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SPT and CPTU for soil characterization: Case studies in offshore windfarm development

SPT et CPTU pour la caractérisation des sols : études de cas dans le développement de parcs éoliens offshore

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ABSTRACT: Cone Penetration Test (CPTU) and Standard Penetration Tests (SPT) are widely used in situ test methods to get variation of soil properties and obtain geotechnical design parameters. It is very beneficial and valuable to study the correlation of CPTU data with SPT N- value. In this study, CPTU and SPT data from two offshore windfarm sites are used for classification and correlation study. Random forest method is used to classify soils to various types and to predict SPT N-value from CPTU data. Machine learning (ML) is a good tool for classification of soils and it is not ideal for prediction purpose in the case studies.

RÉSUMÉ Le test de pénétration de cône (CPTU) et les tests de pénétration standard (SPT) sont des méthodes de test in situ largement utilisées pour obtenir la variation des propriétés du sol et obtenir des paramètres de conception géotechnique. Il est très avantageux et précieux d'étudier la corrélation des données CPTU avec la valeur SPT N. Dans cette étude, les données CPTU et SPT de deux sites éoliens offshore sont utilisées pour l'étude de classification et de corrélation. La méthode de la forêt aléatoire est utilisée pour classer les sols en différents types et pour prédire la valeur SPT N à partir des données CPTU. L'apprentissage automatique (ML) est un bon outil pour la classification des sols et il n'est pas idéal à des fins de prédiction dans les études de cas.

KEYWORDS: Cone penetration test; standard penetration test; case study; offshore wind farm; machine learning.

1 INTRODUCTION

Standard Penetration Test (SPT) has been used widely and subsoils can be classified and characterized by the SPT. In addition, some geotechnical design parameters are associated with SPT N-value. At the same time, Cone Penetration Test (CPTU) is becoming more popular than SPT due to its continuous logging of soil profile, multiple channel measurements, accuracy, repeatability and easy to use in offshore soil investigation. Although the CPTU can give many advantages over the SPT and is generally accepted to give more reliable and accurate data than SPT, the SPT continues to be a commonly used in situ testing method in many parts of the world due to its low cost, extensive past experience, well defined standard for obtaining design parameters and ease of use in liquefaction evaluation.

SPT and CPTU correlations have been studied by many researchers. Most of the empirical correlations considered a constant value of q_c/N (Schmertmann,1970, Emrem and Durgunoglu, 2000, Kara and Gunduz, 2010, among others). In general, this constant value is between 0.2 and 7.0 from literature, with big variations (Tarawneh, 2014). Higher values of q_c/N may be due to cementation, densification and shelly structure or gravel layers (Akca, 2003). However most of the constant values are between 0.2 and 1.0 (Jefferies and Davies, 1993, Duan et al., 2018). Correlations of CPTU and SPT was established between $q_c/p_a/N$ and fines content (Chin, et al.,1988, Kulhawy and Mayne, 1990), between $q_c/p_a/N$ and D_{50} (Robertson et al., 1983, Ahmed, et al., 2014). CPTU and SPT correlations were linked to soil behaviour type (SBT) index, Ic (Jefferies and Davies, 1993, Lunne et al., 1997). Bashar (2014) applied multiple linear regression and symbolic regression to predict N value from CPT data. Developed models by using symbolic regression showed good results with acceptable accuracy. Tarawneh (2017) used ANN to predict N value from CPT data. It was shown that ANN model either under predicted the N-value by 7-16% or over-predicted it by 7-20%.

Machine learning (ML) has been used frequently in Geotechnical engineering field. For example in liquefaction assessment (Garcia, et al.,2012, Ardakani and Kohestani, 2015), in predicting spatial soil type distribution (Ghaderi, et al., 2018), in site characterization (Tsiaousi, et al., 2018), in pile capacity evaluation (Goh, 1995, Maizir et al. 2015, Mazaher and Berneti, 2016), and in settlement prediction of foundations (Shahin, et al., 2002, Alkroosh and Nikraz, 2011). Classical soil classification by using CPTU data is to use empirical soil classification charts by Robertson et al., (1986), Robertson, (1990) and Robertson, (2016). Bhattacharya and Solomatine (2006) used CPT data to classify sub-surface soil by using decision trees, ANN and support vector machines. The case study predicted accuracy of the classifiers of about 83%.

In this study, SPT and CPTU data are from two offshore sites in China. SBT index, Ic, reflects the mechanical behaviour of soils and can distinguish sand like soils from clay like soils without knowledge of particle size distribution and plasticity. Ic is directly calculated from CPTU data and used for soil classification. Correlations of SPT-CPTU are studied by using random forest method.

2 INTERPRETATION OF CPTU AND SPT DATA

2.1 *CPTU data*

All CPTU tests in this study were carried out based on standard T/CCES1 2017 (2017). This is in agreement with international standards. The cross sectional area of the cylindrical cone penetrometer is 10 m2 with a tip angle of 60º, with a cone area ratio of 0.75. CPTU cone is from a.p.van den berg. Each CPTU collects one reading every 2 cm while SPT N-value is obtained every 30 cm, and CPTU data is averaged every 30 cm interval in the data analysis in this study.

Typical raw CPTU data includes the cone tip resistance, q_c, the sleeve friction, f_s and pore water pressure, u_2. Interpretation of raw CPTU data (u_2, f_s and q_c) has traditionally been done by derivation of parameters like friction ratio (R_f), normalized cone tip resistance (Q_t), and normalized friction ratio (F_r) and their subsequent use in existing charts or classifications.

The corrected cone tip resistance, q_t:

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

where α is the net area ratio

The friction ratio (R_f) represents the ratio between f_s and q_t:

$$R_f = \frac{f_s}{q_t} \times 100\% \tag{2}$$

With u_2 the pore pressure measured between the cone tip and the friction sleeve and the net area ratio determined by the characteristics of the used cone. Stress-normalized equivalents of the variables q_t and R_f should be used to account for the in-situ vertical stresses: the normalized cone tip resistance, Qt:

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

and the normalized friction ratio, F_r:

$$F_r = \frac{f_s}{q_t - \sigma_{v0}} \times 100\% \tag{4}$$

where σ_{v0} is the total vertical stress, and σ_{v0}' the effective vertical stress.

Pore pressure ratio, B_q, is defined as:

$$B_q = \frac{u_2 - u_0}{q_t - \sigma_{v0}} \times 100\% \tag{5}$$

Where $u_0$is equilibrium pore pressure.

Jefferies and Davies (JD) (1993) introduced the SBT index Ic to represent the radius of the concentric circles in the classification diagram of Robertson (1990).

Jefferies and Davies (1993) proposed an expression for Ic:

$$Ic = \sqrt{[3.0 - log_{10}\, Q_t\,(1-B_q)]^2 + [1.5 + 1.3log_{10}\,(F_r)]^2} \tag{6}$$

Robertson and Wride (RW) (1998) proposed an expression for Ic:

$$Ic = \sqrt{[3.47 - log_{10}Q_{tn})]^2 + [1.22 + log_{10}\,F_r]^2} \tag{7}$$

$$Q_{tn} = \frac{(q_t - \sigma_{v0})/\sigma_{atm}}{(\sigma_{v0}'/\sigma_{atm})^n} \tag{8}$$

$$n = 0.381Ic + 0.05\frac{\sigma_{v0}'}{\sigma_{atm}} - 0.15,\ n \le 1.0 \tag{9}$$

Where σ_{atm} *is* reference pressures.

Li et al. (2007) updated the above formula, and soil behaviour type index is calculated as the follows:

$$Ic = \sqrt{[3.25 - log_{10}\, Q_t\,(1-B_q)]^2 + [1.5 + 1.3log_{10}\,(F_r)]^{2.25}} \tag{10}$$

Ic in equation (10) is used in this paper.

2.1 *SPT data*

In this study, SPT was performed based on standard YS5213-2000 (2001) and it is in agreement with ASTM standard (ASTM). SPT involves driving a standard thick-walled sample tube into the ground at the bottom of a borehole by blows from a slide hammer with standard weight (63.5kg) and falling distance (76cm). The sample tube is driven 15 mm into the ground and then the number of blows needed for the tube to penetrate each 15 cm up to a depth of 45 cm is recorded. The sum of the number of blows required for the 30 cm penetration is reported as SPT blow count value, commonly termed "N-value". In general, N-values are normalized to 60% hammer efficiency, which is a common practice in many countries. Some standard (BS, 2005) suggested to normalize N- value based on the length of the rod. If the length of the rod is more than 10m, correction factor is 1. The measured N-value is approximately N_{60}, i.e., at 60% hammer efficiency. For the SPT tests in this study, rod length is more than 10 m. No correction is made to the measured blow counts. As mentioned during SPT a disturbed sample is also obtained which can be used for lab tests.

3 MACHINE LEARNING METHOD

Machine learning (ML) is a broad subfield of Artificial Intelligence that uses multivariate, nonlinear, nonparametric regression or classification algorithms and techniques to learn from existing data and develop predictive models. ML can be very useful for solving problems where deterministic solutions are not available or are very expensive in terms of computational cost, but for which there is significant data available.

Random Forest (RF) is one of the many machine learning algorithms used for supervised learning, this means for learning from labelled data and making predictions based on the learned patterns. RF can be used for both classification and regression tasks. Random forests (RFs) are ensemble-based decision trees and were developed to overcome the shortcomings of traditional decision trees. In RF, like other ensemble learning techniques, the performance of a number of weak learners is boosted via a voting scheme.

For big data analysis, collected data may be unbalanced, i.e. number of samples for one kind of soils may be much more than the others. There are various techniques that are involved in improving the performance of imbalanced datasets. Under-sampling and over-sampling are two of them. Under-sampling is to remove samples randomly from over-represented classes, and it is useful for a huge dataset. Over-sampling is to add more samples from under-represented classes and it is useful for a relatively small dataset. SMOTE (Synthetic Minority Over-sampling Technique) is an over-sampling method and it creates synthetic samples of the minority class. Imblearn python package for over-sampling is used in this study for the minority classes.

4 CASE STUDY

4.1 *Data collection*

Data from two offshore windfarm sites in Yellow Sea (YS) and East China Sea (ECS), respectively are collected in this study, including borehole logs, SPT and CPTU data. Common soil types in these two sites include Ooze clay, clay, silty clay, silty sand, sand and weathered rock. Corrected cone resistance from all CPTU results in the studied two sites are shown in Figure 1, including 28 CPTUs from YS site and 15 CPTUs from ECS site. There is a big variation on the values of corrected cone resistance at each area.

SPT was carried out at all two studied sites. Available SPT number of blows along depth for all sites are plotted in the following figure (Figure 2). Number of blows is increasing with depth in general.

4.2 *Separation of sand-like soils and clay-like soils based on CPTU data*

In many geotechnical applications, it is important to develop a simple method to distinguish between clay-like soils and sand-like soils. Based on USCS classification method, if more than 50% of material is larger than No.200 sieve size (0.075mm), it is coarse grained soils. It is referred to sand-like soils in this study. If 50% or more of material is smaller than No.200 sieve size (0.075mm), it is clay –like or fine grained soils. This criterion is not perfect, and several studies have shown that fines content can be important for such classification.

Table 1 shows proposed description and corresponding Ic values for soil classification (Rabertson et al., 1986 and Robertson 1990)

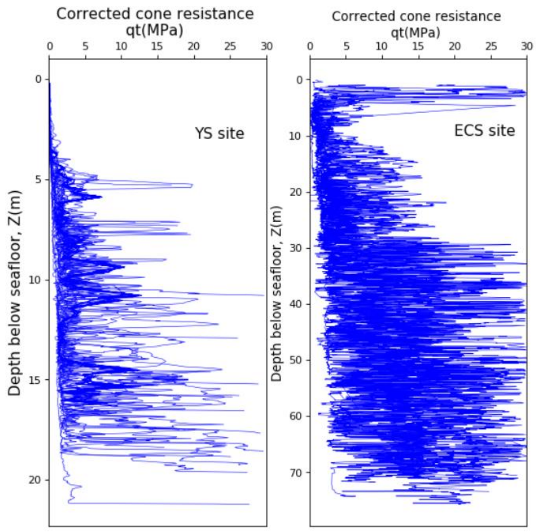

Figure 1. Corrected CPTU cone resistance versus depth

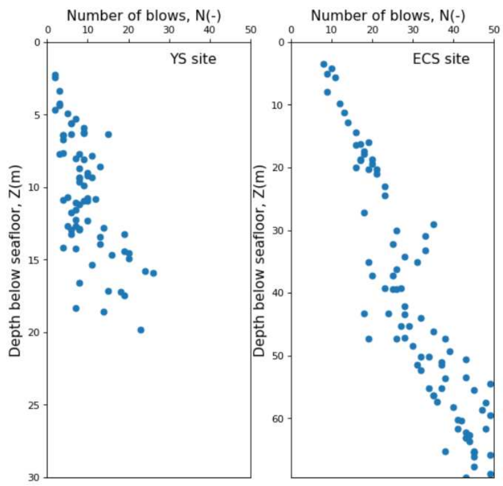

Figure 2. SPT results for YS and ESC site

To determine if any of the soil layers contain "sensitive clays and silts" from zone 1 or "stiff soil" from zones 8 and 9, the following rule can be used:

- The soil layers belong to zone 1, if $Qt < 12e^{-1.4Fr}$,
- The soil layers belong to zone 8 and 9, if $Qt > \frac{1}{0.005(Fr-1)-0.0003(Fr-1)^2-0.002}$,
- Zones 8 and 9 are separated by line Ic=2.6

We define types 2, 3 and 4 are clay-like soils and 5, 6 and 7 are sand-like soils in Table 1. Figures 3 to 4 show examples on soil classification based on Ic values for two sites. For ECS site, soil types vary significantly, as expected based on CPTU data in Figure 1.

Table 1. Proposed unification of zones and SBY index Ic (Robertson et al., 1986 and Robertson 1990)

Proposed description	SBT_n	SBT	I_c
Sensitive fine-grained	1	1	N/A
Clay – organic soil	2	2	>3.6
Clays: clay to silty clay	3	3	2.95–3.6
Silt mixtures: clayey silt & silty clay	4	4 & 5	2.60–2.95
Sand mixtures: silty sad to sandy silt	5	6 & 7	2.05–2.6
Sands: clean sands to silty sands	6	8	1.31–2.05
Dense sand to gravelly sand	7	9 & 10	< 1.31
Stiff sand to clays sand*	8	12	N/A
Stiff fine-grained*	9	11	N/A

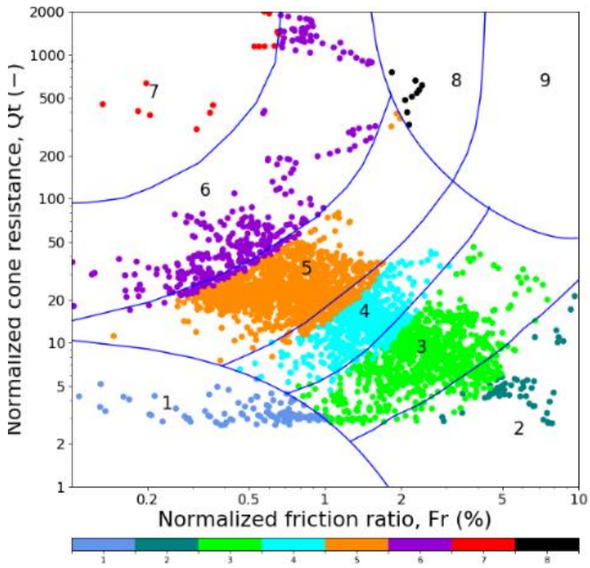

Figure 3. Soil behaviour types at one location from ECS site

In one paper by Liu, et al. (2020), application of machine learning on soil classification based on CPTU data was investigated. One database, including 1367 grain size distribution data and 1801 Atterberg Limit data with corresponded CPTU data, was established from various sites. In total, there are 2792 pairs of CPTU data points and soil types, including 2555 clay like soil and 237 sand like soil. We use this database to train the sand and clay classification model, and CPTU data from YS and ECS sites is used as test dataset.

The procedures used for classification are as follows:

- Random forest classifier is applied to fit the classification model.
- The measured CPTU data "q_c(kPa)", "u_2(kPa)" and f_s(kPa), in addition to overburden effective stress are selected as input parameters in this model and two classes as Sand like soil and Clay like soil as output.
- Accuracy for the test dataset is shown in Table 2. Accuracy on sand like soils is not high. This is due to relatively small datasets for sand like soils in the training dataset. After using data balance technique,

- accuracy is increased from 65% to 73% for sand like
- soils, see Table 3 for details.

From Figure 7, the most important input parameters to soil classification are q_c with 46.9% importance and u_2 with 24.5% importance to soil classification.

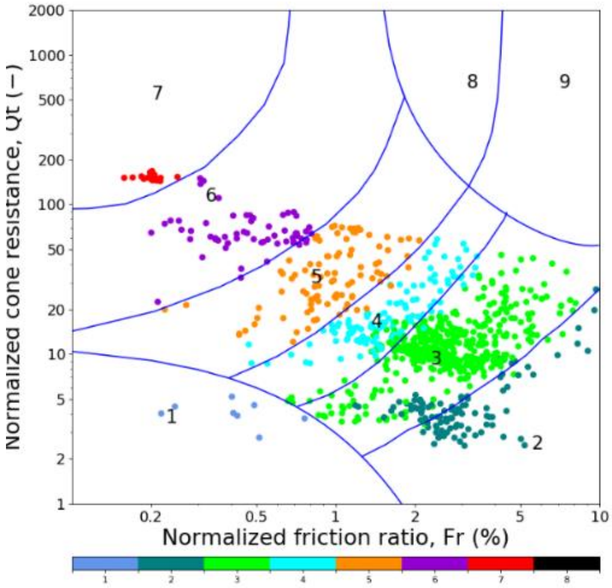

Figure 4. Soil behaviour types at one location from YS site

Figures 5 to 6 show examples from borehole data and classifications based on CPTU data. Classification based on Ic values fits reasonably well with soil types from borehole data.

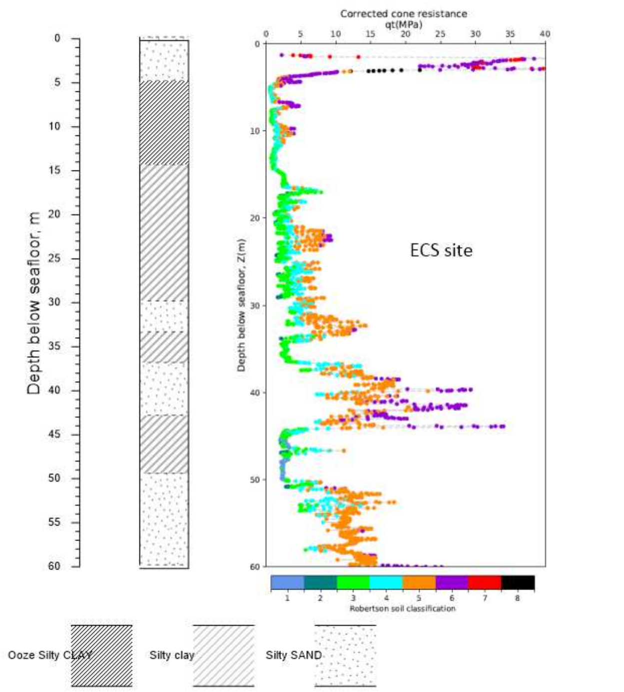

Figure 5. Borehole data and soil classification based on CPTU data at ECS site

Table 2. Accuracy for classification of sand like soil and clay like soil before data balance

	Samples total	Sand Predicted	Clay Predicted	accuracy (%)
Sand like material	124	90	34	73%
Clay like material	93	9	84	90%
sum	217	99	118	78%

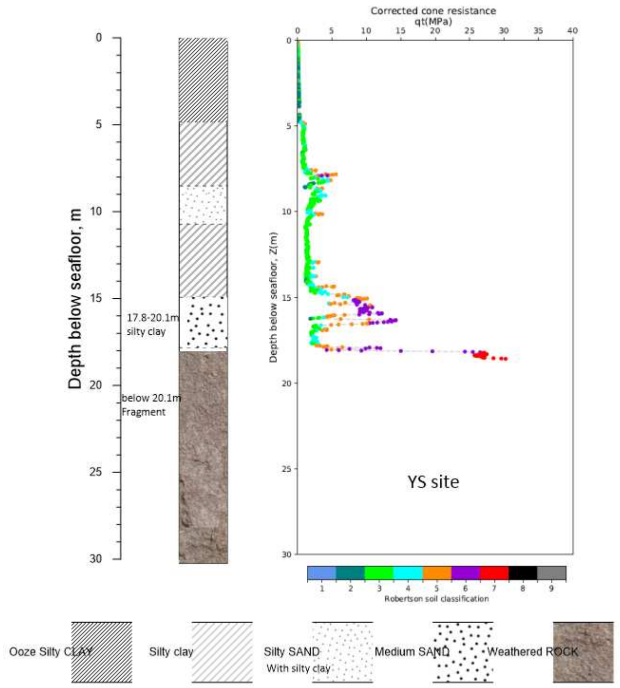

Figure 6. Borehole data and soil classification based on CPTU data at YS site

Table 3. Accuracy for classification of sands and clays after data balance

	Samples total	Sand Predicted	Clay Predicted	accuracy (%)
Sand like material	124	81	43	65%
Clay like material	93	6	87	94%
sum	217	87	130	78%

4.3 Correlations between SPT and CPTU data

Both CPTU and SPT data are collected from two sites in Yellow Sea (YS) and East China Sea (ECS). In total, 71 pairs for YS s ite and 92 pairs for ECS site .

For YS site, more data on clay-like soils than sand-like soils (Figure 8), while for ECS site, more data on sand-like soils than clay-like soils (Figure 9).

As discussed in introduction, most of the empirical correlations considered a constant value of qc/N and this constant value is between 0.2 and 7.0 from literature, with big variations. Figure 10 shows correlation between corrected cone resistance and N for the two sites and this indicates that there is no significant correlations between these two parameters. However there is a significant trend between qt/N and Ic. qt/N is decreasing with increasing of Ic, especially for site ECS (Figure 11).

Mean Squared Error (MSE), Goodness of Fit (GOF) and accuracy are used as indexes to evaluate the regression model by using both random forest regression and linear regression method, where y_i is the true value, $\hat{y}_i$ is predicted value, N is number of samples, and $\bar{y}$ is mean value of $\{y_i\}$

MSE is defined as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{11}$$

GOF (R^2 score) is defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{12}$$

If R^2 score value is closer to 1, the model fits the data better. And R^2 score value is closer to 0, the model fits worse. Usually, if R^2 score value >0.4, it is a good fitting effect

Accuracy is defined as :

$$ACC = (1 - \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|) \tag{13}$$

Results show that data at ECS site fits the model better, while data at YS site does not fit well to the model (Table 4). The analysis above indicates that regression method has limitations in predicting N-Value from CPTU data.

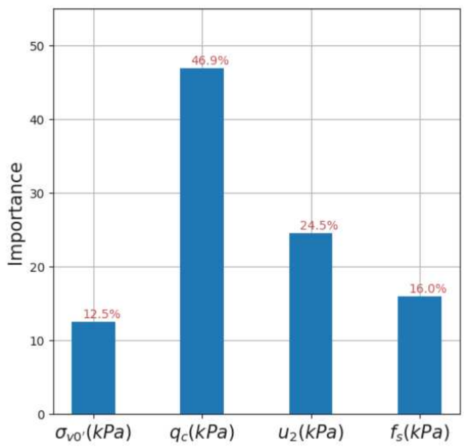

Figure 7. Importance of input parameters

5 DISCUSSION

Data from CPTU is very useful for classifying soils to various soil types, even without any laboratory tests. Random forest method can be used to classify soil to various soil types. However unbalanced datasets has to be processed since accuracy of classification for over-represented classes is higher than that for under-represented classes. There is good correlation between CPTU and SPT data, especially between qt and N. However the correlation is site dependent. Since dataset in the case study is limited and it is recommended to use machine learning method in a larger dataset in order to get better training results.

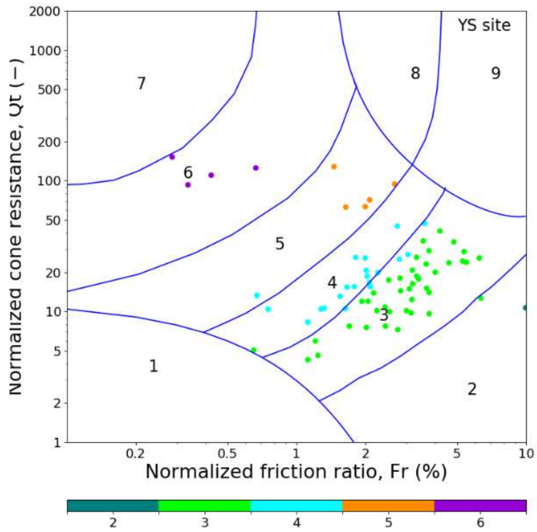

Figure 8. Soil classification for YS site

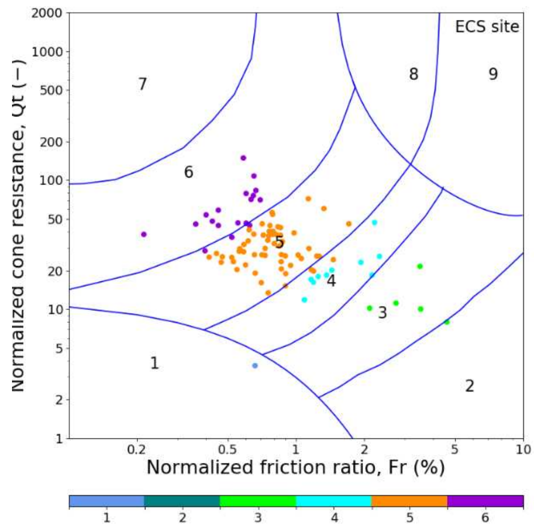

Figure 9. Soil classification for ECS site

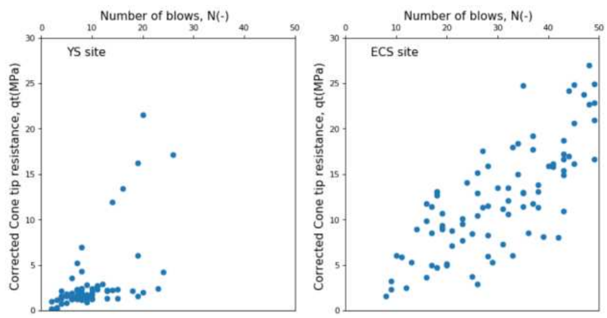

Figure 10. Corrected cone resistance versus N

6 CONCLUSIONS

SPT and CPTU data from two offshore windfarm sites are interpreted. Various soil types are classified by using CPTU data, and correlations between CPTU and SPT are discussed. Soil behaviour type index, Ic, derived from CPTU data is still a key parameter to classify soils to nine different types. Classification based on Ic values fits reasonably well with soil types from borehole data for YS and ECS sites. In addition, the higher the Ic values, the lower the ratios of cone resistance from CPTU to blow counts from SPT. Random forest method is a good method for classification purpose, but not for prediction in the case study.

This study provides a realistic reference case study on CPTU and SPT data for research and industry in offshore windfarm energy.

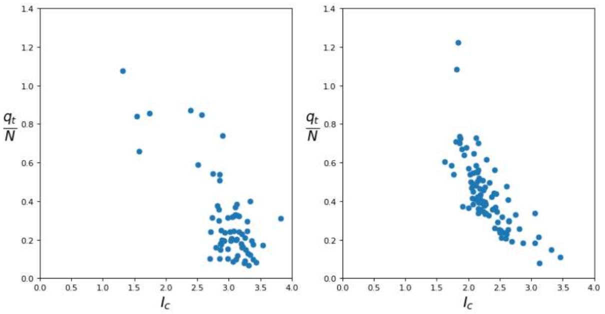

Figure 11. Correlation between qt/N and Ic. Ic>2.6 for clay-like soils and Ic<2.6 for sand-like soils

Table 4. Results from random forest regression and linear regression

location	method	R^2_score	accuracy
ECS Site	Random forrest regression	0.43	65
YS Site	Random forrest regression	0.20	36
ECS Site	Linear regression	0.27	65
YS Site	Linear regression	0.15	42

7 ACKNOWLEDGMENTS

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