Liquefaction prediction using fuzzy neural network model based on SPT

Prévision de liquéfaction en utilisant un modèle du réseau neurologique brouillé basé sur des données de SPT

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ABSTRACT: An integrated fuzzy neural network model is developed for the prediction of liquefaction at a site. The model is trained with a large database of liquefaction and non-liquefaction case histories. A two-stage training algorithm is used to develop a fuzzy neural network model. In the preliminary training stage, the training case histories are used to determine initial network parameters. In the final training stage, the training case histories are processed one by one to develop membership functions for the network parameters. During the testing phase, fuzzy inputs variables are described in linguistic terms such as 'high' and 'low.' The prediction is made in terms of a liquefaction index representing the degree of liquefaction described in fuzzy terms such as 'highly likely,' 'likely,' or 'unlikely.' The results from the model are compared with actual field observations and misclassified cases are identified. The model is found to have a good predictive ability.

1. INTRODUCTION

Ground failures associated with liquefaction are potentially very damaging as observed during many earthquakes of the past. The evaluation of liquefaction potential at a site constitutes an important task of earthquake hazard mitigation and has attracted considerable attention in the past three decades.

The method of liquefaction prediction commonly used in practice is based on the available case-historic database. In this approach, using the known performance of case-historic data, a boundary is established separating the two classes of behavior (i.e. liquefaction and no-liquefaction) in a space of chosen earthquake and site parameters. This method was first developed by Seed (1979), and was subsequently modified by Seed et al (1983).

Recently an alternative approach to modeling has emerged under the rubric of 'soft computing'. One of the constituents of this approach is 'artificial neural network' which is a distributed information processing system in which modeling is viewed as a mapping from one multivariate space of information (input variables) to another (output variables). A neural network model has many remarkable features: (i) it is adaptive and has learning ability, (ii) it can infer solutions from the data often capturing quite subtle, difficult and hard to discern relationship, (iii) it can generalize and handle imperfect or incomplete data, and (iv) it can capture non-linear and complex interaction among variables of the system. The other constituent of 'soft computing' is 'fuzzy logic', which is an approximate reasoning method to cope with the uncertainties. This provides a systematic way of dealing with the imprecise and vague information on input data, their effects on the system, and the response of the system (output). Fuzzy logic based models for liquefaction, have been developed by El Zahaby and Rahman (1996), Chen and Chen (1997) and others. The neural-network models for the prediction of liquefaction have also been developed Goh (1994, 1996). Recently, a number of other neural network models have been developed for other applications (Ghaboussi et al, 1991; Ni et al, 1996; Najjar and Basheer, 1996).

In this study an integrated fuzzy neural network model is developed for the assessment of liquefaction potential. The complexity and non-linearity of the underlying system are handled through neural network while the imprecision associated with the system parameters are incorporated through fuzzy logic. Retaining the basic architecture of a neural network, the model is trained on the case-historic data, and model parameters are developed in fuzzy form. The model in its predictive mode uses the fuzzy input variables and evaluates liquefaction potential in fuzzy terms. The model gives good results and is expected to be very useful for a preliminary evaluation of liquefaction potential of a site for which the input parameters are not available in crisp form but can be described in linguistic terms through expert judgments.

2. ELEMENTS OF ANALYSIS

2.1 *Fuzzy Logic*

The modeling of many systems involves the consideration of some uncertain variables. The statistical uncertainties associated with these variables are handled through probability theory. There also exists non-statistical uncertainty (in the form of 'vagueness' or 'imprecision') associated with many variables. These variables and their influences on the system are defined in linguistic terms. This form of uncertainty can be handled in a rational framework of 'fuzzy set theory'. In relation to the problem of evaluating liquefaction potential, in some situations the governing variables may not be available and can be described only in linguistic terms such as very high, high, medium, low and very low. These linguistic terms, represented by fuzzy numbers A, B, C, D, and E are defined by the membership functions shown in Figure 1. Being a continuous and often ambiguous event, the occurrence of liquefaction may not be appropriate to describe in terms of either/or classification (Agrawal et al., 1997). Instead, liquefaction should be described in terms of degrees of liquefaction represented by fuzzy numbers. In this study a method called FWA (Fuzzy Weight Average), developed by Dong and Wong (1987) is used for all the fuzzy operations.

A fuzzy variable, A is normally expressed as a pair of data

$$A = \{(x, \mu_A(x) \mid x \in X\} \tag{1}$$

where, x is the element, X is a collection of objects denoted by x; $\mu_A(x)$ 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, when $M = \{0,1\}$, the set A is a non-fuzzy set. In most case, M is set to the unit interval [0,1].

An α-cut of a fuzzy set A is a crisp set A_α that contains all the elements of the universal set X that have a membership grade in A greater than or equal to the specified value of α. This definition can be mathematically formulated as:

$$A_\alpha = \{x \in X \mid \mu_A(x) \geq \alpha\}, \qquad \alpha \in (0, 1] \tag{2}$$

A fuzzy set A can be also expressed as:

$$A = \int_0^1 \alpha A_a \tag{3}$$

The above equation indicate that a fuzzy set A can be decomposed into αA_α, $\alpha \in (0,1]$, that is, a fuzzy set can be expressed in terms of its α-cuts.

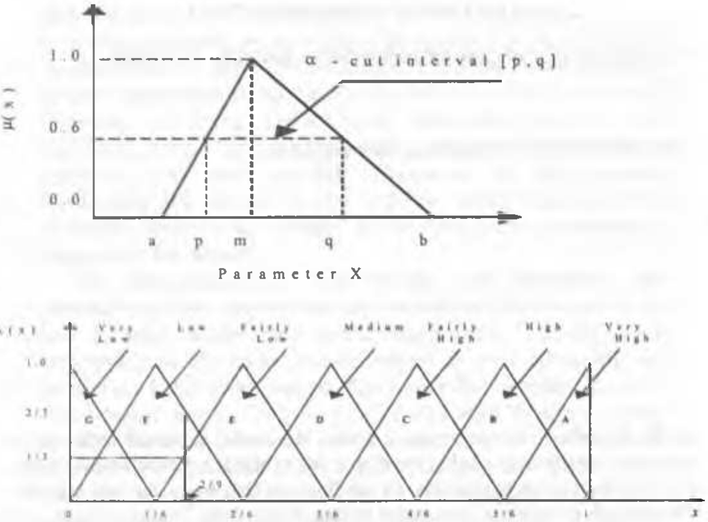

Figure 1. Membership Function and Definition of Linguistic G rades

It should be noted that in the definition of the membership functions above, the variable x has been normalized with respect to their minimum and maximum values, i.e. $x = (x-x_{min})/(x_{max}-x_{min})$.

2.2 *Artificial Neural Network Model*

An Artificial Neural Network is a "computational mechanism able to acquire, represent, and compute a mapping from one multivariate space of information to another, given a set of data representing that mapping" (Garret, 1994). A neural network consists of a large set of interconnected neurons (i.e., processing units). These neurons are arranged in many layers and interact with each other through weighted connections. The basic architecture of neural networks has been covered widely (Lippmann, 1987; Flood and Kartman, 1994). A typical back-propagation artificial neural network is shown in Figure 2. Neural networks are trained by the presentation of a set of examples of associated input and output (target) values. The hidden and output layer neurons process their inputs by multiplying each of their inputs by the corresponding weights, summing the product, and then processing the sum using a nonlinear transfer function to produce a result. The S-shaped sigmoid function is commonly used as the transfer function. The neural-network "learns" by adjusting the weights between the neurons in response to the errors between actual output values and target output values. In this study the back-propagation learning rule (Rumelhart et al, 1986) has been used to train the network. At the end of this training phase, the neural network represents a model, which Figure 2 The Architecture of Artificial Neural Network should be able to predict a target value given the values of input variables.

2.3 *Fuzzy Artificial Neural Network (FANN)*

An approach to integrate fuzzy logic and neural network is to simply fuzzify some of the neural network system parameters and retain the basic properties and architectures of the neural network model In such models, a crisp neuron becomes fuzzy and response of the neuron to its lower-layer activation signal is of a fuzzy form The learning mechanisms and interpretation capability of the neural network system is enhanced by fuzzy representation of the knowledge domain. The mechanism of FANN used in this study is similar to the one used by Ni, Lu and Juang (1996) in their study for evaluation of slope failure. In order for neural network to handle the fuzzy inputs, the network parameters, i.e., the weights that connected each neuron and the bias in each layer are fuzzified using a two-stage training procedure. By using FANN, one will be able to estimate the target value based on the fuzzy inputs expressed in the linguistic terms.

In the first preliminary training stage, the algorithm remains the same as the normal back-propagation algorithm as described earlier. All the available input patterns (non-fuzzy inputs in the case-historic database) are used to build up the network parameters. The acceptable error goal in this stage is set to a relatively large value. By using the preliminary training, the possibility that the final solution gets stuck in a local minimum is reduced. Meanwhile, it can also prevent the over-training of network. Then in the second stage of training, processing the input pattern one by one, with a relatively small error goal, the network parameters W_i, and b_i are obtained. After repeating the fine training process for all the input patterns, a set of these parameters are obtained from which the membership functions of each network parameter is derived. In this study a triangular form (Fig. 1) is used to represent the membership function.

The basic premise of this approach is that for some situations, the crisp information about the governing variables, are not known but these variables can be described in linguistic terms through expert judgments. Therefore, during the prediction stage, the membership function corresponding to the linguistic inputs as shown in Figure 1 are used. The fuzzy input patterns (i.e. all the input variables are fuzzy numbers) are processed by the trained FANN. For each input pattern and network parameters, a set of α-cut intervals is defined. Each α-cut interval is processed separately with FANN. At the end of the process, the final output for the target variables are fuzzy numbers defined in terms of their α - cut values.

The output from FANN represents the degree of liquefaction. In other words, each set of testing data is said to match the pattern representing liquefaction to a certain degree. For instance, the degree

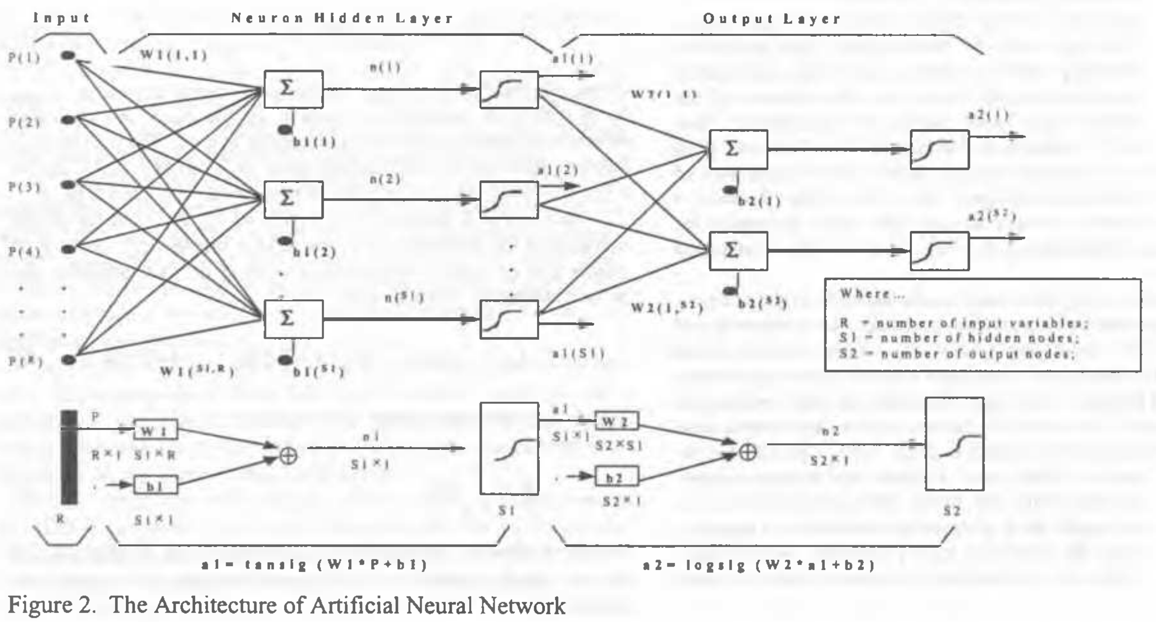

Figure 2. The Architecture of Artificial Neural Network

of 0.1 means the site is highly unlikely to liquefy and the degree of 0.9 means the site is highly likely to liquefy. The following range of linguistic labels are used in this study:

0 to 0.2	Liquefaction *highly unlikely*;
0.2 to 0.4	Liquefaction unlikely;
0.4 to 0.6	Not enough information to decide,
0.6 to 0.8	Liquefaction likely;
0.8 to 1.0	Liquefaction highly likely.

3. CASE HISTORIC DATA

The database used in this study includes 205 field liquefaction records from more than 20 major earthquakes between 1802 and 1990. In this database SPT values represent the liquefaction resistance of soils. After trying different combination of input parameters, ten variables are used in the input layer of the neural network model These are: (i) earthquake magnitude, M, (ii) vertical total overburden pressure σvo, (iii) vertical effective overburden pressure, σ'vo, (iv) corrected standard penetration test (SPT) value (N1) 60; (v) acceleration ratio amax/g; amax is the peak acceleration measured or estimated at the ground surface of the site; g is the acceleration of gravity (9.81 m/s2), (vi) cyclic shear stress ratio (τ/σ'vo), (vii) fine content of the soil, F (%); (viii) median grain diameter of the soil D50, (ix) critical depth of liquefaction Dcr, (x) water table depth Dw.

4. RESULTS

Table 1 presents the prediction on testing case histories from FANN model It can be observed that most case histories can be correctly classified Most case histories which have been observed to be liquefied have the output values in the range of 0.6-0.7, i.e., liquefaction likely; and for most cases which have been observed not to be liquefied the predicted liquefaction indices are in the range of 0.3 - 0.4, i.e. liquefaction unlikely. There are 5 misclassified cases out of 27 cases tested, representing about 19 percent of misclassification. This rate of misclassification is about the same as normally achieved by the traditional method used in practice. However, this should be kept in mind that in this model the input variables are fuzzy and the data on which model is being tested were not included in the data set used for developing the model The SPT $(N_1)_{60}$ value has a significant effect on the output from the FANN. This can be observed by comparison between case No.12 and 13, case No. 24 and 25 in Table 1.

It should be noted here that for the data being tested here the variables are known However to test the validity of this approach these variables have been first fuzzified to be used in FANN model Here the rule which has been used to transfer the crisp value to linguistic value is: from the membership functions (defined in Fig. 1), the linguistic term which gives the maximum degree of membership of the crisp value, is taken as their equivalent fuzzy equivalent. In the situations, for which this approach is intended, the input variables will be known in linguistic terms only. In those situations where some of the variables are available in crisp form, this approach can still be used by either fuzzifying those variables as mentioned above, or representing them as fuzzy 'singletons.'

5. CONCLUSION

A fuzzy neural network model has been developed for the assessment of liquefaction potential at a site for which the input parameters are not well defined The complexity and non-linearity of the underlying system are handled through neural network while the imprecision associated with the system parameters are incorporated through fuzzy logic. Retaining the basic architecture of a neural network, the model is trained on the case-historic data, and model parameters are developed in fuzzy form The model in its predictive mode uses the

Table 1 Liquefaction Prediction Using a FANN Model Based on SPT Data

Case No.	M	σv_0 kPa	$\sigma v_0'$ kPa	SPT N	a/g	$\tau/\sigma v_0'$	F(%)	D_{50} (mm)	Dcr	Dw	Liq.	FANN
1	E	E	E	F	F	F	F	G	E	F	N	0.3
2	E	A	B	G	F	F	E	G	A	F	N	0.3
3	F	F	E	A	G	G	E	G	F	E	N	0.3
4	F	F	E	G	G	G	E	G	F	E	N	0.3
5	F	E	E	D	G	G	E	G	E	E	N	0.3
6	F	G	G	F	F	E	B	G	G	G	N	0.7
7	F	E	F	E	F	E	F	G	E	G	N	0.3
8	F	F	F	F	E	E	F	G	F	F	Y	0.7
9	F	F	E	D	E	E	F	G	F	E	N	0.3
10	F	F	E	E	E	E	F	G	F	E	N	0.4
11	F	E	E	G	E	E	A	G	E	E	Y	0.7
12	F	F	F	G	E	E	C	G	F	E	Y	0.7
13	F	F	E	F	E	E	A	G	F	E	Y	0.7
14	F	G	E	G	F	F	C	G	F	E	Y	0.3
15	F	F	F	E	F	F	F	G	F	E	N	0.3
16	F	F	F	F	F	F	E	G	F	F	N	0.3
17	B	C	C	D	F	E	G	G	C	F	N	0.7
18	B	E	C	E	D	E	G	G	E	F	Y	0.7
19	B	E	F	E	F	E	G	G	E	F	Y	0.3
20	B	E	E	E	F	E	F	G	E	F	N	0.7
21	B	B	C	B	F	E	F	G	C	F	N	0.3
22	B	D	D	C	F	E	F	G	D	F	N	0.3
23	B	E	E	F	E	E	F	G	E	F	Y	0.7
24	B	C	D	E	F	E	F	G	D	F	Y	0.7
25	B	D	D	E	F	E	F	G	D	F	Y	0.7
26	B	C	D	E	F	E	F	G	C	F	Y	0.7
27	B	F	F	D	F	E	F	G	G	F	Y	0.7

Note: A = very high B = high C = fairly high D = medium E = fairly low F = low G = very low Highlighted is the misclassified case histories fuzzy input variables described ion linguistic terms such as 'high' and 'low'. The prediction is made in terms of a liquefaction index representing the degree of liquefaction in fuzzy terms such as 'highly likely', 'likely', or 'unlikely'. Based on the comparison of the results with the actual field observations, the model is found to have reasonably good predictive ability.

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