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Applying the Artificial Neural Network to Predict the Soil Responses in the DEM Simulation

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Abstract. This paper aims to bridge the soil properties and the soil response in the discrete element method (DEM) simulation using the artificial neural network (ANN). The network was designed to output the stress-strain-volumetric response from inputting the soil properties. 31 biaxial shearing tests with varying soil parameters were generated using the DEM simulations. Based on these 31 training samples, a three-layer neural network was established. 2 extra samples were generated to examine the validity of the network, and the predicted curves using the ANN were well matched with those from the DEM simulations. Overall, the ANN was found promising in effectively modelling the soil behaviour.

1. Introduction

The soil behaviour of is significantly regulated by the soil properties and testing condition, such as the initial void ratio [1] and particle shape [2]. These factors interact during the testing process and collectively determine the soil response. However, the associated mechanism is not complicated and an effective way to quantify the effects of soil properties is needed. One of the feasible approaches is to implement the artificial neural network (ANN). In Ellis et al. [3], the ANN was first applied in modelling the stress-strain response of sands with varying grain size distribution and stress history. Penumadu and Zhao [4] considered more parameters in their ANN model, e.g., the grain shape and size distribution. Besides, this technique has also been adopted to evaluate the soil liquefaction resistance [5] and slope stability [6].

Inspired by these pioneer works, in this study, an attempt was made to effectively bridge the soil properties and the soil behavior in the discrete element method (DEM) simulation; that is establish an artificial neural network, which can output the mechanical response from the input soil parameters. This paper will first introduce the details of preparing training samples in the DEM simulation. Then, the network will be established using the training samples. The validity and efficiency of this ANN-based model will be demonstrated by its performance in predicting the response of the untrained samples.

2. Details of the DEM simualtion

The discrete element method (DEM), can numerically generate soil samples and obtain the relevant mechanical responses. An ANN-based model was designed to predict the stress-strain-volumetric responses for the soil samples from the DEM simulation. A total number of 31 biaxial shearing tests have been conducted in the DEM simulation. In the simulations herein, the particles interact via the preset contact model, which includes the Hertz-Mindlin model in the normal and tangential direction and the rolling resistance model in the rotational direction. The normal and tangential contact stiffnesses, k_n and k_s, are determined as in equation (1),

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$$\begin{cases} k_n = \dfrac{G\sqrt{2RU_n}}{(1-\upsilon)} \\ k_s = \dfrac{2(1-\upsilon)}{2-\upsilon} k_n \end{cases} \tag{1}$$

where G and υ are the shear modulus and Poisson's ratio of the particles, respectively; R is the equivalent particle radius; and U_n is the contact overlapping. Then, contact force/torque is aroused due to the contact movement, as expressed in equation (2),

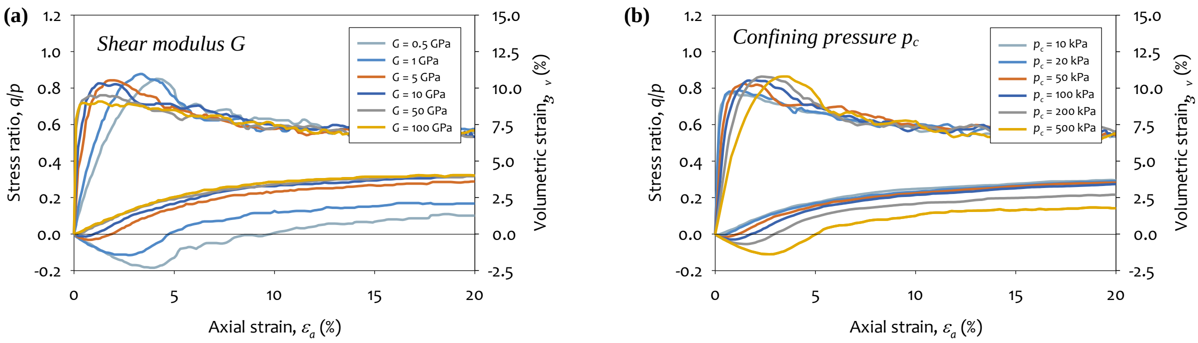
$$\begin{cases} P = 2k_n U_n / 3 \\ \Delta Q = k_s \Delta U_s \text{ and } |Q| \le \mu P \\ \Delta M = 2J_n P \Delta U_r \text{ and } |M| \le \eta RP \end{cases} \tag{2}$$

where P, ΔQ and ΔM are the contact normal force, incremental tangential force and incremental torque, respectively; μ is the friction coefficient; J_n is the rolling coefficient; and η is the rolling sliding coefficient; ΔU_s and ΔU_r are the incremental tangential and rolling displacement.

Table 1. Parameters used in the DEM simulation for ANN training.

	No.	G (GPa)	p_c (kPa)	υ	J_n	η	μ_c †	μ
Ref	1	10	50	0.25	0.0	0.0	0.0	0.5
G	2-6	0.5, 1, 5, 50 and 100	50	0.25	0.0	0.0	0.0	0.5
p_c	7-11	10	10, 20, 100, 200 and 500	0.25	0.0	0	0.0	0.5
J_n	12-16	10	50	0.25	0.05, 0.1, 0.5, 1 and 2	0.25	0.0	0.5
η	17-21	10	50	0.25	0.5	0.05, 0.1, 0.5, 1 and 2	0.0	0.5
μ_c	22-26	10	50	0.25	0.0	0	0.1, 0.2, 0.3, 0.4 and 0.5	0.5
μ	27-31	10	50	0.25	0.0	0	0.0	0.1, 0.2, 0.8, 1 and 2

†μ_c is the friction coefficient in the consolidation stage. A lower value makes the initial packing denser and it is equivalent to effect of initial void ratio.



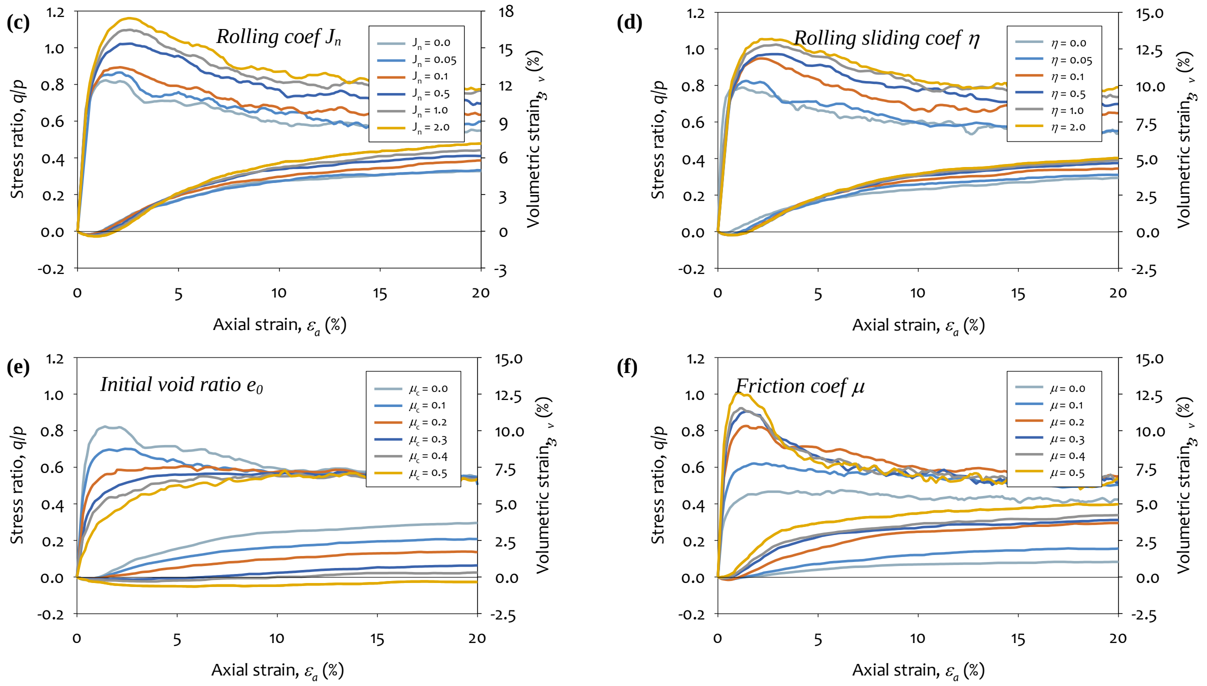


Figure 1. Stress-strain-volumetric responses with varying parameters: (a) shear modulus; (b) confining pressure; (c) rolling coefficient; (d) rotational sliding coefficient; (e) initial void ratio; and (f) friction coefficient.

In these 31 tests, the influences of particle shear modulus, confining pressure, rolling coefficient, rolling sliding coefficient, initial void ratio and friction coefficient on the soil response were examined. Parameters used in the simulations are summarized in Table 1. A reference test was set and six sections were classified, in which only one parameter was changed compared to the reference one. Figures 1(a) to 1(f) illustrate the stress-strain-volumetric responses for each section. Each parameter significantly contributes to the response, but their influences are different. In figure 1(a), with the shear modulus increasing, the peak stress came at a smaller strain with a lower value, and the initial contraction was reduced whereas the dilation enhanced. On the contrary, when the confining pressure was raised, as in figure 1(b), the peak stress then came larger and later and the dilation was inhibited. Obviously, the soil parameters intricately interact during the shearing stage. Such influences from the soil properties may not be quantifiable properties in the conventional way, i.e., the constitutive modeling. Thus, a better modeling method, i.e., the artificial numerical network was adopted.

3. Artificial Neural Network Modeling

Soil parameters of these 31 samples and the associated responses were used to train the artificial neural network (ANN), which was designed to output the stress-strain-volumetric curve by inputting the soil parameters. The ANN is a 3-layer model, including 6 input parameters, 1 hidden layer with 41 neurons and 2 output curves. The associated toolbox in Matlab was utilized and the data are randomly divided for training (87%, 67 samples), validation (6%, 2 samples) and testing (6%, 2 samples) uses. When training the ANN, the “Scaled Conjugate Gradient” algorithm was used since it requires less memory and training stops when generalization stops improving. 112 iterations were carried out and parameters for connecting the neurons in the network finally converged. The ANN was well trained in this process since the fitting quality, i.e. mean square error, has reached to 0.0009. In order to verify the validity and efficiency of this trained ANN, two extra DEM simulations were carried out. The parameters in these simulations were different from those of the training samples, but within the range scope of them. Parameters for ANN verification are summarized in table 2. These sets of parameters were then input into the ANN model and the predicted stress-strain-volumetric curves were obtained. Meanwhile, the responses were also obtained from the DEM simulation using these parameters.

Table 2. Parameters used in the DEM simulation for ANN verification.

No.	G (GPa)	p_c (kPa)	υ	J_n	η	$\mu_c\,(e_0)$	μ
32	7.5	0.25	0.45	0.3	25	0.15	0.55
33	25	0.25	0.6	0.4	50	0.5	0.5

Comparison is plotted in figure 2(a) and figure 2(b) and good agreements between the actual responses from the DEM simulations and the predicted responses from the ANN can be observed. Despite the minor discrepancies, the general trends between the curves from DEM and ANN are quite similar. Therefore, by using this ANN model, the repetitive DEM simulation work can be avoided since the results are predictable now. This ANN model again demonstrates that soil parameters collaboratively contribute to the soil response during the test process and it provides a promising tool for effectively and efficiently modeling the soil behavior. Also, it may be an effective way for the model calibration in the simulation since the ultimate parameters can be obtained by try and error.

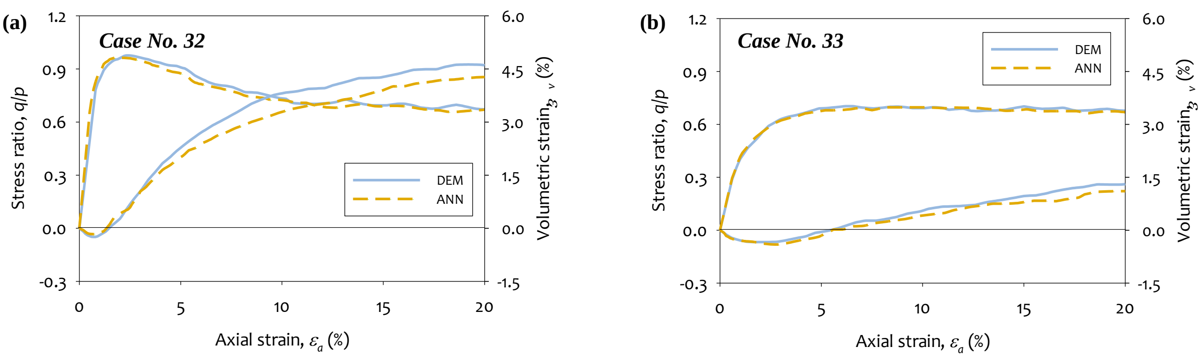


Figure 2. ANN verification using two extra DEM simulations: (a) Case No. 32 and (b) Case No. 33.

4. Conclusions

In this paper, the artificial neural network (ANN) was applied to predicting the soil mechanical response in the discrete element method (DEM) simulation. 31 DEM samples were prepared for the ANN model training. The soil parameters were the inputs and the stress-strain-volumetric response were the output in this network. This ANN model was 3-layer model with 6 input, 41hidden and 2 output neurons. It was well trained and the predicted results using this network matched well with the actual ones from the extra two DEM simulations. Overall, the ANN is a promising tool for effectively and efficiently modeling the soil behavior and thus repetitive simulation work can be reduced.

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