Artificial neural network for prediction of liquefaction triggering based on CPT data

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Abstract. The prediction of the liquefaction potential of soil due to an earthquake is an essential task in civil engineering. In this paper, the artificial neural networks (ANNs) technique is introduced in the prediction of liquefaction potential of soil based on the cone penetration test (CPT) data. ANNs model was developed and validated using a database of 174 field case histories. Six parameters were assigned as input parameters of the model which were earthquake magnitude (M), effective vertical stress (\( \sigma' \)), cone resistance (\( q_c \)), normalized peak horizontal acceleration at the ground surface (\( (a/g) \)), soil mean grain size (D50), and cyclic stress ratio (CSR). The output of the model was liquefaction index (LI) which in turn was used to determine whether liquefaction was taking place or not. The developed ANN model gave well-matched results when compared with the actual results. Also, the study for the relative importance of the input parameters was performed. It showed that \( q_c \) and M exhibited the highest importance of approximately 33% and 23% respectively while the value of \( (a/g) \) yielded the lowest value of 9.7%. Finally, based on the sensitivity analysis of the model, it was found that the results of the ANN model were compatible with prior geotechnical knowledge. Accordingly, it can be concluded that neural networks can be used to simulate the problem of soil liquefaction with high accuracy.

1. Introduction
One of the main destructive results of the dynamic loads resulting from earthquakes is the loss of strength and hardness of the soil, which is called soil "liquefaction". The occurrence of this phenomenon causes a lot of losses as a result of the collapse for some of the structures constructed in that area, and it also often caused civilian losses. This phenomenon occurs mainly in the case of saturated and loose sand. It is believed that liquefaction occurs when the pore water pressure approaches the confining pressure in the saturated loose sand under seismic loading, where the movement of large masses of soil can begin as a result of the rapid and dramatic loss of soil strength[1],[2].

Generally, there are many factors, including those related to earthquake characteristics, and some of them related to the soil itself, which affect the possibility of occurrence of this phenomenon. Generally speaking, the problem of predicting the occurrence of liquefaction due to earthquakes is complex geotechnical task. Many methods have been developed in the past to predict whether or not liquefaction of sand will occur, depending on the results of laboratory tests or field tests (standard penetration test (SPT) and cone penetration test (CPT)), or the results of seismic survey. The most
common methods are that used the results of SPT and CPT because these tests give a general perception of the strength of the soil [2].

In the last decades, there have been many attempts to use artificial intelligence techniques, especially artificial neural networks, to simulate a set of engineering problems, including geotechnical problems. The phenomenon of soil liquefaction is one of the problems that have captured the attention of researchers in this regard [3]–[5].

However, in many studies dealing with the use of artificial neural networks in representing the problem of soil liquefaction based on CPT data, a mathematical expression has not been presented to help the engineer in giving the decision whether liquefaction will occur or not, based on the data available (the seismic characteristics of the earthquake in addition to some soil properties) [6]–[8].

The present study aims to predict the liquefaction potential, based on the CPT data, by developing a mathematical formula for that. And to check the compatibility of the performance of the proposed formula with prior geotechnical knowledge by carrying out sensitivity analysis. It also aims to assign the importance of each of the input variables on the results of the proposed ANN model.

2. Liquefaction analysis

It is well-known that the shear strength of cohesionless soil developed on any plane depends on the soil friction angle and the normal effective stress acting on that plane and can be expressed as follows [1],[10]:

\[ \tau = \sigma' \tan \phi = (\sigma - u) \tan \phi \] (1)

where:
\( \tau \): soil shear strength.
\( \sigma' \): normal effective stress.
\( \sigma \): normal total stress.
\( u \): pore water pressure.
\( \phi \): angle of internal friction of the soil.

When the saturated loose sand is subjected to an earthquake, the pore water pressure is built up. As a result of building up the pore water pressure, the effective stress is reduced which in turn reduces the shear strength of the soil. The phenomenon of losing the soil to its shear resistance is called "soil liquefaction". In the case that the soil loses all its resistance (the effective stress gets zero), very large deformations occur in the soil without mobilizing the necessary resistance [1], [2].

Consequently, structures built on or in such a soil will suffer from significant settlement and stress, causing their failure. This is obviously a condition to be avoided in any type of major construction. Therefore, the prediction of liquefaction triggering is considered as the main task that the geotechnical engineer is interested in [2].

In general, the first step in liquefaction analysis is to determine whether the soil has the capability to liquefy or not. Mostly the saturated loose cohesionless soil is susceptible to liquefaction. The second step is to determine the cyclic stress ratio (CSR) caused during earthquake and the cyclic resistance ratio (CRR) based on the soil strength. When the CSR is less than CRR (FS > 1) liquefaction will not happen and vice versa. The factor of safety is computed as follows [1], [2]:

\[ FS = \frac{CRR}{CSR} \] (2)

However, the cyclic stress ratio is computed based on the earthquake characteristics as:

\[ CSR = \frac{\tau_{cy}}{\sigma_o} = 0.65 \times r_f \left( \frac{\sigma}{\sigma' \sigma} \right) \left( \frac{a_{max}}{g} \right) \] (3)

where:
\( \tau_{cy} \): uniform cyclic shear stress during earthquake.
\( \sigma' \): effective stress.
\( \sigma \): total stress.
\( a_{max} \): maximum horizontal acceleration at ground surface caused by earthquake.
\( g \): gravitational acceleration.
Different procedures have been proposed in the literature to estimate the value of CRR based on the results of penetration tests or based on the data of seismic survey. The procedures that adopt standard penetration test (SPT) are the most common procedures like that proposed by Seed-Idriss (1971), Seed (1979) and Iwasaki (1986) [1], [9]. But in the last time some procedures have been developed to estimate CRR based on the results of the cone penetration test (CPT) because the CPT is considered as simple, reliable and has continuous records. As an example of these methods is that suggested by Robertson-Campanella (1985), Seed-DeAlba (1986) and Shibata-Teparaksa (1988) [7]. Therefore, the current work is an attempt to find an empirical formula that adopts the artificial neural networks technique to predict whether liquefaction will occur or not by considering earthquake characteristics and some soil properties, most notably the cone penetration resistance (qc).

3. Artificial neural networks

The term neural network is used to describe many different techniques proposed for simulation of some functions of the human brain. During the last decades, the ANNs technique is an effective and useful computational tool for solving complex and incomprehensible problems to hold using more traditional computational methods. This technique is used, especially, in geotechnical engineering by many researchers after the 1990s and it is revealed some degree of success to simulate the nonlinear behavior of several geotechnical problems [3], [4].

A typical structure of ANNs consists of the number of artificial neurons variously known as nodes (units) that are usually arranged in layers. Generally, any ANN model has input and output layers with or without one or more hidden layers. Also, each node is fully connected to all nodes in the previous and next two layers only. The nodes in each layer have their own transfer function while the input layer generally, has linear transfer function. The output of any node is computed by entering the sum of product for its input values and the corresponding weights into the transfer function.

Development of any ANNs model includes the following systematic steps [4]:

- Collect the necessary data related to the problem to be modeled.
- Choose the input and output variables of the model.
- Determine the number of hidden layers, the number of nodes in each layer and the transfer function in each layer.
- Divide the database into three sub-sets (training, testing and validation).
- Select the suitable learning rule to obtain the optimum connection weights.
- Assign the stopping criteria to finish the training process of the network and then check the validity of the proposed ANN model.

The database used in the present work consists of a total of 174 case histories from the published literatures [11]. The data is spread over a wide range, and Table 1 shows the statistical parameters (minimum value, maximum value, range, mean and standard deviation) of the selected variables.

| Statistical parameters | Variables | Input | Output |
|------------------------|-----------|-------|--------|
|                        | M (M)     | σr (kPa) | qc (MPa) | α/g | D50 (mm) | CSR | LI |
| Minimum                | 5.9       | 13.9   | 0.38    | 0.1 | 0.0151   | 0.06 | 0  |
| Maximum                | 7.8       | 227.5  | 26      | 0.6 | 0.48     | 0.46 | 1  |
| Range                  | 1.9       | 213.6  | 25.62   | 0.5 | 0.4649   | 0.4  | 1  |
| Mean                   | 7.293     | 79.613 | 6.559   | 0.284 | 0.171   | 0.226 | -  |
| Standard deviation     | 0.599     | 44.311 | 5.274   | 0.132 | 0.102   | 0.087 | -  |
Form geotechnical viewpoint, earthquake magnitude (M), effective stress (\(\sigma'_e\)), cone resistance (\(q_{cc}\)), soil mean grain size (\(D_{50}\)), normalized peak horizontal acceleration at the ground surface (\(\ddot{u}/g\)), and cyclic stress ratio (CSR) are the variables by which it is possible to determine whether or not liquefaction will occur in a soil [7]. Therefore, these variables were chosen to be the input variables of the network while the liquefaction index (LI) was assigned as the only network output.

There is no clear cut criteria that can be used to select the number of hidden layers, number of nodes in hidden layers and the type of transfer function in hidden and output layers rather there are only rules of thumb. It was found that the network with one hidden layer can approximate any continuous function [4]. So, a network with one hidden layer was used in the present work. Several networks have been designed with different number of hidden nodes and transfer function for both hidden and output layers and the ones that give the best performance have been chosen. Tables 2 contains the statistical indices (coefficient of correlation (r), root mean square error (RMSE) and mean absolute error (MAE)) through which choosing the optimal network have been conducted. It can be seen that the optimal performance (highest value of r and lowest values for both RMSE and MAE) achieved with six nodes in the hidden layer.

Table 2. Effect of the number of hidden nodes on the performance of ANN model.

| No. of hidden nodes | r    | RMSE | MAE  |
|---------------------|------|------|------|
| 6                   | 0.8712 | 20.43 | 15.64 |
| 5                   | 0.8672 | 20.43 | 15.95 |
| 4                   | 0.8697 | 20.24 | 15.68 |
| 3                   | 0.8616 | 22.00 | 16.41 |
| 2                   | 0.8622 | 22.30 | 16.43 |
| 1                   | 0.8642 | 22.70 | 16.48 |

Table 3 illustrates the results (statistical parameters) for different model with different combination of transfer functions in hidden and output layers. It can be noticed that the optimal performance obtained by using sigmoid transfer function in both layers.

Table 3. Effect of the type of the used transfer function on the performance of ANN model.

| Type of Transfer Function | r    | RMSE | MAE  |
|--------------------------|------|------|------|
| Sigmoid – Sigmoid         | 0.8914 | 19.94 | 12.41 |
| Tanh – Sigmoid           | 0.8840 | 19.23 | 13.38 |
| Sigmoid-Tanh             | 0.8925 | 21.32 | 15.00 |
| Tanh-Tanh                | 0.8521 | 24.50 | 14.36 |

After dividing the database into three sub-sets, the training set is used to correct the randomly assumed connection weights by comparing the network output with actual value. The process of connection weights correction was performed by using feed forward back propagation learning rule. The purpose of assigning testing set is to check the performance of the network in different stages of training phase. While, the validation (query) set is used to assess the network's performance after the successful completion of the training process. The large the training set, the better the network’s performance. Therefore, in this research, 80% of the data was used in training set and 10% was adopted for both testing and validation sets. However, the data was divided so that the three sub-sets (training, testing and validation) were statistically consistence and represent the same population by carrying out t-test and F-test with significant level of 5% on many random trial divisions of the data as shown in Table 4.

It is necessary to note that before developing the network the data should be normalized to guarantee that all variables have taken equal attention during training process.
Table 4. Tests of null hypotheses for the input and output variables of the proposed ANN model.

| Variable & data sets | t–value | Critical value | t–test | F–value | Critical value |
|----------------------|---------|----------------|--------|---------|----------------|
|                      |         | upper | Lower |         | upper | lower |         |
| Earthquake Magnitude, M |         |       |       |         |       |       |         |
| Testing              | 1.18    | 1.98  | -1.98 | Accept  | 0.81  |       | 2.37  | 0.53  | Accept |
| Validation           | 0.92    | 1.98  | -1.98 | Accept  | 0.97  |       | 2.31  | 0.53  | Accept |
| Effective vertical stress, σ’ (kPa) |         |       |       |         |       |       |         |
| Testing              | -0.58   | 1.98  | -1.98 | Accept  | 0.79  |       | 2.37  | 0.53  | Accept |
| Validation           | 0.65    | 1.98  | -1.98 | Accept  | 0.76  |       | 2.31  | 0.53  | Accept |
| Cone resistance, qc (MPa) |         |       |       |         |       |       |         |
| Testing              | -1.8    | 1.98  | -1.98 | Accept  | 0.87  |       | 2.37  | 0.53  | Accept |
| Validation           | 2.08    | 1.98  | -1.98 | Accept  | 1.07  |       | 2.31  | 0.53  | Accept |
| Normalized peak horizontal acceleration at the ground surface, α/g |         |       |       |         |       |       |         |
| Testing              | -0.4    | 1.98  | -1.98 | Accept  | 0.79  |       | 2.37  | 0.53  | Accept |
| Validation           | -1.79   | 1.98  | -1.98 | Accept  | 0.66  |       | 2.31  | 0.53  | Accept |
| Soil mean grain size, D_{50} (mm) |         |       |       |         |       |       |         |
| Testing              | 0.13    | 1.98  | -1.98 | Accept  | 1.13  |       | 2.37  | 0.53  | Accept |
| Validation           | 3.11    | 1.98  | -1.98 | Accept  | 1.21  |       | 2.31  | 0.53  | Accept |
| Cyclic stress ratio, CSR |         |       |       |         |       |       |         |
| Testing              | -1.29   | 1.98  | -1.98 | Accept  | 0.73  |       | 2.37  | 0.53  | Accept |
| Validation           | -1.86   | 1.98  | -1.98 | Accept  | 0.81  |       | 2.31  | 0.53  | Accept |
| Liquefaction of soil, (LI) |         |       |       |         |       |       |         |
| Testing              | 2.31    | 1.98  | -1.98 | Accept  | 0.84  |       | 2.37  | 0.53  | Accept |
| Validation           | -0.6    | 1.98  | -1.98 | Accept  | 0.86  |       | 2.31  | 0.53  | Accept |

In order to check the accuracy of the results obtained from the proposed ANN model, the number of agreement with the actual results was counted as shown in Table 5. It can be noted that the agreement percentage (number of cases with correct prediction to the total cases) was 82.2%. Also, the Figure showed that the error in prediction in the non-liquefied case is more than that in the liquefied case. Therefore, the proposed ANN model can be considered as a conservative predictor for the soil liquefaction potential.

Table 5. Classification of the results obtained by the proposed ANN model.

| Set        | Observed | Predicted | % correct |
|------------|----------|-----------|-----------|
|            |          | Liquefied | Non-liquefied |    |
| Training   |          | 79        | 9          | 90% |
|            |          | 16        | 35         | 69% |
|            |          | 68%       | 32%        | 82% |
| Testing    |          | 8         | 0          | 100%|
|            |          | 1         | 8          | 89% |
|            |          | 53%       | 47%        | 94% |
| Validation |          | 11        | 1          | 92% |
|            |          | 4         | 2          | 33% |
|            |          | 83%       | 17%        | 72% |
4. Formula of the proposed ANN model

The limited number of connection weights determined by assigning the optimal ANN Model (liquefaction index model) allows the network to be turned into a relatively simple formula. The structure of the proposed model is presented in Figure 1, while the connection weights and biases are listed in Table 6.

![Figure 1. Structure of the proposed ANN model.](image)

Table 6. Summary of all connected weights, biases and transfer functions for the proposed ANN model.

| Sigmoid Transfer Function | Weight $w_{ij}$ from $i^{th}$ input node to $j^{th}$ hidden node | Bias of $j^{th}$ hidden node |
|---------------------------|---------------------------------------------------------------|-------------------------------|
| Hidden layer nodes        |                                                               |                               |
| j = 7                     | 1.675, -2.913, -5.88, -0.534, 3.704, 0.679                 | 0.424                         |
| j = 8                     | -1.499, 1.68, 5.12, -0.954, -2.81, -1.12                  | -0.358                        |
| j = 9                     | -0.454, -0.348, -1.163, -0.313, -0.355, -0.503            | -0.8007                       |
| j = 10                    | 0.708, -1.110, 3.55, -2.601, -1.047, -3.566               | -0.1911                       |
| j = 11                    | -0.052, -1.784, -3.946, -1.381, -0.116, -0.121            | 0.10524                       |
| j = 12                    | -0.527, -0.822, 0.425, -0.104, -0.527, -0.703            | -0.8873                       |
| Sigmoid Transfer Function | Weight $w_{ji}$ from $j^{th}$ hidden node to $i^{th}$ output node | Bias of $i^{th}$ output node |
| Output layer              |                                                               |                               |
| i = 13                    | 2.583, -1.641, 0.584, -3.35, 2.723, -0.327                | -0.1718                       |

The liquefaction index (LI) is obtained by Equations 4 to 8. Then the liquefaction potential is determined based on the LI value where the soil is assigned to be non-liquefied when LI is less than 0.5 otherwise the soil is assigned to be liquefied.

$$LI = \frac{1}{1 + \exp(-X_{out})}$$

where:

$$X_{out} = \begin{bmatrix} y_{H1} & y_{H2} & y_{H3} & y_{H4} & y_{H5} & y_{H6} \end{bmatrix} \begin{bmatrix} 2.583 \\ -1.641 \\ 0.584 \\ -3.350 \\ 2.723 \\ -0.327 \end{bmatrix} + [0.172]$$

(5)
\[ y_{Hi} = \frac{1}{1 + \exp(-X_{Hi})} \]  

\[ X_{Hi} = \begin{bmatrix} X_{i1} \\ X_{i2} \\ X_{i3} \\ X_{i4} \\ X_{i5} \\ X_{i6} \end{bmatrix} = \begin{bmatrix} 1.675 & -2.193 & -5.880 & -0.534 & 3.704 & 0.679 \\ -1.499 & 1.680 & 5.120 & -0.954 & -2.810 & -1.120 \\ -0.454 & -0.348 & -1.163 & -0.313 & -0.355 & -0.503 \\ 0.708 & -1.110 & 3.550 & -2.601 & -1.047 & -3.566 \\ -0.052 & -1.784 & -3.946 & -1.381 & -0.116 & -0.121 \\ -0.527 & -0.822 & 0.425 & -0.104 & -0.527 & -0.703 \end{bmatrix} \]

\[ X_{i} = \frac{X_{i} - \min X_{i}}{\max X_{i} - \min X_{i}} \]  

5. Importance of input variables and sensitivity analysis

To recognize which of the input variables have the highest effect on the liquefaction index (the model's output), the procedure suggested by Garson in 1991 is followed herein which transmits the connection weights of the ANN model into relative importance of the input variables [4]. The relative importance for all input variables of the proposed ANN model are summarized in Figure 2.

It can be noticed that the value of cone resistance (qc) and earthquake's magnitude (M) have the maximum relative importance of about 31% and 23% respectively. On the other hand, the rest of input variables (D50, D50/g and CSR) have relatively the lowest relative importance.

The final stage of testing the proposed ANN model is to conduct a sensitivity analysis to identify the model's ability to estimate liquefaction in the soil. Also, to check the general model behavior with the expected behavior based on geotechnical information. Sensitivity analysis is performed by fixing all input variables with the mean values except one. Then, change the unfixed variable between its minimum and maximum values with appropriate increment and determine the corresponding output values, and then repeated the same steps for other input variables [4].

Figure 3 illustrates the variation of LI with input variables. The red line represents the boundary between liquefied (above the line) and non-liquefied (below the line) cases. It can be seen that the likelihood of liquefaction in soil increases directly with the increase in M, D50 and CSR. On the other hand, the likelihood of liquefaction in the soil decreases with an increase in both \( \frac{\alpha}{g} \) and qc. Finally, the effect of changing \( \frac{\alpha}{g} \) on the likelihood of liquefaction is marginal.
Figure 3. Results of the sensitivity analysis of the proposed ANN model due to changing the input variables.

6. Conclusion
Predicting the liquefaction potential of the soil that are subject to an earthquake loading is considered one of the problem of great importance to the geotechnical engineer, because of the losses caused by this phenomenon if it occurs. Several methods have been proposed that adopt the results of field tests such as the cone penetration test. In the present work a neural network technique was used to obtain a mathematical model to predict the occurrence of liquefaction in the soil based on the cone penetration test data. From the results of the study, the following points can be concluded:

- Artificial neural network (ANN) have the ability to predict the liquefaction potential with a high accuracy when it compared with actual records. The proposed ANN model correctly predicted 82.2% of the total cases.
- The cone penetration resistance and the earthquake's magnitude have the highest importance in the prediction the liquefaction potential 31% and 23% respectively. While, the effective stress, soil mean size, acceleration ratio and cyclic stress ratio have approximately equal lowest importance.
- The behavior of the proposed ANN model was consistent with prior geotechnical knowledge and its results very sensitive to the change in cone resistance value where the value ranges from (0.86 to 0.6). While, the model revealed trivial sensitivity to the change of acceleration ratio ($\alpha/g$) It is equal to approximately 0.67.
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