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Predicting potential of blast-induced soil liquefaction using neural networks and neuro-fuzzy system

F. Asvar, A. Shirmohammadi, and K. Barkhordari Bafghi*

Department of Civil Engineering, Yazd University, Yazd, Iran.

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Sensitivity analysis.

Abstract. In recent years, controlled blasting has turned into an efficient method for evaluation of soil liquefaction on a real scale and of ground improvement techniques. Predicting blast-induced soil liquefaction using collected information can be an effective step in the study of blast-induced liquefaction. In this study, to estimate residual pore pressure ratio, first, a multi-layer perceptron neural network is used in which error (RMS) for the network was calculated as 0.105. Next, a neuro-fuzzy network, ANFIS, was used for modeling. Different ANFIS models are created using Grid Partitioning (GP), subtractive clustering (SCM), and Fuzzy C-Means clustering (FCM). Minimum error is obtained using FCM at about 0.081. Finally, Radial Basis Function (RBF) network is used. Error of this method was about 0.06. Accordingly, RBF network has better performance. Variables, including fine-content, relative density, effective overburden pressure, and SPT value, are considered as input components, and residual pore pressure ratio, R_u, was used as the only output component for designing prediction models. In the next stage, the network output is compared with the results of a regression analysis. Finally, sensitivity analysis for RBF network is tested, and its results reveal that σ'_{v0} and SPT are the most effective factors for determining R_u.

1. Introduction

Severe incidents, such as earthquakes, impacts, vibrations, and explosives, can cause liquefaction. In this paper, liquefaction is defined as a geotechnical phenomenon that occurs most often in loose, saturated sandy soil due to decreasing shear resistance, following the increasing pore pressure [1]. Blast, especially subsurface blasts, can lead to huge ruptures due to liquefaction. In 1935, the rupture of the SWIR III dam in Russia which occurred by involuntary liquefaction was caused by blast operations in its vicinity; therefore, liquefaction reduced soil dam slope from 2:1 to 10:1. Liquefaction due to nuclear tests in the coral reefs of Eniwetok and Bikini in the Pacific Ocean in 1950 was observed with witnesses such as broad and shallow pits, considerable subsidence, and sand boils [2]. Another example of liquefaction-related incidents can be found in the documentation of Charlie et al. [3].

In geotechnical engineering, controlled blasting is used to model soil liquefaction on the real scale in order to improve the ground by densifying sandy soils to increase bearing capacity and decrease permeability coefficient, subsidence, and even liquefaction potential in liquefiable soil.

Many studies are conducted in this context such as densifying sub-foundation soil of the Franklin Falls dam in New Hampshire [4], densifying loose soils in 40 m depth under Jebba dam in Nigeria [5], improving

*. *Corresponding author. Tel.: +98 3531232476;*
Fax: +98 3538200135
E-mail addresses: f.asvar@stu.yazd.ac.ir (F. Asvar); a.shirmohamadi@stu.yazd.ac.ir (A. Shirmohammadi); kbarkhordari@yazd.ac.ir (K. Barkhordari Bafghi)

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effectiveness of soil reinforcement methods in order to decrease liquefaction in New Zealand [6], evaluating liquefaction potential in relatively dense clay-rich sand deposits [7], considering critical lines in liquefied soil such as pipelines and airport infrastructure [8]. In addition, many experimental studies have been conducted regarding blast-induced liquefaction of soil. More information in this regard is reported in the literature, e.g. [1,9-13]. Unlike experimental studies, limited numerical research has been conducted in this regard. Recently, several techniques have been developed for liquefaction modeling. Byrne et al. [14,15] used UBC soil liquefaction model in FLAC-2D software to predict soil liquefaction in sand under dynamic centrifuge test. Gohl in [16] used PGI's single-charge 2D blast-induced liquefaction model in the LS-DYNA finite-element software for 2D symmetrical simulation of soil liquefaction caused by single blasts. Taylor [17] and Bell et al. [18] presented Taylor's effective stress material model for saturated soils in the CTH code. Taylor model was specifically suggested for impact loadings with high magnitude similar to short-term blasts to predict soil liquefaction. Unfortunately, Taylor model and CTH code are not commercially available. Lewis [19] developed FHWA's LS-DYNA soil material model 147. This is a scientific accessible model for predicting blast-induced liquefaction of soil. In addition, several case studies have been conducted in this context. Wang et al. [20] developed a three-phase soil model for simulating stress wave propagation due to blast loading. This model has unique ability to simulate blast-inducted liquefaction of soil, but unfortunately is not available commercially. Wang et al. [21] conducted numerical simulation of quasi-static and shock tests to investigate liquefaction. Simulation was conducted using three-phase soil model and hydrocode AUTODYN. They sought to prove the ability of three-phase soil model and hydrocode AUTODYN in simulating impact and shock-induced liquefaction of soil. Wang et al. [2] performed another numerical study to consider the effect of blast-induced soil liquefaction on surface structure. In this study, the three-phase soil model and hydrocode AUTODYN were used. Lee [16] conducted field tests of blast-induced liquefaction in Vancouver to determine soil characteristics under severe and subsequent blasts to simulate big earthquakes. He simulated the relevant tests using LS-DYNA finite-element software.

Amount of pore water pressure is a key factor in liquefaction. Based on the review of technical literature and available sources, several experimental models have been presented to predict pore pressure response due to blasting. Experimental models of Charlie et al. [22], Kummeneje and Eide [23], and Studer and Kok [24] for single blast and Rollins model [25] as cited by [26] were introduced for multiple blasts. The experimental models suggested by researchers, except that of Kummeneje and Eide [23], do not consider soil characteristics in the prediction of R_u.

Field blast tests of performance on the real scale have high costs and many limitations. Moreover, results of experimental models show great dependency on site conditions and experiment method. Under these conditions, statistical methods and AI-based methods (artificial neural networks and fuzzy systems) with available data have opened up a new world for researchers. Artificial neural network and neuro-fuzzy system, despite its low cost (relative to experimental methods used to predict blast-induced liquefaction), are efficient and reliable methods in data processing, even despite various effective parameters and their complex relations.

By multiple regression analysis, Eller [26] considered predicting pore pressure response in liquefaction studies using controlled blasting.

The artificial neural networks and neuro-fuzzy system have not brought substantial development for the prediction of blast-induced liquefaction potential. The neural network is a powerful prediction tool and is more accurate than other conventional methods for complex problems such as liquefaction, where the relationship between variables is not clear [27]. Artificial neural networks are used in various geotechnical fields such as liquefaction [28-30], soil behavior modeling, earth-retaining structures, prediction of bearing capacity of piles, settlement of structures, slope stability, designing tunnels, and hydraulic conductivity of soil [31]. Another appropriate method in the prediction of liquefaction potential is the neuro-fuzzy system, which is a combination of neural networks and fuzzy logic to determine parameters of fuzzy systems using neural network training algorithm [32]. Fuzzy systems have successful application in geotechnical problems such as prediction of unconfined compressive strength of compacted granular soils [33], prediction of foundation response [34], swelling potential of compacted soil [35], estimation of sand permeability [36], and evaluation of liquefaction potential [37]. Other neuro-fuzzy applications were reported by Cabalar et al. [37].

The present study aims to predict blast-induced liquefaction potential using Multi-Layer Perceptron neural networks (MLP), Radial Basis Functions (RBF), and the Neuro-Fuzzy (NF) model and comparing the efficiencies of these methods. Furthermore, sensitivity analyses on input network variables have been carried out to identify effective parameters in liquefaction.

2. Materials and methodology

2.1. Collected datasets

In this study, the data required for designing neural networks and neuro-fuzzy system are obtained from

Table 1. Features of the proposed MLP model.

Parameter	Description
Type neural network	Feed forward
Training algorithm	Back propagation
Function error	Mean Square Error (MSE)
Optimization method	Levenberg-Marquardt (LM)
Hidden layers	2
The number of neurons in the first hidden layer	15
The number of neurons in the second hidden layer	5
Transfer functions of the hidden layer	Tansig
Transfer functions of the output layer	Tansig
Number of training data	292 sample (70%)
Number of validation data	62 sample (15%)
Number of test data	62 sample (15%)

results of multiple blasts on the real scale performed in seven different parts of the world (1997-2007), as cited by Eller [26].

The following is a brief description of the experiments:

1. Controlled blasting for inducing liquefaction with the purpose of evaluating seismic performance of Japanese airport infrastructures in 2007 [38,39];
2. Controlled blasting for evaluating performance of vertical composite earthquake drains to reduce potential of liquefaction caused by earthquake in the vicinity of Massy Tunnel in Vancouver in 2004 [40,41];
3. Experiment for evaluating liquefaction potential of Coralline sands in Mawi, Hawaii in 2004 [25];
4. Blast experiment for evaluating performance of piles, pipelines, and quay walls against lateral spreading of static and seismic loads in Japan (2002) [42];
5. Testing blast-induced liquefaction with the purpose of investigating liquefaction potential of problematic soils such as low-plasticity silts in Canada (2000) [11];
6. Blast testing to improve deep foundations design under lateral loadings caused by an earthquake in San Francisco, California (1998) [9,43,44];
7. Controlled blasting for simulating earthquake-induced ground movements in Canada (1997) [45].

2.2. Neural network models

2.2.1. Multi-layer perceptron networks

Perceptron network or MLP is one of the mostly used neural networks. This network consists of three layers, i.e. input, hidden, and output layers. The MLP network is a feed-forward network with a back-propagation training procedure. Back propagation means that after determining the network output, if there is a difference

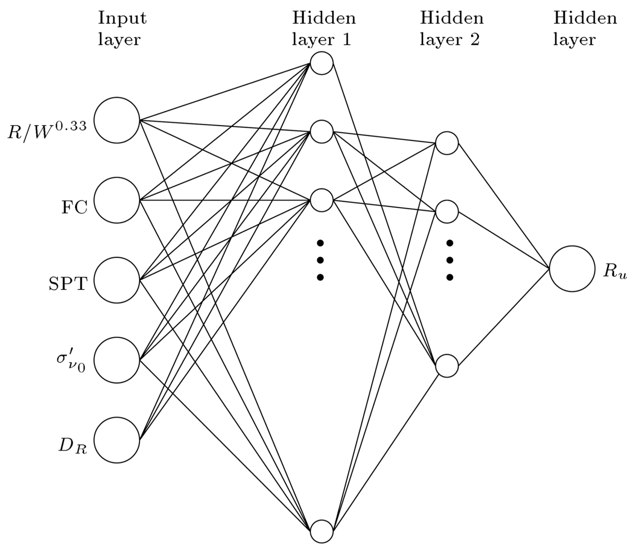


Figure 1. Optimal model of MLP perceptron network.

between obtained output and desired output, weights of the last layer are corrected first, and then weight correction procedure goes toward input layers [46]. To determine network coefficients, Levenberg-Marquardt (LM) algorithm [47] was used. This algorithm is considered a classic method for optimization. Data are inputted into the network in a normalized form in three parts of training (70%), validation (15%), and testing (15%). Number of hidden layers and neurons of every layer is obtained via trial and error to minimize network error. MLP optimal network is shown in Figure 1. In the hidden and output layers, the tansig transfer function is used due to continuity and differentiability. A summary of MLP parameters and specifications is shown in Table 1.

2.2.2. Fuzzy system

Zadeh [48] first proposed the Fuzzy system. In classic logic, truth value of a proposition is either 0 or 1, while truth value of a proposition can be a value between

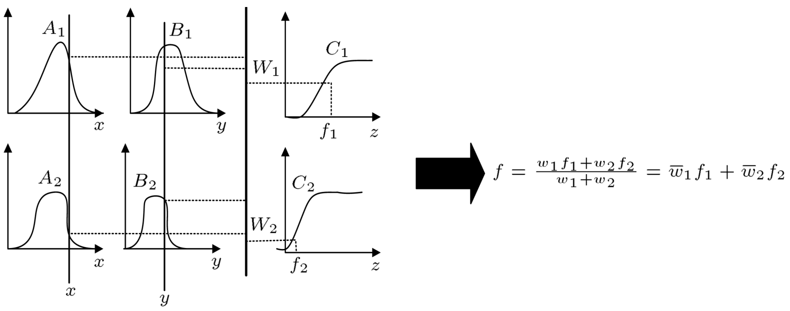


Figure 2. The Sugeno fuzzy model [37].

zero and one in fuzzy logic. In fact, propositions can be relatively true [37]. Neural networks function is based on the data whose pattern is not known. Fuzzy rules are expressed in IF-THEN form [37].

Two types of Fuzzy inference systems have been used in various applications such as Mamdani and Takagi-Sugeno-Kang (TSK). In the Mamdani system, both the antecedent and consequent of rules are expressed as fuzzy sets, while the antecedent part of rules is fuzzy in the Sugeno system, and the consequent part is nonfuzzy and in the form of accurate mathematical relationship of linear combination of input variables. For fuzzy system with two inputs x and y and output z, Eq. (1) is used as in per [37]:

Rule 1: If x is A_1 and y is B_1, then:

$$f_1 = p_1 x + q_1 y + r_1, \tag{1a}$$

Rule 2: If x is A_2 and y is B_2, then:

$$f_2 = p_2 x + q_2 y + r_2, \tag{1b}$$

where p_i, q_i, and r_i are consequent parameters of ith rule. A_i, B_i, and C_i are linguistic labels representing fuzzy sets, shown in Figure 2.

In this study, Sugeno Fuzzy Inference System (FIS) has been used. The inference process in Sugeno fuzzy system is performed in three main steps [37]:

a. *Determining membership degree of input data*: In other words, fuzzification of input signals is done using membership functions;

b. *Determining weight of every rule*: In this stage, the relationship between input and output is expressed with rules such as IF-THEN;

c. *Determining system output*: Output is determined in a non-fuzzy form using OR and AND operators.

2.2.3. Neuro-fuzzy system

Jang et al. [32] first introduced neuro-fuzzy system. This method is a combination of fuzzy logic and neural network training methods. The neuro-fuzzy system used in this study, ANFIS (adaptive neuro-fuzzy inference system), is a Sugeno-type neuro-fuzzy inference system.

In this study, the ANFIS model was created in three methods of Grid Partitioning (GP), subtractive clustering (SCM), and Fuzzy c-Means clustering (FCM). In GP, every part of premise variables is suggested independently. To develop this expert model, membership functions of all premise variables are defined based on former knowledge and experience. Membership functions are designed to create a concept for linguistic expressions in certain content. In most systems, no special knowledge is available for this classification. In such cases, the domain of antecedent variables can simply be classified into equal spaces and membership functions with equal forms. Using available input-output data, membership function parameters can be adjusted and optimized. Chiu [49] first introduced the SCM method. When the number of clusters that should be chosen for data sets is not clear, SCM is a quick method for determining number of clusters and their centers.

The FCM method was first introduced by Bezdek (1981) [50] and is the most popular fuzzy clustering technique. FCM has improved SCM performance. In this method, data are grouped based on their degree of membership. FCM has improved SCM performance [51].

Collected information is classified into two sets of training and testing. 335 data items (80% of data) were considered in train stage, and 81 data items (20% of data) were considered for test.

2.2.4. Radial basic function networks

A Radial Basis Function network (RBF) is a function in which every output is produced corresponding to desired input and with a certain radial distance [52]. Figure 3 schematically shows RBF network. It is a type of monolayer neural networks. Inputs enter the hidden layer space with a non-linear mapping. Outputs of cells in the hidden layer after being multiplied by related weights enter an adder, which is an output for the neural network. The RBF function can be defined in the form of the following mathematical equation:

$$y = w.\phi(x) = w^T \phi(x), \tag{2}$$

where y is network output and ϕ is activation function.

Table 2. Ranges of input and output variables with basic statistics.

Basic statistics	Input variables					Output variable R_u
	$R/W^{0.33}$	SPT	σ'_{v0}	D_R	FC	
Max	20.57	16	136	70	40	1
Min	1.78	1	13.60	12	5	0.02
Mean	6.05	7.49	70.54	31.83	7.57	0.52
SD	3.82	3.71	33.60	14.45	2.97	0.30

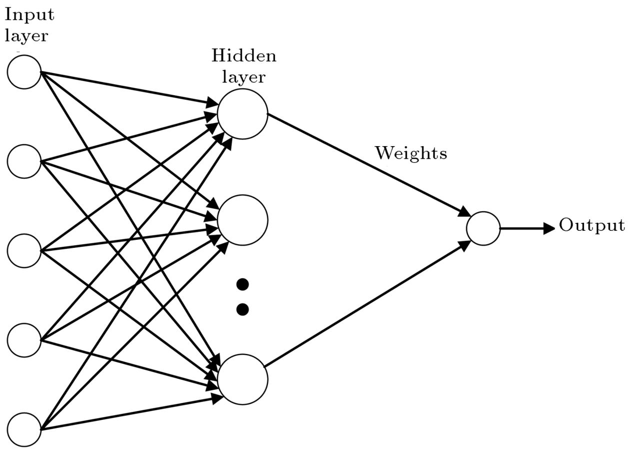


Figure 3. Structure of RBF network.

These functions strongly influence network performance, taking the input into the hidden space. The activation function used in design of RBF network is Gaussian function shown in Eqs. (3) and (4) [53]:

$$\phi(x) = (\phi_1(x), \phi_2(x), ..., \phi_M(x))^T, \tag{3}$$

$$\phi_i(x) = \exp\left(\|x - c_i\|^2\right), \tag{4}$$

where c_i denotes center of Gaussian function which is better to be chosen from data. x is an input variable. 80% of available data (333 data items) are considered for network training and 20% (83 data items) are considered for experiment. The Root Mean Square Error algorithm (RMSE) is used for training. Network training continues until error of total squares is less than the specified target error, or until the maximum specified neuron count is reached. The error that we expect the network to reach is 0.007. The assumed neuron count is equal to the default value.

3. Input and output parameters

3.1. Input parameters

Input parameters of neural network are chosen in such a way as to have appropriate overlapping in evaluating blast-induced liquefaction potential. Four factors influence residual pore pressure ratio (evaluation criterion of soil liquefaction). These factors include soil type, soil density, soil saturation degree, and vibration magnitude [26]. Table 2 shows range of changes for input and output variables. On this basis, the parameters affecting liquefaction potential (parameters input to the neural network) are used as follows:

1. Scaled distance ($R/W^{0.33}$): In this study, Hopkinson of scaled distance, Eqs. (4) and (5) [16], has been used to express specification of blast load (amount of energy needed for liquefaction):

   for single explosions:

   $$SD = R/W^{0.33}, \tag{5}$$

   for subsequent explosions:

   $$R/W^{0.33} = \frac{\bar{R}}{\sum W^{0.33}} = \frac{\left(\frac{R_1+R_2+...+R_i}{N_I}\right)}{\sum\left(W_1 + W_2 + ... + W_i\right)^{0.33}}, \tag{6}$$

   where W and W_i are weights of TNT explosive and R is the distance between explosive and point of observation;
2. SPT $(N_1)_{60}$ value;
3. Effective overburden pressure, σ'_{v0} (kPa);
4. Initial relative density, D_R (%);
5. Fine content FC (%).

3.2. Output parameter

To evaluate potential of liquefaction due to earthquake, various criteria are provided. Some of these criteria are cyclic shear stress [54], cyclic shear strain [55], and energy required for soil liquefaction [37], used as evaluation criteria to predict liquefaction. The typical criterion applied to investigate blast-induced soil liquefaction uses the residual pore pressure ratio, R_u [2,16,21,26]. In this study, R_u is used as the only output parameter according to Eq. (7):

$$R_u = \frac{\Delta u}{\sigma'_{v0}}, \tag{7}$$

where Δu is residual pore pressure. In non-drained conditions, increased R_u leads to decreased σ'_{v0}, when $R_u = \sigma'_{v0}$, the soil loses its shear resistance and liquefaction occurs. R_u greater than zero means excess pore pressure in soil, and $R_u = 1$ means the occurrence of complete soil liquefaction [28]. Given the above criterion, the following conditions are considered when evaluating soil liquefaction [2]:

1. $\frac{\Delta u}{\sigma'_{v_0}} = 0.1$ is considered as a secure range (based on conducted experiments, in some cases, up to $\frac{\Delta u}{\sigma'_{v0}} = 0.6$ is allowed);
2. $\frac{\Delta u}{\sigma'_{v0}} = 0.8$ has been assumed as a dangerous range;
3. $\frac{\Delta u}{\sigma'_{v_0}} \geq 1$ shows the range where contact between soil granules disappears; soil loses its shear resistance and liquefaction occurs.

Neural network training using raw data results in reduced network speed and accuracy. Thus, to achieve the desired error level, data were standardized before entering the network using Eq. (8) [56]:

$$x_N = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})}, \tag{8}$$

where x_N is the normalized value of x, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of every variable.

4. Evaluation criteria

To evaluate efficiency of neural network models and compare their effectiveness, the following statistical indicators have been used:

1. Correlation coefficient (R^2): It represents the degree of relationship between predicted values of neural network and observed values:

$$R^2 = \frac{\sum_{i=1}^{n} (\tilde{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}, \tag{9}$$

where y_i represents observed values, $\tilde{y}_i$ is computed values, and $\bar{y}$ is mean of observed values.

2. Root Mean Square Error (RMSE): It shows the difference between the value predicted by network and actual value:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} e_i^2}, \tag{10a}$$

$$e_i = y_i - \tilde{y}_i, \tag{10b}$$

where e_i is the error between actual and predicted values.

3. Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} e_i. \tag{11}$$

4. Maximum Absolute Error (MAX):

$$MAXAE = \text{Max}\,(|e_i|). \tag{12}$$

Using the above mentioned indicators, the ability of network in identifying liquefaction incident can be investigated.

The parameters given in Eqs. (13) and (14) for this study are given as follows:

- Positive (1): Conditions when soil is liquefied;
- Negative (0): Conditions when soil is secure (non-liquefied);
- TP (True Positive): Number of liquefaction samples correctly reported as liquefied soil;
- TN (True Negative): Number of non-liquefied samples reported as soil without liquefaction conditions;
- FP (False Positive): Number of non-liquefied samples falsely reported as liquefied soil;
- FN (False Negative): Number of liquefied samples falsely reported as non-liquefied soil.

Meaning of these parameters can be expressed in Table 3;

5. TPR (Sensitivity): Percentage of liquefied samples which were truly reported as soils having liquefaction conditions.

$$\text{True Positive Ratio (TPR)} = \text{Sensitivity}$$
$$= \text{Recall} = TP/(TP + FN). \tag{13}$$

6. PPV (accuracy): Percentage of samples for which the predicted liquefaction conditions are true:

$$\text{Positive Predictive Value (PPV)}$$
$$= \text{Precision} = TP(TP + FP). \tag{14}$$

7. TNR (characteristic): Percentage of non-liquefied samples truly reported as safe soil (non-liquefied).

$$\text{True Negative Rate (TNR)} = \text{Specificity}$$
$$= \frac{TN}{TN + FP}. \tag{15}$$

Table 3. Definition of FN, FP, TN, and TP parameters.

	Predicted 1	**Predicted 0**
True 1	TP	FN
True 0	FP	TN

8. Accuracy: Percentage of samples for which liquefaction and non-liquefaction conditions were properly predicted:

$$\text{Accuracy} = \frac{TN+TP}{TN+FP+TP+FN}. \quad (16)$$

5. Results and discussion

5.1. MLP

In this study, to calculate R_u, different models of MLP were created to determine the optimal number of neurons in the hidden layers and transfer functions. In Figure 4, a training curve for selective MLP network with two hidden layers is given. By investigating Figure 4, the following results are obtained:

1. Mean square error is small;
2. Error of experiment set shows a behavior similar to that of evaluation set;
3. No fitting has occurred until iteration 21.

To evaluate MLP network performance, regression coefficient figure for training and testing data is drawn in Figure 5, and evaluation criterion for MLP model is shown in Table 4. For test data, the network has produced three incorrect predictions (accuracy = 0.952). In two cases where soil was liquefied, the network predicted non-liquefaction, and the prediction was opposite to the former in the other case.

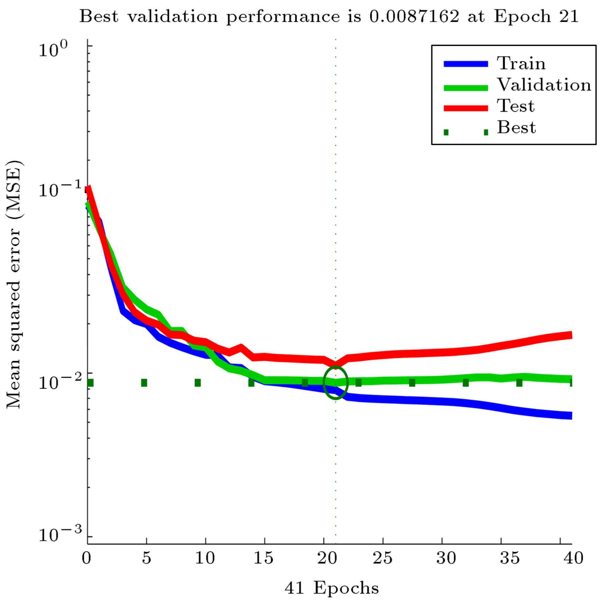


Figure 4. MLP network training curve.

Table 4. Evaluation criteria for MLP.

	R^2	RMSE	MAE	MAXAE
Training set	0.906	0.089	0.057	0.436
Testing set	0.899	0.105	0.07	0.456
	PPV	**TPR**	**TNR**	**Accuracy**
Testing set	0.979	0.959	0.923	0.952

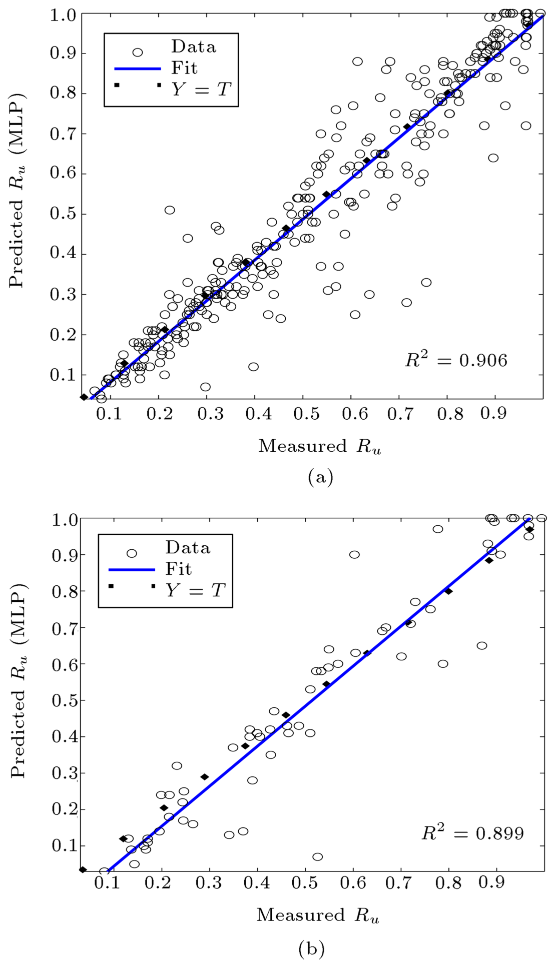


Figure 5. Scatter plots of measured and predicted R_u (residual pore pressure ratio values) using MLP: (a) Training set and (b) testing set.

5.2. ANFIS

ANFIS is the second prediction model used in this study, whose results are reported. Figure of correlation coefficient for three different algorithms of ANFIS is shown in Figures 6 to 8. The most efficient coefficients for training datasets were obtained via GP (R^2 = 0.935) and FCM (R^2 = 0.931) for testing datasets. Index values of evaluation for three methods are provided in Table 5. Given the results shown in the table, the first point to consider is that GP method performed better compared with the two other methods for training dataset, while FCM shows better performance for test data. Predictions made by GP, SCM, and FCM were incorrect in 9, 3, and 1 cases, respectively. Therefore, the best performance in detecting incidence or non-incidence of liquefaction corresponded to FCM and then to SCM. GP performed more poorly than the two other methods.

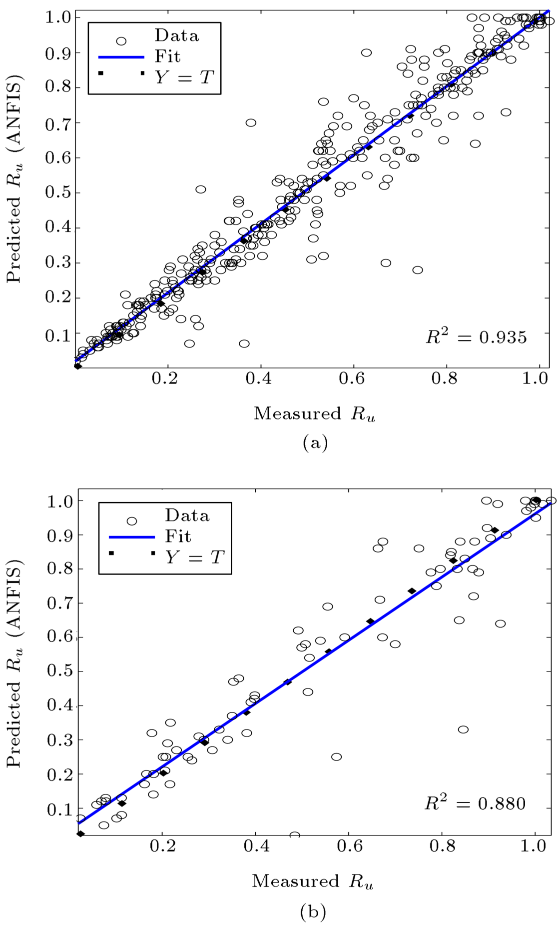


Figure 6. Scatter plots of measured and predicted R_u (residual pore pressure ratio values) using (ANFIS (GP)): (a) Training set and (b) testing set.

Table 5. Evaluation criteria for ANFIS network.

	R^2	RMSE	MAE	MAXAE
Training set:				
GP	0.935	0.076	0.049	0.435
SCM	0.931	0.079	0.05	0.447
FCM	0.916	0.086	0.054	0.44
Testing set:				
GP	0.88	0.113	0.068	0.516
SCM	0.9	0.094	0.06	0.36
FCM	0.931	0.081	0.057	0.331
	PPV	**TPR**	**TNR**	**Accuracy**
Testing set:				
GP	0.953	0.909	0.852	0.89
SCM	1.000	0.952	1.000	0.950
FCM	1.000	0.982	1.000	0.988

5.3. RBF

Besides MLP and ANFIS, another type of neural network called RBF was used. To make a balance between accuracy and training time, the target error (goal) was considered 0.007. The considered prediction

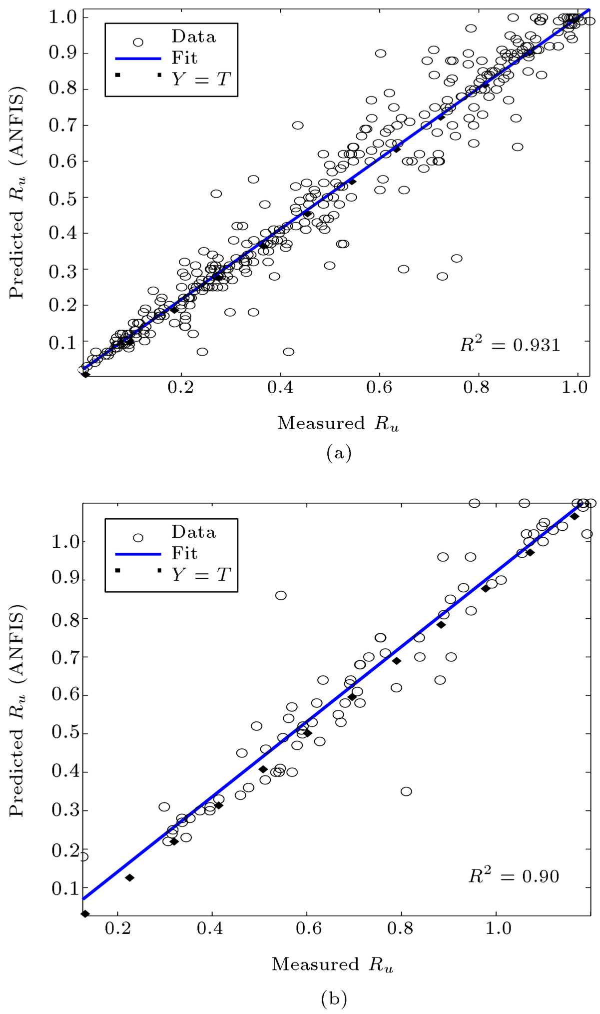
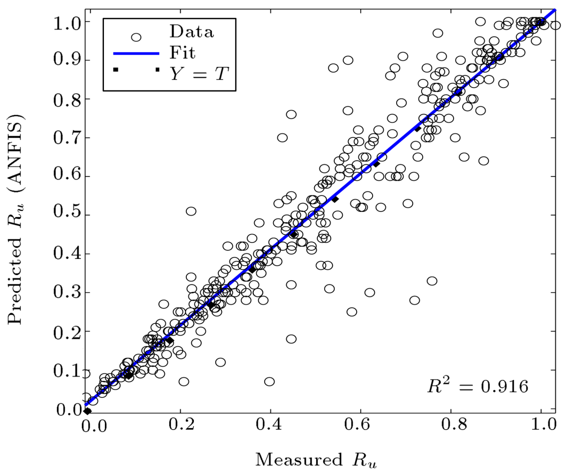


Figure 7. Scatter plots of measured and predicted R_u (residual pore pressure ratio values) using (ANFIS (SCM)): (a) Training set and (b) testing set.

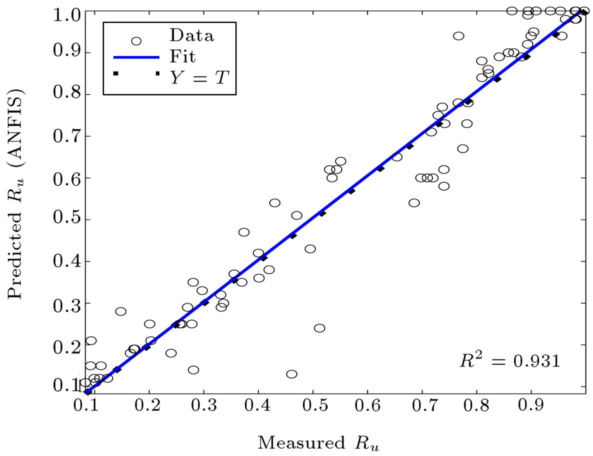
Table 6. Evaluation criteria for RBF network.

	R^2	RMSE	MAE	MAXAE
Training set	0.915	0.088	0.056	0.456
Testing set	0.942	0.06	0.042	0.202
	PPV	**TPR**	**TNR**	**Accuracy**
Testing set	1	0.985	1	0.988

quality of RBF model for training and testing data sets, actual values of R_u, is drawn versus network prediction values in Figure 9. In addition, in Table 6, evaluation criterion for RBF model is shown. Based on the table results, it could be inferred that network error for both datasets is little (RMS (train) = 0.088, RMS (test) = 0.060). In addition, all error criteria for testing have been obtained less than training. Using the criterion given in Table 6, RBF performance in detecting incidence or non-incidence of liquefaction can be evaluated. Network accuracy for test data

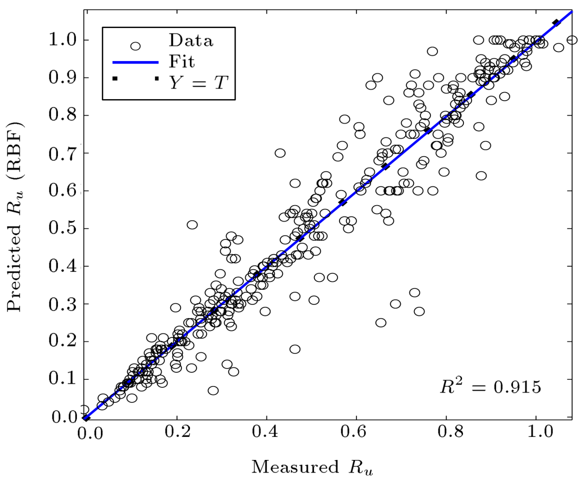


(a)

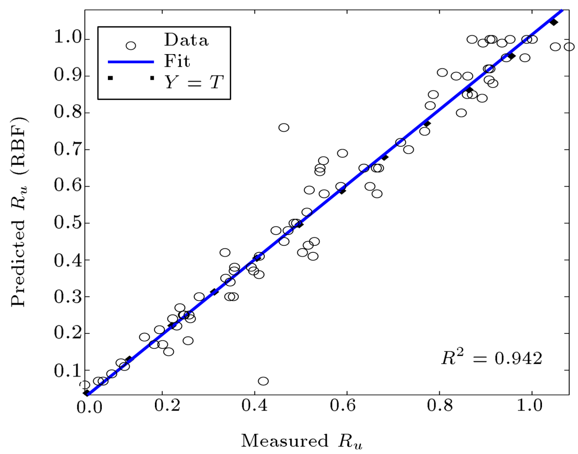


(b)

Figure 8. Scatter plots of measured and predicted R_u (residual pore pressure ratio values) using (ANFIS (FCM)): (a) Training set and (b) testing set.



(a)



(b)

Figure 9. Scatter plots of measured and predicted R_u (residual pore pressure ratio values) using RBF: (a) Training set and (b) testing set.

was 0.98, showing its good performance. In fact, for 98% of test data, correct prediction analysis has been performed. The network prediction corresponded to non-incidence of liquefaction ($R_u = 0.68$) only in one case where soil was liquefied ($R_u = 0.94$). High values of correlation coefficient ($R^2(\text{test}) = 0.942, R^2(\text{train}) = 0.915$) show a good relationship between the predicted values of R_u and observed values.

6. Comparison of neural network results with field results and Eller regression analysis

Based on regression analysis by the datasets used for designing neural networks, an equation was obtained by Eller [26] for calculating residual pore pressure ratio caused by blast load. To evaluate the performance of the given network, its output along with the observed data and results of regression analysis are provided in Table 7, in which in columns 2, 4, and 6, liquefaction potential of soil in all three mentioned cases is given. As seen from the results of Table 7, the network is more accurate than regression analysis. As observed, in detecting soil liquefaction potential for 83 test data items (data in Table 7), the network is incorrect in one item and regression is incorrect in 10 items.

7. *T*-test

To compare the mean of a quantitative variable in two groups, *t*-test is used. In this study, for two datasets, i.e. R_u observed from experiments and R_u from network prediction, *t*-test was performed with the results displayed in Table 8. Given the values of table, critical *t*-value for 95% probability is 1.97. As observed, the calculated value is less than the critical value. Therefore, results of *t*-test show that with 95% confidence interval, no considerable difference exists between these two groups.

Table 7. Comparison of network simulation with field results and regression analysis.

No.	Field results		Network simulation		Regression analysis	
	R_u	Liquefaction	R_u	Liquefaction	R_u	Liquefaction
1	0.5	No	0.57	No	0.60	No
2	0.73	No	0.79	No	0.81	Yes
3	0.37	No	0.41	No	0.32	No
4	0.44	No	0.51	No	0.55	No
5	0.36	No	0.42	No	0.58	No
6	0.04	No	0.06	No	0.03	No
7	0.07	No	0.07	No	0.09	No
8	0.16	No	0.16	No	0.25	No
9	0.3	No	0.23	No	0.27	No
10	0.32	No	0.29	No	0.52	No
11	0.42	No	0.34	No	0.33	No
12	0.95	Yes	0.89	Yes	0.60	No
13	0.8	No	0.83	Yes	0.89	Yes
14	1	Yes	0.85	Yes	0.66	No
15	0.09	No	0.09	No	0.03	No
16	0.37	No	0.41	No	0.44	No
17	0.99	Yes	0.94	Yes	1.09	Yes
18	0.31	No	0.29	No	0.52	No
19	0.12	No	0.14	No	0.23	No
20	0.94	Yes	0.95	Yes	0.87	Yes
21	0.54	No	0.52	No	0.56	No
22	0.62	No	0.54	No	0.49	No
23	0.31	No	0.51	No	0.71	No
24	0.85	Yes	0.92	Yes	0.64	No
25	0.34	No	0.36	No	0.56	No
26	0.89	Yes	0.87	Yes	0.82	Yes
27	0.98	Yes	1.03	Yes	0.65	No
28	0.59	No	0.55	No	0.59	No
29	0.42	No	0.43	No	0.50	No
30	0.37	No	0.56	No	0.54	No
31	0.24	No	0.24	No	0.30	No
32	0.1	No	0.10	No	0.02	No
33	0.31	No	0.26	No	0.48	No
34	0.07	No	0.06	No	0.09	No
35	0.23	No	0.20	No	0.39	No
36	1	Yes	0.91	Yes	0.69	No
37	0.32	No	0.29	No	0.22	No
38	0.48	No	0.52	No	0.65	No
39	0.51	No	0.50	No	0.64	No
40	0.3	No	0.32	No	0.85	Yes
41	0.46	No	0.29	No	0.45	No
42	0.2	No	0.20	No	0.45	No
43	0.65	No	0.64	No	0.52	No
44	0.93	Yes	0.91	Yes	0.88	Yes

Table 7. Comparison of network simulation with field results and regression analysis (continued).

No.	Field results		Network simulation		Regression analysis	
	R_u	Liquefaction	R_u	Liquefaction	R_u	Liquefaction
45	0.5	No	0.50	No	0.64	No
46	0.73	No	0.66	No	0.55	No
47	0.27	No	0.29	No	0.34	No
48	0.72	No	0.72	No	0.51	No
49	0.5	No	0.48	No	0.53	No
50	0.13	No	0.17	No	0.23	No
51	0.32	No	0.35	No	0.55	No
52	0.9	Yes	0.89	Yes	0.93	Yes
53	0.8	No	0.81	Yes	0.56	No
54	0.48	No	0.50	No	0.54	No
55	0.19	No	0.22	No	0.30	No
56	0.12	No	0.10	No	0.28	No
57	0.18	No	0.23	No	0.43	No
58	0.75	No	0.74	No	0.57	No
59	0.28	No	0.22	No	0.34	No
60	0.09	No	0.10	No	0.16	No
61	0.25	No	0.32	No	0.41	No
62	0.84	Yes	0.68	No	0.74	No
63	0.09	No	0.16	No	0.29	No
64	0.09	No	0.09	No	0.09	No
65	0.2	No	0.21	No	0.08	No
66	0.9	Yes	0.87	Yes	0.86	Yes
67	0.7	No	0.75	No	0.78	No
68	0.25	No	0.26	No	0.32	No
69	0.18	No	0.17	No	0.23	No
70	0.69	No	0.64	No	0.66	No
71	0.67	No	0.55	No	0.68	No
72	0.68	No	0.63	No	0.65	No
73	0.92	Yes	0.96	Yes	0.79	No
74	0.87	Yes	0.82	Yes	0.54	No
75	0.35	No	0.38	No	0.58	No
76	0.27	No	0.34	No	0.50	No
77	0.1	No	0.12	No	0.27	No
78	0.26	No	0.28	No	0.34	No
79	0.33	No	0.28	No	0.33	No
80	0.6	No	0.67	No	0.68	No
81	0.12	No	0.13	No	0.23	No
82	0.96	Yes	0.97	Yes	0.88	Yes
83	0.6	No	0.65	No	0.47	No

8. Sensitivity analysis

The parameters mentioned regarding soil specification (network input parameters) include SPT value, effective overburden pressure, relative density, and fine content. To consider the effect of these parameters on residual pore pressure ratio, sensitivity analysis using RBF network was done. The reason for using RBF network is that the analysis results of this model are better than those of the two networks of ANFIS

Table 8. Investigation of neural network model compared to actual values.

	R_u-observed	R_u-predicted
Mean	0.468313	0.46878
Variance	0.085041	0.079251
Observations	83	83
Hypothesized mean difference	0	
D_f	164	
t **stat**	-0.01049	
$P(T <= t)$	0.991646	
t **critical**	1.974535	

Table 9. Sensitivity analysis of parameters pertaining to soil specifications.

	R^2	RMSE	MAE	MAXAE
The best ANN	0.966	0.06	0.042	0.202
ANN no SPT	0.895	0.094	0.063	0.392
ANN no σ'_{v0}	0.903	0.087	0.066	0.200
ANN no DR	0.940	0.070	0.050	0.274
ANN no FC	0.930	0.073	0.054	0.227

and MLP. Analysis results are given in Table 9. As it is observed, maximum error is for the case where SPT parameter is removed. This means that SPT is the most effective parameter in determining R_u. The second effective factor is σ'_{v0}. D_R and FC parameters compared with other two parameters have lower effect on network output.

9. Conclusion

In this paper, using MLP and RBF neural networks and ANFIS model, values of pore water pressure response due to blasting were estimated. Five input variables and one output variable were used for designing prediction models. The best structure of all three networks was selected based on trial and error. For MLP network, the best model was obtained with two hidden layers, 15 neurons in the first hidden layer, and five neurons in the second hidden layer (5-15-5-1). The ANFIS neuro-fuzzy model was tested with three algorithms of FCM, SCM, and GP. Among neuro-fuzzy models constructed, FCM, SCM, and GP had a better performance in terms of prediction quality and the time required for solving. GP model is very slow. So, it is recommended that FCM and SCM methods be used for problems with 5 and more input components (as in the present study). That is because as input variables increase, number of fuzzy rules created in the GP model increases exponentially.

Results of this study show that for all evaluation criteria, RBF has the highest accuracy, and ANFIS (GP) has the lowest accuracy in predicting the results. The networks designed in this paper are of the following order based on the above-mentioned evaluation criteria and their performance: RBF, ANFIS (FCM), ANFIS (SCM), MLP, and ANFIS (GP), respectively.

Networks' ability in predicting incidence or non-incidence of liquefaction was investigated using accuracy, TPR, PPV, and TNR criteria. For RBF and ANFIS (FCM), identical results were obtained.

In the next stage of the study, network output was compared with actual values and formula obtained from statistical analysis. Neural networks can provide predictions with smaller errors than conventional regression methods. In fact, it could be suggested that the network has shown an acceptable performance in data simulation.

In addition, t-test was done between observed and predicted data. Results showed that the assumption about the equality of means with 95% probability is confirmed. Finally, sensitivity analysis was carried out for RBF (the most suitable model) in order to identify the most effective parameters in the production of pore water pressure. Results of sensitivity analysis showed that SPT number is the most effective parameter.

While the designed models have appropriate performance, the results could be improved by increasing the number of data. Neural network model can be a suitable tool for evaluating the potential of soil liquefaction caused by blast loads.

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Biographies

Fariba Asvar received BS degree in Civil Engineering from Shahid Bahonar University of Kerman, Kerman, Iran, in 2011, and MS degree in Geotechnical Engineering from Yazd University, Yazd, Iran, in 2014.

She is currently pursuing a PhD degree in the field of Geotechnical Engineering at Yazd University, Yazd, Iran, since 2016. Her research interests include soil liquefaction, limit analysis in soil mechanics, and application of neural networks in geotechnical engineering.

Arash Shirmohammadi received BS degree in Civil Engineering from Islamic Azad University, Shahrekord, Iran, in 2011, and MS degree in Geotechnical Engineering from Yazd University, Yazd, Iran, in 2014. He is currently pursuing a PhD degree in the field of Geotechnical Engineering at Kharazmi University, Tehran, Iran, since 2016. His research interests include numerical modeling in geotechnical engineering, soil-structure interaction, and environmental geotechnics.

Kazem Barkhordari Bafghi received his MSc degree in Civil Engineering from Tehran University, Iran, in 1986 and PhD degree in Geotechnical Engineering from the University of Surrey, UK, in 1998. He is currently an Associate Professor in the Faculty of Civil Engineering at Yazd University, Iran. His research interests are foundation engineering, earth dam and retaining structures.