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Investigation of the geotechnical properties and estimation of the relative density from the standard penetration test in sandy soils (Case study: north east of Iran)

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ABSTRACT

In the present research, SPT results are adopted to establish relationships for estimation of the relative density in a sandy soil. SPTs are performed in 20 boreholes in Astaneh-ye Ashrafiyeh city in Iran. Laboratory tests including mineralogy, relative density, soil gradation, Atterberg limits, and unit weight were performed on the soil samples. The SPT numbers were then properly corrected. In particular, the correct procedure for correction of the SPT number against the existing overburden effective stress is discussed when the SPT is performed in the vadose zone where the soil may be unsaturated. The soil in the study area is dominantly classified as SP-SM. The relationship between the relative density as one of the most important parameters for dominantly granular soils, with the corrected SPT number ($N_{1(60)}$) and fines content is then

investigated and discussed using artificial neural network and statistical analysis. Results showed that for the soil of interest, the developed relationship performs better than those established in the literature, hence demonstrating the value of developing locally tuned relationships for important projects.

Keywords: artificial neural network, multiple regression, standard penetration test, geotechnical properties, vadose zone

1. Introduction

Estimation of geotechnical parameters of soils using simple field tests is a common practice in site investigation studies. Because these tests are simple, inexpensive, and tangible to practicing engineers (Sivrikaya and Tougrol 2006; Sivrikaya et al. 2013; Kayabasi and Gokceoglu 2018). One of these tests is the standard penetration test (SPT) (Bozbey and Togrol 2010; Yoshida (1988); Meyerhof 1956; Ching et al. 2017). This test is recently used for predicting mechanical properties of the fine-grained soils (Sivrikaya and Tougrol 2006; Yilmaz 2000; Mahmoud 2013).

Many scholars have presented the relationships between the SPT number and geotechnical properties of soils, and many relationships and computational methods have already been developed in this regard (Sivrikaya and Tougrol 2006; Phoon and Kulhawy 1999). In particular, several relations have been suggested for predicting of the relative density of granular soils using the SPT value (Table 1), given the importance of the relative density in characterisation of granular soils. Local relationships established in a particular geologic site may be desirable to universal adjustments (Phoon and Kulhawy 1999; Nia et al. 2017; Abbaszadeh Shahri 2016; Rastegarnia et al. 2017). Furthermore, the effect of soil suction in unsaturated regions of the soil has been overlooked in obtaining many of these correlations, rendering them less reliable in the regions above the water table (Pouranaghiazar et. 2013). The latter issue may lead to correlations over-estimating soil parameters, and hence compromising the safety of geostructures.

*****Table 1 *****

This study aim to develop two models, one based on artificial nural network approach and one based on multiple regression analysis, for estimating of the relative density from the results of the SPT. The relative density is selected as the parameter of interest since it corrlates very well with many engineering properties of granular soils. Test data from 20 boreholes in city of Astaneh-ye Ashrafiyeh, located in northeast of Iran, are used for the developments. Carefull consideration specified to calculate the effective stress correctly above the water table based on soil suction. The parameters that most strongly correlate with the soil relative density are identified from the test data. Derivation and validation of the models are explained and discussed. The application of the models developed along with several well stablished models in the literature for estimation of the relative density using SPT data is then presented and discussed using the data of this study.

2. Test site

The studied region is in Astaneh-ye Ashrafiyeh city in the north east of Iran with geographical coordinates of 37°15'35.38"N and 49°56'38.25"E (Fig. 1). 20 boreholes were drilled in this area and more than 200 samples were taken from the boreholes. Correct characterisation of the sandy soil of this region is particularly important since liquefaction occurred in this area due to Manjil-Rudbar earthquake (magnitude 7.7 Richter) in 1990. Geological formations from Precambrian to Quaternary identified in this area, with some gaps and unconformities in Paleozoic and Mesozoic (Aghanabati 2004).

*****Figure 1.*****

3. Standard penetration test (SPT)

The SPT number is often corrected for different variables. In this study, Equation 1 used to correct the SPT number (Robertson and Fear 1996). The description and values of the correction factors are presented in Table 1.

$$(N_1)_{60} = N_{SPT} \cdot C_N \cdot C_E \cdot C_B \cdot C_S \cdot C_R \quad (1)$$

Where, $(N_1)_{60}$ is the N_{60} normalized to one atmosphere overburden stress. C_N is calculated using equation 2(Liao et al.1986)

$$C_N = 9.78 \sqrt{\frac{1}{\sigma'}} \quad (2)$$

In which σ' is the effective overburden stress in kN/m^2 . Table 2 shows the score of each correction factor (ASTM 2011).

*****Table 2*****

4. Materials

The gradation, Atterberg limits and unit weight of the samples were determined based on the ASTM D421 (ASTM 2007), ASTM D4318 (ASTM 2010) and ASTM D854 (ASTM 2010), respectively. The results of these test are presented in Table 3. Fig. 2 shows a gradation curve of a sample. The soil in the studied area is mainly a uniformly graded sand with angular particles, with a little amount of silt and clay (i.e., SP-SM based on the unified classification system).

*****Table 3*****

*****Fig. 2.*****

In total, 292 samples from 20 boreholes were extracted and analysed in this study. Statistical characteristics of test data related to fines content, $N_{1(60)}$, and relative density of the samples are displayed in Table 4. This table shows that the standard deviations are considerable, indicating large heterogeneity in the soil of the study area. This is often expected in natural soils. Despite this variability in the soil and for the sake of practicality, the whole site is treated as one soil, and all the derivations to follow are based on average soil parameters.

*****Table 4*****

As an example, the geotechnical properties of the samples taken from borehole 2 are presented in Table 5.

*****Table 5*****

The average corrected SPT number for all the SPT tests was obtained 18. Hence, based on Meyerhof (1956) and Terzaghi and Peck (1967) classifications, the soil of the studied area is categorized as compacted and very dense soil, respectively (see Table 6).

*****Table 6*****

Fig. 1 shows the geological map deposits and soil texture map at depths of 10 m and 20 m. The sediments of the studied site consist predominantly of plagioclase, clinopyroxene, epidote, quartz and carbonate minerals (Fig. 3). The abundance of each one is as follows:

Clinopyroxene: The pyroxenes of the samples are dominantly diopside with a little bit of Augite, with a frequency of 10% and an average size of 0.2 mm.

Plagioclase: This mineral is the most abundant mineral in the complex, with a frequency of 40% and a size between 0.1 and 0.3 mm, with a mean magnitude of 0.2 mm.

Epidote: This mineral frequency is 5% and its average size is 0.2 mm.

Carbonate particles: Mainly contains calcite and the frequency of these particles is 20% and varies from 0.1 to 0.3 mm.

The other important minerals of these sediments are metallic minerals with an abundance of 15% and a range from 0.1 to 0.2 mm. Because the sediments are most commonly composed of minerals isolated from Mafic and Ultramafic rocks, it is likely that these minerals are opaque magnetite. Quartz is also rarely seen in these sediments. The sorting of the particle is good (i.e. the sediments gradation is weak) and rounding is weak (i.e. the sediments particles are angular). The parent rocks of these sediments are mainly carbonate rocks with Mafic composition.

*******Figure 3.*******

4.1. The Artificial Neural Network (ANN)

ANN is a framework involving a chain of elements that transfer with each other by many inner weights. These weights are continually adjusted throughout the training stage of the network. During ANN analysis, the operator controls the outputs, inputs, layer nodes and hidden layer numbers. Several functions such as Gaussian, Sigmoid, Hyperbolic Tangent and

Hyperbolic Secant are used among the layers. Among these, the Sigmoid function has the main acceptance in engineering uses, mainly due to their simple derivations which facilitate the evaluation of the back propagation errors. The most appropriate ANN for engineering applications is back propagation networks (BPN) (Rumelhart et al. 1986) in which the calculations start with some optional weights, and then the outputs are calculated, and modified by adjusting certain weights using the computed error from the output and estimated values. This procedure is continued until the minimum error is gained. To obtain the optimal network, the try and error process lasts until the lowest error is gotten (Chatterjee et al. 2000). In this study, the optimum ANN to estimate the relative density was obtained when 2 hidden layers were selected, as will be explained later in the paper.

4.2. Effective stress calculation above the water table

To calculate the effective stress, the effect of suction must be properly considered in vadose zone. The suction values are often small in granular soils, like those dominant in the region of interest in this study, and hence the suction effects can be overlooked in calculation of the effective stresses. However, the procedure to calculate the effective stress is explained here for the sake of completeness, and to be used when the soil of interest contains a considerable amount of fines. To this end, the method of effective stress (Khalili 2004; Ghaffaripour et al. 2019) is used, in which in the unsaturated region of the soil we have,

$$\sigma' = \sigma_{\text{net}} + \chi s \quad (3)$$

where σ_{net} is the net stress, χ is the effective stress parameter and $s = u_a - u_w$ is the soil suction.

Where, u_a and u_w are pore air and water pressures, respectively. In this equation, effective stress, pore water and pore air pressures are assumed positive in compression following the soil mechanics convention.

For soils under static load, we can often assume that $u_a = 0$, so Equation (3) is simplified to equation 4,

$$\sigma' = \sigma + \chi s \quad (4)$$

where σ is the total stress. Several models are available in the literature for estimation of the parameter of effective stress. Here, the model presented by Khalili and Khabbaz (1998) is adopted since it is the most accurate method in the literature. According to this approach and neglecting the hydraulic hysteresis effects, the parameter of effective stress at each point is obtained as follows

$$\chi = \begin{cases} 1 & s \leq s_e \\ \left(\frac{s_e}{s}\right)^\Omega & s > s_e \end{cases} \quad (5)$$

where Ω is a material parameter with best fit of 0.55, and s_e is the air entry value of the soil. The value of air entry of the soil is obtained from the soil water retention curve (SWRC) (Pasha et al. 2019, 2015). Obtaining the SWRC is however time consuming and the test was not performed on the samples obtained in this study. Therefore, a simple SWRC as presented in Figure 4 was assumed for the samples based on their average gradation curve (Khoshghalb et al. 2015). As seen from this figure, an average air entry value of $3kPa$ was assumed for the soil, and it has been assumed that the soil reaches a residual degree of saturation of 5% at a suction of $15kPa$.

*****Figure 4.*****

The suction of the soil can be obtained using tensiometers in the field, or from the SWRC and the in situ water content or degree of saturation of the soil. Since no tensiometers were used to

obtain the suction of the soil, the soil suction was estimated using the degree of saturation of the soil samples, and the assumed SWRC presented in Figure 4. For the samples saturated above the water table (due to capillary rise), the suction of the sample were obtained from:

$$s = -\gamma_w h \quad (6)$$

where γ_w is the unit weight of water, and h is the height of the point of interest above the water table. For the samples with the degree of saturation less than 5%, $s = 0$ was assumed in the calculations.

5. Relative density estimation relationships

The dependency of the relative density of the samples to fines content (FC), $N_{1(60)}$, plastic limit (PL) and depth were investigated as shown in Figure 5. According to these results, the fines content and $N_{1(60)}$ were found to have the greatest effects on the relative density of the soil samples in the studied area. A number of previous studies have also shown the importance of fines content and effective overburden pressure on the behaviour of sandy soils (Payan et al. 2017; Mujtaba et al. 2017; Meyerhof 1956). The ability of the SPT number to estimate the relative density of the coarse-grained soils has also been confirmed by other researchers (Mahmoud 2013; Phoon and Kulhawy 1999; Hettiarachchi and Brown 2009). On this basis, fines content and $N_{1(60)}$ were selected as the main independent variable to estimate the relative density of the soil of interest using artificial neural network and multiple regression analysis.

*****Figure 5.*****

5.1. Relative density estimation using nural network approach

As shown in Fig. 6, using neural network toolbox of MATLAB, version 2014, the designed network contains 2 hidden layers with two inputs and one output. Inputs contain $N_{1(60)}$ and fines content, and the output is the parameter of interest, i.e., the relative density (D_r).

*******Figure 6.*******

The conveying function of the neuron was chosen as Purelin for the output layer and Sigmoid in the middle layer. Different networks with various neurons in the hidden layer were trained and the optimum neurons were chosen according to the error levels in the try and error process of training the network. Algorithms of Bayesian-regularization and Levenberg Marquardt were used for overfitting decreasing and training actions, respectively (Beeravelli et al. 2018; Gorgani et al. 2019). Overfitting occurs when an algorithm accurately predicts the data used in the training of the algorithm, but performs poorly for the data sets outside of the training set. In the Bayesian-regularization algorithm, the training is stopped when the error corresponding to the training and testing data sets is the least possible (García-Díaz et al. 1992; Ahmadi and Shybt 2020; Salazar et al. 2020; Golmohammadi et al. 2014). To develop a reliable network, the 292 data of the study were randomly divided into three sets: training, validation and testing sets. The ratios considered in the separation are 70% of train (204 data), 15% of validation (44 data), and 15% of test (44 data). The training set was used to train the algorithm. The validation set was used to ensure that the network is not highly dependent on the training data sets, hence preventing overfitting. The testing set was not used during the training, and was reserved to test the network robustness in predicting new data (Ansari and Hashemi 2017).

Figure 8 depicts the error of the network associated with training, validation and testing data sets for different epoch numbers. As the number of epochs increases, the error of all data sets decreases, until a point is reached where the error of the validation data set starts increasing.

This indicates that overfitting is likely to occur after this point, as also indicated by a slight increase in the error of the test data set after epoch number 6. Hence, the optimum number of epochs was deemed 6 for the network of this study, and the training process was stopped at this epoch number (Fig. 7).

*******Figure 7.*******

To avoid adverse effects of very large or extremely small values of input variables on the network weights, all input data are first normalized using Equation 7, so that they fall between -1 and 1,

$$X_i = 2\left(\frac{X - X_{\min}}{X_{\max} - X_{\min}}\right) - 1 \quad (7)$$

The precision of the estimated relative density based on the optimum neural network tested by computing the R^2 and root mean square error (RMSE) index which is calculated as follows,

$$RMSE = \frac{1}{s^2 n} \sum_{i=1}^n (y - y')^2 \quad (8)$$

in which y is the measured Dr , y' is the estimated Dr by the model, n is the total number of data and s^2 is the sample variance.

The statistical parameters when various hidden layers are used in the network are presented in Table 7. From this result, the model with 2 hidden layers was selected as the optimum model since no meaningful improvement is observed in the predictions for higher number of hidden layers. The correlation between the measured data and the results of this optimum model for the training, validation, testing, and entire data sets are illustrated in Fig. 8.

*******Table 7*******

*******Figure 8.*******

For comparison, Figure 9 presents the estimated (using the neural network method) versus measured (experimental results) values of the relative densities for all the test data. The coefficient of determination for the estimated values using the neural network approach is $R^2=0.90$ (Fig. 10).

*****Figure 9.*****

5.2. Relative density estimation using multiple linear regression(MLR)

Using the statistical package for the social sciences (SPSS), version 21, the MLR analysis was also used to develop a relationship between the relative density, $N_{1(60)}$ and fines content. The most common way for constructing a MLR model is the step by step (Namdar and Sarabiyan 2020; Radhy 2019) method which has been adopted in this study. In this approach, the first independent variable, which has the maximum effect on dependent variable, is selected and the regression model is developed accordingly. The other potential independent variables are then added to the regression model one by one to examine if they can meaningfully influence the regression model or not (decided by performing a T-test). The regression model gradually improved by inclusion of more relevant independent variables.

Such a regression analysis was performed on the data of this study, resulting in the following relationship:

$$Dr = 1.45N_{1(60)} - 0.17FC + 45.60 \quad (9)$$

where, FC is the fines content (%), and Dr is the relative density in %. Beta coefficients, which express the relative effect of each independent variable on the predictions in terms of standardized data, were obtained for both independent variables of this study as presented in Table 8. The results indicated that $N_{1(60)}$ has a higher effect on the relative density than fines content.

*****Table 8*****

The F -ratio in the one way analysis of variance (ANOVA) test shows that the $N1_{(60)}$ and FC statistically significantly predict the D_r variable, $F(2, 289) = 1063$, $p < .005$ (i.e., the MLR model is an accurate fit of the variables). I.e., the model with 0.95% confidence is significant and based on available data this model is able to express relative density changes.

The significant level (Sig.) in the T-test (the Test of the presence of independent variables in the model) in Table 8 indicates the effect of the coefficient of each independent variables and the constant on the equiton. A value less than 0.05 (Sig.<0.05) indicates that the coefficient is statistically significantly different to zero and the corresponding variable has a meaningful effect on the regression model and must be entered into the model. As can be seen from Table 8, the Sig. values of both independent variables are less than 0.05, hence, both the selected independent variables are suitable for estimating the relative density. This is in agreement with the analysis presented in Fig. 5, as discussed earlier in the paper.

The errors or residuals are the difference between the real and the predicted values using the equation of regression. There is no chance for using the regression equation, if the error is correlated with each other. If the Durbin-Watson (DW) statistic is in a range of 1.50-2.5, the residuals are not correlated (Montgomery et al. 2012). The DW statistic for multiple regression developed in this study was obtained 1.82 as presented in Table 8, hence, the assumption of independence of errors was fulfilled in this analysis.

The collinearity suggests that two predictors are a complete linear combination of each other. As the value of collinearity increases, the error in estimating the coefficients of the equation increases. To check the multicollinearity of independent variables, the concept of “tolerance” of independent variables are used. The tolerance of each independent variable is obtained as follows,

$$\text{Tolerance} = 1 - (R_j)^2 \quad (10)$$

where, R_j^2 is the coefficient of determination of the regression model with the j th descriptive variable as the dependent variable and other descriptive variables as independent variables.

The tolerance of each independent variable is a measure of its influence on the predications that is not captured by other independent variables, therefore very small tolerance values for a predictor show that the predictor is superfluous, and perhaps a function of other independent variables. Often when the tolerance of an independent variable is less than 0.10, further checks are needed to investigate if that independent variable can be removed or not. Low tolerances indicate that the influencing parameters are not properly captured, hence the model may not be reliable (Namdar and Sarabiyan 2020; Radhy 2019). It is worth mentioning that the invese of the Tolerance, which is called the variance inflation factor (VIF), is also used in the literature to check the multicollinearity of independent variablbs. In the regression model developed in this study the tolerance values for inputs are higher than 0.10 and the VIF values are lower than 10, and therefore, multicollinearity does not cause any problems in this MLR (Table 8).

Fig. 10 shows that the supposition of normality of residuals is fulfilled in the regression developed in this study.

*****Figure 10.*****

Figure 11 shows the developed relationship along with all the data of this study.

*****Figure 11.*****

5.3. Comparission with previous relatinships

In this section, several well stablshed relationships in the literature for prediction of soil relative density based on the SPT number is adopted to see how well they can predict the relative

density of the soil of interest compared to the relationships developed in this study. The RMSE and R^2 are used to evaluate the performance of each model. The models adopted for evaluation are as follows:

Mujtaba et al. model: Mujtaba et al. (2017) presented the following model to estimate the relative density in SP-SM soils based on, N_{60} , atmospheric pressure (kPa), and effective stress (kPa).

$$D_r(\%) = 1.96N_{60} - 19.2 \left(\frac{P_a}{\sigma_v'} \right)^{0.23} + 29.2 \quad (11)$$

Gibbs and Holtz model: Gibbs and Holtz (1957) presented the following relationship to estimate the relative density (%) using the effective overburden stress (psi) and SPT-N for sandy soils,

$$D_r = \sqrt{\frac{SPT-N}{1.7(10+\sigma_v')}} \quad (12)$$

Meyerhof model: Meyerhof (1956) proposed a relationship similar to the Gibbs and Holtz [41] relationship between the relative density (%), SPT-N and effective overburden stress (psi) for sandy soils in the form of Eq. (13).

$$D_r = \sqrt{\frac{SPT-N}{(17+24\frac{\sigma_v'}{98})}} \quad (13)$$

Yoshida model: Yoshida (1988) suggested a relationship between the relative density (%), N_{60} and effective overburden stress (kPa) for sandy soils in the form of Eq. (14).

$$D_r = 25N_{60}^{0.46} \sigma_v'^{-0.12} \quad (14)$$

Kibria and Masood model: Kibria and Masood (1998) presented Equation (15) to estimate the relative density in SM soils based on, $N_{1(60)}$.

$$D_r = 16.5\sqrt{N_{1(60)}} \quad (15)$$

All these models were adopted to estimate the relative densities for the data of this study. The results are shown in Figure 12 for Mujtaba et al. model and Gibbs and Holtz (1953) model, in Figure 13 for Meyerhof model and Yoshida and Ikemi model and in Figure 14 for Kibria and Masood model and the model presented in this study. The results show that except for the Kibria and Masood model, the rest of the correlations perform poorly for the soil of this study. The Kibria and Masood model is a crude model which does not include the very important effect of the existing effective stress in estimation of the relative density. Hence, the good performance of this model for the data of this study is, at least in parts, coincidence. Figures 12 to 14 shows that the correlation proposed in this study outperforms all other tested models for the data of this study.

*****Fig. 12*****

*****Fig. 13*****

*****Fig. 14*****

Finally, comparing the ANN results with the MLR results, the ANN manifests a higher value of the coefficient of determination and a lower value of the RSME ($R^2=0.90$ and $RSME=4.03$ seen in Fig. 9) compared to those of the MLR analysis ($R^2=0.88$ and $RSME=4.50$ seen in Fig. 14), indicating the superiority of the neural network approach.

6. Conclusions

Multiple regression analysis and neural network approach were adopted to develop relationships for estimation of the relative density using SPT in a sandy soil. The procedures of identifying the independent variables, constructing the relationships and checking their validity

were explained in details. In particular, the treatment of the effect of suction when the SPT test is performed in the vadose zone was explained, an aspect which is often overlooked in the literature. The relationships obtained were tested against several well established models in the literature for estimation of the relative density from SPT results for the data of this study. The comparisons showed that the locally developed models outperformed the established models in the literature. In particular, some established relationships in the literature performed very poorly in estimation of the relative densities for the soil of interest. Between the two approaches adopted, the neural network yielded better results than the multivariate regression for prediction of the soil relative density. The results indicate that when high accuracies are needed, relationships that are particularly developed for a region of interest must be developed as they can be much more accurate than the established relationships.

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TABLE

Table 1

Equation	Remarks	References	Soil type
$D_r(\%) = 1.96N_{60} - 19.2 \left(\frac{p_a}{\sigma_v'} \right)^{0.23} + 29.2$	σ_v' is effective overburden stress in kPa, p_a is atmospheric pressure in kPa, N_{60} is corrected N values for 60 percent of energy	[34]	sandy soils
$D_r(\%) = \sqrt{\frac{SPT - N}{1.7(10 + \sigma_v')}}}$	σ_v' is effective overburden stress in psi, SPT-N is raw SPT number	[41]	clean sands
$D_r = \sqrt{\frac{SPT - N}{(17 + 24 \frac{\sigma_v'}{98})}}$	σ_v' is effective overburden stress in kPa, Dr is in fraction, SPT-N is raw SPT number	[6]	for clean sands
$D_r = \sqrt{\frac{N_{1(60)}}{C_P C_A C_{OCR}}}$	$N_{1(60)}$, is normalized N_{60} to overburden stress, Dr is in fraction, C_P , C_A and C_{OCR} are correction factors for grain size, aging and over-consolidation	[35]	-
$D_r(\%) = 25N_F^{0.46} \sigma_v'^{-0.12}$	σ_v' is effective overburden stress in kPa, N_F is field SPT-N	[5]	for sand
$D_r(\%) = \sqrt{\left[\frac{N_F \left(0.23 + \frac{0.06}{D_{50}} \right)^{1.7}}{9} \left(\frac{98}{\sigma_v'} \right) \right] * 100}$	N_F is field SPT-N, D_{50} is median grain size in millimeter, σ_v' is effective overburden stress in kPa	[43]	granular soil
$D_r(\%) = 16.5 \sqrt{N_{1(60)}}$	$N_{1(60)}$, is normalized N_{60} to overburden stress, Dr is in percentage	Kibria and Masood (1998)	silty sands
$D_r = \sqrt{\frac{N(e_{max} - e_{min})^{1.7}}{9} \left(\frac{98}{\sigma_v'} \right)^{1/2}}$	Dr is in fraction, σ_v' is effective overburden stress in kPa, N is raw SPT number	[44]	sandy soils

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Table 2

Correction Factor	Equipment Variable	Typical value
C_E : the energy ratio for hammer type	Donut Hammer	0.5 to 1.0
	Safety Hammer	0.7 to 1.2
	Automatic Hammer	0.8 to 1.5
C_B : the correction factor of the borehole diameter	65 – 155 mm	1
	150 mm	1.05
	200 mm	1.15
C_S : the correction factor of the sampler	Standard Sampler	1
	Non-Standard Sampler	1.1 to 1.3
C_R : the correction factor of the drilling rod length	3 – 4 m	0.75
	4 – 6 m	0.85
	6 – 10 m	0.95
	> 10 m	1

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Table 3

e_{min}	e_{max}	Cu	Cc	PL (%)	PI (%)	Specific Gravity	Unit weight (kN/m^3)	Minimum dry unit weight (kN/m^3)	Maximum dry unit weight (kN/m^3)
0.45	0.80	2.2	1.3	71	6	2.67	17.1	13.6	17.7

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Table 4

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Parameters	Min.	Max.	Mean	Std. Deviation
FC	6	72	23.36	18.32
$N_{1(60)}$	6	48	18.15	6.28
Dr	45	100	67.84	13.00

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Table 5

<i>Ground water level</i>	<i>Depth (m)</i>	<i>Overburden Stress (kPa) Total</i>	<i>Effective Overburden Stress (kPa)</i>	<i>Fines Content (%)</i>	<i>Soil type</i>	<i>Unit weight (kN/m³)</i>	<i>N</i>	<i>C_E * C_B * C_S * C_R</i>	<i>CN</i>	<i>N₁₍₆₀₎</i>	<i>Relative Density (%)</i>	<i>D₅₀ (mm)</i>
<i>4.1m</i>	2	33.0	33.0	24	Sand	16.5	24	0.75	1.70	31	95.0	2.0
	3.5	57.8	61.82	24	Sand	16.5	14	0.79	1.24	14	69.5	2.0
	5	82.5	73.67	24	Sand	16.5	13	0.9	1.15	14	65.0	2.0
	6.5	107.2	83.71	24	Sand	16.5	15	0.95	1.08	15	66.7	2.0
	8	132.0	93.75	24	Sand	16.5	17	0.96	1.02	17	68.3	2.0
	9.5	159.6	106.65	12	Sand	18.7	11	0.97	0.96	10	56.8	0.2
	11	187.7	119.99	12	Sand	18.7	10	0.98	0.9	9	53.2	0.2
	13	226.1	138.82	27	Sand	19.5	17	0.99	0.84	14	62.5	2.0
	14.5	255.3	153.36	27	Sand	19.5	11	0.99	0.80	9	51.7	2.0
	16	284.6	167.9	27	Sand	19.5	14	1.00	0.76	11	55.1	2.0
	17.5	311.4	180.04	34	Sand	16.5	14	1.00	0.74	10	54.0	0.1
	19	336.2	190.08	34	Clay	17.0	24	1.00	0.72	17	65.3	0.01
	23	402.2	216.85	34	Clay	17.0	28	1.00	0.67	19	66.7	0.01
	24.5	427.6	227.54	16	Clay	17.0	35	1.00	0.66	23	72.4	0.01

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Table 6

[6]			[24]		
SPT N	Soil packing	Present study	SPT N	Soil packing	Present study
<4	Very loose		<2	Very loose	
4-10	Loose		2-4	Loose	
10-30	Compact	N=18	4-8	medum	
30-50	Dense		8-15	Dense	
>50	Very Dense		15-30	Very Dense	N=18
			>50	Extremely dense	

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Table 7							
Hidden Layer	1	2	3	5	7	9	10
R Square Training	0.88	0.90	0.90	0.90	0.90	0.88	0.92
R Square Validation	0.87	0.90	0.94	0.96	0.94	0.94	0.90
R Square Test	0.90	0.92	0.92	0.92	0.90	0.92	0.88
R Square Total	0.88	0.90	0.90	0.90	0.90	0.90	0.90
RMSE Training	0.17	0.15	0.15	0.15	0.15	0.15	0.13
RMSE Validation	0.14	0.16	0.11	0.11	0.11	0.13	0.14
RMSE Test	0.17	0.13	0.14	0.13	0.16	0.13	0.17

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Table 8

R ²	DW	Anova results		Model coefficient	Unstandardized Coefficients		Standardized Coefficients	T-test	Sig.	Collinearity Statistics	
		F	Sig.		Mean	Std. Error	Beta			Tolerance	VIF
0.85	1.82	F		Constant	45.60	1.21		36.01	0.00		
				Coefficient of FC	-0.17	0.03	-0.129	-5.378	0.00	0.72	1.37
		1063	0.00	Coefficient of N1(60)	1.45	0.04	0.870	36.22	0.00	0.72	1.37

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(c)

Figure 1.

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Figure 2.

Figure 3.

Figure 4.

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Figure 8.

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Figure 10.

Figure 11.

Figure 12.

Figure 13.

Figure 14.