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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