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Modelling using ANN and RNN Approach for Shearing Behavior of Residual Soil

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Abstract. Many researchers with the help of Artificial Neural Network (ANN)have tried to capture the nonlinear behavior of various inputs and output parameters relevant to soil deformation problems. The objective of this study is to calibrate neural network models for prediction of shear stress-shear strain behavioras per the Mohr-Coulomb criterion, from basic soil properties. ANN with Feed-forward Back propagation method and Recurrent Neural Network (RNN) training method is used to predict the desired output. The direct shear test is commonly used by geotechnical engineers to obtain the cohesion and angle of internal friction for field soils. The soil sample used in the experiment is 425 µm passing and also it includes soil as the main constituent with added bentonite of variable proportions. This research aims at investigating the reliability of using the direct shear test for soil sample with different percentage of bentonite with 10% water content by weight under an adequate shearing strain. The test is performed with 3 different loading conditions (a) 0.5 kg/cm^2, (b) 1 kg/cm^2 and (c) 1.5 kg/cm^2.On comparing experimental results with predicted results obtained from the ANN model and RNN model, it is found that the RNN model gives better results.

Keywords: Recurrent Neural Network, Artificial Neural Network, Direct Shear test, Mohr-Coulomb, Shear parameters.

1 Introduction

Recently Geotechnical Engineers are mainly concern about the strength parameters of the soil and the settlements of different types of foundation and it has a crucial role to support different types of structures like buildings, dams power plants etc. Therefore, to avoid the superstructure and foundation failures the shear strength properties must be well understood (Omotoso et al., 2011). It is the property of the soil that enables the soil to keeps it in its state when the surface is not even or when there is a shear force acting on the specimen. These shear strength parameters can be calculated either in the field or in the laboratory. The tests done in the laboratory may include an unconfined compression test, triaxial test, vane shear test, a direct shear test. A direct shear test is used for the calculating the soil strength parameters which includes the angle of internal friction (Ø) and cohesion c (kPa) shown in equation 1.

The shear strength, τ of soil in terms of effective stress(σ') is:

$$\tau = c + \sigma' tan\phi \qquad (1)$$

The slope expressed in degrees is the angle of shearing resistance or the internal angle of friction (Ø) and the intercept is its cohesion *c* (kPa) (Arora, 1988; Murthy, 2008; Mollahasani et al., 2011). The angle of internal friction represents the interlocking between the soil particles whereas cohesion is mainly due to the intermolecular bond between the adsorbed water surrounding each grain, especially in fine-grained soils (Murthy 2008; El-Maksoud, 2006). Soils with high plasticity have a lower angle of internal friction and higher cohesion value; Conversely, as the soil grain size increases, the soil internal friction angle increases and its cohesion decreases. Grain size distribution is shown in Fig 1.

However, experimental determination of the strength parameters is extensive, cumbersome and expensive. Further, it is not always possible to manage and do the tests in every new situation. In order to successfully deal with such problems, artificial intelligence based methods have been developed to estimate shear strength parameters (Mousavi et al., 2011). As per Sorensen and Okkels (2013), empirical relations are widely used in geotechnical engineering practice as a tool to estimate the engineering properties of soils. Considering these, an experimental study is done to generate a data set of geotechnical properties of soil. This paper deals with the relationship of geotechnical properties of soil with shear strength parameters, and to develop neural network based model for its prediction.

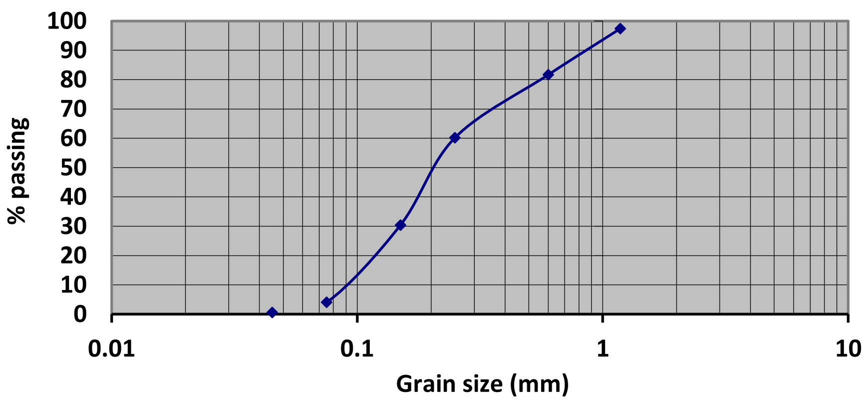


Fig. 1. Sieve size distribution.

2 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) can be described as a computational tool whose design is motivated by the designs and functioning of human brains and components. An ANN is a system composed of a number of artificial neurons. These neurons have multiple numbers of input parameters and single or multiple output parameters to perform elementary calculations.

The particular specification of ANN is that the unit learns from an example in a similar manner to the biological neurons. Biological neurons receive input from sources; merge them in a way to perform a nonlinear operation as result. ANN is similar to the traditional statistical models in which model parameters (i.e. connection weights) are adjusted to calibrate a model called *learning* or *training* (Gupta et al. 2006). If the units are organized into multiple layers, then all units of each layer are connected with subsequent layers and feedforward network is developed.

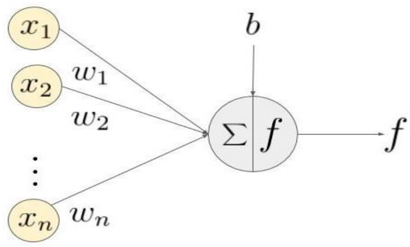


Fig. 2. The relationship between the input and output vector in the artificial neuron.

Each layer in a network contains a satisfactory number of neurons depending on its application. The neurons in a layer are linked to the neurons in the next succeeding layer, and each link carries a weight value. The number of neurons in the input layer relies upon the number of input data, the output and hidden layers process the data. The number of hidden layers and their neurons is often decided by trial and error method. The number of neurons in output layers is decided based on the application. Each hidden neuron responds to the weighted inputs, it collects from the linked neurons from the previous input layer.

Once the combined outcome on each hidden neuron is determined, the activation at this neuron is determined by a transfer function. For transfer function any nonlinear differentiable function can be used, but a sigmoid function is broadly used, nevertheless, there are many other functions (Schalkoff, 1997). The sigmoid function restrains the outputs of a network between 0 and 1. The input vector (X_m^n) is related output vector (X_j^{n+1}) by the below equation and can be described as shown in Fig.2.

$$x_j^{n+1} = F\left(\sum_i W_{jm}^n X_m^n\right)$$

where $F(x) = \frac{1}{1+e^{-x}}$ log sigmoid function.

3 Recurrent Neural Network (RNN)

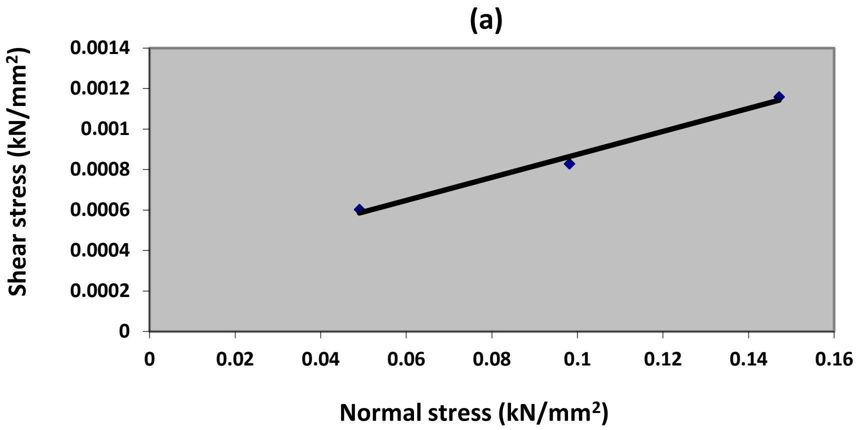
In this case, a Recurrent Neural Network (RNN) model is found to be more effective than standard backpropagation network in simulating and predicting non-linear shear behavior of residual soil. The direct shear test was performed on residual soil are used to train the models developed in this study. The good simulation and prediction of stress-strain behavior prove that the RNN approach can be effectively used to model complex soil behavior (Jian-Hua Zhu et al., 1997)[6]. A fair agreement between experimental and the RNN model is observed. The significant variations inherent in the soil behavior are successfully captured by using an appropriate algorithm function and architecture of the neural network.

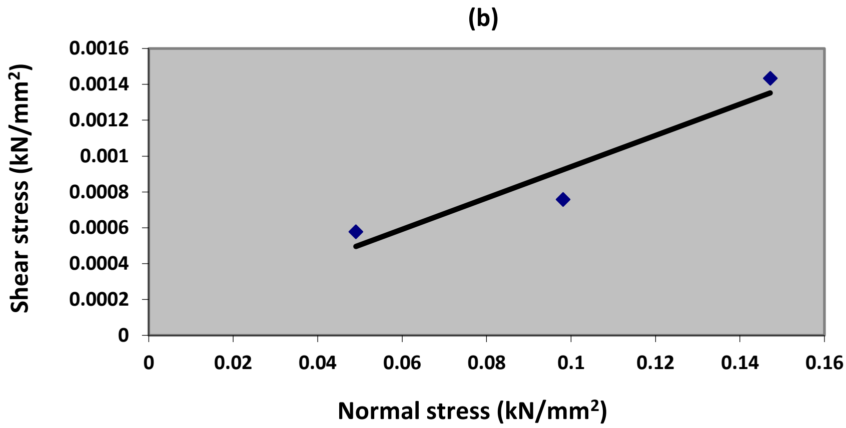
4 Experimental Setup

Fig. 3. Direct shear test apparatus.

The soil sample is taken from F-block, Pandit Deendayal Petroleum University, Gandhinagar which is under construction. Sieve analysis is performed to find the gradation of soil. For Direct Shear Test (shown in Fig 3 and Fig 4.) the soil mass which is used for the experiment is passing 425µm sieve. The experiment is performed in 6 batches of soil starting with 0% bentonite to 50% bentonite addition with soil and the water content was taken as 10% for each batch. For each batch 3 direct shear test is performed with 0.5kg/cm^2, 1 kg/cm^2 and 1.5kg/cm^2 normal stresses. Moisture content is evaluated for each set of soil samples. A total of 18 shear tests are performed with the help of the Direct Shear Test apparatus. The angle of internal friction Φ (^{o}) and cohesion c (kPa) is calculated for each set of test samples (Fig.5).

Fig. 4. Direct shear mould.


(a)
0.0014
0.0012
0.001
0.0008
0.0006
0.0004
0.0002
0
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
0.16
Shear stress (kN/mm²)
Normal stress (kN/mm²)


(b)
0.0016
0.0014
0.0012
0.001
0.0008
0.0006
0.0004
0.0002
0
0
0.02
0.04
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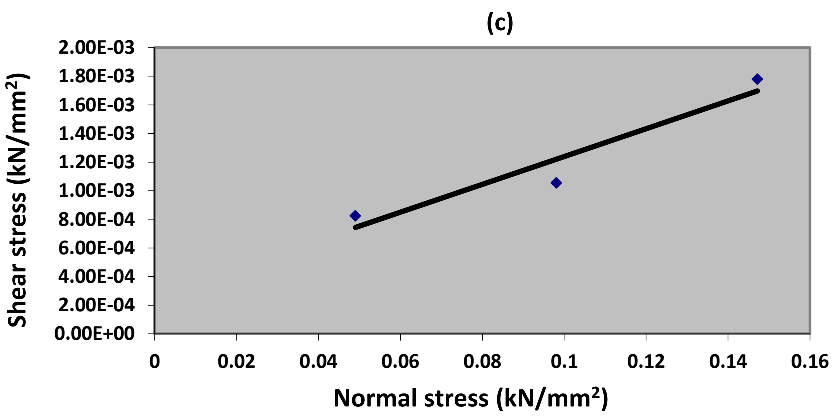
0.08
0.1
0.12
0.14
0.16
Shear stress (kN/mm²)
Normal stress (kN/mm²)


(c)
2.00E-03
1.80E-03
1.60E-03
1.40E-03
1.20E-03
1.00E-03
8.00E-04
6.00E-04
4.00E-04
2.00E-04
0.00E+00
0
0.02
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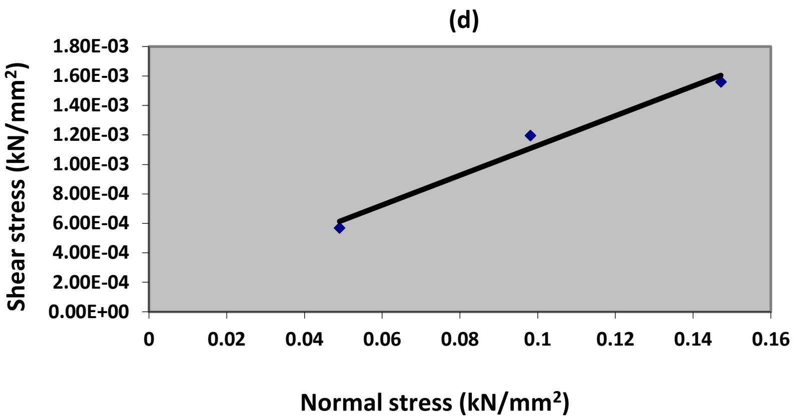
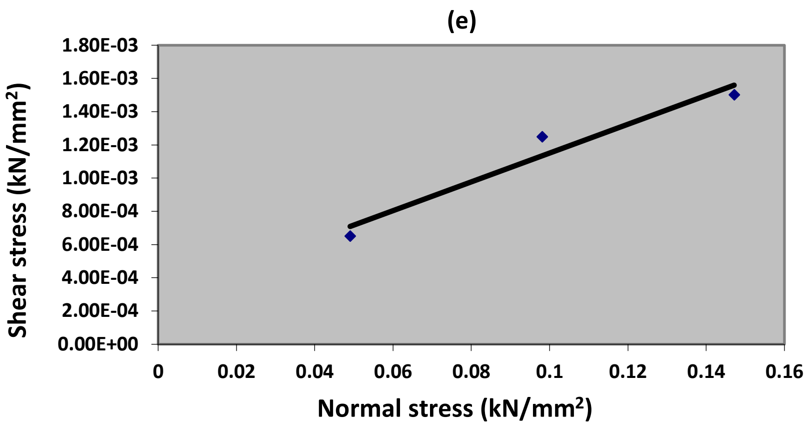
Shear stress (kN/mm²)
Normal stress (kN/mm²)





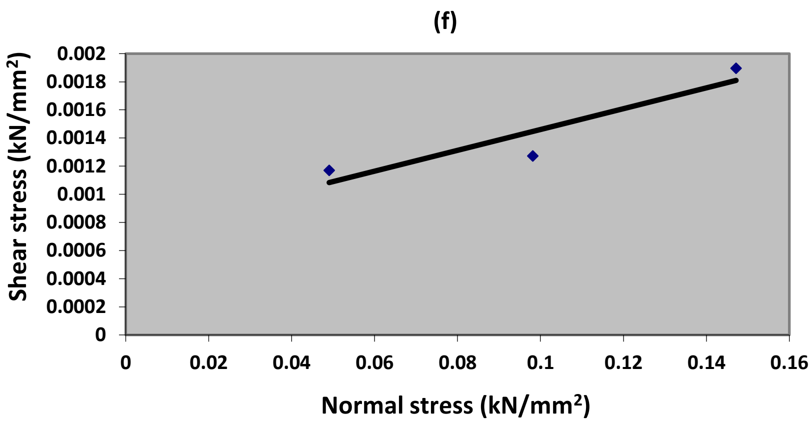


Fig. 5. Relation between Normal stress and shear stress for; (a) for 0% bentonite, (b) for 10% bentonite, (c) for 20% bentonite, (d) for 30% bentonite, (e) for 40% bentonite, (f) for 50% bentonite

3.1 ANN

The MATLAB-Neural Network Tool is used to do the necessary computing work. All computations has been carried out on a windows 10 server with Intel Xeon E5 CPU (10 core). 16GB of RAM and 4GB Dual Nvidia Quadro K1200.

In this project we have selected 6 input parameters from Direct Shear Test that is moisture content, clay(Bentonite) content, cohesion (c), angle of internal friction(Φ), normal stress(σ') and shear strain whereas output parameter selected is shear stress(τ); an interdependency between the input and the output is established keeping in mind the contribution of all input which contributed for good training of the data. Out of the 662 Direct shear result, 0%,10%,20%,30%,50% clay content soil sample batches are chosen for training sets and 40% is used for predicting the data relation in the training network. The Mean Square error (R) value obtained is equal to 0.96775; for developing the network shown in Fig.6. various permutations were tried. Partial data sets are given in Table 1 and Table 2 used for training and testing data sets respectively.

Table 1. Training data sets for ANN model in summarized form.

Moisture Content	Clay content	Cohesion	Angle of internal friction	Normal Stress	Shear strain	Shear stress
%	*%*	*kN/mm²*	*degree*	*kN/mm²*	*mm/mm*	*kN/mm²*
10	0	0.0003	18.678	0.04905	0.011	0.0002174
10	0	0.0003	18.678	0.0981	0.014	0.0005184
10	0	0.0003	18.678	0.14715	0.017	0.000719
10	10	0.00007	28.533	0.04905	0.008	0.000223
10	10	0.00007	28.533	0.0981	0.022	0.0006577
10	10	0.00007	28.533	0.14715	0.036	0.0010368
10	20	0.0003	31.799	0.04905	0.011	0.00068
10	20	0.0003	31.799	0.0981	0.025	0.0009977
10	20	0.0003	31.799	0.14715	0.031	0.0017837
10	30	0.0001	33.154	0.04905	0.014	0.0005017
10	30	0.0001	33.154	0.0981	0.021	0.0010591
10	30	0.0001	33.154	0.14715	0.037	0.0015161
10	50	0.0007	24.236	0.04905	0.018	0.0010089
10	50	0.0007	24.236	0.0981	0.029	0.0011092
10	50	0.0007	24.236	0.14715	0.045	0.0018952

Table 2. Testing data sets for ANN model in summarized form.

Moisture Content	Clay content	Cohesion	Angle of internal friction	Normal Stress	Shear strain	Shear stress
%	*%*	*kN/mm²*	*degree*	*kN/mm²*	*mm/mm*	*kN/mm²*
10	40	0.0003	28.533	0.04905	0.017	0.000474
10	40	0.0003	28.533	0.0981	0.028	0.00112
10	40	0.0003	28.533	0.14715	0.043	0.001332

While choosing a number of Neurons in particular hidden layer and number of hidden layers in activation function, the output varies significantly.

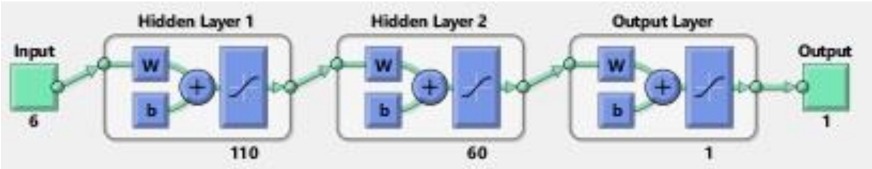


Fig. 6. ANN model.

3.2 RNN

For RNN, again 6 input parameters from Direct Shear Test were chosen that is moisture content, clay content, cohesion (*c*), angle of internal friction (*Φ*), normal stress and shear strain whereas output parameter as shear stress, the training network include 0%, 10%, 20% of clay content soil samples batches as input whereas selected datasets of 30%, 40%, and 50% batch were used as simulation shown in Fig 7. i.e., 30% at 0.5 kg/cm^2 normal stress; 40% at 0.5 kg/cm^2 and 1.5 kg/cm^{2}normal stress; and 50% at 1 kg/cm^2 and 1.5 kg/cm^{2}normal stress. The data sets for training and testing stages are given in Table 3 and Table 4 respectively in summarized manner.

Table 3. Training data sets for RNN model in summarized form.

Moisture Content	Clay content	Cohesion	Angle of internal friction	Normal Stress	Shear strain	Shear stress
%	*%*	*kN/mm^2*	*degree*	*kN/mm^2*	*mm/mm*	*kN/mm^2*
10	0	0.0003	18.678	0.04905	0.015	0.000345588
10	0	0.0003	18.678	0.0981	0.017	0.000629862
10	0	0.0003	18.678	0.14715	0.026	0.000897414
10	10	0.00007	28.533	0.04905	0.011	0.0002787
10	10	0.00007	28.533	0.0981	0.027	0.000719046
10	10	0.00007	28.533	0.14715	0.039	0.00105906
10	20	0.0003	31.799	0.04905	0.016	0.000785934
10	20	0.0003	31.799	0.0981	0.027	0.00103119
10	20	0.0003	31.799	0.14715	0.030	0.001772532
10	30	0.0001	33.154	0.0981	0.026	0.001159392
10	30	0.0001	33.154	0.14715	0.039	0.001571868
10	40	0.0003	28.533	0.0981	0.024	0.001047912
10	50	0.0007	24.236	0.04905	0.016	0.00097545

To develop the network, training method is changed to recurrent neural network to compare the change in the predicted values of datasets with ANN prediction. In this network, the data points were divided into two equal layers, one for training and another for simulating. The 1st layer was trained to have an initial delay layer as zero, after training the network; the final delay layer obtained was used as an initial delay layer for repeating the training process. The 2nd layer is used as simulation which included 30%, 40% and 50% clay content soil sample batches. It has been observed that the predicted results were quite similar to the original one.

Table 4. Testing data sets for RNN model in summarized form.

Moisture Content	Clay content	Cohesion	Angle of internal friction	Normal Stress	Shear strain	Shear stress
%	*%*	*kN/mm²*	*degree*	*kN/mm²*	*mm/mm*	*kN/mm²*
10	30	0.0001	33.154	0.04905	0.019	0.000552
10	40	0.0003	28.533	0.04905	0.013	0.000435
10	40	0.0003	28.533	0.1471	0.051	0.00146
10	50	0.0007	24.236	0.0981	0.031	0.001171
10	50	0.0007	24.236	0.14715	0.044	0.00189

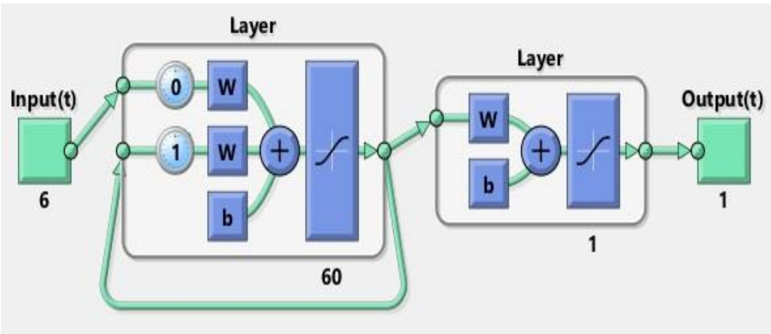


Fig. 7. RNN model.

4 Simulation Results

The proposed solutions have been designed using the ANN and RNN model, to predict the shear stress for different batches of soil. The calibrated RNN model considered experimental results of 30% at 0.5 kg/cm^2 normal stress; 40% at 0.5 kg/cm^2 and 1.5 kg/cm^{2}normal stress; and 50% at 1 kg/cm^2 and 1.5 kg/cm^{2}normal stress as testing data and remaining experimental data are used as training data. Fig. 8. shows the comparison of experimental data and predicted data using RNN model.

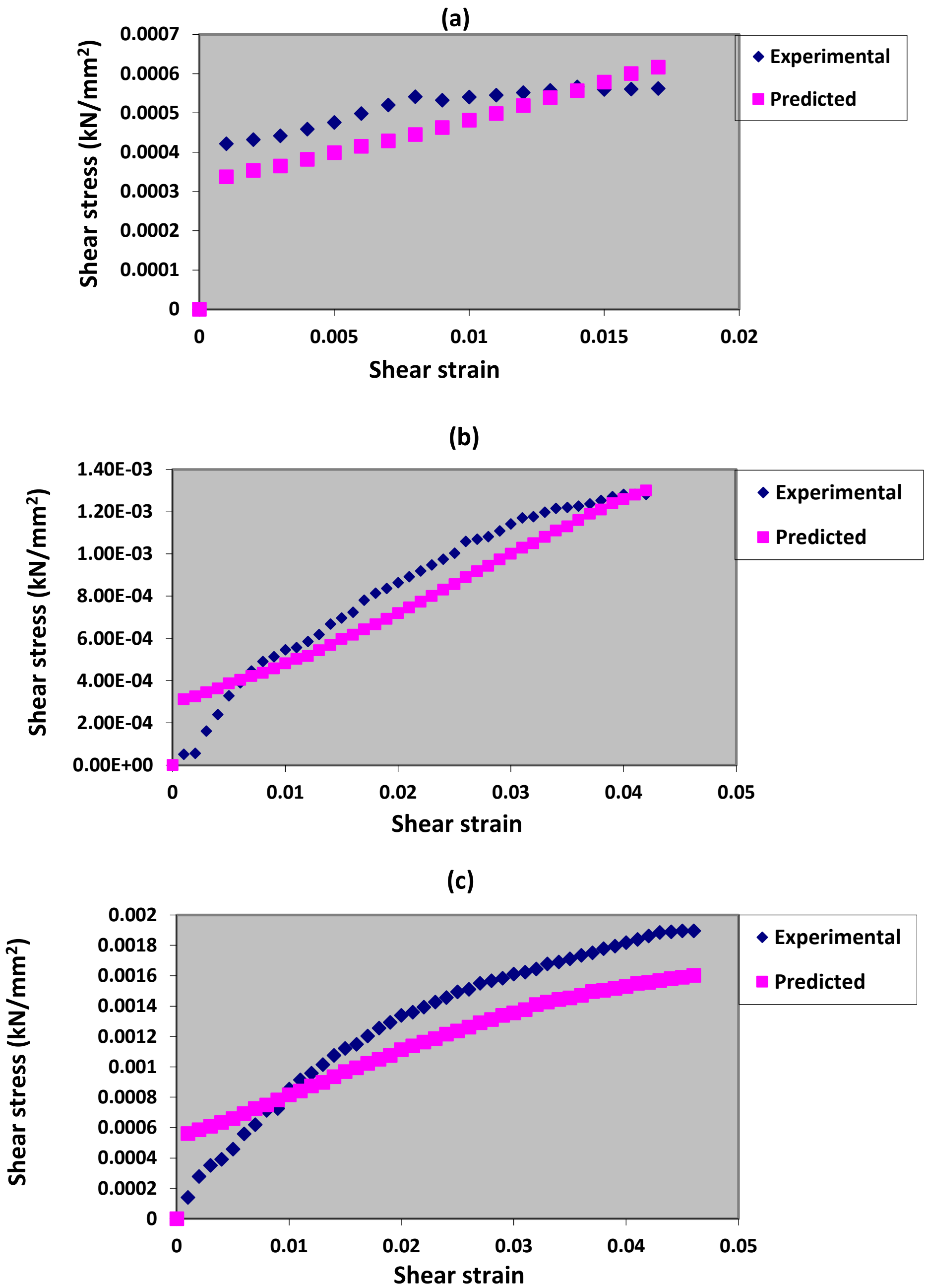


Fig. 8. Simulated Results of RNN model; (a) 30% bentonite @ 0.5 kg/cm^2 Normal stress,(b) 50% bentonite @ 1 kg/cm^2 Normal stress, (a) 50% bentonite @ 1.5 kg/cm^2 Normal stress.

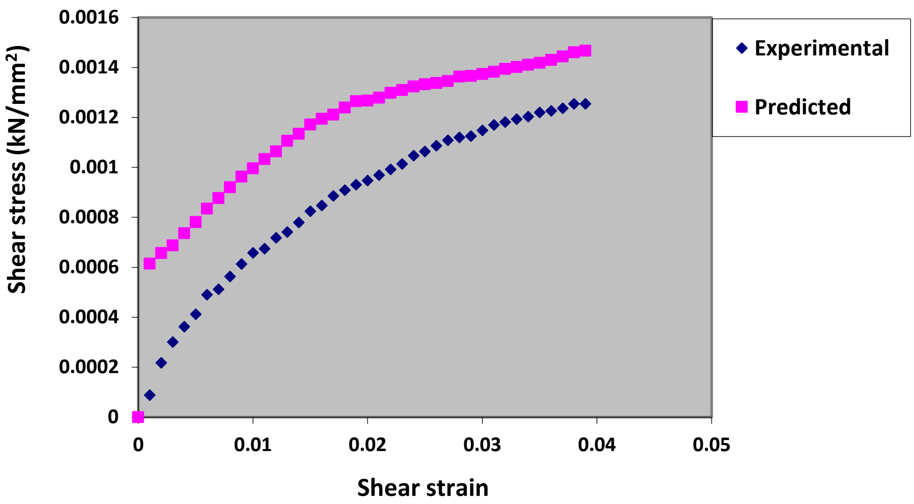
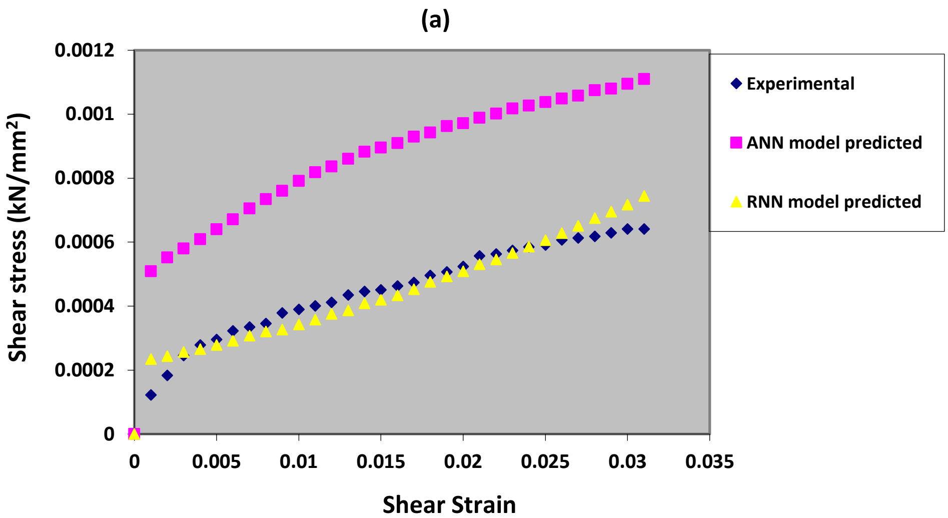


Fig. 9. Simulated Results of ANN model for 40% bentonite @ 1 kg/cm^2 Normal stress.

Similarly, ANN model considered experimental results of all test conducted at 0%, 10%, 20%, 30% and 50% bentonite batches as an input and the result for all test conducted at 40% bentonite batch is predicted. Fig. 9. Shows the comparison of experimental data and predicted data using ANN model.



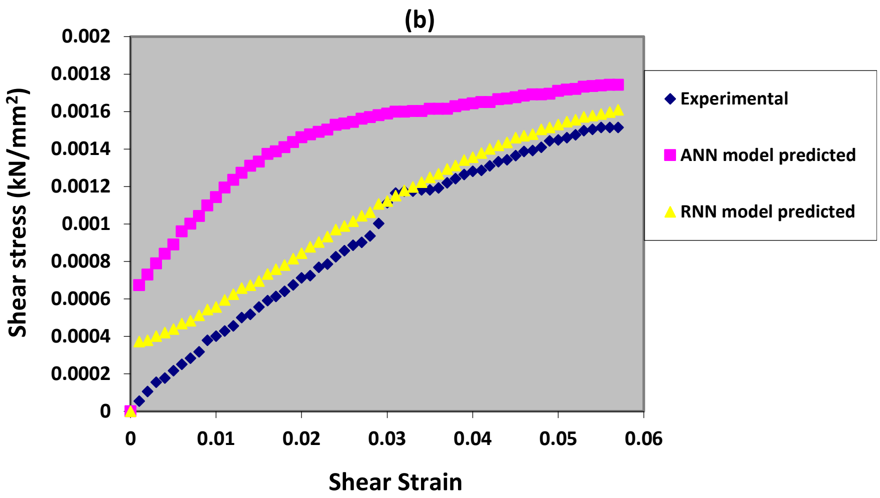


Fig. 10 Simulated Results of ANN and RNN model compared with experimental data; (a) 40% bentonite @ 0.5 kg/cm^2 Normal stress,(b) 40% bentonite @ 1.5 kg/cm^2 Normal stress.

5 Conclusions

Based on the experimental results and subsequent simulation of the same using neural network method, the following conclusions are made:

1. On comparing experimental results with predicted results obtained from the feed forward back propagation based ANN model and RNN model, it can be seen that the RNN model gives better results.
2. The RNN based prediction model can be used in the actual field cases also as it is simulating the nonlinear behavior with a good accuracy.
3. Based on the simulated results obtain, it can be concluded that there is still a lot of scope for further improvement in predicting the nonlinear stress-strain behavior more accurately using RNN by increasing the no of input parameters and number of data points.

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