# A NEW METHOD FOR PREDICTION OF SOIL LIQUEFACTION POTENTIAL

Yasaman Jafari Aval[1], Ali Derakhshani[2]

1) M. Sc. Student, Dept. of Civil Eng., Engineering Faculty, Shahed university, Tehran, Iran, Y.jafari@shahed.ac.ir

2) Assistant Professor, Dept. of Civil Eng., Engineering Faculty, Shahed university, Tehran, Iran, adera@shahed.ac.ir

## 1. Introduction

Estimation of soil liquefaction potential is among the most investigated topics of modern geotechnical engineering but still remains to be one of the challenging aspects of earthquake geotechnics. Liquefaction is a type of ground failure, which usually occurs in loose saturated soil. The generation of excess pore pressure under undrained loading conditions results in liquefaction. Researchers presented various correlations to estimate liquefaction potential but many of derived models have complicated formulas. This study presents simple correlations that are also accurate.

## 2. Model Trees (MTs)

Decision tree (DT) is a well-known technique of classification. DT includes answer nodes or leaf which indicate a class and decision nodes that contain an attribute name and branches to other decision trees, one for each value of the attribute. In DTs, classification starts from a root node and continues to generate sub-trees until creation of leaf nodes.

One of the most simple and suitable methods for prediction and categorizing data is model tree. Model tree is more accurate than regression trees, simpler and more understandable than ANN (Nahm-Chunget al., 2010). Model trees generalize the concepts of regression trees (Witten & Frank, 2000). MT is a classification method that its structure follows rules of the decision trees and has multivariate linear regression models at the leaf nodes.

## 3. Developing Numerical Correlations

In the literature, there are several studies addressing the estimation of soil liquefaction based on strain energy (e.g., Hsu, 1995; Polito et al., 2008).

For creation of a relationship between characteristics of soil, cyclic load and capacity energy, results of undrained cyclic tests are useful.

Multiple linear regression (MLR) was used to propose relationships for capacity energy of Sands in some studies (Figueroa et. al.,1994; Kusky, 1996; Liang et. al.,1995; Rokoff, 1999; Tao, 2003).

Baziar and Jafarian (2007) developed a new MLR-based relationship by their compiled database and proved drawbacks of previous relationships which were found considering a limited number of data.Some research programs focused on developing the relationships based on MLR, ANFIS and MARS were concluded with accurate results. Nevertheless, the presented formulas are too complex while they cannot show the effect of each parameter on the output, clearly. Some of these correlations can be seen in Table 1.

***Table 1. Comparison of two available accurate models***

Baziar (2011)

$$Log\ W = 3.69-\left(\frac{0.154x3+1.25x4x5-11.8\times10-4x2x3}{x3x5}\right)-\left(\frac{0.04x4}{x3-2.798x4}\right)+\left(\frac{1.4\times10-3(x1+5.382)}{x3(x3x5-x4)}\right)-\left(\frac{0.08(1.252-x4)}{5.218x5-x4}\right)-\left(\frac{0.003x3}{x4-6.214}\right)+\left(\frac{5.9\times10-5(x1+x4+x5)}{2.5837-x4}\right)-\left(\frac{0.056x2(x4-6.214)}{x3x5-6.214(x4-6.214)}\right)+\left(\frac{1}{x}\right)\left(\frac{0.202x4(2.5837-x4)}{(x1+x3)(2.5837-x4)-x2}\right)+3.7\times10^{-5}((x_1+x_2)(x_1-x_3)-1.2\times10^{-3}(x_2-x_4)(x_5-4.973)+9.5\times10^{-7}(x_2)^2(x_2x_5+x_4)+0.01x_3(x_5)^2(x_4-5.214)-0.019x_2-4.5\times10^{-5}(x_1)^2+0.003x_1$$

| $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ |
|---|---|---|---|---|
| $\sigma_c$ | $D_{50}$ | Dr+50 | Cu | FC+5 |

Zhang (2015)

| | |
|---|---|
| BF1 | max(0, 0.107 -$D_{50}$) |
| BF2 | max(0, 71.51 -Dr) |
| BF3 | max(0, 160 - $\sigma_c$ mean) |
| BF4 | max(0, FC -10) |
| BF5 | max(0, 10 -FC) |
| BF6 | max(0, $D_{50}$ -0.107) × max(0, Cu -5.88) |
| BF7 | max(0, $D_{50}$ -0.107) × max(0, 5.88 -Cu) |
| BF8 | BF5 × max(0, 0.16 -$D_{50}$) |
| BF9 | BF5 × max(0, Dr +9) |
| BF10 | BF5 × max(0, -9 -Dr) |
| BF11 | BF3 × max(0, $D_{50}$ -0.31) |
| BF12 | BF3 × max(0, 0.31 -$D_{50}$) |
| BF13 | max(0, Dr -71.51) × max(0, Cu -5.88) |
| BF14 | max(0, Dr -71.51) × max(0, 5.88 -Cu) |
| BF15 | BF4 × max(0, Dr -84.3) |
| BF16 | BF4 × max(0, 84.3 -Dr) |
| BF17 | BF4 × max(0, Cu -1.68) |
| BF18 | BF4 × max(0, 1.68 -Cu) |
| BF19 | BF5 × max(0, Cu -2.27) |
| BF20 | BF5 × max(0, 2.27 -Cu) |
| BF21 | BF4 × max(0, $D_{50}$ -0.25) |
| BF22 | max(0, $D_{50}$ -0.107) × max(0, $\sigma_0$ mean -132.7) |
| BF23 | max(0, $D_{50}$ -0.107) × max(0, $\sigma_0$ mean -100.3) |
| BF24 | max(0, $D_{50}$ -0.107) × max(0, 100.3 – $\sigma_0$mean) |
| BF25 | BF1 × max(0, 9.19 -Cu) |
| BF26 | BF3 × max(0, 2.8 -Dr) |

Log(W)=3.774+24.91×BF1-0.0061×BF2-0.025×BF3-0.012×BF4-0.091×BF5+0.519×BF6+1.554×BF7+3.713×BF8+0.00061×BF9+0.002×BF10-0.057×BF11+0.0984×BF12+0.0014×BF13+0.0053×BF14+0.00023×BF15+0.0001×BF16-0.0018×BF17+1.7×BF18+0.254×BF19+0.039×BF20+0.302×BF21+0.119×BF22-0.115×BF23+0.085×BF24-3.741×BF25-0.00013×BF26

## 4. Numerical model

A large database was used to develop the model which includes various types of cyclic element tests such as triaxial, torsional and simple shear. This data base contains 399 cyclic test results and it was reported and used by Baziar and Jafarian (2007) and Baziar et. al. (2011).

In this study, the whole data set was divided into two parts of training and testing. 80 % of data points were selected randomly and used for training to develop the model and 20 % were used for testing the model. Data range in test and train parts were approximately the same.

M5' model tree only presents a linear relationship between input and output variables, while the relation between governing parameters and strain energy is not necessarily linear. Thus, the model was developed with log (inputs) and log (output) to overcome this constraint (Etemad-Shahidi et. al., 2010).

## 5. Results and discussion

For developing the model, Weka, a powerful intelligent data mining tool was used.

Five parameters ($\sigma_c$, $D_{50}$, $D_r$, $C_u$, FC) were used as inputs to develop the model. Where, FC = percentage of fines, Cu = uniformity coefficient, $D_r$ = relative density, $D_{50}$ = mean grain size, W = capacity energy and $\sigma_c$ = initial mean effective confining pressure.

Different combinations of parameters were studied to develop the model. The best model from the accuracy and simplicity viewpoints, is described here. This shows a reasonably good performance for the dataset.

The following equations were obtained using M5':

Cu<= 1.663413

$$\text{LogW} = 0.9161 * \text{logs}\ \sigma_c + 2.0071 * \log(\text{Dr}+50) + 0.2778 * \log(\text{FC}+5) - 0.0334 * \log(\text{Cu}) + 1.2421 * \log(D_{50}) - 1.9209$$

Cu >1.663413

$$\text{LogW} = 0.8746 * \log \sigma_c + 0.8808 * \log(\text{Dr}+50) - 0.2412 * \log(\text{FC}+5) - 0.0119 * \log(\text{Cu}) - 0.2414 * \log(D_{50}) - 0.2299$$

***Table 2. Comparision of different models accuracy.***

| Researchers | CC | MAE | RMSE |
|---|---|---|---|
| Alavi, (2012) | 62.729 | 0.381 | 0.474 |
| Zhang, (2015) | 74.6 | 0.248 | 0.42 |
| Zhang-Goh, (2015) | 76.499 | 0.621 | 0.701 |
| Baziar, (2011) | 94.358 | 0.116 | 0.16 |
| Current study | 89.253 | 0.176 | 0.223 |

The derived model in this study is more user-friendly than the other formulas. Engineers can simply observe the effect of each parameter on capacity energy and the calculation of the capacity energy is so simple and the model is more accurate than several other models such as those proposed by Alavi (2012), Zhang (2015), etc.

As can be seen in Table.1 the derived formulas are so simpler than those presented in recent years for example formulas presented by Baziar (2011) and Zhang (2015).

As presented in Table 2., RMSE (root mean square error) and MAE (mean absolute error) of the new model are less than those of older models. Influence of all parameters are in agreement with other studies and are justifiable by principles of liquefaction phenomenon.

## 6. Refrences


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