ENERGY-BASED EVALUATION OF LIQUEFACTION POTENTIAL USING A NEURO-FUZZY SYSTEM

Mohammad H. BAZIAR¹, Mehdi T. YAZDIAN², Yaser JAFARIAN³

ABSTRACT

Evaluation of liquefaction potential in granular soils is one of the most interesting subjects in geotechnical earthquake engineering. Soft computing methods are efficient enough to solve the complicated problems that include many parameters. In recent years, artificial intelligent methods were employed in this field to capture the complicated behavior of soils in liquefaction condition. Neuro–Fuzzy which is one of the most recent soft computing methods is a hybrid system that combines artificial neural network and fuzzy logic. In this paper, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was built to create a correlation between soil parameters (σₘₑᵃぬ, Dr, FC, Cu, D₅₀) and the total strain energy required to trigger liquefaction in sandy soils. A large database containing numerous published cyclic triaxial, torsional shear, and simple shear tests results was employed to obtain an efficient and rigorous model. In this research, at first, the database was divided into two groups randomly. Subsequently, ANFIS was trained by 70% of the database and then validated with the rest 30%. The results of ANFIS prediction were considerably accurate for both training and testing stages.

Keywords: Liquefaction, Neuro-Fuzzy, Energy, Evaluation, ANFIS

INTRODUCTION

Liquefaction refers to the state at which sand loses shear strength and behaves as a viscous fluid. This loss of shear strength is not regained, independently of strain, until the excess pore-water pressure is dissipated (Figueroa et al. 1994). In the last century, liquefaction was one of major causes of damages during earthquakes such as Niigita and Alaska (1964), Loma Prieta (1989), Kobe (1995), Chi-Chi (1999), and Haiti (2010). The mechanism of liquefaction has been well recognized. The cyclic shearing of saturated granular soils causes a progressive buildup of pore water pressure which eventually approaches a value equal to the initial confining pressures, thereby softening the soil causing large strain (Wang & Rahman 1999).

When a seismic wave propagates through a saturated soil deposit, shear strains are mobilized in the soil and the energy of shaking damps due to the mechanical behavior of particles. Study on the nature of earthquake-induced pore pressure build up in the soil subjected to a strong shock provides a basis for better recognition of liquefaction occurrence. Dissipated energy density is the cumulative area of hysteresis stress-strain loops created by cyclic loading.

During the past three decades, many researchers have tried to explore a correlation between potential of pore pressure buildup and stress–strain dissipated energy in liquefiable soils. These studies have

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established a foundation for the energy-based liquefaction assessment approaches. The use of energy concept in liquefaction assessment of soils is a logical step due to the fact that the parameters used in this approach can be directly related to seismological parameters (Baziar & Jafarian 2007). Nemat-Nasser and Shokooh (1979) showed a functional relationship between the dissipated energy in laboratory samples and generated pore pressures (Green 2001). Considerable efforts were made to find a direct relationship between pore pressure and dissipated energy per unit volume of soils (e.g., Davis and Berrill, 1982; Simcock et al., 1983; Berrill and Davis, 1985; Law et al., 1990; Figueroa, 1990; and Figueroa and Dahisaria, 1991). According to previous findings, the shear energy required to liquefy soil deposit is approximately independent of the loading history. This is an advantage of strain energy method over other liquefaction assessment methods. Towhata and Ishihara (1985) found that there is a unique relationship between dissipated shear energy and pore water pressure buildup, independent of shear stress path.

Various studies have been carried out to propose energy-based models relating pore water pressure ratio, $r_u$, to dissipated strain energy density, $\Delta W$, loading parameters such as cyclic stress ratio (CSR) or strain level, stress-density parameters of soils such as initial void ratio ($e$) or relative density ($D_r$), initial effective confining pressure ($\sigma_c'$), and some calibration parameters obtained from the curve fitting of experimental data. Based on the energy-based laboratory liquefaction data, several liquefaction evaluation procedures have been developed (e.g., Baziar & Jafarian 2007). It is clear that developing a unique relationship between the mentioned parameters needs advanced statistical tools.

A relationship between capacity energy ($W$), soil initial parameters and calibration parameters could be derived by setting $r_u = 1$ at any energy-based pore pressure buildup model (Baziar and Jafarian 2007). Figueroa et al. (1994) introduced a relationship based on strain controlled cyclic torsional on Reid Bedford sand result that correlates $W$ to soil parameters:

$$\log W = 2.002 + 0.00477\sigma_c' + 0.0116D_r \quad \text{with } R^2 = 0.937$$

Where $W$ = strain energy per unit volume or capacity energy (J/m$^3$), $\sigma_c'$ = initial effective confining pressure of the sample (kPa), and $D_r$ =relative density of the sample. Coefficient of determination in this relationship is high but only for 27 cyclic torsional tests.

Baziar and Jafarian (2007) employed the results of more than 250 cyclic tests and developed a capacity energy model using Multiple Linear Regression (MLR) as below:

$$\log W = 2.1028 + 0.004566\sigma_c' + 0.005685D_r + 0.001821FC - 0.02868C_u + 2.0214D_{50} \quad R^2 = 0.65$$

Where FC = fine content (%), $C_u$ = coefficient of uniformity, and $D_{50}$ =grains mean diameter (mm). Figure 1 illustrates performance of this model using a comparison between its prediction and measured laboratory data.

Furthermore, Baziar and Jafarian (2007) proposed an ANN-based capacity energy model that correlates soil parameters ($\sigma_{\text{mean}}$, $D_r$, $C_u$, $D_{50}$) to $W$ with more accuracy ($R^2=0.9$) than the MLR-based models. They found that coefficient of curvature ($C_c$) is not very effective in the database and the proposed network that they used. Figure 2 illustrates results of the proposed ANN model when compared with the measured data.
Table 1: Comparison between performances of ANN model and other statistical models (after Baziar and Jafarian 2007)

<table>
<thead>
<tr>
<th>Models</th>
<th>Number of data</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of data</td>
<td>$R^2$</td>
</tr>
<tr>
<td>Figueroa et al.(1994)-MLR</td>
<td>27</td>
<td>0.94</td>
</tr>
<tr>
<td>Figueroa et al.(1994)-MLR</td>
<td>284</td>
<td>0.36</td>
</tr>
<tr>
<td>Baziar and Jafarian (2007)-MLR</td>
<td>284</td>
<td>0.65</td>
</tr>
<tr>
<td>Baziar and Jafarian (2007)-MLR</td>
<td>284 element test data</td>
<td>0.9</td>
</tr>
<tr>
<td>Baziar and Jafarian (2007)-MLR</td>
<td>18 centrifuge tests data</td>
<td>0.9</td>
</tr>
</tbody>
</table>
In this paper, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was built to create a correlation between soil parameters ($\sigma_{\text{mean}}$, $D_r$, FC, $C_u$, $D_{50}$) and the total strain energy required to trigger liquefaction in sandy soils. The database used in this study was gathered from Baziar and Jafarian (2007) and Kanagalingam (2006). This database was divided into three sets of data, 213 sets for training, 85 sets for testing, and 18 sets for checking the developed system.

**ANFIS MODEL**

Recently, some artificial intelligence techniques such as artificial neural networks, fuzzy systems, and evolutionary computation have been successfully combined to obtain new and more efficient techniques. These techniques are attracting more attention in several research fields because they tolerate a wide range of uncertainty (Jin and Jiang 1999).

The basic idea of merging fuzzy systems and neural network is to design an architecture that uses a fuzzy system to represent knowledge in an interpretable manner and profits from the learning ability of a neural network to optimize its parameters. This hybrid system can constitute an interpretable model that is capable of learning and can use problem-specific prior knowledge. Neuro-fuzzy (NF) models are specifically suited for applications where user interaction in model design or interpretation is desired (Garcia et al. 2007).

**Fuzzy Logic**

The human brain interprets imprecise and incomplete sensory information provided by perceptive organs. Fuzzy set theory provides a systematic calculus deal with such information linguistically, and it perform numerical computation by using linguistic labels stipulated by membership functions. Moreover, a selection of fuzzy if-then rules forms the key component of a fuzzy inference system (FIS) that can effectively model human expertise in a specific application (Jang et al. 1997).

The implementation of fuzzy logic considers the following steps (Ying and Zhuang 2006):
1. Fuzzification which requires conversion of classical data or crisp data into fuzzy data or Membership Functions (MFs)
2. Fuzzy Inference Process which connects membership functions with the Fuzzy rules to derive the fuzzy output
3. Defuzzification which computes each associated output.

**Artificial Neural Network**

ANNs are advanced tools stimulated by the physical and computational characteristics of the human brain. Like biological neurons, they consist of interconnected information processing neural elements, neurons, working in union to make decisions, classifications, predictions, and forecasts. Neural networks are capable to learn linear and nonlinear functions that make them influential tools to analyze complex relations. Interconnections among neurons are established by weights, which are applied to all values passing through one neuron to another. Changing weights improve adaptabilities and prediction capabilities of the neural networks (Hanna et al. 2007). The comprehensive hypothetical information about ANN can be found in (Haykin 2005).

**Adaptive Neuro-Fuzzy Inference System (ANFIS)**

ANFIS is a Neuro-Fuzzy system that developed by Jang et al. (1997) which fuzzy system use learn parameters of an adaptive back propagation learn algorithm (Jang et al., 1997). Neuro-fuzzy hybrid systems combine the advantages of fuzzy systems, which deal with explicit knowledge which can be
explained and understood, and neural networks which deal with implicit knowledge which can be acquired by learning (Gokceoglu et al. 2004).

**ANFIS Architecture**

For simplicity we assume that fuzzy inference system under consideration has two input $x$ and $y$ and one output $z$. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rule is the following:

Rule 1: If $x$ is $A_1$ and $y$ is $B_1$, then $f_1 = p_1 x + q_1 y + r_1$.

Rule 2: If $x$ is $A_2$ and $y$ is $B_2$, then $f_2 = p_2 x + q_2 y + r_2$.

where $A_1$, $A_2$ and $B_1$, $B_2$ are the membership functions for inputs $x$ and $y$, respectively; $p_1$, $q_1$, $r_1$ and $p_2$, $q_2$, $r_2$ are the parameters of the output function. Fig. 3(a) illustrates the reasoning mechanism for this Sugeno model to derive an output function ($f$) from a given input vector $[x, y]$ (Padmini et al. 2008).

![ANFIS Architecture Diagram]

Figure 3. ANFIS structure: (a) fuzzy inference system (FIS) and (b) equivalent ANFIS architecture (After Jang et al. 1997).

The corresponding equivalent ANFIS architecture is presented in Fig. 3(b), where nodes of the same layer have similar functions. The functioning of the ANFIS is as follows:

**Layer 1**: Each node $i$ in this layer creates membership grades of an input variable. The node output $OP_i^1$ is defined by

$$\text{(1)}$$

where $x$ (or $y$) is the input to the node $i$. $Ai$ (or $Bi-2$) is a linguistic label (like as “hot” or “cold”) associated with this node, characterized by the shape of the MFs in this node and can any appropriate functions that are continuous and piecewise differentiable such as Gaussian, generalized bell, trapezoidal...
and triangular shaped functions. Assuming a generalized bell function as the MF, the output $OP^1_i$ can be computed as (Padamini et al. 2008)

$$OP^1_i = \mu_{A_i}(x) = \frac{1}{1+(\frac{x-a_i}{b_i})^{2c_i}}$$

(3)

Where \{ai, bi, ci\} is the parameter set that changes the shapes of the membership function with maximum equal to 1 and minimum equal to 0. Parameters in this layer are referred to as premise parameters.

**Layer 2:** Every node in this layer multiplies the incoming signals, denoted as $\prod$, and the output $OP^2_i$ as

$$OP^2_i = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2$$

(4)

Each node output represents the firing strength of a rule.

**Layer 3:** Each node in this layer is fixed node, labeled as $N$, computes the normalized firing strengths as

$$OP^3_i = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2$$

(5)

Output of this layer are called normalized firing strengths

**Layer 4:** Node $i$ in this layer computes the contribution of the $i$th rule towards the model output, with the following node function:

$$OP^4_i = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i)$$

(6)

Where $\bar{w}_i$ is the output of layer 3 and \{p_i, q_i, r_i\} is the parameter set. This node is an adaptive node and called consequent parameters

**Layer 5:** The single node in this layer computes the overall output of the ANFIS as (Jang et al. 1997)

$$OP^5_i = \text{Overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

(7)

In ANFIS, input parameters are fuzzified with Membership Functions then initial MFs are changed with trial, and at the end the final MFs are selected by system to generate a system for non-trained input parameters.

Since liquefaction phenomenon is a complicated problem, use of advanced tools such as ANFIS can be useful and more efficient than neural network models.

**RESULT AND DISCUSSION**

The ANFIS structure explained above used to process the database to generate a system for predicting the strain energy for liquefaction triggering. To be more similar to field condition, the database was filtered and the cases having negative relative density were omitted from the database. The database includes 299 sets of data with 5 inputs ($\sigma_{\text{mean}}$, Dr, FC, $C_u$, $D_{s0}$) and one output ($W$). Number of 213 sets (approximately 70%) of all data were used to train the system and 85 sets (approximately 30%) of the database were used to test the trained system. Furthermore for validating the ANFIS model, another data
set which consists several centrifuge ground level liquefaction tests were employed (Dief 2000, Baziar and Jafarian 2007).

Table 2 includes the results of the developed model and error parameters. Comparison between these results and results of the previous models cited in Table 1 confirms that the Neuro-Fuzzy method improves the prediction of liquefaction triggering. It is observed that in spite of the increase in the number of data sets, accuracy of the system does not change. In this study, two types of membership function (MF) were used for evaluating how the type of MF affects the results. These MFs involve 2 triangular and 3 sigmoidal MFs for each input parameters. Although triangular MF is simple and consumes only a few seconds for run of the system, its accuracy is low compared with sigmoidal one. In contrast, sigmoidal MF takes more runtime and obtains higher accuracy instead. Table 2 shows that number and type of MF affect the results. But both of the analyses result in more accuracy than the previously proposed ANN model.

![Figure 4](image1.png)

*Figure 4. Predicted capacity by ANFIS model versus measured values for training and testing set with triangle membership function*

![Figure 5](image2.png)

*Figure 5. Predicted capacity by ANFIS model versus measured values for all database and checking set with triangle membership function*
Figure 6. RMSE versus number of epoch with triangle membership function

Table 2: Result of ANFIS model for the database

<table>
<thead>
<tr>
<th></th>
<th>2 Triangle Membership No. epoch=100</th>
<th>3 Sigmoidal Membership No. epoch=16</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>RMSE</td>
</tr>
<tr>
<td>Train</td>
<td>0.151</td>
<td>0.192</td>
</tr>
<tr>
<td>Test</td>
<td>0.1649</td>
<td>0.2117</td>
</tr>
<tr>
<td>All</td>
<td>0.1545</td>
<td>0.1969</td>
</tr>
<tr>
<td>Check</td>
<td>0.1326</td>
<td>0.1538</td>
</tr>
</tbody>
</table>

Figures 4 and 5 illustrate the capacity energy values predicted by the proposed model versus the corresponding measured values for training, testing, all data, and also the checking centrifuge data sets. Also, Figure 6 illustrates the values of root mean squared error (RMSE) versus number of epochs for 2 triangular membership functions. Figures 7 to 9 illustrate same plots for 3 sigmoidal MFs.

Figure 7. Predicted capacity by ANFIS model versus measured values for training and testing set with sigmoidal membership function
Figure 8. Predicted capacity by ANFIS model versus measured values for all database and checking set with sigmoidal membership function

Figure 9. RMSE versus number of epoch with sigmoidal membership function
Figure 10. Variation of $W$ versus $\sigma^{\prime}$ and other parameters kept constant by ANFIS model

Figure 11. Variation of $W$ versus $D_r$ by ANFIS model
A parametric study was performed to show how the ranges of soil parameters affect capacity energy (W). For the parametric study of a given soil parameter, other parameters were kept constant. Figures 10 to 12 illustrate the results of the developed system on the variations of $\sigma$, FC, $D_r$. It is observed in Figure 10 that increasing the initial effective mean confining pressure ($\sigma$) increases the corresponding values of capacity energy. Experimental results have also shown that by increasing the confining pressure the capacity energy increases (e.g. Liang et al. 1995).

The same procedure is observed for increasing the initial relative density ($D_r$) in Figure 11. Several laboratory and field observations have also confirmed that dense soils have lower probability for liquefaction occurrence and possess higher capacity energy (e.g. Liang 1995). Figures 10 and 11 demonstrate a reasonable agreement between the proposed ANFIS model and those observed in reality. For fines content, there is a more complicated behavior and previous studies lack a unique conclusion regarding the effect of fines content on liquefaction resistance. In Figure 12, the variation of fines content versus capacity energy is shown. Accordingly, increase of fines content decreases capacity energy. Baziar and Jafarian (2007) showed that capacity energy increases versus increasing fines up to 10 % and then decreases for the higher fractions of fines. The current study, however, has obtained an absolute descending trend, as seen in Figure 12.

CONCLUSION

In this study, an ANFIS model was developed to predict stain energy required for liquefaction onset, capacity energy. Also, a parametric study was conducted for validation of the system. The developed model gets better results compared with the previous studies conducted for the prediction of capacity energy. It is confirmed that ANFIS is a very powerful system to predict complex problems. Results of the parametric study not only demonstrate sensitivity of the developed model versus the variations of input but also confirm behavior of the model. The developed model shows that capacity energy increases versus initial effective stress and relative density and decreases versus fines percentage of the sand-silt mixture. Since effect of fines content is a matter of discussion in liquefaction potential assessment, finding of this study can be useful in this regard since it was evolved from the correlation of numerous laboratory data.
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