
# Correlation between Cone and Standard Penetration tests

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**Abstract**

Extensive application of CPT in recent years and SPT-based experience of soil behavior has brought to attention the importance of correlation between these tests. In this paper a review on available correlations has been carried out. Also influence of parameters such as friction ratio, pore water pressure, fines content and mean particle size on these correlations have been studied in detail. Employing a CPT-SPT database collected from two sites and using evolutionary regression method new correlations have been proposed. Although the new correlations do not provide a precise approximation of the $q_c/N_{60}$ ratio but considering the inherent variability of penetration tests and soil behavior, it presents a good estimation of this ratio.

**Key words:** SPT, CPT, Correlation, Penetration Tests, Regression

## 1 Introduction

The Standard Penetration Test (SPT) is one of the most commonly used in-situ tests for site investigation and foundation designs. Many empirical correlations have been created between the SPT N-value, and other engineering properties of soils. Although this test has disadvantages such as discrete strength measurement and dependence on operator and apparatus, but it is still the most popular and economic mean for subsurface investigation. On the other hand the Cone Penetration Test (CPT) is becoming progressively popular for its high ability to delineate stratigraphy of soil and assess soil properties rapidly and continuously. For many geotechnical projects, it is common to determine that the preliminary design based on soil parameters obtained from standard penetration tests, whereas the final design is based on cone penetration test results, or vice versa. Thus it is very valuable to find reliable CPT-SPT correlations so that available database of the test sites performances and property correlations with SPT N-value could be effectively used.

The artificial intelligence techniques have been applied in many scientific fields using large quantities of data. These methods have been successfully applied in geotechnical problems

while traditional and classical procedures are incapable of handling such cases (Goh 1999; Itani and Najjar 2000; Shahin, Jaksa et al. 2008). Evolutionary Polynomial Regression (EPR) is a new data-driven technique that has been widely utilized in environmental engineering, water management and lately in geotechnics (Doglioni, Giustolisi et al. 2008; Giustolisi, Doglioni et al. 2008; Rezania, Javadi et al. 2010; Rezania, Faramarzi et al. 2011).
The purpose of this study is to investigate the capabilities of EPR in prediction of correlations between the $q_c/N$ ratio and some of the other parameters associated with this ratio.

## 2 Previous works

Previous studies in this field are categorized in 4 groups according to the relationship form and variables used in the correlations, as summarized in table1. Most of the primary empirical correlations considered a constant value of $q_c/N$ for different soil types. Some others proposed constant values for $(q_c+f_s)/N$. New investigations suggested $q_c/N$ as a function of grain characteristic indices such as mean grain size or fines content.

| **Researcher(s)** | **Relationship** |
|---|---|
| Robertson et al. (1983) | $q_c/N$= fun($D_{50}$) |
| Seed & DeAlba(1983) | |
| Kulhawy & Mayne(1990) | |
| Stark & Olson(1995) | |
| Emrem et al. (2000) | |
| Muromachi (1981) | $q_c/N$= fun(FC) |
| Jamiolkowski et al. (1985) | |
| Kasim et al. (1986) | |
| Chin et al.(1988) | |
| Kulhawy & Mayne(1990) | |
| Jefferies & Davies (1993) | |
| Robertson (1986), | Soil classification chart with suggested $q_c/N$ ratio for each soil behavior type |
| Lunne et al.(1997) | |
| De Alencar Velloso(1959) | Suggested constant values for $q_c/N$ or $(q_c+f_s)/N$ in different soil types |
| Meigh & Nixon(1961) | |
| Franki Piles(1960) | |
| Schmertmann(1970 | |
| Barata et al.(1978) | |
| Ajayi & Balogun(1988) | |
| Chang(1988) | |
| Danziger & de Valleso(1995) | |
| Danziger et al.(1998) | |
| Akca( 2003) | |

Table1. Summary of previous SPT-CPT correlations

## 3 Evolutionary Polynomial Regression

Evolutionary Polynomial Regression (EPR) is a recently developed hybrid regression method that combines the best features of conventional numerical regression techniques with the genetic programming/symbolic regression technique. A general EPR expression can be presented as following

$$y = \sum_{i=1}^{n} F(X, f(X), a_i) + a_0 \tag{1}$$

where y is the estimated vector of outputs; $a_i$ is a constant; F is a function constructed by the process; X is the matrix of input variables; f is a general function selected by the user; and n is the number of terms of the target expression. The general functional structure represented by $f(X,a_i)$ is constructed from elementary functions by EPR using a genetic algorithm (GA) strategy. The input vectors are selected by GA. The building blocks (elements) of the structure are defined by the user based on understanding of the physical process .While the selection of feasible structures to be combined is done through an evolutionary process; the parameters $a_i$ are estimated by the least square method (Giustolisi and Savic 2006; Rezania, Faramarzi et al. 2011)**.**

# 4 Proposed Correlation

## 4.1 Database

Datasets for this study are selected from SPT-CPT pairs collected from Turkey and Taiwan. After the 1999 Chi-Chi earthquake($M_w$=7.6) and 1999 Kocaeli earthquake ($M_w$=7.4) in Turkey, an extensive field-testing program started for characterization of subsurface condition at sites where ground failure was or was not observed, which leaded to large database of in-situ tests.  Site characterization carried out through the application of the cone penetration testing (some with pore pressure and shear wave velocity measurements) and rotary wash borings with primarily standard penetration testing (with energy measurements with the SPT Analyzer). A total of 42 CPT in combination with 30 exploratory borings were performed in Adapazari, Turkey. Similar investigations in Taiwan completed with totally 98 CPT and 98 exploration borings performed in Wufeng, Yuanlin and Nantou sites. These tests were accomplished by sponsorship of Pacific Earthquake Engineering Research (PEER) with incorporation of local and global universities and institutes. Although other testing data were available even for these sites but energy measurement for SPT was the main reason for selection of these datasets in this study.

## 4.2 Data selection and preprocess

From the entire SPT and CPT tests introduced before, 48 SPT-CPT pairs were picked out for this study considering a reasonable distance between two tests locations and energy measurement in SPT as the main selection criteria. Considering accessibility of additional parameters like mean grain size (D50) and fines content (d<75μm), a total of 256 datasets provided. The selected datasets were obtained from tests in various soil types consisting of sand, clay and silt which were located in different depth from 1m to 15m. Figure.1 illustrates the soil type variation for the selected data. Representative data selection from CPT sounding was done in accordance to Douglas & Olsen's  method, averaging CPT measurements over 30cm of the adjacent SPT split-spoon sample's depth (Douglas and Olsen 1981). As SPT N values are mostly influenced by energy transferred from hammer to the sampler, the measured values were corrected to account for this energy ratio and then were normalized to the 60% energy by the simple equation(1) below suggested by Seed et al (Seed, Tokimatsu et al. 1985).

$$N_{60} = \frac{N_{field} * E.R}{60} \tag{2}$$

The resultant is then corrected for hammer type, rod length, borehole diameter and sampler's liner according to existing recommendations to standardize NSPT for different test conditions (Schmertmann 1978; Seed, Tokimatsu et al. 1985; Skempton 1986; Bowles and Guo 1996; Coduto 2001).

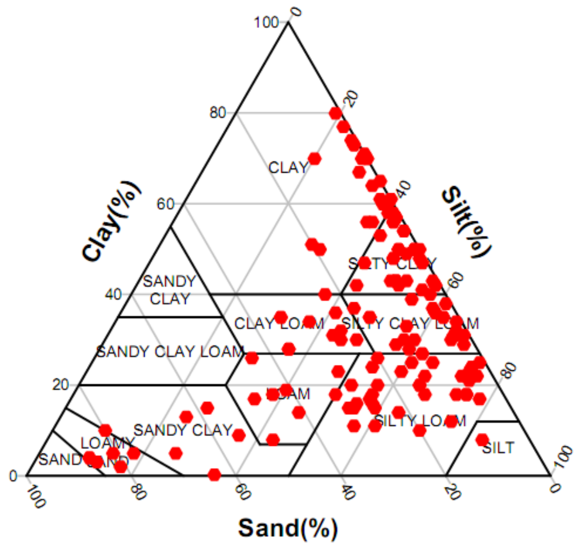


**Fig1.** Soil type distribution of database according to USDA

According to literature review there are three main parameters (F.C, $D_{50}$ & $R_f$ ) which may influence the qc/ N60 ratio. Therefore in this study these factors have been considered as independent variables and the n (=$q_c$/ $N_{60}$) as the dependent variable. Furthermore pore water pressure ($u_o$) have been also selected as an input variable since it seems to affect the n value. The aforementioned factors have been employed in diverse combinations to achieve the best combination assembly and also for evaluation of factors effectiveness in predicting n value. Since different soil types have been selected for this study, input and output parameter have a wide range of variation according to table 2. This wide range makes it difficult to present a unique and accurate relationship between inputs and outputs for all of the soil types. Therefore data divided into two main categories separating sand from silt and clay considering the 50% fines content as distinction criterion. Then data have been analyzed separately.

| Parameter | F.C(%) | $D_{50}$(mm) | $q_c$(kPa) | $R_f$(%) | $u_o$(kPa) | $q_c$/ $N_{60}$ (MPa/Blow counts) |
|---|---|---|---|---|---|---|
| **Min** | 3 | 0.01 | 70 | 0.056 | 0 | 0.0112 |
| **Max** | 100 | 9.5 | 30998 | 10 | 139.16 | 3.793 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Mean** | 58.837 | 0.695 | 4329.148 | 1.512 | 38.402 | 0.502 |
| **S. D.**[1] | 37.320 | 1.562 | 5304.058 | 1.233 | 27.118 | 0.449 |

Table 2.Statistics of the datasets

## 4.3 Regression analysis by EPR

The provided data were employed in the regression analysis by EPR code. Four various assemblies of the parameters are considered to reach the best correlation and also to study the parameters' effectiveness in prediction of n value. The first combination only consists of two factors (uo & Rf), while the other three also have mean grain size and fines content as the independent variables. A polynomial expression with ten terms and different functions, including logarithmic, Exponential, tangent hyperbolic and secant hyperbolic, were employed to obtain the best fit over the data.
For evaluation of the models performance in prediction of n three different statistical criteria have been chosen. Coefficient of Determination (R2), Root Mean Squared Error and Sum Square of Error are three main criteria for quantifying the models absolute and relative performance with respect to the others. Results of four models for each soil type have been summarized in tables 3. Although the correlation coefficients are less but there is no such statistical criteria for previous works in this field to be compared. It is clearly inferred from the results that increasing the input parameters improve model performance which show n value is influenced by many factors. Models number 2 and 3 in both soil types have almost identical performance which may show similar effects of fines content and mean particle size on n value prediction as opposed to conclusions made by previous works (Chin, Duann et al. 1988).

| Soil Group | Model No. | Inputs | Output | $R^2$ | RMSE | SSE |
|---|---|---|---|---|---|---|
| coarse grain soil | 1 | $R_f$, $U_0$ | $q_c/ N_{60}$ | 47.2 | 0.326 | 0.095 |
| | 2 | $R_f$, $U_0$, F.C | $q_c/ N_{60}$ | 52.2 | 0.310 | 0.088 |
| | 3 | $R_f$, $U_0$, $D_{50}$ | $q_c/ N_{60}$ | 52.1 | 0.310 | 0.088 |
| | 4 | $R_f$, $U_0$, F.C, $D_{50}$ | $q_c/ N_{60}$ | 59.7 | 0.283 | 0.072 |
| fine grain soil | 1 | $R_f$, $U_0$ | $q_c/ N_{60}$ | 43.2 | 0.333 | 0.101 |
| | 2 | $R_f$, $U_0$, F.C | $q_c/ N_{60}$ | 47.5 | 0.316 | 0.092 |
| | 3 | $R_f$, $U_0$, $D_{50}$ | $q_c/ N_{60}$ | 46.0 | 0.327 | 0.097 |
| | 4 | $R_f$, $U_0$, F.C, $D_{50}$ | $q_c/ N_{60}$ | 54.1 | 0.298 | 0.081 |

Table3. Models statistics

Models predictions in comparison to reference values have been illustrated in figure2. Scatter in data points is obvious but considering the inherent variability in both tests notably in SPT, it seems natural and acceptable. Overall model predictions are in good agreement with reference values. Furthermore mathematical relationship provided by EPR, which is its advantage over other computational intelligence techniques such as neural networks, could be utilized in spreadsheets. However these equations have not been presented in this paper because of their long terms.

[1] **S**tandard **D**eviation

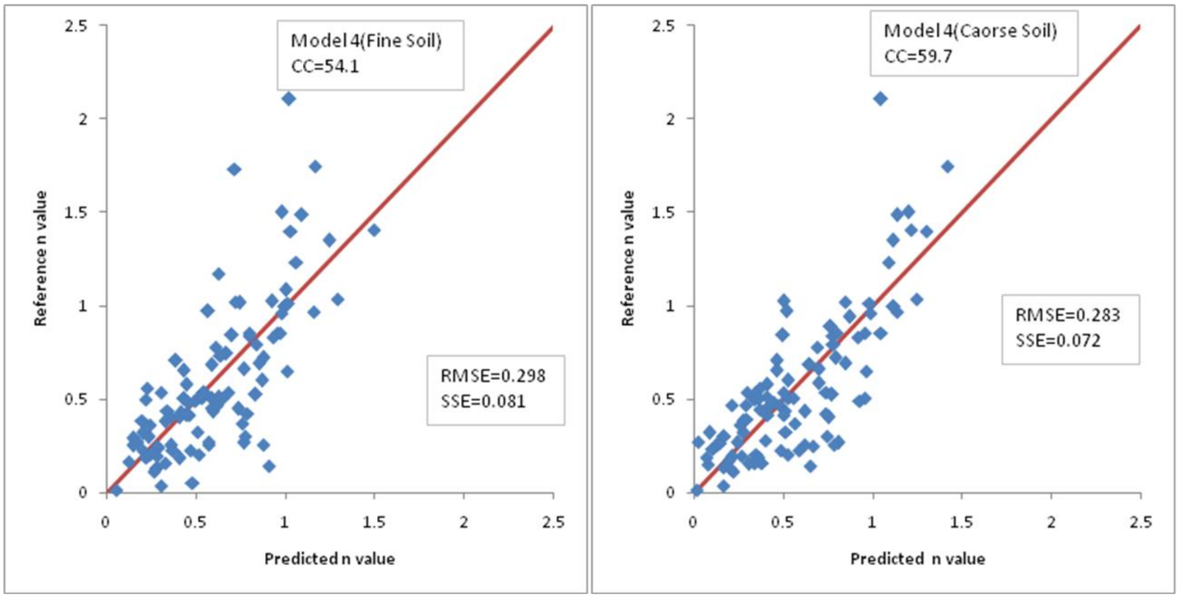


**Fig2.** n value prediction by EPR model with respect to reference values

## 5 Conclusion

Evolutionary polynomial regression have been successfully utilized for correlation between SPT and CPT results. This method introduces an attractive alternative to empirical relationships developed for SPT-CPT correlations. For practical purposes, the EPR models, presented in this study, for coarse and fine grain soils can be easily utilized in spreadsheets and provide results accurate comparing conventional empirical methods even though it is based on empirical data. Fines content and mean grain size showed identical effects on models performance in prediction of n value in both soil types. Using these parameters simultaneously improved the model performance considerably. Proposed models performance is overall good, although the correlation coefficients for all models are low which maybe because of structural heterogeneity of soil and inaccuracy involved in all in-situ tests.

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