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Development of Correlations between SPT-CPT Data for Liquefaction Assessment using R

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Abstract. This paper presents a method for selecting and processing the field data for correlation and comparison of standard penetration test – cone penetration test (SPT-CPT). The correlations of SPT-CPT were done using traditional and statistical methods. SPT, CPT field tests were used in conjunction with variety of borehole seismic testing for a number of locations to adapt traditional site research approaches to geotechnical earthquake engineering. The correlations between N_{60} of SPT and cone tip resistance q_c and other parameters of CPT data under liquefaction conditions, were developed using regression modelling. In this paper, the SPT-CPT correlations have been developed using different type of regression methods namely linear regression (LR), locally estimated scatterplot smoothing (LOESS), multivariate adaptive regression splines (MARS) and support vector machine (SVM). Correlation between N_{60} and q_c which was developed using support vector regression (SVR) model is giving 90.53% efficiency. Correlation which was developed between N_{60} and q_c taking other parameters of CPT data such as fines content and mean particle size D_{50} in SVR model is giving 99.99% efficiency. By using the above theses correlations, SPT N-value may be evaluated using CPT data. Predicted N_{60} values from these correlations are compared with measured N_{60} values from existing literature and seismic tests and it was found to be good.

Keywords: Liquefaction; Seismic; SPT-CPT data; Regression.

1 Introduction

Correlations are prevalent in the geotechnical engineering practice. This paper presents the application of machine learning for developing geotechnical correlations. In the realm of machine learning, multiple input variables of significance can be readily and coherently incorporated into the model. The methodology is presented in a general form to facilitate adaptation to other geotechnical correlations.

Empirical correlations are often utilized in geotechnical engineering to estimate the different engineering features of soils. In most cases, correlations are derived using statistics and data collected from field and laboratory tests bearing high importance.

Analysis of linear regression (LR), multivariate adaptive regression splines (MARS), support vector machine (SVM), artificial neural network (ANN) and locally estimated scatterplot smoothing (LOESS) are some of the techniques used in machine learning. Machine learning has the ability to create a model from the data and learn from the experience. Therefore, machine learning is more superior than the traditional modeling techniques.

SPT test is the better for the site investigation because its results are reliable and it costs less to carry out the tests. Many works have done in the advancement of CPT and various field tests as an alternative to SPT. CPT and SPT are destructive in-situ tests but CPT is less time taking test when compared with SPT and error percentage is more in SPT. Therefore, there is still a progressive need to develop more acceptable and highly reliable correlations between SPT-CPT data in order to use reliable and more acceptable CPT test data. To correlate the SPT N- value to static cone tip resistance (q_c), there have been ample number of empirically developed correlations.

In the present study, new SPT-CPT correlations were developed using various regression methods. A comparative analysis is presented among the used regression analysis techniques, namely Simple linear regression (SLR), Locally estimated scatterplot smoothing (LOESS), Multiple linear regression (MLR), Multivariate adaptive regression splines (MARS), Stepwise linear regression (SLR), and Support vector machine (SVM). The best method is suggested on the basis of the statistical study.

2 Review of literature

The soil liquefaction resistance can be estimated in laboratory. CPT and SPT are field methods for geotechnical design and investigation. Seed and Idriss (1971) had given the simplified procedure to estimate the soil liquefaction which depends on the cyclic stress ratio (CSR) which in turn depends on SPT blow numbers.

2.1 Existing SPT-CPT correlation works

There are some already proposed correlations having K_c ratio as (q_c/N_{SPT}) given by Schmertmann (1970), Lacroix (1971), Folque (1988), Danziger (1982), Ramaswami et al. (1982), Burland & Burbidge (1984), Viana da Fonseca (1996), Acka (2003), Mayne (2006), Ahmed et al. (2014), Shahri et al. (2014), Lingwanda et al. (2015).

2.2 Observation data used in SPT-CPT correlations

In this research, the site data of Hstina Power Plant in Taiwan is used (Chin et al. 1990). In order to prepare the preliminary design for two generator units, seven boreholes were drilled and eighteen CPTs were conducted. The level of water in ground is typically at 2.5m below the ground surface. Split spoon sampler is used and soil classified as SM. SPT tests were conducted by using a rope and cathead assembly to raise and drop donut type hammer having hammer efficiency of 55% while comparing kinetic energy computed from impact velocity to the theoretical free fall energy.

Table 1. Summary of correction factor used for computation of N_{55} in Taiwan

Corrections to account for	Hammer Energy Ratio (C_H)	Rod Length (C_R)	Sampler (C_S)	Borehole Diameter (C_B)
Parameter	Donut type hammer	10-30m	Standard sampler	65-115mm
Correction factor	1.0	1.0	1.0	1.0

Energy correction for SPT was considered for field SPT N-values (N_M) as:

$$N_{55} = N_M{*}C_H{*}C_S{*}C_B{*}C_R$$

$$N_{60} = (0.55{*}N_{55})/0.60$$

Cone penetration soundings were made using a Hogentogler type electronic cone. Tip resistance (q_c), skin fraction (f_s) and cone inclination were continuously recoded during penetration. A total of 35 data points of sand deposits were selected from this investigation. A summary of these field measurements and laboratory tests results are tabulated in Table 2, where *FR* is friction ratio and *FC* is fines content in %, depth of soil in meters, N_{55} SPT blow count for 55% hammer efficiency, N_{60} for 60% hammer efficiency.

Table 2. Summary of test results for SPT and CPT in Taiwan

Parameters	**Depth (m)**	N_{55}	q_c **(kg/cm^2)**	D_{50} **(mm)**	***FR***	f_s **(kg/cm^2)**	***FC*** **(%)**	N_{60}
Minimum value	1.00	5.00	13.46	0.077	0.02	1.083	13.00	4.58
Maximum value	48.50	77.07	208.08	0.290	1.82	336.573	48.00	70.64

3 Methodology

3.1 SPT-CPT Correlation for Liquefaction Assessment

In this paper, the correlations of SPT-CPT have been developed using SPT data and CPT data for identical location. This site data has 35 data points of sand deposits. This database has a parameter named as SPT blow count having 55% hammer efficiency (N_{55}). Standard value of SPT blow count N_{60} (having 60% hammer efficiency is used) is used in civil engineering applications. Sleeve friction (f_s) is an independent parameter of CPT. So, the developed correlations in this study contains N_{60}, cone tip resistance

(q_c) using some independent parameters of CPT like sleeve friction (f_s), fines content, mean particle size with respect to depth of soil.

The assessment and prediction of correlations of SPT-CPT are widely classified into two categories, first one is traditional methods, and another one is statistical machine learning techniques or Artificial Intelligence Techniques.

3.2 Regression Analysis

In the 19th century, a term 'regression' was conceived by Francis Galton for description of biological phenomenon. Regression analysis is a collection of procedures related to statistics to determine the relationships among one or more dependent and an independent variable (response variable) in statistical modelling. Y_i is assumed to be a function of X_i in most regression models, with e_i signifying an additive error component that could represent modeled Y_i determinants:

$$Y_i = f(X_i, \beta) + e_i \tag{1}$$

The researcher's goal is to determine which function $f(X_i, \beta)$ is fitting best to the data. In order to perform regression analysis, the form of the function f must be provided.

Simple Linear Regression (SLR). The below mentioned two variables are linked with the help of an equation in Linear Regression where 1 is the exponent (power) in both the cases. The line joining the predicted values getting from this regression method gives the shape of straight line in mathematical form. The mathematical equation for a SLR in general form is as shown below where 'y' is response variable, 'x' is predictor variable and (a & b) are coefficients:

$$Y = a X + b \tag{2}$$

Multiple Linear Regression (MLR). Linear regression is extended into multiple regression. In multiple linear regression, an equation connects more than two variables. Multiple linear regression has only one response variable and more than one predictor variable. The general mathematical equation for multiple regression is:

$$y = a + b_1x_1 + b_2x_2 + \ldots\ldots b_nx_n \tag{3}$$

Here, y is the outcome variable, (a, b_1, b_2…. b_n) coefficients and (x_1, x_2..... x_n) predictor variables in this equation.

Support Vector Regression (SVR). Support vector machine (SVM) is a simple supervised machine learning algorithm for regression and classification. SVM generally, splits data points into groups (classes) by using optimal decision boundary and then guesses the class of observed values by using that decision function.

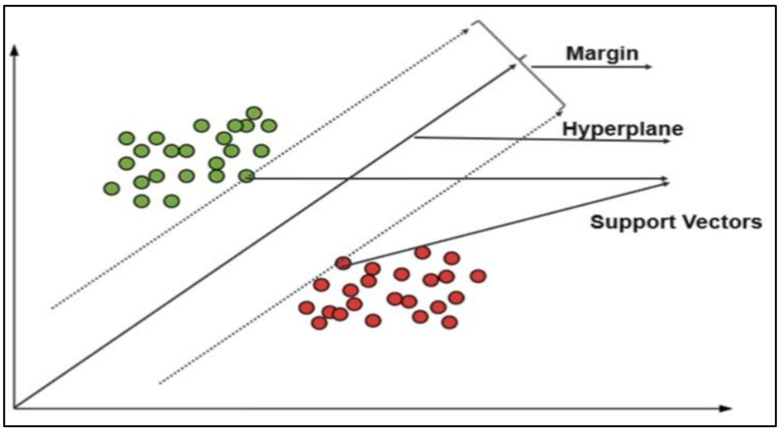

Figure 1. Support Vector Regression

The distinct groups may be distinguished by a regular linear line or a non-linear boundary line, depending on the circumstances. Both linear and non-linear class borders are handled using support vector machine algorithms. It may be used to solve issues with two or more classes.

Multivariate Adaptive Regression Spline (MARS). Multi-variate adaptive regression splines is an algorithm which is non-parametric in nature that creates a piecewise linear model to capture non-linearity and interaction effects. A weighted sum of basis functions $B_i(x)$ is the outcome of resulting model:

$$y = \sum^{k}_{i=1} w_i B_i(x) \tag{4}$$

The basis functions are either a hinge function of the form max (0, x-x_o), max (0, x_o-x) or products of two or more hinge functions (for interactions) or constant (for the intercept).

Locally Estimated Scatterplot Smoothing (LOESS). A non-parametric technique for fitting various regressions in a tiny geographic space is identified as local regression, or Loess. This could come in quite effective if you are mindful knowing your *X* variables are restricted within a specific range. On a numerical vector, the loess () function may be used to smooth it out and estimate the *Y* locally (i.e., within the trained values of *X*).

3.3 Evaluation Metrics in Regression Analysis

Any model of machine learning cannot give 100% efficiency; otherwise, that model is referred to be a biased model. This also encompasses the concepts of overfitting and underfitting. Some of the evaluation metrics are used in this study to compare the efficiency and reliability of correlations as given below.

Root Mean Squared Error (RMSE). Another name of RMSE is Root Mean Square Deviation. It is used for evaluating the performance of the model in the regression analysis approach, given by equation (5), where the absolute value of *y* is Y_i, and the mean value of *y* is *Y*.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} Y_i - Y}{n}} \tag{5}$$

R-Squared (R^2). In a regression model, another name of R-squared (R^2) is coefficient of determination. R^2 tells about the amount of variation of one variable with respect to the other and performance of relationship among number of independent variables is given by equation (6), where Y_i is absolute value, *Y* is predicted value and *Y* is mean value of *y*.

$$R^2 = 1 - \frac{sum\ of\ squares\ of\ errors\ of\ regression}{total\ sum\ of\ squares\ of\ errors}$$

$$R^2 = 1 - \frac{\Sigma(Yi - Y)2}{\Sigma(Yi - \yen)2} \tag{6}$$

4 Results and Discussions

The correlations between SPT-CPT have been developed between N_{60} and q_c along with combinations of parameters of CPT data using regression analysis. There are 35 data points taken from the site data of Hstina Power Plant in Taiwan (Chin et al. 1990) used in SPT-CPT correlations.

4.1 SPT-CPT correlation using N_{60} and q_c only

First, by taking N_{60} and q_c only, the correlations obtained by using different regression methods with R^2 and *RMSE* values are given in Table 3. The correlation obtained from support vector regression is giving higher efficiency when compared to other methods, as R^2 = 0.9053 and a lower *RMSE* value of 5.6021.

The plots of the correlation curve of N_{60} and q_c using different regression models are shown in Figure 2. It can be seen that the support vector regression N_{60}-q_c correlation curve in green color is covering almost all the data points. That's why the support vector regression model is giving higher accuracy when compared to other regression models. The correlations developed by using N_{60} and q_c only, is not giving more reliable efficiency. So, further parameters of CPT data have been used for correlations to increase the efficiency.

Table 3. Correlations using different regression methods between N_{60} and q_c

Correlation name	Correlation	R^2 value	*RMSE* value	Remarks
SLR model	$N_{60}=0.346q_c-2.41$	0.8848	6.1776	NA
Power Regression model	$N_{60}=0.149q_c^{1.16}$	0.8747	6.1021	NA
SVR model	$N_{60}\sim q_c$	0.9009	5.7293	before tuning: kernel=radial
	$N_{60}\sim q_c$	**0.9053**	**5.6021**	after tuning: kernel=radial epsilon=(0:0.1:1) cost=$2^{(2:7)}$
MARS model	$N_{60}\sim q_c$	0.8944	5.9142	NA
LOESS model	$N_{60}\sim q_c$	0.8977	5.8198	surface=direct

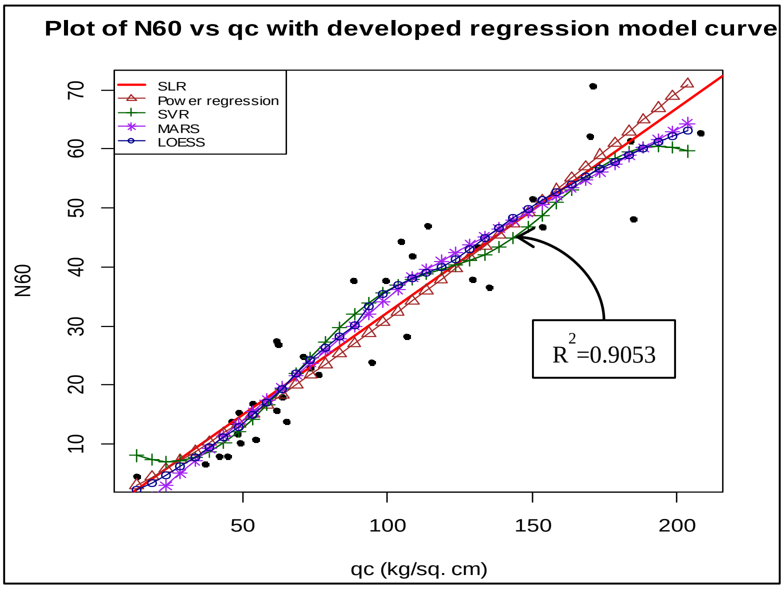

Figure 2. Plot of N_{60}-q_c correlation curves for SLR, Power regression, SVR, MARS and LOESS model

4.2 SPT-CPT correlation using N_{60} and q_c along with other parameters

In this study, N_{60} is the response variable and all other parameters of CPT data are predictor variables. The correlations obtained by taking combinations of all the parameters of CPT data are as shown in Table 4 with R^2 and RMSE values.

From the table 4, again support vector regression model is giving higher efficiency as R^2 =0.999 and *RMSE* value of 0.0045 when compared to other models. This support vector regression model takes predictor variables as q_c, z_c, *FC*, and D_{50}. This support vector regression model can be considered as an accurate model due to R^2

= 0.9999. On using other parameters of CPT data as q_c, z_c, FC, and D_{50}, the efficiency of getting more reliable and accurate result is increased compared to that of by using N_{60} and q_c only. This developed SPT-CPT correlation may be used to evaluate N_{60} using CPT data.

Table 4. Correlations using different regression models between N_{60} and q_c along with depending parameters

Correlation name		Correlation	R^2 value	*RMSE* value	Remarks
Multiple Linear Regression model		$N_{60} = 0.28q_c + 0.28z_w - 2.81$	0.9098	5.4659	NA
SVR model	Model-1	$N_{60} \sim q_c + z_c + FC + D_{50} + f_s$	0.9466	4.2029	before tuning: kernel=radial
		$N_{60} \sim q_c + z_c + FC + D_{50} + f_s$	0.9991	0.5224	after tuning epsilon=(0:0.1:1) cost = $2^{(2:7)}$
	Model-2	$N_{60} \sim q_c + z_c + FC + D_{50}$	0.9271	4.9119	before tuning kernel=radial
		$N_{60} \sim q_c + z_c + FC + D_{50}$	**0.9999**	**0.0045**	after tuning epsilon=(0:0.1:1) cost = $2^{(2:7)}$
MARS model		$N_{60} \sim q_c + z_c$	0.9138	5.3414	NA
LOESS model	Model-1	$N_{60} \sim q_c + z_c + FC + f_s$	0.9964	1.0828	surface=direct
	Model-2	$N_{60} \sim q_c + z_c + f_s$	0.9708	3.1061	surface=direct
	Model-3	$N_{60} \sim q_c + f_s$	0.9245	4.9995	surface=direct

The above developed highly efficient correlations can be used only when all the required parameters other than N_{60} and q_c are known.

4.3 Comparison of developed model with existing models

The dataset of 35 data points used in this study has been taken. A simple correlation between N_{55} and q_c was established based on available data. The correlation is given as:

$$q_c/N_{55} = 4.70 - 0.05 \times FC(\%) \tag{7}$$

On the basis of available data, N_{55} is evaluated and further converted into N_{60}. The predicted value of N_{60} is evaluated based on available data. The developed SVR model (named as model-2) is giving R^2 value of 0.9999. Figure 3 shows the scatter plot of observed and predicted N_{60} values by correlation developed by Chin et al. (1990) and the present study.

In Figure 3, It can be seen that all predicted N_{60} values obtained from this study is lying near the line of equality representing as predicting approximately same values with respect to original and some predicted values obtained from correlation developed by Chin et al. (1990) are outside of the 10% and -10% line of equality line.

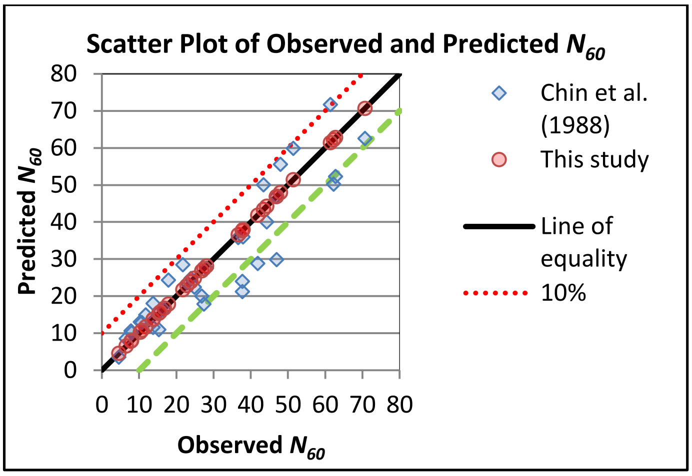

Figure 3. Scatter plot of observed and predicted N_{60}

There are numerous numbers of SPT-CPT correlations exist in the literature, most of which are given in the form of (q_c/N_{60}). The R^2 and RMSE values are evaluated and shown in Table 5 for these previously developed correlations of the given datasets. On taking into the table, the maximum value of R^2 of 0.7335 is obtained for the Lingwanda et al. (2015) correlation, which is lower than the R^2 value obtained from this study.

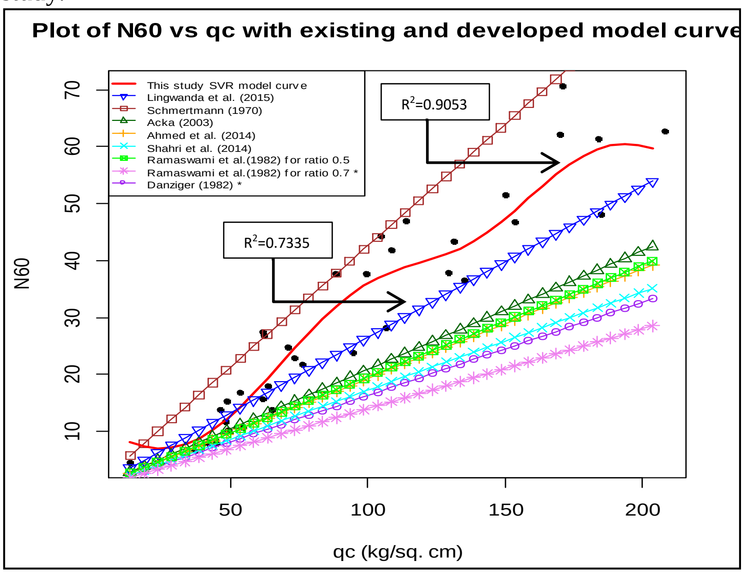

Figure 4. Plot of existing and developed SPT-CPT correlation curves

In table 5, some of the previously developed correlations shown in '*' are giving the negative value of R^2 for the present data set. Here, the negative value of R^2 indicates that the predicted values are far away from their original values. The previously developed Danziger (1982) '*' correlation curve, shown in purple with a circle marker in Figure 4, does not cover any data points in the plot. That's why this previously developed correlation is giving a '–' ve value of R^2 with these data points.

Taking into account Figure 4, this study support vector regression SPT-CPT correlation curve with a R^2 of 0.9053 covers almost all of the points, whereas the previously developed Lingwanda et al. (2015) correlation with an R^2 of 0.7335 covers almost all of the points. So, the correlation developed from this study is giving more efficient and reliable results than the previously developed correlations.

Table 5. R^2 and *RMSE* values for previous existing and developed SPT-CPT correlations

References	$K_C=(q_c / N_{60})$ **(MPa)**	**Remarks**	**R^2 value**	**RMSE value**
Schmertmann 1970	0.230	Both medium and fine sands are used (USA)	0.5357	12.4017
Danziger 1982 *	0.600	Rio de Janeiro sandy soils	-0.0249	18.4273
Ramaswami et al. 1982*	0.500-0.700	For sandy soil	0.3027- (-0.3038)	15.1986- 20.7840
Acka 2003	0.470	For high cemented sandy soils(UAE)	0.4088	13.9945
Mayne 2006	0.438	For sandy soils (China, Canada, Norway, Japan and Italy): D_{50} = 0.35 $\pm$ 0.23mm	NA	NA
Ahmed et al. 2014	0.508	For sandy silts and clean sands; FC = 3% - 35%	0.4009	13.5321
Shahri et al. 2014	0.568	Sweden sands	0.0747	17.508
Lingwanda et al. 2015	0.370	Tanzanian silty sands and clayey soils: D_{50} = 0.38mm	**0.7535**	**9.0352**
Developed correlation	N_{60}~q_c	Using SVR model after tuning	**0.9053**	**5.5602**

The references shown in ' * ' is giving negative value of R^2 for the available SPT-CPT data for predicting under fitting values with respect to mean of absolute values as shown in Figure 4.

5. Conclusions and Future Scope

5.1. Conclusions

- The correlations between SPT-CPT data have been developed using regression analysis approach.
- The SPT-CPT developed support vector regression (SVR) model is giving higher efficiency as R^2 of 0.9053 on taking N_{60} and q_c only.
- On taking N_{60} and q_c with other parameters of CPT data, a SPT-CPT developed SVR model (named as model-2) is giving higher efficiency as an R^2 value of 0.9999.
- SPT-CPT developed correlations are giving higher efficiency and reliability than that of existing correlations. So, these correlations may be used to evaluate SPT N-value using CPT and other test data.
- By using N_{60} value, the bearing capacity, settlement, cohesion value, friction angle, etc. can be estimated.

For both SPT-CPT, if the observation data is available in a large number of locations, the developed correlation will be more reliable and acceptable for any location provided the input parameters are within the range of the present dataset.

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