SDS-based liquefaction prediction using artificial neural network

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ABSTRACT
During the 2010-2011 Canterbury Earthquake Sequence (CES), many residential houses and structures were damaged considerably as a result of the liquefaction of loose, saturated sands. Correlations based on in-situ tests are widely used in engineering practice to estimate the liquefaction potential of soil. Screw Driving Sounding (SDS) is a relatively new method where a machine drills a rod into the ground in several loading steps while the rod is continuously rotated. Several parameters such as torque, load and speed of penetration are recorded at every rotation of the rod. Previously, a simplified procedure has been developed by the authors to estimate the liquefaction potential of soils using case studies of liquefaction/no liquefaction during CES. In this paper, artificial neural network (ANN) method is used as a supplementary tool to evaluate the liquefaction potential of soil. ANN method is able to train itself with available data sets and extrapolate the outcome for unknown scenarios based on the training. In this study, a database containing 50 different sites in Christchurch where SDS has been performed adjacent to CPT sites was used. For the purpose of analysis, the liquefaction potential of soil along the depth at each site was evaluated using three different CPT-based methods popularly used in conventional practice. Next, the ANN model was trained and the results were compared to the previously developed simplified procedure. In the modelling, 70% of the randomly selected data points were used for the training phase while the remaining 30% was utilized for the testing phase. In the ANN model, liquefaction occurrence/ non-occurrence was correlated with the primary SDS and soil parameters as well as earthquake parameters. Assuming that the used CPT-based methods for predicting liquefaction of soil are accurate, the results of the study showed that ANN method achieved a high degree of accuracy in identifying the liquefaction potential of soil.

1 INTRODUCTION

The city of Christchurch is vulnerable to earthquake hazards, especially liquefaction due to the loosely deposited sands and silts and high water table. During the 2010-2011 Canterbury Earthquake Sequence (September 2010, February 2011, June 2011 and December 2011 among others), many residential houses and structures in Christchurch were damaged considerably as a result of liquefaction and associated ground deformation (Cubrinovski et al., 2011, Bray et al., 2014, Bray et al., 2017). Adequate knowledge of soil properties helps engineers to design proper foundations for different structures.

Correlations based on in-situ tests are widely used in engineering practice to estimate the liquefaction potential of soil. Screw Driving Sounding (SDS) is a new in-situ method that has recently been developed in Japan. In this method, a rod is drilled into the ground in several loading steps at the same time as the rod is being continuously rotated. It was found that SDS has the capability of identifying the soil type and can be used for soil characterisation (Mirjafari et al., 2016). The SDS test is fast, the machine is small in size and the implementation is relatively cheap, compared to other in-situ testing methods and these advantages make it a good alternative for soil characterisation.

Previously, a procedure for evaluating the liquefaction potential of soil using the SDS-derived data was developed (Mirjafari et al., 2016). The basis of the procedure is similar to the framework that was used to develop CPT-based methods as proposed by different researchers (Boulanger & Idriss, 2014; Robertson & Cabal, 2012; Moss et al., 2006). In this method which is based on a simplified procedure, the cyclic shear stress ratio (*CSR*) along the soil profile was calculated and compared to the energy of penetration. Three graphs corresponding to different ranges of fines content (*FC*) were generated that showed the relationship between *CSR* and average specific energy of penetration ($E_{s,1}$) from the SDS method. Using logistic regression analysis, different boundary lines corresponding to different probabilities of occurrence of liquefaction were developed that separate the liquefiable data from the unliquefiable ones.

Artificial Neural Network (ANN) has recently become a popular and powerful tool for solving complex multifactor geotechnical problems. This method using an available database can train itself and extrapolate the results to an unknown scenario using the introduced training data. Based on the researches done in predicting liquefaction potential of soil using CPT data (Goh, 1996; Juang et al. 2006), it was found that ANN can predict the occurrence of liquefaction more accurately than conventional methods. In ANN approach, there is no need to normalise or calibrate parameters as ANN can take the influence of all the parameters into consideration and determine the relationship between them. The great ability of ANN is that the network learns and, by adding more data to the initial database, the performance of the network in identifying the relationship between input and output parameters can be improved (Goh, 1994; Wang and Rahman 1999).

In this study, the primary input parameters are identified based on the equations of conventional liquefaction assessment method and important SDS parameters for soil characterisation. An ANN network model is developed that can be used for evaluating liquefaction potential of soil based on such primary input parameters.

2 THE SDS METHOD

2.1 Principle and test procedure

A monotonic loading system is used in the SDS test and the number of load steps is set to 7. The rod is continuously rotated at a constant rate of 25 rpm while it is being penetrated into the ground. The load steps are 0.25, 0.38, 0.50, 0.63, 0.75, 0.88, 1kN, in this order, and the load is increased during each revolution of the rod. The parameters measured in the test are: maximum torque (T_{max}), average torque (T_{avg}), minimum torque (T_{min}) on the rod, penetration length (L), penetration velocity (V) and number of rotations of rod (N). These data are measured on the completion of each revolution of the rod. In SDS, after each 25cm penetration the rod is automatically moved up by 1cm and then rotated to measure the rod friction. Figure 1 shows the SDS machine during operation.

Figure 1. SDS test conducted in Christchurch

As shown in Figure 2, SDS does not need large space for operation (especially without the crawler) and the SDS machine is much smaller than the smallest CPT rig.

Figure 2. SDS test on the left side and small CPT rig on the right side

The procedure in performing the SDS test is summarised in Figure 3. Further details of the SDS method are discussed by Mirjafari (2016).

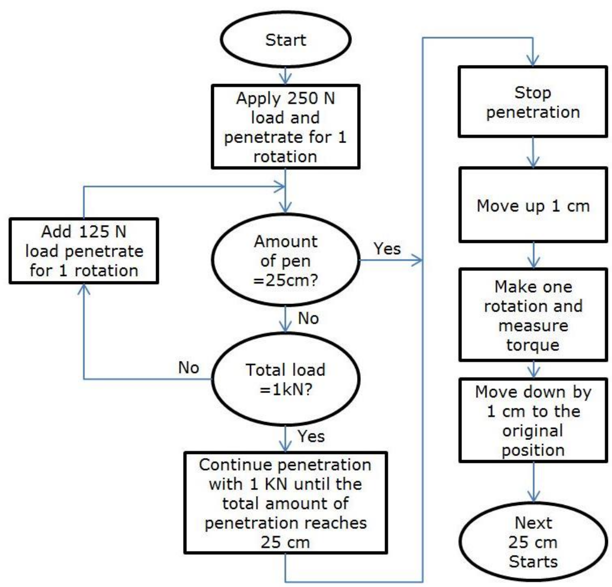

Figure 3. Test procedure for the SDS test (modified from Sugano, 2012).

2.2 Definition of energy and specific energy

In SDS test, both load and torque are applied to the rod at the same time. The energy which is required for penetration is a parameter that represents the combined effect of both vertical load and torque. The incremental work done, δE, by the torque and vertical load for a small rotation can be calculated as (Suemasa et al. 2005):

$$\delta E = \pi T \delta n_{ht} + W \delta s_t \qquad [1]$$

where T is the required torque to rotate the screw point, W is the required vertical load, δn_{ht} is the number of incremental half turns and δs_t is the incremental settlement caused by the load and torque. The average specific energy, E_s, is defined as the average of the amount of penetration energy for different steps of loading, E, divided by the volume of penetration:

$$E_s = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{E}{L \times A}\right)_i \qquad [2]$$

where L is the depth of penetration and A is the maximum cross-sectional area of the screw point.

2.3 Previously developed method for assessing liquefaction potential of the soil

Between June-August 2013, 69 SDS tests were conducted in Christchurch. These sites are located at both liquefied and non-liquefied areas following the CES (see Figure 4). SDS tests were conducted within 1–3 m from CPT sites, as described in the CGD (2013).

Figure 4. Location of the SDS sites in Christchurch

The simplified procedure developed by Seed and Idriss (1971) for estimating earthquake-induced cyclic shear stresses continues to be the basis of analysis, although there have been a number of refinements to the various components of this framework. Cyclic shear stress ratios (CSR) induced by earthquake ground motions with magnitude M=7.5 at a depth z below the ground surface is estimated using the following expression:

$$(CSR)_{M=7.5} = 0.65\left(\frac{\sigma_{v0} a_{\max}}{\sigma'_{v0}}\right)\frac{r_d}{MSF} \qquad [3]$$

where a_{max} is the peak ground acceleration; σ'_{v0} and σ_{v0} are the effective and vertical overburden stresses, respectively; r_d is a stress-reduction factor; MSF is magnitude scaling factor; and g is the gravitational acceleration. The r_d parameter represents the ratio of cyclic stresses for a flexible soil column to the cyclic stresses for a rigid soil column while MSF adjusts the cyclic resistance ratio, CRR, to a specific value of M (conventionally M = 7.5), as the CRR depends on the number of loading cycles, which in turn correlates with M (Seed et al. 1975).

Different methods use certain expressions for r_d and MSF in calculating the cyclic stress ratio and their defined thresholds of liquefaction triggering are slightly different from each other. Hence to minimise the uncertainty involved in modelling the liquefaction potential of soil, three different methods are used for liquefaction analysis: i.e. methods developed by Moss et al., (2006), Boulanger and Idriss (2014) and Robertson and Cabal (2012). Data from various layers at each site were analysed using all of the above-mentioned methods, with each data point being judged to have liquefied if the factor of safety against liquefaction, F_L<1.0 based on all three methods; similarly, each data point was judged to be unliquefied if the factor of safety against liquefaction, F_L≥1.0 based on all three methods. Note that while surface manifestations of liquefaction in Christchurch are well-documented, the locations of the layers which liquefied were uncertain; for this purpose, CPT data were used to back-calculate the layers that liquefied.

The SDS data points obtained in Christchurch were compiled and divided into three groups depending on their FC. For this purpose, the value of FC used for each layer was estimated from the CPT data using the correlation proposed by Robertson and Wride (1998). In the developed graph, $E_{s,1}$ is the average specific energy during penetration (in N-mm/mm^3) normalised by the reference overburden pressure of P_a=100 kPa (or 1 atm) by

$$E_{s,1} = E_s\left(\frac{P_a}{\sigma'_{v0}}\right)^m \qquad [4]$$

In the above equation, σ'_{v0} was calculated from estimated unit weight using CLiq computer software (GeoLogismiki 2006), which is based on the soil behaviour type (Lunne et al., 1997). After several analyses, it was found that m=0.5 is the best value to correlate the energy with the overburden pressure (Mirjafari, 2016).

Based on the position of the liquefied and non-liquefied data points in each *FC* group, different curves were drawn to estimate the threshold for liquefaction triggering based on the probability of the occurrence of liquefaction. To draw the boundary lines, logistic regression analysis was performed (Mirjafari et al., 2016). Figure 5 shows the probability lines of CRR versus normalised specific energy of penetration for 15%, 50% and 85% probability of liquefaction occurrence based on the SDS tests conducted in Christchurch considering layers with *FC*≤5%; here the data points from the 2010 Darfield earthquake (M_w=7.1) were used, with the a_{max} based on conditional median peak ground accelerations (Bradley & Hughes 2013).

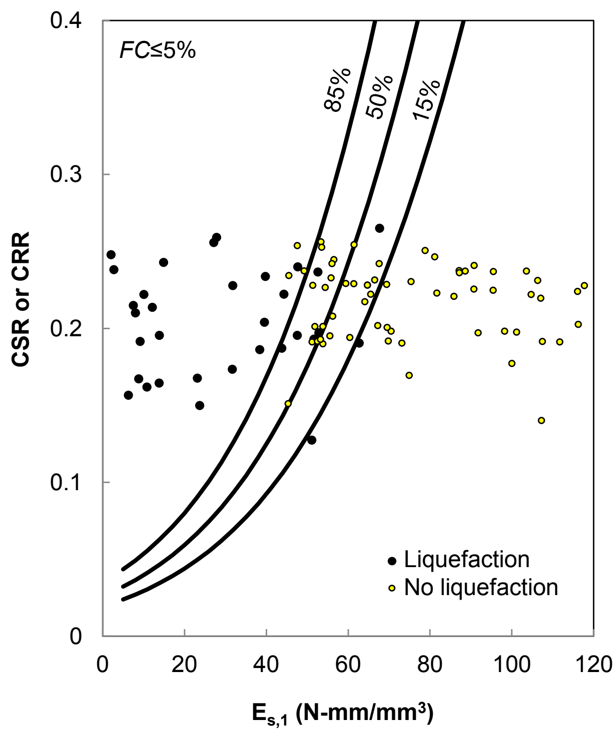

Figure 5. Probability lines of *CRR* versus normalised specific energy of penetration for probability of 15%, 50% and 85% occurrence of liquefaction based on the SDS tests conducted in Christchurch for *FC*≤5% and 2010 Darfield earthquake data.

2.4 Primary parameters

Five parameters were initially selected to be used as input parameters for the ANN model. Four of these parameters are the primary SDS parameters: average changes of torque (*Ave δT*), average specific energy of penetration (E_s), speed of penetration (V), and effective overburden pressure (σ'_{v0}). In addition, peak ground acceleration (a_{max}) was employed as earthquake parameter.

Ave δT is a parameter that can be used for soil classification and is defined as follows (Mirjafari 2016):

$$Ave\delta T = \frac{1}{n}\sum\nolimits_{n=1}^{6} T_{n+1} - T_n \qquad [5]$$

where n is the number of load steps, while T_{n+1} and T_n are the sequence of measured torques. As investigated by Mirjafari (2016), there is a correlation between *FC* and *Ave δT* and therefore *FC* is not included in the initial set of primary parameters. In addition, the depth (z) is not included as primary parameter because its effect is already incorporated in σ'_{v0}.

3 THE NEURAL NETWORK

3.1 Background of ANN

ANN method uses mathematical algorithm to create patterns to match an existing set of input and output values so that extrapolation for prediction of outputs of a new set of data can be made. The operation of ANN is similar to biological neural functioning in the brain as human can solve new problems from the experiences gained in the past. It takes previously solved examples to create a system of neurons that can predict the results of new inputs. The process of learning from previously solved examples is called training (Goh, 1994)

In every neural network system three layers of neurons are excited: Input layer that receive the data from outside of the network, output layers that send the data as output out of the network and hidden layer that connects the input layer to the output layer. Figure 6 shows the architecture of a multilayer neural network.

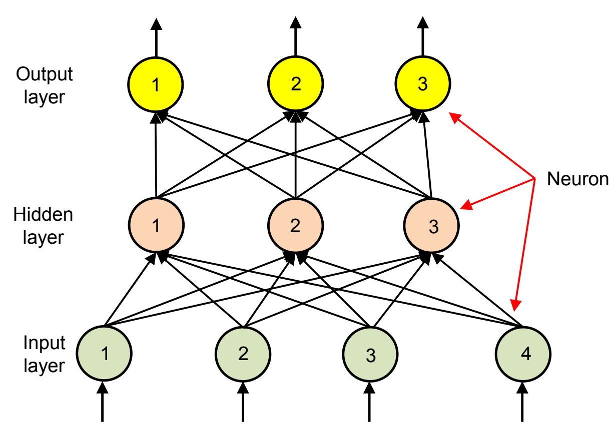

Figure 6. The architecture of a multilayer neural network (adapted from Goh, 1994)

A neural network pattern recognition approach available in Matlab R2015b (Matlab, 2015) is used in this study. In pattern recognition problems, a neural network classifies outputs into a set of target categories which, in this study, are the two categories: liquefaction and non-liquefaction. A two-layer feed-forward network, with sigmoid hidden and softmax output neurons, can classify vectors arbitrarily well, given enough neurons in its hidden layer. Further details of ANN and the algorithms developed are discussed in relevant documentation of Matlab (2015).

The network is trained with 70% of the total data, selected in random, 15% for validation and 15% for testing. The training dataset is presented to the network during training and the network is adjusted according to its errors. The validation dataset is used to measure network generalisation and to halt training when generalisation stops improving. The testing data set has no effect on training and therefore provides an independent measure of network performance during and after training.

3.2 Modeling of field liquefaction data

Data from 50 sites in Christchurch were collected to train the ANN network for the 2011 Christchurch earthquake (M_w6.3). These records are primarily from sites with level ground conditions with sand or silty sand layers. The total number of points is 890 (640 liquefied points and 250 non-liquefied ones). Liquefied points were identified based on the methodology discussed in the previous section.

The output of the ANN model consisted of a single neuron representing the liquefaction occurrence. The binary value of 1 represents liquefaction occurrence and 0 for non-liquefaction. A total of 622 case records were used for the training phase and 134 (randomly selected) for the testing phase.

3.3 Liquefaction model

Two different ANN models were developed in this study. The first one includes all the 5 primary parameters which were mentioned earlier. In the second model, the effective overburden pressure is removed from the analysis. Table 1 shows the summary of the developed models. It should be noted that only one earthquake event (2011 Christchurch earthquake) was used to train the network and hence the effect of earthquake magnitude cannot be considered in the model; therefore, it is not used as input parameter.

Different ANN models with 1 and 2 hidden layers and different neurons in each hidden layer were examined; in this study, it was found that a network with 1 hidden layer with 5 neurons can predict the output accurately.

Table 1. Summary of developed models for predicting liquefaction potential of soil

Model	Input parameters	Hidden layers	Number of hidden neurons
ANN1	$Ave\delta T$, E_s, V, σ'_{v0}, a_{max}	1	5
ANN2	$Ave\delta T$, E_s, V, a_{max}	1	5

Figure 7 shows the confusion matrix for all the data in ANN2 model. Note that a confusion matrix is a table used to describe the performance of a classification on a set of test data for which the true values are known. The network outputs are very accurate, as can be seen by the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares. The blue square shows the total correct and incorrect percentage of prediction. Each grey cell represents the percentage of correct and incorrect predictions for the different classes. For example, for the target class of 0, which means no liquefaction based on case histories, 226 cases were available in which 178 of them were predicted correctly by the ANN model (equivalent to 78.8% as shown in the matrix) while 48 cases were predicted incorrectly (equivalent to 21.2%).

Table 2 shows the accuracy of the ANN model in predicting the liquefaction potential of soil in the training phase, validation phase, test phase and all the samples for both ANN1 and ANN2 models. As can be seen from the table, both models show almost similar degree of accuracy in predicting the liquefaction potential of soil; this means that removing σ'_{v0} from the model does not decrease the performance of the network. As the SDS parameters already reflect the effect of overburden pressure, it is reasonable to remove σ'_{v0} from the model.

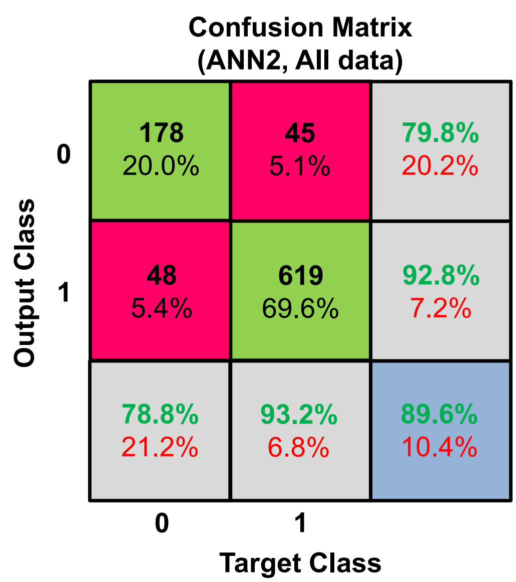

Figure 7. Confusion matrix for all the data using ANN2 model.

Table 2. Accuracy of the proposed networks

Model	Training	Validation	Test	All
ANN1	88.4%	91.0%	91.3%	89.1%
ANN2	87.9%	91.8%	94.8%	89.6%

3.4 Comparison with conventional method

For use in engineering practice, the ANN approach using ANN2 model is simpler than the other model as it has less input parameters. To check the accuracy of the model for other earthquake events, a number of data points which were used in the conventional graph for *FC*≤5% are tested (see Figure 5); the data points were for the 2010 Darfield earthquake. A total of 104 points were tested using ANN2 model and it predicted 94 points (90.4%) correctly (10 points were incorrectly predicted). The performance of the model is better than all the 3 probability lines which were developed before, as the number of points plotted on the "wrong" side of the lines is more than 10. By introducing the primary parameters to the model, the network is able to do the liquefaction susceptibility analysis. One of the advantages of the ANN approach is the ability of the model to learn. By adding more input data from different case histories to the ANN network, the model can be improved and higher performance can be achieved. Since in this study, only data from one earthquake event is used, it is necessary to improve the performance of the model by adding more data from different earthquakes with variable range of magnitudes.

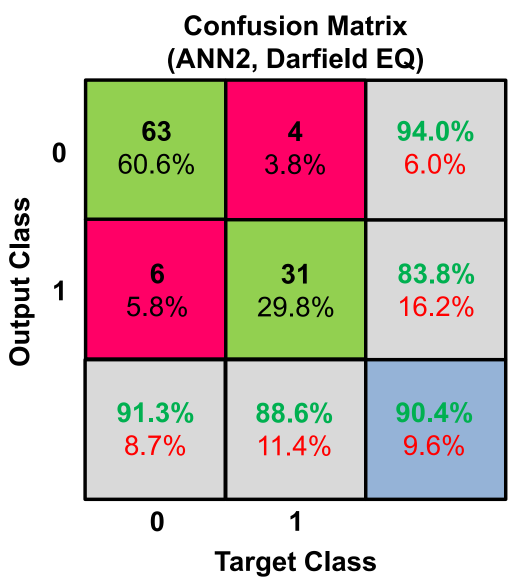

Figure 8. Confusion matrix for the 2010 Darfield earthquake data.

4 CONCLUDING REMARKS

ANN model was used to predict the liquefaction potential of soil using SDS-derived parameters. It was shown that the model performed well and the network was able to capture the complex relationship between SDS parameters and liquefaction potential of soil. Two different combinations of the input parameters were tested and both models show almost similar responses; the results proved that the ANN can be used as a quick tool for predicting liquefaction potential of soil.

Although ANN approach does not provide a linkage between input and output parameters from mechanical point of view, the achieved results showed the capability of the ANN method.

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