Application of Neural Network in Civil Engineering Problems

D.-S. Jeng, D. H. Cha and M. Blumenstein

***Abstract*—In this paper, an artificial neural network (ANN) is applied to several civil engineering problems, which have difficulty to solve or interrupt through conventional approaches of engineering mechanics. These include tide forecasting, earthquake-induced liquefaction and wave-induced seabed instability. As shown in the examples, ANN model can provide reasonable accuracy for civil engineering problems, and a more effective tool for engineering applications.**

***Index Terms*—neural network, artificial intelligence, civil engineering, engineering design.**

I. Introduction

The origins of artificial neural networks (ANN) are in the field biology. The biological brain consists of billions of highly interconnected neurons forming a neural network. Human information processing depends on this connectionist system of nervous cells. Based on this advantage of information processing, neural networks can easily exploit the massively parallel local processing and distributed storage properties in the brain.

A classical comparison of information processing by a human and a computer is focused on the ability of pattern recognition and learning. The computer can calculate large numbers at high speeds but it cannot recognize something such as a classification problem, written text, data compression and a learning algorithm. On the contrary, a human easily recognizes and deals with the challenges mentioned above by processing information with highly distributed transformations through thousands of interconnected neurons in the brain.

Generally speaking, an ANN is an informational system simulating the ability of a biological neural network by interconnecting many simple neurons (Fig. 1). The neuron accepts inputs from a single or multiple sources and produces outputs by simple calculations, processing with a predetermined non-linear function. Therefore, the primary characteristics of an ANN can be presented as following: (1) the ability of learning; (2) distributed memory; (3) fault tolerance and (4) operating in parallel.

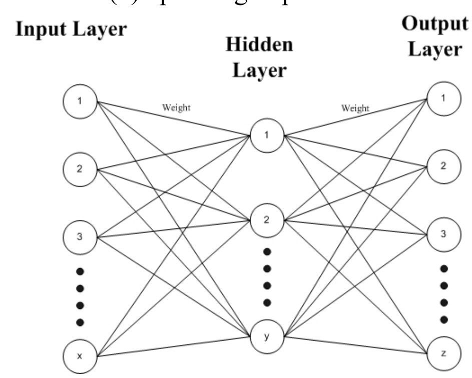

Fig. 1. Structure of Artificial Neural Network model.

Recently, artificial neural network (ANN) models have been widely applied to various relevant civil engineering areas such as geotechnical engineering, water resources and coastal engineering [1-6].

In this paper, three civil engineering problems will be re-examined by neural network model. These include: tide forecasting (coastal engineering), earthquake-induced liquefaction (earthquake engineering) and wave-induced seabed instability (coastal geotechnical engineering). Several numerical examples will be used to demonstrate the application of ANN on the above civil engineering problems.

II. APPLICATION OF ANN in Tidal LEVEL forecasting

A. Tidal Level Forecasting

Tidal level record is an important factor in determining constructions or activity in maritime areas. To describe the property of the tidal-level variations for an open sea, Darwin [7] proposed the equilibrium tidal theory, but it did not accurately estimate the tidal level for the complex bottom topography in the near-shore area. Later, Doodson [8] employed the least-squares method to determine harmonic constants. Since then, the least-squares analysis in determining harmonic parameters has been widely used to predict the tidal level. However, the shortcoming of this method is that the parameters of the tidal constituents are determined by using a long-term tidal record in site.

Kalman [9] proposed the Kalman filtering method to calculate the harmonic parameters instead of the least squares

Manuscript received July 30, 2003.

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method. In this model, a large tidal data was not required. Mizumura [10] also proved that the harmonic parameters using the Kalman filtering method could be easily determined from only a small amount of historical tidal records. Yen et al. [11] utilized the Kalman filtering method in determination of parameters in the harmonic tide-level model as well. The estimation of harmonic parameters could predict accurately the tidal level using the Kalman filtering method, which is solved by the covariance matrix. However, it is necessary to determine the available parameters of the local tide before predicating the tidal level. Tsai and Lee [5] applied the back-propagation neural network to forecast the tidal level using the historical observations of water levels without determining the harmonic parameters. However, their model is used only for the instant forecasting of tidal levels, not a long-term prediction.

Besides the prediction of tidal level, supplement of tidal record is also important for a complete observation tide database. The discontinuous observations may come from the damage of recording facilities, natural disasters or inappropriate operation and so on. The discontinuous record could either be short-term (few hours) or long-term (few months even up to one year). Thus, establishing a simple and executable supplementary model for tidal record is desired.

B. *ANN Model for Tide Forecasting*

To demonstrate the ANN model, we use different data based in the training procedure to predict the one-year tidal level in Taichung Harbor. Based on the 15-day collected data (1-15 Jan 2000), the one-year prediction of tidal level (Jan 2000- Dec, 2000) against the observation is illustrated in Fig. 2. In the figure, solid lines denote the observation data, and dashed lines are the predicted values. The prediction of the present model overall agree with the observation. The correlation coefficient over one yea is 0.9182, which is reasonable good.

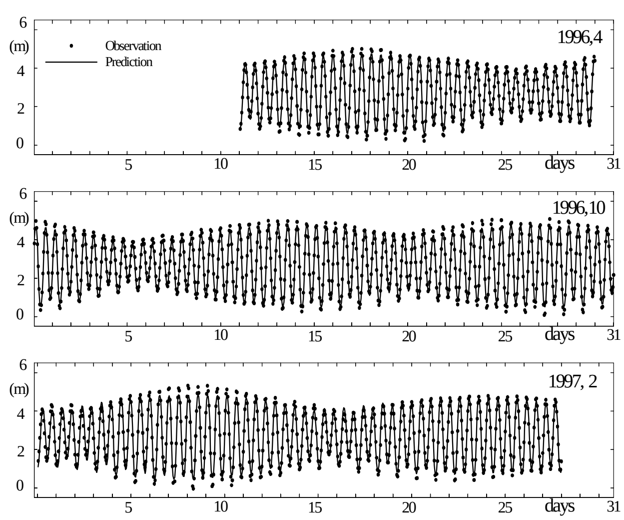

Fig. 2. Comparison of observed tide levels with those predicted over one year for Taichung Harbor (4/1996, 10/1996, 2/1997).

III. APPLICATION OF ANN IN EARTHQUAKE-INDUCED LIQUEFACTION

A. *Earthquake-Induced Liquefaction*

Recently, numerous strong earthquakes occurred worldwide, such as North American, Taiwan, Japan, Turkey, China and so on. The occurrence of earthquakes does not only destroy the residents' properties, but also cause the instability of the whole societies. For example, the earthquake with Richter magnitude of 7.3 occurred at Chi-Chi City on September 21, 1999 has been recognized as the most serious disaster by public concerns in Taiwan. During the earthquake, numerous civil structures, such as buildings, highway embankments and retaining structures etc. have been damaged or completely destroyed. The resident regions affected by the earthquake have not been re-established until now.

In general, damage of civil structures during earthquakes occurs with two general failure modes evident. The first mode is that of structural failure, caused by strong acceleration of the earthquake, results in the damage of the structure itself. The second mode is that of foundation failure, caused by liquefaction, resulting in collapse of the structure as a whole. Therefore, estimation of the earthquake-induced liquefaction potential is essential for the civil engineers in the design procedure.

Since the 1960s, numerous researches have been devoted to the evaluation of earthquake-induced liquefaction. The penetration resistance of the standard penetration test (SPT) is commonly used as an index of liquefaction potential. The reason why SPT test has been commonly used in the prediction of the liquefaction potential is because the in-site SPT-N value is easily obtained with reasonable accuracy. In the SPT-N value method, the earthquake-induced cyclic stress ratio (CSR) must be determined first, and then the cyclic resistance ratio can be calculated for the estimation of earthquake-induced liquefaction potential [12, 13]. Also, Japanese Road Association [14] proposed an empirical procedure for liquefaction assessment.

B. *ANN Earthquake Model*

Conventional SPT-N method for evaluating the liquefaction potential requires soil and seismic variables, including the magnitude of the earthquake, vertical stress, effective vertical stress, N value, average shear stress, depth, peak horizontal acceleration at ground surface, fines content, average grain of soil and so on. Since only limited amount of in site material parameters are available, the desired material parameters are obtained from correlation formula. However, some parameters cannot be directly obtained by from the test site. Thus, the methodology of determining the optimal value is a challenge.

In this study, we try to employ the ANN to assess the liquefaction potential. Firstly, we chose the parameters determining form the field measurement as the input neurons, such as depth, N value and fines content. Then, liquefaction site is expressed as the "output" column, in which "1" denotes the observation of liquefaction, while "0" represents no liquefaction. By using the existing correlations and the given parameters, the corresponding values of unknown soil and seismic parameters are determined.

To illustrate the capability of the ANN model, a site in the Wufeng city, Taiwan is selected. There are fourteenth boring holes at Wufeng city. These situations are categorized by in-situ survey, including for settlements, no damaged and sand boil.

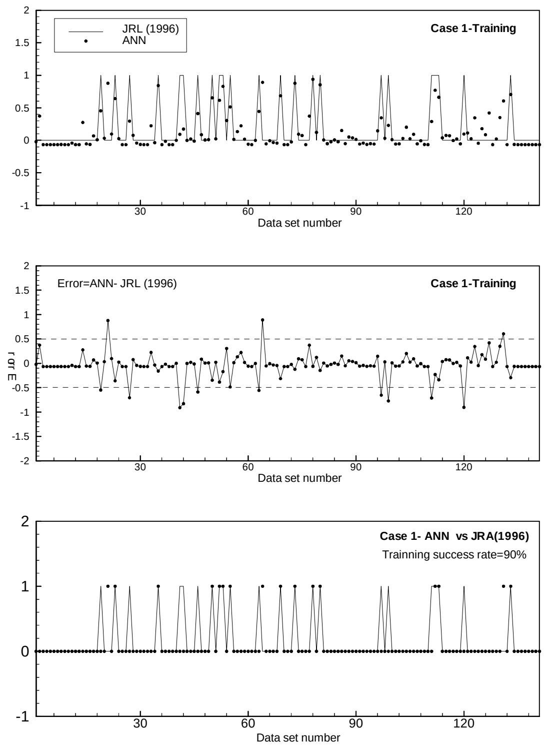

Fig. 3. Train results of CASE 1 between the present ANN model and JRA [14].

Since the soil in Wefeng City is gravel, the cost of using SPT test is more economic than CPT test. Also, the depth of boring hole is limited to 20 m, because the soil conditions are difficult to control. The liquefaction assessment for the fourteenth boring holes was performed with the following steps:

(a) Firstly, we use the boring data with 1.5 m interval to obtain the corresponding SPT-N value and fine content (FC).

(b) Since the conventional methods have difficulties to determine whether liquefaction occurs or not at particular soil depth. In general, the conventional methods can only determine the occurrence of liquefaction, based on the failure condition at the surface of the ground. Thus, we consider the effect of the depth in this model, and use the conventional methods to calculate the possibility of liquefaction at each depth. We use "1" to represent the occurrence of liquefaction, and "0" to denote no liquefaction.

(c) To ensure the ANN model can effectively predict the occurrence of liquefaction, we choose 12 boring data (about 150 sets of data) for training of ANN model. The other two boring data (about 30 sets of data) are used to forecast the occurrence of the liquefaction.

Figure 3 show the training result of CSAE 1 （no damaged and no settlement）, the solid lines are the results of JRA [14]; the symbols are the results of the proposed ANN model. As shown in Fig. 3(a), overall good agreement between JRA and ANN models are observed. The accuracy of the ANN predicted model can be also seen in the Fig. 3(b). An error value greater than |0.5| denotes an error; whereas if the results are less than 0.5. Fig. 3(c) demonstrates a 90% success rate in liquefaction assessment. Comparing the result of the ANN and JRA, there are still good correlation. In other words, only three parameters data input at the training example can be learned in ANN model.

It is desirable to predict the liquefaction for the unknown boring hole. The comparisons between the ANN and JRA [14] of CASE 1 for liquefaction's prediction are also illustrated Figure 4. As shown in the figure, there are three incorrect simulations out of 30 data sets, which claim a 90% success rate.

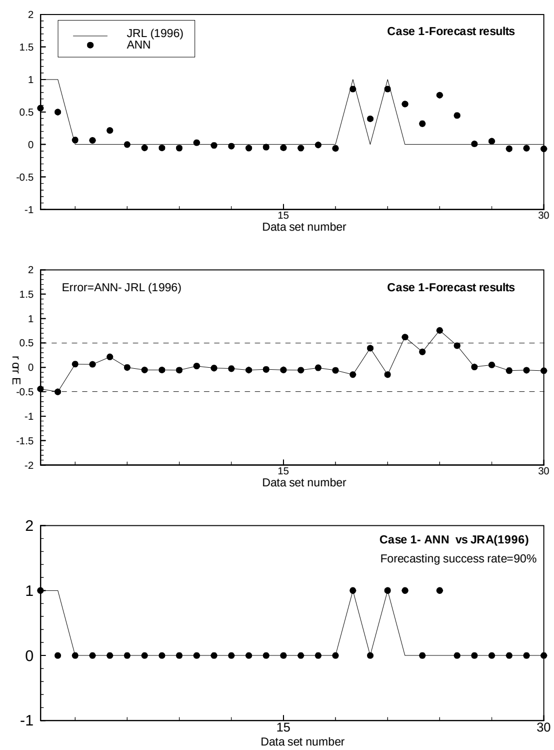

Fig. 4. Forecast results of CASE 1 between the presented ANN model and JRA [14].

Similarly, we compare the results of ANN model and another two conventional methods, Seed's method [12] and T&Y method [13] in Figs. 5 and 6. Again, an overall good agreement between ANN model and Seed's model [12], T&Y method [13] has been found.

Based on the above comparisons, more than 80% of success rate between ANN model and three conventional methods have been achieved in CASE 1. This demonstrates that the proposed ANN model with three parameters (depth, SPT-N values and FC) can predict the occurrence of the earthquake-induced liquefaction well.

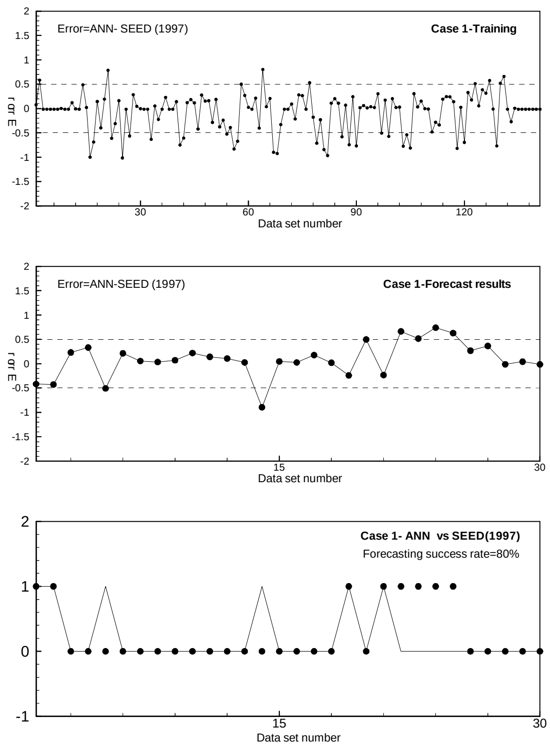

Fig. 5. Train and Forecast results of CASE 1 between the present ANN model and Seed et al. [12].

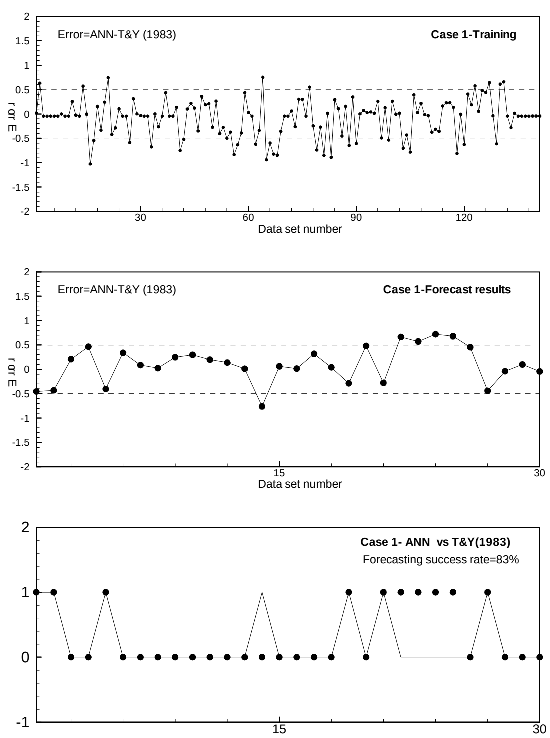

Fig. 6. Train and Forecast results of CASE 1 between the present ANN model and T&Y model [13].

Figs. 7-9 illustrate the prediction of the occurrence of the earthquake-induced liquefaction in CASE 2, 3 and 4. Among these, CASE 2 is the cases with no damaged, but sand boiling occurs (Fig. 5), while CASE 3 is for settlement and sand boiling occur (Fig. 6). Case 4 is of the case with sand boiling (Fig. 7). The above comparisons indicate that the proposed ANN model can provide a high accurate prediction of the earthquake-induced liquefaction.

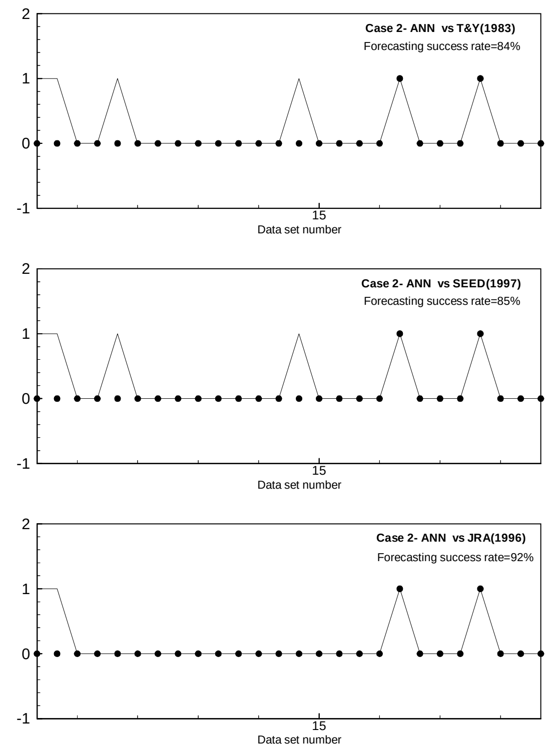

Fig. 7. Forecast results of CASE 2 using by ANN with three different methods.

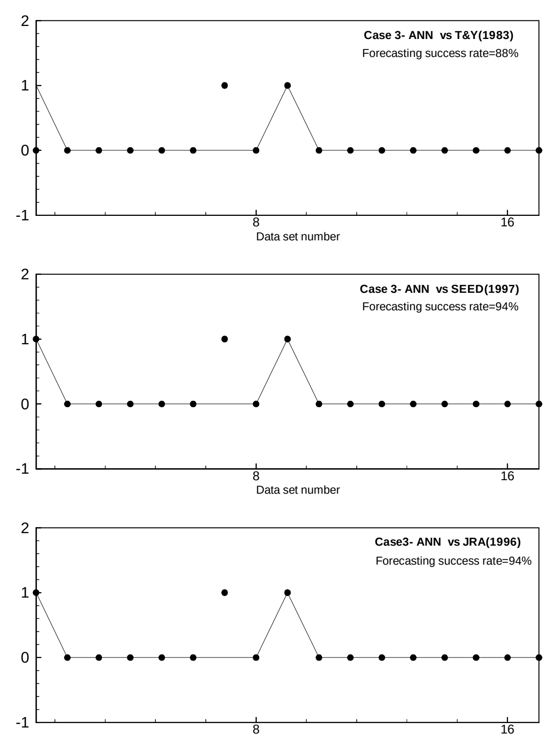

Fig. 8. Forecast results of CASE 3 using by ANN with three different methods.

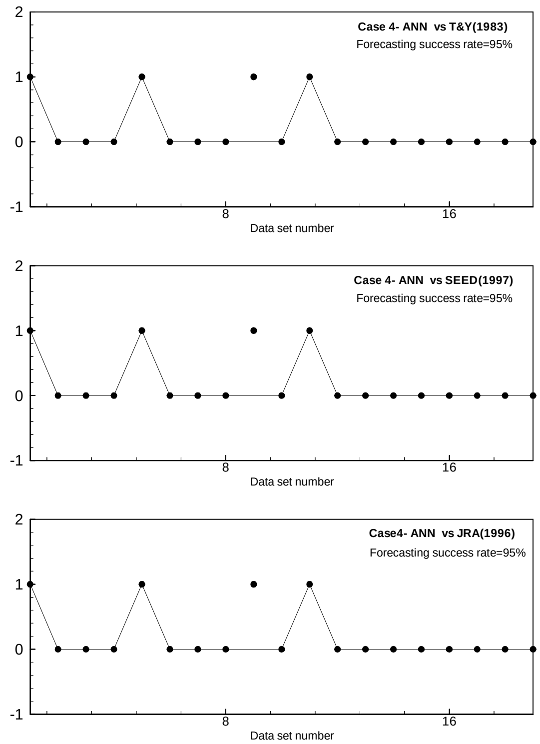

Fig. 9. Forecast results of CASE 4 using by ANN with three different methods

IV. Application of ANN in Wave-induced seabed instability

A. *Wave-Induced Seabed Instability*

The evaluation of the wave-induced seabed instability is particular important for coastal geotechnical engineers involved in the design of marine structures (such as offshore platform, pipeline and caisson etc.). In general, when ocean waves propagate over the ocean, they create dynamic pressure fluctuation on the sea floor. These fluctuations further cause changes in effective stress and excess pore pressure within the soil skeleton, and can be potentially lead to partial liquefaction (and thus loss in strength) of the seabed sediments.

Numerous investigations for the wave-induced seabed instability have been carried out. Most of them have been based on the poro-elastic theories proposed by Biot [15]. These include analytical approaches [16, 17], numerical modeling [18, 19] and physical modeling [20].

B. *ANN Model for Wave-Induced Liquefaction*

All the aforementioned approaches have their limitations, as reviewed in Jeng [21]. Thus, in this section, we attempt to apply ANN model to the predication of the wave-induced liquefaction potential.

To illustrate the application of ANN model, we established the database base don the poro-elastic model proposed by Jeng [17], which cover most wave and soil characteristics in real situations. Fig. 10 illustrates the convergence of training procedure. A comparison of the predication of ANN model and theoretical results is given in Figure 11 with 5% and 10% control error. As shown in the figure, the successful rate of ANN model is 78% with 5% error, while it is 85% with 10% error. This result can be further improved by increasing the size of the database.

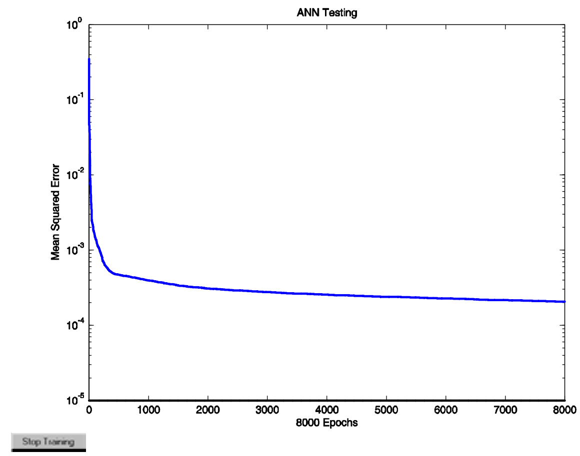

Fig. 10. Training procedure of ANN model for wave-induced liquefaction in a porous seabed.

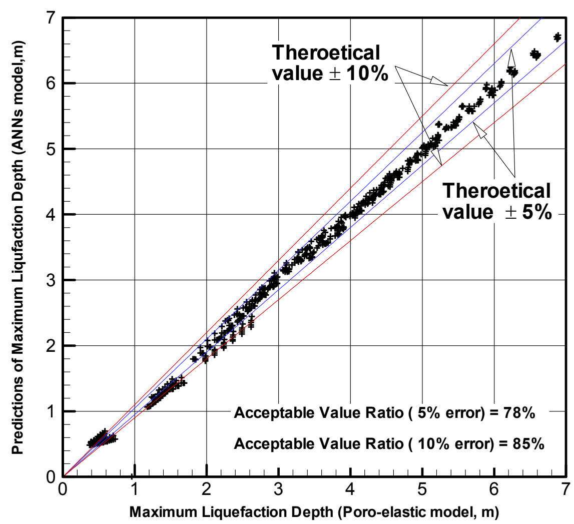

Fig. 11. Comparison of the predication of ANN model and theoretical results.

V. Conclusion

In this paper, three civil engineering problems have been re-investigated by artificial neural network model. The numerical examples demonstrate the application of ANN model in civil engineering problems.

Based on this study, ANN models are expected to be applicable to other civil engineering problems, and will have wider applications in various engineering problems.

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