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Kovacevic, Meho Sasa; Gavin, Kenneth; Reale, Cormac; Libric, Lovorka

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# Cone Penetration Testing 2018

*Editors*

Michael A. Hicks
*Section of Geo-Engineering, Department of Geoscience and Engineering, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands*

Federico Pisanò
*Section of Geo-Engineering, Department of Geoscience and Engineering, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands*

Joek Peuchen
*Fugro, The Netherlands*

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# The use of neural networks to develop CPT correlations for soils in northern Croatia

M.S. Kovacevic
*Faculty of Civil Engineering, University of Zagreb, Zagreb, Croatia*

K.G. Gavin & C. Reale
*Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands*

L. Libric
*Faculty of Civil Engineering, University of Zagreb, Zagreb, Croatia*

ABSTRACT: The evaluation of soil parameters for design is best undertaken through comprehensive laboratory test programmes. However, due to sampling difficulty, time and cost constraints correlations between in-situ tests and physical-mechanical properties of soils are routinely applied in practice. This paper presents data collected from five sites in Northern Croatia at which Cone Penetration Tests (CPT) and comprehensive laboratory test data was available. One of the advantages of using CPT data in preference to other types of in-situ tests for establishing correlations, is the large volume of high-quality data available at each probe location allows for the application of advanced statistical approaches. In this paper, the use of neural networks in developing such correlations is demonstrated. Using a database of 216 data pairs, obtained from the five sites, a correlation between CPT $q_c$ and soil unit weight is established. A validation exercise was performed in which the correlation was tested against data from the recent Veliki vrh landslide that occurred in the same geographical region as the database sites. In addition, by using the soil behaviour type index, *Ic*, normalised cone tip resistance, *Qtn*, and normalised sleeve friction, *Fr*, the results can be compared to correlations developed for soils from geotechnical diverse regions to check for consistency in the derived correlations.

## 1 INTRODUCTION

Evaluating design values for soil parameters in a laboratory environment is a time consuming, challenging task, which involves painstaking attention to detail and numerous retests to validate results and ensure representation of reality. As with any methodology, there are advantages and disadvantages to such an approach. Some of the advantages of laboratory testing include repeatability, high accuracy and precision, and importantly the explicit measurement of the parameter in question. While the disadvantages include significant cost, substantial processing time, sampling difficulty, and the perennial problem of determining whether the laboratory investigation adequately represents site conditions.

In-situ CPTs can easily overcome these disadvantages, while still providing high accuracy and repeatability and although they may not provide explicit measurements of critical geotechnical parameters many correlations (Librić et al., 2017; Mayne, 2014; Robertson, 2009) have been developed over recent years indirectly relating CPTs to various geotechnical parameters. Additionally, CPTs generate large volumes of near continuous data during testing which means that the sample size of CPT based correlations is much higher than that of laboratory tests, thus greatly reducing the influence of erroneous tests. CPT based correlations greatly streamline the construction process allowing for savings in both time and money. They are typically developed using either statistical approaches or curve fitting or both. However, it is important to note that while these correlations typically perform well, they are not exact solutions and consequently are not infallible and need to be applied with caution by experienced geotechnical engineers.

This paper investigates the use of both statistical regression and a machine learning technique, artificial neural networks (ANN), for developing CPT based correlation between cone tip resistance, $q_c$, depth, $z$, sleeve friction, $f_s$, and soil unit weight, $\gamma_t$. These correlation are developed using a database of 216 pairs of corresponding CPT and laboratory

results, obtained from five sites across Northern Croatia. The resultant correlations are verified using results from a separate test site in the same geographical region, Veliki vrh, a site which was not used in the initial development of the models.

## 2 SELECT EXISTING CORRELATIONS

CPT based soil correlations and classification charts are typically expressed in terms of normalised piezocone parameters, to evaluate normalised piezocone parameters it is first necessary to evaluate the total and effective overburden pressure, both of which first require an estimate of the soil unit weight. Naturally, the precise measurement of soil unit weight involves a laboratory test, however, in an attempt to expedite the process and save both time and money, many authors have developed CPT correlations to describe soil unit weight.

Mayne (2007) described a relationship between sleeve friction and total unit weight by linking the relationships between shear wave velocity and sleeve friction and shear wave velocity and total unit weight. The database used contained a wide variety of soil types ranging from soft clays to gravel. The relationship can be seen in Equation 1.

$$\gamma_t = 2.6 \log f_s + 15 G_s - 26.5 \quad (1)$$

where $G_s$ is the specific gravity of the soil solids in question. Mayne et al. (2010) expanded this relationship using data from 44 sites to incorporate depth, $z$, and cone resistance corrected for pore pressure, $q_t$, see Equation 2 and 3. An $R^2$ value of 0.72 was obtained using the relationship.

$$\gamma_t = 11.46 + 0.33 \log z + 3.1 \log f_s + 0.7 \log q_t \quad (2)$$

$$q_t = q_c + u_2(1 - a) \quad (3)$$

where $u_2$ is the pore pressure measured behind the cone and a is the cone area. Robertson & Cabal (2010) proposed a similar relationship which utilises the friction ratio ($R_f = \left(R_f = (f_s / q_t)100\right)$ instead of directly using the sleeve friction, their relationship presented in Equation 4, was trialled using published data from around the world and generally reported a good fit.

$$\frac{\gamma_t}{\gamma_w} = \left[ 0.27 \log R_f + 0.36 \log \frac{q_t}{P_a} + 1.236 \right] \frac{G_s}{2.65} \quad (4)$$

where $P_a$ is atmospheric pressure and $\gamma_w$ is the unit weight of water. Mayne & Peuchen (2012) proposed a regression method that takes account of unit weight variations with depth. They accomplished this using a parameter $m_q$ which is the change in normalised cone resistance with depth $(\Delta q_t / \Delta z)$, see Equation 5.

$$\frac{\gamma_t}{\gamma_w} = 0.886 \left( \frac{q_t}{\sigma_{atm}} \right)^{0.072} \left[ 1 + 0.125 \frac{m_q}{\gamma_w} \right] \quad (5)$$

Ghanekar (2014) noted that these relationships work much better in uniform soil deposits and typically break down when used in layered soil profiles.

## 3 NEURAL NETWORKS

Artificial neural networks are an advanced machine learning technique developed by computational scientists (Basheer and Hajmeer, 2000; Rojas, 2013; Rosenblatt, 1958) based on how we perceive the human brain and nervous system to interpret information and perform calculations. Mimicking real life brain neurons, interconnected artificial neural elements work together, passing information to and fro so as to establish the relationship between different parameters within a system, in order to learn or emulate how it functions. The major advantage of neural networks lies in their ability to adapt and update hypotheses when supplied with new data. Neural networks can be used to perform regression analysis, classification analysis and predict future system response. Every connection between a neuron and another neuron receives a weighting. These weightings determine how the neural network responds and adapts by assigning more or less importance to relationships of note. These systems of weightings are trained by mapping inputs onto some output or outputs, and optimising the weightings until the neural network reacts as the system does.

Neural networks are typically arranged into an input layer; a hidden layer or layers, and an output layer (see Figure 1). The number of input and output nodes required is typically dictated by the underlying engineering problem. While the number of hidden neurons needed is a lot more subjective and requires investigation on a problem by problem basis. Too many hidden neurons and the neural network will be slow to converge while also at the same time being at an increased risk of over-training. Too few, and the neural network will be too general and will be inconsistent with unseen data. A multi-layer feed forward neural network with a sigmoid activation function for hidden neurons and a linear activation function for output neurons was used in this example. In a feed-forward neural network, information only moves in one direction from the input nodes through the hidden nodes to the output nodes, i.e. there is no recursive programming involved.

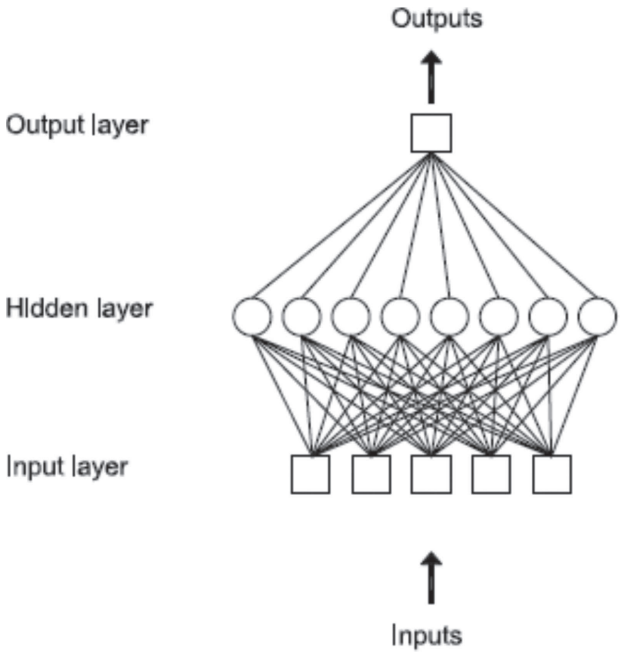


Figure 1. General schematic of a feed-forward artificial neural network.

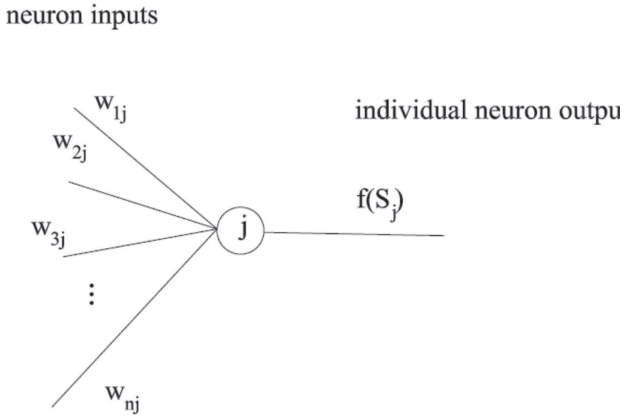


Figure 2. Close up of an individual neuron and how it interacts with the neurons around it.

During training, both the inputs and outputs of the specified problem are given. The weightings are then developed automatically without human intervention in the hidden layer by the ANN. This process is shown in Equation 6, where $j$ represents an individual neuron, $w_{ij}$ represents the individual weighting between input neuron $i$ and hidden neuron $j$ i.e. the factor by which every value passing from node $i$ to node $j$ is multiplied. These weightings are then summed at each node and a bias term $w_{0j}$ is added, See Equation 6. An activation function needs to then be applied to this term ($S_j$) to generate the individual neuron's output, see Figure 2. Any function can be used for this purpose, but if backpropagation is used to train the model then the function needs to be continuously differentiable. The sigmoid function is the activation function most commonly used in feedforward neural networks and is shown in Equation 7. The two layer feed forward neural network used in this study was trained using the Bayesian Regularisation backpropagation algorithm.

$$S_j = \sum_{i=1}^{n} w_{ij} u_j + w_{0j} \tag{6}$$

$$f(x) = \frac{1}{1+e^{-x}} \tag{7}$$

This training phase continues until the ANN can adequately model the system response or until all available training data has been exhausted. The ANN should then be validated using a new set of input data, which had not previously been used during model training. If the ANN can determine the outputs of this dataset, then it can be said to model the system accurately. Provided enough input and output data has been provided during training, an ANN model should be able to determine the significance each individual parameter has on the outcome.

The ANN developed in this study used $q_t$, depth, and $f_s$ as inputs, to predict the soil unit weight $\gamma_t$ as an output. Three hidden layers were utilised in this application.

## 4 TEST SITES

Five test sites from Northern Croatia were used to train, validate, and test the developed neural network model, while a sixth site Veliki vrh was used as an external unseen verification measure. Four of the 6 sites consisted of highly over consolidated soil, while the remaining two *Biđ-Bosut* and *Ilok port* were found to be slightly over consolidated (Reale et al., 2018). The initial dataset used to train, develop, and test the model consisted of 216 pairs of CPT/ Laboratory results. A short overview of each test site and the geotechnical testing carried out at each site is given below. All laboratory unit weight tests were carried out in accordance with the European Standard (HRS CEN ISO/TS 17892–2:2004) for the determination of density of fine grained soil (Tehni and Specifikacija, 2013).

### 4.1 *Biđ-Bosut Irrigation canal*

A 14 km long irrigation canal was constructed as of the multi-purpose Danube-Sava canal. The canal geometry consists of two stepped slopes the upper slope has a 1:2 gradient while the lower slope is at 1:3. The total excavation is approximately 7 m deep and a relatively wide step exists between the

two slopes. The geotechnical site investigation at the site consisted of 12 m deep boreholes at 300 m centres with core classification and extraction of representative soil samples for lab tests (consistency levels, particle size distributions, and direct shear tests). At 150 m intervals, 4 to 5 m deep trial pits were excavated along the canal route. Representative samples were extracted from each pit and tested in the laboratory. Cone Penetration Tests and standard penetration tests (SPT) were carried out at each borehole together with two hold tests to measure pore pressure dissipation on the CPT cone. 15 piezometers were installed to a depth of 8 m, to monitor trial pumping conducted in exploration wells. In total 75 pairs of laboratory tests and CPT, results were obtained at the site.

### 4.2 *Ilok port*

Ilok port which is currently under construction will be located on the right bank of the Danube 1296.5 to 1297.0 km, downstream from the Ilok-Bačka Palanka Bridge, in the Danube inundation area. The geotechnical investigation carried out at the site consisted of a total of 9 exploration wells with continuous coring to a maximum depth of 30 m. Dynamic (SPT) and static (CPTU) testing, geophysical testing using seismic refraction, multichannel analysis of surface waves (MASW), seismic static cone penetration test (SCPT), together with laboratory tests. The site yielded 36 pairs of laboratory testing and CPT results.

### 4.3 *Krsišće landslide*

The Krsišće landslide occurred on the southern slopes of the Medvednica Mountain, in the Markuševec area, at an altitude of approximately 300 meters. On Kršišće street, an unstable slope was detected, adjacent to house no. 43. Soil movement at the site occurs periodically along the interface between the Clay and Marl materials, where excess pore pressures develop during wet periods. Investigation work included 5 boreholes, with continuous coring to a maximum depth of 8 m, dynamic (SPT) and static (CPTU) testing, together with laboratory tests. 20 pairs of laboratory and CPT results were obtained at the site.

### 4.4 *Mirogoj landslide*

The Mirogoj landslide is located on the southern slope of the Medvednica Mountain. Adjacent to the Mirogoj cemetery is a slope that drops uniformly towards the north-east. The slope inclination in the area affected by the landslide is between 20° and 25°. A total of 5 borings were made, with continuous coring to a depth of 8 m, dynamic (SPT) and static (CPTU) testing was carried out in conjunction with laboratory testing. 25 pairs of laboratory tests and CPTs were gathered from the site.

### 4.5 *Krematorij landslide*

The Krematorij landslide is located east of Kameniti stol street, in the Gornji grad—Medveščak area, on the southern, more cavernous slopes of the Medvednica mountain. The unstable area is located between 250 and 225 m above sea level. The geotechnical investigation carried out at the site comprised of 5 exploration wells with continuous coring to a maximum depth of 12 m, dynamic (SPT) and static (CPTU) testing, together with laboratory tests. 60 pairs of laboratory testing and CPT results were obtained from the site.

### 4.6 *Verification site: Veliki vrh landslide*

The site located on the southern slopes of Medvednica Mountain, at an altitude between 205 and 225 metres, is a shallow translational landslide. The landslide was the result of pore pressure build up along the contact zone between Clay and Marl layers after heavy rainfall. The site investigation consisted of 4 boreholes with continuous coring to a depth of 12 m, dynamic (SPT), and static (CPTU) testing in conjunction with laboratory tests. In total 19 pairs of laboratory tests and CPT, results were gathered at the site. Table 1 shows the results of the CPT and laboratory tests for the site.

## 5 NEW CORRELATION

Using the data obtained from the five test sites, this paper proposes another log regression model similar in formulation to the model proposed by Mayne et al. (2010), but with a higher initial intercept value and lower constants for $z$, $f_s$, and $q_t$ respectively. Initially, it was proposed to develop the model using just $q_t$ and $f_s$, as it was postulated that the depth trend would already be accounted for within the CPT results. While this approach yielded similar accuracy and regression values, it was significantly less precise than a regression model containing $z$. The best fit relationship found in this study is shown in Equation 8. Both Mayne et al.'s relationship and the proposed have very similar regression values when applied to the dataset, however, as can be seen from Figure 3: The statistical correlation developed in this study, with Mayne et al. (2010) for comparison et al's equation significantly overpredicts unit weight magnitude but captures the relative increase reasonably well. The relationship from this paper effectively reduces the magnitude of Mayne et al's relationship to more closely approximate reality.

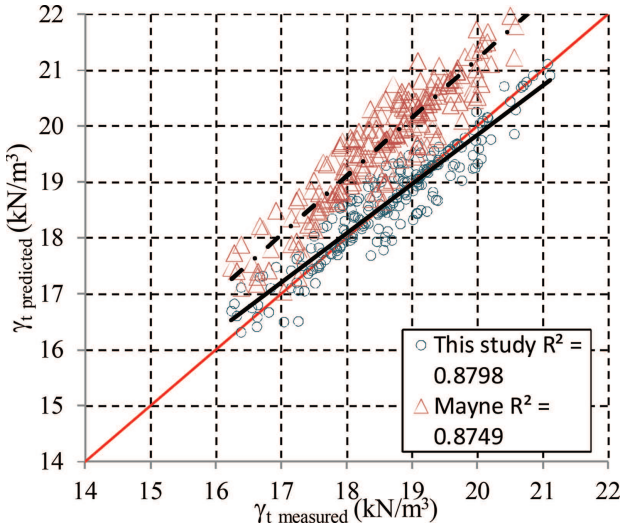


Figure 3. The statistical correlation developed in this study, with Mayne et al. (2010) for comparison.

$$\gamma_t = 11.849 + 0.109 \log z + 2.595 \log f_s + 0.561 \log q_t \quad (8)$$

## 6 ANN RESULTS AND DISCUSSION

The model development dataset which comprised of sleeve friction, depth, and corrected tip resistance as inputs and soil unit weight as an output was split randomly into the following proportions 80% for training, 10% for testing, and 10% for validation. For training, the ANN had access to both inputs and outputs allowing it to learn the sensitivity of each variable and understand each parameters effect on the system response. The next 10% was used as a test set, during the testing process only the inputs were supplied to the model. At the end of the testing phase, the neural network performed a system recalibration on itself so that system inputs could be more accurately mapped onto system outputs based on the test results. Following completion of the testing phase the final 10%, or the validation set, was sent to the neural network. Only inputs are sent in the validation phase, thus allowing the direct comparison of outputs from the validation set to actual measured values. Provided a good correlation has been achieved the neural weightings are saved and the entire data set is subsequently inputted blind. The resultant outputs are compared to actual outputs, see Figure 4. A regression coefficient of 0.8853 was achieved for the entire dataset, with a correlation coefficient of 0.94. As can be seen from Figure 3, there is very little data scatter, and importantly no extreme outliers. Therefore while a misclassification could occur, an extreme difference between predicted soil unit weight and measured soil unit weight is unlikely.

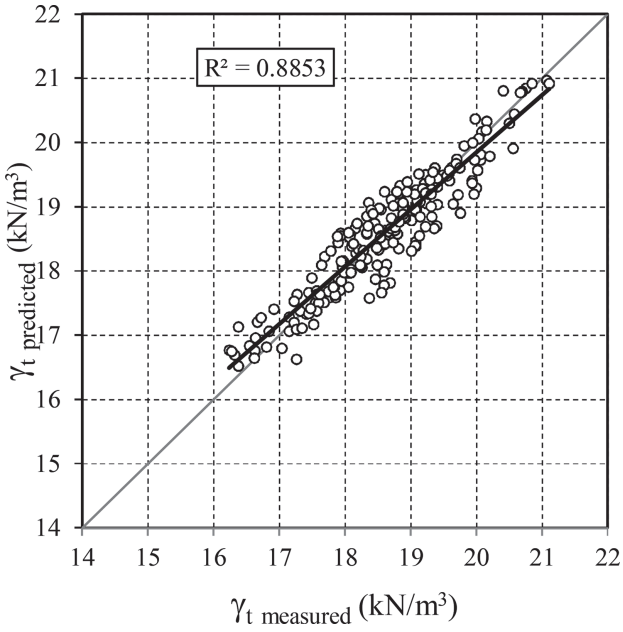


Figure 4. ANN predicted unit weight for five test sites used in model development.

Table 1. Unit weight and CPT results from Veliki vrh.

| GB/CPTU | Sample no | $z$ [m] | $q_t$ [MPa] | $f_s$ [kPa] | $\gamma_t$ [kN/m³] |
|---|---|---|---|---|---|
| B 1/CPTU 1 | 1 | 2.20 | 1.63 | 116.00 | **19.05** |
| | 2 | 2.80 | 0.74 | 62.00 | **18.20** |
| | 3 | 3.30 | 0.60 | 38.00 | **17.61** |
| | 4 | 5.00 | 3.38 | 172.00 | **19.72** |
| B 2/CPTU 2 | 5 | 2.10 | 1.55 | 93.00 | **18.84** |
| | 6 | 2.80 | 0.79 | 72.00 | **18.72** |
| | 7 | 3.60 | 0.62 | 55.00 | **18.52** |
| | 8 | 4.40 | 1.29 | 69.00 | **18.76** |
| | 9 | 5.60 | 1.12 | 90.00 | **18.73** |
| | 10 | 6.60 | 1.51 | 101.00 | **18.90** |
| | 11 | 7.20 | 1.58 | 96.00 | **18.90** |
| B 3/CPTU 3 | 12 | 1.60 | 0.81 | 54.00 | **17.43** |
| | 13 | 2.20 | 0.62 | 26.00 | **17.18** |
| | 14 | 3.80 | 4.69 | 188.00 | **20.46** |
| | 15 | 5.80 | 2.24 | 104.00 | **18.62** |
| B 4/CPTU 4 | 16 | 1.80 | 2.04 | 122.00 | **19.11** |
| | 17 | 2.20 | 1.99 | 84.00 | **18.79** |
| | 18 | 3.10 | 4.99 | 193.00 | **19.27** |
| | 19 | 3.70 | 6.59 | 203.00 | **19.99** |

To ensure the model was working correctly input data from an additional site within the same geographic region, Veliki vrh was supplied to the model. This data which can be seen in Table 1, consisted of 19 pairs of CPT and laboratory unit weight results.

An extremely good $R^2$ of 0.8495 was obtained for this external verification with a correlation coefficient of 0.92. The predicted unit weight versus measured unit weights is shown in Figure 5.

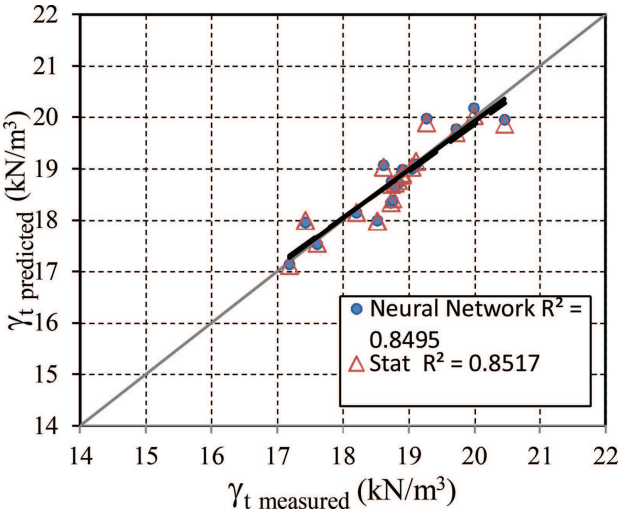


Figure 5. predicted unit weights for Veliki Vri using closed loop ANN and regression approach.

The statistical approach proposed earlier in Equation 8 performed equally well on the unseen dataset, Veliki vrh, achieving an $R^2$ of 0.8466. Both are shown in Figure 5, giving virtually identical results.

## 7 CONCLUSION

This paper presents two approaches, regression and neural network, for automatically calculating soil unit weight using CPT measurements as inputs. Both approaches could easily be performed automatically onsite as the CPT is ongoing, thus allowing for an extremely fast interpretation of soil unit weight. This would reduce the quantity of laboratory tests needed per site thus saving time and money. An additional benefit of such an approach is that any laboratory tests that are carried out can then combined with their respective CPT soundings become additional data entries for both the regression and ANN models, thus improving their future accuracy. In this way, the models can continue to evolve over time, gradually increasing in both accuracy and precision.

The approaches were developed using 216 pairs of CPT/laboratory unit weight tests from five different locations across Northern Croatia. An entirely separate sixth site Veliki vri was used as an external verification measure for the saved neural networks. The models performed extremely well on both the initial dataset and the subsequent verification dataset.

Unfortunately, ANN-based models have some drawbacks, of particular concern is the black box nature of the results, which makes proof of concept hard to verify, while also making their standalone implementation a risky process for the engineer involved. The authors think that much of this can be mitigated by testing a small number of samples from every site in the laboratory for local verification. Thus, allowing the training database to continue to grow in size over time making incorrect classifications less likely to occur. Over time reducing the cost, time, and labour involved.

This study confirms the functional link between CPT results, and soil unit weight..The developed neural network and regression models performed admirably for a wide range of soil types closely predicting soil unit weights between 16 and 21 kN/m$^3$. The close prediction between the neural networks and the regression model is a testament to the accuracy of log regression models for predicting soil unit weights and further validates their use in everyday design situations, given their simplicity and transparency. One caveat which needs mentioning is all soils tested were either heavily or slightly over consolidated and the correlations may not perform as well in normally consolidated deposits.

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