New RSM Equations to Evaluate Strain Energy Required to initiate Liquefaction and Sensitivity Analysis

Nima Pirhadi[1], Xiaowei Tang[2] and Qing Yang[3*]

[1]Ph.D researcher, Dalian University of Technology, Dalian, China
[2]Asistant Professor, Dalian University of Technology, School of Geotechnical Engineering, Dalian, China
[3] Professor, Dalian University of Technology, School of Geotechnical Engineering, Dalian, China

Qing Yang E-mail: qyang@dlut.edu.cn

Abstract

Soil liquefaction during earthquakes is one of the most destructive and complicated phenomena and has caused extensive damage to buildings, lifelines and earth embankments. The energy based procedure, which defines potential of liquefaction in saturated sandy soil subject to dynamic loads, is used in this study to present new equation for evaluating strain energy for triggering liquefaction. To achieve this goal, a dataset of high quality laboratory test of cyclic simple shear, cyclic triaxial, and cyclic torsional tests were collected from the literature with 6 input soil parameters and strain energy for triggering liquefaction as a target. Then, through a new tool, namely the Response Surface Method (RSM) new equation was presented. The RSM equation is generated on full quadric base due to main Designs of experiment (DOE) of Central Composite. Foremost, an Artificial Neural Network (ANN) was employed to model correlations between soil parameters and liquefaction resistance determining coded input values for design of experiment (DOE) for the RSM. Next, to demonstrate the accuracy and capability of the presented equation, they were applied to calculate strain energy with a new dataset and results were compared with other correlations and models published previously. Finally, a sensitivity analysis is performed using Monte Carlo Simulation (MCS) to show the influence of soil parameters and their uncertainties on the probability of liquefaction.

Keywords: Liquefaction, Response Surface Method, Strain Energy
.

1. INTRODUCTION

When seismic shear waves propagate upward to surface layers, the tendency of volume decreasing causes pore water pressure going up in saturated, relatively loose or loose sandy deposits whereas rapid earthquake motion prevents drainage. Excess pore water pressure increases to as much as initial effective overburden stress causing liquefaction. Researchers have studied this phenomenon since the first liquefaction caused destruction during large earthquakes of 1964 Alaska with magnitude 9.2 and Niigata 1964 with magnitude 7.6.

3 main approaches have been introduced to evaluate the liquefaction potential of soils: 1) Stress-based approach on the base of procedure developed by Seed and Idriss [1] 2) Strain-based approach which first time introduced by Dobry, R. et al. [2] 3) The strain energy-base approach has been developed by using seismic energy dissipated in the soil on the base of studies of Nemat-Nasser, S. et al. [3].

In this study, a new ANN model was used to predict Log (W), the 6 input laboratory test results parameters (σ_c^', Dr%, FC%, Cu , D50 (mm) and Cc) selected as most influential parameters, have been confirmed by other researchers [4-11]. The database collected from literature as a biggest and completest database have been applied which cover larger range of parameters. Then the ANN model was used to predict log (W) to develop Design of Experiment (DOE) to utilize Response Surface Method (RSM) to drive three equations to estimate Log (W). Finally according to uncertainties of parameters a sensitivity analysis was conducted through Monte Carlo Simulation (MCS) to show the influence of parameter uncertainties on liquefaction resistance.

2. LITERATURE REVIEW OF ENERGY-BASED APPROACHES TO EVALUATE POTENTIAL OF LIQUEFACTION

Nemat-Nasser et al. [3], by utilizing laboratory test results presented a mathematical correlation to define the relationship between generated pore water pressure or densification and dissipated energy, to develop the strain energy approach for evaluating the potential of liquefaction as given below:

$$\delta W = v \frac{e\Delta e}{f(1+u_w)g(1+e)} \tag{1}$$

This model has been applied to present new models and equations. Some models were developed on the basis of earthquake case histories [7-11] as well as models and equations due to Arias Intensity [12, 13], and models based on laboratory test results [4-6, 8-11].

By collecting a large data set from laboratory tests conducted of shear, cyclic triaxial and torsional shear laboratory test results, including 284 samples from the literature Baziar, M. H. et al [7] developed 2 Artificial Neural Network (ANN) models to achieve a relation between input parameters and Logarithm of capacity strain energy of liquefaction in silty sands (Log (W)). Then Baziar, Mohammad H. at el. [8], applying multigene Genetic Programming to the same dataset developed a model to estimate Log (W). Alavi A et al [9] developed 3 correlations to estimate (Log W). Cabalar. Ali Firat et al. [10] applied Neuro-Fuzzy Interface system (ANFIS) as well as the database collected by Baziar, M. H. et al. [7] and showed the influence of input parameters by graphical representation. By adding some new data to the database of Baziar, M. H. et al. [7] and using Genetic Programming (GP), Baziar, Mohammad H. [8] stablished an equation to calculate Log (*W*) with similar parameters as from Baziar, M. H. et al [7] . Zhang. W. et al. [11] used multivariate adaptive regression splines (MARS), which is a nonparametric regression procedure, and on the basis of the Baziar, M. H. et al. database [7] presented a correlation to estimate Log (*W*) with 5 of the same input parameters as from [7, 8, 10]..

3. DATABASE AND ANN MODEL

Due to the complexity and non-linearity of liquefaction, an Artificial Neural Network is a powerful tool for studying this issue. It is trained for predicting Log (W).
In this study, a multilayer perceptron network with a backpropagation algorithm was constructed and the samples divided in three parts, including a validation set to avoid over-training. Sample division was performed on the basis of similar statistics certificates according to tables (1-4) and tables (6-9) and avoided random division in order to increase accuracy and capability of trained networks. 6 input parameters σ_c^', Dr%, FC%, Cu , D50 (mm) and Cc were selected to develop ANN models for predicting Log (W). The database includes 284 samples [11] containing 217 cyclic trixial laboratory test results [20], 22 centrifuge test results [8], 6 cyclic simple tests [27] and 61 cyclic torsional laboratory test results [5, 28] in addition to new data added from 22 samples from VELAS program [9, 26, 27], 48 cyclic trixial laboratory test results [10], 27 cyclic torsional laboratory test results [9], and 22 centrifuge test results [8]. In total 403 samples were collated. The database was divided into 3 groups. Around 15% (60 samples) for testing, the same portion for validating, and an extra 283 samples for ANN training.

4. RESPONSE SURFACE METHOD

Response surface method is consist of mathematical and statistical techniques and originated through graphical perspective. In this study RSM applied to present a relationship between 6 input parameters and output parameter(s) and target which is Log (W) herein. For this purpose the volume of input parameters must be fitted by experimental data, called design of experiment (DOE), and to estimate the Log (W) in coded points, the ANN model was used. In this study the Central Composite Design (CCD) which is the most usual used design was applied. The mathematical framework function of second-degree polynomial with cross terms, which is the most complicate and accurate, selected in this study.

Table 1

Characteristics of complete input parameters used for first developed ANN model.

Parameters	min value	max value	mean value	average value
σ_c	40.00	400	103.29	220
Dr	-44.50	105.10	51.65	30.30
FC	0.00	100.00	18.69	50.00
Cu	1.52	28.12	4.15	14.82
D50	0.03	0.46	0.21	0.25
Cc	0.53	10.89	1.52	5.71

Table 2

Characteristics of ANN model for first dataset.

Data	Training	Testing	Validating	All
R^2	0.945	0.903	0.815	0.917

Then the RSM equation's terms inspected through hypothesis test by using *P*-value, herein the commonly used value of 0.05 is considered, to accept or reject. The final equations can be seen in Table 6. It must be noted that to use the Equation at first the real value must transferred to codded value according to Eq. 2 then the RSM equation can utilized to estimate value of Log (W).

$$Coded\ value = \frac{Real\ value - mean\ value}{Max\ value - mean\ value} \quad (2)$$

Table 3
RSM equation with DOE of Central Composite based on first ANN model (R-Sq=73.89%, R-Sq(adj)=66.81%)

Terms	Constant	σ'_c	Dr	FC	Cu	D50	Cc	$\sigma'_c*\sigma'_c$	Dr*Dr	FC*FC
Coef	2.13752	0.21066	0.5284	0.04392	0.0966	0.0777	-0.059	0.14882	0.31044	0.155

Terms	D50*D50	Cc*Cc	σ'_c*Dr	σ'_c*FC	σ'_c*Cc	Dr*FC	Dr*D50	Dr*Cc	FC*Cu	FC*D50
Coef	0.253135	0.27647	0.1039	0.15012	0.1627	0.2512	0.3619	-0.1242	0.12629	-0.644

5. COMPARISON OF THE PREDICTED CAPACITY ENERGY LIQUEFACTION BY THE RSM EQUATION, ANN MODEL AND EXISTING MODELS.

20 samples selected from Dief, H.M. [8] of Nevada sand and Reid Bedford sand, which are not contributed in the database to develop ANN model to compare the predicted value by ANN model and RSM equation with GP, LGP and MEP [13] and MARS [15] models . The summary of this comparison through 3 criteria of coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) presented in Table 7.

Table 7.

Summary of comparison between new RSM equation, ANN model and 4 available models.

Model	R square	RMSE	MAE
LGP	0.627	0.402	0.369
MEP	0.584	0.182	0.157
GP	0.664	0.259	0.227
Zhang	0.614	0.620	0.600
ANN	0.916	0.108243	0.092522
RSM	0.830	0.376	0.348

6. SENSITIVITY ANALYSIS

Because of the uncertainties in most geotechnical parameters, soil properties, and applied loads researchers have studied and applied reliability methods to quantify these uncertainties. In this study, sensitivity analysis was performed through Monte Carlo Simulation for two parameters of FC and D_{50}. The effect of these parameter uncertainties were studied by changing COV or ν and mean value. All variables are assumed to have normal distributions because when ν has a small value, the error of distribution function is minimal. All statistical properties of parameters are shown in Tables 8. It must be mentioned that during sensitivity analysis of any parameters extra parameters confirmed in their mean value and mean COV value.

Table 8

Statistics certificate of ANN model.

Input variable	Statistical Parameters

	Mean	Min	Max	Mean COV	Range COV	Distribution Function
σ_c	220	40.00	400	0.1	0.05-0.15	Normal distribution
Dr	30.30	-44.50	105.10	0.2	0.1-0.3	Normal distribution
FC	50.00	0.00	100.00	0.2	0.1-0.3	Normal distribution
Cu	14.82	1.52	28.12	0.2	0.1-0.3	Normal distribution
D50	0.25	0.03	0.46	0.2	0.1-0.3	Normal distribution
Cc	5.71	0.53	10.89	0.2	0.1-0.3	Normal distribution

7. RESULTS AND CONCLUSIONS

Through comparing 3 criteria of R^2, RMSE and MAE, the ANN model showed the best capability and accuracy, then RSM equation presented herein, showed more fitting with R^2=0.830 but MEP showed the less error then that RSM equation. Consequently, the RSM equation is capable to predict liquefaction resistance due to capacity energy (W). The sensitivity analysis carried out to evaluate the effect of parameters and their uncertainties on FC and D50 is illustrated in Figs. (1, 2). It can be seen that by increasing FC from 0% to 100% the probability of (Log W)>2.9 will change from 0 to 100%. By increasing COV of FC from 0.1 to 0.2 then 0.3 when FC=90, the probability of (Log W)>2.9 decreases 4% and 3% respectively. When the D50=0.12 the probability of (Log W)>2.9 by increasing from 0.1 to 0.2 then 0.3 is increased 6% and 5% respectively.

ACKNOWLEDGMENTS

This research was supported by the National Natural Sciences Foundation of China Grant No. 51639002. The authors are grateful for the support.

REFERENCES

1. Seed, H.B. and I.M. Idriss, *'Simplified procedure for evaluating soil liquefaction potential.'.* J. Geotech. Engrg. Div. , ASCE, , 1971.
2. Dobry, R., et al., *Prediction of pore water pressure buildup and liquefaction of sands during earthquakes by the cyclic strain method.* National Bureau of Standards Building Science Series, 138, U.S. Dept, of Commerce., 1982.
3. Nemat-Nasser, S. and A. Shokooh, *A unified approach to densification and liquefaction of cohesionless sand in cyclic shearing.* Canadian Geotechnical Journal, 1979. **16**(4): p. 659-678.
4. Dief, H.M., *Evaluating the Liquefaction Potential of Soils by the Energy Method in the Centrifuge.* 2000, Reserve University: Cleveland, OH.
5. Tao, M., *Case History Verification of the Energy Method to Determine the Liquefaction PotentialofSoilDeposits*, in *DepartmentofCivil Engineering*. 2003, CaseWesternReserveUniversity: Cleveland,OH. p. 173.
6. Kanagalingam, T., *Liquefaction Resistance of Granular Mixes Basedon Contact Densityand Energy Considerations.*, in *Department of Civil,Structural,and Environmental Engineering*. 2006, and Environmental Engineering,The State Universityof New YorkatBuffalo: Buffalo,NY. p. 386.
7. Baziar, M.H. and Y. Jafarian, *Assessment of liquefaction triggering using strain energy concept and ANN model: Capacity Energy.* Soil Dynamics and Earthquake Engineering, 2007. **27**(12): p. 1056-1072.
8. Baziar, M.H., et al., *Prediction of strain energy-based liquefaction resistance of sand–silt mixtures: An evolutionary approach.* Computers & Geosciences, 2011. **37**(11): p. 1883-1893.

9. Alavi, A.H. and A.H. Gandomi, *Energy-based numerical models for assessment of soil liquefaction.* Geoscience Frontiers, 2012. **3**(4): p. 541-555.
10. Cabalar, A.F., A. Cevik, and C. Gokceoglu, *Some applications of Adaptive Neuro-Fuzzy Inference System (ANFIS) in geotechnical engineering.* Computers and Geotechnics, 2012. **40**: p. 14-33.
11. Zhang, W., et al., *Assessment of soil liquefaction based on capacity energy concept and multivariate adaptive regression splines.* Engineering Geology, 2015. **188**: p. 29-37.
12. Running, D.L. *An energy-based Model for soil Liquefaction*. 1996.
13. Green, R.A., *Energy-based evaluation and remediation of liquefiable soils*. 2001, Virginia Polytechnic Institute and State University: Blacksburg.