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Sensitivity analysis on a multilayer perceptron model for recognizing liquefaction cases

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ABSTRACT

In this paper, a new approach is presented for quantifying the system sensitivity of key parameters influencing the recognition of field liquefaction cases in a multilayer perceptron neural network (*MLP* model). A novel index, the average sensitivity factor, SF_i, derived from the mathematical formulation of neural network is proposed to quantify the result of the sensitivity analysis. The SF_i is a robust index of sensitivity analysis for the *MLP* model and can be used in the other problems not just in the recognition of field liquefaction problem. A well-trained *MLP* model is first developed to discriminate between the cases of liquefaction and non-liquefaction. Excellent performance and good generalization is achieved, with the higher recognition rate 98.9% in the training phase, 91.2% in testing phase and 96.6% on the overall cases. Using this model, the SF_i values are then calculated and reveal that peak ground acceleration (*PGA*) is the most sensitive factor in both the liquefaction and non-liquefaction cases. Earthquake parameters (M_w and *PGA*), the stress state parameters of the soil layer (r_d, σ_V and σ'_V), and the soil resistance parameters (*SPT-N*, C_N, C_E and *FC*) play approximately equal roles. The seismic demand factors (M_w, *PGA*, r_d, σ_V, and σ'_V) is more sensitive than the liquefaction resistance capacity factors (*SPT-N*, C_N, C_E, and *FC*) in the two-class liquefaction recognition problem.

1. Introduction

Soil liquefaction is known to be one of the most severe seismic hazards, causing damage to structures founded on both shallow and deep foundations, harbor structures, and disrupting buried infrastructure such as communication lines [1–3]. In engineering practice, it is essential to identify those sites vulnerable to liquefaction-induced damage and to then mitigate possible damage by taking appropriate measures in advance of a seismic event. Seed and Idriss's [4] "simplified procedure" methodology has evolved as standard practice in evaluating liquefaction potential. Various simplified methods (the *SPT*-based, *CPT*-based, and V_s-based methods) have been proposed and have become standard practice throughout the world because of the difficulty and cost involved in obtaining high-quality undisturbed samples of saturated sandy soils to be tested in the laboratory [5,6]. These three simplified methods generally involve the presentation of data in a chart that defines the boundary between liquefaction and non-liquefaction in an empirical plot of cyclic resistance ratio (*CRR*) versus corrected *SPT-N* values, the normalized *CPT* tip resistance, and the normalized V_s, respectively. Liquefaction cases arising from the Taiwan Chi-Chi Earthquake have recently become available for calibrating and modifying the boundary between liquefaction and non-liquefaction cases in these empirical plots [1]. Cetin et al. [7] also presented improved correlations for assessment of the likelihood of initiation of soil liquefaction. These new correlations can eliminate several sources of bias intrinsic to previous similar correlations and provide greatly reduced overall uncertainty and variance.

In recent years, a useful and powerful computation tool, Artificial Neural Networks (*ANNs*), has been introduced for solving the problem of recognizing liquefaction cases (two-class pattern recognition). Many researchers have reported similar or superior accuracy to that of simplified methods using *ANNs* in discriminating between liquefaction and non-liquefaction cases. Goh [8–10] and Juang and Chen [11] adopted different types of neural networks and various combinations of input variables in assessing liquefaction potential from actual field records (both *CPT*-q_c and *SPT-N* datasets), concluding that neural networks are simpler than and as reliable as conventional simplified methods. Baziar and Nilipour [12] used *CPT* dataset to analyze the occurrence of liquefaction using a multilayer perceptron network and the back-propagation algorithm. Again, the authors concluded that the neural network provided a more accurate prediction of liquefaction than the conventional *CPT*-based method. Lee and Hsiung [13] adopted both a probabilistic neural network (*PNN*) and multilayer perceptron model (*MLP* model) to identify liquefaction and non-liquefaction cases; both approaches provided nearly perfect performance in terms of

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classifying liquefaction potential. The *MLP* model achieved a slightly higher rate of recognition; however, longer searching time was required to overcome the local minima problem that potentially interrupts the process that corrects for the back-propagation error in obtaining the optimal result. A cyclic resistance ratio limit state curve established from the successfully trained and tested neural network was proposed by Juang et al. [14] and it can accurately predict the occurrence of liquefaction and non-liquefaction cases.

The shortcoming of the *ANN* approach is the difficulty involved in interpreting the knowledge gained by "black-box" type models. The evaluation of liquefaction potential is a complicated multivariable problem with non-linear input and output relationships. It is necessary to examine not only the predictive power of liquefaction potential but also the key parameters that control liquefaction occurrence, and to evaluate the relative importance of the parameters. In the liquefaction problem, both the simplified procedures and the existing *ANN* models are unable to provide information regarding the degree to which the model output (liquefaction or non-liquefaction occurrence) is sensitive to changes in the key parameters.

Sensitivity analysis of a neural network is an important tool in solving engineering problems, especially when non-linearity is involved. It is possible to infer the behavior of the system faces in response to variations in parameters without the need to solve complex non-linear relations. Sensitivity analysis is therefore required to identify those input variables that are important in terms of contributing to predicting the output variable and in quantifying how changes in the values of the input parameters alter the value of the outcome variable. Baziar and Nilipour [12] and Goh [8,9] considered the relative importance of effective parameters in liquefaction assessments using the concept proposed by Garson [15], however, this index cannot give clear physical meanings on justifying the contribution of each input variable.

In the present study, a total of 644 *SPT*-based cases of liquefaction and non-liquefaction were compiled and used to train and test a *MLP* model with nine input parameters. The final optimal architecture of the *MLP* model, with the optimal interconnection weights and threshold values, was attained via repeated trial-and-error. A novel index, the average sensitivity factor, was first derived to calculate the degree of variation in the output subject in response to a small change in the input in the architecture of the *MLP* model. The average sensitivity factor for the well-trained *MLP* model with the best performance was then calculated to quantify the relative importance of each input parameter used in the liquefaction identification of the 644 *SPT-N* based field cases. Moreover, the effect of uncertainty and noise in the case dataset and the robustness of the average sensitivity factor (SF_i) were also discussed.

2. Neural network

2.1. Multilayer perceptron model

Artificial Neural Networks are highly simplified models of biological structures that mimic the behavior of the human brain. The layered structure is composed of a large number of interconnected processing elements designed to mimic biological neurons. One of the most popular types of *ANN* is the *MLP* model with the back-propagation algorithm. Fig. 1 shows the typical architecture of an *MLP* model consisting of three layers of interconnected neurons (input layer, hidden layer, and output layer). This architecture is represented as $m \times n \times p$. Here, m is the number of neurons in the input layer, n is the number of neurons in the hidden layer, and p is the number of neurons in the output layer. Each neuron in each layer is fully connected to all neurons in the higher layer, and each connection has a weight (a scalar) associated with it.

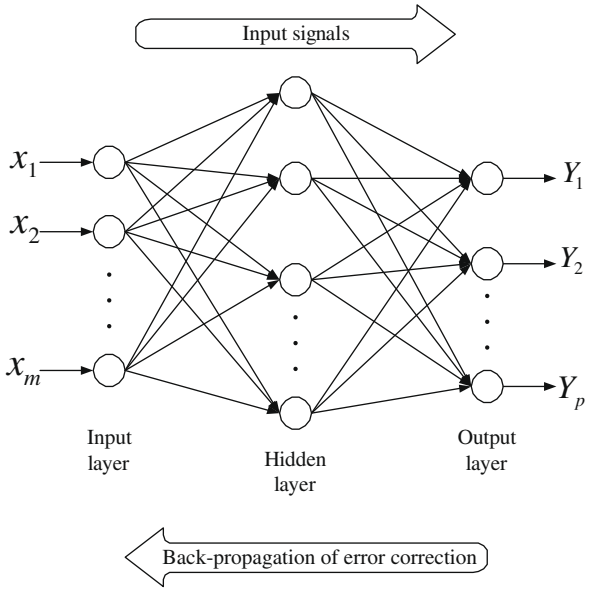

Fig. 1. Typical architecture of an *MLP* network.

These weights determine the nature and strength of the influence between the interconnected neurons. The output signals from one layer are transmitted to the subsequent layer through links that amplify or attenuate (inhibit) the signals based on the associated interconnection weights. Except for the neurons in the input layer, the net input to each neuron is the sum of the weighted outputs of the neurons in the previous layer. An activation function such as the sigmoid logistic function is used to calculate the output of the neutrons in the hidden and output layers. The neurons in the hidden layer perform a non-linear transformation that enables the *MLP* model to simulate a more complex and non-linear system within the constraints of a three-layer *MLP* model. It is possible to use more than one hidden layer; however, one layer is sufficient in simulating a non-linear problem.

The *MLP* model has a generalized curve-fitting capability by employing an incremental adaptation approach. Training of the *MLP* model was carried out via a set of input patterns and associated output patterns (input–output pairs) randomly selected from the collected cases in specified proportions. The back-propagation algorithm is used as a learning mechanism to correct the connection weights iteratively and to minimize the system error produced by each forward processing of the input signal. In the first stage of the learning process, the input pattern generates a forward flow of signals from the input layer to the output layer. The error for each output neutron was then computed from the difference between the computed and desired outputs. The system error in the nth training pattern, $E(n)$, is defined as

$$E(n) = \frac{1}{2}\sum_{j=1}^{p}(d_j(n) - y_j(n))^2, \tag{1}$$

where $d_j(n)$ and $y_j(n)$ are the jth component of desired output and computed output, respectively, and p is the number of neurons in the output layer.

The second stage involves readjustment of the weights in the hidden and output layers using a "generalized delta rule" to reduce the difference between the computed and desired outputs. The incremental correction of each interconnection weight can be computed by

$$\Delta w_{ji}(n) = -\eta\frac{\partial E(n)}{\partial w_{ji}} + \alpha\Delta w_{ji}(n-1), \tag{2}$$