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Parametric study on the Prediction of Wave-induced Liquefaction using an Artificial Neural Network Model

Hong Zhang†, Dong-Sheng Jeng‡, Deaho Cha† and Michael Blumenstein∞

† Griffith School of Engineering
Griffith University, Gold Coast Campus
Australia
hong.zhang@griffith.edu.au

‡ School of Civil Engineering
University of Sydney
Australia

∞ School of Information and Communication Technology
Griffith University
Australia.

ABSTRACT

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The prediction of the wave-induced liquefaction potential is particularly important for coastal engineers involved in the design of marine structures. An artificial neural network (ANN) model is used to estimate the wave-induced liquefaction in terms of wave and seabed sediment conditions. The sensitivity of wave and seabed sediment parameters is extensively investigated to get the most accurate results. The deterministic wave and liquefaction models are used to explain the parameter features physically. Numerical examples demonstrate the capacity of the ANN modelling approach in simulating complex mechanisms such as wave-induced liquefaction with adequate information.

ADDITIONAL INDEX WORDS: *Liquefaction; artificial neural networks; parametric study; wave-induced*

INTRODUCTION

The phenomenon of wave-induced liquefaction is an important feature in coastal engineering problems such as stability of breakwaters and sinking or uplift of pipelines. In general, ocean waves propagating over a porous seabed, the dynamic wave pressure along the seabed surface will further induce excess pore pressure and effective stress within the soil matrix. When the excess pore pressure increases to a certain level, the seabed may be liquefied, then the foundation around the coastal structure will become unstable and further cause the instability of the structure.

Numerous investigations for the wave-induced seabed response have been carried out since the 1970's. Among these, analytical approximations (Jeng, 1997), numerical modelling (Lin and Jeng, 2004), and experimental work (Summer et al., 1999; Sassa et al. 2001) have been used to investigate the wave-induced liquefaction potential. The contributions and limitation of previous studies in the area have been systematically reviewed in Jeng (2003). Recently, an integrated model incorporating wave and soil models, was developed to investigate the wave-induced pore pressure and effective stresses in a porous seabed (Zhang and Jeng, 2005, Jeng and Zhang, 2005).

Recently, Artificial Neural Networks (ANNs) have been applied to various engineering fields, such as predicting of rainfall intensity (French et al., 1992), generating of wave parameters based on hydraulic data (Yonas et al., 1999), forecasting of tidal elevation (Lee & Jeng, 2002), predicting the settlement of shallow foundations (Mohamed et al., 2002) and modelling the confinement efficiency of reinforced concrete (Tang et al., 2003). Recently, Cha et al. (2006) applied ANNs for the prediction of wave-induced liquefaction in a porous seabed. Their research demonstrated the capability of ANN models for the prediction of the maximum wave-induced liquefaction depth within various wave and soil conditions.

To date there is no parametric study on ANN liquefaction depth prediction. In the present study, the deterministic wave and liquefaction models are used to explain the parameter features physically. A further study of the sensitivity of wave and soil parameters is extensively investigated using an ANN model in order to improve the wave-induced liquefaction prediction models.

THEORETICAL BACKGROUND

Deterministic Modelling

The conventional wave-induced liquefaction equations are applied to describe the physical phenomenon, which can be solved analytically or numerically. In recent wave modelling the evolution of the wave spectrum is described by the spectral action balance equation, which for spherical coordinates is (Holthuijsen et al., 2003):

$$\frac{\partial N}{\partial t} + \frac{\partial c_\lambda N}{\partial \lambda} + (\cos\varphi)^{-1}\frac{\partial c_\varphi N}{\partial \varphi} + \frac{\partial c_\sigma N}{\partial \sigma} + \frac{\partial c_\theta N}{\partial \theta} = \frac{S}{\sigma} \qquad (1)$$

where λ is longitude;, φ is latitude; θ is the wave direction (the direction normal to the wave crest of each spectral component); σ is the relative frequency (as observed in a frame of reference moving with current velocity); $N(\sigma, \theta)$ is the action density spectrum,; c_λ, c_φ, c_θ and c_σ are propagation velocities in λ, φ, θ and σ space. The source term, S, in terms of energy density representing effects of generation, dissipation and nonlinear wave-wave interactions. The model provides estimates of the wave parameters such as wave heights and frequencies in coastal areas.

The phenomenon of ocean waves propagating over a porous seabed is an important concern in the design procedure of coastal offshore structures. When gravity waves propagate over the ocean, fluctuations of wave pressure induce variations in effective stresses and pore water pressure within the seabed. With excess pore-pressure and diminishing vertical effective stress, part of the seabed may become unstable or even liquefied. Furthermore, when liquefaction occurs, the soil particles are likely to be carried away as a heavy fluid by any prevailing bottom currents or mass transport due to the wave action. Numerous poro-elastic models for the wave-induced soil response have been developed since the 1970's. For a three-dimensional problem, and treating the porous bed as hydraulically anisotropic, with same permeability in the x-, y- and z-directions respectively, the governing equation can be expressed as

$$K\nabla^2 p - \gamma_w n_e \beta \frac{\partial p}{\partial t} = \gamma_w \frac{\partial \varepsilon}{\partial t} \tag{2}$$

where p is the wave-induced pore-pressure; γ_w is the unit weight of the pore-water; n_e is the soil porosity; and ε is the volume strain.

Artificial Neural Networks

ANNs were originally based on the biological brain, whereby the basic idea is that they model the simplest brain functions. A basic artificial neuron is shown in Figure 1.

In an ANN model (as seen in Figure 1) each layer contains several neurons and the layers are interconnected by sets of weights. The input layer neurons receive initial input information; subsequently outputs are produced by a transformation using various transfer functions.

In a learning procedure, the interconnection weights are adjusted using the relationships between input and output values, which are an important part of the ANN model. There are various types of ANN training algorithms that may be employed to adjust these weights. The back-propagation algorithm is one of the most popular for training artificial neural networks for various applications. The error function is shown in equation (3), where D_i

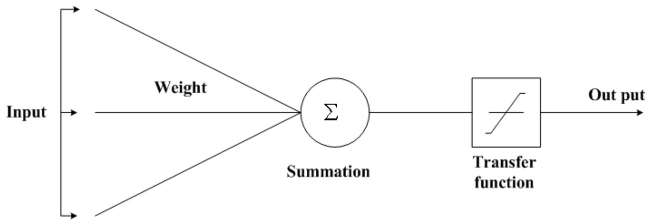


Figure 1. Basic representation of an artificial neuron.

and O_i are the desired and actual output values respectively. M is the total number of training data. Since the error is the difference between the actual output and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimise the error. We can hence adjust the weights using the method of gradient descent as described above. The details of the back-propagation training algorithm can be found in Rumelhart et al. (1986).

$$E = \frac{1}{M}\sum_{i}^{M}(D_i - O_i)^2 \tag{3}$$

WAVE-INDUCED LIQUEFACTION PARAMETERS

Reviewing the conventional wave and wave-induced liquefaction equations as in (1)-(2) helps in selecting the dominant parameters for wave-induced liquefaction depth prediction. The most pertinent variables are the water depth (D), wave parameters such as the wave height (h_s), the wave direction (θ) and the wave length (λ), and soil parameters such as the soil permeability (K), the degree of saturation (S_r) and the porosity (n_e). The final developed expression for wave-induced liquefaction depths yields

$$L_D = f(D, h_s, \theta, \lambda, K, S_r, n_e). \tag{4}$$

It is common to have gas (air) within marine sediment, especially in shallow water regions. Thus, for most marine sediments the degree of saturation varies between 0.95 and 1.0 (Pietruzczak and Pande, 1996).

TRAINING THE NETWORK AND VERIFICATION OF RESULTS

The network was set up with the seven parameters of equation (4) as input and the liquefaction depth as the output pattern. In other words, the input layer has 7 neurons whilst the output layer has one. The network is trained with 2000 training pairs. Between the two layers there are 10 hidden units. Another 1691 test data set is used for verification. Figure 2 shows the best fit verified results. The mean squared error of liquefaction depth between the estimation and the database is 0.0321 (m), which is 6.75% of the mean liquefaction depth.

PARAMETER SENSITIVITY

The wave and soil parameters governing the liquefaction process is shown in equation (4). In the following parametric study, the sensitivity of each parameter is examined by removing the parameter from the database sets. Then, an ANN model is setup for prediction for each case. The prediction results are shown in Figure 3 and the models' performance is summarised in Table 1. It can be seen that the water depth and wave height are important parameters for liquefaction prediction. Similar conclusions have been made by Maeno et al. (1989) by employing the empirical formula of Maeno and Hasegawa (1987).

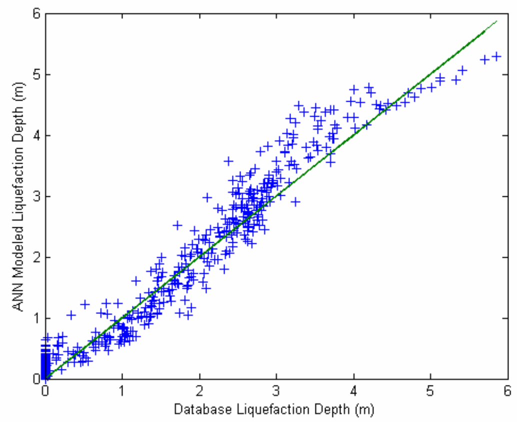
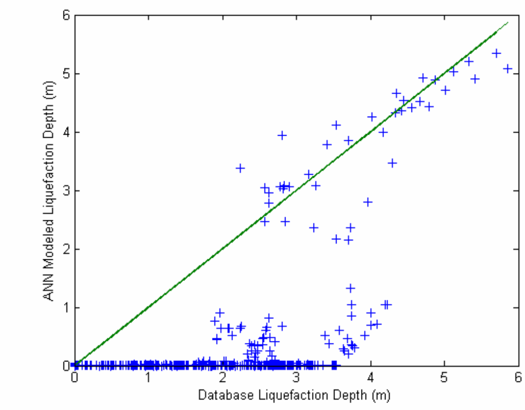
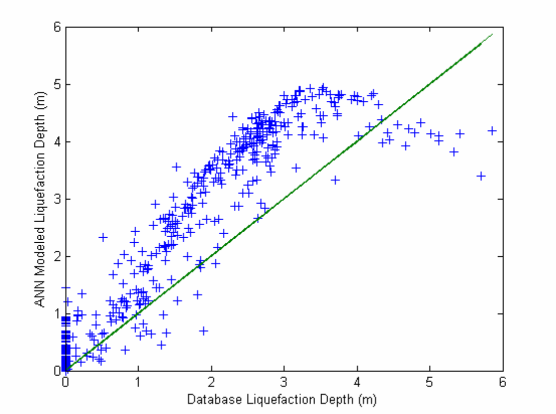


Figure 2. The liquefaction depth comparison between the ANN prediction and the database values.



(a)



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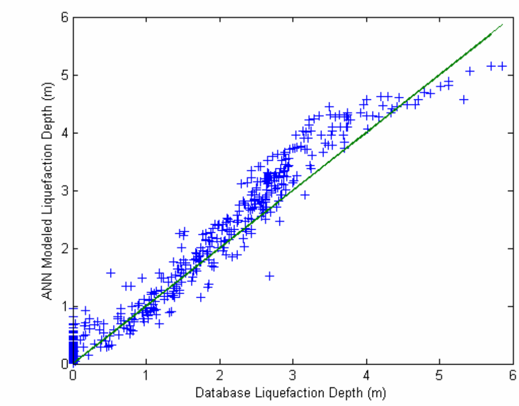

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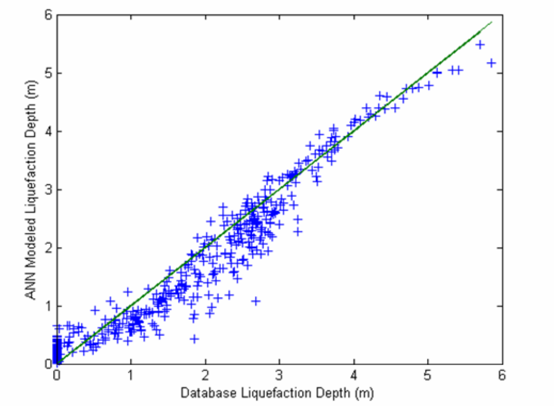

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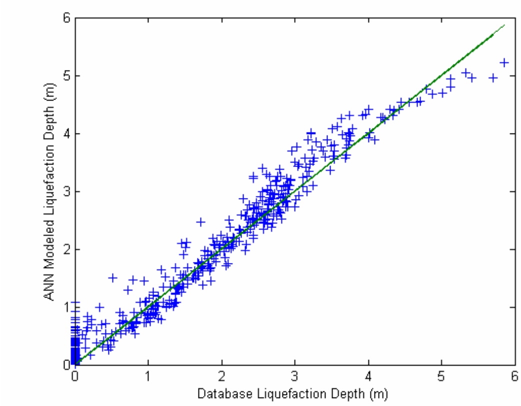

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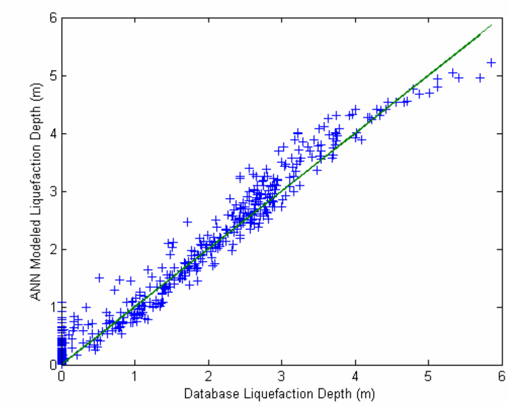

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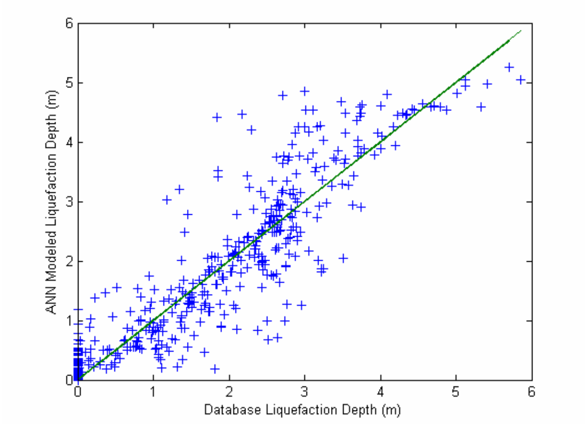


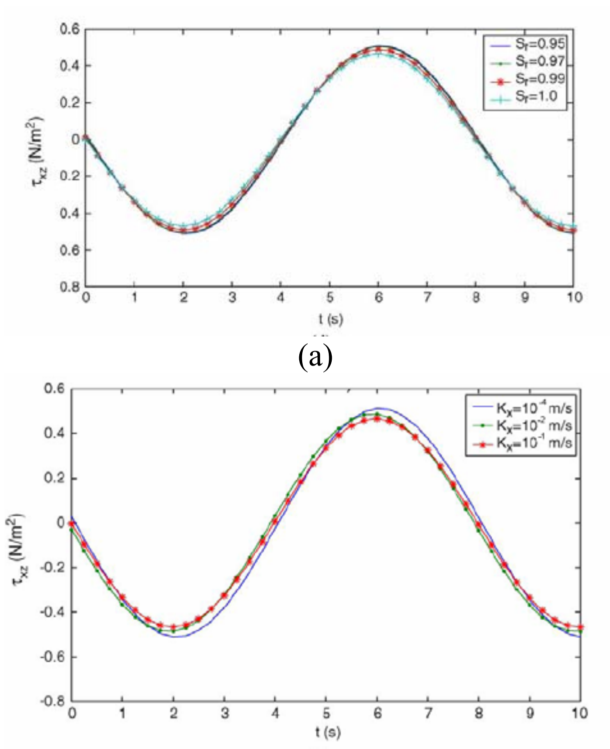
(g)

Figure 3: The liquefaction depth comparison between the ANN prediction and the database values. (a) Water depth is removed. (b) Wave height is removed. (c) Wave direction is removed. (d) Wave length is removed. (e) Soil permeability is removed. (f) Saturation degree is removed. (g) Soil porosity is removed.

Table 1: Model performance for parametric study.

Parameters (removed)	Correlation Coefficient	Mean Squared Error of Prediction (m)	% of Prediction Error
water depth	0.58	0.86	181
wave height	0.96	0.29	61
wave direction	0.99	0.04	8.4
wave length	0.98	0.037	7.8
soil permeability	0.99	0.025	5.2
degree of saturation	0.99	0.052	10.9
porosity	0.95	0.098	20.6

However, it is noted that the saturation degree and soil permeability are not sensitive for modelling. The deterministic models are used to examine the two parameters. Figure 4 shows the vertical shear stress x_z is not sensitive to both S_r and K. These agree with the ANN model's parametric study findings.



(a)

(b)

Figure 4. The influence of S_r and K to the vertical shear stress.

Therefore, the non-sensitive parameters are removed. An ANN model based on the water depth, wave height and porosity is established and the modelling result is shown in Figure 5. The mean squared error of liquefaction depth between the estimation

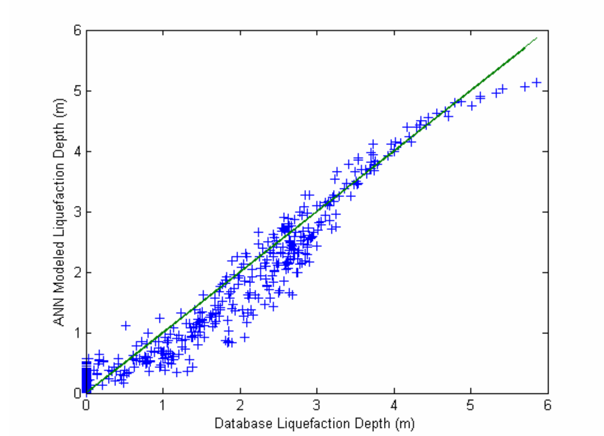


Figure 5. The liquefaction depth comparison between the ANN prediction and the database values with the non-sensitive parameters removed.

and the database is 0.036 (m), which is 7.7% of the mean liquefaction depth, which has the same prediction accuracy when the ANN model is provided with 7 input parameters.

CONCLUSIONS

In this research, an artificial neural network (ANN) model is used to estimate the wave-induced liquefaction in terms of wave and seabed sediment conditions. The sensitivity of wave and seabed sediment parameters is extensively investigated to get the most accurate results. The deterministic wave and liquefaction models are used to explain the parameter features physically. Numerical examples demonstrate the capacity of the ANN modelling approach in simulating complex mechanisms such as wave-induced liquefaction with adequate information.

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