Simulation of Stress-Strain Behavior of Saturated Sand in Undrained Triaxial Tests Based on Genetic Adaptive Neural Networks

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ABSTRACT

This study applies artificial neural networks (ANN) to simulate the soil stress-strain relationship observed in test data from triaxial shear testing of saturated sand. A genetic algorithm is used to obtain an optimal framework for the ANN. The results show that the proposed genetic adaptive neural network (GANN) can effectively model undrained monotonic and cyclic triaxial behaviour of saturated sand under isotropic or anisotropic consolidation. Therefore, the proposed GANN soil behaviour simulation can be used as a simple, reliable and practical analysis method.

KEYWORDS: artificial neural networks, genetic algorithm, triaxial test, soil behaviour simulation.

INTRODUCTION

Before land development, testing and understanding soil characteristics is necessary. From the results of testing on core specimens, the bearing capacity and liquefaction potential are determined. Geo-engineers base their predictions on stress-strain relationship models, but the current empirical formula is obtained by regression from limited data and is based on uncertain assumptions, since soil is a complex material.

Computer simulation of soil testing in general saves money and time and provides more information. Artificial Neural Networks have the further advantages that they can solve complex
nonlinear problems with high accuracy, and require no prior assumptions on the mathematical nature of the relationships being simulated. ANN’s are accordingly used to simulate the triaxial stress-strain relationship of saturated soil in this study, and a genetic algorithm is employed to evolve the parameters used in the artificial neural network to obtain a globally optimal solution.

Triaxial test apparatus are widely used. They subject the soil sample to lateral pressure and axial force. Pore water pressure, volume change, and stress history in each stage are measured and recorded. The testing conditions are adjusted for specific tests with different objectives. Many researchers have used the triaxial test apparatus to explore the stress-strain relationship of saturated sand (Castro, 1975; Ishihara et al., 1975; Poulos, 1981).

Neural networks are known for their ability to identify non linear relations, which are commonly encountered in the field of soil mechanics and they model the soil stress-strain relationship efficiently. However, the fact that they produce a “black box” model of unknown underlying physical mechanism, limits their usefulness for theory development, and is not completely acceptable in academic research.. Ellis et al. (1995) used an ANN to simulate the undrained triaxial stress-strain relationship of eight kinds of sand with different grain size under various consolidation conditions. The input to the network included relative density, axial strain, effective lateral stress, over consolidation ratio, uniformity coefficient, effective axial stress and pore water pressure. The variables in the output layer were effective axial stress and pore water pressure. The output layer results were immediately fed back to the input layer for the next iteration of the process. In this way, the soil stress-strain relation converged on an accurate model of the pore water pressure behavior. Penumadu and Zhao (1999) employed ANN to simulate the drained triaxial consolidation test under strain control. Forty four sets of soil data were used for network learning, and 80% of them for training, 20% of them for testing. The simulation was consistent with the test results. Zhu et al. (1998) employed a recurrent neural network to simulate residual soil behavior. The results output in the hidden layer and output layers were immediately feedback to the input layer for the next stage. An undrained triaxial consolidation test under strain control, and a drained triaxial consolidation test under stress control were both simulated effectively. This kind of network was also appropriate since it could accommodate many input variables. Hsieh et al. (2006) compared back propagation and recurrent neural networks in simulations of the triaxial stress-strain behavior of fine sand, and found recurrent networks better for modeling axial stress and pore water pressure.

The optimal framework of the networks is varied to fit the problem under investigation and no single method is applicable to all of them. Genetic algorithms offer an efficient way to select an appropriate framework. Genetic algorithms model the process of natural selection observed in evolutionary biology, mimicking aspects such as competition, differential survival, gene crossover and mutation to arrive at a solution (Holland, 1975; Goldberg, 2007). The GA’s ability to find a globally optimal solution has been applied to the search for an optimal neural network design framework. Yang et al. (2003) employed GA to evolve the parameters used in artificial neural networks used to select optimal composite materials and operation conditions. An ANN was used to analyze the materials function; and a GA was used to select optimal neural network design parameters. The results showed that the error in predicted values from genetic adaptive neural networks was 1%. Furthermore, they believed that genetic adaptive neural networks could deal with complicated optimization problems not solvable by analytical equations. Javadi (2006) used genetic adaptive neural networks with eleven different training and prediction datasets to predict the air loss in a 60mm compressed-air tunnel. The results showed that measured values and predicted values were consistent.
This study uses ANN techniques to construct a simulation model of a triaxial test, based on, and validated against triaxial test data. Both traditional trial-and-error ANN and genetic adaptive neural networks (GANN) were used to model the soil stress-strain relation from limited data. The results show that artificial neural networks can simulate the shrinkage and dilation of soil. Undrained triaxial tests for isotropic and anisotropic consolidation can also be simulated effectively. The proposed simulation framework can be used as a practical analysis method.

METHODS

Artificial Neural Network (ANN)

An artificial neural network (ANN) is an information system composed of a connected mass of simulated artificial neurons which mimic the signal processing in the brain cells of an organism. In general, an ANN consists of three layers: an input layer, a hidden layer, and an output layer. External signals are input to the network via the input layer and processed digitally by the connected nodes. The network can store signals. The final results of processing are output from the output layer. An recurrent neural network (RNN) is a network of neurons with feedback connections. The feedback between neurons gives a static ANN dynamic or short term memory. The advantages of RNN include fast learning, a stable network, short execution times, and fast convergence. The feedback in a RNN can happen in the hidden layer or the output layer. This study uses RNN with time-delay recurrent connections within the hidden layer. The input data are normalized between -1 and 1. The tansig function as shown in Figure 1 is used as a transfer function. The algorithm used is the “steepest descent” method. The connection weights of the network layers are changed proportional to the negative gradient of the performance function until the output values approach the observed values.

![Figure 1: Tansig function](image)

Genetic algorithm (GA)

In the genetic algorithm, most commonly used to solve optimization problems like this one: the parameters in a problem to be solved are recoded as a sequence, simulating the arrangement of genes in chromosomes. A population is created with a group of individuals created randomly. A fitness function is designed according to the conditions of the problem. The individuals in the population are then evaluated. The evaluation function is provided by the programmer and gives
the individuals a score based on how well they perform at the given task. Two individuals are then selected into the mating pool based on their fitness, the higher the fitness, the higher the chance of being selected. These individuals then reproduce to create one or more offspring, after which the offspring are mutated randomly. This selection procedure continues until an optimal solution has been found (Goldberg, 2007).

The parameters of a GA include population size, selection rate, crossover rate, mutation rate and a fitness function. Each chromosome consists of several genes that represent possible solutions. An algorithm is started with a set of solutions (represented by chromosomes) called a population. Chromosomes are diversified through crossover and mutation and they are selected from the population by roulette wheel selection. Uniform crossover is done according to a certain probability. The objective of the mutation element is to avoid a locally optimal solution. The fitness function is the objective function. Solutions from one population are taken and used to form a new population, hopefully better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce. The searching for an optimal solution terminates when the fitness converges to the observed value, or when successive iterations no longer produce better results, or when a fixed number of generations is reached.

Genetic Adaptive Neural Networks (GANN)

In the application of ANNs, problems such as the existence of many local minima, overtraining and failure to converge may be encountered. To improve the ANN’s performance, this study uses GA to get optimal values of the parameters used in the ANN’s framework. The basic principle is to set a weighting matrix and other parameters used in ANN’s framework as GA “chromosomes”. The fitness function to evaluate the fitness of chromosomes is the difference between predicted values and real values, i.e., the mean squared error, (MSE). GA optimization can produce an ANN framework with minimum error between predicted values and real values. (Adeli and Hung, 1995)

This study uses the numerical simulation software MATLAB as a working platform to complete GANN modules. The selection process starts with factor number $x = 5$, data record $n = 1000$, generation $g = 200$, and selection rate $s = 0.1$.

Step 1: Set parameter values or upper limits for GA and ANN framework.
Step 2: Obtain 200 ANN frameworks randomly according to the given generation.
Step 3: Load 200 set of framework parameters (number of hidden layers, neuron numbers, learning rate, training time) and 1000 sets of data to start training. Compute fitness (i.e. mean squared error between predicted values and real values)
Step 4: Check if one of the stopping criteria is satisfied. If it is satisfied, then execute step 9, otherwise continue step 5.
Step 5: Sort according to fitness and encode framework parameters. Select the first 180 set (i.e. $g \times (1-s)$) for the mating pool.
Step 6: Execute uniform crossover if the randomly generated crossover number is less than the crossover rate.
Step 7: Execute mutation if the randomly generated mutation number is less than the mutation rate.
Step 8: When the above steps are completed, one cycle of GANN is finished and 180 offspring values of framework parameters are obtained to replace original parameters
in the 21st to 200th set and shape a new generation. Repeat from step 3.

Step 9: Obtain an optimal ANN framework when validation and stopping criteria are satisfied.

The GANN optimization process shown in the flowchart in Figure 2 continues until one of the following suitable stopping criteria is satisfied.

1. Fitness reaches an acceptable value.
2. Successive iterations no longer produce better results after 1000 iterations.
3. A predetermined, fixed number of generations reached.

**Figure 2:** Flow chart of GANN

**SIMULATION OF TRIAXIAL SHEAR TEST FOR SATURATED SAND**

**Triaxial shear test**

Sand was collected from an industrial area in Mailiao Port of Taiwan. To avoid dry surface sand subject to wind action, wet sand at a depth between 30cm to 50cm was collected. The sand was washed, desalted and dried by standard methods (NIEA W407.51C) in the laboratory. The physical properties of the sand are as follows: mean grain size, $D_{50}=0.25\text{mm}$, coefficient of uniformity, $C_u=1.3$, coefficient of curvature, $C_d=5.95$, specific gravity, $G_s=2.7$, maximum void ratio, $e_{\text{max}}=1.058$, minimum void ratio, $e_{\text{min}}=0.664$. This study used a triaxial shear test apparatus (Li et al., 1988) for undrained monotonic and cyclic triaxial testing of the saturated sand under isotropic or anisotropic consolidation.

1. *Monotonic undrained shear tests*

The initial relative density ($D_r$) of the sample was around 60%. In isotropic consolidation, the different values of initial mean effective normal stresses $(p' = (\sigma_1' + 2\sigma_3') / 3)$ = 100, 200 and
300kpa) were applied. In anisotropic consolidation, initial effective lateral stress ($\sigma_3^{'}$) and initial mean effective normal stress were different. In this study, the different values of $K_c$ ($K_c = \sigma_3^{'} / \sigma_1^{'} = 0.4, 0.5$ and $0.67$) were used. The relative deviatoric stresses ($\sigma_d$) were 50, 100 and 150kpa. Shear was applied in compression and extension. The initial degree of saturation was between 95% and 99%. The test was under strain control. The range of axial strain in the monotonic loading path was 10% (compression) and -10% (extension), respectively. The number and condition of the undrained monotonic triaxial tests are shown in Table 1. The results of tests identified with the symbol “*” were used as network training data. The symbol 60 represents a relative density of 60%. The label ICU corresponds to an undrained monotonic triaxial test under isotropic consolidation, while ACU signifies an undrained monotonic triaxial test under anisotropic consolidation, and IEU an undrained monotonic extension test under isotropic consolidation.

Table 1: Number and condition of undrained monotonic triaxial shear tests

<table>
<thead>
<tr>
<th>No</th>
<th>$K_c$</th>
<th>$\sigma_3^{'}$ (kPa)</th>
<th>$\sigma_d$ (kPa)</th>
</tr>
</thead>
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<tr>
<td></td>
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</tr>
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<td>60ICU200K100</td>
<td>✓</td>
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</tr>
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<td>✓</td>
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<tr>
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<td>✓</td>
<td>✓</td>
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<td>✓</td>
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</tr>
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<tr>
<td>*60IEU300K100</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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</tbody>
</table>

2. Cyclic undrained shear tests

The loading path of cyclic undrained shear tests was simulated by applying a constant mean normal stress, $p$, while sinusoidally varying the loading in the axial direction. Prior to cyclic undrained shear, the soil sample was subjected to isotropic consolidation with different mean effective normal stresses of 50 and 250kpa, individually. Cyclic undrained shear was applied in the direction of compression. The initial relative density of the soil sample was set at around 60%. The initial degree of saturation was between 95% and 99%. The sample was subjected to cyclic shear with a period of 300 seconds and a maximum of 50 cycles. The range of axial strain was between -10% and 10%. The descriptive codes and conditions of the undrained cyclic triaxial test are shown in Table 2. The cyclic stress ratio (CSR) was the ratio of deviatoric stress and two times the initial confining pressure ($\sigma_c^{'}$). The results of tests with the symbol “*” were used as network training data. The symbol 60 represents a relative density 60%. The code Cy corresponds to an undrained monotonic triaxial test under isotropic consolidation. R represents the cyclic stress ratio. Cp is for constant $p$ test.
Table 2: Number and condition of undrained cyclic shear test

<table>
<thead>
<tr>
<th>Code</th>
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<th>p</th>
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<td>✓</td>
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<tr>
<td>*60CyR020Cp050</td>
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<tr>
<td>*60CyR020Cp250</td>
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<td></td>
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<tr>
<td>*60CyR025Cp250</td>
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<td></td>
</tr>
</tbody>
</table>

Construction of ANN and selection of parameters

1. Selection of input and output parameters for the model

This study uses a built-in RNN in the MATLAB numerical simulation software package to implement GANN modules for the simulation of soil stress-strain relationship. The selection of input and output parameters for the models with different loading paths is described as follows.

a. Monotonic shear test

Referring to the framework proposed by Zhu et al. (1998), the input parameters of the ANN for the undrained monotonic shear test are axial strain (ε1,i), deviatoric stress (σd,i), lateral stress (σ3c,i), effective lateral stress (σ3,i), and relative density (Dr). The output values of deviatoric stress (σd,i+1), lateral stress (σ3c,i+1), and effective lateral stress (σ3,i+1) in the next time step were used for training.

b. Cyclic shear test

Yun et al. (2008) referred to the method proposed by Dang and Tan (2005) and used a dynamic ANN with a hysteretic loop as shown in Figure 3. Their model could effectively simulate the cyclic behavior of engineering materials.

![Hysteretic loop](image)

**Figure 3:** Hysteretic loop (Yun et al., 2008)

To refine the model of the stress-strain relationship and stress control path, Yun et al. added the following two variables:

\[ \xi_n = \sigma_{n-1} \epsilon_{n-1} \]  

(1)
\[ \Delta \eta_{\sigma,n} = \varepsilon_{n-1} \Delta \sigma_n \]  

\( \varepsilon_n \) represents the state of the previous loading path and equals the corresponding energy produced by that loading path. \( \Delta \eta_{\sigma,n} \) is the increment of energy under stress control for the next step. The stress control behavior is shown in Figure 4.

\[ Figure 4: \text{Schematic plot of the definition of the internal variables in an ANN network under stress control (Yun et al., 2008)} \]

Referring to the framework proposed by Yun et al. (2008), the input parameters of the ANN for the undrained cyclic shear test are axial strain (\( \varepsilon_{1,i} \)), deviatoric stress (\( \sigma_{d,i} \)), deviatoric stress (\( \sigma_{d,i+1} \)) in the next time step, hysteretic loop energy (\( \xi_i \)), increment of hysteretic loop energy (\( \Delta \xi_i \)), effective lateral stress (\( \sigma_{3,i}^{'} \)), mean normal stress (\( p \)), and relative density (\( D_r \)). The output values of axial strain (\( \varepsilon_{1,i+1} \)) and effective lateral stress (\( \sigma_{3,i+1}^{'} \)) in the next time step were used as the training pair.

2. Preprocessing of data

Before the training and prediction of the ANN, the data were normalized to avoid divergence of the network due to extreme numerical values. Normalization can accelerate training speed. The normalized output values are constrained between -1 and 1 using the following formula.

\[ p_{new} = \frac{2(p - p_{min})}{p_{max} - p_{min}} - 1 \]  

Where \( p_{new} \) is normalized data; \( p_{max} \) and \( p_{min} \) are the maximum and minimum values of the original data; and \( p \) is the original data before normalization.

3. Configuration of network parameters

The network parameters for trial-and-error and genetic ANN’s are configured as follows.

a. Trial-and-error type ANN

First, the number of neurons in hidden layer was adjusted with the other parameters fixed until the minimum function was reached. The learning rate or step size that affects convergence speed was tested from 0 to 1 in increments of 0.1. ANN training was tested from 1000 to 10000
in increments of 1000. From previous studies, the optimal value for momentum producing the greatest change in convergence speed in the steepest descent method was 0.9. Besides mean square error, relative error was also used to investigate training results to avoid over learning due to too many neurons.

\textit{b. GANN}

This study used binary encoding, tournament selection and uniform crossover. The number of generations in the algorithm was always between 50 and 500. To limit the computation time and variance of the solution, the same number of generations (200) as D’Ambrosio, et al. (2006) was chosen. The selection rate was usually around 0.1. In general, the crossover rate was between 0.5 and 0.8. The higher the crossover rate, the higher the searching speed for the optimal solution. Searching with a lower crossover rate stagnated easily. In general, the mutation rate used in genetic algorithms is not high. Heng et al. (1999) proposed that mutation rate should be between 0.001 and 0.1 to avoid the loss of optimal searching ability. Searching with larger mutation rate becomes equivalent to a random search. This study took 0.1 as mutation rate.

Case study determines the upper limit for the number of neurons. When the number of neurons is greater than 30 the duration of the computations increases significantly. The mean squared error is at a minimum with 20 neurons, as used operationally in the present study, and does not change a lot when the number of neurons is increased to 30. Empirically, learning rates between 0.1 and 1 get a good convergence, so the upper limit of the learning rate used in this study is 1. Too many learning epochs may cause overtraining; while too few do not find an optimal solution. Empirically, the network converges as the learning epoch value reached 10000, which was accordingly selected as the upper limit for the present study.

4. Construction of an optimal network framework

This study uses trial-and-error and GA to train and test the ANN to construct an optimal ANN model for soil stress-strain relation in the triaxial test. The steepest descent method was used to search for the solution with minimum error. It took a long time for a trial-and-error type ANN to find an optimal solution. GA with its characteristic searching ability found an optimal solution more quickly. The optimal framework obtained from GANN is shown in Table 3. The symbol "*" indicates that MSEs of both GANN and trial and error networks have essentially the same MSE. Table 3 shows that the MSEs of both network are less than 1×10⁻³ or even the same. That is, a GANN can save time without sacrificing accuracy. The relation between MSE and training epoch of an optimized GANN is shown in Figure 5.

<table>
<thead>
<tr>
<th>No of tests</th>
<th>Input layers</th>
<th>neurons</th>
<th>Learning rate</th>
<th>Output layers</th>
<th>Training epoch</th>
<th>MSE (GANN)</th>
<th>MSE (Trial &amp; Error)</th>
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</tr>
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</table>
Since a GANN is better than a trial-and-error type ANN, the following simulation data are all from GANN.

**Simulation of test results**

1. **Isotropically consolidated undrained monotonic compression test**

   The input parameters axial strain, deviatoric stress, lateral stress, effective lateral stress and relative density were the values used in the experiments. The output values of deviatoric stress, lateral stress and effective lateral stress in the next time step were used for training. Simulation number 60ICU100K100 is shown in Figure 6 as an example. The symbol “+” represents data from the triaxial test. The solid line indicates the GANN simulation result. At the beginning of simulation, the initial conditions of the live test were input. The comparison of the data from simulation and experiment, in Figures 6(a), (b) and (c), shows that the relations for deviatoric stress, lateral stress and effective lateral stress versus axial strain are consistent between simulation and experiment. Figure 6(d) shows that the relationship between mean effective normal stress and deviatoric stress, the state of contractive-dilative transition (Chen and Kutter, 2009) (called “phase transformation” by Ishihara et al., 1975) and the linear trend are consistent between simulation and experiment.
Figure 6: Comparison of experimental results and simulated results in undrained monotonic compression test under isotropic consolidation (60ICU100K100)

To understand the predictive ability of the proposed ANN model of the triaxial shear test, the predicted results, as shown in Figure. 7, and experimental results (test number 60ICU200K100) for the case with confined pressure 200kpa were compared, where the predicted results used experimental data from confined pressure 100kpa (test number 60ICU100K100) and 300kpa (test number 60ICU300K100) as training data. In the beginning of the simulation for the case with confined pressure 200kpa, the initial and only simulation input was the initial conditions of the experimental test. Figures 7(a) and (b) show the relations of deviatoric stress versus mean effective normal stress and deviatoric stress ratio \( (q/p') \) versus mean effective normal stress, respectively. The symbol “+” represents data from training. The dash line indicates experimental results; the solid line is for simulation results. Figure 7(a) shows that the location of phase transformation from simulated data and experimental data are almost coincident. The extension of the linear portion for training data, experimental data and predicted data all pass the origin with similar slope. Figure 7(b) shows that the predicted maximum deviatoric stress ratio \( (q/p')_{max} \) is also close to the experimental data. In the experimental data, plastic shrinkage and extension occur, respectively, near deviatoric stress values of 100kpa and 200kpa. These phenomena are not found in the predicted data. This may be because these phenomena are not obvious in training data, either.
2. Isotropically consolidated undrained monotonic extension test

Figure 8 shows the comparison between experimental results (test number 60IEU100K100) and simulation results for an undrained monotonic extension test under isotropic consolidation. Experimental data input to the simulation was limited to the starting conditions of the experimental test. The symbol “+” represents data from experimental results. The solid line indicates simulation results. The simulated and experimental output shown in Figures 8(a) and (b), show that the relations for deviatoric stress and effective lateral stress versus axial strain are consistent between simulation and experiment. The relationship between lateral stress and axial strain shows that, for a given value of axial strain, simulated lateral stresses are greater than experimental lateral stresses by up to 5%. However the trends of increase and decrease are the same for experimental and simulated data. Figure 8(d) shows that the location of phase transformation is consistent between simulated and experimental data. The extension of the linear portion of the line of phase transformation is consistent between experimental and simulated data.
Figure 8: Comparison of experimental and predicted data for an undrained monotonic extension test under isotropic consolidation (60IEU100K100)

To understand the predictive ability of the proposed ANN model of the extension test, the predicted results, as shown in Figure 9, and experimental results (test number 60IEU200K100) for the case with confined pressure 200kpa were compared, where the predicted results used experimental data from confined pressure 100kpa (test number 60IEU100K100) and 300kpa (test number 60IEU300K100) as training data. The input parameters axial strain, deviatoric stress, lateral stress, effective lateral stress and relative density were the observed values from the experiments. The output values of deviatoric stress, lateral stress and effective lateral stress in the next time step were used for training Figures 9(a) and (b) show relationship between deviatoric stress and mean effective normal stress and deviatoric stress ratio \((q/p')\) and mean effective normal stress, respectively. The symbol “+” represents data from training. The dash line indicates experimental results; the solid line represents simulation results. Figure 9(a) shows that the phase transformation plots from predicted data, training data and experimental data are almost coincident. The extension of the linear portion for training data, experimental data and predicted data all pass the origin with the same line. Figure 9(b) shows that the predicted deviatoric stress ratios at phase transformation are also the same as experimental data and the predicted maximum deviatoric stress ratio are also close to the experimental data. However, the deviatoric stress (about 120kPa) at phase transformation in the predicted data is greater than the deviatoric stress
(about 70kPa) in the experimental data. This indicates that the predicted value for plastic shrinkage is a little smaller than the experimental value. In Figure 9(b) there seems to be an unusual peak that also appeared in the research results of Chen and Kutter (2009) and was thought to be due to a small error in the zero offset for the pore water pressure measurement.

![Figure 9: Comparison between experimental data and predicted data for an undrained monotonic extension test under isotropic consolidation](image)

3. Anisotropically consolidated undrained monotonic compression test

The simulation was initialized with the initial conditions of the experimental test, the only input from the test to the simulation. Figure 10 compares experimental predicted data for the undrained monotonic compression test under anisotropic consolidation. The symbol “+” represents data from experimental results. The solid line indicates simulation results. Figures 10(a) and (b) show that the relations for deviatoric stress, lateral stress and effective lateral stress versus axial strain are consistent between simulation and experiment. The relation of mean effective normal stress versus axial strain shows that the linear portion of the simulated results plot is consistent with the experimental results.
To understand the predictive ability of the proposed ANN model of the extension test, the predicted and experimental results (test number 60ACU100K050) for the case with $K_c = 0.5$ were compared, where the predicted results used experimental data from $K_c = 0.4$ (test number 60ACU100K040) and $K_c = 0.67$ (test number 60ACU100K067) as training data, as shown in Figure 11. The input parameters axial strain, deviatoric stress, lateral stress, effective lateral stress and relative density were the observed values from the experiments. The output values of deviatoric stress, lateral stress and effective lateral stress in the next time step were used for training. Figures 11(a) and (b) show the relations of deviatoric stress versus mean effective normal stress and deviatoric stress ratio versus mean effective normal stress, respectively. The symbol “+” represents data from training. The dash line indicates experimental results; the solid line is for simulation results. Figure 11(a) shows that the trend of the predicted data is close to training data, though the difference is larger than for other simulations. This may be because the range for prediction exceeds the range of the experimental data. This study also compares the differences in deviatoric stress ratio between various sources. Figure 11(b) shows deviatoric stress ratios of 1.43, 1.44 and 1.57 for training data, predicted data and experimental data, respectively. The average shear stress ratios in the linear portion of the plot are 1.36, 1.4 and 1.54, respectively.
Figure 11 Comparison between experimental data and predicted data for undrained monotonic compression test under anisotropic consolidation

4. Isotropically consolidated undrained cyclic shear test

Figure 12 shows the comparison between experimental results (test number 60CyR025Cp250) and simulation results for an undrained cyclic shear test under isotropic consolidation. The simulation was initialized with the starting values from the experimental test. The symbol “+” represents experimental results, while the solid line indicates simulation results. Figure 12(a), shows that the trend of axial strain change is consistent for simulation and experiment. The simulated axial strain at failure of test sample (strain up to -4%) is a little smaller than the observed experimental value. The simulation and experimental results agree again when strain is up to +6%, perhaps because axial strain did not change a lot during the test but changed significantly at failure of the soil sample, causing error in the feedback of the next time step due to a smaller axial strain in the previous time step. Figure 12(b) shows the consistent effective lateral stress history for experimental results and simulation results. Although the relation of axial strain versus deviatoric stress, as shown in Figure 12, is not exactly coincident between experimental and simulation results, the variation between the curves is acceptable. The average effective lateral stress for experimental results and simulation results decrease to zero gradually with the increasing axial strain, as shown in Figure 12(d), due to the sustained increase of pore water pressure. Figure 12(e) shows that the trend of the two paths for compression or extension direction is similar but the location of phase transformation [phase transition?] is lower for simulated data.
Figure 12: Comparison between experimental data and predicted data for undrained cyclic shear test under isotropic consolidation (60CyR025Cp250)

By using the test data of the undrained cyclic shear test under isotropic consolidation and the corresponding simulation results, as shown in Table 2, the consistent relation of cyclic stress ratio versus number of cycles to cause 3% axial strain is shown in Figure 13. The number of cycles to cause 3% axial strain decreases with increasing CSR.
Figure 13: The relation of cyclic stress ratio versus number of cycles to cause 3% axial strain

CONCLUSIONS

This study used triaxial test data of sutured sand and GANN to simulate soil stress-strain relations. The conclusions are summarized as follows.

1. Two types of triaxial test loading were included in this study: monotonic shear test under strain control and cyclic shear test under stress control. Under strain control, axial strain, deviatoric stress, lateral stress, effective lateral stress and relative density were chosen as inputs to the neural network. Output values for deviatoric stress, lateral stress and effective lateral stress in the next time step were used for training. Under stress control, axial strain, deviatoric stress, effective lateral stress, mean normal stress, relative density, hysteretic loop energy, increment of hysteretic loop energy and deviatoric stress in the next time step were chosen as inputs to the neural network. The output values of axial strain and effective lateral stress in the next time step were used for training. The GANN simulations were initialized with the starting conditions observed in the experimental tests they were simulating. The results showed that GANN could simulate triaxial test under strain or stress control very well.

2. The running time for GANN is half of that for trial-and-error type ANN, which means that GANN is effective in time saving.

3. A lower MSE would normally be expected for a GANN with more neurons. However, the MSE did not decrease when more than 20 neurons were used in cyclic shear test under strain control path. The time for convergence increase and the accuracy of the simulation decrease when the number of neurons is greater than 20.

4. Although a lower MSE indicates efficient training of the ANN, but does not guarantee an accurate simulation. This might be due to the magnification of error produced in the feedback stage during validation of the network. Therefore, not only MSE but also relative error should be investigated in the determination of the number of the hidden layer in optimal framework of the network.

5. The locations of the phase transformation were almost on the same phase transformation line for predicted experimental data for isotropic compression/extension or anisotropic...
compression test. The extension of the linear portion for training, experimental and predicted data all pass the origin with a similar slope. The predicted maximum deviatoric stress ratio was also close to the experimental data. However, the obvious phenomenon of plastic shrinkage in the experimental data for the undrained compression test under isotropic consolidation did not occur in the simulated data. This might due to the subtle phenomenon of plastic shrinkage-extension in the training data. The predicted data was close to the training data but not the experimental data in the undrained compression test under anisotropic consolidation, since the prediction corresponding to experimental data values is out of the range of the training data. The predicted values were also a little smaller than the experimental data for undrained extension test under isotropic consolidation.

6. The trend of axial strain or effective lateral stress history is consistent between simulation and experimental results for undrained cyclic shear test under isotropic consolidation. The differences of the curves in axial strain versus deviatoric stress are within acceptable limits. The average effective lateral stress decreased to zero gradually for all experimental data and simulated data. Although the trends for compression or extension are similar for mean effective normal stress versus deviatoric stress, the location of the phase transformation is lower for simulated data.

7. The relation of cyclic stress ratio versus the number of cycles to cause 3% axial strain is consistent for predicted data and experimental data. The number of cycles to cause 3% axial strain decreases with increasing CSR.

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