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Automatic classification of fine-grained soils using CPT measurements and Artificial Neural Networks

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ABSTRACT

Soil classification is a means of grouping soils into categories according to a shared set of properties or characteristics that will exhibit similar engineering behaviour under loading. Correctly classifying site conditions is an important, costly, and time-consuming process which needs to be carried out at every building site prior to the commencement of construction or the design of foundation systems. This paper presents a means of automating classification for fine-grained soils, using a feed-forward ANN (Artificial Neural Networks) and CPT (Cone Penetration Test) measurements. Thus representing a significant saving of both time and money streamlining the construction process. 216 pairs of laboratory results and CPT tests were gathered from five locations across Northern Croatia and were used to train, test, and validate the ANN models. The resultant Neural Networks were saved and were subjected to a further external verification using CPT data from the Veliki vrh landslide. A test site, which the model had not previously been exposed to. The neural network approach proved extremely adept at predicting both ESCS (European Soil Classification System) and USCS (Unified Soil Classification System) soil classifications, correctly classifying almost 90% of soils. While the soils that were incorrectly classified were only partially misclassified. The model was compared to a previously published model, which was compiled using accepted industry standard soil parameter correlations and was shown to be a substantial improvement, in terms of correlation coefficient, absolute average error, and the accuracy of soil classification according to both USCS and ESCS guidelines. The study confirms the functional link between CPT results, the percentage of fine particles *FC*, the liquid limit w_L and the plasticity index I_P. As the training database grows in size, the approach should make soil classification cheaper, faster and less labour intensive.

1. Introduction

Soil classification is a means of grouping soils into categories according to a shared set of properties or characteristics that exhibit similar engineering behaviour under loading. Due to its natural formation, geological history, and particulate nature, amongst other features, soil behaves differently than other engineering materials such as steel or concrete. The engineering characteristics of soil (stiffness, permeability, and strength) are dictated by particulate shape, size, microstructural composition, stress history, degree of saturation, and weathering [17]. Traditionally soils were classified into cohesive (fine-grained) or non-cohesive (granular or coarse-grained) soils based on their particle size distributions. Granular soils were categorised exclusively on the relative percentage mass of the different constitutive particles, with increasing grain size determining the difference between sand, gravel, cobbles, and boulders.

The fines content of a soil is determined by the percentage of soil by mass which passes through a 0.075 mm sieve. If the fines content exceeds some predetermined percentage of the soil, typically 50% but maybe less depending on the soil classification system in use, the soil is deemed to be Cohesive or Fine grained. Fine grained soils are classified using relative percentage mass as above with additional hydrometer tests to determine the relative percentage of Clays and Silts in the soil. Finally, they are sub classified based on their consistency. Soil consistency describes how a fine-grained soil holds together, describing its transition from a solid through to a liquid as its water content is varied. Two measures are typically used to describe soil consistency; namely the Plastic Limit and the Liquid Limit. Moderately organic soils are usually classified as cohesive soils while highly organic soils are classified separately as Peats.

A number of different soil classification procedures have been developed and remain in common use today. One of the most widely used being the Unified Soil Classification System (USCS), which was a development of Casagrande's Airfield Classification System (ACS) and was

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developed in-line with the US standard [2]. In Europe classifications such as the British Soil Classification System (BSCS) as detailed in [5] and the Deutsches Institut fur Normung (DIN 2011) are commonly used. However through the advent of EN ISO 14688-1:2002 [9], EN ISO 14688-2:2004 [10], and EN ISO 2013, the ISO (International Standards Organisation) and CEN (Comité Européen de Normalisation), have developed new European standards for describing and identifying soils. The application of different soil classification principles can result in significant differences in the classification of a given soil.

As CEN members 33 European countries have pledged to introduce and implement European standards through their national standards authority. As such the soil classification system prescribed by the Eurocode should be universally adopted across the European Union moving forward. However to date, this has not been the case, as the European standards provide classification principles, yet leave the interpretation of these principles open, in the expectation that individual countries will develop national classification systems based on these principles. Until this has been accomplished practising engineers have no choice but to continue used past standards. Recently Kovačević et al. [11] developed a European Soil Classification System (ESCS) in accordance with the soil classification principles outlined in EN ISO 14688-2 using the soil descriptors and symbols from EN ISO 14688-1.

Because of the somewhat laborious and time-consuming nature of laboratory soil classification, a number of workers [23,24,8,15] have developed soil classification charts based on Cone Penetration Tests (CPT). Whilst CPTs do not directly measure soil properties the installation of the penetrometer is controlled by the soils strength and stiffness parameters. The addition of pore pressure probes allows the development and dissipation of pore pressures to be directly measured. An advantage of using CPTs is they give near continuous measurement with depth in a single probe location and do not require the use of disturbed or remoulded laboratory samples to classify plasticity [15]. This is a significant advantage as the in-situ response to loading is controlled by the depositional processes involved in its formation, the stress history of the soil as well as numerous chemical and biological processes. A disadvantage with the developed classification charts which link CPTs to soil type is that these charts tend to be developed on a regional basis and therefore may not be universally applicable.

This paper examines the application of Artificial Neural Networks (ANN) for automatically determining ESCS and USCS soil classifications using the CPT tip resistance, q_c and sleeve friction, f_s as inputs. Neural networks were developed to predict (a) the percentage of fine particles in a soil and (b) the consistency of the soil by predicting a soils liquid limit and corresponding plasticity index. Where the plasticity index, I_P, is the liquid limit minus the plastic limit and is the range of water contents over which the soil exhibits plastic behaviour. 216 pairs of laboratory results (173 of which had fines content and soil consistency measurements) and CPT tests were gathered from five locations across Northern Croatia and were used to train, test, and validate the machine learning models. The resultant Neural Networks were stored and subjected to a further external verification using CPT data from the Veliki vrh landslide, an entirely separate test site not used in the model development. The model is seen to be extremely successful at predicting both ESCS and USCS soil classifications for the fine-grained soils encountered. Nevertheless, ANN based classification models have some drawbacks, namely they are unable to predict Granular soils accurately as they cannot consistently predict d_{50} and d_{10} values based on CPT data alone and they require a significant data set to initially train, test and validate the model. The main advantages of the proposed approach applied to fine grained soils, are the speed of classification and the prospect of increasing model accuracy as more laboratory results/CPT test pairings become available. The authors suggest the use of the method as a first pass filter to determine likely ground conditions, while testing a small number of soil samples in the laboratory for local verification. The results of which can then be assimilated into the model to improve future accuracy, thus making soil classification cheaper, faster and less labour intensive.

2. CPT based soil classification methodologies

The Cone Penetration Test is an in-situ geotechnical test. It works by pushing a specifically designed probe into the ground at a controlled rate, while continuously measuring the tip resistance, shaft friction and pore pressure (u) using sensors located on the probe. CPTs are fast, reliable and output near continuous measurement profiles with depth. Unfortunately, CPTs have noted poor performance in gravels and cemented soils. Since the 1960s researchers have developed CPT based soil classification systems. Begemann [4] noted that coarse grained soils typically have a higher tip resistance, q_c, than fine grained soils, whilst sleeve friction, f_s, values can be comparable in both fine and coarse grained soils with similar consistency. As a result, the ratio of the sleeve friction to the tip resistance (friction ratio) of a soil at a given depth can be used to distinguish soil type, with lower friction ratios being exhibited by coarse grained soils. Begemann developed a classification diagram showing this dependency where lines of constant friction ratio serve as the boundary between different soil types.

Following the work of Begemann, a number of researchers have developed CPT based soil classification charts. Sanglerat et al. [23] proposed a classification chart which plotted q_c versus friction ratio. While Schmertmann [24] identified that the presence of pore water pressure could affect soil classification and accounted for this effect in his design chart. Douglas and Olsen [8] were the first to relate CPT measurements to the USCS system diagrammatically. Robertson et al. [19] introduced a correction factor to modify the tip resistance based on the measured pore pressure, see Eq. (1).

$$q_t = q_c + u_2(1-a) \tag{1}$$

where q_t is the corrected cone resistance, u_2 is the pore pressure measured behind the cone and a is the cone area:

Their study produced two classification charts one relating corrected tip resistance to friction ratio and the second chart plotting corrected tip resistance versus pore pressure ratio, B_q, see Eq. (2).

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

where u_0 and σ_{vo} are the in-situ pore pressure and total vertical stress respectively prior to CPT installation.

Robertson [15] noted that CPT classification charts tended to perform poorly at depths greater than 30 m, to rectify this discrepancy he introduced normalised values for both tip resistance, Q_t and sleeve friction, Fr, see Eqs. (3) and (4).

$$Q_t = \frac{q_t - \sigma_{v0}}{\sigma'_{vo}} \tag{3}$$

$$F_r = \frac{f_s}{q_t - \sigma_{vo}} \tag{4}$$

Robertson [16] further improved his classification chart using normalised values of vertical effective stress. He also introduced the use of the soil behaviour index I_c to approximate the boundaries between different soil types using an I_c formulation from one of his earlier papers [20]. Libric et al. [12] collated existing soil correlations allowing one to describe and classify soil using only the sleeve friction and corrected tip resistance from a CPT as these measurements are universally available. They show the successful prediction of soil type using the USCS classification 72% of the time and achieve 76% success with ESCS. Das and Basudhar [7] used self-organising maps and fuzzy clustering methods to determine soil stratification from CPTs, using Robertson and Campbellas [18] classification chart as a verification measure with both methods proving promising.

3. Artificial neural networks

Artificial neural networks are an advanced machine learning technique developed by computational scientists [22,3,21] based on how we perceive the human brain and nervous system to interpret information and perform calculations. Similar to real life brain neurons, interconnected artificial neural elements work in unison, sharing information to develop an awareness of the relationship between different parameters in order to learn or emulate how a system functions. The major advantage of neural networks is that, because of their adaptability and learning capabilities, when supplied with sufficient data they can learn how complex non-linear systems perform. Neural networks can be used to perform regression analysis, classification analysis, and predict future system response. They have also been utilised for decision making purposes. Each neuron can be connected to every other neuron and every interconnection between this neuron and another receives a weighting. These weightings determine how the neural network predicts and adapts. Neural networks train themselves by mapping system inputs onto some output or outputs, this is achieved by optimising the aforementioned weightings, until the neural network reacts as the system does.

Neural networks are typically arranged into an input layer, a hidden layer(s), and an output layer (see Fig. 1). The number of input and output nodes are entirely problem dependant and are dictated by the engineering problem in question. The number of hidden neurons needed is a lot more uncertain and needs to be investigated on a problem by problem basis. If there are too many hidden neurons, then the neural network will be slow and there is a risk of over-training. If there are too few, the neural network will be too general and will not consistently converge for unseen data. A two-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. it contains no loops or recursive programming.

In the learning phase, both the input and output data of the specified engineering problem is given. The weightings are then developed within the hidden layer by the ANN without human consultation. The goal of the training process is to minimise the error function by changing the individual neural weightings to attain the optimum neural weightings which allow the neural network to replicate system response. This process is shown in Eq. (5), 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 summated at each node and a bias term w_{0j} is added, See Eq. (6). An activation function is then applied to this summation (S_j) to generate that individual neuron's output, see Fig. 2. While in theory this can be any function, the chosen function must always be continuously differentiable in order to train the model using back propagation. The sigmoid function is the activation function most commonly used in feed forward neural networks and is shown in Eq. (6). The two layer feed forward neural network used in this study was trained with the Levenberg-Marquardt backpropagation algorithm [14]. The Levenberg-Marquardt algorithm interpolates between the Gauss-Newton and the steepest descent algorithms. Effectively using the steepest descent algorithm when far from a local minimum and a second order convergence rate when near. While not guaranteed to find the true global minimum, it is considered to be more robust than the Gauss-Newton method alone.

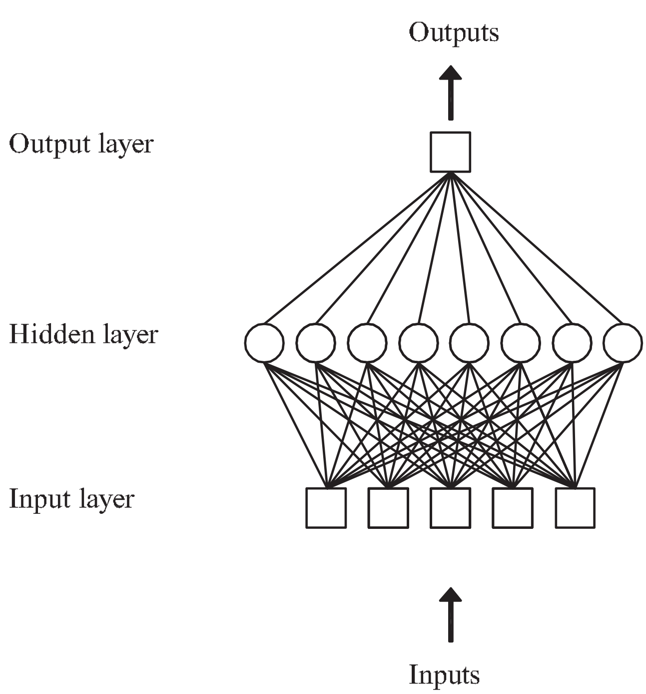

Fig. 1. General schematic of a feed forward artificial neural network.

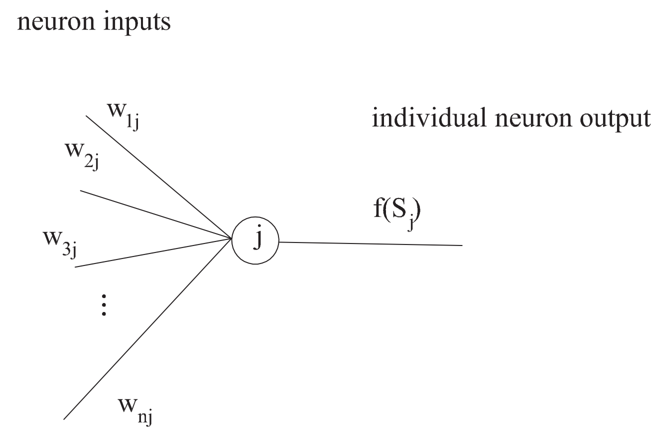

Fig. 2. Close up of an individual neuron and how it interacts with the neurons around it.

$$S_j = \sum_{i=1}^{n} w_{ij} u_j + w_{0j} \tag{5}$$

$$f(x) = \frac{1}{1 + e^{-x}} \tag{6}$$

The training phase continues until the ANN is satisfied that it can correctly model the system response or until all available training data has been utilised. The ANN must then be validated using a new set of input data, not used in the training phase. If the ANN can correctly predict the outputs of this data, then it can be said to model the system accurately. This should occur provided enough input and output data has been provided during the training phase to allow the ANN to determine the significance each individual parameter has on the outcome.

However, it is important to note that the training process may lead to overfitting if there is insufficient training data and the network error has been reduced too much [6]. In general, to prevent this from occurring the number of weights in the network should be far less than the number of training samples. The exact ratio is a topic of much discussion with Maier and Dandy [13] suggesting 1 to 10 to be a suitable ratio, while Amari et al. [1] suggest that overfitting is only present if the number of training samples is less than 30 times the number of free parameters. In geotechnical engineering, training datasets typically don't reach this size due to the relatively poor return on such an investment. The number of weights in a network is defined by Eq. (7).

$$w = (I + 1)H + (H + 1)O \tag{7}$$

where I is the number of inputs, H is the number of hidden layers and O is the number of outputs.

It is important that the network reacts similarly to new data during testing and validation, i.e. that the network can generalise well. To ensure this occurs early stopping criteria were implemented. The early stopping criteria monitors the discrepancy between errors in the validation and test sets during the training process. Both errors should decrease during the initial training phase, however as overfitting starts to occur the validation set will typically become less accurate. When the validation error increases for a set number of times in a row, in this case 6, then the training is stopped and the weights and biases that resulted in the minimum validation error are taken.

Two neural networks were developed in this study the first neural network termed *NetFC* was developed to predict the fines content of the soil and the second neural network named *NetLLPI* was developed to predict both the liquid limit of the soil and it's corresponding plasticity index. Both neural networks utilised three hidden layers. Both *NetFC* and *NetLLPI* have two input nodes namely corrected tip resistance and sleeve friction. *NetFC* has one output the fines content of the soil in question, whilst *NetLLPI* has two output nodes the liquid limit and the plasticity index of the respective soil. Using these three outputs a cohesive soil can be fully classified using either the USCS or the ESCS systems. *NetFC* has 13 distinct weightings and *NetLLPI* 17 weightings. 216 samples exist for fines content, 173 of which have corresponding plasticity index and liquid limit results. *NetFC* therefore has a sample training size of 173, while *NetLLPI* has a sample training size of 138, giving them a training sample size to weights ratio of 13.3 and 8.1 respectively. While, these values are considerably less than the 30 recommended by Amari they compare favourably with other Geotechnical ANN studies whose ratios rarely exceed 5, a compilation of such studies can be found in Table 10.7 in [6].

4. Description of test sites

Five test sites located across Northern Croatia were used to train, validate and test the model. In total 216 pairs of CPT/ Laboratory test pairs were collated from the test sites. A short overview of each test site is given below.

4.1. Biđ-Bosut irrigation canal

A 14,772 m long irrigation canal was excavated in Biđ-Bosut, as part of the 1st construction phase of the multi-purpose Danube-Sava canal. The canal consists of a 7 m deep stepped excavation with a 1:2 upper slope and a 1:3 lower slope with a relatively wide berm in between. 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

The Danube-Sava canal, when completed, will connect the Danube with the Adriatic. Following its construction, the town of Ilok will be connected with both the North and Black Seas through the Rhine-Main-Danube river system. Ilok port 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, multi channel 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 m. 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.

5. Laboratory and neural network classification results

This section summarises the main results from the CPTs, laboratory tests, and neural network classifications. The full laboratory results for all 216 CPTs needed for classification can be found in the associated Mendeley Data webpage. To visually represent the range in soil type across the sites, the five test sites have been plotted on a Robertson Classification chart, see Fig. 3. A full laboratory ESCS and USCS soil classification was performed for all test points using the results from Appendix Table A1 in conjunction with the Classif program previously developed by Zagreb University, the program is available publically online at http://www.grad.unizg.hr/zavod_za_geotehniku. The Classif program automatically classifies soils according to USCS and ESCS rules and nomenclature, once it has been provided with the following parameters; fines content; plasticity index, and the liquid limit.

The total dataset, comprising of sleeve friction and corrected tip resistance as inputs and fines content, plasticity index, and liquid limit as outputs, was randomly split into the following proportions 80%, 10%, and 10%. The largest proportion, 80%, was used as the training set. During training, both inputs and outputs were supplied to the neural networks allowing them to learn the sensitivity of each individual parameter. The next 10% was used as a test set, during testing only the inputs were supplied to the model. At the end of the testing phase, the neural network system recalibrates itself based on the testing results so that system inputs are more accurately mapped onto system outputs. When the testing phase is completed the remaining 10% known as the validation set was sent to the neural network. The outputs from the validation set are compared to the actual outputs, see Figs. 4, 5

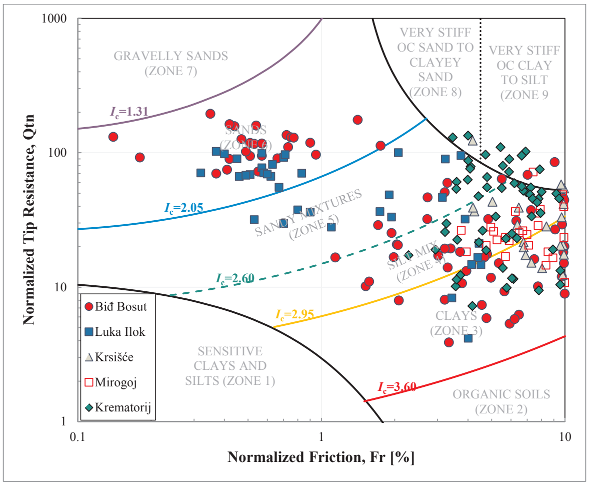

Fig. 3. Robertson classification chart for the five test sites used in model development.

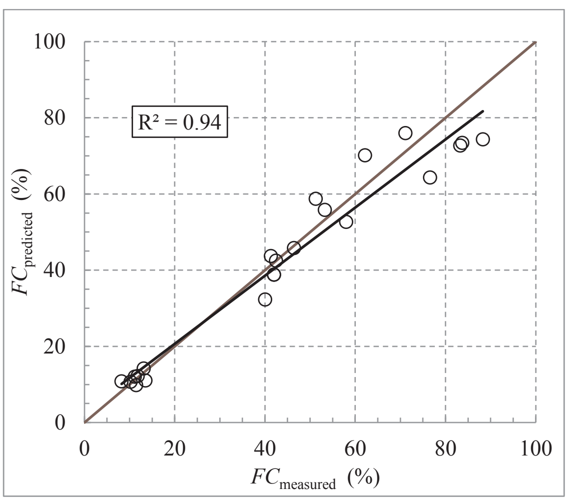

Fig. 4. Validation dataset showing predicted fines content verus meaured values.

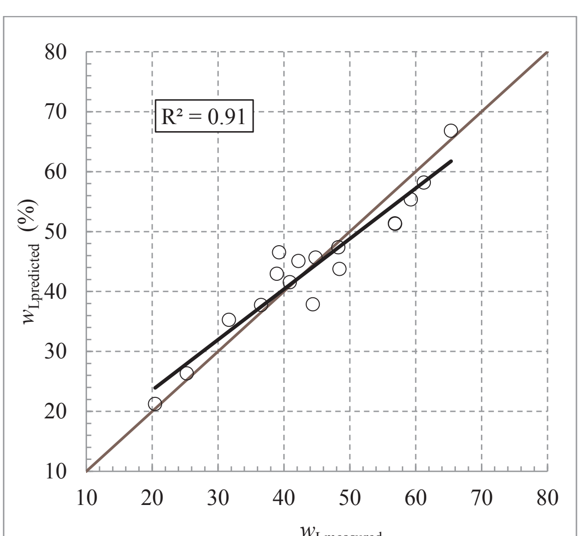

Fig. 5. Randomly selected validation dataset showing predicted versus measured Liquid Limit.

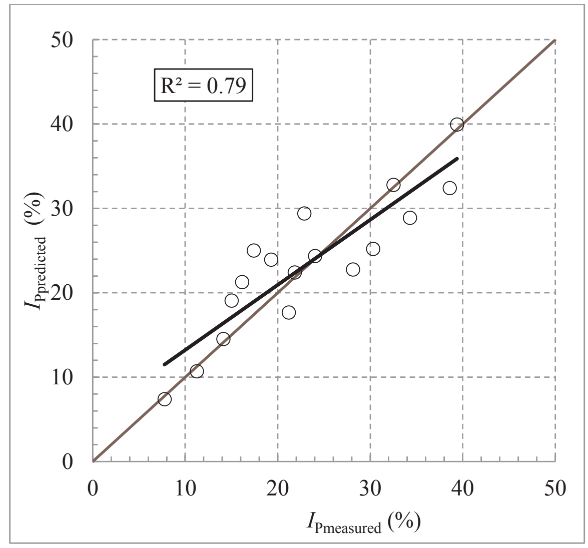

Fig. 6. Randomly selected validation dataset showing predicted versus measured Plasticity Index.

and 6. The regression coefficients achieved during validation were extremely good. An R^2 of 0.94 and was achieved when comparing measured and predicted fines contents. A similarly high linear regression coefficient of 0.91 was obtained for the Liquid Limit with the Plastic Limit performing slightly worse attaining a regression value of 0.79. These neural weightings were saved and the entire data set inputted blind. The resultant outputs were then compared to actual outputs.

The correlations achieved from the total dataset are shown in Figs. 7–9 for the ANN predictions of Fines Content, Liquid Limit, and Plasticity Index respectively. An R^2 of 0.85 was achieved between the neural network predicted liquid limit and the measured value, while a R^2 of 0.78 was achieved for the plasticity index. In reality, the determination of soil consistency in a laboratory setting is highly subjective (particularly in determining the plastic limit) and in many cases, results are assumed based on a relatively small sub-sample. Despite this, the correlations are statistically significant and rank far higher than those achieved using accepted geotechnical correlations [12]. The extremely strong correlation of 0.95 between measured and predicted

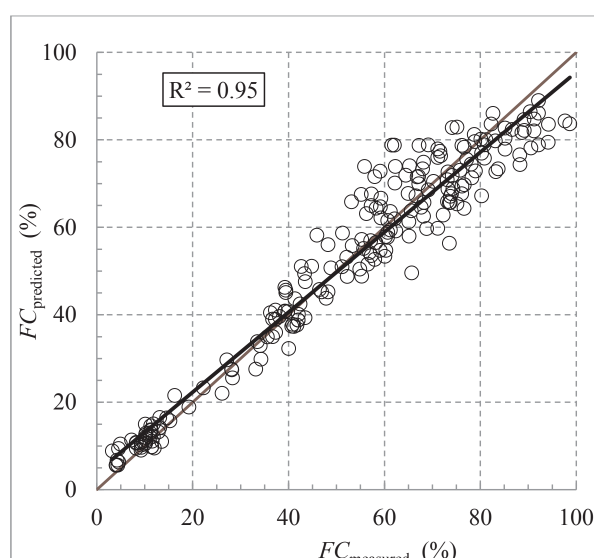

Fig. 7. Correlation between ANN predicted fines content and measured value.

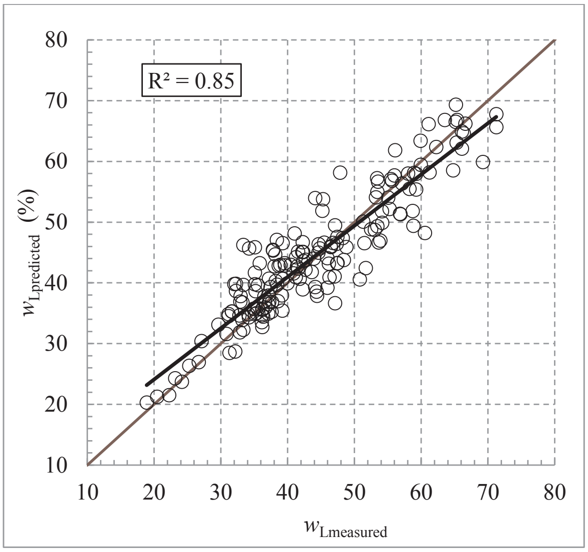

Fig. 8. ANN predicted Liquid Limit and the laboratory measured value.

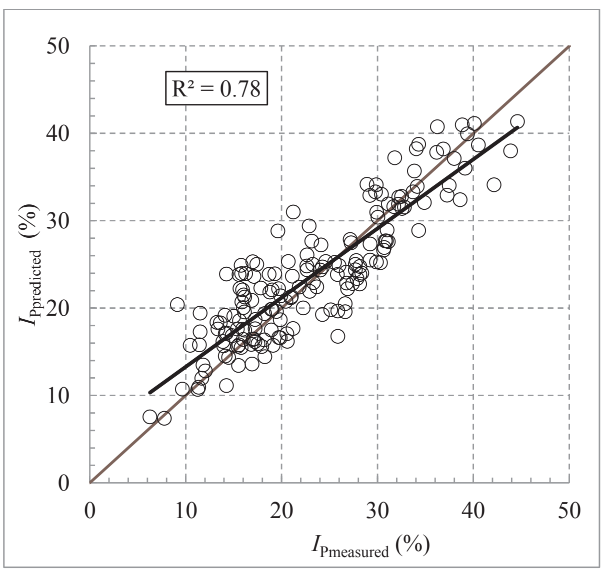

Fig. 9. Measured plasticity index versus ANN predicted plasticity index.

Table 1
Results of CPT and laboratory tests at the VelikiVrh landslide.

GB/CPTU	Num	z [m]	q_t [MPa]	f_s [kPa]	w_L [%]	I_P [%]	FC [%]
B 1/CPTU 1	1	2.20	1.63	116.00	47.22	23.25	65.72
	2	2.80	0.74	62.00	62.15	34.05	84.15
	3	3.30	0.60	38.00	60.72	35.72	83.25
	4	5.00	3.38	172.00	43.35	24.11	59.72
B 2/CPTU 2	5	2.10	1.55	93.00	44.56	23.21	61.83
	6	2.80	0.79	72.00	69.95	37.21	85.16
	7	3.60	0.62	55.00	72.07	38.12	89.25
	8	4.40	1.29	69.00	51.24	29.15	79.22
	9	5.60	1.12	90.00	66.83	36.55	90.25
	10	6.60	1.51	101.00	65.23	35.58	83.88
	11	7.20	1.58	96.00	59.22	35.55	81.00
B 3/CPTU 3	12	1.60	0.81	54.00	51.25	23.02	68.12
	13	2.20	0.62	26.00	52.15	24.12	71.45
	14	3.80	4.69	188.00	37.25	16.28	46.02
	15	5.80	2.24	104.00	44.44	24.12	65.58
B 4/CPTU 4	16	1.80	2.04	122.00	41.15	19.25	49.32
	17	2.20	1.99	84.00	36.25	18.67	48.25
	18	3.10	4.99	193.00	35.55	15.55	44.15
	19	3.70	6.59	203.00	28.25	12.35	37.26

fines content is particularly noteworthy. Significantly more spread was observed in predictions at higher fines content than that seen at lower fines content.

6. Further verification and discussion

To ensure that the developed neural network approach was viable outside of the immediate study area, but within the same geologic region, an entirely separate test site in Northern Croatia, Veliki vrh, was used as an external verification measure. Veliki vrh is a small shallow translational landslide on the southern slopes of Medvednica mountain, between Čućerje and Vugrovec, which occurred between 205 and 225 m above sea level. The initial landslide transpired because of pore pressure build up along the contact zone between the Clay and Marl layers during heavy rainfall with additional movements detected following subsequent heavy rainfall events.

A site investigation consisting of 4 boreholes were drilled, with continuous coring to a maximum depth of 12 m, dynamic (SPT) and static (CPTU) testing were carried out in conjunction with laboratory tests. A total of 19 pairs of laboratory testing and CPT results were obtained. Table 1 shows the results of the CPT and laboratory tests for the site. Fig. 10 shows the Robertsons chart for the test site depicting soils types varying from Clays through Silts to Sandy mixtures.

NetFc and *NetLLPI* were used to determine the fines content, the liquid limit, and the plasticity index at the site using the q_t and f_s values given in Table 1. Extremely good correlations between measured and predicted values were achieved for all parameters. Correlations of 0.974, 0.983, and 0.991 were obtained for the measured versus predicted response for the liquid limit, the plasticity index and the fines content respectively. Tables 2, 3, and 4 compare these correlation coefficients and the average absolute error to that obtained using the same data with the correlations developed by Libric et al. [12]. The neural network approach performs better in all correlations, if only marginally so. An interesting point of note, is the average absolute error is much higher for the published correlations approach than for the neural network approach. This suggests that while the approaches predict similar mean trends there is significantly more data scatter using the established soil correlations approach.

USCS and ESCS soil classifications were carried out using the Classif program for the laboratory data, the neural network results, and the results using the methodology from [12] respectively. The resultant soil classifications using the USCS methodology are given in Table 5, while

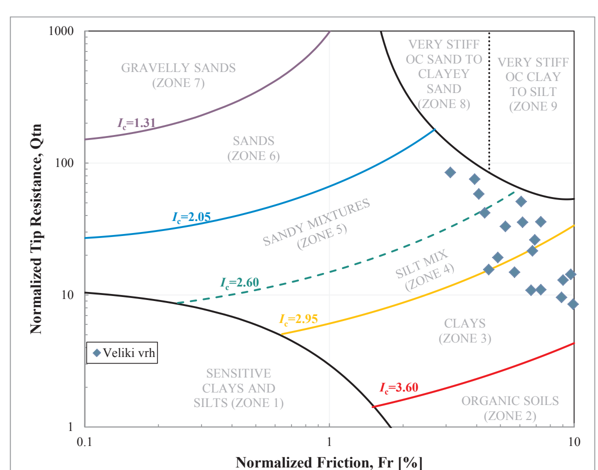

Fig. 10. Robertson chart for Veliki vrh.

Table 2
Comparison of regression values and average absolute errors for the prediction of the percentage of fine particles *FC*.

Percentage of fine particles *FC* (%)	Regression value R	Average absolute error
Published correlation [12]	0.9824	13.24
Neural network (*NetFC*)	0.9914	1.74

Table 3
Comparison of regression values and average absolute errors for the prediction of liquidity limit w_L.

Liquidity limit w_L (%)	Regression value R	Average absolute error
published correlation [12]	0.9738	7.21
neural network (*NetLLPI*)	0.9743	2.67

Table 4
Comparison of regression values and average absolute errors for the prediction of plasticity index I_P.

Plasticity index I_P (%)	Regression value R	Average absolute error
Published correlation [12]	0.9697	3.40
Neural network (*NetLLPI*)	0.9829	1.12

the ESCS results are shown in Table 6. In both tables the laboratory classifications are assumed to be correct and accepted as the standard, all soils which have been correctly classified are displayed in roman font type, while all soils that are classified incorrectly are displayed in bold font type. In both cases, the neural network approach performs much better than the accepted soil correlation approach. The neural network approach correctly predicts 89.47% (17/19) of soil classifications at Veliki vrh for both ESCS and USCS, while the approach by Libric et al. which is based on established geotechnical parameter correlations performs poorly only predicting 63.16% (12/19) of soil classifications correctly. This large discrepancy in classification predictions is interesting when one considers that the correlation coefficients obtained by both approaches are broadly similar. However, there is significantly more scatter in the soil correlations approach, albeit relatively evenly dispersed scatter (particularly in the fines content), which appears to be responsible for most of the incorrect classifications as the published correlations seem to predict soils slightly more granular than in reality. Given the extremely strong fines content prediction across all six sites, this appears unlikely to happen with the neural network approach.

Another interesting point of note is that of the soils that were incorrectly classified by the neural network approach, all were classified into the next soil band, i.e. Clays of high plasticity were classified as Clays of medium plasticity. While this is still an incorrect classification, it is not a complete misclassification.

The results of this study would indicate that there is a strong functional connection between CPT results, the percentage of fine particles FC, liquid limit w_L and plasticity index I_P, for the samples considered. Thus partly confirming one of the underlying assumptions of this research that the static cone penetration test could be directly linked to the particle size distribution and soil consistency limits used in standard soil classification.

7. Conclusion

This paper presents an application of neural networks for automatically classifying soils according to ESCS and USCS guidelines. One of the main advantages of such an approach is that it could be performed instantaneously using an onsite computer removing the significant time and monetary cost typically involved with classification. The approach needs just the CPT shaft sleeve friction, f_s, and cone tip resistance, q_c, as inputs. Using these two parameters it predicts the fines content, the liquid limit and the plasticity index of the soil in question. Having obtained these three parameters it is possible to accurately classify any fine grained soil in line with USCS and ESCS specifications. This process can easily be automated.

The approach was developed using 216 pairs of CPT/ laboratory results, which were gathered from five locations across Northern Croatia and were used to train, test, and validate the machine learning models. The resultant Neural Networks were saved and were subjected to a further external verification using CPT data from the Veliki vrh landslide. A test site, which the model had not previously been exposed to. The neural network approach proved extremely adept at predicting both ESCS and USCS soil classifications, correctly classifying almost 90% of soils. While the soils that were incorrectly classified were only partially misclassified. The model was compared to a previously published model, which was compiled using accepted industry standard soil parameter correlations and was shown to be a substantial improvement, in terms of correlation coefficient, absolute average error,

Table 5
Comparison of the laboratory, existing CPT, and neural network classifications using the USCS on the Veliki vrh test site.

	USCS – laboratory		USCS – CPT NN		USCS - CPT	
Number	Symbol	Group name	Symbol	Group name	Symbol	Group name
1	CL	Sandy lean clay	CL	Sandy lean clay	**SC**	**Clayey sand**
2	CH	Fat clay with sand	CH	Fat clay with sand	CH	Fat clay with sand
3	CH	Fat clay with sand	CH	Fat clay with sand	CH	Fat clay with sand
4	CL	Sandy lean clay	CL	Sandy lean clay	SC	Clayey sand
5	CL	Sandy lean clay	CL	Sandy lean clay	**SC**	**Clayey sand**
6	CH	Fat clay with sand	CH	Fat clay with sand	CH	Fat clay with sand
7	CH	Fat clay	CH	Fat clay	CH	Fat clay
8	CH	Fat clay with sand	CH	Fat clay with sand	**CL**	**Sandy lean clay**
9	CH	Fat clay	CH	Fat clay	CH	**Fat clay with sand**
10	CH	Fat clay with sand	CH	Fat clay with sand	CH	Fat clay with sand
11	CH	Fat clay with sand	CH	Fat clay with sand	CH	Fat clay with sand
12	CH	Sandy fat clay	**CL**	**Sandy lean clay**	**CL**	**Sandy lean clay**
13	CH	Fat clay with sand	**CL**	**Sandy lean clay**	**CL**	**Sandy lean clay**
14	SC	Clayey sand	SC	Clayey sand	SC	Clayey sand
15	CL	Sandy lean clay	CL	Sandy lean clay	CL	Sandy lean clay
16	SC	Clayey sand	SC	Clayey sand	SC	Clayey sand
17	SC	Clayey sand	SC	Clayey sand	SC	Clayey sand
18	SC	Clayey sand	SC	Clayey sand	SC	Clayey sand
19	SC	Clayey sand	SC	Clayey sand	SC	Clayey sand

Table 6
Comparison of the laboratory and CPT soil classifications in line with the ESCS on the Veliki vrh landslide using neural networks.

	ESCS – laboratory		ESCS – NN		ESCS CPT	
Number	Symbol	Group name	Symbol	Group name	Symbol	Group Name
1	saClI	Sandy clay of medium plasticity	saClI	Sandy clay of medium plasticity	**clSa**	**Clayey sand**
2	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity
3	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity
4	saClI	Sandy clay of medium plasticity	saClI	Sandy clay of medium plasticity	**clSa**	**Clayey sand**
5	saClI	Sandy clay of medium plasticity	saClI	Sandy clay of medium plasticity	**clSa**	**Clayey sand**
6	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity
7	ClH	Clay of high plasticity	ClH	Clay of high plasticity	ClH	Clay of high plasticity
8	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity	**saClI**	**Sandy clay of medium plasticity**
9	ClH	Clay of high plasticity	ClH	Clay of high plasticity	**saClH**	**Sandy clay of high plasticity**
10	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity
11	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity	saClH	Sandy clay of high plasticity
12	saClH	Sandy clay of high plasticity	**saClI**	**Sandy clay of medium plasticity**	**saClI**	**Sandy clay of medium plasticity**
13	saClH	Sandy clay of high plasticity	**saClI**	**Sandy clay of medium plasticity**	**saClI**	**Sandy clay of medium plasticity**
14	clSa	Clayey sand	clSa	Clayey sand	clSa	Clayey sand
15	saClI	Sandy clay of medium plasticity	saClI	Sandy clay of medium plasticity	saClI	Sandy clay of medium plasticity
16	clSa	Clayey sand	clSa	Clayey sand	clSa	Clayey sand
17	clSa	Clayey sand	clSa	Clayey sand	clSa	Clayey sand
18	clSa	Clayey sand	clSa	Clayey sand	clSa	Clayey sand
19	SC	Clayey sand	SC	Clayey sand	SC	Clayey sand

and accuracy of soil classification according to USCS and ESCS guidelines. An additional benefit of the model is that the accuracy improves over time as more CPT and laboratory datasets are added to the database.

ANN based soil classification models have some drawbacks, in particular, any attempts this study made to classify Granular soils were unsuccessful as it was not possible to consistently predict d_{50} and d_{10} values based on CPT data alone (based on a statistically significant sample size of 47 pairs of CPT/laboratory tests). These values are required to determine the uniformity coefficient c_u and the curvature coefficient c_c which in turn determine how well graded the granular particles are. While this is a substantial draw back, as it means this approach is not universally applicable to all soil types, it is a problem which is also encountered in existing correlations where low correlation coefficients are frequently observed for these parameters. To date, academic literature contains no relevant research that connects CPT results with the necessary distinctive grain sizes d_{10}, d_{30}, and d_{60}. Furthermore, all CPT based soil classification charts to date fail to provide diagrams that contain information on soil grading level. Indeed, it may not be possible to conclusively determine the particle size distribution of a soil based on tip resistance, sleeve friction, and pore pressure alone. In support of this hypothesis is the work by Tillmann et al. [25] who managed to get accurate correlations between CPTs and distinctive grain sizes by equipping his probe with a number of additional sensors to monitor the change in electrical resistance and to measure neutron and gamma radiation. Using these sensors, it was also possible to measure electric resistance ρ, the intensity of natural gamma radiation γ, soil bulk density ρ_b and soil moisture content w at various depths.

Another concern with using ANN is the black box nature of the results, which makes proof of concept hard to verify. Whilst this is obviously a concern 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. An additional benefit of this approach is that the training database will grow in size over time making incorrect classifications less likely to occur. Over time the approach should make soil classification cheaper, faster and less labour intensive.

The study confirms the functional link between CPT results, the percentage of fine particles FC, the liquid limit w_L and the plasticity index I_P. Thus, partially confirming the hypothesis of this research, namely that the results of the static penetration test can be directly linked to the particle size distribution and soil consistency limits used in standard soil classification. It should be noted that while the plasticity index had the poorest ANN predictions, the means of determining soil plasticity within a laboratory environment remains quite subjective and results tend to differ greatly between practitioners, it can therefore not be expected to produce as reliable results. As a final note, it is important to point out that due to variations in regional geology a suitable training database will have to be developed for each region to ensure correct classification.

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