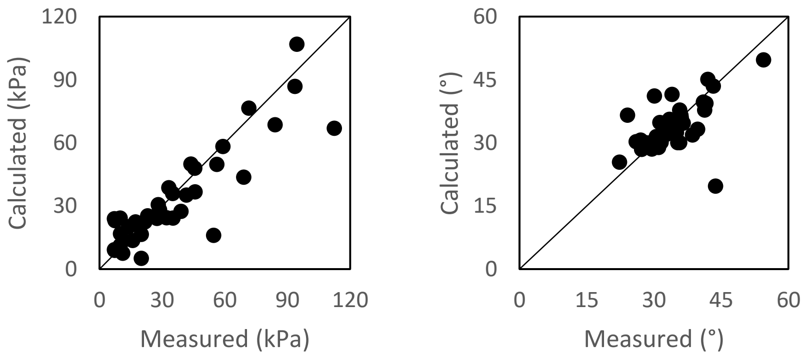

Figure 4. Adjustment of outputs to targets: (a) cohesion prediction; (b) friction angle prediction

QNET 2000 also gives as output the input node interrogator (NI), which gives information about the percentage of contribution of each input variable to the calculation of outputs. Figure 5 presents the values of NI for cohesion and friction angle prediction, illustrating that all three variables chosen as input (σ_{v0}', N_{SPT} and soil type) presented similar results and thus their use on soil shear strength prediction may be validated.

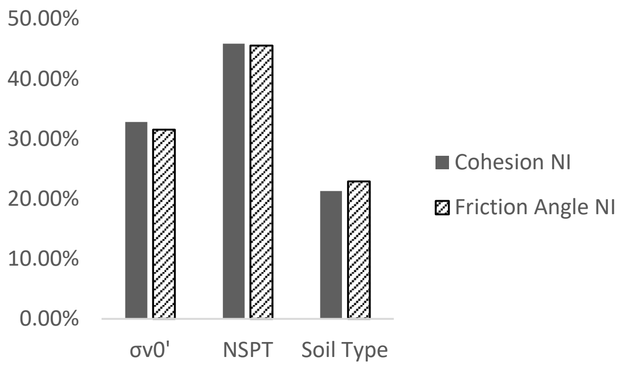

Figure 5. Input node interrogator results for the best model during training for: (a) cohesion prediction; (b) friction angle prediction

The advantage of using ANN lies on the possibility setting a simple spreadsheet base on the weights and biases adjusted during training. In order to do so, it is necessary to use Eq. (5), (6), (7) and (9), which represent the functioning of the networks. The weights and biases obtained for the chosen architecture, A: 3-5-3-2, are shown in Tables 3, 4 and 5.

Table 3. Weights and biases for first layer of neurons

Inputs	1	2	3	4	5
x1	4.46486	9.83136	-1.06893	-8.37437	-6.80742
x2	-7.62829	5.70232	-3.01215	8.00378	14.06121
x3	5.04268	5.94829	4.26727	-7.31992	-1.03876
bias	-1.01599	-4.4028	0.98038	2.67593	-3.70099

Table 4. Weights and biases for second layer of neurons

Hidden layer 1 outputs	1	2	3
x1	2.28075	7.46633	3.5719
x2	5.03525	-0.82626	-7.45851
x3	6.27463	-5.6352	-1.42538
x4	-4.63629	3.89302	-3.79581
x5	-11.8769	-3.87687	-6.79259
bias	-2.41088	0.06966	5.60651

Table 3. Weights and biases for output layer of neurons

Hidden layer 2 outputs	1	2
x1	-7.08198	-4.34984
x2	11.53031	7.37514
x3	-5.29956	-3.85045
bias	-0.33727	-0.15532

5 Conclusions

This paper has produced a multilayer perceptron artificial neural network for the prediction of soil shear strength parameters, having as input variables easily collected field data, whose correlations with c' and ϕ' are proved: σ_{v0}', N_{SPT} and soil type. After analyzing several architectures, the A: 3-5-3-2 network trained up to 1,000,000 iterations using the hyperbolic tangent activation function was chosen as the optimized model. This model obtained high correlations, equal to 0.94 and 0.40 for training and testing respectively, proving to have reasonable predictive ability. Scatterplots of measured versus calculated have proven the good generalization capacity.

However, further studies on the modeling of soil mechanical behavior by ANN are recommended to implement the proposed model. Suggestions for future researches include use of other easily collected variables as input and implementation of a greater database for training that has more heterogeneity. Nevertheless, the efficiency of models made from ANN is evident.

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