A NEUROFUZZY TECHNIQUE TO PREDICT SEISMIC LIQUEFACTION POTENTIAL OF SOILS

Vijay Kumar, Kumar Venkatesh, R.P. Tiwari[*]

Abstract: Liquefaction potential is a scientific assessment parameter to assess liquefaction of medium to fine grained cohesion-less soil due to earthquake shaking. In this paper alternative liquefaction potential prediction models have been developed using adaptive neuro fuzzy inference system (ANFIS) and multiple linear regression (MLR) technique. Geological survey of the study area was performed and forty locations were identified to perform standard penetration test (SPT). Disturbed and undisturbed soil samples were collected from the borehole to execute the laboratory tests. The bore-log datasets were used for determining liquefaction potential of the cohesion-less soils. The analytical approach by Idriss and Boulanger (I & B) has been applied initially to estimate liquefaction potential of soil on the basis of standard penetration test datasets obtained from the field investigations. To develop the ANFIS models 101 datasets were collected and incorporated for the development of fuzzy neural network models. Multiple linear regression (MLR) models have also been developed and the results were compared with neuro-fuzzy models. Based on obtained results it can be stated that the developed adaptive neuro fuzzy inference system models have better prediction ability to predict liquefaction potential with satisfactory level of confidence and can be used as an alternative tool.

Key words: *Liquefaction potential, ANFIS, standard penetration test, Idriss and Boulanger multiple linear regression*

Received: May 29, 2013 **DOI:** 10.14311/NNW.2014.24.015
Revised and accepted: May 12, 2014

1. Introduction

On 26$^{\text{th}}$ January 2001, an earthquake originated in Bhuj (India) with maximum horizontal acceleration 0.35 g, damaged many medium and high rise buildings in and around Bhuj city [1]. The city buildings experienced differential settlement by violent shaking; this phenomenon was due to liquefaction which is caused by earthquake. Soil liquefaction occurs in loose, saturated cohesion-less soil units (sands

*Kumar V. – Correspondence Author, Venkatesh K., Tiwari R. P., Civil Engineering Department, Motilal Nehru National Institute of Technology, Allahabad, Uttar Pradesh, Pin-211004, India, Tel.: +91-9616848223, E-mail: `vijay03c34@gmail.com`

and silts) and sensitive clays. Different methods like modified Seed's method, Tokimatsu and Yoshimi method and Idriss and Boulanger method etc. are used to estimate liquefaction potential using soil properties and seismic parameters. Soil properties are determined using in situ SPT and laboratory testing. However, in-situ testing is tedious method involving skilled labour, high cost and extra time. Therefore, alternative approach with economical and reliable prediction of liquefaction has been executed considering the soft computing and multi linear regression approach.

Though soft computing methods have been applied in various field of civil engineering however limited applications are available in the area of assessment of liquefaction potential using ANFIS. Some researchers like Goh, 1995, 2002; Wang et al., 2010; Moradi et al, 2011; Wang and Rahman, 1999; Hanna et al., 2007a, 2007b; Hsu et al. 2006; kayabah, 1996; Sitharam, et al., 2004; Rao et al., 2007; Chiru-Danger et al. 2001; Juang et al. 2000, 2001; Hsu et al. 2006;Ramakrishnan et al., 2008;Gracia et al., 2008;kayadelen et al., 2009 etc. [4–13, 1, 14–17] have developed the models using neural network technique for assessing liquefaction potential.

Fuzzy neural network which is integration of well-known fuzzy and neural network technique has been applied for the assessment of liquefaction potential in this work. Fuzzy neural network which was first proposed by Jang [2] in fuzzy modeling environment is divided into two areas: linguistic fuzzy modeling which is focused on interpretability is mainly the Mamdani model [3]; and precise fuzzy modeling that is focused on accuracy is mainly the Takagi-Sugeno-Kang (TSK) model. Adaptive Neuro-Fuzzy Inference System (ANFIS) falls in the category of precise fuzzy modeling.

Current research is the effort of assessing liquefaction potential of Allahabad city situated near the banks of river Ganga and Yamuna. Since alluvial soil is abundantly present in this vicinity and soil strata on the bank of river are mainly consist of sand, silt and clay soil at various depths. The upper part of strata contains major portion of silty soil and sandy silt enhancing probability of liquefaction. So there is a major chance of liquefaction occurrence in the upper soil strata during the earthquake. Analytical method given by Idriss and Boulanger (I & B) was used initially for liquefaction potential assessment, later on it was incorporated in Neuro-fuzzy and MLR modeling approach for predicting liquefaction potential of soils.

2. Liquefaction Potential Assessment

2.1 Idriss and Boulanger's method

Geotechnical professionals generally investigate subsurface to evaluate the potential for liquefaction. The most common techniques using standard penetration test (SPT) i.e. blow count (commonly referred as to the "N-value"). The liquefaction potential assessment by analytical approach follows certain protocols:

1. Estimation of the cyclic stress ratio (CSR) induced at various depths within the soil by the earthquake.

2. Estimation of the cyclic resistance ratio (CRR) of the soil, i.e. the cyclic shear stress ratio which is required to cause initial liquefaction of the soil.

3. Evaluation of factor of safety against liquefaction potential of in situ soils

Calculation of CSR: Modus operandi by Idriss & Boulanger [18] for evaluation of CSR is same as "simplified method". Right after CSR calculated from the equation (1).

$$\mathrm{CSR} = \tau_{avg}/\sigma'_{\mathrm{v}} = 0.65\,(a_{max}/g)\,(\sigma_v/\sigma'_v)\,\mathrm{r_d} \tag{1}$$

Value of CSR is adjusted for the moment magnitude M = 7.5. Accordingly the value of CSR is given as

$$(CSR)_{M=7.5} = CSR/MSF = 0.65\,(\sigma_v a_{max}/\sigma'_v)\,\frac{r_d}{MSF} \tag{2}$$

A new parameter $\mathrm{r_d}$ which could be adequately expressed as a function of depth and earthquake magnitude (M) was introduced and can be explain from following relations:

$$\ln(r_d) = \propto(z) + \beta(z)\,M \tag{3}$$

$$\propto(z) = -1.012 - 1.126 sin\,(z/11.73 + 5.133) \tag{4a}$$

$$\beta(z) = 0.106 + 0.118 sin\,(z/11.28 + 5.142) \tag{4b}$$

where z is the depth in meters and M is moment magnitude. These equations were appropriated for depth $z \leq 34$ m however for depth $z > 34$ m; the following expression can be used:

$$\mathrm{r_d} = 0.12\exp(0.22\mathrm{M}) \tag{5}$$

$\mathrm{CSR}_{7.5}$ is the cyclic stress ratio for magnitude of 7.5 earthquakes, magnitude smaller or larger than 7.5, introduces a correction factor namely magnitude scaling factor MSF defined by the following equation given by [19]:

$$\mathrm{MSF} = 10^{2.24}/\mathrm{M}^{2.56} \tag{6}$$

Calculation of CRR: Idriss and Boulanger [18] adjusted the equation of CRR for clean sands as follows

$$\mathrm{CRR} = \exp\left\{\frac{(\mathrm{N_1})_{60cs}}{14.1} + \left(\frac{(\mathrm{N_1})_{60cs}}{126}\right)^2 - \left(\frac{(\mathrm{N_1})_{60cs}}{23.6}\right)^3 + \left(\frac{(\mathrm{N_1})_{60cs}}{25.4}\right)^4 - 2.8\right\} \tag{7}$$

Subsequent expressions describes the way parameters in the above equation is calculated

$$(N_1)_{60cs} = (N_1)_{60} + (\Delta N_1)_{60} \tag{8a}$$

$$(\Delta N_1)_{60} = exp\,(1.63 + 9.7/FC - (15.7/FC)) \tag{8b}$$

$$(N_1)_{60} = C_N\,(N)_{60} \tag{8c}$$

The use of equations in preceding articles provides a convenient means for evaluating the cyclic stress ratio required to cause liquefaction for cohesion-less soils with varying fines content.

Calculation of Factor of Safety: If the cyclic stress ratio caused by an earthquake is greater than the cyclic resistance ratio of the in situ soil, then liquefaction could occur during the earthquake, and vice versa. The factor of safety (FOS) against liquefaction is defined as:

$$\mathrm{FS}_{\mathrm{Liquefaction}} = \mathrm{CRR}/\mathrm{CSR} \tag{9}$$

Liquefaction is predicted to occur when $FS \leq 1.0$, and liquefaction predicted not to occur when $FS > 1$. The higher the factor of safety, the more resistant against liquefaction [20], however, soil that has a factor of safety slightly higher than 1.0 partially liquefy during the earthquake.

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the most successful schemes which combine the benefits of ANN and FIS into a single capsule [1]. The attractive features of an ANFIS include: easy to implement, fast and accurate learning, strong generalization abilities, excellent explanation facilities through fuzzy rules, and easy to incorporate both linguistic and numeric knowledge for problem solving [21, 22]. According to the neuro-fuzzy approach, a neural network is proposed to implement the fuzzy system. A typical architecture of an ANFIS, in which a circle indicates a fixed node, whereas a square indicates an adaptive node, is shown in Fig. 1. In this structure, there are input and output nodes, and in the hidden layers, there are nodes functioning as membership functions (MFs) and rules. For simplicity, we assume that the examined FIS has two inputs and one output. For a first-order Sugeno fuzzy model [3], a classic rule set with two fuzzy "if then"rules is as following:

$$\text{Rule 1: if } a \text{ is } A_1 \text{ and } b \text{ is } B_1, \text{ then } f_1 = p_1 a + q_1 b + r_1, \tag{10a}$$

$$\text{Rule 2: if } a \text{ is } A_2 \text{ and } b \text{ is } B_2, \text{ then } f_2 = p_2 a + q_2 b + r_2. \tag{10b}$$

where a and b are the two crisp inputs, and A_i and B_i are the linguistic labels associated with the node function.

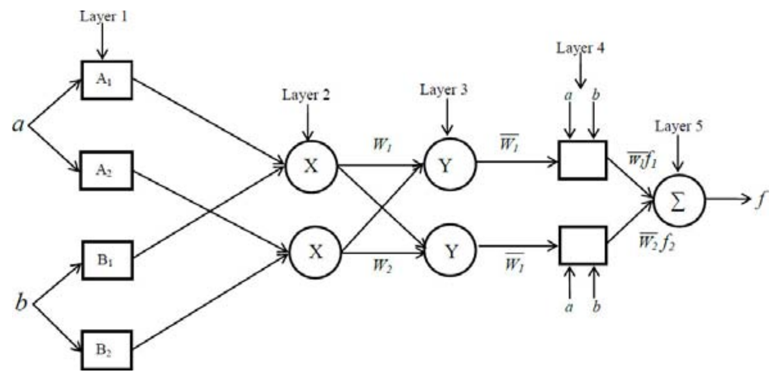

Fig. 1 *First order Sugeno ANFIS architecture.*

As indicated in Fig. 1, the system has a total of five layers. The functioning of each layer is described as follows [1].

Input node (Layer 1): Nodes in this layer contains membership functions. Parameters in this layer are referred to as premise parameters. Every node i in this layer is a square and adaptive node with a node function:

$$O_i^1 = \mu_{A_i}(a) \text{ for } i = 1, 2. \tag{11}$$

where x is the input to node i, and A_i is the linguistic label (small, large, etc.) associated with this node function. In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i.

Rule nodes (Layer 2): Every node in this layer is fixed node labeled X, whose output is product of all incoming signals.

$$O_i^2 = w_i = \mu_{A_i}(a) \times \mu_{B_i}(b) \text{ for } i = 1, 2 \tag{12}$$

Average nodes (Layer 3): Every node in this layer is fixed node labeled Y. The i$^{\text{th}}$ node calculates the ratio between the i$^{\text{th}}$ rule's firing strength to the sum of all rule's firing strengths. Every node of these layers calculates the weight, which is normalized. For convenience, outputs of this layer are called normalized firing strengths.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \text{ for } i = 1, 2 \tag{13}$$

Consequent nodes (Layer 4): Every node i in this layer is an adaptive node with a node function

$$O_i^4 = \bar{w}_i \times\, f_1 = \,\bar{w}_i \times (\,p_i a + q_i b + r_i) \tag{14}$$

Where $\bar{w}_i$ is a normalized firing strength from layer 3 and $(p_i,\ q_i,\ r_i)$ is the parameters set of this node. Parameters in this layer are referred to as consequent parameters.

Output node (Layer 5): The single node in this layer is a fixed node labeled $\sum$, which computes the overall output as the summation of all incoming signals:

$$\text{Overall output } = O_i^5 = \sum_i \bar{w}_i \times\, f_1 = \frac{\sum_i w_i \times f_i}{\sum_i w_i} \tag{15}$$

2.3 Multiple Linear Regression (MLR) Analysis

Regression analysis is the study of establishing the functional relation between independent and dependent variables. The independent variables may vary from one or greater than one depending on the requirement of the dependent models. However, the number of dependent variables is strictly restricted to one. The general formula of regression establishing relationship between different independent variables and a dependent variable is shown below [23]:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \ldots b_p x_p \tag{16}$$

$$\text{or, } y = b_0 + \Sigma b_i x_i \tag{17}$$

where, $i = 1, 2, \ldots, p$
y is the dependent variable (liquefaction potential in this case)
$x_1, x_2 - x_p$ are independent variables,
and $b_0, b_1, b_2 - b_\mathrm{p}$ are the coefficients that has to be determined using regression analysis.

3. Methodology

After geological survey, soil investigation of the sites and its surroundings were carried out initially for pertinent data collection. In-situ standard penetration test was conducted to collect disturbed and undisturbed soil samples from the 40 boreholes. The required soil properties were investigated in the laboratory to determine liquefaction potential of cohesion-less soils using I & B analytical approach. The bore-log charts of different boreholes were used to collect the input datasets whereas output datasets were obtained from I & B analytical method. To develop the ANFIS and MLR models 101datasets were collected in terms of input and output values of the models.

3.1 Experimental method

Standard penetration test was conducted in order to collect disturbed and undisturbed soil samples. Disturbed and undisturbed soil samples were collected from these boreholes up to the depth of 10 meters. The SPT N-value was also determined at a regular interval of 1.5 m depth [24]. Disturbed soil samples were used to determine liquid limit; plastic limit; angle of internal friction; particle size finer than 2 mm, 0.075 mm and 0.002 mm and undisturbed samples were used to determine natural water content [25-27], bulk unit weight. All experiments were conducted according to bureau of Indian standard's guidelines for soil testing.

Data modification: Corrected SPT-N values are required to estimate liquefaction potential using I & B method hence standard procedure for correcting SPT-N value was adopted as per the Indian Standard IS: 2131-1981 [24]. A brief discussion on corrected SPT-N value is discussed hereunder:

Correction for overburden pressure: N-value obtained from SPT test is corrected first which is either calculated by the equation:

$$\mathrm{N}_1 = \mathrm{C}_\mathrm{N} \tag{18}$$

C_N is correction factor obtained directly from the graph given in Indian Standard Code (IS: 3121-1981) (Fig. 2).

It can also be calculate from the following relationship i.e.

$$\mathrm{C}_\mathrm{N} = 0.77 log_{10} \frac{2000}{p} \tag{19}$$

where, p is effective overburden pressure in $\mathrm{kN/m^2}$ [28].

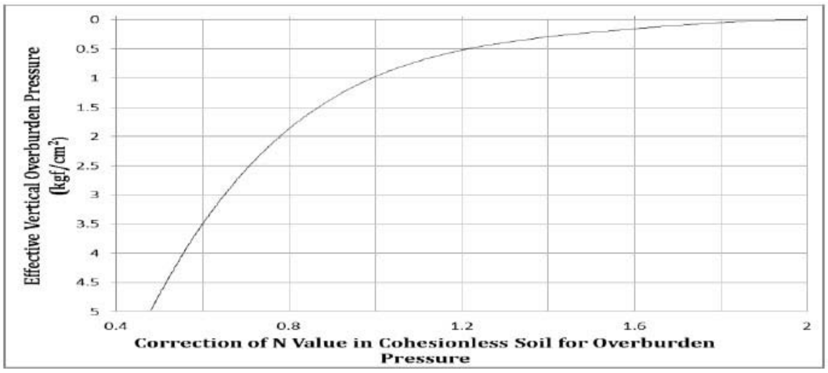

Fig. 2 *Correction due to overburden pressure.*

Dilatancy Correction: The values obtained in overburden pressure (N_1) shall be corrected for dilatancy if the stratum consist of fine sand and silt below water table for the values of N_1 greater than 15 by following equation [29]:

$$N_c = 15 + 0.5(N_1 - 15) \tag{20}$$

The range of soil properties found through SPT and other laboratory test used as input vectors in ANFIS method is shown in Tab. I. Two parameters i.e. water table (W) and earthquake magnitude (M) were varied for parametric studies. Level of water table varied from 0, 2, 4, 6 and 8 m from ground surface and earthquake magnitude varied for 6.0, 7.0 and 8.0. Hence, 15 combinations were formed for calculating CSR value by I & B method for the specific depth of water table and earthquake magnitude as shown in Tab. II. Similarly, CSR values were obtained for different combination of depth and earthquake magnitude.

Input Parameters	**Ranges**
depth (m)	0-10
SPT-N value	0-50
Bulk unit weight (γ_t)	1.31-2.36
Particle finer than 0.075 mm (%)	18.34-99.64
Natural water content	1.16-32.3

Tab. I *Ranges of Input Parameters.*

Depth of water table (m)	0	2	4	6	8
Earthquake magnitude (Richter scale)	6.0	7.0	8.0	—	—

Tab. II *Assumed Water Table and Earthquake Magnitude.*

4. Development of ANFIS and MLR Models

Since this study is based on SPT and bore log chart datasets. Initially two fundamental input variables i.e. depth (z) and SPT-N value (N) were chosen for the development of the fuzzy neural network models for predicting liquefaction potential. Subsequently input variables were increased to develop an optimum liquefaction potential model with minimum error. Study carried out up to five input variables comprising depth (d), SPT-N value (N), bulk density (ρ_f), particle size finer than 0.075 mm (D_x) and natural/field moisture content (w_f). In this, 30 borehole datasets were used for training and testing whereas 10 borehole datasets were reserved for validating the fuzzy neural network models. Normalized datasets were used for models using following equation [30].

$$\alpha = \frac{\alpha_{actual} - \alpha_{min.}}{\alpha_{max.} - \alpha_{min.}} \tag{21}$$

where, α = Normalized value.
α_{actual} = data which has to be normalized, the input and output parameter's value.
α_{min} = minimum value of data.
and, α_{max} = maximum value of data.

ANFIS modeling tool was used for all operations in which networks were trained for varying numbers of epochs. Grid partitioning method and triangular membership function were used to generate fuzzy inference system from input variables, whereas linear membership function was used for target variable. Hybrid optimization technique was used for training FIS [31]. Inputs were increased gradually to study the effect of individual parameter on liquefaction. Output parameter (that is occurrence of liquefaction) in the ANFIS model is designed to answer in like/unlike format based on I & B method [32].

To identify different network architecture with its fundamental attributes a coding method was used for different networks, as such $W_X M_Y$ where, W_X denotes depth of water table and M_Y is earthquake magnitude value. The predicted values of liquefaction potential by developed models are discussed in subsequent heading.

Regression analyses were also carried out to establish the functional relation between independent and dependent variables to develop MLR models. The developed multivariate liner equations from MLR analysis are presented in Tab. VIII. These equations are shown for all fifteen combinations of water table and earthquake magnitude. The generalized form of MLR equations to predict liquefaction potential (LP) is as follows

$$\mathrm{LP} = A_1 - A_2 d + A_3 N + A_4 D_x + A_5 w_f - A_6 \rho_f \tag{22}$$

where, A_1 to A_6 represents the constant of the equation with the adopted variables i.e. depth (d), SPT-N value (N), percentage finer then 0.075 (D_x), moisture content (w_f) and bulk density (ρ_f).

5. Results and Discussion

The developed ANFIS and MLR models were validated using reserve datasets. As mentioned above five levels of water table and three earthquake magnitudes were considered for assessing liquefaction potential using I & B, ANFIS an MLR technique. These parameters resulted in total of fifteen set of liquefaction values. Tab. III(a), IV(a) and V(a) show liquefaction potential values for these combinations predicted by ANFIS models. Using the same datasets MLR models were developed, validated and compared with observed values obtained by conventional methods are depicted in Tab. III(b), IV(b) and V(b).

Tab. III to V displays the results of liquefaction potential on the basis of CRR/CSR obtained from I & B method where as ANFIS and MLR models predictions are based on five input parameters. In some of the combinations, the liquefaction potential values predicted by ANFIS and MLR models is not in accordance with I & B method. The comparison between the predicted values of optimum ANFIS models and I & B method are also shown in Figs. 3 to 5. This study also highlights the drawbacks with respect to predicted value by ANFIS method are as follows: W_6M_2 ANFIS model is giving liquefaction potential as 0.952 instead of 1.25; similarly W_6M_4 model predicting 1.109 compared to 0.826. In case of W_6M_6 model it is 1.027 and 1.25 compared to 1.00 and 0.995 similarly in W_6M_8 it is 1.25, 1.25, 1.024 and 1.25 in comparison to 0.942, 0.874, 0.918 and 0.815 as displayed in Tab. III(a). In Tab. IV(a) liquefaction potential is predicted by ANFIS model for W_7M_{24} is 0.993 compared to 1.037. In case of Tab. V(a) liquefaction potential predicted by ANFIS model for W_8M_8 is 1.001 and 1.25 in comparison to 0.884 and 0.956. Similarly MLR also predicted some results incorrectly for example model M_6W_0 gave four incorrect prediction as 1.129, 1.154, 1.312, & 1.154, model M_6W_2 gave five incorrect prediction as 1.799, 1.224 & 1.749, 1.749 & 1.749 model M_6W_4 gave six incorrect prediction as 1.010, 1.539, 2.113, 2.113, 1.800 & 2.113 model M_6W_6 also gave six incorrect prediction as 0.000, 2.134, 2.134, 1.808, 2.134 & 0.829 and model M_6W_8 gave five incorrect prediction as 0.000, 2.025, 2.025, 1.719, 2.025. Above incorrect predictions were found for earthquake magnitude of 6.0. The details of predicted value for earthquake magnitude of seven and eight respectively may also viewed in Tab. IV(b) & V(b) to observe the limitations of these methods.

The results obtained from lesser input vectors were ignored since liquefaction values obtained with the combination of five input vectors were close to I & B method. Coefficient of determination (COD or R^2), mean absolute error (MAE) and root mean square error (RMSE) obtained for fifteen cases by ANFIS and MLR models are summarized in Tab. VI. The coefficient of determination is as high as 0.998 for the earthquake magnitude 7.0 whereas water table is at ground level for ANFIS models. As per the results, most of the ANFIS models have coefficient of determination greater than 0.9 which illustrate good prediction capabilities of ANFIS models. The ANFIS models from combinations M_6W_0, M_7W_0 and M_8W_6 having the coefficient of determination values of 0.9943, 0.9979 and 0.9922 respectively, that illustrate that ANFIS models needs improvement with a lot of datasets. However, the incorrect predicted liquefaction potential from these models varied from one to four (bolded results in respective Table) out of total 30 validation

S. No.	Depth (z)	SPT-N value	For network M_6W_0				For network M_6W_2				For network M_6W_4				For network M_6W_6				For network M_6W_8			
			lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS	
			ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status
1	4.5	22	0.618	Like	0.618	Like	0.895	Like	0.895	Like	1.172	Unlike	1.172	Unlike	1.241	Unlike	1.24	Unlike	1.241	Unlike	1.241	Unlike
2	6	21	0.569	Like	0.576	Like	0.755	Like	0.776	Like	0.941	Like	0.954	Like	1.127	Unlike	1.12	Unlike	1.127	Unlike	1.194	Unlike
3	7.5	20	0.615	Like	0.601	Like	0.753	Like	0.731	Like	0.89	Like	0.919	Like	1.027	**Unlike**	1	**Like**	1.13	Unlike	1.166	Unlike
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	3	28	0.957	Like	0.931	Like	1.25	Unlike	1.09	Unlike	1.25	Unlike	1.123	Unlike	1.25	Unlike	1.1	Unlike	1.25	**Unlike**	0.942	**Like**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
18	3	27	1.06	Unlike	1.023	Unlike	1.25	**Unlike**	0.952	**Like**	1.25	Unlike	1.092	Unlike	1.25	Unlike	1.03	Unlike	1.25	**Unlike**	0.874	**Like**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
25	9	14	0.469	Like	0.432	Like	0.58	Like	0.48	Like	0.692	Like	0.549	Like	0.803	Like	0.816	Like	0.914	**Like**	1.035	**Unlike**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
30	7.5	17	0.505	Like	0.452	Like	0.648	Like	0.55	Like	0.791	Like	0.657	Like	0.934	Like	0.775	Like	1.042	**Unlike**	0.918	**Like**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
34	7.5	28	0.746	Like	0.688	Like	0.928	Like	0.763	Like	1.109	Unlike	0.826	Like	1.25	**Unlike**	0.995	**Like**	1.25	Unlike	0.815	Unlike

Tab. III(a) *Liquefaction potential from ANFIS model for earthquake magnitude 6.0 with varying water level.*

S. No.	Depth (z)	SPT-N value	For network M_6W_0				For network M_6W_2				For network M_6W_4				For network M_6W_6				For network M_6W_8			
			lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR	
			ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status
1	4.5	22	**0.618**	**Like**	**1.129**	**Unlike**	**0.895**	**Like**	**1.799**	**Unlike**	1.172	Unlike	2.229	Unlike	1.241	Unlike	2.418	Unlike	1.241	Unlike	2.423	Unlike
2	6	21	0.569	Like	0.660	Like	0.755	Like	0.879	Like	**0.941**	**Like**	**1.010**	**Unlike**	1.127	Unlike	1.160	Unlike	1.127	Unlike	1.238	Unlike
3	7.5	20	0.615	Like	0.000	Like	0.753	Like	0.000	Like	0.89	Like	0.000	Like	**1.027**	**Unlike**	**0.000**	**Like**	**1.130**	**Unlike**	**0.000**	**Like**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8	4.5	28	**0.75**	**Like**	**1.154**	**Unlike**	1.054	Unlike	1.703	Unlike	1.358	Unlike	2.025	Unlike	1.434	Unlike	2.234	Unlike	1.434	Unlike	2.286	Unlike
9	6	45	1.556	Unlike	2.171	Unlike	2.029	Unlike	3.036	Unlike	2.502	Unlike	3.819	Unlike	2.975	Unlike	4.304	Unlike	2.975	Unlike	4.437	Unlike
10	4.5	13	0.469	Like	0.458	Like	0.683	Like	0.791	Like	0.897	Like	0.919	Like	0.951	Like	0.971	Like	0.951	Like	0.967	Like
11	6	21	0.562	Like	0.853	Like	**0.755**	**Like**	**1.224**	**Unlike**	**0.947**	**Like**	**1.539**	**Unlike**	1.14	Unlike	1.729	Unlike	1.14	Unlike	1.783	Unlike
12	1.5	6	0.344	Like	0.824	Like	**0.761**	**Like**	**1.749**	**Unlike**	**0.761**	**Like**	**2.113**	**Unlike**	**0.761**	**Like**	**2.134**	**Unlike**	**0.761**	**Like**	**2.025**	**Unlike**
13	6	12	0.394	Like	0.120	Like	0.533	Like	0.070	Like	0.673	Like	0.000	Like	0.813	Like	0.042	Like	0.813	Like	0.123	Like
14	1.5	6	0.344	Like	0.824	Like	**0.761**	**Like**	**1.749**	**Unlike**	**0.761**	**Like**	**2.113**	**Unlike**	**0.761**	**Like**	**2.134**	**Unlike**	**0.761**	**Like**	**2.025**	**Unlike**
15	3	28	**0.957**	**Like**	**1.312**	**Unlike**	1.83	Unlike	2.071	Unlike	1.83	Unlike	2.449	Unlike	1.83	Unlike	2.642	Unlike	1.830	Unlike	2.656	Unlike
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
21	1.5	8	0.436	Like	0.731	Like	0.932	Like	1.538	Unlike	**0.932**	**Like**	**1.800**	**Unlike**	**0.932**	**Like**	**1.808**	**Unlike**	**0.932**	**Like**	**1.719**	**Unlike**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
26	1.5	6	0.344	Like	0.824	Like	**0.761**	**Like**	**1.749**	**Unlike**	**0.761**	**Like**	**2.113**	**Unlike**	**0.761**	**Like**	**2.134**	**Unlike**	**0.761**	**Like**	**2.025**	**Unlike**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
31	9	23	0.618	Like	0.565	Like	0.763	Like	0.436	Like	0.909	Like	0.576	Like	**1.055**	**Unlike**	**0.829**	**Like**	1.201	Unlike	1.014	Unlike
32	4.5	28	**0.75**	**Like**	**1.154**	**Unlike**	1.054	Unlike	1.703	Unlike	1.358	Unlike	2.025	Unlike	1.434	Unlike	2.234	Unlike	1.434	Unlike	2.286	Unlike
33	6	45	1.556	Unlike	2.171	Unlike	2.029	Unlike	3.036	Unlike	2.502	Unlike	3.819	Unlike	2.975	Unlike	4.304	Unlike	2.975	Unlike	4.437	Unlike
34	7.5	28	0.746	Like	0.839	Like	0.928	Like	0.967	Like	1.109	Unlike	1.177	Unlike	1.291	Unlike	1.417	Unlike	1.427	Unlike	1.545	Unlike

Tab. III(b) *Liquefaction potential from MLR model for earthquake magnitude 6.0 with varying water level.*

S. No.	Depth (z)	SPT-N value	For network M_7W_0				For network M_7W_2				For network M_7W_4				For network M_7W_6				For network M_7W_8			
			lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS	
			ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status
1	4.5	22	0.452	Like	0.452	Like	0.654	Like	0.654	Like	0.857	Like	0.857	Like	0.907	Like	0.907	Like	0.907	Like	0.907	Like
2	6	21	0.41	Like	0.378	Like	0.544	Like	0.549	Like	0.678	Like	0.695	Like	0.812	Like	0.798	Like	0.812	Like	0.823	Like
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8	4.5	28	0.548	Like	0.582	Like	0.77	Like	0.778	Like	0.993	Like	1.037	Unlike	1.048	Unlike	1.072	Unlike	1.048	Unlike	1.029	Unlike
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
33	6	45	1.121	Unlike	1.134	Unlike	1.25	Unlike	1.27	Unlike	1.25	Unlike	1.192	Unlike	1.25	Unlike	1.249	Unlike	1.25	Unlike	1.25	Unlike
34	7.5	28	0.529	Like	0.464	Like	0.658	Like	0.594	Like	0.787	Like	0.691	Like	0.916	Like	0.82	Like	1.013	Unlike	0.812	Like

Tab. IV(a) *Liquefaction potential from ANFIS models for earthquake magnitude 7.0 with varying water level.*

S. No.	Depth(z)	SPT-N value	For network M_7W_0				For network M_7W_2				For network M_7W_4				For network M_7W_6				For network M_7W_8			
			lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR	
			ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status
1	4.5	22	0.452	Like	0.824	Like	0.654	Like	1.316	Unlike	0.857	Like	1.629	Unlike	0.907	Like	1.766	Unlike	0.907	Like	1.769	Unlike
2	6	21	0.410	Like	0.472	Like	0.544	Like	0.630	Like	0.678	Like	0.723	Like	0.812	Like	0.829	Like	0.812	Like	0.884	Like
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8	4.5	28	0.548	Like	0.836	Like	0.770	Like	1.238	Unlike	0.993	Like	1.471	Unlike	1.048	Unlike	1.621	Unlike	1.048	Unlike	1.657	Unlike
9	6	45	1.121	Unlike	1.563	Unlike	1.462	Unlike	2.191	Unlike	1.803	Unlike	2.756	Unlike	2.144	Unlike	3.104	Unlike	2.144	Unlike	3.197	Unlike
10	4.5	13	0.343	Like	0.336	Like	0.499	Like	0.582	Like	0.656	Like	0.676	Like	0.695	Like	0.713	Like	0.695	Like	0.710	Like
11	6	21	0.405	Like	0.613	Like	0.544	Like	0.882	Like	0.682	Like	1.110	Unlike	0.821	Like	1.246	Unlike	0.821	Like	1.284	Unlike
12	1.5	6	0.258	Like	0.625	Like	0.571	Like	1.313	Unlike	0.571	Like	1.582	Unlike	0.571	Like	1.600	Unlike	0.571	Like	1.524	Unlike
13	6	12	0.284	Like	0.078	Like	0.384	Like	0.040	Like	0.485	Like	0.000	Like	0.585	Like	0.014	Like	0.585	Like	0.070	Like
14	1.5	6	0.258	Like	0.625	Like	0.571	Like	1.313	Unlike	0.571	Like	1.582	Unlike	0.571	Like	1.600	Unlike	0.571	Like	1.524	Unlike
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
18	3	27	0.785	Like	1.494	Unlike	1.810	Unlike	2.428	Unlike	1.810	Unlike	3.104	Unlike	1.810	Unlike	3.368	Unlike	1.810	Unlike	3.368	Unlike
19	4.5	40	1.493	Unlike	2.020	Unlike	2.359	Unlike	3.090	Unlike	3.226	Unlike	4.011	Unlike	3.442	Unlike	4.429	Unlike	3.442	Unlike	4.479	Unlike
20	6	49	1.389	Unlike	2.222	Unlike	1.906	Unlike	3.280	Unlike	2.422	Unlike	4.260	Unlike	2.939	Unlike	4.745	Unlike	2.939	Unlike	4.824	Unlike
21	1.5	8	0.327	Like	0.554	Like	0.699	Like	1.154	Unlike	0.699	Like	1.349	Unlike	0.699	Like	1.358	Unlike	0.699	Like	1.295	Unlike
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
26	1.5	6	0.258	Like	0.625	Like	0.571	Like	1.313	Unlike	0.571	Like	1.582	Unlike	0.571	Like	1.600	Unlike	0.571	Like	1.524	Unlike
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
32	4.5	28	0.548	Like	0.836	Like	0.770	Like	1.238	Unlike	0.993	Like	1.471	Unlike	1.048	Like	1.621	Unlike	1.048	Unlike	1.657	Unlike
33	6	45	1.121	Unlike	1.563	Unlike	1.462	Unlike	2.191	Unlike	1.803	Unlike	2.756	Unlike	2.144	Unlike	3.104	Unlike	2.144	Unlike	3.197	Unlike
34	7.5	28	0.529	Like	0.591	Like	0.658	Like	0.678	Like	0.787	Like	0.827	Like	0.916	Like	0.997	Like	1.013	Unlike	1.087	Like

Tab. IV(b) *Liquefaction potential from MLR model for earthquake magnitude 7.0 with varying water level.*

S. No.	Depth (z)	SPT-N value	For network M_SW_0				For network M_SW_2				For network M_SW_4				For network M_SW_6				For network M_SW_8			
			lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS		lique. Pot. by I & B method		lique. Pot. by ANFIS	
			ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status
1	4.5	22	0.329	Like	0.3291	Like	0.477	Like	0.477	Like	0.624	Like	0.624	Like	0.661	Like	0.661	Like	0.661	Like	0.661	Like
2	6	21	0.295	Like	0.2891	Like	0.391	Like	0.357	Like	0.487	Like	0.477	Like	0.583	Like	0.573	Like	0.583	Like	0.621	Like
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
15	3	28	0.523	Like	0.427	Like	1.001	Unlike	0.968	Like	1.001	Unlike	1.061	Unlike	1.001	Unlike	1.049	Unlike	1.001	Unlike	0.884	Like
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
18	3	27	0.58	Like	0.485	Like	1.336	Unlike	1.104	Unlike	1.25	Unlike	1.222	Unlike	1.25	Unlike	1.214	Unlike	1.25	Unlike	0.956	Like
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
34	7.5	28	0.374	Like	0.2931	Like	0.466	Like	0.41	Like	0.557	Like	0.479	Like	0.648	Like	0.608	Like	0.716	Like	0.582	Like

Tab. V(a) *Liquefaction potential from ANFIS models for earthquake magnitude 8.0 with varying water level.*

S. No.	Depth (z)	SPT-N value	For network M_SW_0				For network M_SW_2				For network M_SW_4				For network M_SW_6				For network M_SW_8			
			lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR		lique. Pot. by I & B method		lique. Pot. by MLR	
			ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status	ratio	status
1	4.5	22	0.329	Like	0.600	Like	0.477	Like	0.960	Like	**0.624**	**Like**	**1.187**	**Unlike**	**0.661**	**Like**	**1.286**	**Unlike**	**0.661**	**Like**	**1.288**	**Unlike**
2	6	21	0.295	Like	0.336	Like	0.391	Like	0.450	Like	0.487	Like	0.516	Like	0.583	Like	0.591	Like	0.583	Like	0.630	Like
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
8	4.5	28	0.399	Like	0.604	Like	0.561	Like	0.898	Like	**0.723**	**Like**	**1.065**	**Unlike**	**0.764**	**Like**	**1.172**	**Unlike**	**0.764**	**Like**	**1.198**	**Unlike**
9	6	45	**0.805**	**Like**	**1.122**	**Unlike**	1.050	Unlike	1.576	Unlike	1.294	Unlike	1.983	Unlike	1.539	Unlike	2.232	Unlike	1.539	Unlike	2.297	Unlike
10	4.5	13	0.250	Like	0.246	Like	0.364	Like	0.427	Like	0.478	Like	0.495	Like	0.506	Like	0.522	Like	0.506	Like	0.520	Like
11	6	21	0.291	Like	0.440	Like	0.390	Like	0.634	Like	0.490	Like	0.798	Like	0.590	Like	0.895	Like	0.590	Like	0.922	Like
12	1.5	6	0.193	Like	0.472	Like	0.427	Like	0.981	Like	**0.427**	**Like**	**1.179**	**Unlike**	**0.427**	**Like**	**1.195**	**Unlike**	**0.427**	**Like**	**1.141**	**Unlike**
13	6	12	0.204	Like	0.050	Like	0.276	Like	0.020	Like	0.348	Like	0.000	Like	0.420	Like	0.000	Like	0.420	Like	0.038	Like
14	1.5	6	0.193	Like	0.472	Like	0.427	Like	0.981	Like	**0.427**	**Like**	**1.179**	**Unlike**	**0.427**	**Like**	**1.195**	**Unlike**	**0.427**	**Like**	**1.141**	**Unlike**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
18	3	27	**0.580**	**Like**	**1.088**	**Unlike**	1.336	Unlike	1.771	Unlike	1.336	Unlike	2.262	Unlike	1.336	Unlike	2.453	Unlike	1.336	Unlike	2.453	Unlike
19	4.5	40	1.087	Unlike	1.462	Unlike	1.719	Unlike	2.239	Unlike	2.350	Unlike	2.906	Unlike	2.507	Unlike	3.208	Unlike	2.507	Unlike	3.242	Unlike
20	6	49	**0.997**	**Like**	**1.603**	**Unlike**	1.368	Unlike	2.369	Unlike	1.739	Unlike	3.078	Unlike	2.110	Unlike	3.427	Unlike	2.110	Unlike	3.482	Unlike
21	1.5	8	0.245	Like	0.418	Like	0.522	Like	0.863	Like	**0.522**	**Like**	**1.007**	**Unlike**	**0.522**	**Like**	**1.015**	**Unlike**	**0.522**	**Like**	**0.971**	**Unlike**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
26	1.5	6	0.193	Like	0.472	Like	0.427	Like	0.981	Like	**0.427**	**Like**	**1.179**	**Unlike**	**0.427**	**Like**	**1.195**	**Unlike**	**0.427**	**Like**	**1.141**	**Unlike**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
32	4.5	28	0.399	Like	0.604	Like	0.561	Like	0.898	Like	**0.723**	**Like**	**1.065**	**Unlike**	**0.764**	**Like**	**1.172**	**Unlike**	**0.764**	**Like**	**1.198**	**Unlike**
33	6	45	**0.805**	**Like**	**1.122**	**Unlike**	1.050	Unlike	1.576	Unlike	1.294	Unlike	1.983	Unlike	1.539	Unlike	2.232	Unlike	1.539	Unlike	2.297	Unlike
34	7.5	28	0.374	Like	0.415	Like	0.466	Like	0.474	Like	0.557	Like	0.579	Like	0.648	Like	0.699	Like	0.716	Like	0.762	Like

Tab. V(b) *Liquefaction potential from MLR models for earthquake magnitude 8.0 with varying water level.*

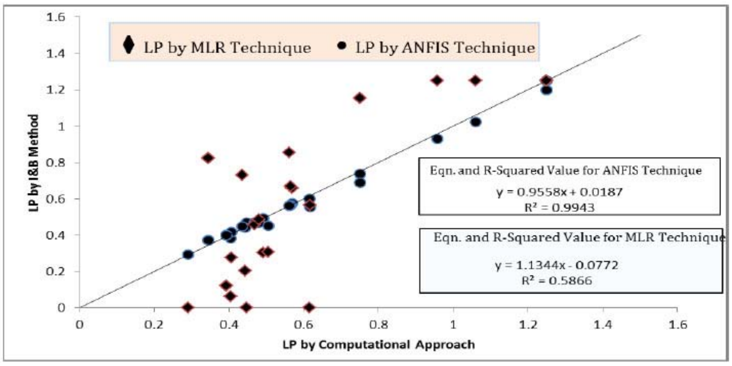

Fig. 3 *ANFIS model for W.T. 0 m and M 6.0.*

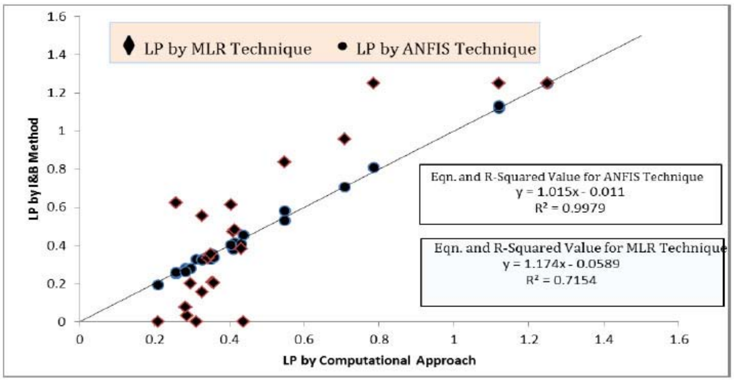

Fig. 4 *ANFIS model for W.T. 0 m and M 7.0.*

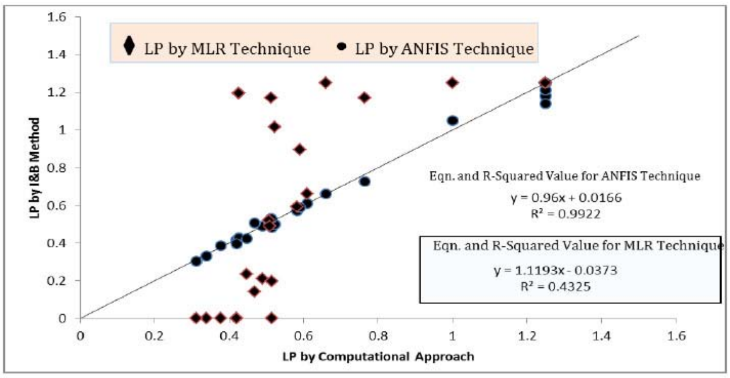

Fig. 5 *ANFIS model for W.T. 6 m and M 8.0.*

datasets, which is within acceptable limit. The comparative study depicts that results obtained from ANFIS models can be used cautiously and performance of models can be upgraded by introducing more sets of data inputs. It can also be observed from Tab. VI that the coefficient of determination obtained from MLR models is in the range of 0.8. In this case mean absolute error and root mean square error is also high. It is also indicative from the above discussion that numbers of incorrect prediction from MLR models is greater than ANFIS models. The comparison of these statistical parameters clearly indicates that COD, MAE and RMSE obtained by ANFIS models are far better than MLR models.

S. No.	Models	By ANFIS			By MLR		
		COD	MAE	RMSE	COD	MAE	RMSE
1	$\mathbf{M_6W_0}$	**0.995**	**3.140**	**4.490**	**0.852**	**59.93**	**71.47**
2	M_6W_2	0.872	6.161	9.212	0.8475	63.09	73.09
3	M_6W_4	0.911	6.349	8.908	0.8274	70.49	84.77
4	M_6W_6	0.777	**8.085**	10.904	0.8338	69.76	84.54
5	M_6W_8	**0.732**	8.024	11.341	0.8380	67.38	80.65
6	$\mathbf{M_7W_0}$	**0.998**	**2.877**	**3.995**	**0.8515**	**60.80**	**72.58**
7	M_7W_2	0.901	5.807	8.711	0.8455	63.52	73.56
8	M_7W_4	0.927	5.667	8.730	0.8265	70.59	84.82
9	M_7W_6	0.942	4.221	6.934	0.8334	70.09	84.85
10	M_7W_8	0.904	5.624	9.576	0.8378	67.85	81.18
11	M_8W_0	0.969	2.923	5.612	0.8514	61.55	73.51
12	M_8W_2	0.945	4.856	6.968	0.8433	63.94	74.05
13	M_8W_4	**0.988**	2.966	5.642	0.8254	70.70	84.86
14	$\mathbf{M_8W_6}$	**0.992**	**2.604**	**3.606**	**0.8330**	**70.35**	**85.08**
15	M_8W_8	0.963	4.005	7.722	0.8376	68.24	81.58

Tab. VI *Calculations of coefficient of correlation and average absolute error for each model.*

The datasets of one borehole, which was not used in training, and testing of models were used for validation of these models in the end to check the ability of the models if these models are likely to be adopted for prediction of liquefaction potential. The result obtained by conventional I&B method was compared with the predicted condition of liquefaction in like/unlike terms as shown in Tab. VII. This comparison indicates that prediction capability of ANFIS model with high coefficient of determination is in better agreement with the conventional approach in comparison to MLR models.

6. Conclusions

Estimation of liquefaction potential by soft computing and regression methods using SPT data can be advantageous over the conventional approach. Therefore, ANFIS & MLR models were developed to predict liquefaction potential for a site or region. The results of liquefaction potential obtained in like/unlike form for

Depth	SPT-N Value	Soil Description	Classification	Particle Size Distribution			Natural Moisture Content	Bulk Unit Weight	Specific Gravity	Angle of Internal Friction	LP by I & B Method	LP Prediction by ANFIS Model	LP Prediction by MLR Model
				% Finer than Size in mm									
meter				2.0	0.075	0.002	%	gm/cc		φ			
1.5	6	Non Plastic Silty Soil with Gravel	ML	90.44	81.6	3.67	32.30	1.74	2.67	20	Like	Like	Unlike
3.0	5	Non Plastic Silty sand	SM	99.07	46.36	0.00	25.76	1.9	2.65	20	Like	Like	Like
4.5	12	Non Plastic Silty sand	SM	99.07	46.36	0.00	25.76	1.9	2.65	20	Like	Like	Like
6.0	12	Non Plastic Silty sand	SM	99.07	46.36	0.00	25.76	1.9	2.65	20	Like	Like	Like
7.5	17	Non Plastic Silty sand	SM	99.07	46.36	0.00	25.76	1.9	2.65	20	Like	Like	Like
9.0	23	Non Plastic Silty sand	SM	99.07	46.36	0.00	25.76	1.9	2.65	20	Like	Like	Like

Tab. VII *The comparison depicts that ANFIS model & MLR Technique can predict the LP after proper training and testing.*

Combination	Developed Multi-Linear Equation
0.35;6;0	$= 2.281494-(0.10516\ d)+(0.069095\ N)+(0.006684\ D_x)+(0.021259\ w_f)-(1.6931\ \rho_f)$
0.35;7;0	$= 1.698935-(0.08183\ d)+(0.049976\ N)+(0.005053\ D_x)+(0.015554\ w_f)-(1.24449\ \rho_f)$
0.35;8;0	$= 1.259794-(0.06314\ d)+(0.036033\ N)+(0.003799\ D_x)+(0.011341\ w_f)-(0.91134\ \rho_f)$
0.35;6;2	$= 4.410201-(0.24532\ d)+(0.100098\ N)+(0.013324\ D_x)+(0.035717\ w_f)-(2.95095\ \rho_f)$
0.35;7;2	$= 3.266915-(0.18662\ d)+(0.072495\ N)+(0.009962\ D_x)+(0.026115\ w_f)-(2.16428\ \rho_f)$
0.35;8;2	$= 2.410765-(0.1412\ d)+(0.052338\ N)+(0.007413\ D_x)+(0.019029\ w_f)-(1.5816\ \rho_f)$
0.35;6;4	$= 5.941853-(0.2828\ d)+(0.130454\ N)+(0.018231\ D_x)+(0.049365\ w_f)-(4.17785\ \rho_f)$
0.35;7;0	$= 4.390949-(0.2148\ d)+(0.094525\ N)+(0.013583\ D_x)+(0.036071\ w_f)-(3.06187\ \rho_f)$
0.35;8;4	$= 3.232732-(0.16227\ d)+(0.068275\ N)+(0.010076\ D_x)+(0.026268\ w_f)-(2.23602\ \rho_f)$
0.35;6;6	$= 6.255334-(0.27224\ d)+(0.145815\ N)+(0.018823\ D_x)+(0.054184\ w_f)-(4.52546\ \rho_f)$
0.35;7;6	$= 4.624643-(0.20787\ d)+(0.105596\ N)+(0.014052\ D_x)+(0.039575\ w_f)-(3.31681\ \rho_f)$
0.35;8;6	$= 3.406151-(0.15777\ d)+(0.076229\ N)+(0.010442\ D_x)+(0.028807\ w_f)-(2.42232\ \rho_f)$
0.35;6;8	$= 6.050938-(0.24685\ d)+(0.148326\ N)+(0.017493\ D_x)+(0.054252\ w_f)-(4.43984\ \rho_f)$
0.35;7;8	$= 4.480592-(0.19007\ d)+(0.107361\ N)+(0.013118\ D_x)+(0.039626\ w_f)-(3.25637\ \rho_f)$
0.35;8;8	$= 3.304963-(0.14533\ d)+(0.077465\ N)+(0.009789\ D_x)+(0.028845\ w_f)-(2.37979\ \rho_f)$

Tab. VIII *Multi-varied linear equation.*

different combination of water table and earthquake magnitude demonstrate the closeness of ANFIS models to I & B method. Thirty-four datasets were used for predicting liquefaction potential for fifteen models which form 510 validated results. Out of 510 predictions, only 12 predictions by ANFIS models deviated from the correct prediction which supports the prediction capabilities of ANFIS models. In this, 98% of predictions are analogous. The mean absolute error varies from 2.604% to 8.085%; root mean square error varies from 3.61 to 11.34% whereas coefficients of determination obtained by these models are more than 0.9 except for a few models. On the other hand MLR, models gave more than 20 incorrect results with high mean absolute error and root mean square error. Based on ANFIS prediction capability ANFIS modeling technique to predict liquefaction potential of soils can be adopted in comparison to MLR models. The analysis of results evidently demonstrates that these ANFIS models can be used effectively and it is more reliable since developed models predicts liquefaction potential correctly for one bore log case.

References

[1] Rao K. S., Satyam D. N.: Liquefaction studies for seismic microzonation of Delhi region. Current science, 92, (5), 2007, pp. 646-654.

[2] Jang J. S. R.: ANFIS: Adaptive-Network-Based Fuzzy Inference Systems. IEEE Transactions on System, Man, and Cybernetics, 23, (5), 1993, pp. 665-685.

[3] Kalkan E., Akbulut S., Turtum A., Celik S.: prediction of the unconfined compressive strength of compacted granular soils by using inference system. Environ. Geo., 58, 2008, pp. 1429-1440.

[4] Goh A. T. C.: Seismic liquefaction potential assessed by neural networks, Journal of Geotechnical Engineering. ASCE 120, (9), September-1994, pp. 1467-1480.

[5] Goh A. T. C.: Probabilistic neural network for evaluating seismic liquefaction potential. Can. Geotech. J., 39, 2002, pp. 219-232.

[6] Moradi G., Khatiba B. R., Sutubadi M. H.: Determination of liquefaction potential of soil using (N1)60 by numerical modeling method. EJGE, 16, 2011, pp. 407-417.

[7] Wang J., Rahman M. S.: A neural network model for liquefaction-induced horizontal ground displacement. Soil Dynamics and Earthquake Engineering, 18, 1999, pp. 555-568.

[8] Hanna A. M., Ural D., Saygili G.: Neural network model for liquefaction potential in soil deposits using Turkey and Taiwan earthquake data. Soil Dynamics and Earthquake Engineering, 27, 2007, pp. 521-540.

[9] Hanna A. M., Ural D., Saygili G.: Evaluation of liquefaction potential of soil deposits using artificial neural networks. International journal for computer-aided engineering and software, 24, (1), 2007, pp. 5-16.

[10] Hsu S., Yang M., Chen M., Lin J.: Artificial Neural Network of liquefaction evaluation for soils with High Fines Content. Iinternational joint conference on neural networks, Canada, July 16-21, 2006, pp. 2643-2649.

[11] Kayabah K.: Soil liquefaction evaluation using shear wave velocity. Engineering Geology, 44, 1996, pp. 121-127.

[12] Sitharam T. G., Govindaraju L., Sridharan A.: Dynamic properties and liquefaction potential of soils. Current science, 87, (10), 2004, pp. 1370-1378.

[13] Chiru-Danzer M., Juang C. H., Cristopher R. A., Suber J.: Estimation of liquefaction induced horizontal displacements using artificial neural networks. Can. Geotech. J., 38, 2001, pp. 200-207.

[14] Juang C. H., Chen C. J., Jiang T., Androus R. D.: Risk-based liquefaction potential evaluation using Standard penetration tests. Can. Geotech. J., 37, 2000, pp. 1195-1208.

[15] Ramakrishnan D., Singh T. N., Purwar N., Barde K. S., Gulati A., Gupta S.: Artificial neural network and liquefaction susceptibility assessment: a case study using the 2001 Bhuj earthquake data, Gujarat, India. Comput Geosci, 12, 2008, pp. 491-501.

[16] Gracia S. R., Romo M. P., Botero E.: A neurofuzzy system to analyze liquefaction-induced lateral spread. Soil Dynamics and Earthquake Engineering, 28, 2008, pp. 169-180.

[17] Kayadelen C., Gunaydin O., Fener M., Demir A., Ozvan A.: Modeling of the angle of shearing resistance of soils using soft computing systems. Expert Systems with Applications, 36, 2009, pp. 11814-11826.

[18] Idriss I. M., Boulanger R. W.: Semi-empirical procedures for evaluating liquefaction potential during earthquakes. Soil Dynamics and Earthquake Engineering, 26, 2006, pp. 115-130.

[19] Youd T. L., Idriss I. M.: NCEER Workshop on Evaluation of Liquefaction Resistance of Soils. Nat. Ctr. for Earthquake Engg. Res., State Univ. of New York at Buffalo eds., 1997.

[20] Youd et al.: Liquefaction resistance of soils: summary report from the 1996 NCEER and 1998 NCEER/NSF workshops on evaluation of liquefaction resistance of soils. J. Geotech. Engg. Div., 127, (10), 2001, pp. 817-833.

[21] Jang J. S. R., Sun C. T.: Fuzzy neural network modeling and control. The proceedings of the IEEE, 83, (3), Mar. 1995, pp. 378-406.

[22] Jang J. S. R., Sun C. T, Mizutani E.: Fuzzy neural network and soft computing. USA: Prentice Hall Inc, 1997.

[23] IS: 2131-1981: Method for standard penetration test (SPT) for soils. BIS, New Delhi, 1981.

[24] IS: 2720 (Part 5): Method of test for determination of liquid and plastic limit of soils. BIS, New Delhi, 1985.

[25] IS: 2720 (Part 4): Method of test for grain size analysis of soils. BIS, New Delhi, 1985.

[26] IS: 2720 (Part 2): Methods of determination of water content for soils. BIS, New Delhi, 1973.

[27] Terzaghi K., Peck R. B., Mesri G.: Soil mechanics in engineering practice (2nd Ed.), Wiley & Sons Inc., New York, 2006.

[28] Varghese P. C.: Foundation Engineering, Prentice hall of India private limited, New Delhi – 110001, 2005, p. 15.

[29] Gijnaydin O.: Estimation of soil compaction parameters by using statistical analyses and artificial neural networks. Environ. Geol., 57, 2009, pp. 203-215.

[30] Orlov M. L.: Multiple linear regression analysis using microsoft excel. Chemistry Department, Oregon State University, 1996, Available from `http://chemistry.oregonstate.edu/courses/ch361-464/ch464/RegrssnFnl.pdf`

[31] Venkatesh K., Kumar V., Tiwari R. P.: Appraisal of liquefaction potential using neural network and neuro fuzzy approach. Applied Artificial Intelligence: An International Journal, 27, 8, 2013, pp. 700-720.

[32] Kumar V., Venkatesh K., Kumar Y. Liquefaction Potential Evaluation of Alluvial Soil by Neuro Fuzzy Technique. International Journal of Emerging Technology and Advanced Engineering, ISSN 2250-2459, Volume 2, Issue 3, March 2012.