TECHNICAL NOTE

An Alternative Method for Determination of Liquefaction Susceptibility of Soil

Pijush Samui · J. Jagan · R. Hariharan

Abstract This article focuses on the application of extreme learning machine (ELM) for prediction of liquefaction susceptibility of soil based on cone penetration test data. The determination of liquefaction susceptibility of soil has been taken as a classification problem. ELM predicts liquefaction susceptibility of soil based on earthquake magnitude (M), cone resistance (q_c), mean grain size (D_{50}), total vertical stress (σ_0), effective vertical stress (σ'_0), normalized peak horizontal acceleration at ground surface (α/g), cyclic stress ratio $\left(\frac{\tau}{\sigma'_0}\right)$. Six models have been developed. The results of ELM have been compared with the artificial neural network models. This study shows that the developed ELM is a potential robust method for solving different problems in geotechnical engineering.

Keywords Extreme learning machine ·
Liquefaction · Cone penetration test · Artificial neural network

P. Samui (✉)
Department of Civil Engineering,
NIT Patna, Patna, Bihar, India
e-mail: pijushsamui@gmail.com

J. Jagan · R. Hariharan
Centre for Disaster Mitigation and Management, VIT University, Vellore 632014, India
e-mail: janyfriends57@gmail.com

R. Hariharan
e-mail: rhariharan88@yahoo.com

1 Introduction

In view of the rising number of earthquakes in the recent past, the determination of liquefaction susceptibility of soil is an important task in geotechnical earthquake engineering. Liquefaction causes severe loss to life and property due to sinking/overturning of buildings, ground cracking and sand blows. Geotechnical engineers use several in situ {Standard Penetration Test (SPT), cone penetration test (CPT) and Shear wave velocity} based techniques for determination of liquefaction susceptibility of soil (Seed and Idriss 1967, 1971; Seed et al. 1983, 1984; Robertson and Campanella 1985; Seed and De Alba 1986; Stark and Olson 1995; Olsen 1997; Robertson and Wride 1998; Dobry et al. 1981; Seed et al. 1983; Stokoe et al. 1988a; Tokimatsu and Uchida 1990; Andrus et al. 1999 and Andrus and Stokoe 2000). Every method has limitations. Geotechnical engineers successfully use artificial neural network (ANN) for determination of liquefaction susceptibility of soil (Goh 1994b, 1996; Agrawal et al. 1997; Najjar and Ali 1998; Ural and Saka 1998; Juang and Chen, 1999; Goh 2002; Javadi et al. 2006; Young and Byung Tak 2006; Goh and Goh 2007). However, ANN suffers from different drawbacks such as black box approach, arriving at local minima, low generalization capability, overtraining problem, etc. (Park and Rilett 1999; Kecman 2001).

This article examines the capability of extreme learning machine (ELM) for determination of liquefaction susceptibility of soil based on cone penetration

test (CPT) data. This article adopts the database collect from the work of Goh (1996). The dataset contains information about earthquake magnitude (M), cone resistance (q_c), mean grain size (D_{50}), total vertical stress (σ_0), effective vertical stress (σ'_0), normalized peak horizontal acceleration at ground surface (α/g), cyclic stress ratio $\left(\frac{\tau}{\sigma'_0}\right)$ and status of soil during earthquake. ELM is sophisticated learning algorithm for single-hidden-layer feedforward neural network (SLFN; Huang et al. 2004a). It chooses input weights and hidden biases randomly. It adopts Moore–Penrose (MP) generalized inverse for calculating output weights. There are lots of applications of ELM in the literatures (Bharathi and Natarajan 2011; Balbay et al. 2012; Gao et al. 2013; Yang et al. 2014). The developed ELM has been compared with the ANN model developed by Goh (1996).

2 Details of ELM

This section will serve the methodology of ELM for prediction of liquefaction susceptibility of soil. ELM is developed by Huang et al. (2004b). Let us consider the following datasets (D):

$$D = \{(x_i, y_i)\}_{i=1}^N \tag{1}$$

where x is input, y is output and N is the number of datasets. Table 1 shows the different inputs for determination of liquefaction susceptibility of soil.In SLFN, the relation between x and y is given below:

$$y = \sum_{i=1}^L \beta_i \cdot g\left(w_i x_j^T + b_i\right) \tag{2}$$

where β_i is the output weights from the hidden unit to the output units, w_i is the hidden unit weights, L is the

number of hidden nodes and g is the non-linear activation function. The above equation can be written in the following way.

$$H\beta = y \tag{3}$$

where $H = \begin{pmatrix} g\left(w_1 x_1^T + b_1\right) & \cdots & g\left(w_m x_1^T + b_m\right) \\ \vdots & \ddots & \vdots \\ g\left(w_1 x_n^T + b_1\right) & \cdots & g\left(w_m x_n^T + b_m\right) \end{pmatrix},$

$\beta = (\beta_1, \ldots, \beta_m)^T$ and $y = (y_1, \ldots, y_n)^T$.

The value of β is determined by solving the following equation.

$$\beta = H^{-1}y \tag{4}$$

where H^{-1} is the Moore–Penrose inverse of H (Rao and Mitra 1971).

In ELM, the datasets have been divided into the following two groups:

Training Dataset: This is used to develop the ELM. This article uses the same training datasets as used by Goh (1994b).

Testing Dataset: This is used to verify the developed ELM. This article adopts the same testing dataset as used by Goh (1994b).

The datasets are normalized between 0 and 1. The program of ELM has been developed by using MATLAB.

3 Results and Discussion

For developing the ELM, radial basis function has been adopted as activation function. Different number of hidden neurons have been tried to get best performance. The performance of ELM has been determined by using the following equation.

$$Performance = 1 - \frac{\text{No of misclassified datasets}}{\text{No of total datasets}} \tag{5}$$

For a good model, the value of performance should be close to one. Table 2 shows the performance of different models and number of hidden neurons. From Table 2, it is clear that

MODEL I,III and V give best testing performance. MODEL IV gives the best training performance. However, the performance of testing dataset of MODEL IV is not good. A comparative study has been

Table 1 Input variables for the different models

Model	Input variables
I	M, q_c, D_{50}, τ/σ'_0
II	M, q_c, τ/σ'_0, α, σ'_0
III	M, q_c, τ/σ'_0, α, D_{50}, σ'_0
IV	M, q_c, τ/σ'_0, α, D_{50}, σ'_0, α
V	M, q_c, D_{50}, α, σ'_0

Table 2 Performance of the developed ELM models

Model	Number of hidden neurons	Training performance	Testing performance
I	8	0.986	0.971
II	10	0.986	0.942
III	12	0.972	0.971
IV	10	1	0.942
V	7	0.986	0.971

Table 3 Comparison between the ANN (Goh 1996) and ELM models

Model	Performance of the ANN (Goh 1996)	Performance of the ELM
I	0.971	0.942857
II	0.942	0.857143
III	0.971	0.942857
IV	0.942	0.857143
V	0.971	0.942857

carried out between the developed ELM and ANN models. Comparison has been carried out for testing dataset. The performance of MODEL II and IV is not good. Table 3 shows the comparison. It is clear from Table 3 that the developed ELM outperforms the ANN. ELM has minimum human intervention compare to the ANN. The developed ELM is very fast. The major advantage of ELM is that all parameters of ELM are determined analytically. ELM uses only one tuning parameter. However, ANN uses many tuning parameters.

4 Conclusions

This article describes ELM for prediction of liquefaction susceptibility of soil based on CPT data. Five models have been developed. The developed ELM shows excellent performance. The results show that the developed ELM successfully captured the relationship between soil parameters and earthquake parameters for determination of liquefaction susceptibility of soil. It gives better performance than the ANN model. The developed ELM can be used as a quick tool for determination of liquefaction susceptibility of soil. Our experimental results show that the

developed ELM is a robust model for prediction of liquefaction susceptibility of soil.

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