EVALUATION OF LIQUEFACTION POTENTIAL OF SOIL BASED ON SHEAR WAVE VELOCITY USING EXTREME LEARNING MACHINE

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ABSTRACT: Soil liquefaction is one of the main causes for the heavy damages to the infrastructures and lifeline systems caused by the earthquakes and its identification is first step towards mitigation. In recent past soft computing techniques such as artificial neural network (ANN), support vector machine (SVM) and genetic programming (GP) are found to be more efficient compared to statistical methods. In the present study, relatively new soft computing technique known as extreme learning machine (ELM) is used to predict the liquefaction susceptibility of soil based on shear wave velocity (V_s) measurement data. The ELM is only suitable for single hidden layer back propagation neural network (BPNN), in which the input weights and hidden layer biases are chosen arbitrarily but, the hidden layer output weights and biases are determined analytically by inverse operation of hidden layer output matrices. As the parameters are obtained analytically, chances of solution getting stuck in local minima is less, hence the generalization of the model improves. Based on the obtained model parameters empirical equation is presented, which can be used by the geotechnical professionals for prediction of liquefaction potential of a soil in a future seismic event. The performance of the developed model is compared with that of other available soft computing model in terms of rate of successful prediction.

Keywords: *shear wave velocity; liquefaction index; extreme learning machine; root mean square error*

1 INTRODUCTION

Earthquake induced soil liquefaction is the most important cause of both losses of life and damage to infrastructures and lifeline systems. Though, soil liquefaction phenomena have been recognized since long, it was more comprehensively brought to the attention of engineers, seismologists and scientific community of the world by several devastating earthquakes around the world; Niigata and Alaska (1964), Loma Prieta (1989) and Kobe (1995) earthquakes.

The standard penetration test (SPT)-based simplified method, developed by Seed and Idriss (1971), has been modified and improved through several revisions (Seed et al. 1983; Youd et al. 2001) and remains the most widely used method around the world for evaluation of liquefaction potential. Robertson and Campanella (1985) first developed a cone penetration test (CPT) based method for evaluation of liquefaction potential as SPT method cannot identify thin layers. But, it is difficult to conduct CPT through gravelly soil. A potential alternative to the above penetration based methods is the in-situ measurements of small-strain shear-wave velocity (V_s). The use of V_s as an index of liquefaction resistance is firmly based on the fact that both V_s and liquefaction resistance are equally controlled by most of the same factors (e.g., void ratio, state of stress, stress history, and geological age). The V_s is a basic mechanical property of soil materials, directly related to small-strain shear modulus, G_{max} as given below:

$$G_{max} = \rho V_s^2 \tag{1}$$

where ρ is the mass density of soil. G_{max}, or V_s, is in general a required property in earthquake site response and soil-structure interaction analyses; and V_s can be measured by the spectral analysis of surface waves (SASW) technique at sites where borings may not be permitted or where sampling is difficult (Youd et al. 2001).

Over the past three decades, a number of investigations have been performed to study the relationship between V_s and liquefaction resistance, which include field performance observations (Andrus et al. 2004), Penetration-V_s correlations (Seed et al. 1983), analytical investigations (Stokoe et al. 1988) and laboratory tests (Tokimatsu and Uchida 1990).

Most common soft computing techniques such as; artificial neural network (ANN) (Juang and Chen

2000), support vector machine (SVM) (Samui and Sitharam, 2011) and genetic programming (GP) (Muduli et al. 2013) and its variant multi-gene genetic programming (MGGP) (Muduli and Das 2013) have been used to develop liquefaction prediction models based on an in-situ test database and are found to be very efficient.

In the recent past a modified learning algorithm called extreme learning machine (ELM) has been proposed by Huang et al. (2006) for single hidden layer feed forward neural network (SLFN). This learning algorithm for SLFN is very fast and hence named as extreme learning machine (ELM). In ELM the hidden nodes are randomly selected and output weights are computed analytically to avoid the problem of local optima. The ELM and its variants have been used for different large complex applications (Huang et al. 2006; Huang et al. 2012) with success and are found to be efficient and have better generalization compared to ANN and SVM (Huang et al. 2006). However, its use in geotechnical engineering is limited (Muduli et al. 2013, Muduli et al. 2015).

In the present study, an attempt has been made to predict the liquefaction potential of soil in terms of liquefaction field performance indicator referred herein as liquefaction index (*LI*) (Juang et al. 2001) on the basis of a large database consisting of post liquefaction V_s measurements and field manifestations using ELM and compare the efficacy of the developed model in terms of rate of successful prediction of liquefaction and non-liquefaction with that of the available MGGP-based model (Muduli and Das 2015).

2 METHODOLOGY

As ELM is not very common to geotechnical engineering professionals, hence, is discussed below in brief.

2.1 Extreme learning machine (ELM)

Huang et al. (2006) proved that the input weights and hidden layer biases of SLFN can be randomly assigned if the activation functions in the hidden layer are infinitely differentiable, which is true as sigmoid activation function is generally used in ANN. The SLFN can simply be considered as linear system and the output weights (linking the hidden layer to output layer) can be analytically determined through inverse operation of the hidden layer output matrices.

In the present study proposed ELM model can be presented as:

$$LI_p = F(V_s, \sigma'_v, FCI, CSR_{7.5}) \tag{2}$$

where, LI_p= predicated liquefaction index (LI = 1 for liquefied case and LI= 0 for non-liquefied case), F= the function referred herein as liquefaction index function. σ'_v= vertical effective stress of soil at the depth under consideration, FCI = fines content index (FCI =1, for fines content of soil, $FC \leq$ 5%; FCI =2, for 5%$\leq FC \leq$ 35%; FCI =3, for FC $\geq$ 35%) (Juang et al. 2001). Here, in the present study, the general formulation of cyclic stress ratio, *CSR* as presented by Seed and Idriss (1971) is adopted with minor modification, i.e., $CSR_{7.5}$ is adjusted to the benchmark earthquake (moment magnitude, M_w, of 7.5) by using the parameter, magnitude scaling factor (MSF) as provided in Youd et al. (2001).

The ELM model relating the input variables and the output for the prediction of liquefaction index can be written as,

$$LI_p = \sum_{i=1}^{L} \beta_i f\left(w_i * x_j + b_i\right) \tag{3}$$

where, w_i= $[w_{i1}, w_{i2,\ldots,} w_{in}]^T$ = weight vector connecting the i^{th} hidden node and the input nodes, β_i = weight vector connecting the i^{th} hidden node and the output node, b_i = the bias of the i^{th} hidden node, x_j= normalized input variable at j^{th} input node in the range [0,1]. L= number of hidden nodes. f is the sigmoid activation function as described in Eq. (4).

$$f(x) = \left(\frac{1}{1+e^{-x}}\right) \tag{4}$$

The detailed algorithm is presented in Hunag et al. (2006). In the present study ELM model is developed using Matlab (Math Work Inc, 2005).

3 DATABASE AND PREPROCESSING

In the present study, V_s based dataset of post liquefaction case histories from various earthquakes is used (Juang and Chen 2000). It contains information about soil and seismic parameters: depth (d), measured V_s, soil type, total vertical stress of soil at the depth under consideration (σ_v), σ'_v, peak horizontal ground surface acceleration a_{max}, M_w and $CSR_{7.5}$with field performance observations (LI). The depths at which V_s measurements are reported in the database range from 2m to14.8m. The V_s values range from 79 to 274 m/s. The *FCI* values are in the range of 1-3. The a_{max}, M_w and $CSR_{7.5}$values are in the range of [0.02, 0.51g], [5.9, 8.3] and [0.01, 0.41] respectively. The database consists of total 186 cases, 88 out of them are liquefied cases and other 98 are non-liquefied cases. Out of the above data 130 cases are randomly selected for training and remaining 56 data are used for testing the developed model. Muduli and Das (2015) also used the above database with the above number of training and testing data while developing their MGGP-based liquefaction model. Herein, the ELM approach normalization of the data is done in the range of [0, 1].

4 RESULTS AND DISCUSSION

Table 1 Statistical performances of the developed ELM-based model

Input variables	Data	R	E	AAE	RMSE
V_s, σ'_v, $FCI, CSR_{7.5}$	Training	0.73	0.53	0.28	0.34
	Testing	0.73	0.52	0.28	0.34

The "best" ELM model has been developed with a six hidden nodes SLFN (architecture of 4-18-1) after several trials with different number of hidden nodes. Fig. 1 shows the plot of RMSE value of training as well as testing data versus hidden nodes indicating the generalization performance of the ELM is stable on a wide range of hidden nodes though the generalization performance gets worst when very large number of hidden nodes is randomly generated. It is observed that the RMSE of testing data and training data is very close and minimum of the developed ELM model corresponding to 18 numbers of hidden nodes. Table 1 shows the statistical performances of both training and testing data for the developed ELM model for prediction of *LI* in terms of correlation coefficient (R),Nash-Sutcliff coefficient of efficiency*(*E) (Das and Basudhar2008), average absolute error (AAE)and root mean square error (RMSE). The performances of the above ELM model for training and testing data are found to be comparable showing good generalization. It is evident from the results presented in Table 2 that the proposed ELM based model is able to learn the complex relationship between the liquefaction index, *LI* and its main contributing factors with a very high accuracy. A prediction in terms of *LI* is said to be successful if it agrees with field observation of database. The successful prediction of liquefied and non-liquefied cases is 87% and 88% for training and testing data respectively. The above result is comparable with that of the MGGP based model (Muduli and Das 2015), where the rate of prediction of liquefied and non-liquefied cases are 88% and 86% respectively for training and testing data. It is important that the efficiency of different models should be compared in terms of testing data than that with the training data (Das and Basudhar 2008). Thus, it is found that the performance of ELM based prediction model is marginally better than that of the MGGP-based model (Muduli and Das 2015) in terms of rate of successful prediction of liquefaction and non-liquefaction cases.

4.1 Development of model equation

According to the Eq. (3) the ELM model equation can be written using the weights and biases of the trained model as provided in Table 3.The developed model equation can be used to predict the liquefaction index by the geotechnical engineers with the help of a spread sheet without going into the complexities of model development using ELM.

Table 2 Comparison of results of the developed ELM-based model with available MGGP –based model (Muduli and Das 2015)

Input Variables	Performance in terms of rate of successful prediction(%)			
	MGGP	ELM	MGGP	ELM
V_s, σ'_v, $FCI, CSR_{7.5}$	Training Data		Testing Data	
	88	87	86	88

Table 3 Weights and biases as per the proposed trained ELM-based model

Hidden Neuron	Weights					Biases (Hidden nodes)
	Input				Output	
	V_s (m/s)	σ'_v (kPa)	FCI	$CSR_{7.5}$	LI	b_i
1	0.53	-0.75	0.13	0.97	305.79	0.35
2	0.16	-0.59	0.28	0.72	-640.91	0.45
3	0.86	-0.71	-0.16	0.57	-34.85	0.05
4	0.160	-0.62	-0.59	0.026	-75.77	0.18
5	-0.97	-0.91	0.89	-0.64	210.09	0.66
6	-0.76	0.27	-0.83	-0.20	131.39	0.33
7	0.72	-0.44	-0.79	-0.73	206.50	0.90
8	-0.03	0.08	-0.71	-0.94	-45.83	0.12
9	0.69	0.39	-0.67	0.88	78.34	0.99
10	-0.58	-0.001	0.24	-0.39	-291.36	0.54
11	0.10	0.07	0.15	-0.41	51.99	0.71
12	0.26	-0.11	-0.89	-0.33	-246.07	0.99
13	-0.93	-0.75	0.86	-0.06	-161.36	0.28
14	0.23	-0.02	0.45	0.29	-63.09	0.41
15	-0.27	0.70	0.47	-0.95	-52.35	0.46
16	-0.90	0.75	-0.87	0.68	117.87	0.76
17	-0.02	-0.46	0.72	0.12	345.83	0.82
18	-0.61	-0.58	0.87	0.71	100.37	0.10

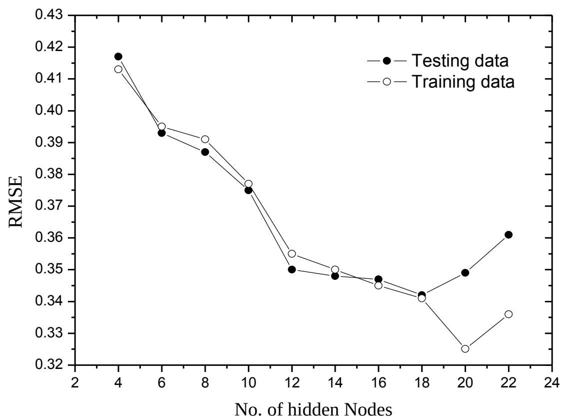

Fig. 1. Generalization performance of ELM on a wide range of hidden nodes.

5 CONCLUSION

V_s-based post liquefaction database (Juang and Chen 2000) is analyzed using ELM-based approach to predict the liquefaction potential of soil in terms of liquefaction field performance indicator, *LI*. The efficacy of the developed ELM-based model is compared with that of the available MGGP-based model (Muduli and Das 2015). It is found that the performance of ELM based model is marginally better than that of the MGGP based model in terms of rate of successful prediction of liquefaction and non-liquefaction cases. The statistical performance parameters (R, E, AAE and RMSE) for training and testing data are comparable in the proposed ELM-based model, which shows good generalization capabilities of ELM approach. The proposed model equation can be used by geotechnical engineering professionals with the help of a spreadsheet to predict the liquefaction potential of soil for future seismic event without going into the complexities of model development using ELM.

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