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Shuh-Gi Chern Department of Habor and River Engineering, National Taiwan Ocean University, Keelung, Taiwan, R.O.C., sgchern@ntou.edu.tw

Ching-Yinn Lee Department of Habor and River Engineering, National Taiwan Ocean University, Keelung, Taiwan, R.O.C.

Chin-Chen Wang Department of Habor and River Engineering, National Taiwan Ocean University, Keelung, Taiwan, R.O.C.

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CPT-BASED LIQUEFACTION ASSESSMENT BY USING FUZZY-NEURAL NETWORK

Shuh-Gi Chern*, Ching-Yinn Lee*, and Chin-Chen Wang*

Key words: fuzzy-neural, network, CPT, liquefaction.

ABSTRACT

Because of the increasing popularity worldwide of the cone penetration test (CPT) for site characterization, significant progress on the simplified CPT-based methods has been made for evaluation of earthquake induced liquefaction potential of soils. In this study, a fuzzy-neural network combined with 466 CPT field observations is developed to evaluate liquefaction potential of soils. The proposed model combines fuzzy theory with subtractive clustering algorithm to establish a fuzzy-neural system. The study indicates that fuzzy-neural network can successfully describe the complex relationship between seismic parameters, soil parameters, and the liquefaction potential. The fuzzy-neural network model is found to have very good predictive ability and is expected to be very reliable for evaluation of liquefaction potential.

I. INTRODUCTION

The liquefaction is known as one of the most destructive phenomena caused by earthquake and has been widely seen in loose saturated soil deposit (Niigata, 1964; Alaska, 1964; Tangshan, 1979; Loma Prieta, 1989; Kobe, 1995; Turkey, 1998; Chi-Chi, Taiwan, 1999). In view of serious damages caused by earthquake induced liquefaction, geotechnical engineers are actively engaged in the study of soil liquefaction induced by earthquakes. As of now, they have developed many assessment methods for soil liquefaction. However, it is hard to choose a suitable empirical equation for regression analysis due to the high uncertainty of earthquake environment and soil characteristics. Thus, many scholars and experts attempt to seek analytical models that are more reasonable, simple, easy and accurate than traditional empirical equations for soil liquefaction analysis.

Many of the existing assessment methods were developed from observations of the performance of sites during earthquakes. Previously, geotechnical engineers generally accepted the simple liquefaction analytical model developed by STP-N due to computer speed and analytical ability. In recent years, data processing and analytical ability have greatly increased and CPT has the advantages in being a fast, continuous and accurate measurement of soil parameters. At the same time, the related testing data continued to accumulate, so the potential of applying CPT to liquefaction research has grown significantly. For example, Shibata and Teparaksa [25], Stark and Olsen [26], Olson [21], Robertson and Companella [23], Robertson and Wride [24], and Juang and Chen [11] all adopted CPT-based liquefaction to establish soil liquefaction models and acquired great achievement.

To assess soil liquefaction induced by earthquakes, it is necessary to find the correlation between soil parameters and earthquake factors. However, the relationship between them is highly non-linear. Therefore, an induction cannot be made by pure linear regression or empirical rules. Artificial neural network simulates human thinking and learning and finds corresponding rules with mapping relationship between inputs and outputs for complicated non-linear problems. Many scholars approved that neural network method is a powerful and effective tool and is more accurate and reliable than conventional method to deal with liquefaction problem [3, 10, 12]. However, previous attempts at using neural networks to determine liquefaction potential were inadequate because they can not meet required accuracy without increasing network layers or hidden neurons. Those deficiencies can be addressed by the fuzzy-neural system developed in this study. Subtractive clustering algorithm is used to extract hidden classification rules from data and analyze the system in the study with the divided-and-conquer methodology. Through neural network's learning and reminding ability, 466 collected CPT field observations with a wide range of parameters are incorporated in this fuzzy-neural network to evaluate earthquake induced liquefaction potential.

II. ELEMENTS OF ANALYSIS

1. Fuzzy logic

The modeling of many systems involve the consideration of some uncertain variables. Besides the statistical uncertainties that handle variables through probability theory, there also exists non-statistical uncertainty that handles variables in a rational framework of "fuzzy set theory". Like human brain that can interpret imprecise and incomplete sensory information,

Paper submitted 11/10/06; accepted 03/16/07. Author for correspondence: Shuh-Gi Chern (e-mail:sgchern@ntou.edu.tw).

^{*}Department of Habor and River Engineering, National Taiwan Ocean University, Keelung, Taiwan, R.O.C.



Fig. 1. Illustration of membership function.

"fuzzy logic" provides a systematic and approximate reasoning method to cope with the uncertainties.

In a classic set, the set has a crisp boundary, and the membership value of an object in a class is only 0 or 1. When the element x belongs to A set, degree of membership $\mu A(x)$ is 1; while x does not belong to A set, degree of membership becomes 0. On the contrary, a fuzzy set is a set without a crisp boundary. The transition from" belong to a set" to "not belong to a set" is gradual, and this transition is characterized by membership functions that give fuzzy sets flexibility in modeling commonly used linguistic expressions, such as poor, good, and excellent, as shown in Fig. 1.

Being a continuous and often ambiguous events, the occurrence of liquefaction may not be appropriate to describe in terms of either/or classification [1]. Instead, liquefaction should be described in terms of degree of liquefaction represented by fuzzy numbers [22].

A fuzzy variable, "A" is normally expressed as a pair of data [22].

$$A = \left\{ \left(x, \mu_A(x) \right) | x \in X \right\}$$

$$\tag{1}$$

in which x is the element of "A" set; X is a collection of objects denoted by x, i.e. X is the universe of discourse; $\mu A(x)$ is called the membership function for the fuzzy set A, which defines the degree of an element belonging to a set. The membership function maps X to the membership space M, where $M = \{0, 1\}$.

Fig. 2 shows the basic framework of fuzzy set that contains several functions, such as fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification. In addition to establishing fuzzy rule base through linguistic fuzzy rules that are transformed from expert knowledge and experience, fuzzy rule base can also be established through special algorithmic rules that obtain inputs and outputs with mathematical calculation. This study adopts subtractive clustering algorithms and obtains normalization to analyze the hidden rules and establishes a fuzzy rule base.



Fig. 2. Basic Frameworks for Fuzzy System.

2. Subtractive clustering

Clustering of numerical data forms the basis of many classification and system data from a large data set, producing a concise representation of a system's behavior [9]. Based on the Mountain Method that was developed by Yager *et al.* [32], Chiu [9] proposed subtractive clustering that considers each data point as a potential cluster center and a measure of the potential of data point xi is define as:

$$P_{i} = \sum_{j=1}^{n} e^{-\alpha \|x_{i} - x_{j}\|^{2}}$$
(2)

$$\alpha = \frac{4}{r_a^2} \tag{3}$$

in which r_a is a positive constant, and $\| \cdot \|$ is Euclidean distance. Thus, the measure of potential for a data point is a function of its distance to all other data points.

A data point with many neighboring data points will have a high potential value [9]. The constant r_a is effectively the radius defining a neighborhood; data points outside this radius have little influence on the potential.

After computing the potential of every data point, the data point with the highest potential is selected as the first cluster center x_{cl} with potential value P_{cl} . The potential of each data point is then revised by the following formula:

$$P_i \leftarrow P_i - P_{cl} \times e^{-\beta \|x_i - x_{cl}\|^2} \tag{4}$$

$$\beta = \frac{4}{r_b^2} \tag{5}$$

in which r_b is a positive constant. Thus, an amount of potential from each data point is subtracted as a function of its distance from the first cluster center. The data points near the first cluster center will have greatly reduced potential, and therefore are unlikely to be selected as the next cluster center. The constant r_b is effectively the radius defining the neighborhood that will have measurable reductions in potential. To avoid obtaining closely spaced cluster centers, r_b is set to be somewhat greater than r_a . Chiu [9] suggested $r_b = 1.5 r_a$.

When the potential of all data points have been revised according to (4), the data point with the highest remaining potential is selected as the second cluster center x_{c2} with potential value P_{c2} . After the k^{th} cluster center has been obtained, the potential of each data point is revised by the formula:

$$P_i \leftarrow P_i - P_{ck} \times e^{-\beta \|x_i - x_{ck}\|^2} \tag{6}$$

in which x_{ck} is the location of the k^{th} cluster center; and P_{ck} is its potential value.

The process of acquiring new cluster center and revising potentials is repeated until

$$P_{ck} < \underline{\mathcal{E}} P_{c1} \tag{7}$$

in which $\underline{\varepsilon}$ is a small fraction and is an important factor that will affect the results. If $\underline{\varepsilon}$ is too small, too many cluster centers will be generated; if $\underline{\varepsilon}$ is too large, too few data points will be accepted as cluster centers. Chiu [9] suggested $\underline{\varepsilon} = 0.15$.

III. FUZZY-NEURAL SYSTEM

1. Establishment of Fuzzy Rule

Based on subtractive clustering algorithm proposed by Chiu [9], a fuzzy rule base in fuzzy-neural system is established in this study. Fig. 3 shows the flow chart for subtractive clustering. Once all cluster centers are chosen, each cluster center is a fuzzy rule used to describe system behavior. Depending on the membership function, a data point is assigned to a fuzzy rule. Also, membership is defined as adopting the α -cut concept, only when the grade of membership for data is larger than the present threshold α do they have the membership of the cluster. Subtractive clustering is used to obtain the cluster center, then the membership function (8) of fuzzy c-means (FCM) clustering analysis and α -cut concepts are combined do the data points have the membership of the cluster.

$$u_{ji} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - x_{cj}\|}{\|x_i - x_{ck}\|} \right)^{\frac{2}{m-1}}}$$
(8)

in which u_{ji} is the grade of membership; x_i is the *i*th input data in input vector $\{x_1, x_2, \dots, x_n\}$; *m* is fuzzy index; and x_{cj} is the *j*th cluster center. Though a cluster is assigned to a datum point depending on the distance, relationship between data and clusters is not absolute. Its grade of membership is determined by distance. The sum of the membership values for a datum point with respect to all clusters is 1. Thus, every datum point is not only related to other clusters but also depends on its grade of membership.

FCM is a common method in clustering analysis. However, it is a supervised algorithm, clustering should start with a predefined cluster number. If the cluster number is not predefined, the trial and error method needs to be combined to obtain optimum results through iteration. Otherwise, an unsupervised algorithm is used as a solution.



Fig. 3. Flow Diagram for subtractive clustering.

The cluster analysis of a subtractive clustering algorithm is based on the potential value in the feature space. In addition, the location and number of cluster centers is defined by density and the effective radius of space data points. As for automatic system, subtractive clustering is hence more adequate than FCM and more reliable in this study. Moreover, like most nonlinear optimum methods, depending on selection of initial value, i.e., FCM needs to initialize membership matrix, through iteration, the cluster analysis result is judged by the convergence of objection functions. However, like most clustering analysis methods, objection function may converge into the local minimum value instead of the global minimum value.

2. Neural Network

An artificial neural network is a computational mechanism able to acquire, represent, and compute a mapping from multivariate space of information to another, given a set of data representing that mapping [22]. It has learning and reminding ability. A variety of networks can be formed with a multiple member of interconnected neurons. Parameters are used as inputs and outputs. Further, the complicated relationship among parameters can be found. The learning and induction process also helps solve complicated problems.

The network used for assessment of liquefaction in this study is the multi-layer perception associated with the back propaga-



Fig. 4. Illustration of Sub-Network.

tion algorithm, which is a supervised learning algorithm.

To minimize error function during network learning process, the gradient steepest descent method is used to search for optimum solution of error function.

After the determination of its sub-network by membership function, the input vector goes to framework learning. Each sub-network has a hidden layer. The activation function is set to be a nonlinear logic function. The illustration of the sub-network is shown in Fig.4. The output for each sub-network is transformed through the weighted average formula and hyperbolic tangent function into a value between -1 and 1. When it is larger than 0, it is within the liquefaction zone. When it is smaller than 0, it is in the non-liquefaction zone.

Neuron output from the hidden layer in sub-network is:

$$y_{j} = f_{j}(v_{j}(n)) = \frac{1}{1 + exp(-v_{j}(n))}$$
 (9)

in which y_j is the neuron output value from a hidden layer in a sub-network; v_j is a network net value for a hidden layer; n is a number of learning cycles; and f_j (.) is a linear activation function.

Neuron output from the hidden layer in a sub-network :

$$y_{k}(n) = f_{k}(v_{k}(n)) = v_{k}(n)$$
 (10)

in which y_k is the neuron output value from the hidden layer in the sub-network; v_k is the network net value of output layer; nis the number of learning cycles; and $f_k(.)$ is the linear activation function.

The sub-network output value corresponding to each fuzzy rule uses a weighted average formula and the grade of membership as the weighed coefficient for defuzzy as follows:

$$\hat{v}(n) = \frac{\sum_{p=1}^{c} m_{p} \cdot y_{kp}(n)}{\sum_{p=1}^{c} m_{p}}$$
(11)

in which \hat{v} is sub-network integrated output; *p* is the *p*th fuzzy rule; *c* is the number of fuzzy rules, i.e. number of fuzzy rules to

the sub-network; and m_p is the grade of membership for the p^{th} fuzzy rule.

The final system output is:

$$\hat{y}(n) = \hat{f}(\hat{v}(n)) = \frac{exp(\hat{v}(n)) - exp(-\hat{v}(n))}{exp(\hat{v}(n)) + exp(-\hat{v}(n))}$$
(12)

in which \hat{y} is the final system output.

Focusing on learning framework for network parameters, least square method (LSM) and chain rule send back weight error for each layer.

At first, error function is defined as:

$$E(n) = \frac{1}{2} [y(n) - \hat{y}(n)]^2$$
(13)

in which *n* is number of learning cycles; *y* is expected output, i.e. actual value; and \hat{y} is the final system output.

The updated sub-network weight is as follows:

$$\Delta w_{kj}(n) = -\eta \cdot [-(y(n) - \hat{y}(n))] \cdot (1 - \hat{y}^{2}(n))$$

$$\cdot \frac{m_{p}}{m_{1} + m_{2} + \dots + m_{c}} \cdot 1 \cdot y_{j}(n)$$
(14)

in which η is the learning rate; *n* is the number of learning cycles; *y* is the expected output; \hat{y} is the final system output.; *m_p* is the grade of membership for the *p*th fuzzy rule; *y_j* is the neuron output for the sub-network hidden layer; and *c* is the number of fuzzy rules.

The updated sub-network weight is as follows:

$$\Delta w_{ji}(n) = -\eta \cdot [-(y(n) - \hat{y}(n))] \cdot (1 - \hat{y}^{2}(n)) \cdot \frac{m_{p}}{m_{1} + m_{2} + \dots + m_{c}}$$
$$\cdot 1 \cdot w_{kj}(n) \cdot [y_{j}(n) \cdot (1 - y_{j}(n))] \cdot x_{i}(n)$$
(15)

in which x_i is the input of the sub-network; and w_{kj} is the weight between the network output layer and the hidden layer.

Through δ rule, bonding correction is defined as follows:

$$\Delta w_{kj}(n) = \eta \cdot \delta_k(n) \cdot y_j(n) \tag{16}$$

$$\Delta w_{ii}(n) = \eta \cdot \delta_i(n) \cdot x_i(n) \tag{17}$$

$$\delta_{k}(n) = [y(n) - \hat{y}(n)] \cdot (1 - \hat{y}^{2}(n)) \cdot \frac{m_{p}}{m + m_{p} + \dots + m_{p}}$$
(18)

$$\delta_j(n) = \delta_k(n) \cdot w_{kj}(n) \cdot [y_j(n) \cdot (1 - y_j(n))]$$
(19)

in which η is the learning rate; δ_k and δ_j is the area gradient parameter; y_j is the output value for the sub-network hidden layer; and x_i is the input value for the sub-network.

This study uses the subtractive clustering algorithm to obtain hidden rules among data. Then it uses the IF-THEN rule of fuzzy control to link each rule established after cluster analysis to one artificial neural network. Because the artificial neural sub-network adopts parallel framework, it is possible that several sub-networks are activated at the same time. All activated

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Table 2. The maximum and minimum values of the reference data set.

	М	$\sigma_o(kPa)$	$\sigma'_o(kPa)$	$q_c(Mpa)$	$a_{max}(g)$	q_{clN}
Max.	7.8	364.5	227.5	25.00	0.80	300.06
Min.	5.9	16.7	16.7	0.18	0.08	2.69

sub-networks undergo learning. Finally, each sub-network output is through defuzzy with weighted average formulas and is transformed into the final output with hyperbolic tangent functions.

IV. DATA SET AND PREPROCESSING

The case records listed in Table 1 are evaluated using the fuzzy-neural networks. The data base includes 466 CPT-base field liquefaction records from more than 11 major earthquakes between 1964 and 1999 [2, 4-8, 13-20, 25-31]. 21 case records were collected from Japan, 85 from China, 7 from Canada, 219 from the USA, and 134 from Taiwan. 250 of them liquefied and 216 sites did not liquefy. And then, 5 parameters were selected from 466 sites, they are: 1) earthquake magnitude, M; 2) total overburden pressure, σ_0 ; 3) effective overburden pressure, σ_0 ; ; 4) q_c value from CPT; and 5) maximum ground acceleration, a_{max} . Moreover, the liquefaction index is also listed in Table 1, it is 1 for liquefaction site and -1 for non-liquefaction site. In Table 2, the maximum and minimum values of each parameter are summarized, where, q_{cIN} is defined by $q_{cIN} = (q_c/100)/(\sigma_0'/100)$ [24].

Before using a data set to train the neural network, in order to avoid any inaccuracy and obtain better training results, the data set should be preprocessed. Data is pretreated by using (20). Each parameter is normalized between 0 and 10.

$$y = \frac{10 \times x}{x_{max} - x_{min}} - \frac{10 \times x_{min}}{x_{max} - x_{min}} = \frac{x - x_{min}}{x_{max} - x_{min}} \times 10 \quad (20)$$

in which y is normalized input parameter; x is the original input parameter; x_{max} and x_{min} are the maximum and minimum parameters, respectively.

In this study, system output is between 1 and -1. When it is larger than 0, it means within the liquefaction area. When it is smaller than 0, it indicates in non-liquefaction area. After the database is processed through data collection, organization and preprocessing, training is done iteratively until the Root Mean Square Error (RMSE) over all the training patterns are minimized. Training is terminated when RMSE is smaller than the threshold set point 0.1. Additionally, the calculation will be terminated when RMSE is still equal or larger than 0.1 after 10,000 times of iteration.

V. DETERMINATION OF NEURONS IN SUB-NETWORK

It is very important to optimize the number of neurons in the hidden layer. Depending on the complexity of problem, one may increase or decrease the number of neurons. If the number of

Table 3. Results and details of designed fuzzy-neural networks models.

Model	Intert workhier	No. of elements in	No. of	No. of E	iner	Error ta	Total error	
	input variables	every training cluster	neurons	Taining	Texing	Training	Tening	rate (%)
C4	$M, \sigma_{\theta}^{*}, q_{c}, a_{max}$	217,116,82,79	5	14	6	4.0	5.17	4.29
C4H6	$M, \sigma_0, q_c, a_{max}$	217,116,82,79	6	14	5	4.0	4.31	4.08
C5	$M, \sigma_0, \sigma_0', q_c, a_{mer}$	190,93,114,89	5	7	5	2.0	431	2.58
C9N	$M, \sigma_{\theta}, \sigma_{\theta}', q_{cis}, a_{mit}$	190,91,113,91	5	11	5	3.14	4.31	3.43

neurons in hidden layer is less than optimal, the training process cannot reach the global minimum error or the network is not able to learn properly. If the number of neurons in hidden layer is more than optimal, the possibility of over-learning or over-fitting becomes a problem. The back propagation algorithm with a three layer neural network is commonly utilized to analyze the liquefaction occurrence in different sites. Though neural network can have more than one hidden layer, Goh [10], Baziar *et al.* [3] and Juang *et al.* [15] found that one hidden layer is good enough for modeling liquefaction problem. The sub-network in this study follows divided-and- conquer methodology for solving liquefaction problem. Therefore, it is not necessary to have too many neurons in hidden layer. After trying different combination of hidden neurons, 5 or 6 neurons are used in the hidden layer of the fuzzy-neural network model.

1. Effective Radius of Optimized Subtractive Clustering

The criteria to choose a cluster center for subtractive clustering method is based on potential value of a point and the density of data points nearly. Effective radius r_a also plays an important role for the estimation of cluster center. Therefore, effective radius r_a determines the number of fuzzy rules in this study, and influences the complexity of model development and the ability of generalization. It should be optimized and an optimum r_a that is most suitable for this study is found. r_a is a positive constant with value between 0 and 1. r_a is determined by changing r_a and remaining system parameters kept unchanged, then Root Mean Square Error (RMSE) is checked if it is smaller than a threshold value. 466 data sets are tested to decide r_a value, test results are illustrated in Fig. 5. The range of r_a value tested is between 0.4 and 0.9. Dashed line in Fig. 5 represents number of fuzzy rules (number of clusters) computed with effective radius r_a . The smaller the radius value, the more the number clusters. From RMSE curve lines in training and testing phases, it can be seen that when r_a is smaller than 0.55, Even RMSE has much better convergent value (i.e. RMSE has smaller value) during training process, the RMSE in testing phase can not be reduced to a smaller value. (i.e. RMSE value is always larger than minimum value of 0.42). That means too many fuzzy rules and sub-networks will be produced, hidden characteristics and classification of database is over-estimated, resulting in too many composite parameters for mapping training data. If r_a value is chosen as 0.55, optimum result can be obtained either in training or testing phase.



Fig. 5. No. of rules and RMSE vs. different cluster radius r_a.



2. Adopted α-cut

It should make sure all data points at least belong to one cluster and no empty cluster exists. Membership is defined as adopting the α -cut concept, as shown in Fig.6. Only when the grade of membership for data is larger than the preset threshold α do they have the membership of the cluster. A fuzzy rule will be activated when the grade of membership is larger than α . The membership function of FCM (Fuzzy c-means) is used in this study. The sum of the membership values for a datum point with respect to all clusters is 1. Through optimized effective radius r_a , 466 data sets are separated into 4 clusters. To make sure all data points at least belong to one sub-network, α -cut value is set 0.25. If there exists any empty cluster, i.e., no any data point belongs to this cluster, rule patching will be processed until better result is met.

VI. ANALYSYS RESULTS

The 466 collected sets of CPT cases are used for analysis in this study. They are randomly divided into two groups, training group has 350 sets and testing group has 116 sets of data. Depending on different parameter combinations and number of hidden neurons, 4 kinds of neural network models are established. Table 3 shows the results of 4 different models. In model C4 and C4H6, the input parameters are earthquake magnitude *M*, effective overburden pressure σ_0 ', cone resistance q_c , and maximum ground acceleration a_{max} . Model C4H6 has one more hidden neuron than C4. Both two models developed by this

Table 4. Relative importance (%) of input parameters.

Model -	Relative importance(%)										
	М	a _{max}	σ'_{θ}	σ_0	q_{c}	q_{cIN}					
C4	25.5	22.2	31.6	-	20.7	-					
C4H6	26.4	25.2	18.9	-	29.5	-					
C5	17.9	24.9	17	20.7	19.5	-					
C5N	18.4	24.5	17.8	20	-	19.3					

Table 5. Relative importance (%) of parameters in each cluster of model C5.

Chuster	Relative importance(%)									
Cluster -	M	amax	σ'_{0}	σ_{θ}	q_c					
Ι	23.8	18.7	16.1	28.2	13.3					
п	17.1	26.5	22.6	7.3	26.5					
ш	10.0	28.8	18.8	21.5	20.9					
IV	16.5	31.4	10.7	17.5	23.9					

study have 4% error rate in training phase. Model C4H6 has one less error in testing phase than model C4. However, both models have nearly overall 96% success rate for judging liquefaction. It shows that very good results can be achieved in this study system with only 5 hidden neurons. Compared with model C4, models C5 and C5N additionally consider the effect of total overburden pressure σ_0 on liquefaction occurrence. In model C5N, normalized cone resistance q_{c1N} is considered as input parameter in stead of cone resistance q_c . From analysis results, model C5 with only overall error rate 2.58% has better accuracy than model C5N in training phase. Apparently, model C5 is the best model in this study for liquefaction assessment. Models C5 and C5N with additional consideration of σ_0 have better success rate than models C4 and C4H6 without consideration of σ_0 , shows that σ_0 is an important factor for the assessment of liquefaction. The outputs of training and testing results for model C5 are shown in Figs. 7 and 8. In this study, system output value is between 1 and -1. When it is larger than 0, it is within the liquefaction zone. When it is smaller than 0, it is in non-liquefaction zone. Solid circle points in Figs. 7 and 8 represent the cases with liquefaction, while empty circle points indicate the cases without liquefaction.

Table 4 shows the relative importance for the different models and the different parameter combinations in this study. Model C4 and C4H6 have similar relative importance for parameters *M* and a_{max} , while different for parameters σ_0 ' and q_c . The trend of parameters' relative importance for model C5 is generally similar to model C5N. In models C5 and C5N, the importance of earthquake parameters (*M* and a_{max}) is 43%, and 38% for the in-site stress factors (σ_0 ' and σ_0), 19% for the cone resistance factor (q_c or q_{c1N}). The fuzzy-neural system established in this study follows divide-and–conquer methodology for assessment of liquefaction potential. Table 5 shows the



Fig. 8. Results of testing phase in model C5.

relative importance of the four clusters in the C5 model. It can be seen that the main factor for liquefaction assessment in different cluster is different. For example, the liquefaction potential for the 1^{st} cluster is mainly affected by M and σ_0 . The 2^{nd} cluster is mainly controlled by a_{max} , σ_0' and q_c . The 3^{rd} cluster is mainly controlled by a_{max} . The 4^{th} cluster is mainly controlled by a_{max} and q_c . Since soil liquefaction induced by earthquake involves great uncertainty and is deeply affected by local geological condition, local stress condition and local earthquake parameters, the model is not limited to use the same neural network for analysis but follows data characteristics for classification and finds hidden rules. It provides a sub-network of learning for similar data clusters and meets the efficiency principle.

Site	Boring	Depth(m)	σ _o (kPa)	σ'o(kPa)	q _c (Mpa)	amax(g)	Liquefaction	Reference
1964 Nügata Earthquake	(M = 7.5)							
Kwagishi-Cho Building		2.8	52.0 85.3	35.3	3.14	0.16	1	Shibata and Teparaksa (1988) and Stark et al. (1995)
		5.2	97.1	56.9	7.06	0.16	1	Survey at (1993)
		8.0	149.1	81.4	5.49	0.16	1	
		4.8	89.2	61.8 78.5	5.34 7.80	0.16	1	
		11.1	206.9	117.1	9.51	0.16	1	
South Bank		4.5	84.3	45.1	7.85	0.16	-1	
		5.0	93.2	49.0	14.27	0.16	-1	
1971 San Fernando Valley	Earthauak	M = 6.4						
Juvenile Hall, California	2-B1	8.5	167.6	166.1	6.37	0.50	1	Bennett (1989) and Stark et al.
	2-B1	10.2	200.5	182.6	6.86	0.50	1	(1995)
	2-C 2-C	13.3	260.3	212.5	19.32	0.50	-1	
	2-C	14.8	290.3	227.5	21.57	0.50	-1	
	4-B1	6.4	125.7	119.7	3.14	0.50	1	
	4-B2 4-C	8.4	164.0	138.9	0.69	0.50	-1	
	4-C	10.7	209.5	161.7	9.81	0.50	-1	
	4-C	11.6	227.4	170.7	8.73	0.50	-1	
	4-C	12.8	251.4	182.7	5.39	0.50	-1	
	6-B1	4.6	89.8	86.8	0.69	0.50	1	
	6-C	9.1	179.6	131.7	7.06	0.50	-1	
	6-C	10.7	209.5	146.7	10.79	0.50	-1	
	6-C 6-C	11.3	221.4	152.7	8.83	0.50	-1 -1	
	6-C	15.1	296.3	190.2	6.86	0.50	-1	
	10-B1	5.0	98.8	95.8	1.96	0.50	1	
	10-B1 10-B1	5.8	113.7	103.3	0.69 2.94	0.50	1	
	10-C	10.2	200.5	146.7	0.69	0.50	-1	
	10-C	11.1	218.5	155.7	1.96	0.50	-1	
	10-C	12.2	239.4	166.2	4.90	0.50	-1	
	10-C 10-C	13.1	257.4 287.3	1/5.2	9.81 15.69	0.50	-1 -1	
	11-B1	6.3	122.7	119.7	1.96	0.50	1	
	11-B1	7.3	143.6	130.2	1.96	0.50	1	
	11-C	9.8	191.5	154.2	20.60	0.50	-1	
1975 Haicheng Earthquak	M = 7.3)						
Paper mill site		4.0	74.6	50.0	0.65	0.15	1	Arulanandan et al. (1986) and
Glass fiber site		3.0	55.9	41.2	0.53	0.15	1	Stark et al. (1995)
Fishery and shipbuilding		7.0	150.5	76.5	0.38	0.15	1	
site		3.5	65.2	45.6	1.30	0.15	1	
Middle school site		10.3	191.0	105.2	0.73	0.15	-1	
Chemical fiber site		1.5	139.8	80.9	1.20	0.15	1	
1976 Tangshan Earthquak	M = 7.8)						
Tanghsan area	T-10	3.0	55.9	41.2	1.67	0.40	1	Shibata and Teparaksa (1988) and
		6.0 7.8	111.8	67.7 83.4	9.22 5.59	0.40	1	Stark et al. (1995)
		8.5	158.9	90.2	7.45	0.40	1	
	T-11	0.9	16.7	16.7	1.47	0.40	1	
		1.3	24.5	20.6	0.98	0.40	1	
	T-12	2.0	37.3	33.3	2.45	0.40	1	
		3.0	55.9	42.2	2.55	0.40	1	
		4.0	74.5	51.0	3.14	0.40	1	
		6.4	119.6	72.6	3.43	0.40	1	
		9.5	177.5	100.0	8.24	0.40	1	
	T-13	2.0	37.3	28.4	1.67	0.40	1	
		2.1	39.2 50.0	28.4	3.43	0.40	1	
	T-14	1.5	28.4	26.5	5.39	0.40	i	
		3.0	55.9	39.2	8.83	0.40	1	
	T-15	1.2	22.6	20.6	6.86	0.40	1	
		2.5	47.1	32.4	4.16	0.40	1	
	T-16	4.0	74.5	69.6	11.25	0.40	-1	
	T-17	8.4	156.9 57.9	108.9 54.9	15.46	0.40	-1	
	• • •	4.1	76.5	63.7	11.89	0.20	-1	
		5.2	97.1	73.5	17.42	0.20	-1	
	T-18	4.7	87.3	76.5	1.62	0.20	1	
	T-19	1.5	28.4	24.5	1.01	0.20	1	
		2.9	53.9	36.3	4.90	0.20	1	
		4.0	74.5	46.1	2.85	0.20	1	
	T-20	1.2	22.6	21.6	12.98	0.20	-1	
		1.7	31.4	25.5	12.81	0.20	-1	
	т 21	2.1	39.2	29.4	16.27	0.20	-1	
	1-21	3.3	61.8	59.8	8.94	0.20	-1	
		4.0	74.5	65.7	11.07	0.20	-1	
	T-22	3.7	68.6 74.5	40.2	1.90	0.20	1	
	T-23	3.9	68.6	45.1	2.20	0.20	1	
		3.9	72.6	48.1	2.60	0.20	1	
	T-24	2.8	52.0	34.3	4.31	0.20	1	
	T-25	3.2 8.2	153.0	36.2 79.4	2.94	0.20	1	
	T-26	5.2	97.1	53.9	1.96	0.10	1	
	T-27	5.0	93.2	51.0	1.08	0.20	1	
	1-28	11.0	205.0	105.9	15.20 6.37	0.10	-1 -1	
	T-29	4.8	89.2	52.0	8.83	0.10	-1	
		5.3	99.0	56.9	2.45	0.10	-1	
	T-30	5.9 4.8	109.8	61.8 66.7	16.18	0.10	-1 -1	
		6.0	111.8	77.5	13.85	0.10	-1	
	_	8.5	158.9	100.0	18.57	0.10	-1	
	T-31	2.3	43.1 57 9	43.1 50.0	3.35 2.68	0.20	1	
	T-32	3.0	55.9	49.0	3.23	0.20	1	
		3.2	59.8	51.0	4.04	0.20	1	

Table 1. Summary of testing data.

Site	Boring	Depth(m)	σ _o (kPa)	σ'o(kPa)	q _c (Mpa)	amax(g)	Liquefaction	Reference	Site	Boring	Depth(m)	σ _o (kPa)	σ'₀(kPa)	q _c (Mpa)	a _{max} (g)	Liquefa	faction	Reference
Tanghsan area		3.8	70.6	55.9	2.88	0.20	1			MAR3	3.1	60.5	56.5	7.20	0.24	-1	1	
	T-33	3.2	59.8	51.0	2.94	0.20	1			MAR3	5.3	103.4	77.4	15.20	0.24	-1	1	
		5.0	93.2	66.7	5.74	0.20	1			MAR4	5.9	115.1	85.1	1.30	0.24	1	I	
		5.6	103.9	77.6	8.83	0.20	1			MAR5	2.8	54.6	50.6	1.90	0.24	1		
	T-34	2.6	48.1	47.1	1.84	0.20	1		Maral andrea	MAR6	8.4	172.2	143.2	5.90	0.24	-1	I	
	1-35	3.9	74.5	62.8	2.50	0.20	1		State Beach	UC-14 UC-15	3.0	57.0	45.0	3.00	0.25	1	ь в I et	al (2003)
		5.6	103.9	77.5	4.41	0.20	1			UC-17	4.4	83.6	65.6	5.40	0.25	1		()
	T-36	6.0	111.8	75.5	7.85	0.20	-1			UC-18	4.0	76.0	70.0	16.40	0.25	-1	1	
	L-I	6.9	111.8	57.2	8.31	0.20	-1		Sandholt Road	UC-4	2.5	47.5	40.5	7.70	0.25	1	I	
		12.0	223.6	110.6	4.46	0.20	-1			UC-4	9.5	180.5	103.5	25.00	0.25	-1	1	
		13.1	244.2	120.4	5.68	0.20	-1			UC-3	2.5	47.5	39.5	8.70	0.25	-1	1	
	L-2	5.9	111.8	54.3	2.43	0.20	1			RC-1	1.4	26.6	26.6	3.00	0.25	1		
		6.0	118.7	55.3	1.54	0.20	1			RC-I	3.9	74.1	53.1	11.70	0.25	-1	1	
		11.2	208.9	101.8	2.11	0.20				UC-2	1.0	36.1	34.1	10.40	0.25			
		12.1	225.5	109.7	2.55	0.20				RC-4	5.0	95.0	63.0	9.00	0.25	1		
	L-3	11.2	208.9	101.8	2.68	0.20	1			RC-4	6.8	129.2	79.2	20.80	0.25	-1	1	
		11.5	214.8	104.6	1.75	0.20	1			UC-6	6.5	123.5	75.5	18.20	0.25	-1	1	
	L-4	11.1	206.9	106.5	7.49	0.20	-1		MBARI No. 3	RC-5	3.5	66.5	49.5	15.50	0.25	-1	1	
										RC-6	4.1	77.9	62.9	13.00	0.25	-1	1	
1977 Vrancea Earthquake	(M = 7.2)								MELETY /	RC-7	4.7	89.3	79.3	9.20	0.25		1	
Dimbovitza (Site 1)		4.2	78.5	47.1	5.12	0.22	1	Shibata and Teparaksa (1988) and Sturk et al. (1995)	MBARI NO. 4	CPT-1 CPT-2	3.4 2.5	47.5	49.6	8.50	0.25		1	
		5.0	95.2	62.8	3.00	0.22	1	Stark et al. (1995)		CPT-3	41	77.9	59.9	9.40	0.25	-	I	
		7.0	130.4	71.6	1.29	0.22				CPT-4	1.9	36.1	32.1	8.40	0.25	-1	1	
		8.0	149.1	80.4	5.12	0.22	1		General Fish	CPT-5	2.1	39.9	33.9	2.50	0.25	1	I	
										CPT-6	2.6	49.4	40.4	10.00	0.25	-1	1	
1979 Imperial Valley earth	quake (M =	= 6.6)							Harbor office	UC-12	4.1	77.9	55.9	6.20	0.25	1	I	
Heber Road	Unit A2	4.0	76.0	56.0	2.00	0.80	1	Bennett et al. (1981, 1984),		UC-13	4.1	77.9	55.9	4.30	0.25	1		
	Unit A3	4.0	76.0	56.0	4.90	0.80	1	Bierschwale and Stokoe (1984)		UC-20	4.7	89.3	72.3	4.10	0.25	1		
KIVER Park Wildlife	Unit C	5.0	95.0	45.0	6.90 2.00	0.20	-1	and Juang et al. (2000a, 2003)	Woodward Marine	UC-9	4.2 2.9	79.8 55 1	38.1	4.90 6.60	0.25	1		
nume	iCg ICp	4.6 4.8	90.3	51.8	2.90 3.00	0.15	-1			UC-10	2.0	38.0	28.0	3.10	0.25	1	ı	
	2Cg	4.8	90.3	51.8	5.20	0.15	-1			UC-11	2.2	41.8	29.8	3.10	0.25	1		
	3Cg	4.8	90.3	51.8	5.90	0.15	-1			15-A	2.9	55.1	39.1	5.10	0.25	i	I	
	3Cp	4.8	90.3	51.8	3.80	0.15	-1			14-A	3.6	68.4	44.4	7.80	0.25	1	ı	
	4Cg	4.8	90.3	51.8	4.80	0.15	-1		Marine Laboratory	UC-1	11.0	209.0	123.0	4.60	0.25	1	I	
	5Cg	4.8	90.3	59.8	4.50	0.15	-1			UC-7	8.3	157.7	88.7	4.30	0.25	1		
	6Cg	4.8	90.3	59.8	5.10	0.15	-1			UC-8	8.6	163.4	90.4	4.30	0.25	1	l .	
	6Ct	4.8	90.3	59.8	4.30	0.15	-1			C2	9.8	186.2	110.2	3.80	0.25	1		
V-B Court	7Cg	4.8	90.3	59.8	5.10	0.15	-1			0	4.4	0.3.0 10.4 5	.54.6 77 5	6.20	0.25	1		
Vail Canal	VI	4.2	78.9	63.8	10.10	0.13	-1		East Roy shoraling sites	DOP 2	5.5	104.5	70.7	2.20	0.25	1	i v	auan at al. (1002, 1009) and
	V2 V2	3.9	77.0	63.3	6.40	0.13	-1		East bay storetine sites	POR-2 POR-3	6.0	114.0	79.7	2.20	0.16	1	i K	ayen et al. (1992, 1998) and iang et al. (2003)
	V3 V4	4.1	827	65.6	5.90	0.13	-1			SFOBB-1	6.3	119.7	77.5	4.10	0.28	1		ang et al. (2005)
	V5	4.7	89.3	68.7	9.00	0.13	-1			SFOBB-5	7.0	133.0	84.0	8.50	0.28	1	I	
Kornbloom Road	KI	11.0	209.0	119.0	6.40	0.08	-1			POO7-2	6.0	114.0	84.6	6.40	0.28	1	I	
	K3	11.0	209.0	119.0	6.40	0.08	-1			POO7-3	9.5	180.5	116.8	12.10	0.28	-1	1	
	K4	4.0	76.0	56.0	2.30	0.08	-1			ACPT7	2.5	47.5	42.6	3.40	0.27	1	I	
	K4	11.0	209.0	119.0	9.10	0.08	-1			BFI-P6	3.3	62.7	50.0	6.20	0.27	1		
	K5	4.0	76.0	56.0	1.90	0.08	-1		Clint Miller France	CSU-3	5./	82.4	75.4	2.20	0.53	1		(ayne et al. (1998) and Juang et
D - lis town	K5	11.0	209.0	119.0	15.50	0.08	-1		Clint Miller Farms	CSU-8	60	00.8	86.4 79.0	4.50	0.53	1	i ai	. (2003)
Radio tower	RI P2	3.0	955	47.0	4.20	0.18			Sea Mist-Leonardini	CSU-30	2.1	28.4	22.5	1.00	0.21	1		
	R4	2.5	47.5	42.5	5.50	0.18	-1			CSU-31	3.3	57.5	32.5	1.00	0.21	1		
McKim Ranch	MI	4.8	91.2	58.2	3.20	0.55	1			CSU-38	2.1	32.7	27.1	1.30	0.21	1	I	
	M5	6.5	123.5	73.5	5.80	0.55	1			CSU-39	2.7	42.1	33.1	1.00	0.21	1	I	
	M7	3.2	59.9	43.4	3.30	0.55	1		Southern Pacific Bridge	CSU-48	7.3	116.3	96.9	4.00	0.49	1	I	
	M8	4.5	84.6	55.1	3.50	0.55	1		Santa Cruze and Monterey	CMF2	10.3	195.7	157.5	5.50	0.53	1	В	ennett and Tinsley (1995).
									Counties	CMF3	6.8	128.3	118.0	3.70	0.53	1	Т	insley et al. (1998), Toprak et al.
1981 Imperial Valley earth	quake (M =	= 6.0)		61.0	2.00	0.00			Clint Miller Farms	CMF5	6.9	131.1	109.5	7.00	0.53	1	(1	999) and Juang et al. (2003)
Wildlife	ICg	4.8	90.3	51.8	2.90	0.33	1	Bennett et al. (1984), Bierschwale		CMES	9.3	1/5.8	131.1	2.00	0.53	1		
	1Cp	4.8	90.3	51.8	3.90	0.33	1	and Stokoe (1984) and Juang et al.		CMEI0	83	156.8	105.3	5.40	0.55			
	3Cg	4.8	90.3	51.8	5.20	0.33	1	(2000a, 2003)		CMF12	9.8	185.3	134.7	1.10	0.53	1		
	3Cp	4.8	90.3	51.8	3.80	0.33	i		Moss Landing	ML14B	5.8	109.3	67.6	9.40	0.27	1	I	
	4Cg	4.8	90.3	51.8	4.80	0.33	1		Model Airport	AIR17	2.8	53.2	46.3	2.60	0.38	1	I	
	5Cg	4.8	90.3	59.8	4.50	0.33	1			AIR18	3.8	71.3	58.0	4.30	0.38	1	I	
	6Cg	4.8	90.3	59.8	5.10	0.33	1			AIR21	4.3	80.8	62.6	4.60	0.38	1	I	
	6Ct	4.8	90.3	59.8	4.30	0.33	1		Scattini	SCA23	2.3	42.8	35.4	2.80	0.23	1	l	
N 36 1	7Cg	4.8	90.3	59.8	5.10	0.33	1			SCA24	2.6	48.5	40.1	2.20	0.23	1		
vail Canal	VI V2	4.2	78.9	63.8	10.10	0.37	-1			SCA28	3.2 5.0	59.9 95 n	40.7 57 7	4.30	0.23	1	1	
	V2 V3	3.9 4 1	77.0	63.2	7.20 6.40	0.37	1		Sea Mist	SEA31	1.8	33.3	23.0	140	0.23	-1		
	V4	4.4	82.7	65.6	5,90	0.37	1		Jefferson Ranch	JRR32	2.8	52.3	42.9	2.80	0.21	1	I	
Kornbloom Road	KI	11.0	209.0	119.0	6.40	0.37	-1			JRR32	10.8	204.3	116.5	9.50	0.21	-1	1	
	К3	11.0	209.0	119.0	6.40	0.37	-1			JRR33	5.8	109.3	65.6	4.10	0.21	1	I	
	K4	4.0	76.0	56.0	2.30	0.37	1			JRR33	8.3	156.8	88.6	10.30	0.21	-1	1	
	K4	11.0	209.0	119.0	9.10	0.37	-1			JRR34	2.5	46.6	39.2	7.50	0.21	-1	1	
D. F	K5	11.0	209.0	119.0	15.50	0.37	-1		Leffrence D	JRR34	4.3	80.8	55.7	5.40	0.21	1		
readio tower	RI D2	3.0	57.0	47.0	1.40	0.29	1		Jenerson Ranch	JKK121 IRR141	4.6	1.30.8	99.5 62.4	3.70	0.21	1		
	R2 R4	4.5	65.5 47.5	42.5	4.20	0.29	-1			JRR142	4.3	80.8	57.7	4,30	0.21	1		
McKim Ranch	MI	4.8	91.2	58.2	3,20	0.10	-1			JRR150	5.8	109.3	79.3	6.80	0.21	1	I	
	M5	6.5	123.5	73.5	5.80	0.10	-1			JEF-121	5.8	111.0	87.4	6.80	0.21	1	I	
	M7	3.2	59.9	43.4	3.30	0.10	-1			JEF-141	3.7	70.8	55.1	1.80	0.21	1	I	
	M8	4.5	84.6	55.1	3.50	0.10	-1			JEF-148	7.3	140.7	98.5	7.70	0.21	1	I	
										JEF-149	5.8	111.3	83.8	4.80	0.21	1	I	
1983 Nihonkai-Cho Earthq	uake (M =	7.7)								JEF-32	2.4	45.6	39.7	2.20	0.21	1		
Noshiro-Cho		3.1	56.9	47.1	9.81	0.23	-1	Shibata and Teparaksa (1988) and	Coyote Creek	CCK-1	9.8	187.7	145.5	8.60	0.17	-1	1	
		3.8	71.6	53.0	15.69	0.23	-1	stark et al. (1995)	Leonardini	UCK-23 LEN27	8.2	158.8	101.9	6.90	0.17	-1		
		2.8	53.0	451	1.5.08	0.25	-1			LEN39	2.8	52.3	43.9	2.40	0.21	1	ı	
		3.4	62.8	51.0	4,02	0.23	1			LEN51	2.8	52.3	42.9	1.40	0.21	1	I	
		5.1	94.1	65.7	7.80	0.23	1			LEN52A	3.6	67.5	59.1	4.10	0.21	1	I	
		6.0	111.8	73.5	8.80	0.23	1			LEN53	3.0	56.1	47.7	4.30	0.21	1	ı	
									Pajaro Dunes	PAJ44	6.8	128.3	95.4	11.80	0.32	-1	1	
1988 Sanguenay Earthquak	$ke \ (M = 5.5)$	9								PAJ79	2.5	47.5	37.7	10.50	0.32	-1	1	
Ferland, Quebec, Canada		2.5	50.8	43.1	4.26	0.25	-1	Tuttle et al.(1990) and Stark et al.		PAJ83	2.8	52.3	35.1	12.80	0.32	-1	1	
		3.5	70.4	53.1	4.91	0.25	-1	(1995)		PAJ85	2.0	37.1	28.7	8.30	0.32	-1	1	
		4.5	90.0	63.0	2.76	0.25	1			PAJ86	2.2	40.9	29.6	12.60	0.32	-1	1	
		5.5 6.5	109.6	12.8	5./1	0.25	-1			5PR/15	5.7	10.4	39.7 QG D	7.90	0.22	-1		
		7.5	148.0	02.0 92.4	0.01	0.25	-1		Southern Pacific Bridge	SPR46	4.2	79.8	70.0	5.50	0.49	1	I	
		8.5	168.5	102.2	7.77	0.25	-1			SPR47	6.2	117.8	101.1	7.20	0.49	1	I	
							•			SPR48	6.2	117.8	109.0	4.50	0.49	1	ı	
1989 Loma Prieta earthaua	ike (M = 7.	1)							Farris	FAR58	5.8	109.3	99.9	10.50	0.54	1	I	
San Francisco Marina	MARI	3.0	58.5	51.5	4.70	0.24	-1	USGS (1990) and Juang et al.		FAR59	6.6	124.5	107.3	8.00	0.54	1	I	
district	MARI	6.6	128.7	85.7	7.70	0.24	-1	(2000a, 2003)		FAR61	6.8	128.3	103.2	3.90	0.54	1	I	
	MAR2	3.3	64.4	58.4	8.60	0.24	-1		Marinovich	MRR65	7.3	137.8	121.6	6.70	0.59	1	l .	
	MAR2	5.9	115.1	83.1	14.50	0.24	-1		Suuman	SIL68	4.3	80.8	/3.4	5.30	0.57	1		
										31L/1	2.8	109.5	100.9	+.0U	U.3/	1		

MAA (2000a, 2000b), Juang et a
(2001) and Ku et al. (2004)

Reference

σ. (kPa

82.7 69.4 78.1 7.70 3.60 0.56

100.

128.3 96.4 7.40 0.56

104.8 144.2 8 50

194.8 166.3 105.5 96.0 144.2 139.3 98.1 87.6

137.8 129.4 5.50 0.16

137.8 129.4 6.10 0.16

137.8 204.3 137.8 52.3 61.8 129.4 161.6 115.7 34.1 53.4 6.20 5.70 0.90 0.16 0.50 0.38

46 3 36.3 1.27 0.77

46.3 46.3 64.8 83.3 120.3 2.5 2.5 3.5 4.5 6.5 7.5 12.2 13.8 WF-c10 WF-c10

120.5 138.8 224.8 255.3

191.5 68.5 170.2 64.8 83.3

249.8 57.4 75.9 185.0 74.0 148.0

57.4 189.0 207.0 68.5 41.4 99.0 107.0 46.5 2.54 7.46 7.62 2.70 8.03 0.19 0.19 0.19 0.19

138.8 78.8

231.3 249.8 166.5 186.9 314.5 92.5

259.0 268.3 46.3 64.8

205.4 231.3 109.4 6.70 9.19 0.19

259.0 268.3 59.2 83.3 194.3 212.8

83.3 249.8 268.3 286.8 346.0 364.5

212.8 231.3 74.9 148.0 249.8

216.5 257.2

46.3 64.8 96.2 120.3 138.8 31.3 39.8 48.3 65.3 73.8

249.8 268.3 286.8 305.3 63.0 84.6

136.8 237.6 48.6 66.6 120.6 138.6

156.6 228.6 246.6 111.6

138.6 228.6

10.4 3.5 9.0 3.5 4.5 13.5 3.1 4.1 10.0 4.0 8.0

3.1

10.5 11.5 3.7 7.5 12.5 13.5 9.0 10.1 17.0 5.0

2.5 3.5 11.8 46.3 64.8 218.3 36.3 44.8 115.3 2.54 2.62 8.15 0.19 0.19 0.19 0.19

2.5 3.5 11.1 12.5

3.2 4.5 10.5 11.5

5.0 12.5 14.0 2.6 5.0 4.5 92.5 231.3 259.0 48.1 92.5 83.3

15.5 18.5 19.5 11.5 12.5

4.1 8.0 13.5

2.5 3.5 4.5 7.5 13.5 14.5 15.5 16.5 3.5 4.5 7.4

13.0 2.5 3.5 6.5 7.5 8.5 12.5 13.5 6.0 7.5 12.5

36.3 36.3 44.8 1.97 0.72 1.79 1.35 0.77 0.77 0.77 0.77

53.3

70.3 11.66 0.77

/8.8 118.3 132.3

49.8 1.47 0.43

49.8 96.5 49.8

58.3

134.8 16.30 0.43

46.4 1.41 0.43

54.9 105.0 1.41 0.90 11.96 1.87 5.77 0.43 0.43 0.43 0.43

49.0 83.0

41.4

121.3

91.5 100.9 159.5

57.5

134.0 12.43 0.19

138.3 16.80 0.19

36.3 44.8 1.62 2.45 0.19

121.3

134.0 138.3 13.65 17.08 0.19

42.2 53.3 104.3

112.8 7.41 2.54 0.19

57.5

121.3 134.0 37.1 57.5

53.3

129.8 138.3 8.00 8.01 0.19 0.19

146.8 172.3 8.74 10.05 0.19 0.19 0.19 0.19

180.8 11.26

112.8 6.83 0.21

121.3 7.52 0.21

49.4 83.0 129.8

112.8 8.32 0.19

133.2 11.58 0.19

124.8 14.67 0.19

133.3 10.61 0.19

141.8 150.3 43.0 51.0 14.74 13.65 1.28 0.64 0.19 0.19 0.19 0.12

74.2 5.46 0.12

119.0 35.0 5.16 3.26 0.12

35.0 43.0 67.0 75.0 3.26 2.65 7.40 7.04

83.0 7.47 7.68 6.54 6.64 0.12

115.0

113.0 123.0 63.0 75.0 115.0

2.61 6.61 8.30 0.19

3.00 0.19

2.09 2.78 2.69 3.05 0.19 0.19 0.19 0.19 0.19

10.8 7.3 2.8 3.3 GRA123 MCG128

σ'_(kPa a-(Mpa

30.5

4.20 4.80

3.90

2.30 0.38

13.89 14.45 20.05 0.77 0.77 0.77

11.47 11.32 11.56 12.89 3.86 108.0

0.77

0.43

0.43 0.43 0.43 6.01

0.43

0.19

0.19

0.19

0.19

0.19 0.19

0.19

0.19

0.19

0.19

0.19 0.19 0.19 0.19 2.66 1.82 8.25

0.19

0.19 12.77 0.19 0.19 2.96 1.73 0.19

0.21

0.19

0.12

0.12

0.12

0.12

0.12

0.12 0.12

0.12

amax(g

Liquefaction

Reference

5.59 7.58 0.12 0.12

6.80 7.02 6.67 7.72 7.68 2.22 129.8

> 12.15 0.19

Liquefactio

Boring Denth(m)

KET74

RAD95 RAD96

RAD97 9.3 6.8 175.8 117.4 5.00 0.56

RAD98

RAD99 5.4 10.3 101 3 89.4 5.00 0.56 0.55 0.55 0.19 0.19

TIR 100

TJR100 TJR101 TAN103 8.8 5.6 5.1 7.3 7.3

TAN105

SRB116

SRB117

SPB117

MCG136

(M - 7.6)WF-4

WF-c7 WF-c10

WE-3h

WF-3b WF-3b WF-4b WF-c8

NT-1 NT-1 2.5 3.5 46.3 64.8 41.3 0.94 0.43

NT-1 NT-5 NT-5 NT-C2

NT-C2

NT-C2

NT-C

NT-C7 NT-C7 NT-C15 NT-C15

YL-CI YL-C2 12.5 231.3 57.4 121.3 8.27 2.54 0.19

YL-C2 YL-C3 YL-C3 YL-C4

YL-C5

YL-C5 YL-C5

YL-C5 YL-C7 YL-C9 YL-C10 YL-C19

YL-C19 YL-C21 YL-C22 YL-C22 YL-C22 YL-C22 7.5 14.0 138.8 259.0 78.8 134.0 6.23 0.19

YL-C22 12.5 231.3 121.3 10.08 0.19

YL-C22 YL-C22 14.0 14.5

YL-C22 YL-C24 YL-C24 YL-C24 YL-C24

YL-C24 YL-C24 YL-C25 YL-C25 YL-C25 YL-C25 14.0 14.5

YL-C25

YL-C3

YL-C31 YL-C31 YL-C32 YL-C32 YL-C35

YL-C36 YL-C36 13.5 14.5

YL-C36 YL-C36 YL-C36 YL-C36

YL-C42

YL-C42

YL-C42 YL-C43 YL-C43 YL-C43

YL-C44 YL-C44 11.5 13.9

YL-2 YL-2 YL-2 YL-2 YL-2 YL-2

YL-2 YL-2

YL-2 YL-2 LW-A1 LW-A1

LW-AI

LW-A1 LW-A2

LW-A2 LW-A2

LW-A2

LW-A2 LW-A2

LW-A2 LW-A3

LW-A3 LW-A3

Boring Depth(m) σ_o(kPa) σ'_o(kPa) q.(Mpa)

Kett

Radovich Radovich

Tome Jones Ranch

Salinas River Brider

Granite Co McGowan

1999 Chi.Chi earth

Dachur

Yuanlii

Yuanlii

Shetor

Vuanlii

Luwei in Chang-Bir

ndustrial park

Luwei in Chang-Bin	LW-A5	6.5	124.0	70.3	6.68	0.12	-1	
industrial park	LW-A5	7.5	142.5	78.8	5.21	0.12	-1	
	LW-A5	8.5	161.0	87.3	6.12	0.12	-1	
	LW-A5	9.5	179.5	95.8	7.18	0.12	-1	
	LW-A7	7.5	138.6	75.0	5.91	0.12	-1	
	LW-A7	8.5	156.6	83.0	5.38	0.12	-1	
	LW-A7	9.5	174.6	91.0	6.62	0.12	-1	
	LW-A7	11.5	210.6	107.0	7.99	0.12	-1	
	LW-A7	12.5	228.6	115.0	7.38	0.12	-1	
	LW-A7	13.5	246.6	123.0	7.41	0.12	-1	
	LW-A9	6.5	120.6	67.0	7.03	0.12	-1	
	LW-A9	8.5	156.6	83.0	6.73	0.12	-1	
	LW-A9	10.5	192.6	99.0	6.49	0.12	-1	
	LW-A9	12.5	228.6	115.0	5.47	0.12	-1	
	LW-A9	13.5	246.6	123.0	6.32	0.12	-1	
	LW-A10	2.5	48.6	35.0	0.92	0.12	1	
	LW-A10	3.5	66.6	43.0	1.50	0.12	1	
	LW-A10	4.5	84.6	51.0	0.64	0.12	1	
	LW-A10	7.9	145.8	78.2	6.05	0.12	-1	
	LW-A10	9.5	174.6	91.0	6.76	0.12	-1	
	LW-C1	3.5	68.5	44.8	2.49	0.12	1	
	LW-C1	4.5	87.0	53.3	2.01	0.12	1	
	LW-C1	5.5	105.5	61.8	1.89	0.12	1	
	LW-C1	6.5	124.0	70.3	1.54	0.12	1	
	LW-C1	9.5	179.5	95.8	7.43	0.12	-1	
	LW-C1	11.6	218.3	113.6	7.72	0.12	-1	
	LW-C2	5.0	93.6	55.0	6.61	0.12	-1	
	LW-C2	6.5	120.6	67.0	7.12	0.12	-1	
	LW-C2	10.5	192.6	99.0	6.08	0.12	-1	
	LW-C2	12.5	228.6	115.0	7.76	0.12	-1	
	LW-C2	18.5	336.6	163.0	9.48	0.12	-1	
	LW-D1	3.5	68.5	44.8	0.20	0.12	1	
	LW-D1	5.0	96.2	57.5	5.93	0.12	-1	
	LW-D1	6.5	124.0	70.3	7.94	0.12	-1	
	LW-D1	7.5	142.5	78.8	7.57	0.12	-1	
	LW-D3	2.5	50.0	36.3	0.23	0.12	1	
	LW-D3	3.5	68.5	44.8	0.18	0.12	1	
	LW-D3	6.1	116.6	66.9	7.24	0.12	-1	
	LW-D3	8.5	161.0	87.3	6.21	0.12	-1	
	LW-D3	12.5	235.0	121.3	8.83	0.12	-1	

VII. CONCLUSION

Fuzzy-neural network has been used to establish the assessment of liquefaction potential, based on 466 CPT field records collected from the world. This study combines fuzzy theory with subtractive clustering algorithm to constitute a fuzzy-neural system.

Using multiple neural networks, and subtractive clustering analysis to develop a fuzzy-neural network. It has the ability to find the relations between basic parameters and to achieve better results.

In model C5, adding 0 as an input parameter could decrease the total error to 2.58%, and σ_0 also played a more important role than q_c in liquefaction assessment.

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