

Application of an Artificial Neural Network for the CPT-based Soil Stratigraphy Classification

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Abstract: Subsurface soil profiling is an essential step in a site investigation. The traditional methods for in situ investigations, such as SPT borings and sampling, have been progressively replaced by CPT soundings since they are fast, repeatable, economical and provide continuous parameters of the mechanical behaviour of the soils. However, the derived CPT-based stratigraphy profiles might present noisy thin layers, and its soil type description might not reflect a textural-based classification (i.e. Universal Soil Classification System, USCS). Thus, this paper presents a straightforward artificial neural network (ANN) algorithm, to classify CPT soundings according to the USCS. Data for training the model have been retrieved from SPT-CPT pairs collected after the 2011 Christchurch earthquake in New Zealand. The application of the ANN to case studies show how the method is a cost-effective and time-efficient approach, but more input parameters and data are needed for increasing its performance.

Keywords: Soil Classification, Deep Learning, Artificial Neural networks, Cone Penetration Test, Data Analysis.

1. Introduction

Determining the layering of different soil types and their thickness is crucial for the development of many geotechnical engineering projects. For instance, the state-of-practice methods for the liquefaction potential assessment depend on a preliminary evaluation of in-situ characteristics of the soil layering (Idriss & Boulanger, 2008). Typically, site investigations are carried out through soil borings with standard penetration test (SPT), and laboratory analysis on the soil samples extracted. Soils are then commonly classified based on their physical and textural characteristics according to the Unified Soil Classification System (USCS).

Due to the laborious and time-consuming approach of laboratory tests, site investigations based on cone penetration test (CPT) are gaining popularity. A CPT consists of pushing a cone probe of usually 10/15 cm into the ground at a controlled rate, while specific sensors place on the probe continuously measure the tip resistance q_c , sleeve friction f_s and pore pressure u . Thus, this test results in being fast, repeatable, cost-effective and can provide almost continuous soils strength and stiffness data (Robertson, 2012). These parameters can reveal invaluable information about the mechanical behaviour and variability of soils, which cannot be determined with sampling and laboratory tests. However, a CPT does not allow visual inspection of

undisturbed soil samples for the identification of thin layers and a textural-based classification.

Specific CPT-based classifications have been developed to aid the identification of soil strata. The soil type is determined directly linking the retrieved cone parameters to behavioural soil class using graphic charts. The most widely used one is the Soil Behaviour Type (SBT) proposed by Robertson *et al.* (1986), which is based on the normalised friction ratio F_r , and the normalised tip resistance Q_{tn} :

$$F_r = 100f_s / (q_t - \sigma_{v0}) \quad (1)$$

$$Q_{tn} = [(q_t - \sigma_{v0}) / P_a] (P_a / \sigma'_{v0})^n \quad (2)$$

where q_t , σ_{v0} , σ'_{v0} , P_a , n are, respectively, the corrected tip resistance, total vertical stress, vertical effective stress, atmospheric pressure and normalisation factor. The boundaries of each soil class in the SBT charts can be found estimating the SBT index I_c (Robertson, 2009) or I_b , in the latest classification proposed (Robertson, 2016):

$$I_c = \sqrt{(3.47 - \log Q_{tn})^2 + (\log F_r + 1.22)^2} \quad (3)$$

$$I_b = 100 (Q_{tn} + 10) / (Q_{tn} F_r + 70) \quad (4)$$

Thus, for engineering practitioners, the most cost-effective and time-efficient method to identify a subsurface stratigraphy is to consider the profile of the SBT Indices. Given the continuous nature of the CPT-based parameters, the obtain soil profiles might contain noisy ‘thin layers’ which do not have a physical meaning or misclassified the soil due to ‘transition zones’. However, these effects are relevant in some circumstances, such

as for the liquefaction methodologies, and must be carefully evaluated (Boulanger *et al.*, 2018). To solve this problem, an extensive range of approaches has been proposed in the literature. By way of illustration, Zhang & Tumay (1999), and Jung *et al.* (2008) have used the concept of probability fuzzy sets, whereas Liao & Mayne (2007), Wang *et al.* (2019), Hegazy & Mayne (2002), and Facciorusso & Uzielli (2004) have adopted clustering analysis approaches. Other studies have attempted to identify layer boundary locations using advanced algorithms based on wavelet functions (Ching *et al.*, 2013) as well as Bayesian methods (e.g. Wang *et al.*, 2013). Taken together, these approaches are sophisticated methods that require advanced mathematical knowledge and, thus, might not be of easy implementation for practitioners.

Therefore, this paper provides a first step in understanding if deep learning methods, such as artificial neural networks (ANNs), are a viable and more straightforward option for determining a soil stratigraphy. ANNs have been used in a variety of tasks for solving complex nonlinear classification problems, without requiring any specific assumption related to the underlying physical problem. In particular, the paper aims to determine a soil stratigraphy profile using the USCS classification given the CPT-based parameters as input. In the following, a brief overview of ANNs and their application in geotechnical engineering are illustrated. Data and methodology adopted for building a soil multi-classification ANN are then presented. The paper concludes by discussing the results of the ANN model with consideration made of the adequacy of ANNs and SBT classifications for assessing subsurface profiles.

2. Artificial neural networks in geotechnical engineering practice

ANNs are a powerful deep learning technique able to model complex classification problems (Basheer & Hajmeer, 2000; Fausett, 1994). Similarly to human nervous systems, these computational tools are composed of artificial ‘neurons’ or ‘nodes’ interconnected to each other. Nodes are commonly arranged into an input layer, an output layer and one or more intermediate/hidden layers. The linkings from neuron to neuron, equivalent to humanlike

synapsis, are mathematical ‘weighting functions’. These functions are the ones that determine the ability of a neural model to provide accurate predictions.

ANNs can train themselves in classification analysis without requiring human development of algorithms. In particular, a supervised ANNs modelling approach can be schematised into three-step phases: training, validation and testing. In the training phase, the weighting functions are calibrated by matching known input-output data pairs. Each neuron X computes a summation Σ of its inputs weighted by a weight vector w and then applies an activation function Φ , to Σ and derive the output (Fig.1). The described procedure continues iteratively until when an optimal combination of weighting functions is reached. In the validation phase, a new set of input-output data pairs are used to evaluate how accurately the ANN can predict the outputs. If its performance results being acceptable, the determined weighting functions and model structure are used to test unseen output data.

Thus, the strength of ANNs is that they are data-driven (Shain *et al.*, 2008). In contrast to classical statistical approaches, ANNs can learn and adapt themselves without the need of either simplify the problem or incorporate any assumptions. Besides, they usually outperform conventional techniques both in terms of efficacy and accuracy. For instance, in the geotechnical engineering field they have been successfully applied for the estimation of several soil properties, such as soil composition (i.e. Kurup *et al.*, 2006; Reale *et al.*, 2018; Bhattacharya & Solomatine, 2006) and soil liquefaction potential (i.e. Hanna *et al.*, 2007; Goh, 2002). Thus, ANNs result in being a powerful approach to solve a soil classification problem.

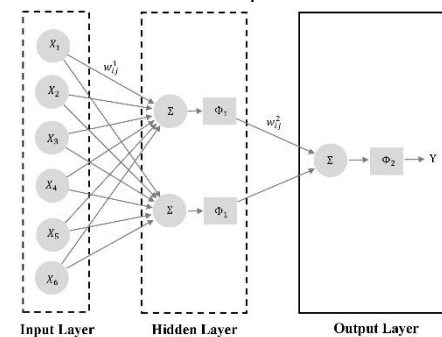


Figure 1. Schematic representation of an ANN.

3. Prediction of soil stratigraphy using ANN

The soil profile stratigraphy requires the identification of several soil classes. For this purpose, the multi-classification ANN is implemented in Python through the Scikit-learn (Pedregosa *et al.*, 2011) and Keras (Chollet, 2015) libraries. In the next paragraphs, first the data sources used are introduced followed by a description of the cleaning procedure executed on the available data; then, the approach adopted to train, validate and test the ANN is illustrated.

3.1 Data Sources

A considerable amount of data are necessary to train and validate an ANN. For this purpose, Christchurch (New Zealand) offers a unique opportunity as a case study. Following the 2010-2011 Canterbury Earthquake Sequence, an in-depth soil characterisation programme was conducted to aid the reconstruction; approximately 18,000 SPT and more than 30,000 CPT tests have been performed and made available through the New Zealand Geotechnical Database (NZGD). Through this dataset, 35 sites spread around the entire Christchurch City Council are selected. This arbitrary selection is based on the availability of both SPT and CPT soundings in approximately the same location. Christchurch is placed in a complex geologic and geomorphic environment, formed prevalently by alluvial, coastal, and swamp depositional processes (Bertelli *et al.*, 2019). Particularly, the superficial soil conditions broadly include the Springston and Christchurch Formations. The first is an alluvial soil deposit mainly originated from the periodic floods of the northern Waimakariri River through the city. These deposits of gravel, sand, and silt sediments eroded from the Southern Alps overly the Christchurch Formation marine sands which, in turn, are mixed with silt-clay estuarine and swamp deposits accumulated following the last glaciation. Below these deposits, there is an older Riccarton Gravel formation deposited during the last glaciation. As a consequence, the data used for training the ANN would comprise all main types of soils.

Despite the availability of supplementary sites from the NZGD for testing the ANN, three CPT tests provided by the TC304 Student Contest are used. Additional information regarding

geomorphological features, water regime and soil stratigraphy from where these tests are taken rest unknown. However, these soundings might provide an insight into the suitability of the proposed ANN to be applied for the soil stratigraphy classification of a wider variety of geological contexts than the Christchurch area.

3.2 Pre-processing procedure

A preprocessing analysis is carried out before using the CPT soundings and SPT borings data for the training and validation of the ANN. The raw data are examined in order to identify and exclude outliers from the dataset. This procedure consists of a screening of the borehole stratigraphy, estimation of relevant information from the CPT tests, side-by-side comparison of SPT and CPT profiles, statistical outliers detection and re-sampling of data.

First, SPT borings are checked in order to assure consistency in the soil label classification. The drilling reports provided contain a soil description, a graphic log as well as a label class according to the USCS rating. In some cases, percentages of fines content and pictures of retrieved specimens are also available to provide a well-rounded overview of subsurface conditions. Thus, characteristics of the soil layering are examined, and data which show differences among information are discarded. Instead, tabulated CPT data include basic attributes; namely depth z , tip resistance q_c , sleeve resistance f_s and penetration pore pressure u . These values are transformed into Q_{tn} and F_r (Eq. 1 and Eq.2) in order to account the influence of overburden stresses. Since CPT-based soil classification is commonly based on various combination of these parameters, Q_{tn} , F_r , and z are chosen as input variables for the ANN. However, the SBT Indices I_c (Robertson, 2009) and I_b (Robertson, 2016) are also estimated to be consistent with existing soil classification methodologies.

Following this treatment, the CPT soundings and SPT borings are compared side-by-side in order to correlate z , Q_{tn} , and F_r attributes with the confirmed information about the soil stratigraphy. This comparison is necessary to identify differences in stratifications between the two soil profiles. The typical 10-15 cm cone penetrometers cannot penetrate in hard soils, such

as rocks and gravel layers. Similarly, SPT boreholes cannot clearly distinguish between silt and clay soils for which detailed laboratory tests are recommended (Robertson, 2012). Therefore, the USCS is re-arranged in broader classes; namely, 'gravels', 'clean sands', 'sands with fines', 'silt and clay', 'peat'. Data corresponding to 'peat' and 'gravels' are removed due to the relatively low number of entries and high uncertainties associated with these class.

To further detect outliers, a more rigorous exploratory data analysis is applied (Iglewicz & Hoaglin, 1993). Initially, each data is grouped according to the soil class and plot on the SBTn chart proposed by Robertson (2009). Also, each soil class is visually inspected, examining the variability of I_c and I_b values. From a statistical standpoint, standard deviation σ and z-scores are calculated for the Q_{tn} and F_r distributions of each soil class and entries with σ and/or z-score greater than three are labelled as outliers. The interquartile range method is then applied and results are cross-referenced with the previous ones, before discarding the data identified as outliers. The resulting dataset is resampled through the 'resample' metrics in Scikit-learn (Pedregosa *et al.*, 2011) in order to handle the imbalance between the soil classes and increase the performance of the ANN.

3.3 ANN structure and methodology

After the pre-processing procedure, the soil dataset is randomly split into two nonoverlapping groups; approximately 75% of them are assigned to the role of training, whereas the remaining ones are used for validation. The attributes z , F_r and Q_{tn} are identified as input variables; the soil class vector is instead turned into a one-hot encoded binary matrix to be used for comparison with the output variables.

The ANN model itself is built by adopting a 'KerasClassifier' as an estimator (Chollet, 2015). A base-model function is defined to be used as an argument in the classifier, which creates and return the ANN model ready for the training. The function constructed for this particular study is a simple sequential network with an input layer and a number of hidden layers, each of which is characterised by several neurons, activation function and back-normalisation. Instead, the output layer creates many output variables, one

for each soil class. The output value with the highest value is taken as the predicted soil class by the model using the activation function 'softmax' in Keras (Chollet, 2015). The model is then compiled using an optimisation algorithm and the Keras logarithmic loss function 'categorical_crossentropy' (Chollet, 2015). The resulting base-model function is passed to the KerasClassifier with the number of epochs and back-size dimensions to train the model.

The training process involves the tuning of several parameters to optimise the predictive performance of the ANN. A Gridsearch hyperparameter optimisation technique is used for ease of computation as it is provided by the 'GridSearchCV' class in the Scikit-learn library (Pedregosa *et al.*, 2011). A dictionary of parameters is passed to this class for the evaluation based on the ones available and offered by Keras. For instance, the number of neurons and hidden layers, activation functions, optimiser, epochs, and back-size dimension inside the aforementioned KerasClassifier are tuned based on their accuracy score. Then, the GridSearchCV process constructs and evaluates one model for each combination of parameters based on a 3-fold cross-validation technique. The combination of parameters that achieved the best results are used for training the final ANN model. In order to evaluate the ANN model, the data left untouched from the splitting are tested. The performance of the estimator is assessed using metrics from the Scikit-learn metrics (Pedregosa *et al.*, 2011). In particular, the predicted and the given output variables are compared plotting a 'confusion matrix' and a 'classification report' which include precision, recall, F1-score for each soil class, and accuracy of the entire model. The best performing ANN is then used to test and classify unseen data, such as the CPT provided by the 2019 TC304 contest.

4. Results

This section provides an overview of the results obtained by applying the ANN. First, concise evaluation of the data collected from the NZGD is provided. This is followed by the description of the optimised ANN architecture with a particular focus on its performance. The section concludes with presenting the soil stratigraphy for three different CPT soundings.

4.1 Data Exploratory Analysis

The resulting dataset obtained comparing the SPT-CPT pairs is presented in Table 1. It contains more than 24,500 entries for depths z ranging from 0 to roughly 26m. The soil class ‘clean sand’ reported significantly more entries than the other two groups. Thus, the data loaded in the ANN environment are resampled to 9500 entries for each class in order to avoid unbalanced classes.

Table 1. Adopted Soil Classification.

Soil Description	Entries	I_c ranges	I_b ranges
Clean Sand	12898	1.43 - 2.10	53 - 127
Sand with fines	3902	1.66 - 3.02	13 - 87
Silt and Clay	7761	1.98 - 3.59	8 - 43

The most striking aspect of Table 1 is the correlation between the soil classes, which were derived directly from the USCS rates, and the SBT Indices ranges. For the ‘Clean sand’ class, both I_c and I_b correspond quite well to either the SBT6 class (Robertson, 2009) or SD/SC classes (Robertson, 2016). Instead, the ‘Sand with fines’ and ‘Silt and Clay’ classes show significant overlap between the sandlike and claylike classes in the SBT classifications. These anomalies are confirmed by the SBTn Robertson (2009) charts reported in Fig.2. Indeed, they set out how the soil classification criteria based on textural-based features relate quite well with the SBT for the ‘clean sand’ class, but differences arise looking at the ‘Sand with fines’ and ‘Silt and Clay’ classes.

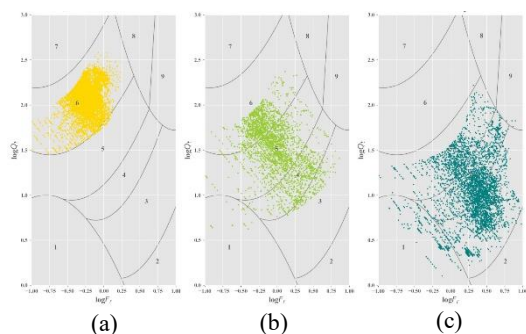


Figure 2. Application of SBTn Robertson (1990) chart in logarithmic scale according to SBT boundaries suggested by Wang *et al.* (2013): a) ‘Clean Sand’ (yellow); b) ‘Sand with Fines’ (light green); c) ‘Silt and Clay’ (dark green).

These results reflect those of Robertson (2012, 2016), who also highlighted how the SBTn chart is less useful in recognising structured soils. The SBT is a behaviour-type classification and not a textural-based one; similarities on terms used in the description of the SBT might be misleading in the geotechnical practise for the extrapolation of soil stratigraphy profiles as soil behaviour might not relate to textural features.

In order to overcome this confusion, Robertson (2016) has suggested identifying soils on a modified SBTn classification. Following the introduction of the I_b parameter, soils which behaviour is somewhere between either sandlike or claylike ideal soil-based are identified as the ones in the range between $22 < I_b < 32$. In this regard, the I_b histogram reported in Fig. 3 is revealing in several ways. First, the ‘Clean sand’ class corresponds perfectly to soils with $I_b > 32$. Secondly, the statistical mode of the ‘Silt and Clay’ soils distribution agrees with the claylike interpretation of $I_b < 22$, but the range is slightly broader. Nonetheless, the I_b values of the ‘sand with fines’ cover the clay-like, sand-like and transitional soils ranges. These result may partially be explained by the limited number of entries for this class or misclassification errors and, thus, further research is suggested to understand if a better behavioural-textured correlation exists.

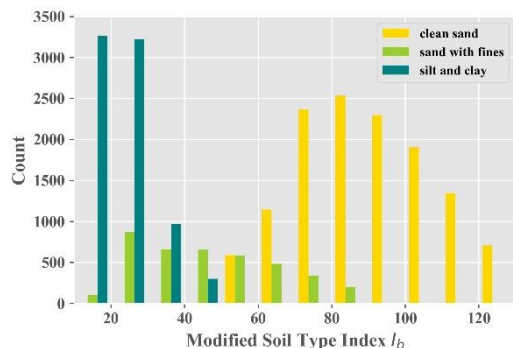


Figure 3. Histograms of I_b values for each class: ‘Clean Sand’ (yellow), ‘Sand with Fines’ (light green), and ‘Silt and Clay’ (dark green)

4.2 Model performance evaluation

Based on the hyperparameter optimisation, the final ANN structure consists of five fully connected layers. In particular, one layer each for

the input and output neurons and three hidden layers (Table 2). Among all the activators and optimisers offered by the Keras package (Chollet, 2015), the ones which suit better the data are respectively the linear rectifier ‘Relu’ and the first-order gradient-based stochastic optimiser ‘Adam’ (Kingma & Ba, 2014). The back-size and epochs are also set to 80 and 200. Table 2 summarises the adopted structure with specifications of neurons (output shape) and parameters used at each step.

Table 2. Summary of the ANN structure.

Layer	Output Shape	Activation	Parameters
Input	240	Relu	960
Hidden 1	140	Relu	33740
Hidden 2	120	Relu	16920
Hidden 3	18	Relu	3025
Output	3	Softmax	130

A positive correlation is found between the input z , Q_{tn} , F_r attributes and the adopted soil classes through this model. Indeed, the results reported in Table 3 show a total accuracy of the ANN equal to 0.91. The class which is better classify is the ‘clean sand’, followed by the ‘silt and clay’ as also the precision, recall and F1-score values are proximate to the unit. Instead, the ‘sand with fines’ class shows borderlines values. Its metrics are all closed to 0.85, which is the commonly accepted reference target for an acceptable multi-class classification.

Table 3. Classification Report.

Soil Class	Precision	Recall	F1-score
Clean Sand	0.98	0.94	0.96
Sand with fines	0.84	0.88	0.86
Silt and Clay	0.91	0.90	0.90
Accuracy			0.91

These uncertainties are confirmed by the confusion matrix. Fig.3 illustrates how entries classified as ‘sand with fines’ could be instead ‘silt and clay’ with a 10% probability. This ambiguity in the classification might be due to the limited number of entries in the original dataset adopted for this class, which could be solved using more CPT-SPT input pairs. Contrary to conventional statistical approaches, deep learning models increase their performance augmenting the number of input data as they can better

understand the non-linearity of the problem. Nonetheless, this uncertainty could also be related to soil misclassification from the retrieved SPT. These borings provide a continuous but rough characterisation of the subsurface profile and major strata (Wentz & Dickenson, 2013). Thus, in future investigations, it might be possible to improve these results carrying out high-quality continuous borings and laboratory tests for assessing precisely the soil class.

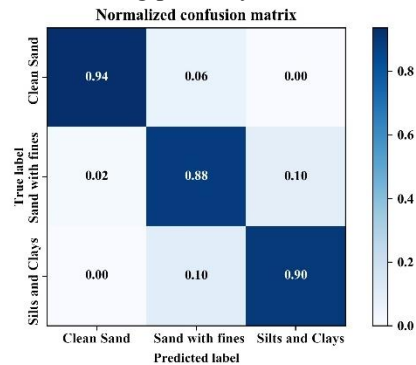


Figure 4. Normalised confusion matrix

4.3 Application

The results of the ANN on the CPT testing data provided by the 2019 TC304 contest are shown in Fig.5, Fig.6 and Fig7. The figures report for each soil profile the continuous I_c and I_b values, and the soil classification based on the ‘clean sands’, ‘sands with fines’ and ‘silts and clays’ classes.

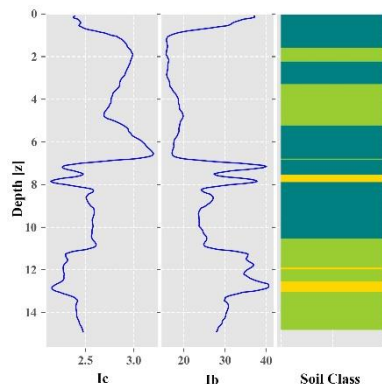


Figure 5. CPT- test 1: I_c , I_b , and soil classes: ‘Clean Sand’ (yellow), ‘Sand with Fines’ (light green), and ‘Silt and Clay’ (dark green).

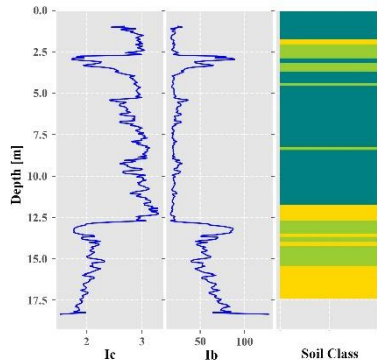


Figure 6. CPT- test 1: I_c , I_b , and soil classes: 'Clean Sand' (yellow), 'Sand with Fines' (light green), and 'Silt and Clay' (dark green).

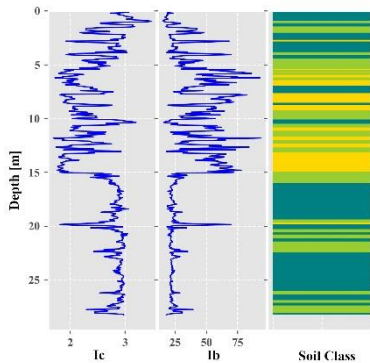


Figure 7. CPT- test 1: I_c , I_b , and soil classes: 'Clean Sand' (yellow), 'Sand with Fines' (light green), and 'Silt and Clay' (dark green).

These results need to be interpreted qualitatively. I_c and I_b are parameters based on the mechanical behaviour of the soils, whereas the classification adopted in the ANN derived from the textural-based USCS. To verify the efficacy in the classification these results should be instead compared with SPT borings. Concerns are also expressed regarding the ANN predictions. The training dataset does not include 'gravels' and 'peats', which might be present in the testing profiles. Indeed, more input data are needed in the training dataset. In future studies, it might be possible to develop a more reliable ANN increasing the number of CPT-SPT pairs, compare the soil classes with more reliable laboratory test and include more parameters as inputs such as the fines and water content.

6. Conclusion

The present research has attempted to investigate if ANNs are a viable and more straightforward option for determining a USCS based soil stratigraphy from CPT tests. Adopting SPT-CPT data pairs, the analysis has confirmed that SBT classifications might not coincide with textural features, and caution might be necessary for the interpretation of soil stratigraphy.

Taken together, the ANN approach is fast, straightforward, less labour intensive than laboratory tests and does not require extensive statistical knowledge. In this regards, it suits well the needs of a cost-effective and time-efficient methodology for the soil stratigraphy profile for engineering practitioners. Nonetheless, the method does not allow to check and control how it assigns the weighting functions and, hence, its efficacy is compromised by acting as a 'black box'. Thus, at the state-of-art, it might be better using the ANN method as first pass filter to determine the likely soil stratigraphy.

7. Acknowledgement

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References

- Basheer, I. A., & Hajmeer, M. (2000). Artificial neural networks: fundamentals, computing, design, and application. *Journal of microbiological methods*, 43(1), 3-31.
- Bertelli, S., Manzanal, D., Lopez-Querol, S., Rossetto, T., Mira, P., Giovinazzi, S. & Ruiter, R. (2019). Numerical simulation of observed liquefaction phenomena from the 2011 Christchurch event. In *Proceedings of SECED 2019 Conference*.
- Bhattacharya, B., & Solomatine, D. P. (2006). Machine learning in soil classification. *Neural networks*, 19(2), 186-195.
- Boulangier, R. W., & DeJong, J. T. (2018). Inverse filtering procedure to correct cone penetration data for thin-layer and transition effects. In *Proceedings of the 4th International Symposium on Cone Penetration Testing (CPT'18)*, Delft.

- Cal, Y. (1995). Soil classification by neural network. *Advances in Engineering Software*, 22(2), 95-97.
- Ching, J., Wang, J. S., Juang, C. H., & Ku, C. S. (2015). Cone penetration test (CPT)-based stratigraphic profiling using the wavelet transform modulus maxima method. *Canadian geotechnical journal*, 52(12), 1993-2007.
- Chollet, F. (2015). Keras: Deep learning library for theano and tensorflow. URL: <https://keras.io/>.
- Facciorusso, J., & Uzielli, M. (2004). Stratigraphic profiling by cluster analysis and fuzzy soil classification from mechanical cone penetration tests. *Proceedings ISC-2 on Geotechnical and Geophysical Site Characterization*.
- Fausett, L. (1994). *Fundamentals of neural networks: architectures, algorithms, and applications*. Prentice-Hall, Inc.
- Goh, A. T. (2002). Probabilistic neural network for evaluating seismic liquefaction potential. *Canadian Geotechnical Journal*, 39(1), 219-232.
- Hanna, A. M., Ural, D., & Saygili, G. (2007). Neural network model for liquefaction potential in soil deposits using Turkey and Taiwan earthquake data. *Soil Dynamics and Earthquake Engineering*, 27(6), 521-540.
- Hegazy, Y. A., & Mayne, P. W. (2002). Objective site characterization using clustering of piezocone data. *Journal of Geotechnical and Geoenvironmental Engineering*, 128(12), 986-996.
- Hegazy, Y. A., & Mayne, P. W. (2002). Objective site characterization using clustering of piezocone data. *Journal of Geotechnical and Geoenvironmental Engineering*, 128(12), 986-996.
- Idriss, I. M., & Boulanger, R. W. (2008). *Soil liquefaction during earthquakes*. Earthquake Engineering Research Institute.
- Iglewicz, B., & Hoaglin, D. C. (1993). *How to detect and handle outliers*. American Society for Quality Control, Milwaukee WI.
- Jung, B. C., Gardoni, P., & Biscontin, A. (2008). Probabilistic soil identification based on cone penetration tests. *Geotechnique*, 58(7), 591-603.
- Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization.
- Kurup, P. U., & Griffin, E. P. (2006). Prediction of soil composition from CPT data using advanced general regression neural network. *Journal of Computing in Civil Engineering*, 20(4), 281-289.
- Liao, T., & Mayne, P. W. (2007). Stratigraphic delineation by three-dimensional clustering of piezocone data. *Georisk*, 1(2), 102-119.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Vanderplas, J. (2011). Scikit-learn: Machine learning in Python. *Journal of machine learning research*, 12(Oct), 2825-2830.
- Reale, C., Gavin, K., Librić, L., & Jurić-Kačunić, D. (2018). Automatic classification of fine-grained soils using CPT measurements and Artificial Neural Networks. *Advanced Engineering Informatics*, 36, 207-215.
- Robertson, P. K. (1990). Soil classification using the cone penetration test. *Canadian Geotechnical Journal*, 27(1), 151-158.
- Robertson, P. K. (2009). Interpretation of cone penetration tests—a unified approach. *Canadian geotechnical journal*, 46(11), 1337-1355.
- Robertson, P. K. (2012). Interpretation of in-situ tests—some insights. *Mitchell Lecture-ISC*, 4, 1-22.
- Robertson, P. K. (2016). Cone penetration test (CPT)-based soil behaviour type (SBT) classification system—an update. *Canadian Geotechnical Journal*, 53(12), 1910-1927.
- Robertson, P. K., Campanella, R. G., Gillespie, D., & Greig, J. (1986). Use of piezometer cone data. In *Use of in situ tests in geotechnical engineering* (pp. 1263-1280). ASCE.
- Shahin, M. A., Jaksa, M. B., & Maier, H. R. (2008). State of the art of artificial neural networks in geotechnical engineering. *Electronic Journal of Geotechnical Engineering*, 8(1), 1-26.
- Wang, X., Wang, H., Liang, R. Y., & Liu, Y. (2019). A semi-supervised clustering-based approach for stratification identification using borehole and cone penetration test data. *Engineering geology*, 248, 102-116.
- Wang, Y., Huang, K., & Cao, Z. (2013). Probabilistic identification of underground soil stratification using cone penetration tests. *Canadian Geotechnical Journal*, 50(7), 766-776.
- Wentz, F. J., & Dickenson, S. E. (2013). Pore pressure response during high frequency sonic drilling and SPT sampling in liquefiable sand. In *19th NZGS Geotechnical Symposium* (p. 9).
- Zhang, Z., & Tumay, M. T. (1999). Statistical to fuzzy approach toward CPT soil classification. *Journal of Geotechnical and Geoenvironmental Engineering*, 125(3), 179-186.