Soil Dynamics and Earthquake Engineering 25 (2005) 1–9

SOIL DYNAMICS AND EARTHQUAKE ENGINEERING

www.elsevier.com/locate/soildyn

Evaluation of lateral spreading using artificial neural networks

M.H. Baziar*, A. Ghorbani

College of Civil Engineering, Iran University of Science and Technology, Narmak 16844, Tehran, Iran

Accepted 3 September 2004

Abstract

Liquefaction-induced lateral spreading has been a very damaging type of ground failure during past strong earthquakes. Although the occurrence of liquefaction and lateral spreading at a given site can be predicted, the methods to estimate the magnitude of resulting deformations is still the focus of many researches. In this study, using professional software called STATISTICA, a neural network model is developed to predict the horizontal ground displacement in both ground slope and free face conditions due to liquefaction-induced lateral spreading. The database, implemented in this work, is the one compiled by Youd and his colleagues in their revised MLR model. The influence of seismological, topographical and geotechnical parameters on resulting deformations and their degrees of importance are investigated. The results indicate that the model presented in this research serves as a reliable tool to predict horizontal ground displacement. The correlation factors and the root mean square errors obtained in this model show the superiority of the Neural Network approach over the traditional regression analysis.

Keywords: Lateral spreading; Neural network; Database; Regression equation

1. Introduction

Lateral spreading, a phenomenon observed after occurrence of liquefaction, has caused extensive damage during many earthquakes including San Francisco 1906, Niigata, 1964, San Fernando, 1971, Nihonkai-Cihubu 1983, and Superstition Hills, 1987. For example during the 1964 Alaska earthquake, many bridges were damaged due to lateral spreading of their abutments.

The mechanism of liquefaction has been well recognized, but the problem of predicting the value of liquefaction-induced horizontal displacement is a very complex problem and it is not entirely understood yet. The uncertainly associated with the factors affecting the magnitude of horizontal displacement has attributed to this complexity. These factors can be categorized as earthquake, topographical, and soil factors.

Several methods have been developed to predict lateral ground displacements using analytical [1], laboratory [2,3], and finite element methods [4]. However, due to their limitations, none of these methods has been able to predict lateral displacements caused by liquefaction with a good degree of accuracy.

For this reason, many researchers have developed empirical methods based on ground displacement records [5–9]. Bartlet and Youd [8], using multiple linear regression analyses (MLR), and the database gathered from eight major earthquakes between 1906 and 1987 in the Japan and US, developed three regression equations for free-face, ground slope, and combination of these two models. After discovering errors in their data base, they proposed revised multilinear regression equations in 2002 [9].

In recent years, artificial neural networks (ANN) have been applied to many geotechnical engineering problems with some success. The ANN applications in the geotechnical engineering include of modeling pile capacity [10,11], settlement of foundation [12], soil properties and behavior [13,14], site characterization [15], slope stability [16], tunnels and underground openings [17], and liquefaction [18,19].

In this research, based on the corrected data reported in 2002, a new model, using Artificial Neural Network (ANN) algorithm, is developed to predict lateral spreading.

* Corresponding author.. Tel./fax: +21 7491031.
E-mail addresses: baziar@iust.ac.ir (M.H. Baziar), al-ghorbani@yahoo.com (A. Ghorbani).

0267-7261/$ - see front matter © 2004 Elsevier Ltd. All rights reserved.
doi:10.1016/j.soildyn.2004.09.001

2. Data set

The most important requirement for using the ANN method is an adequate data set. For any set of data, three main characteristics are required: (1) reliability which includes being real and accurate, (2) having sufficient data in relation to the dimensions and complexity of the problem and (3) covering all aspects of the problem.

Bartlett and Youd [8] compiled 467 cases from eight major earthquakes in United States and Japan in developing their multilinear regression model (MLR) of lateral spreading. Among these data, 19 data sets reported by Ambrasys [6] were without topographical, geological and soil parameters. Later in 1999, Wang and Rahman [20] used the other 448 cases to propose a ANN model for prediction of lateral spreading. They compiled this data set to two different types of free face and gentle ground slopes where their difference is related to topographical condition.

In 2002, Youd and his colleagues [9] made three important corrections to 1992 data set.

1. *Corrections of displacement*: in the 1992 data set, the displacement of the 1983 Nihonkai-chubu, Japan earthquake, including 72 cases (15% of data set) were 1.9 times larger than the measured values reported by Hamada et al. (1986). These errors were corrected in new 2002 data base.
2. *Deletion some cases*: Bartlett and Youd [8] deleted data from eight sites from their 1992 data set where boundary effects significantly impeded free lateral movement of the mobilized ground.
3. *Addition of new sites*: twenty-four case histories, including three cases from 1983 Borah peak, Idaho, two cases from 1989 Loma prieta, Calif, and 19 cases from 1995 Hyogo-ken Nanbu, Kobe, were added to the 1992 data set.

The 2002 data set, in total, consists of 483 cases from 11 sites including two cases from 1906 San Francisco, seven cases from 1964 Alaska, 299 cases from 1964 Niigata, 23 cases from 1971 San Fernando, 31 cases from 1979 Imperial Valley, 72 cases from 1983 Nihonkai-Chubu, six cases from 1987 Superstition earthquake selected from data set 1992, 19 cases reported by Ambrasys [6], and the 24 new cases previously noted.

3. Revised empirical models of 2002

Youd and his colleagues adjusted their 1992 multilinear regression model based on 2002 data set with two changes as follows

1. The logarithm of the mean grain size is used rather than the arithmetic value.
2. Distance from the earthquake is specified by log (R^*) instead of log (R) with $R^* = R_0 + R$ where R_0, a distance constant that is a function of earthquake magnitude, ($R_0 = 10^{(0.89M-5.64)}$).

The above adjustments imply that the prediction of displacement is very sensitive to two mentioned factors (R and $D50_{15}$) and they have high relative importance [9].

The correlation coefficient, R^2, for the revised model and for the combination of free face and ground slope was reported to be 83.6%, not very different from the 82.6% reported for the 1992 model.

4. Artificial neural-network models

For complex problems where the relationship between the variables is unknown, the artificial neural network is a powerful predictive tool. Complex phenomena such as liquefaction have been predicted more accurately by ANN than by the conventional methods [19].

In the general form of a neural network, the unit analogous to the biological neuron is referred to as processing element (PE). The network consists of many of these element usually organized into a sequence of layers or slabs with full or partial connections between successive layers specifically designated. Fig. 1 shows simple two-layer network architecture. The neural network has an input buffer (not considered as a layer) to which data is presented to the network, and an output layer, which holds the response of the network to a given input. Layers distinguished from the input buffer and the output layer are called hidden layers. As shown in Fig. 1, a processing element (artificial neuron), usually excluding those in the input buffer, performs summation ($\sum$) and transfer function (F) to determine the value of its output. The S-shaped sigmoid function is commonly used as the transfer function. Neural networks, typically are of two types: (1) 'feed-forward' or nonrecurrent, where the network PE connections and thus the information flow are in one direction as shown in Fig. 1; (2) 'recurrent' which exhibits a more general network structure, allows feedback connections, through weights, extending from one layer to another or to itself. The type of network used in this research is feed-forward network.

There are two main phases in the operation of a neural network: learning and recall. Learning is the process of adapting the connection weights in response to a number of examples (stimuli) being presented at the input buffer and, optionally, at the output buffer. The task is to arrive at a unique set of weights that are capable of correctly associating all example pattern(s), used in learning, with their desired output pattern(s). Usually, a training algorithm is used and held responsible for specifying how weights adapt in response to a learning example.