Artificial Neural Network Methodology for Soil Liquefaction Evaluation Using CPT Values

Ben-yu Liu, Liao-yuan Ye, Mei-ling Xiao, and Sheng Miao

Institute of Public Safety and Disaster Prevention, Yunnan University,
650091 Kunming, China
{liubenyu, lyye, mlxiao, msheng}@ynu.edu.cn
http://www.srees.ynu.edu.cn/structure/index.html

Abstract. With the 413 soil liquefaction records with cone penetration testing values collected after strong earthquakes, the Bayesian Regularization Back Propagation Neural Networks (BRBPNN) method was presented to evaluate the soil liquefaction potential in this paper. Cone resistance (q_c), equivalent dynamic shear stress (τ/σ_0'), mean grain size (D_{50}), total stress (σ_0), the effective stress (σ_0'), earthquake magnitude (M) and the normalized acceleration horizontal at ground surface (a/g) are used as input parameters for networks. Four networks are constructed for different source of input data. The model M7 seems more efficient for the given data, since it only contain 109 records. The model M5 contains 413 samples, and the correct ratio for training data and testing data are 88.5% and 90% respectively. By compared with the square of the weight of the input layer for each network, the importance order of the input parameters should be q_c , M , σ_0' , σ_0 , a/g , τ/σ_0' and D_{50} .

1 Introduction

The devastating damage of liquefaction induced ground failures in the Alaska 1964 and Niigata 1964 earthquakes serve as a clear reminder of such events. The liquefaction potential evaluation of a given site under certain seismic forces is a big problem facing engineers. The soil liquefaction prediction methods can be divided into two categories. One is the method developed based on the liquefaction mechanism simulation, such as nonlinear effective stress method, equivalent linear method and elastic-plastic method, etc. The other procedure is constructed based on the liquefaction records collected strong earthquakes, the parameters like the Standard Penetration Test (SPT), the Cone Penetration Test (CPT) and the shear wave velocity of the site are used to predict the liquefaction potential of site [1, 2]. About 40 formulae were constructed to predict the soil liquefaction potential, although most of them were not efficient to use [1]. In the laboratory tests, reliability of the results depends on simulation of idealized filed conditions. Unfortunately, in situ stress states generally cannot be reestablished in the laboratory, and specimens of granular soils retrieved with typical drilling and sampling techniques are too disturbed to yield meaningful results. To avoid the difficulties associated with sampling and laboratory testing, field tests have become the state-of-practice for routine liquefaction investigations. Several field tests

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have gained common usage for evaluation of liquefaction resistance, including the standard penetration test (SPT), the cone penetration test (CPT), shear-wave velocity measurements (*Vs*), and the Becker penetration test (BPT).Since the neural network is a nonlinear method which can fit the nonlinear data with great efficiency, the artificial neural networks are employed to predict the soil liquefaction potential in recent years [3-11].

2 Neural Network Prediction for Soil Liquefaction Potential

The main characteristics of neural networks are their ability to learn nonlinear functional relationships from examples and to discover patterns or regularities in data through self-organization. The neural network learning process primarily involves the iterative modification of the connection weights until the error between the predicted and expected output values is minimized. It is through the presentation of examples, or training cases, and application of the learning rule that the neural network obtains the relationship embedded in the data.

2.1 Back Propagation Neural Networks Design

It is nature that the neural network designed for this problem should be accordance with the sample data. Thus, the input vector of the network contains 7 components. While for the output vector, it includes only one component.

2.2 Theory on the Bayesian Regularization Back Propagation Neural Networks

We divided the datasets into two parts: training and testing. In using multiply layer propagation network, the problem of over-fitting on noise data is of major concern in network design strategy. The initial results of using a standard BP algorithm showed poor generalization performance and slow speed of training. To overcome these shortcomings, we incorporated Bayesian learning to this work. In the Bayesian framework, a weight decay term is introduced to the cost function (or performance index) given by

$$F(w) = \alpha E_W + \beta E_D \,. \tag{1}$$

where E_W is the sum square of the networks weights, E_D is the sum square of the error between network outputs and targets, α and β are hyper-parameters for the target function. The relative value of α and β determined the emphasis on the network training on minimization of the output errors or the volume of the network. As shown in Equation (1), the main problem with implementing regularization is to set/learn the correct values for the parameters in the cost function. Ref. [12, 13] has presented extensive works on the application of Bayesian rule to neural network training and to optimizing regularization.

In the Bayesian framework, the weights of the network are considered the random variables. The weights in the network are adjusted to the most probable weight parameter, w_{MP}, given the data $D\{(x^m, t^m)\}$, network configuration (M_i), and hyper-parameters, i.e., α and β .

Set the α and β as stochastic variables, the Bayesian rule is used for evaluating the posterior probability of α and β. This is given by

$$P(\alpha,\beta \mid D,M_i) = \left(P(D \mid \alpha,\beta,M_i)P(\alpha,\beta \mid M_i)\right)/P(D \mid M_i). \tag{2}$$

where $P(\alpha,\beta \mid M_i)$ represents the prior probability of the hyper-parameters and are generally chosen to be uniformly distributed. Since $P(D \mid M_i)$ is independent of α and β, maximum posterior values for hyper-parameters can be found by maximizing the likelihood term $P(D \mid \alpha,\beta,M_i)$.

Using Bayesian rule, the posterior probability of the weight parameters is:

$$P(w \mid D,\alpha,\beta,M_i) = \frac{\left(P(D \mid w,\beta,M_i)P(w \mid a,M_i)\right)}{P(D \mid \alpha,\beta,M_i)}. \tag{3}$$

Assume the error and the weight is distributed in Gaussian form,

$$P(D \mid w,\beta,M_i) = \exp(-\beta E_D)/Z_D(\beta). \tag{4}$$

$$P(w \mid \alpha,M_i) = \exp(-\alpha E_W)/Z_W(\alpha). \tag{5}$$

If the $P(D \mid \alpha,\beta,M_i)$ in Equation (3) is regularized factor, $P(w \mid D,\alpha,\beta,M_i)$ must equal to $\exp(-F(w))/Z_F(\alpha,\beta)$. Take them into Equation (2),

$$P(D \mid \alpha,\beta,M_i) = Z_F(\alpha,\beta)/(Z_W(\alpha)Z_D(\beta)). \tag{6}$$

where

$$Z_W(\alpha) = (2\pi/\alpha)^{N/2}. \tag{7}$$

$$Z_D(\beta) = (2\pi/\beta)^{N/2}. \tag{8}$$

$$Z_F(\alpha,\beta) \approx \exp(-F(w_{MP}))(2\pi)^{N/2}|A|^{-1/2}. \tag{9}$$

where $A = \beta\nabla^2 E_D + \alpha\nabla^2 E_W$ is the Hessian matrix of the target function F. Further, the log the Equation (6), then differentiating it with respect to α and β, and setting it to zero, the optimal values of α and β can be obtained by

$$\alpha_{MP} = \gamma/(2E_W(w_{MP})). \tag{10}$$

$$\beta_{MP} = (n-\gamma)/(2E_D(w_{MP})). \tag{11}$$

$$\gamma = N - \alpha_{MP}\mathrm{trace}^{-1}(A_{MP}). \tag{12}$$

where n is the number of sample, N is the number of parameter in the network, γ is the number of effective parameters which may reduce the error function for the network in training process.

2.3 Training and Testing for BRBPNN Model

For the soil liquefaction evaluation problem, the influence parameters may be divided into three categories. The parameters can be earthquake intensity, the epicenter distance, peak ground acceleration for describing the earthquake ground motion characteristics, and the depth of underground water, the depth of standard penetration test point (soil layer), the thickness of the covered non-liquefied soil layer, effectively overlaying pressure describing the embedding environment of soil layers, and standard penetration blow-count, mean diameter, non-uniformity coefficient, modified standard penetration blow-counts for denoting the sandy soil feature [2]. As in the case of CPT data, cone resistance (q_c), equivalent dynamic shear stress (τ/σ_0'), mean grain size (D_{50}); total stress (σ_0); the effective stress (σ_0'); earthquake magnitude (M) and the normalized acceleration horizontal at ground surface (a/g) was used, and 109 samples were collected [15]. While in [4], only q_c, σ_0, σ_0', M and a/g are used, the D_{50} is missed; and 134 samples were recorded. In [5], only q_c, σ_0, σ_0', M and a/g are used, the D_{50} and τ/σ_0' is missed; and 170 samples were recorded. Part of data is listed in Table 1.

As for data listed in [4], the equivalent dynamic shear stress τ/σ_0' can be calculated by an expression suggested by Tokimatsu and Yoshini [16]. As per the proposed relation, the value of equivalent dynamic shear stress at a depth z will be

$$\frac{\tau}{\sigma_0'} = 0.1\frac{a}{g}(M-1)\frac{\sigma_0}{\sigma_0'}(1-0.015z). \tag{13}$$

Table 1. Parts of training and testing records samples

M	σ_0 (kPa)	σ_0' (kPa)	q_c (MPa)	a/g	τ/σ_0'	D_{50} (mm)	Remark
7.5	53	36	3.2	0.16	0.15	0.33	liquefaction
7.5	99	58	7.2	0.16	0.17	0.33	liquefaction
7.5	152	83	5.6	0.16	0.17	0.33	liquefaction
7.5	86	46	8	0.16	0.19	0.3	no
7.5	95	50	14.55	0.16	0.18	0.3	no
7.7	58	48	10	0.23	0.18	0.32	no
7.7	73	54	16	0.23	0.2	0.32	no
7.7	54	46	1.79	0.23	0.17	0.32	liquefaction
7.7	64	52	4.1	0.23	0.19	0.32	liquefaction
7.8	114	69	9.4	0.4	0.41	0.25	liquefaction
7.8	148	85	5.7	0.4	0.42	0.25	liquefaction
7.7	96	65	15.38	0.23	0.21	0.32	no
7.5	87	52	1.6	0.16	0.16	0.33	liquefaction

Four BRBPNN models are constructed for the problem. The M7 include all the parameters metioned above and only 109 records are used. The M6a include all the parameters metioned above but D_{50} and 243 records are used. The M6b include all the parameters metioned above but τ/σ_0' and 279 records are used. The M5 include all the parameters metioned above except τ / σ_0' and D_{50}, and all the 413 records are used. Different types of networks are listed in Table 2 with its sumary of the square of the weight of the input layer, along with the correct ratio for training data and testing data. Figure 1- 4 showed the training and testing errors for the giving data for different neural network models. The errors out of 0.5 can be taken as wrong prediction.

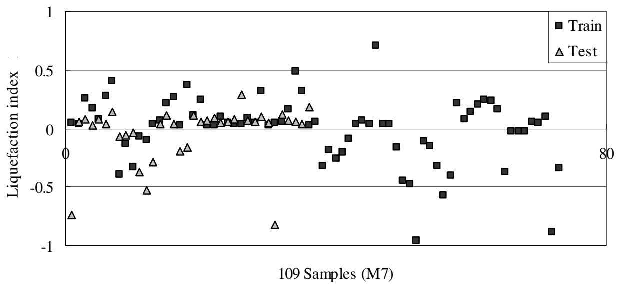

Fig. 1. The errors of original data with network simulating data (109 samples) [15]

Table 2. The summaration of the square of weight for the input layer and the correct ratio for trainging data and testing data

Model	M	σ_0 (kPa)	σ_0' (kPa)	q_c (MPa)	a/g	τ / σ_0'	D_{50} (mm)	Correct Ratio Train	Test
M7	1.12	0.15	0.44	2.25	0.01	0.02	0.09	93.2%	91.6%
M6a	6.40	0.54	0.81	8.19	0.19	0.97		96.7%	87.1%
M6b	0.33	2.44	2.42	3.32	0.11		0.12	94.4%	71.6%
M5	0.40	0.013	0.014	0.29	0.0007			88.5%	90%

From the square of the weight in the first layer, the importance order of these factors is q_c, M, σ_0', σ_0, a/g, τ / σ_0' and D_{50}.

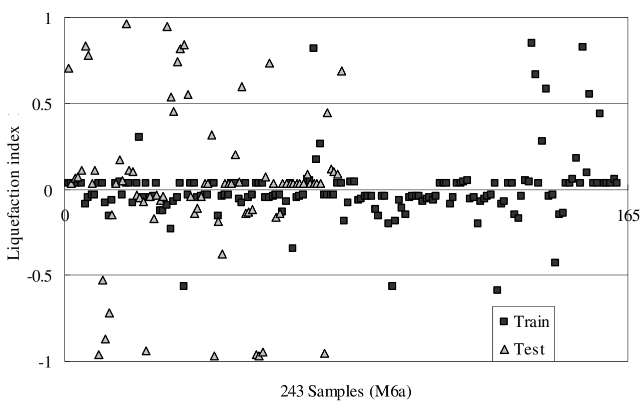

Fig. 2. The errors of original data with network simulating data (243 samples) [5, 15]

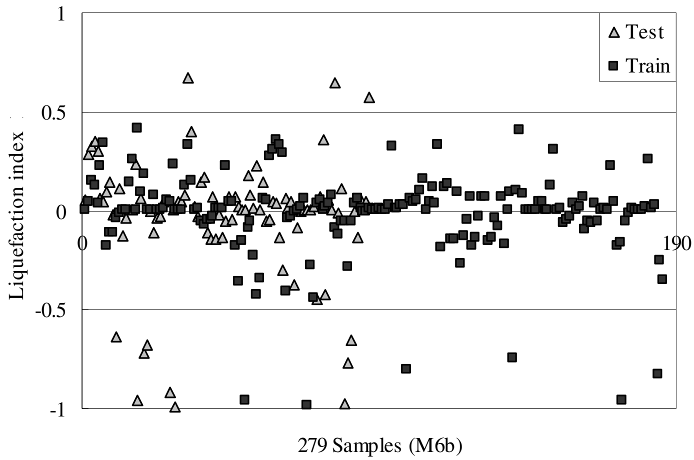

Fig. 3. The errors of original data with network simulating data (279 samples) [4, 15]

The model can predict the soil liquefaction with good satisfaction since it cover small samples in M7 (only 109 samples, correct ratio is 91.6% for testing data). When the records increase as for model M5 (413 samples included), the ratio dropped to 89%. Maybe this ratio is the average value for all records for this neural network method.

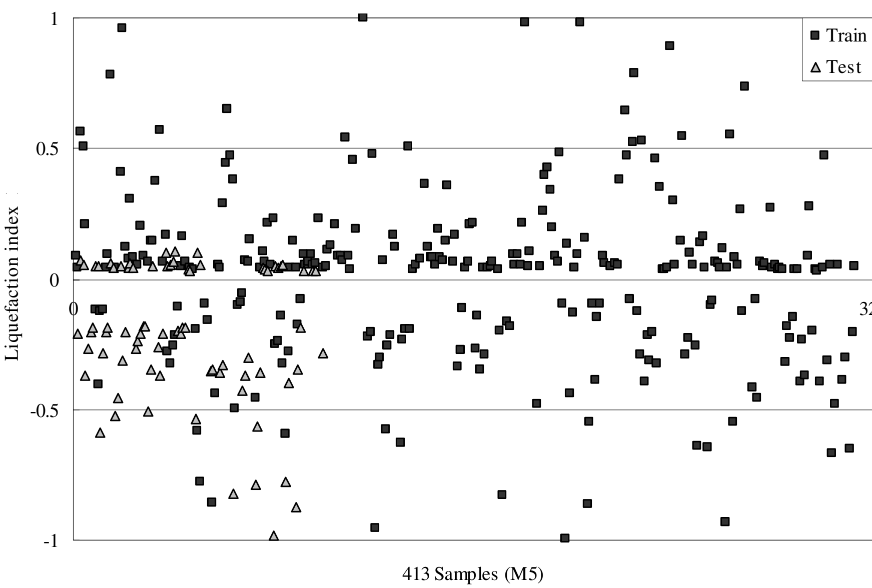

Fig. 4. The errors of original data with network simulating data (413 samples) [4, 5, 15]

3 Conclusions and Suggestions

413 soil liquefaction records with cone penetration testing values are collected in this paper. After presenting a Bayesian Regularization Back Propagation Neural Networks (BRBPNN) method to evaluate the soil liquefaction potential, the M7, M6a, M6b and M5 model are used according to the sample data. The M7 used 109 samples; the M6a used 243 samples; the M6b used 279 samples and the M5 used 413 samples. The M7 model seems more efficient for the given data since it contains the least records than other models. The M5 contains the all the records discussed in this paper, and the correct ratio for the training and testing are 88.5% and 89% respectively. After checking the square of the weight of the input layer for each network, the importance order of the input parameters should be q_c , M , σ_0' , σ_0 , a/g , τ/σ_0' and D_{50} .

The training and testing of network seems less efficient when the records increase, which demonstrated again the complex nature of the soil liquefaction problem. Of course, the neural network is quite good than the traditional regression equations, which was proved in many literature. Further research of this problem should include more parameters to describe the nature of this phenomenon, and the regression should focus on data collected in certain region.

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