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A polynomial model for predicting liquefaction potential from cone penetration test data

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Abstract. Liquefaction is a serious geotechnical hazard leading to catastrophic damage to life and property. In many instances, it may be preferable to predict liquefaction susceptibility indirectly by common in-situ tests, such as the Cone Penetration Test (CPT). A new approach for prediction of liquefaction susceptibility is proposed, which presents a polynomial model to correlate the Cyclic Resistance Ratio (CRR) predicated on subsoil geotechnical properties from CPT tests, that is, normalized cone tip resistance (q_{C1}) and friction resistance (f_s). The derived model is applied to a total of 182 data sets, including field investigation records from eighteen earthquakes. The performance of the proposed approach is compared to other available methods within a quantitative validation framework (e.g., precision, recall, and F-score). Results indicate the accuracy and generalization of the proposed new approach in predicting liquefaction susceptibility.

1. Introduction

Soil liquefaction can lead to drastic destruction and damage to infrastructures and buildings. By definition, liquefaction is viable in loose saturated sand deposits during earthquakes, as a result of an increase in excess pore water pressure induced by cyclic loading shear stresses [1]. A number of approaches have been proposed for predicting liquefaction under different circumstances, which can be designated into the following major groups;

- Empirical methods based on synthesis of laboratory test data, or statistical analyses of liquefaction case histories;
- Simplified analytical methods;
- Numerical analyses in the form of finite element and/or finite difference techniques;
- Soft computing techniques.

From another aspect, by viewing approaches based on their basic inputs, liquefaction prediction methods may be classified into computational and experimental categories, as described in Figure 1.

Although experimental correlations remain a major practice [2], some advanced procedures of probabilistic analysis or various forms of identification techniques have been combined with experimental methods to provide enhanced evaluations of model parameters and liquefaction susceptibility predictions [3].

All prediction methods based on any of the above-mentioned approaches require the determination of input parameters. The effect of any inaccuracies of input data in the numerical and analytical approach can be studied by analyzing the sensitivity of predictions regarding varying input data.

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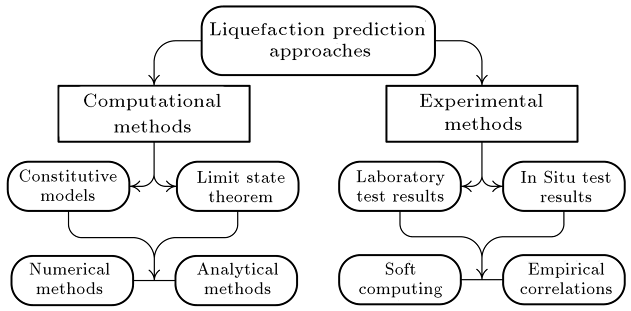

Figure 1. General classification of approaches for liquefaction predictions.

This study aims to develop a polynomial model for the prediction of liquefaction based on parameters obtained from the Cone Penetration Test (CPT). To this end, the paper first reviews previous efforts in liquefaction prediction, then explains the data base of case histories incorporated in this study, while discussing the phenomena and principles of the modeling technique. Finally, the developed model is described and validated.

2. Review of current methods

Following the concept presented in Figure 1, in computational methods, basic input parameters are used to predict the liquefaction potential, whereas, in experimental correlations, laboratory and/or field test records are employed in conjunction with case histories.

Owing to the complex and interactive nature of the liquefaction phenomenon, constitutive models, as well as computational methods, have failed to capture the overall aspects. Thus, experimental models based on case histories have remained popular methods over several decades [4]. For this purpose, testing, especially in situ soundings, is the most adequate task to be done. With regard to the difficulties in soil sampling, and the high cost of representative undisturbed specimens, in-situ investigations are preferred in lieu of laboratory element testing. Common in-situ tests used in liquefaction prediction are the Standard Penetration Test (SPT), the Cone Penetration Test (CPT) and Shear Wave Velocity Measurements [5].

The CPT is versatile and reliable compared to other in situ tests. The major merits of CPT are in its production of continuous and precise records, simple and rapid application, economical aspects, and reduction in operator influence. In the CPT, a cone at the end of a series of rods is pushed into the ground at a constant rate, and resistance to cone penetration, q_c, and the friction of the outer surface sleeve, f_S, are continuously measured. There are few types of CPT, piezocone, i.e. CPTu, being one of them. CPTu is a "direct-penetration" device that is hydraulically penetrated into the ground at a constant rate of 2 cm/sec with the ability of measuring excess water pressure induced at the cone shoulder as a result of soil penetration [6]. Figure 2 shows a typical CPTu record included in the database of this study.

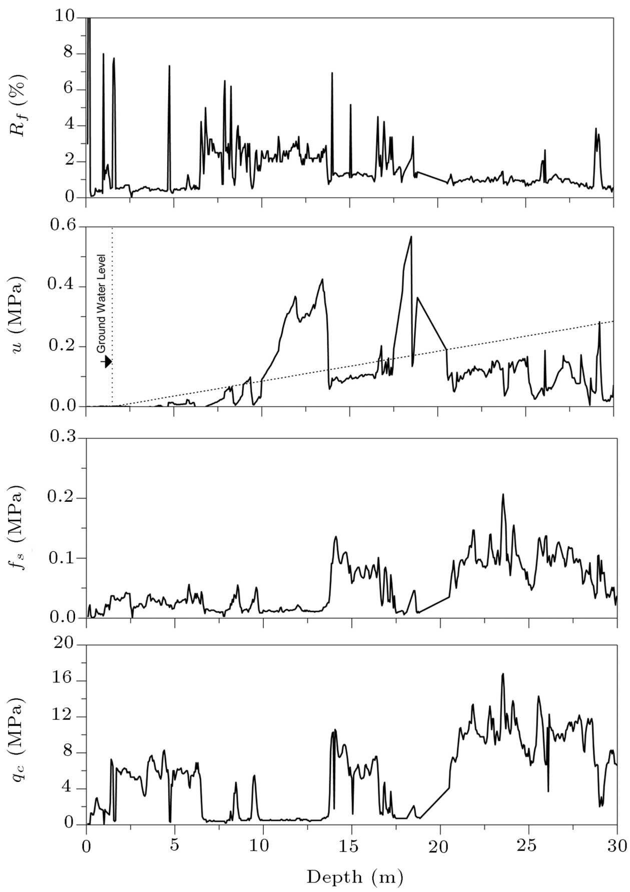

Figure 2. A typical CPTu record used in this study-redrawn from [2].

A host of correlations have been established that relate CPT measurements to various soil parameters, including un-drained shear strength, stress history, compressibility, soil classification, bearing capacity and liquefaction potential [6-9].

Seed et al.'s procedure [10] is viewed as a basic method that follows a classical format of liquefaction analyses. Suzuki et al. [11], Youd et al. [12], Andrus et al. [13], Idriss and Boulanger [14] and Moss et al. [2] provided updates to this method. As conceptually illustrated in Figure 3, this method correlates the safety factor (i.e. FS) for liquefaction susceptibility from input parameters through a stepwise procedure. If the value of FS for a particular case is less than 1, the occurrence of liquefaction is possible. Otherwise, it is considered a non-liquefiable case. Several experimental methods are available which offer predictions of liquefaction susceptibility from CPT data. Robertson and Wride [15,16], and Eslami and Fellenius [9] presented standardized charts for determination of liquefaction susceptibility from CPT data. These charts, which

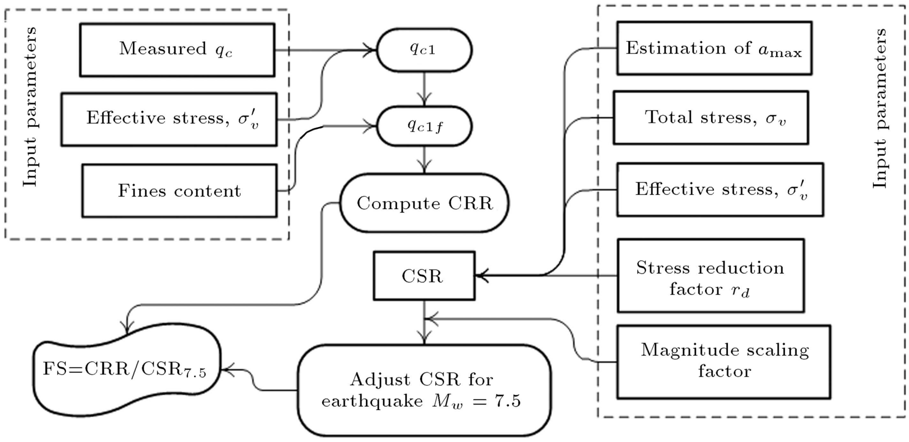

Figure 3. General procedure of simplified approaches based on CPT data (Note: M_W = earthquake magnitude, $a_{\max}$ = maximum ground surface acceleration, CSR= cyclic stress ratio, CRR=cyclic resistance ratio, FS = safety factor of liquefaction, q_{c1} = normalized cone tip resistance, q_{c1f} = q_{c1} corrected for the soil fines content, and CSR$_{7.5}$ = CSR adjusted for $M_W = 7.5$.

are taken from CPT information of liquefied and non-liquefied case histories, delineate different soil types regarding liquefaction potential. Furthermore, normalized, total cone bearing stress, i.e. Q_{tn}, which indicates soil dilation, has been modified by Kangarani et al. [17] to represent an index of liquefaction susceptibility. However, a limitation of the latter methods includes their inability to provide a safety factor.

Moss et al. [2] incorporated a Bayesian updating method for probabilistic evaluation of liquefaction potential. Rezania et al. [18] analyzed 170 liquefied and non-liquefied field case histories, and predicted the liquefaction potential of sand by Evolutionary Polynomial Regression (EPR). The model related the liquefaction potential to earthquake characteristics, as well as soil geotechnical parameters, for three major soil classes, namely, clean sand, silty-sand, and silty-sand to sandy-silt. Rezania et al. [19] further used the EPR to develop a highly accurate function for liquefaction prediction.

In recent years, soft computing techniques such as artificial intelligence and Genetic Algorithms (GAs) have gained widespread applications in geotechnical engineering and liquefaction potential predictions (e.g. [20,21]). Another computing technique, known as the Support Vector Machine (SVM) algorithm, combines the principles of structural risk minimization and the statistical learning theory pioneered by Cortes and Vapnik [22]. SVM has been successfully employed in liquefaction studies [3,23]. Sadoghi et al. [24] implemented an Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier for determination of the liquefaction potential.

3. Modeling using polynomial approach

A polynomial model can connect input and output data sets by means of a quadratic function. Such representation can be used for input-output mapping. The formal explanation of the identification problem is to find a function, F, that can be approximately used instead of the observed one, f, to predict output Y for a given input vector, $X = (x_1, x_2, x_3, \ldots, x_n)$, as close as possible to its observed output, y. Therefore, for M observations of input data, single output data pairs are:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, ..., x_{\text{in}}), \quad (i = 1, 2, 3, ..., M). \quad (1)$$

It is possible to use a polynomial model to predict the output values, y_i, for any given input vector, $X(x_{i1}, x_{i2}, x_{i3}, ..., x_{\text{in}})$, that is;

$$Y_i = F(x_{i1}, x_{i2}, x_{i3}, ..., x_{\text{in}}), \quad (i = 1, 2, 3, ..., M). \quad (2)$$

The problem is now to determine a polynomial model such that the square of differences between the observed and predicted output is minimized. Hence:

$$\text{Sum}[F(x_{i1}, x_{i2}, \cdots, x_{i3}) - y_i]^2 \rightarrow \min. \quad (3)$$

The general connection between input and output variables can be expressed by a complicated discrete form of the Volterra functional series known as the Kolmogorov-Gabor polynomial. This full form mathematical description can be represented by a system of partial quadratic polynomials consisting of only two variables in the arrangement of:

$$Y = F(x_i, y_i) = a_0 + a_1 x_i + a_2 y_i + a_3 x_i^2 + a_4 y_i^2 + a_5 x_i y_i. \quad (4)$$

By this means, the partial quadratic description is recursively used to build a general mathematical relation between inputs and outputs. The coefficients, a_i, in Eq. (4), are calculated using regression techniques, such that input data are correctly related to observed liquefied or non-liquefied conditions.

Table 1. Inventory of case study earthquakes adapted from Moss et al. [2].

No.	Earthquake	Soil type	Significant events
1	1964 Nigata	SP	Loss of bearing capacity
2	1968 Inangahua	SM	Sand boils
3	1975 Haicheng	SM/ML	Surface evidence, sand boils
4	1976 Tangshan	SP/SM/ML	Surface evidence, sand boils and cracking
5	1977 Vrancea	SP	No surface evidence of liquefaction
6	1979 Imperial Valley	SP/SM/ML	Sand boils
7	1980 Mexicali	SP/SM/ML	Sand boils
8	1981 Westmorland	SM/ML	Sand boils, slumping and ground fissures
9	1983 Borah Peak	GM	Sand boils and lateral spreading
10	1983 Nihonkai-Chubu	SW/SP/GW	Lateral spreading, dike failure and sand boils
11	1987 Edgecumbe	SP/SM/ML/SW	sand boils and sateral spreading
12	1987 Elmore Ranch	SM/ML	No liquefaction
13	1987 Superstition Hills	SM/ML	Liquefaction
14	1989 Loma Prieta	SP/SM/ML/SW	Lateral spreading and sand boils
15	1994 Northridge	SM/ML	Cracking, sand boils and lateral spreading
16	1995 Hyogoken-Nanbu	SM	Marginal, edge of liquefaction
17	1999 Chi-Chi	SP/SM/ML/SW	Sand boils and lateral spreading
18	1999 Kocaeli	GW/SP/SM/ ML/SW	Lateral spreading, building tilts and sand boiling

4. Database specifications

The database used in this study, extracted from earthquake data, was collected by Moss et al. [2]. Field test results consist of eighteen earthquakes with observed liquefaction incidents. The soil types mostly encountered in the investigations are sand, silt and cohesionless deposits. Significant events and the soil classification of earthquake sites are reported in Table 1.

The earthquake events presented in Table 1 include 182 CPT probings, namely, 139 and 43 tests for liquefied and non-liquefied sites, respectively. Each CPT record includes measurements of earthquake magnitude (M_W), normalized cone tip resistance (q_{C1}), friction resistance (f_s), effective stress (σ'), and observed liquefied condition ($''Y''$) or non-liquefied condition ($''N''$). The frequency distribution of these parameters in the database is presented in Figure 4.

5. Liquefaction modeling by new polynomial model

In order to predict the liquefaction potential, several iterations of the new polynomial model were performed. The evolved model results in a simple polynomial equation for the Cyclic Resistance Ratio (CRR). Thereafter, the liquefaction potential can be predicted by the safety factor, defined as FS=CRR/CSR$_{7.5}$, where CSR$_{7.5}$ stands for cyclic stress ratio adjusted for an earthquake, with $M_W = 7.5$.

The magnitude scaling factor is implemented to determine CSR$_{7.5}$ from CSR, calculated as [10]:

$$\mathrm{CSR} = 0.65\left(\frac{a_{\max}}{g}\right) \times \left(\frac{\sigma_v}{\sigma'_v}\right) \times r_d, \tag{5}$$

where $a_{\max}$ is the maximum ground surface acceleration; g is the acceleration of gravity; σ_v is the total overburden stress, σ'_v is the effective overburden stress; and r_d is the stress reduction factor.

The corresponding polynomial representation for CRR is as follows:

$$CRR = 0.075 + 0.002\,q_{C1} - 0.0005\,f_S + 0.00018\,q_{C1}^2 - 0.0001\,f_S^2 + 0.0016\,q_{C1} f_S. \tag{6}$$

The isometric view of CRR variation with respect to f_s and q_{C1} is shown in Figure 5. The ability of the polynomial model in predicting liquefaction susceptibility is tested for all the datasets. Table 2 presents sample data from the datasets and the corresponding predictions by the polynomial model.

A comparison of results by the proposed model with field observations for the earthquakes under study is provided in Figure 6. As seen, in most cases, incorrectly predicted instances are a small fraction of the overall records for each earthquake. From Figure 7, it is obvious that the proposed model is particularly effective in correctly predicting liquefied cases. However, in non-liquefied cases, prediction errors are higher. This outcome accentuates the need for a more

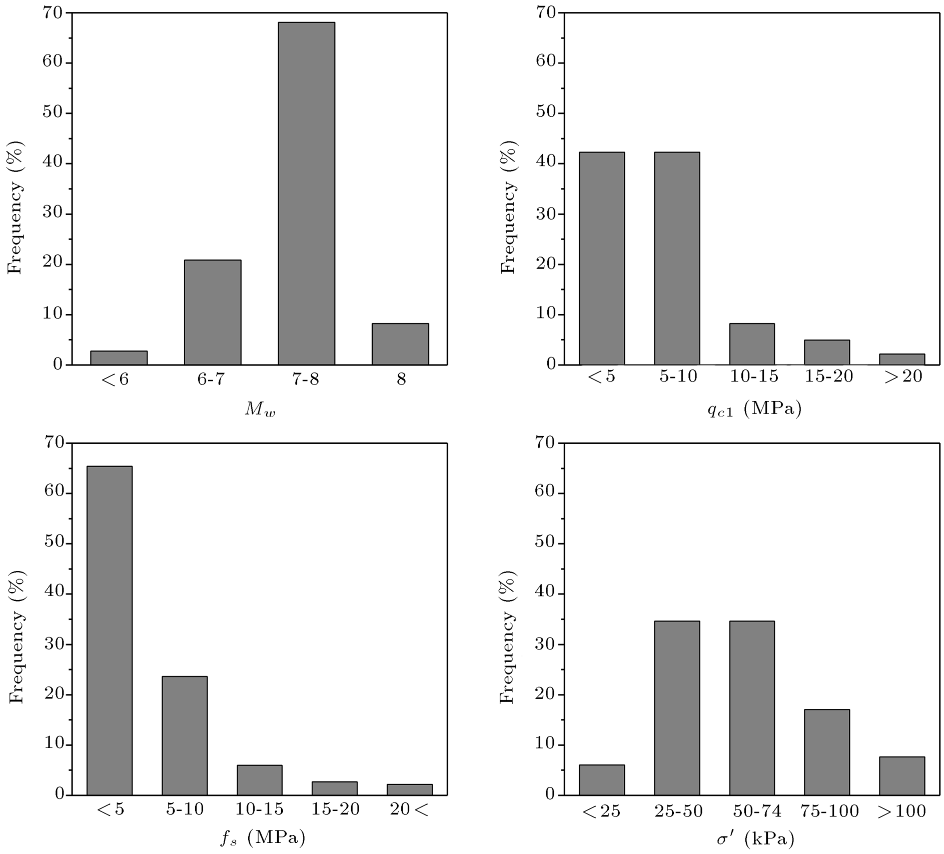

Figure 4. Frequency distribution of q_{c1}, M_W, f_s and σ' included in the database.

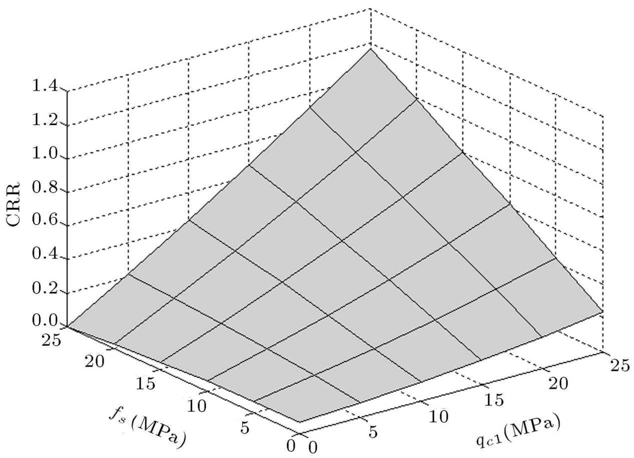

Figure 5. Variation of CRR versus q_{c1} and f_s.

rigorous validation method, which is discussed in the forthcoming section.

6. Validation and comparison with other methods

The proposed model is validated by computing the number of case histories where liquefaction is correctly/incorrectly predicted. A common statistical validation criterion is Overall Accuracy (OA), which represents the percentage of correctly classified instances, as follows [25]:

$$\text{OA} = (\text{TP} + \text{TN}) \;/\; (\text{TP} + \text{TN} + \text{FP} + \text{FN}), \qquad (7)$$

where TP is liquefied instances correctly predicted; TN is non-liquefied instances correctly predicted; FP is non-liquefied instances classified as liquefied; and FN is liquefied instances classified as non-liquefied.

As an example, OA = 0.85 means that 85% of the data have been correctly predicted. This does not imply that in each liquefied and non-liquefied class 85% of case histories have been predicted correctly. Therefore, evaluation of OA alone cannot be a comparison criterion when a class imbalance exists or the number of instances from each class is not equal in the data set (i.e., for the 182 CPT case histories, 139 are liquefied and 43 are non-liquefied instances). In order to overcome this situation, precision (P) and recall (R) are applied separately to each class in the data set. This is particularly valuable when the class imbalance in the data set is significant. Precision measures the accuracy of predictions for a single class, whereas recall measures the accuracy of predictions only considering predicted values. Thus [25];

$$\text{Precision} = \text{P} = \text{TP} \;/\; (\text{TP} + \text{FP}), \qquad (8)$$

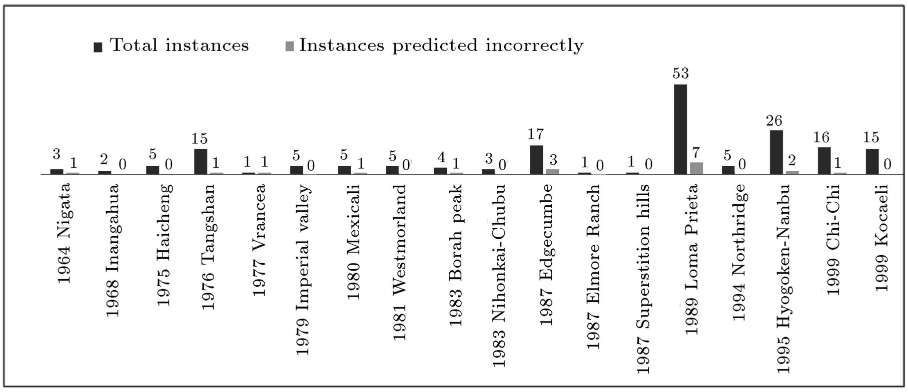

Figure 6. The accuracy of the proposed approach for each of eighteen earthquakes.

Table 2. Example database records.

M_w	q_{c1} (MPa)	f_S	σ' (kPa)	$CSR_{7.5}$	CRR	Prediction by proposed approach	Liquefaction occurrence in field
7.4	4.13	3.7	67.71	0.38	0.108	Y[a]	Y
7.2	2.93	1.14	75.24	0.45	0.087	Y	Y
7	5.16	2.4	43.5	0.12	0.00014	Y	N
5.9	4.61	4.01	50.43	0.14	0.114	Y	Y
6.6	13.84	1.38	16.19	0.48	0.167	Y	Y
8	8.83	3.33	76.25	0.19	0.15	Y	Y
7	6	6.37	42.92	0.18	0.00011	Y	N[b]

[a]: Y: Yes; [b]: N: No.

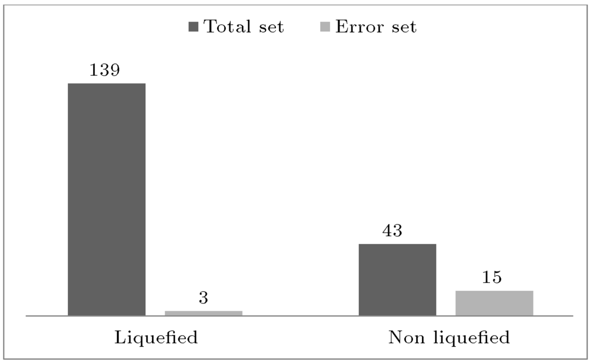

Figure 7. Accuracy of the method in predicting liquefied and non-liquefied instances.

$$\text{Recall} = \text{R} + \text{TP} \ / \ (\text{TP} + \text{FN}). \tag{9}$$

Considering the assessment of liquefaction potential, a precision of 1.0 for the liquefaction class implies that every case predicted as liquefaction experienced liquefaction. Yet, instances of observed/actual liquefaction that are misclassified are not accounted for.

In contrast, a recall of 1.0 suggests that the model correctly predicted every instance of observed liquefaction. However, this does not account for instances of observed non-liquefaction that are misclassified. Of note, precision and recall are inversely related, thus it is possible to increase one while decreasing the other.

The F-score combines precision and recall values to a single evaluation metric. That is to say, F-score is the weighted harmonic mean of precision and recall, defined as:

$$\text{F-score} = (1+\beta^2)(P \times R)/(\beta^2 P + R), \tag{10}$$

where the F-score is evenly balanced with $\beta = 1$, whilst it favors precision when $\beta > 1$, and recall otherwise. In fact, β is determined by the user for a specific project, who attaches β times as much importance to recall as precision [25].

A complete comparison between results of this study and previous methods/investigations, for the database under consideration, is presented in Table 3. Statistical measures, such as OA, precision, recall and F-score, are reported for all 182 cases initially used for model development [3]. Accordingly, the proposed polynomial model is significantly accurate in predicting liquefaction potential.

The methodology presented herein is more generalized and significantly simpler than previous similar studies. Although only two input parameters are required for calculation of CRR, the proposed method is rather more accurate. The relation suggested by

Table 3. Comparison of various estimation methods in predicting liquefaction from CPT data-based on database of Moss et al. [2].

Approaches		Data set of Moss et al. [2]						
		OA[a]	Liquefied			Non-liquefied		
			R^b	P^c	F-score[d]	R	P	F-score
Youd et al. [12][e]		0.846	0.877	0.917	0.897	0.744	0.653	0.695
Moss et al. [2] ($TH_L{}^f = 0.15$)[e]		0.879	0.985	0.872	0.925	0.534	0.92	0.676
Moss et al. [2] ($TH_L = 0.5$)[e]		0.857	0.913	0.9	0.907	0.674	0.7	0.69
Oommen et al. [3][e]		0.89	0.978	0.888	0.931	0.604	0.896	0.722
Rezania et al. [18][g]	Clean sand	0.900	1.000	0.889	0.941	0.500	1.000	0.667
	Silty sand	0.840	0.939	0.869	0.903	0.462	0.667	0.545
	Silty sand to sandy silt	0.556	0.294	1.000	0.455	1.000	0.455	0.625
	All soils	0.808	0.854	0.892	0.843	0.548	0.690	0.577
Rezania et al. [19][g]		0.841	0.878	0.91	0.894	0.721	0.646	0.681
Sadooghi et al. [24][g]		0.89	0.878	0.91	0.894	0.721	0.646	0.681
This study		0.901	0.900	0.978	0.937	0.903	0.651	0.756

[a]: OA = Overall accuracy; [b]: R = Recall; [c]: P = Precision; [d]: F-score in all cases considering β=1;
[e]: Statistical measures calculated and reported by Oommen et al. [3];
[f]: TH_L stands for threshold of liquefaction which is a parameter involved in the probabilistic analysis presented by Moss et al. [2]; [g]: Statistical measures calculated and reported by Sadoghi et al. [24].

Sadoghi et al. [24] relies on determining 56 multipliers through complex mathematical calculations. Herein, however, only six multipliers require determination. Rezania et al. [18] delineated various soil types and proposed equations for each. In our study, the soil properties are reflected in f_s and q_{c1}. Hence, a single relation is applied to all soils. In comparison to the Youd et al. [12] and Moss et al. [2] studies, it is evident (cf. Table 3) that the method proposed in this study is more accurate.

7. Conclusions

In this study, an attempt was made to develop an evolved polynomial model identification technique for predicting liquefaction potential via CPT data. The database of case histories consisted of 182 data sets from well documented earthquakes. The polynomial model developed was predicated on normalized cone tip resistance (q_{C1}) and friction resistance (f_s). The validity and performance of the new model have been assessed, and contrasted with contemporary methods, for all 182 case records, using various statistical measures such as precision, recall, and F-score. Accordingly, the developed model is superior in predicting liquefaction.

As a major advantage, the proposed approach is mathematically simpler, while more generalized, in comparison to similar techniques. Also, effective stress is not independently considered since it contributes to the definition of q_{C1}.

It is important to note that soil heterogeneity and stratification variations may alter CPT soundings and this can be a source of error. Hence, predictive correlations are best suited for homogenous sites. Therefore, these proposed relationships should be used with caution in geotechnical engineering and must be rechecked by other common in-situ liquefaction prediction approaches.

Nomenclature

β	Coefficient of F-Score
CPT	Cone penetration test
CRR	Cyclic resistance ratio
CSR	Cycle stress ratio
$CSR_{7.5}$	Cycle stress ratio adjusted for earthquake with M_W=7.5
EPR	Evolutionary polynomial regression
F	Prediction function
FP	Non-liquefied instances classified as liquefied
FN	Liquefied instances classified as non-liquefied
f_s	Friction resistance from CPT test
GAs	Genetic algorithms
M	Total numbers of input variables
M_W	Earthquake magnitude

n	Total numbers of input data
OA	Overall accuracy
P	Precision
q_c	Cone tip resistance
q_{C1}	Normalized cone tip resistance
Q_{tn}	Normalized total cone bearing stress
R	Recall
SPT	Standard penetration test
SVM	Support vector machine
σ'	Effective stress
TP	Liquefied instances correctly predicted
TN	Non-liquefied instances correctly predicted
TH_L	Threshold of liquefaction
X	Input variable
x_i	Input vector
Y_i	Vector of output's value from observation

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