EVALUATION OF LIQUEFACTION-INDUCED LATERAL SPREADING BY A NEURAL NETWORK (NN) MODEL

B.Siyahi[1], B.Akbas[2] and N.Dogan Onder[3]

[1] *Professor, Dept. of Earthquake and Structural Science, Gebze Institute of Technology, 41400 Gebze, Kocaeli, Turkey*

[2] *Assoc.Professor, Dept. of Earthquake and Structural Science, Gebze Institute of Technology, 41400 Gebze, Kocaeli, Turkey*

[3] *Graduate Student, Dept. of Earthquake and Structural Science, Gebze Institute of Technology, 41400 Gebze, Kocaeli, Turkey*

Email: bilge.siyahi@gyte.edu.tr

ABSTRACT:

Liquefaction-induced lateral spreading during an earthquake ground motion (EQGM) is considered to be one of the major soil failure types. The observations from the previous earthquakes show that the magnitude of lateral spreading can reach to the level of a few meters that can severely damage the surrounding area most of the times. Since liquefaction is a complex soil failure problem that involves soil and earthquake parameters, liquefaction-induced soil deformations should be investigated by nonlinear methods. In this study, a NN model has been developed to investigate the liquefaction-induced lateral spreading during an earthquake ground motion. The NN model used in this study was constructed using 8 input parameters (magnitude of EQGM, σ_0 (kPa), σ_0' (kPa), N (SPT), a/g, τ_{ort}/σ_0, F (%), D_{50}) and 1 output parameter (lateral spreading). A relationship is established between the lateral spreading and the soil and earthquake ground motion parameters by developing and testing a multi-layered feed-forward NN model trained with the back-propagation algorithm. A total of 175 cases were used for constructing the NN model. Results indicates that N (SPT) is the most effective parameter; whereas a/g is the least effective parameter on liquefaction-induced lateral spreading. The approach adapted in this study was shown to be capable of providing the best accurate estimates of liquefaction-induced lateral spreading during an earthquake ground motion.

KEYWORDS: Liquefaction, Lateral Spreading, Neural Network

1. INTRODUCTION

One of the major causes of demolition during an earthquake is the failure of the soil. The loss of the shear strength of the soil due to an increase in pore water pressure is the cause of this failure. This phenomenon called liquefaction occurs mainly in loose and saturated sands. Liquefaction of soils during earthquakes causes large amount of damage to buildings, highway embankments, retaining structures as well as other civil engineering structures. During past earthquakes large areas of ground were observed to shift laterally due to soil liquefaction. These liquefaction-induced lateral ground deformation have amplitudes ranging from small (1cm) to very large (>10m) in the case of flow slides. They can take place for gently sloping ground conditions (0.1% to 6%). The deformations are usually driven by a combination of transient and static shear stresses and attributed to the loss of shear strength of underlying saturated soils. Several analytical approaches have been proposed to model liquefaction-induced ground deformation. These models are capable of explaining effectively a few, but not all, aspects of liquefaction-induced deformations. Most of the analytical models need the calibration of many parameters for predicting liquefaction-induced deformation. Goh (1994) researched Neural Network applications to liquefaction likelihood. Comparisons between the neural network model and conventional dynamic stress method proposed by Seed et al. (1985), and Shibata and Teparaksa (1988) indicated that neural network model was simpler to apply and gave more reliable results (Goh, 1994).

In order to construct a relationship between the lateral spreading and the soil and earthquake ground motion parameters, a Neural Network (NN) algorithm has been established in this study. Neural Network (NN) modeling has gained great attention in recent years as an alternative approach for investigation of nonlinear relationships in engineering problems (Ren and Zhao 2002; Cladera and Mari 2004; Tehranizadeh and Safi 2004; Ashour and Alqedra 2005; Papadrakakis *et al*. 2005; Fonseca *et al*. 2007; Papadrakakis *et al*. 2008). NNs learn and generalize from examples and experience to produce meaningful solutions to the problems even in cases where the input data contains error or is incomplete (Rafiq *et al.* 2001). The main objective of this study is to develop and test multi-layered feed forward NNs trained with the back-propagation algorithm to assess the lateral spreading through the use of soil and earthquake ground motion parameters.

2. LIQUEFACTION CASE RECORDS

Several critical factors influencing the liquefaction of soils during earthquakes were identified at previous studies (Tokimatsu and Yoshimi, 1983; Seed et al., 1985; Berrill and Davis, 1985; Liao et al., 1988; Law et al., 1990; Goh, 1994). The magnitude and intensity of the earthquake, properties of soils, fault distance, and the seismic attenuation properties can be defined as among these factors. This study utilizes past liquefaction data observed during different 19 earthquakes between 1891 and 1999. Liquefaction case records were essentially taken from the study proposed by Tokimatsu and Yoshimi (1983) and added Erzincan 1992 and Kocaeli (1999) earthquakes in Turkey. Data set includes Mina-Owaki (1891), Kanto (1923), Tohnankai (1944), Fukui (1948), San Fransisco (1957), Niigata (1964), Alaska (1964), Tokachi-Oki (1968), San Fernando (1971), Guatemala (1971), Imperial Valley (1979), Miyaginen-Oki (1978), Imperial Valley (1979), Chibaken-Chubu (1980), Loma Prieta (1989), Manjil (1990), Luzon (1990), Erzincan (1992), Kocaeli (1999) earthquakes.

3. LATERAL SPREADING

Liquefaction-induced lateral spreading is defined as the finite, lateral displacement of gently sloping ground as a result of pore pressure build-up or liquefaction in shallow underlying deposit during an earthquake. Lateral spreading occurs on mild slopes of 0.3 to 5% underlain by loose sands and a shallow water table. In addition topographical factors; earthquake magnitude, distance to the seismic source, and the thickness, fines content, and mean grain size of the liquefied layer strongly to moderately correlated with lateral spread (Bartlett and Youd, 1995). Keeping all other factors constant, ground displacement clearly increases with earthquake magnitude and proximity to the seismic energy source.

4. NEURAL NETWORK (NN) MODEL

NNs consist of simple mathematical structures and easily handle highly non-linear problems. Figure 1 represents a typical three-layer feedforward NN with *n* input nodes, *m* hidden nodes and one output. The input nodes in a NN model represent the data presented to the NN, whereas the output nodes represent the produced NN output. The hidden layer (Figure 1) functions as the interface. The hidden layer in Figure 1 serves as the interface to extract and to remember the useful features and the sub features from the input patterns to predict the outcome of the NN model (Rafiq *et al.* 2001; Gunaydin and Dogan 2004).

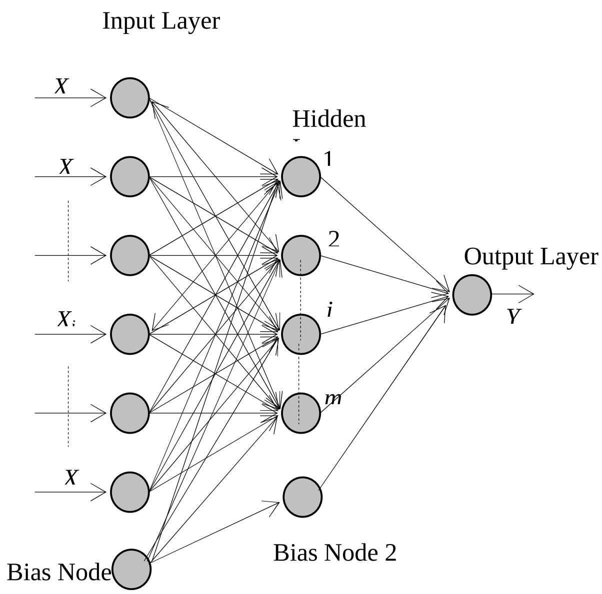

Figure 1. A typical NN model

A typical NN consists of a group of processing elements (PEs). All PEs are connected to the other PEs in the next layer and operate in parallel. An activation function defines the output of a PE in terms of the activity level at its input. The activation function can be linear or non-linear. The most common form of activation function used in the construction of NN is the hyperbolic tangent function that generates output values between -1 and 1 as given below (Neuro Solutions 2003). In this study, a NN model with 8 input nodes was constructed to evaluate the liquefaction induced lateral spreading. The NN model was developed in three phases: the modeling, the training, and the testing phases.

3.1. Modeling the Neural Network

The six design parameters for the input layer were selected to assess the lateral spreading (Table 1). These parameters are ML (X1), σ_0 (X2), σ_0' (X3), N (SPT) (X4), a/g (X5), τ_{ave}/σ_0 (X6), F (X7) and D_{50} (X8). ML is local earthquake magnitude, σ_0 is total vertical stress, σ_0' effective vertical stress, N is SPT value, a/g is peak ground acceleration at ground surface, τ_{ave}/σ_0 equivalent dynamic shear stress, F is fines content of soil, D50 is mean grain size of soil. Output parameter in the NN model is the lateral spreading which is designated as No/Yes based on field observations (Table 1). The ranges of date for the input parameters are given in Table 1.

Table 1. Input parameters

Input Parameters	Definition	Range
X_1	ML	5.50-8.30
X_2	σ_0 (kPa)	11.80-686.70
X_3	σ_0' (kPa)	17.66-160.08
X_4	N (SPT)	1.00-41.00
X_5	a/g	0.10-0.60
X_6	τ_{ave}/σ_0	0.08–0.45
X_7	F (%)	0.00-47.00
X_8	D_{50} (mm)	0.00-3.20
Y_1	Lateral spreading	0.00-1.00 (No/Yes)

A total of 175 cases were used for the NN model. The data for these cases consist of 19 earthquake ground motions. The cases in the NN model were divided into two sets. The first set was used for the training of the NN model (140 cases) and the second set was used for testing the performance of the trained network. For testing purposes, %20 of the data (35 cases) was selected.

3.2. The Training Phase

In this study, back-propagation algorithm for the training of the NN model was employed (Neuro solutions, 2003). The NN model was created using 8 input and 1 output parameters and one hidden layer. Hyperbolic tangent function was used as the activation function. An adequate epoch number for the NN model were found to be 30,000 for the final training process after more than 100 runs.

3.3. The Testing Phase and Sensitivity Analysis

Testing of the NN model shows the performance of the network. The testing phase is performed with the best weights obtained during the training phase and the weighting factors were kept constant in this phase. The trained weighting factors of the NN model were validated with testing data to test the accuracy of the predictions of the trained NN model. The performance of the NN model in this study was measured by using the percentage error formula as follows:

$$PE = \frac{x(i)-X(i)}{X(i)} x100(\%) \quad (1)$$

In Eqn.1, *x(i)* is the NN model output related to the sample i (i=1, 2, ..., n) and *X(i)* is the target output. The overall performance of the NN model can be evaluated by using the weighted error (*WE*) as follows (Hegazy ve Ayed, 1998):

$$WE\ (\%) = 0.5\ (\text{Average } PE \text{ for Training Set}) + 0.5\ (\text{Average } PE \text{ for Testing Set}) \quad (2)$$

the average *PE* for the testing phase in the NN model was calculated to be 6.26%; whereas the average *PE* for the training phase was 4.13%. Thus, the *WE* was found to be 5.20%.

Sensitivity analysis provides significant information about the effect that each input parameter has on the NN output. Insignificant input parameters can be removed from the NN model reducing the size of the NN model after the sensitivity analysis. During the sensitivity analysis, the input parameters are shifted slightly and the corresponding change in the NN model output is recorded as a percentage summing to 100% in total (Neuro solutions, 2003). In this study, X4 (N(SPT)) was found to be the most effective parameter (25.14%) on the NN model; whereas X5 (a/g) was observed to be the least effective parameter (2.19%) (Figure 2). The effects of X1 (ML), X2 (σ_0), X3 (σ_0'), X6 (τ_{ort}/σ_0), X7 (F) and X8 (D_{50}) was recorded as 10.33%, 18.20%, 13.01%, 16.47%, 6.27% and 8.39%, respectively (Figure 2).

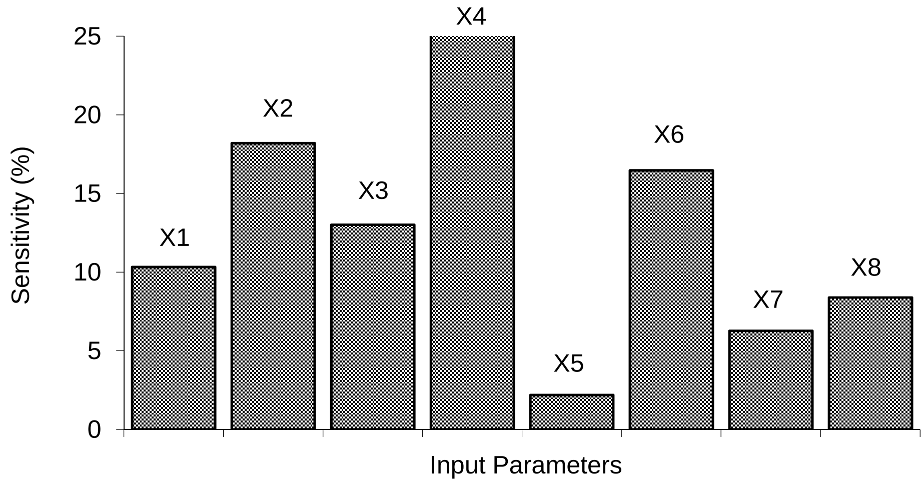

Figure 2. Sensitivity analysis results

4. RESULTS

In this study, a NN model with 8 input parameters was constructed to evaluate the liquefaction-induced lateral spreading. For this purpose, data from past earthquake ground motions were collected. Results indicated that N(SPT) was the most effective parameter and the a/g was the least effective parameter on lateral spreading. This study has shown that NN models can effectively be used in evaluating lateral spreading. The data of 140 cases were used to train the NN model; whereas the testing of the model was carried out on the data of 35 cases. The accuracy of the model was 94.80%. The accuracy of the model might be increased by using more input parameters, i.e. the more parameters there are, the higher accuracy is.

Neural networks have been used successfully to model complex relationship between the seismic and soil parameters, and the liquefaction-induced lateral spreading potential. As further field case records become accessible, these data can be readily included in the NN training and testing data to progress the modeling of liquefaction potential and liquefaction-induced lateral spreading and then the proposed NN model can be improved in generalization and applicability.

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