SOIL BEHAVIOR MODELLING USING CPTU DATA AND NEURAL NETWORKS FOR OFFSHORE OIL WELL DESIGN

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Abstract. Piezocone Penetration Test (CPTu) is widely used in Petroleum Engineering for soil profiling and estimation of soil parameters (undrained shear strength, submerged weight), which are essential geotechnical parameters used in the design of oil wells. The *in situ* test results are used in several techniques for soil characterization, aiming the design of the conductor casing, which is the tubular that provide structural support to the well, serving as its foundation element. Despite its efficiency, this test bears some logistic limitations regarding depth of analysis since CPTu data is usually obtained within a range of 40% to 50% of the conductor casing drilling depth. Data of undrained shear strength of the soil beyond the depths covered by CPTu tests are beneficial to the safety of the drilling operation. Due to the natural variability of the materials, the evaluation technique of this soil property must consider soil heterogeneity as a premise. The present work uses artificial neural networks (ANNs) to predict undrained shear strength behavior in offshore soil for depths not reached by CPTu equipment. The MLP (Multilayer Perceptron) networks are trained with test data of different types of soil from two Brazilian offshore basins, using classification techniques to define soil strata and segment the soil response estimation. The error is evaluated using cross-validation procedures for different proportions of training/prediction data. The expected results include the definition of the network architecture and prediction accuracy in different types of soil strata. This kind of study on the soil characterization aims to support the decision-making process on well casing design, allowing a robust structural well integrity analysis.

Keywords: Soil characterization, Neural Networks, Petroleum Engineering

1 Introduction

Cone penetration test (CPT) and piezocone penetration test (CPTu) are widely used in geotechnical investigations worldwide. This is mainly due to their simplicity, velocity and the possibility of incorporating sensors to the penetrometer to measure a wide range of soil parameters, such as undrained shear strength and submerged unit weight. Their results can be used in the determination of soil stratigraphy, evaluation of the material's properties, bearing capacity estimation, among other applications (Schnaid and Odebrecht [1]).

CPTu tests have logistic and depth limitations, especially when performed in deep water (depth $>$ 30-40m). Depth limitations can be attributed to reaching the equipment's capacity, soil conditions or problems during execution such as obstructions or deviation from the vertical (Lunne et al. [2]).

Parameters obtained in CPTu tests are essential to design the conductor casing, which provides structural support to the well and serves as its foundation element. Due to the CPTu depth limitations, its data is usually obtained within a range of 40% to 50% of the conductor casing drilling depth.

Knowledge of the undrained shear strength profile beyond the depths reached by the CPTu equipment would benefit the safety of the drilling operation. The objective of this work is to develop a methodology to model soil behavior using CPTu data and Artificial Neural Networks (ANNs) in order to estimate the undrained shear strength below depths reached in the CPTu tests until the depth of interest to the design of the conductor casing.

The purpose of this research is to aid the decision-making process when there is not enough soil data. It should not be seen in any way as encouragement for performing less tests. Tests should always be encouraged, since the reliability of ANNs results is deeply dependent of the input data. The more quality data you have available, the better your results.

Given the natural heterogeneity of the materials, there have been several developments in the use of ANNs in geotechnical engineering. Artificial intelligence has been used in several geotechnical applications such as prediction of index properties, prediction of bearing capacity, studies in slope stability, settlement analysis, subsurface characterization, among others (Juwaied [3]).

Besaw et al. [4] used ANN to develop a subsurface characterization methodology using multiple types of data aiming to give parameter estimates and delineate groundwater contamination at a leaking landfill in New York. Their study showed that counterpropagation ANN is a promising tool to estimate parameters when dealing with multiple types of data, since it increases the prediction accuracy and reduces uncertainty.

Shahin [5] developed a recurrent neural network (RNN) model to reliably predict the load-settlement of piles under axial loading. Calibration of the method involved use of CPT data and pile load tests. The comparison between model and test results indicated the model's ability to capture the highly nonlinear load-settlement response of piles.

Tizpa et al. [6] used ANNs to predict soil index properties using geotechnical parameters such as permeability, drained shear strength and compaction characteristics. 580 datasets were used in the model's calibration and the results indicated a 95% confidence interval of the predictions. The study also indicated which parameters were more relevant in the determination of the index properties.

Mazaheri and Berneti [7] applied a multilayer perceptron (MLP) neural network to predict the bearing capacity of steel piles in sandy soils using as input parameters pile's length and diameter, soil elastic modulus and soil internal friction angle.

2 Artificial Neural Networks

Artificial Neural Networks are traditionally defined as a modeling tool inspired by the brain's behavior when performing an activity. To reproduce these actions, networks must go through a learning process in which the processing units (neurons) are adaptively trained (Haykin [8]). A few examples of ANNs are:

- Feedforward networks: the information follows a single flow, without loops.

  - Simple Networks: acyclic networks with one layer. There are input nodes and an output layer of neurons.
  - Multilayers Networks: there are one or more hidden layers between the input and output layers. According to Haykin [8], adding hidden layers helps achieve higher order statistics.
- Recurrent Networks (feedback, cyclic): there are information loops because of the feedback between iterations (closed path)
- Convolutional Networks: specialized type of MLP network generally used to process bidimensional data.

Learning in the context of neural networks means updating the architecture and the weights of the connections so that the network can perform the tasks efficiently. The networks' ability to learn from the examples automatically is what essentially makes them attractive to users. This is because they do not follow a predetermined set of rules defined by the programmers, but seek to learn the implicit rules that coordinate the relationship between input and output data (Jain et al. [9]).

2.1 Dense Networks

Dense networks are ANNs where the information flows in one direction (feedforward) and where adjacent network layers are fully connected to one another (Figure 1). Each neuron in one layer is connected to all the other neurons in the adjacent layer (Nielsen [10]).

In this case, information from the input layer is what activates the hidden layer and, subsequently, its information is used as input for the output layer. Each layer only deals with the input from the previous layer (feedforward flow). Multilayer feedforward networks can be fully connected (as in Figure 1) or partially connected, which is when some of these connections are missing (Haykin [8]).

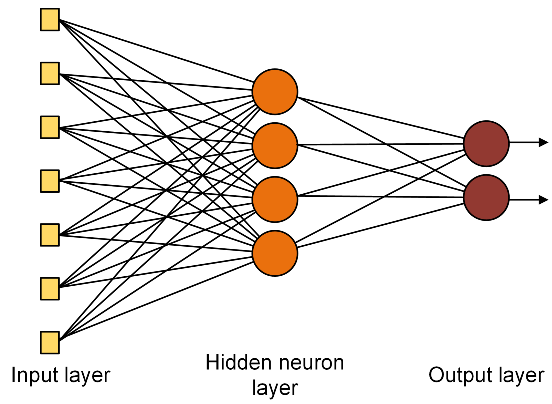

Figure 1. Dense network representation (feedforward). Adapted from Haykin [8]

2.2 Recurrent Networks

Recurrent Neural Networks (RNNs) are characterized by the backpropagation involved in the flow of information. This feedback deeply affects the network's performance and learning rate. The RNNs' dynamic approach can result in non-linear behavior (Haykin [8]). According to LeCun et al. [11], the use of RNNs is advisable for applications involving sequential inputs, which is the case for speech and language recognition.

RNNs process each component of an input individually and save information regarding the history of all the previous elements of the sequence. This information feeds the backpropagation process because the network views it as outputs of different neurons within a MLP network (LeCun et al. [11]).

Long short-term memory (LSTM) units can be incorporated into RNNs to help solve the gradient problem, which can become unstable and difficult to learn from in this type of network (Nielsen [10]). LSTM does this by truncating the gradient data and enforcing constant error flow within its units; this approach leads to a faster learning rate and helps solve tasks that RNN algorithms cannot (Hochreiter and Schmidhuber [12]).

2.3 Convolutional Networks

Convolutional Neural Networks (CNNs) are MLP networks that present convolutional layers in its architecture. CNNs were developed to process data with multiple arrays, such as images. CNNs have been used in phoneme, handwriting, speech and face recognition, document reading and object detection in natural images (LeCun et al. [11]).

Nielsen [10] explains that ANNs with fully-connected layers don't perform well to classify images because the spatial structure of the images is not considered when training the network. CNNs, on the other hand, consider the spatial structure by employing 3 mechanisms: local receptive fields, shared weights and subsampling/pooling.

Instead of using matrix multiplication in its layers, convolution operation allows CNNs to perform better with variable size inputs. This is due to CNNs' sparse weights - not every output unit is connected to every input unit. This methodology results in reduction of memory requirements and improvements in statistical efficiency (Goodfellow et al. [13]).

3 Soil Classification Methodology

Since soil samples are not obtained during piezocone testing, many methods were developed to classify these soils using parameters measured in tests. These parameters include tip resistance (qt), pore pressure (u_2), hydrostatic pore pressure (u_0), total vertical stress ($\sigma_v 0$) and sleeve friction (fs). These indirect classifications methods do not involve the utilization of soil samples and therefore their results cannot inform the soil's composition precisely. They are based on mechanical and physical properties, that is, on the soil's behavior patterns (Schnaid and Odebrecht [1]).

Robertson [14] has developed a method based on the normalization of a few parameters obtained in CPTu tests. According to this methodology, the results are to be plotted in two abacus where nine zones of soil types can be specified, each one associated to a different soil behavior.

$$Q_t = \frac{q_t - \sigma_{v0}}{\sigma_{v0} - u_0}. \tag{1}$$

$$B_q = \frac{u_2 - u_0}{q_t - \sigma_{v0}}. \tag{2}$$

$$F_r = \frac{f_s}{q_t - \sigma_{v0}} \cdot 100\%. \tag{3}$$

where Q_t is the normalized tip resistance, B_q is the normalized pore pressure ratio and F_r is the normalized friction ratio.

Jefferies and Davies [15] contributed to the classification developed by Robertson [14]. They defined the material classification index (I_c), allowing the methodology to be easily implemented without the use of an abacus (Eq. 4). This index defines 6 types of soil according to its behavior, as show in Table 1.

$$I_c = \sqrt{(3 - log(Q_t)[1 - B_q])^2 + (1.5 + 1.3log(F_r))^2}. \tag{4}$$

Table 1. Soil classification using the material classification index. Adapted from Jefferies and Davies [15]

Soil Classification	Zone	Index I_c
Gravelly sands	6	$I_c < 1.25$
Sands - clean sand to silty sand	5	$1.25 < I_c < 1.90$
Sand mixtures - silty sand to sandy silt	4	$1.90 < I_c < 2.54$
Silt mixtures - clayey silt to silty clay	3	$2.54 < I_c < 2.82$
Clays	2	$2.82 < I_c < 3.22$
Organic soils - peats	1	$I_c > 3.22$

The Jefferies and Davies [15] method was tested with data from 17 CPTu boreholes. The comparison of the method's classification with the results of laboratory tests and seismic reports proved to be very satisfactory for this research's purpose.

4 Results

Following the source's copyright policy, data from CPTu tests was modified in order to be publicized. In the analysis, we used data from two boreholes located in two Brazilian offshore basins. These boreholes were specifically selected to demonstrate how the methodology can differ based on the soil's heterogeneity.

To implement ANNs in Python, we used Keras (Chollet et al. [16]), a high-level ANN Application Programming Interface (API). This research's objective is to predict the soil's undrained shear strength beyond the depths reached by the CPTu tests until 80m. As input data we used the CPTu data, soil's classification using the methodology proposed by Jefferies and Davies [15] and soil type information from seismic reports.

4.1 Validation

In order to validate the methodology, we took each borehole's data, classified it by depth and divided it in half. The first half was used to train the network to predict the other half. The results for dense (Figure 2), recurrent (Figure 3) and convolutional networks (Figure 4) are presented in the sequence.

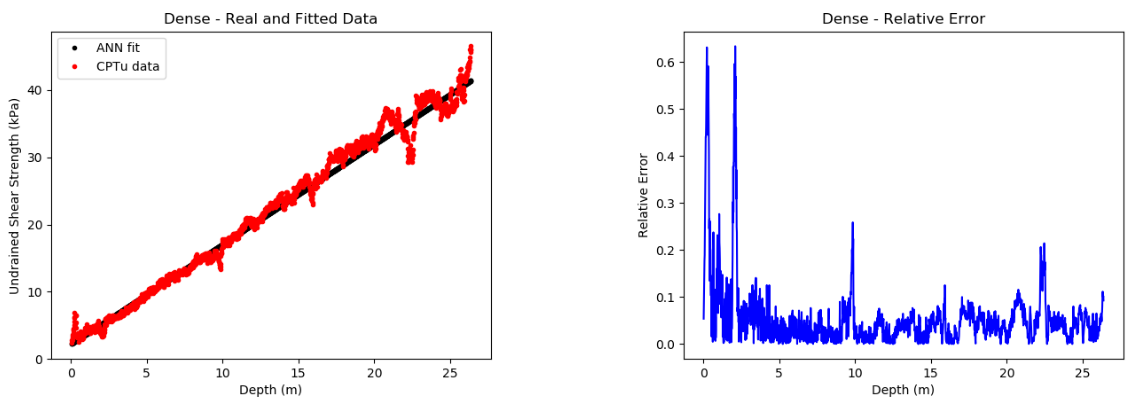

Figure 2. Dense Network validation for Borehole 1 (left) and its relative error (right)

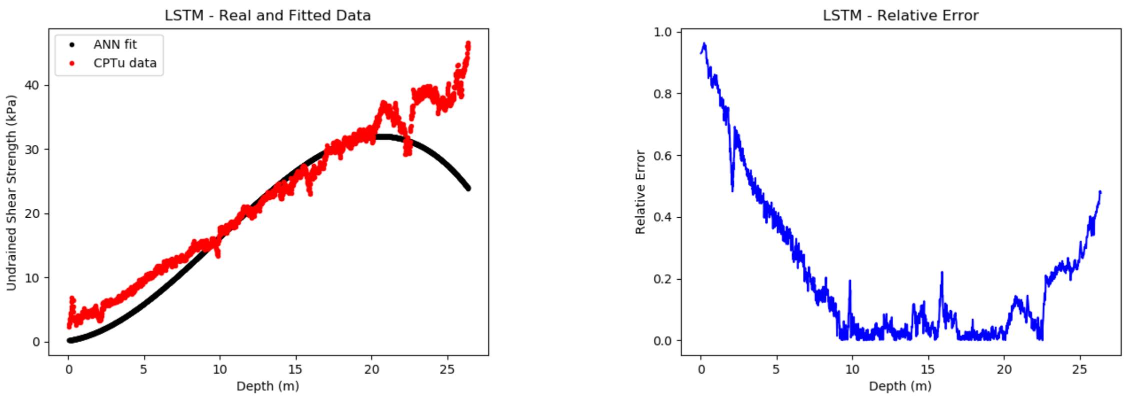

Figure 3. Recurrent Network validation for Borehole 1 (left) and its relative error (right)

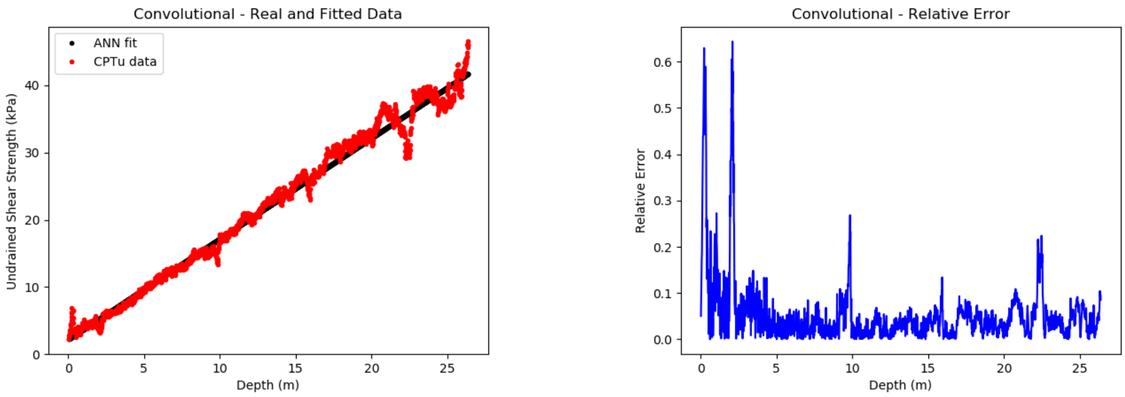

Figure 4. Convolutional Network validation for Borehole 1 (left) and its relative error (right)

Given the overall linear behavior of the soil in this borehole, it is observed that Dense and Convolutional networks can predict the undrained shear strength more accurately along the depth (Table 2). Nevertheless, local disturbances in the strength could not be modeled and caused spikes in the relative error values.

Table 2. Relative error in the ANNs predictions

ANN	Mean	Standard Deviation	COV
Dense	0.053	0.069	1.316
Recurrent	0.215	0.237	1.104
Convolutional	0.052	0.071	1.353

Even though LSTM was used in the RNN model, gradient sensitivity problems were still observed - in this case the network had to be trained with 90% of the data in order to obtain acceptable strength values in the extrapolated portion. Training with 50% of the data resulted in strength values superior to 140kPa in larger depths. Using other proportions of data sometimes resulted in negative strength values along the depth.

The validation of the methodology for Borehole 2 followed the same process of subdivision of the data. However, since Borehole 2 has three different soil layers, according to Jefferies and Davies [15] classification, the extrapolation was done considering three intervals, instead of one.

4.2 Extrapolation

After validating the methodology, we proceeded to the actual extrapolation of the data in order to obtain a strength profile of 80m. Following are the results for dense (Figures 5 and 8), recurrent (Figure 6) and convolutional (Figure 7) networks.

Applying the classification methodology (Jefferies and Davies [15]), it was identified one soil layer in Borehole 1 and three soil layers in Borehole 2 (3). This resulted in a different approach for the extrapolation of the strength data in Borehole 2. We trained the networks for each soil layer and used soil type information from seismic reports to extrapolate the data. The prediction of the values beyond the depths reached by the CPTu tests was done by identifying soil layers in the depths of interest, comparing with the layers identified using the classification methodology and extrapolating within the layer.

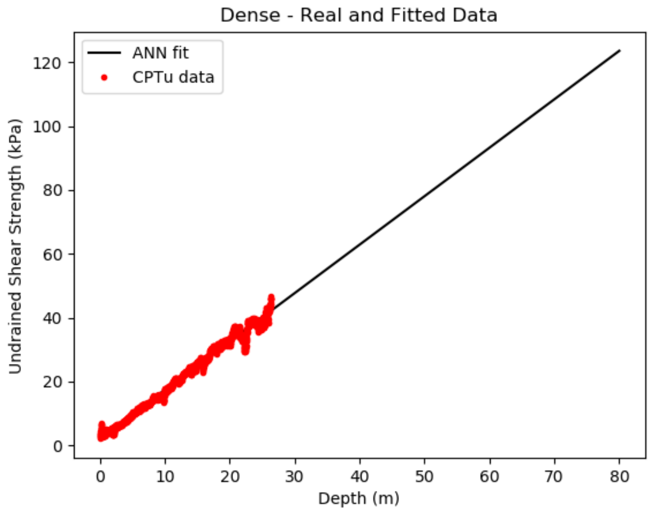

Figure 5. Extrapolation of CPTu data using a Dense Network - Borehole 1

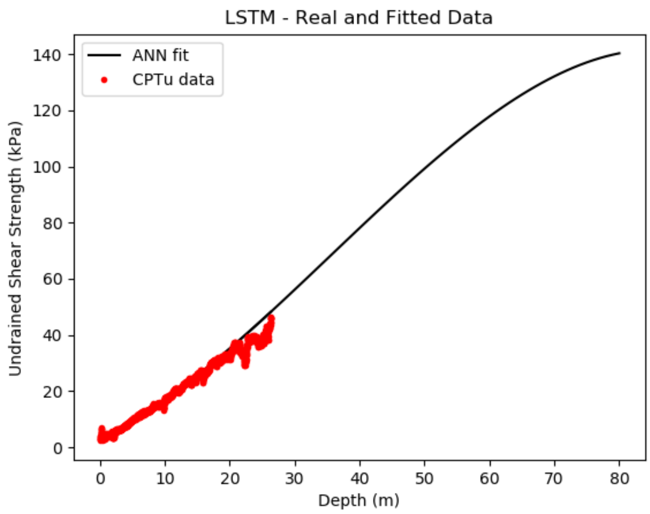

Figure 6. Extrapolation of CPTu data using RNN - Borehole 1

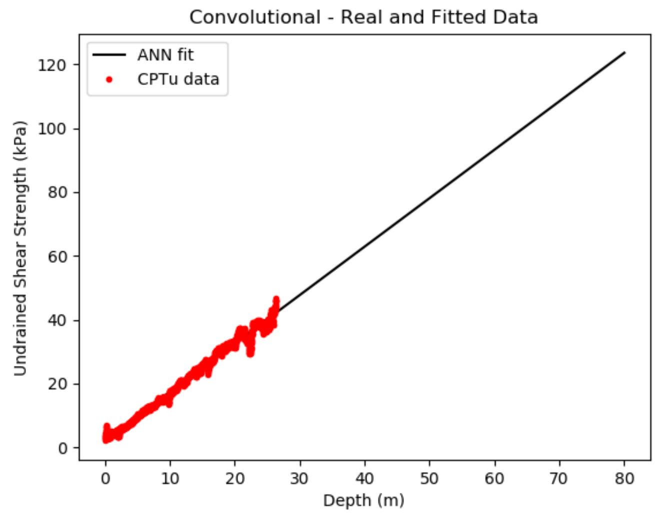

Figure 7. Extrapolation of CPTu data using CNN - Borehole 1

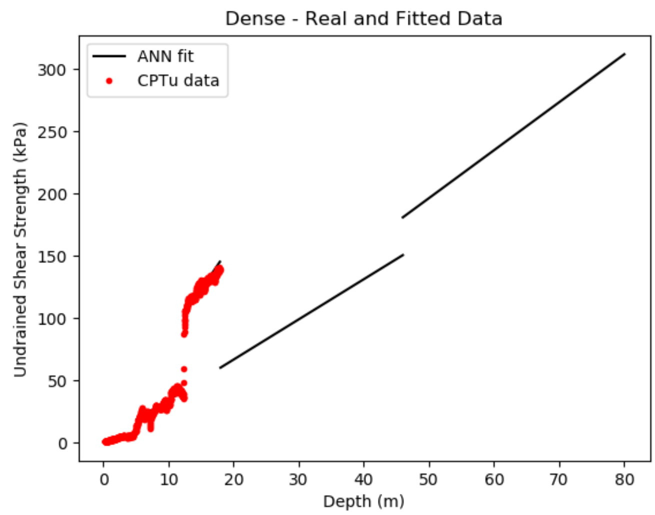

Figure 8. Extrapolation of CPTu data using a Dense Network - Borehole 2

Table 3. Soil layers in Borehole 2

	Soil type	Classification origin	Depth (m)
Layer 1	Clay		0 - 5.25
Layer 2	Silt mixtures	Jefferies and Davies (1993) methodology	5.25-12.40
Layer 3	Sand mixtures		12.40-18.00
Layer 4	Equivalent to layer 2	Seismic reports	18.00-46.00
Layer 5	Equivalent to layer 3		46.00-80.00

It is observed that dense and convolutional networks present nearly identical results while the recurrent network provide rather less conservative results. It was noticed once again the gradient sensitivity of RNNs. While for the other networks we used all of the CPTu data as input for the extrapolation, for the RNN we used a little over 50% (Borehole 1) in order to obtain plausible non-negative results. The extrapolated strength values for the 3 networks analyzed are within an acceptable interval for the soil types and local conditions.

The extrapolation in Borehole 2 was done within layers, which means that we considered the continuity of the layer along the depth (as if it was only one soil layer) attempting to preserve the linear tendencies observed in general. This approach meant that for the extrapolation of Layers 4 and 5, we used Layers 2 and 3 as training data, respectively. The extrapolation of Layer 5 included ponderations of depth and maximum acceptable values of strength. The results for dense and convolutional networks, once again, were practically identical, so only the dense network is shown for Borehole 2.

It must be noted that ANNs are more often used to interpolate rather than extrapolate information. Kiran et al. [17] and Khanlari et al. [18], for example, use ANNs to predict strength values within a depth interval using other soil properties (measured in the same depth range) as input data. This is a safer approach in the prediction of soil properties.

For the study conducted in this paper, there was no soil data available in the depths of interest (from the larger depth reached by CPTu tests to 80m), apart from soil type analysis from the seismic reports. The authors suggest that to apply this methodology, all possible soil data must be used as input for the ANN in order to increase the reliability of the results. It is also suggested careful consideration about soil type, depth evaluation, maximum values of strength, and possibly the incorporation of a safety factor in order to obtain satisfactory and reliable results.

4.3 Conclusions

In this research, ANNs were used to predict the soil's undrained shear strength beyond the depths reached by the CPTu tests. Three types of Neural Networks were employed: dense, recurrent and convolutional. The methodology was applied to two boreholes from different offshore basins: Borehole 1 and Borehole 2, which presented more homogeneous and heterogeneous soil data, respectively.

The method's validation indicated that dense and convolutional networks were able to predict the strength more accurately. Given the overall linear behavior of the property, these methods also provided better results when extrapolating the values. It was noted that when using recurrent networks, extra care should be employed in the training process in order to avoid gradient issues and obtain suitable results.

Even though the presented methods present satisfactory results for the analyzed depths, it must be emphasized that the soil's real complex heterogeneity can only be effectively quantified with a sufficient number of quality laboratory and *in situ* tests. This means that only with quality information as the model's input, it is possible to model the soil's expected behavior as efficiently as possible. This information includes the soil's anomalies and peculiarities that can only be obtained by performing tests. The methods discussed in this paper should be seen as tools to support the decision-making process.

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