Correlation of Standard and Cone Penetration Tests for Sandy and Silty Sand to Sandy Silt Soil

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ABSTRACT

Standard Penetration Test (SPT) and Cone penetration Test (CPT) are the most commonly used in situ tests to delineate soil stratigraphy and determine the geotechnical engineering properties of subsurface soils. Several geotechnical design parameters of the soil are associated with the SPT. In contrast CPT is becoming increasingly more popular for site investigation and geotechnical design. It is very valuable to correlate the SPT N-value to CPT data (tip resistance and friction resistance) so that the available database of the field performances and property correlations with N-value could be effectively utilized. In this paper multiple linear regression (MLR) and symbolic regression (SR) were used to develop formulas that can predict N-value using CPT data for sand, sandy silt, and silty sand soils in Dubai, UAE. The developed MLR and SR formulas were tested using a different set of SPT-CPT data. It was concluded that using SR showed some improvement to the developed MLR model and those developed models can be used to predict N-value from CPT data with acceptable accuracy.

KEYWORDS: SPT, CPT, Correlation, Regression, Sand, Silt

INTRODUCTION

Standard Penetration Test (SPT) and Cone penetration Test (CPT) are the most commonly used in situ tests to delineate soil stratigraphy and determine the geotechnical engineering properties of subsurface soils. Several geotechnical design parameters of the soil are associated with the SPT. In contrast CPT is becoming increasingly more popular for site investigation and geotechnical design, especially in deltaic areas, based on the soil type and testing method. For many construction projects, it is common to use SPT for the preliminary soil investigation, whereas CPT is used for detailed soil investigation and construction quality control.

It is very valuable to correlate the SPT N-value to CPT data (tip resistance and friction resistance) so that the available database could be effectively utilized. Hence, many empirical relations have been established between the SPT N-values and CPT cone bearing resistances, q_c.

The main objective of this research is to propose formulas that can predict N-value from CPT data for sand, sandy silt, and silty sand in Dubai area.

PREVIOUS WORK

Most of the empirical correlations considered a constant value (n) of $n = \frac{qc}{N}$ and some other researchers proposed $n = \frac{qc+fs}{N}$ for different soil types as shown in table 1. Where q_c is the cone tip resistance, fs is the frictional resistance, and N is the SPT blow count.

Table 1: CPT-SPT relationships from literature [Shahri et al. (2014)]

Researcher (s)	Soil type	Proposed relationship
De Alencar Velloso (1959)	Clay and silty clay Sandy clay and silty sand Sandy silt Fine sand	$n=(q_c/N)=0.35$ $n=(q_c/N)=0.2$ $n=(q_c/N)=0.35$ $n=(q_c/N)=0.6$ $n=(q_c/N)=1.00$
Meigh and Nixon (1961)	Coarse sand Gravelly sand	$n=(q_c/N)=0.2$ $n=(q_c/N)=0.3\text{-}0.4$
Engineers Franki Piles (1960)	Sand	$n=(q_c/N)=1.00$
(From Acka, 2003)	Clayey sand	$n=(q_c/N)=0.6$
	Silty sand	$n=(q_c/N)=0.5$
	Sandy clay	$n=(q_c/N)=0.4$
	Silty clay	$n=(q_c/N)=0.3$
	Clays	$n=(q_c/N)=0.2$
Schmertmann (1970)	Silt, sandy silt and silt-sand mix.	$n=([q_c+f_s]/N)=0.2$
	Fine to medium sand, silty sand	$n=([q_c+f_s]/N)=0.3\text{-}0.4$
	Coarse sand, sand with gravel	$n=([q_c+f_s]/N)=0.5\text{-}0.6$
	Sandy gravel and gravel	$n=([q_c+f_s]/N)=0.8\text{-}1.0$
Barata et al., (1978)	Sandy silty clay Clayey silty sand	$n=(q_c/N)^*=1.5\text{-}2.5$ $n=(q_c/N)^*=2.0\text{-}3.5$
Ajayi and Balogun (1988)	Lateritic sandy clay Residual sandy clay	$n=(q_c/N)^*=3.2$ $n=(q_c/N)^*=4.2$
Chang (1988)	Sandy clayey silt Clayey silt, sandy clayey silt	$n=(q_c/N)^*=2.1$ $n=(q_c/N)^*=1.8$
Danziger and De Valleso (1995) * q_c/N (bar/30cm)	Silt, sandy silt and silt-sand Fine to medium sand, silty sand Coarse sand, sand with gravel Sandy gravel and gravel Silty sand	$n=([q_c+f_s]/N)=0.2$ $n=([q_c+f_s]/N)=0.3\text{-}0.4$ $n=([q_c+f_s]/N)=0.5\text{-}0.6$ $n=([q_c+f_s]/N)=0.8\text{-}1.0$ $n=(q_c/N)^*=7.0$
Danziger et al., (1998) * q_c/N (bar/30cm)	Sand Silty sand, Silty clay Clayey silt Clay, silt and sand mixtures Clayey sand and silty clay Sandy clay Clay	$n=(q_c/N)^*=5.7$ $n=(q_c/N)^*=5.0\text{-}6.4$ $n=(q_c/N)^*=3.1$ $n=(q_c/N)^*=1.0\text{-}3.5$ $n=(q_c/N)^*=4.6\text{-}5.3$ $n=(q_c/N)^*=1.8\text{-}3.5$ $n=(q_c/N)^*=4.5$
Emrem and Durgunoglu (2000)	Turkey soils	$n=(q_c/N)=\text{func}(D_{50})$
Acka (2003)	Sand Silty sand Sandy silt	$n=(q_c/N)=0.77$ $n=(q_c/N)=0.70$ $n=(q_c/N)=0.58$

Robertson et al. (1983) presented the q_c/N ratio as a function of mean grain size, 'D_{50}'. They proposed a soil behavior-type classification, giving q_c/N ratio for each soil classification zone based on cone penetration test with pore pressure measurement tests (CPTU, piezocone).

Ismael and Jeragh (1986) correlated CPT q_c values with SPT N-values for calcareous desert sands in Kuwait and compared their results with the values presented by Schmertmann (1970) for clean, fine to medium sands and slightly silty sands. Their proposed n- values were higher than those proposed by Schmertmann for clean, fine to medium sands and slightly silty sands. A close agreement of their test results in the form of q_c/N versus mean grain size 'D_{50}' where found when compared with the historical data of Robertson et al. (1983).

Danziger and de Velloso (1995) proposed a correlation between CPT and SPT for some Brazilian soils. Values found were in the same range obtained by Schmertmann (1970). Different types of correlation were tested, and a linear correlation was found better suited for practical applications. A general trend was obtained in a similar pattern of Robertson's curve (increasing n-values with increasing grain size).

Lunne et al. (1997) cited Jefferies and Davies (1993) who presented a soil classification chart estimating N-values. This new development considers qc by taking into account pore water pressure (u) and overburden stress (□' vo), using piezocone.

Akca (2003) proposed SPT-CPT correlation for United Arab Emirates Soils. Results of his study showed higher values of $n = \frac{qc}{N}$ when compared to values found in the literature. He explained that higher values are due to cementation, densification and Shelly structure or gravel layers in the United Arab Emirates soils.

Shahri et al. (2014) proposed a correlation between qc and N-value for various soil layers, particularly in clayey soils with significant clay content in an area in southwest Sweden. They proposed linear and power relationships to predict qc using N-value. The results of their study showed a good agreement with previous work by other researchers.

GEOLOGY OF THE UNITED ARAB EMIRATES

Rahman and Harris (1984) pointed out that the geotechnical environment of the United Arab Emirates (UAE) coastline owes its characteristics to some minor sea level changes, but more significantly, to the climate which is dominated by low precipitation, high evaporation and high ambient temperatures. These extremes have the following direct effects on the

Geology:

- Dunes, which remain mobile, owing to a lack of vegetation;
- Evaporate deposits which are caused by the precipitation of salts during evaporation of near surface groundwater;
- Gravel plains at the base of the mountains, resulting from rapid water runoff during the briefly rainy season.

DATA COLLECTION AND PROCESSING

This study was carried out using existing SPT-CPT pairs collected in Dubai, UAE. Data used in this study consisted of 66 CPT-SPT pairs for sand, sandy silt, and silty sand soils. Distance between each CPT-SPT pair ranged from 3 to 40m. The depth of the SPT-CPT pairs ranged from 3 to 9m. Water table was encountered in all CPT-SPT pairs between 0.9 to 5.5m below existing ground level. Soil was classified as sand, sandy silt, and silty sand using the collected samples of the SPTs and the soil behavior type (SBT) charts. Figure 1 shows Interpretation of CPT data in terms of Soil behavior type as proposed by Lunne (1997) and Robertson (2009). It can be noted that all data points have fallen in region five and six. Region five represents silty sand to sandy silt while region six represents clean sand to silty sand.

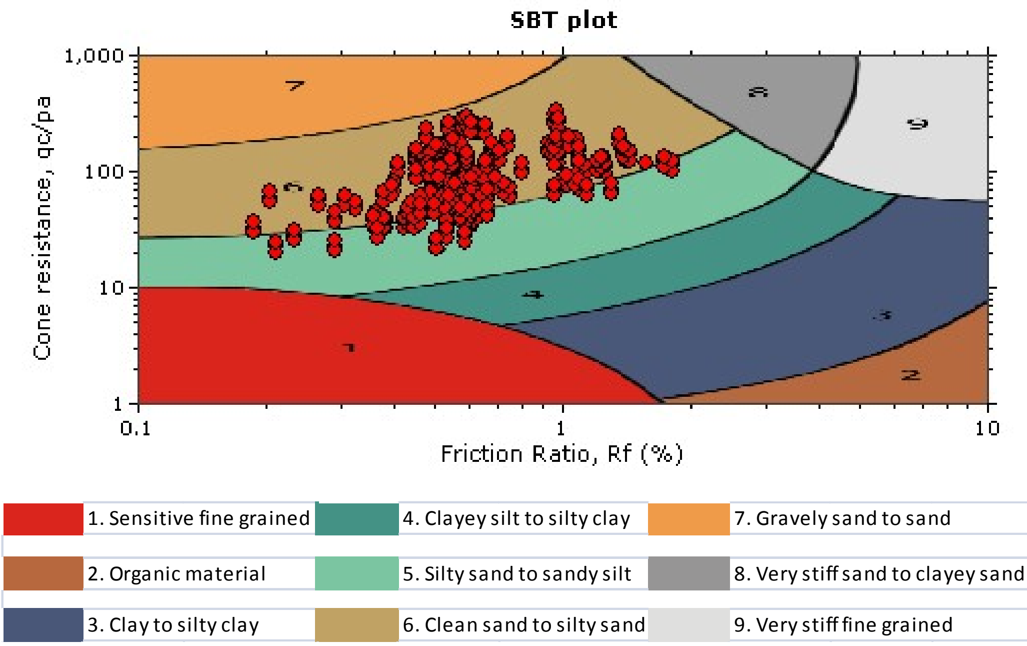

Figure 1: Interpretation of CPT data in terms of Soil behavior type (SBT)

Each CPT collects one reading every 0.02m while the SPT has one reading every 0.5m. Therefore, CPT results were averaged over 0.5m intervals. This average was compared with the SPT N-value located over the same depth range.

It is essential to normalize the N-values measured by any hammer to a standard rod energy ratio. Researchers show that the blow count in a given soil is inversely proportional to rod energy ratio (ERr) (Skempton, 1986). N-values measured with a known or estimated rod energy ratio (ERr) value can be normalized to this standard using N_{60} = N (ERr/60). Standard penetration tests were carried out using Pilcon-type hammer and trip release system. Skempton (1986) gave the rod energy ratio for different hammer types and release systems. Based on that, ERr ratio is 60% and ERr/60 ratio is 1.0. Therefore, N_{60} is the same as the measured N-value which can be used directly in the analysis.

Table 2 summarizes the mean, standard deviation, minimum, maximum, and range of the collected field data, calculated friction ratio R_f= (f_s/q_c) x100% and the n-value ($n=q_c/N$). It can be noted that the average n-value is 0.629. The average friction ratio for the collected CPT data is 0.6%. It should be noted that the friction ratio for clean sand is about 0.5% and it increases as soil grains becomes finer.

Table 2: Data statistics

Variable	Mean	Standard Deviation	Min.	Max.	Range
N-value	15.6	13.64	2	50	48
Tip resistance q_c (MPa)	10.2	9.095	0.32	37.49	37.17
Sleeve friction f_s (MPa)	0.074	0.11	0.001	0.583	0.582
Friction ratio (R_f %)	0.6	0.346	0.08	1.76	1.68
Effective stress (kPa)	42.1	22.0	7.66	123.3	115.64
Depth of collected data (m)	3.16	1.81	0.5	9	8.5
$n=q_c/N$	0.629	0.21	0.31	1.09	0.78

DATA ANALYSIS AND RESULTS

A comprehensive statistical analysis was carried out to develop models that can predict N-value using the collect CPT-SPT data. Definitions and ranges of variables used in this study are provided in Table 1.

Multiple Linear Regression (MLR) Model to Predict N-value

Analysis was carried out to develop MLR model that better predict the N-value. MLR analysis is a well-known approach which identifies the relationship between a set of dependent and independent variables using statistical methods. The relations between the dependent variable and number of independent variables are in the form:

$$Y_i = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + \ldots + a_kX_k + \varepsilon_i \qquad (1)$$

where, for a set of "*i*" successive observations, the predicted variable *Y* is a linear combination of an offset "a_0", a set of "*k*" predictor variables "*X*" with matching "*a*" coefficients, and a residual error ε. The "*a*" values are commonly derived via the procedure of ordinary least squares. When the regression equation is used in predictive mode, ε (the difference between actual and predicted values not accounted for by the model) is omitted because its expected value is zero.

It should be noted that in equation 1, "Y" represents the N-value which is denoted as N. While X represents the independent variables (q_c, effective stress, f_s, friction ratio (R_f %), and depth at which data collected).

A stepwise MLR analysis was performed to identify the important independent variables that affect the prediction of the N-value. A Stepwise Iteration (SI) procedure was used where the termination of the independent variables elimination process is based on the t-test and F-test outcomes. The stepwise regression analysis combines the forward and backward stepwise regression methods. It fits all possible simple linear models and chooses the one with the largest F-test statistic value. At each step, a variable is removed if its significance value falls below the threshold. Elimination of insignificant variables gives more accurate forecasts according to Sonmez and Rowings (1998). The process is completed when no more variables outside the model have the required significance level to enter. However, at each stage of the procedure the deletion of early selected independent variables is permitted. In order to eliminate the insignificant variables, the regression statistics used are significance level (P value less than 0.05) and the coefficient of determination (R2).

The adequacy of the developed models was assessed in this study using the coefficient of determination, R2, mean square error, and the standard error of estimate. The R2 represents the proportion of variation in the dependent variable that is accounted for by the regression model and has values from zero to one. If it is equal to one, the entire observed points lie on the suggested least square line, which means a perfect correlation exists. In addition, the mean standard square error of estimate measures the accuracy in the predicted values. It was found that Rf% and depth are statistically insignificant in the regression model. Three regression models were developed as shown in Tables 3 and 4.

Table 3: Significance of Variables in Each MLR Model

Model		Unstandardized Coefficients		Standardized Coefficients	t	P-value (Significance)
		a	Std. Error	Beta		
1	(Constant)	3.465	0.72		4.812	0.0001
	Tip resistance q_c (MPa)	1.227	0.053	0.892	23.244	0.0001
2	(Constant)	1.258	1.038		1.212	0.228
	Tip resistance q_c (MPa)	1.176	0.054	0.855	21.599	0.0001
	Effective Stress	0.065	0.022	0.114	2.886	0.005
3	(Constant)	1.59	1.027		1.549	0.124
	Tip resistance q_c (MPa)	0.993	0.09	0.722	11.019	0.0001
	Effective Stress (kPa)	0.069	0.022	0.122	3.124	0.002
	Sleeve friction f_s (MPa)	18.185	7.229	0.16	2.516	0.013

Table 4: MLR Models Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Mean Square Error
1	0.892[a]	0.797	0.795	5.66	32.03
2	0.899[b]	0.808	0.805	5.52	30.42
3	0.904[c]	0.817	0.813	5.41	29.28

a. Predictors: (Constant), q_c
b. Predictors: (Constant), q_c, Effective Stress
c. Predictors: (Constant), q_c, Effective Stress, f_s

Table 5: Developed formulas to predict N-value using Symbolic Regression

No.	Formula	R^2	Mean Square Error	Std. Error of Estimate
1	$N = 36.2 fs + \frac{54.5 qc}{27.3 + qc}$	0.829	25.109	3.379
2	$N = 0.517 fs Sv' + \frac{48.5 qc}{21.2 + qc}$	0.828	25.235	3.289
3	$N = 36 fs + \frac{Sv' + 53.2 qc - 39.5}{26.4 + qc}$	0.837	23.875	3.285
4	$N = 1.76 qc + qc fs + 0.00698 qc Sv' - 0.0415 qc^2$	0.836	24.082	3.222
5	$N = 1.91 qc + 1.72 qc fs + 0.00612 qc Sv' - 0.0534 qc^2$	0.839	23.591	3.154
6	$N = 1.84 qc + 0.00719 qc Sv' + 0.0468 fs qc^2 - 0.0487 qc^2$	0.832	24.651	3.137

Sv': the effective stress in kPa, q_c: tip resistance in MPa, N: Blow count number, f_s: Sleeve friction in MPa,

Table 3 provides the standardized and the unstandardized regression coefficients resulting from the stepwise procedure, these coefficients are the weights used for the independent variables in the prediction model.

Model 3 has the highest adjusted R2 value equal to 0.813, the least standard error of estimate (5.41), and the least mean square error. This model included the variables: tip resistance (qc), effective vertical stress, and sleeve friction (fs). As summarized in Table 3, MLR model 3 is presented in equation 2 as follows:

$$N = 1.59 + 0.993 q_c + 0.069\ Effective\ Stress + 18.185\ f_s \qquad (2)$$

Table 4 shows the change in the R2 values for all the MLR models. The R2 value increases with the addition of terms to the regression model. The amount of change in R2 is a measure of the increase in predictive power of a particular independent variable or variables, given the independent variable or variables already in the model. It can be noted that qc has the highest effect on the adjusted R2 value.

Symbolic Regression (SR)

To further optimize and improve the developed model that predicts N-value, symbolic regression analyses were carried out. SR is a powerful machine learning modeling technique introduced by John Koza (1991). SR develops models when the underlying physical relationships between input and output data can't be abstracted. Moreover, it provides a direct insight into the underlying process structures, as well as making accurate numeric predictions compared to the empirical values.

Symbolic regression (Koza, 1992) is a method for searching the space of mathematical expressions, while minimizing various error metrics. Unlike traditional linear and nonlinear regression methods that fit parameters to an equation of a given form, symbolic regression searches both the parameters and the form of equations simultaneously. This process automatically forms mathematical equations that are amenable to human interpretation and help explicate observed phenomena.

SR is one of the most popular applications of genetic programming and an attractive alternative to standard regression approaches due to its flexibility in generating free form mathematical models from observed data without any domain knowledge. Indeed, user-friendly genetic programming based symbolic regression (GP-SR) tools such as Eureqa (Schmidt and H. Lipson 2009) have started to gain more attention from the scientific community over the few years.

A Genetic Programming (GP) package Eureqa was used to regress functional relationships to predict N-value using qc, fs, and effective stress. Eureqa uses symbolic regression to find an analytical solution to explain experimental data. The input for Eureqa, the symbolic regression toolbox used in this study, consists of a set of input variables along with the corresponding experimental results. Additionally, mathematical operators are specified that shall be used in the equation. Several combinations of operators and variables are then generated by a genetic algorithm to find a suitable approximation in form of a symbolic equation. Derived equations are rated for their complexity and fit.

Table 5 presents the results of the symbolic regression analysis. It can be noted that six models were developed to predict N-value using qc, fs, and effective stress. Those models showed some improvement when compared to the developed MLR model. R2 values for those models ranged from 0.828 to 0.839, a slight improvement is shown when comparing those values to the R2 value of the MLR model which is 0.813. Mean square error ranged from 23.591 to 25.235, a good improvement is shown when compared to 29.28 for the MLR model. Standard error of estimate ranged from 3.137 to 3.379, a good improvement is shown when compared to 5.41 for the MLR model. It can be concluded that using the SR improved the developed MLR model.

VERIFICATION OF THE DEVELOPED MODELS

To secure a higher reliability of the developed models, a different set of SPT-CPT data were used to predict N-value using the MLR model and the SR models. CPT data of 4 CPTs were used to predict N-value at different depths ranging from 0.3 to 4.5m. Predicted N-values were compared to the field N-value. Table 6 presents the ratio of N-field to N-predicted using the developed model. The table also presents the minimum, maximum, range and the average ratios. It can be noted that the developed models under predicted the N-value by (13% to 59%) and over predicted the N-value by (41% to 147%). SR Model-1 has the lowest range of prediction (1.0) while the SR Model-4 has the highest range of prediction (1.6). When comparing the average of the ratios, MLR model has the best prediction ratio (1.02) while SR model-4 has the highest average (1.49). To get better results, it is important to use the model with the lowest range of prediction which is SR model-1. However, SR model-5 and 6 showed low ranges of

1.02 and 1.04, respectively. It can be concluded that the using SR showed some improvement to the developed MLR model and those models can be used to predict N-value satisfactorily from CPT data.

Table 6: Verification of the developed models using different data set

	N-Field/ N-Predicted						
	MLR Model	Symbolic Regression Models					
		Model-1	Model-2	Model-3	Model-4	Model-5	Model-6
	0.94	1.41	1.37	1.24	1.96	1.31	1.30
	0.97	0.93	1.00	1.10	1.24	1.05	1.08
	0.86	1.02	1.04	1.14	1.32	1.09	1.11
	0.82	1.10	1.12	1.14	1.47	1.18	1.20
	0.71	1.05	1.05	0.98	1.30	0.97	0.97
	0.76	1.03	1.03	0.96	1.43	0.99	0.99
	1.24	0.85	1.03	1.09	1.21	1.09	1.15
	1.20	1.31	1.30	1.72	1.63	1.43	1.47
	0.72	0.89	0.89	1.08	1.13	0.97	0.99
	0.90	0.56	0.88	0.85	1.07	0.85	0.88
	0.68	0.41	0.69	0.66	0.87	0.67	0.69
	1.05	0.61	1.07	1.00	1.54	1.00	1.00
	1.74	1.13	1.72	1.72	2.30	1.62	1.66
	1.26	1.15	1.25	1.58	1.56	1.40	1.46
	0.78	1.25	1.19	2.07	1.52	1.34	1.37
	1.88	1.40	1.78	1.79	2.16	1.69	1.73
	0.99	0.61	1.02	1.00	1.37	1.00	1.00
	0.90	0.53	1.00	0.99	1.71	1.10	1.02
	1.13	0.68	1.28	1.30	2.47	1.46	1.29
	0.91	0.59	0.79	0.74	0.91	0.81	0.88
	0.88	0.84	0.84	1.08	1.04	0.91	0.93
	0.87	0.52	0.94	0.91	1.26	0.99	0.96
	0.93	0.61	0.94	0.93	1.16	0.88	0.87
	1.57	1.20	1.53	1.54	1.91	1.42	1.43
	0.82	0.50	0.90	0.93	1.69	0.98	0.89
Min.	**0.68**	**0.41**	**0.69**	**0.66**	**0.87**	**0.67**	**0.69**
Max.	**1.88**	**1.41**	**1.78**	**2.07**	**2.47**	**1.69**	**1.73**
Range	**1.20**	**1.00**	**1.09**	**1.41**	**1.60**	**1.02**	**1.04**
Average	**1.02**	**0.89**	**1.11**	**1.18**	**1.49**	**1.13**	**1.13**

CONCLUSIONS

This paper presented the results of a study that was conducted to assess the use of MLR and SR to develop models that can accurately predict N-value using CPT data.

A comprehensive statistical analysis was carried out to develop MLR model to predict N-value using CPT data such as: tip resistance, sleeve friction, and effective stress.

The developed MLR model was further optimized and improved using symbolic regression analysis. Six symbolic regression models were developed to predict N-value using tip resistance, sleeve friction, and effective stress. In those models, higher R2 values, lower mean square and standard errors were achieved.

To test the developed models, a different set of SPT-CPT data were used to predict N-value using the MLR model and the SR models. Predicted N-values were compared to the field N-value. It was concluded that using SR showed some improvement to the developed MLR model and those models can be used to predict N-value from CPT data with acceptable accuracy.

REFERENCES

[1] Akca, N. (2003) "Correlation of SPT–CPT data from the United Arab Emirates", Engineering Geology, 67, 219 –231.

[2] Danziger, F.A.B., M.S.S. Almeida, E. N. Paiva, L. G.F.S. Mello and Danziger, B.R. (1998) "The piezocone as a tool for soill stratification and classification". Proc. XI COBRAMSEG, Brasília, v. 2, pp. 917-926.

[3] Danziger, B.R. and D. A. Velloso (1995) "Correlations between the CPT and the SPT for some Brazilian soils", Proc. CPT'95, Linkoping, v. 2, pp. 155-160.

[4] Lunne, T., P. K. Robertson and J. J. M. Powell (1997) "Cone penetration testing in geotechnical practice", Blackie Academic, EF Spon/Routledge Publ., New York, 1997, 312 pp.

[5] Ismael, N.F., Jeragh, A.M. (1986) "Static cone tests and settlement of calcareous desert sands", Canadian Geotechnical Journal, 23 (3), 297– 303.

[6] Koza, J. (1991), "Evolving a computer program to generate random numbers using the genetic programming paradigm," in Proceedings of the Fourth International Conference on Genetic Algorithms, Morgan Kaufmann, La Jolla, CA.

[7] Koza, J. (1992), "Genetic Programming: On the Programming of Computers by Means of Natural Selection". The MIT Press.

[8] Rahman, S.Z., Harris, R.W. (1984) "The nature and characteristics of the soils in the regions of Dubai and Abu Dhabi", Symposium on the nature and characteristics of oils in the UAE and Foundation Engineering, Dubai. No. 1, pp. 7– 17.

[9] Robertson, P. K., R. G. Campanella and A. Wightman (1983) "SPT-CPT correlations", Journal of the Geotechnical Engineering Division, ASCE, 109(11), 1449-1459.

[10] Robertson, P. K. (2009) "Interpretation of cone penetration tests- a unified approach", Canadian Geotechnical Journal, 46 (11), 1337– 1355.[11] Schmidt M.

and H. Lipson (2009), "Distilling free-form natural laws from experimental data," Science, vol. 324, no. 5923, pp. 81–85.

[12] Schmertmann, J. H. (1970) "Static cone to compute static settlement over sand", Journal of the Soil Mechanics and Foundations Division, ASCE, 96 (3), 1011-1043.

[13] Shahri, A.A, Juhlin, C. and Malemir A. (2014) "A reliable correlation of SPT-CPT data for southwest of Sweden", Electronic Journal of Geotechnical Engineering, 19, 1013-1032

[14] Skempton, A.W. (1986), "Standard penetration test procedures and the effects in sands of overburden pressure, relative density, particle size, aging and overconsolidation", Geotechnique, 36 (3), 425–447.

[15] Sonmez, R. and Rowings, J.E. (1998). "Construction Labor Productivity Modeling with Neural Networks." Journal of Construction Engineering and Management, Vol. 124, No. 6, pp. 498–504.