Behavioral Study of Raft Reinforced with Geogrid and Geocell Through Experiments and Neural Models

Kumar, V.[1]* , Priyadarshee, A.[2] , Chandra, S.[3] , Jindal, A.[4] and Rana, D.[4]

[1] Assistant Professor, Department of Civil Engineering, SoET Block, Central University of Haryana, Mahendergarh, India.
[2] Assistant Professor, Department of Civil Engineering, MIT Muzaffarpur, Bihar, India.
[3] Ph.D. Candidate, Scientist, CSIR-NEERI, Delhi Zonal Centre, India.
[4] Assistant Professor, Department of Civil Engineering, School of Engineering and Technology, Central University of Haryana, India.

ABSTRACT: The stability of a structure could be achieved either by adopting strong foundation or by improving the strength of the soil. This study is an attempt to investigate the behavior of a raft foundation (U-R_F) upon reinforcing with geogrid (R_F-R-G_r) and reinforcing with geocell (R_F-R-G_c). The results of the study showed that optimal depth for placement of geogrid was found to be 0.3B (B is width of raft) while optimal depth for geocell varied from 0.1B to 0.15B. It was also found that the Bearing Capacity Ratio (BCR) for R_F-R-G_r was typically six times higher than U-R_F, while for R_F-R-G_c it was eleven times higher than U-R_F. Further, the outcomes of experimental study were modeled using Artificial Neural Networks (ANN) to predict the settlements. It was found that ANN models predicted settlement with higher values of correlation coefficient (r) as 0.9996 for R_F-R-G_r and 0.9995 for R_F-R-G.

Keywords: ANN, BCR, Geocell, Geogrid, Raft.

1. Introduction

India is accelerating at a rapid rate on the infrastructural front with smart city based development implemented in different parts of the country. These developments in the geographically diverse country are challenged with existing topography and varied soil conditions. The challenges range from stability of substructure to durability of the superstructure. The focus on substructure is obvious of the fact that big and complex structures like skyscrapers, bridges, and industrial plants, etc. require stable and economical foundations.

A raft foundation (UR_F) is generally used when the area required under the isolated footing is much higher for the distribution of load with low bearing capacity of soil. However, under poor soil conditions the raft undergoes differential settlement in instances. In such cases, available ground improvement techniques like utilization of the admixture, stone column, soil reinforcement, etc., can be implemented (Jindal and G.D. Ransinchung, 2021, Priyadarshee et al., 2020; Verma et al., 2018; Kumar and Thyagaraj, 2020). Also,

* Corresponding author E-mail: vikaskumarnitk@gmail.com

to improve the behavior of the raft different geosynthetic materials are brought into applications with soil strata. The inclusions of geogrid and geocell as reinforcement has opened new avenues for the constructions of structures even in those areas too which have poorly graded sand beds. In this study, the behavior of raft reinforced with geogrid (R_F-R-G_r) and raft reinforced with geocell (R_F-R-G_c) were explored under loose sand and dense sand condition.

Reinforced Soil Foundation (RSF) has been an area of interest for various researchers in the past too. Binquet and Lee (1975) evaluated the bearing capacity of sand reinforced with metal strips and later many studies were conducted to evaluate footings rested on reinforced sandy soil. Priyadarshee et al. (2014) discussed that, different forms of reinforcement like planar, geocell etc., are available for improving the BCR of soil; however planar and geocells are the most popular alternatives practiced amongst engineers. In planar reinforcement technique geogrids, geotextiles etc., are placed in layers of soil which mobilizes the reinforcing action through interaction between soil and reinforcement. Different works carried out by researchers such as Adams and collin (1997), Sawaaf (2007), etc., describes the mechanism of planar reinforcement and the factors affecting the same.

Geocell is another important form of reinforcement wherein three-dimensional confinement provided by geosynthetic material resists the deformation during the shearing action which increases the load carrying capacity of soil. Different model tests on shallow foundations like strip footing, circular footing etc., and numerical analysis were carried out by different researchers such as Bathurst and Karpurapu (1993), Latha et al. (2008) and many more.

Most of the studies on model foundation supported by reinforced soil have been done on the isolated foundations. Under the isolated foundations like circular footing, square footing etc., reinforcements are extended beyond the footing. Because of this additional resistance mobilizes due to additional length of the reinforcement. Also, numerical analysis done by different researchers like Han et al. (2008), Latha et al. (2008) etc. on the foundation supported by reinforced soil, is mainly based on the mesh analysis to predict the performance of soil-foundation system (Han et al. 2008). Also statistical analysis is used for prediction by different researchers. Different studies using ANN have been done on problems like prediction of compressive strength for stabilized soil using ANN, evaluation of lateral spreading using ANN (Baziar et al., 2005), assessing geotechnical properties using neural model models (Yang et al., 2002). A hybrid PSO-ANN model for rock-socketed piles was developed by Armaghani et al. (2017) for predicting the ultimate bearing capacity. The intricate problems in geotechnical engineering have used AI models for comparatively better results than statistical models as discussed by Suman et al. (2016) and Doley et al. (2021, 2022).

However, performance of the planner reinforcement and geocell reinforcement is not yet properly investigated under the raft foundation. This study, thus investigates the performance of soil reinforced with planar and geocell reinforcement under raft footing. Also, a comparative study is done to understand the relative performance of these reinforcement under the raft footing. Under different experimental setups, series of test are performed on the reinforced soil-raft foundation systems. Also, to predict the load carrying capacity of the reinforced soil Artificial Neural Network (ANN) is applied in the present study.

2. Methodology and Test Set up

The methodology adopted for this study is illustrated in Figure 1. For studying the performance of U-R_F, R_F-R-G_r and R_F-R-G_c, model raft 300 mm × 300 mm × 25 mm was prepared, and property of sand were investigated. The photographic view of raft and testing tank are shown in Figures 2a and

2b.

As per the Unified Soil Classification System (USCS), (ASTM D 2487-06) sand used in this study could be classified as poorly graded sand (SP) as shown in Figure 3. Biaxial geogrid made of polypropylene was used in this study as planar reinforcement and for preparation of geocell. The Height of Geocell (HG) used in R_F-R-G_c was equal to the number of geogrid layers used for preparation of geocell. The photographic view of geogrid and geocell are shown in Figures 4a and 4b.

The resultant load-deformation behavior of geogrid is presented in Figure 5 as per ASTM D 6637-01. Experimental test series was designed to conduct tests on UR_F, R_F-R-G_r and R_F-R-G_c. The test series G_0 were conducted on unreinforced raft at 40% and 70% Relative Density (RD). In case of R_F-R-G_r and R_F-R-G_c, the laboratory tests were conducted under test series G_1, G_2, G_3, G_4 and G_{C1}, G_{C3}, G_{C5}, respectively, as shown in Table 1. The schematic diagram for R_F-R-G_r and R_F-R-G_c is shown in Figures 6a and 6b. For R_F-R-G_r, the design variables were N, b/B, d_r, u/B and for R_F-R-G_c, the variables were h_g/ and U_g.

2.1. Development of Neural Models

Artificial Neural Network (ANN) models using feed-forwarded and back propagated technique were used for making the neural model for this study. The basic structure of the neural network is divided into three components namely input layer, hidden neuron and output. For optimization of the ANN, fixation of neurons was done by trial-and-error method. The architecture of neural model for geogrid and geocell is shown in Figures 7a and 7b, respectively. The database consisted of matrix of outcomes of experiments for R_F-R-G_r and R_F-R-G_c for constructing neural model. For training the neural model, 70% data was used and 30% data was used for testing the model.
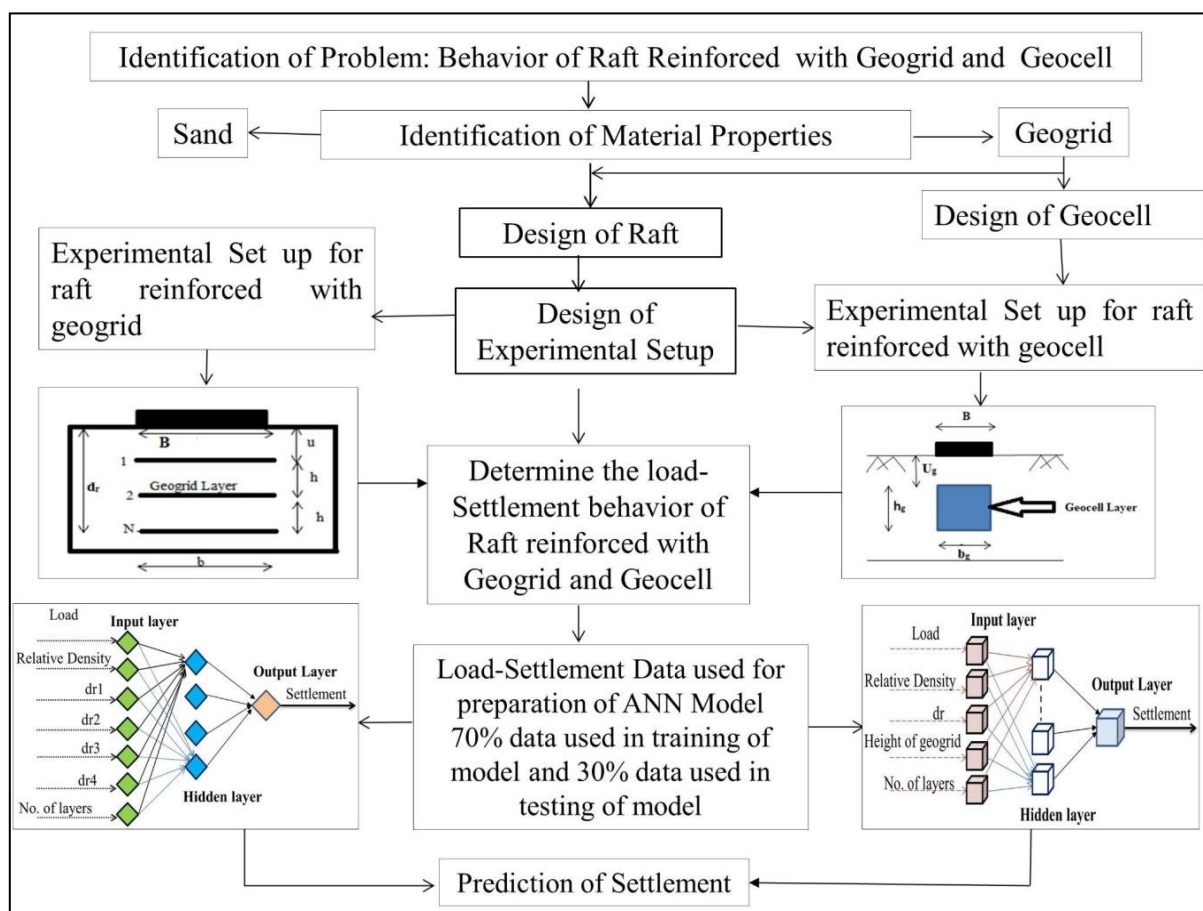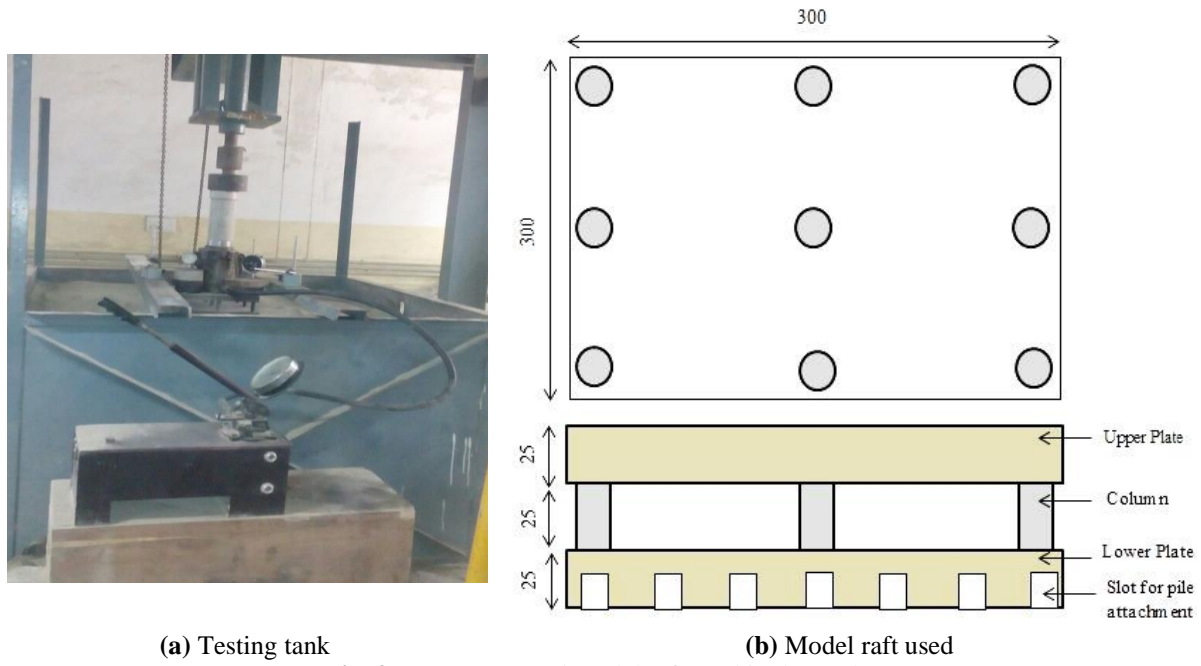

Fig. 1. Methodology employed in study

(a) Testing tank   **(b)** Model raft used

Fig. 2. Test Set up and model raft used in the study
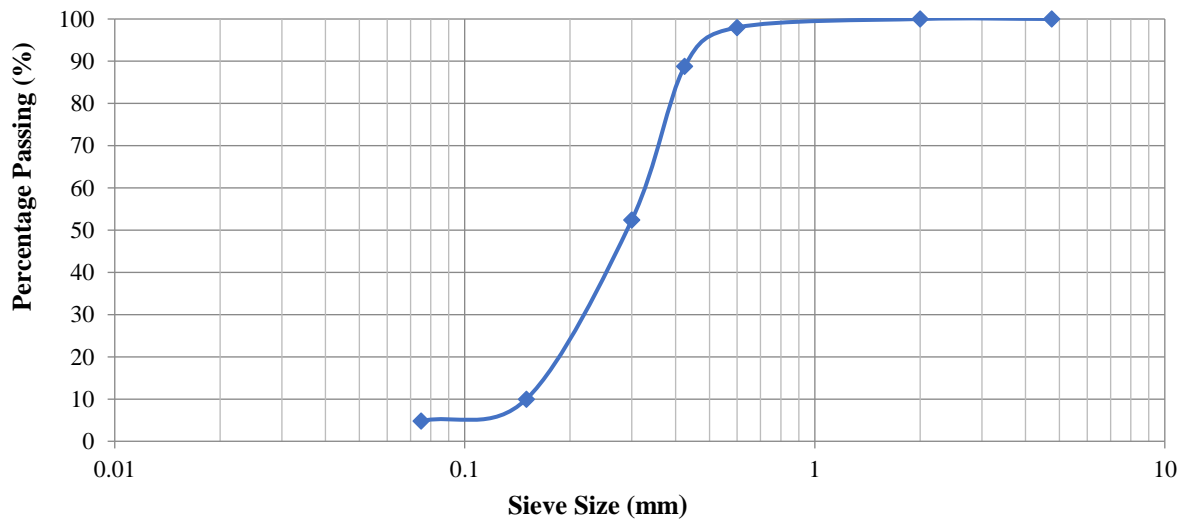

Fig. 3. Grain size distribution of sand

Table 1. Test details for U-RF, RF-R-Gr and RF-R-Gc

| RD (%) | Test series | U-R_F and R_F-R-G_r | | | | R_F-R-G_c | |
		Number of layer (N)	d_r/B	U/B	Test series	U_g/B
	G_0	----	-----	----	----	---
	G_1	1	0.1	0.1	G_{C1}	0.1
			0.3	0.3		0.3
			0.5	0.5		0.5
			0.7	0.7		0.7
	G_2	2	0.1 and 0.3	0.1	G_{C3}	0.1
			0.1 and 0.5	0.1		0.3
			0.1 and 0.7	0.1		0.5
			0.3 and 0.5	0.3		0.7
			0.3 and 0.7	0.3		
			0.5 and 0.7	0.5		
40,70						0.1
	G_3	3	0.1, 0.3 and 0.5	0.1	G_{C5}	0.3
			0.3,0.5 and 0.7	0.3		0.5
						0.7
	G_4	4	0.1,0.3,0.5 and 0.7	0.1		

(a) Geogrid used   **i)** GC1   **ii)** GC3   **iii)** GC5
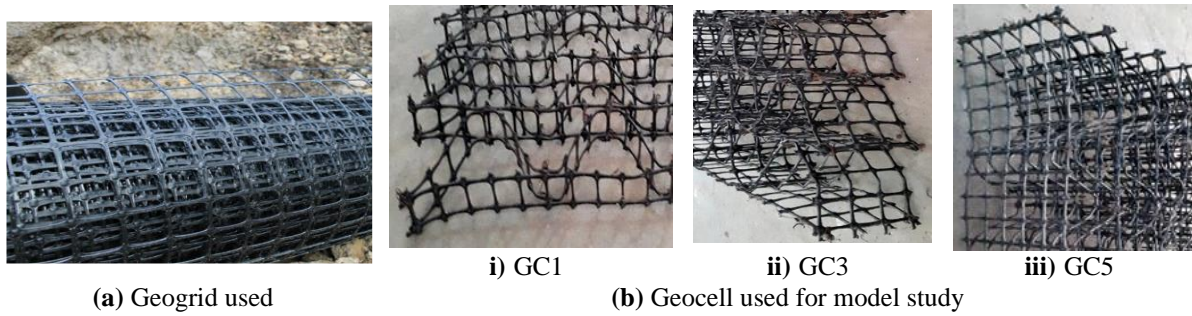**(b)** Geocell used for model study

Fig. 4. Geogrid and Geocell used in the study
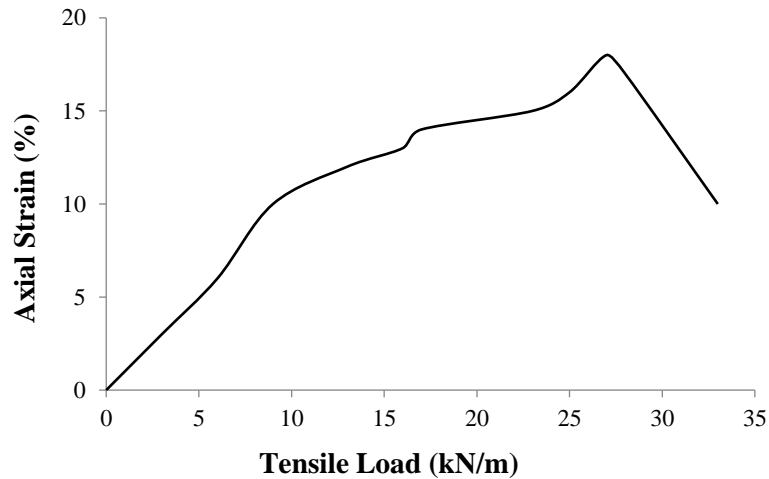
Fig. 5. Load-deformation behavior of biaxial geogrid used in the study

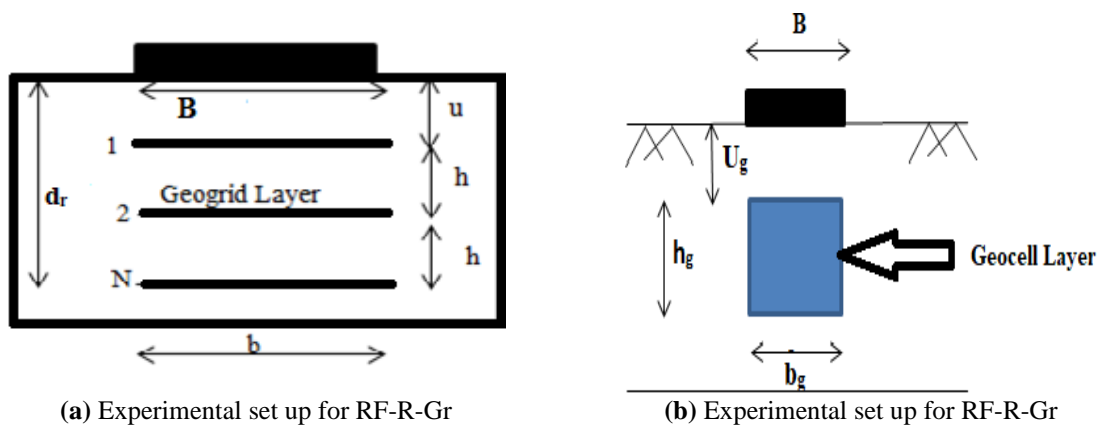**(a)** Experimental set up for RF-R-Gr   **(b)** Experimental set up for RF-R-Gr
Fig. 6. Experimental Setup for Reinforced foundation

3. Results and Discussion

The effect of design variables considered for U-R_F, R_F-R-G_r and R_F-R-G_c model tests are discussed in the following section. The results obtained were further used to develop a prediction neural model. For comparing the performance of reinforcements, parameters like density, type of reinforcement, reinforcement's top-spacing and number of layers are discussed.

3.1. Effect of Density

Direct Shear test was conducted to study the interaction effect of geogrid with sand. From Figure 8, it can be inferred that peak shear stress would increase with increase in the relative density of soil. This enhancement will increase with the inclusion of planar reinforcement. Peak stress was improved from 65.49 kN/m² to 74 kN/m² for unreinforced sand and from 75.54 kN/m² to 93.05 kN/m² for reinforced sand when the relative density was observed to be increased from 40% to 70%.
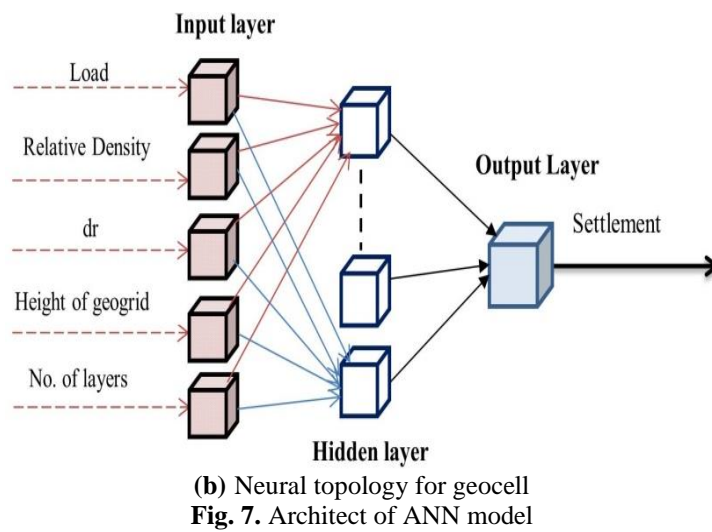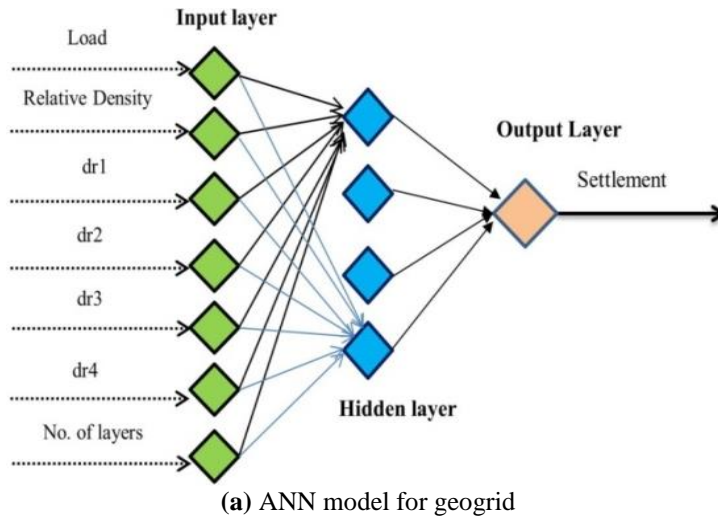
(a) ANN model for geogrid

(b) Neural topology for geocell
Fig. 7. Architect of ANN model

For R_F-R-G_r: dr1, dr2, dr3 and dr4 represent different depths of reinforcement when one, two, three and four layers were used, respectively.

No. of layers = No. of geogrid layers.

For R_F-R-G_c: dr = different depth of reinforcement (30 mm, 90 mm, 150 mm).

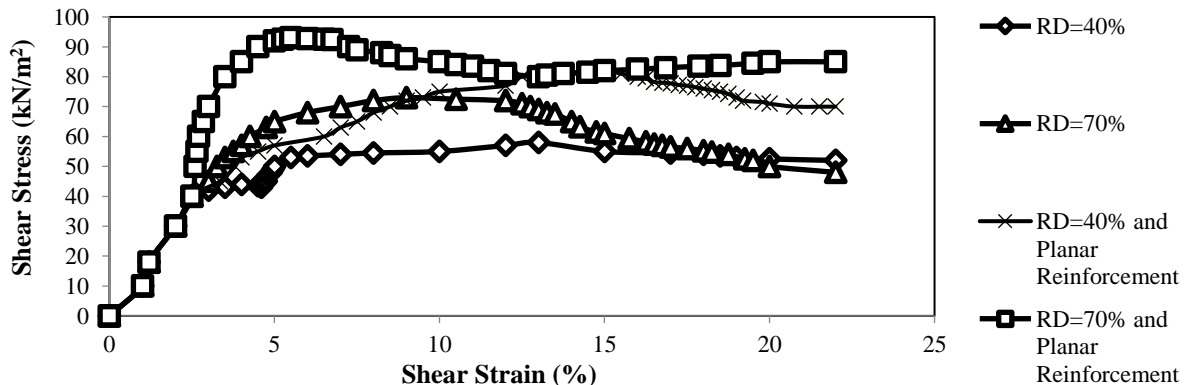Height of geocell = No. of layers $\times$ 30 mm

Fig. 8. Stress-strain response for reinforced and unreinforced sand at different relative densities

3.2. Effect of Reinforcement

The pressure–settlement responses were compared through a non-dimensional parameter i.e. Bearing Capacity Ratio (BCR) as in Eq. (1).

$$BCR = \frac{q_{UR}}{q_U} \tag{1}$$

where, q_{UR}: is bearing capacity of reinforced foundation and q_U: is bearing capacity of U-R$_F$.

The BCR for R$_F$-R-G$_r$ was typically five times higher than that of U-R$_F$ while for R$_F$-R-G$_c$ it was seven times than that of U-R$_F$ as shown in Figures 9a and 9b. This is due to the fact that geocell confine the sand more significantly as compared to geogrid. Also an anchorage action will take place if foundation is reinforced by geocell which develop the hoop stress. This combined action resulted in significant improvement in the BCR.
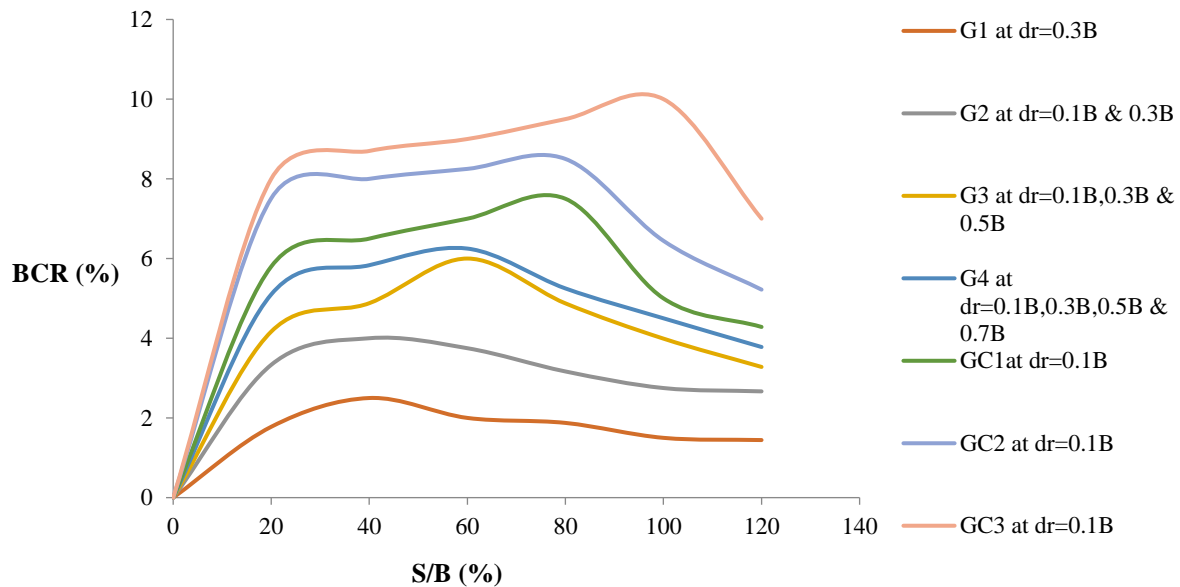
(a) Pattern of BCR for RF-R-Gr and RF-R-Gc at RD = 40%
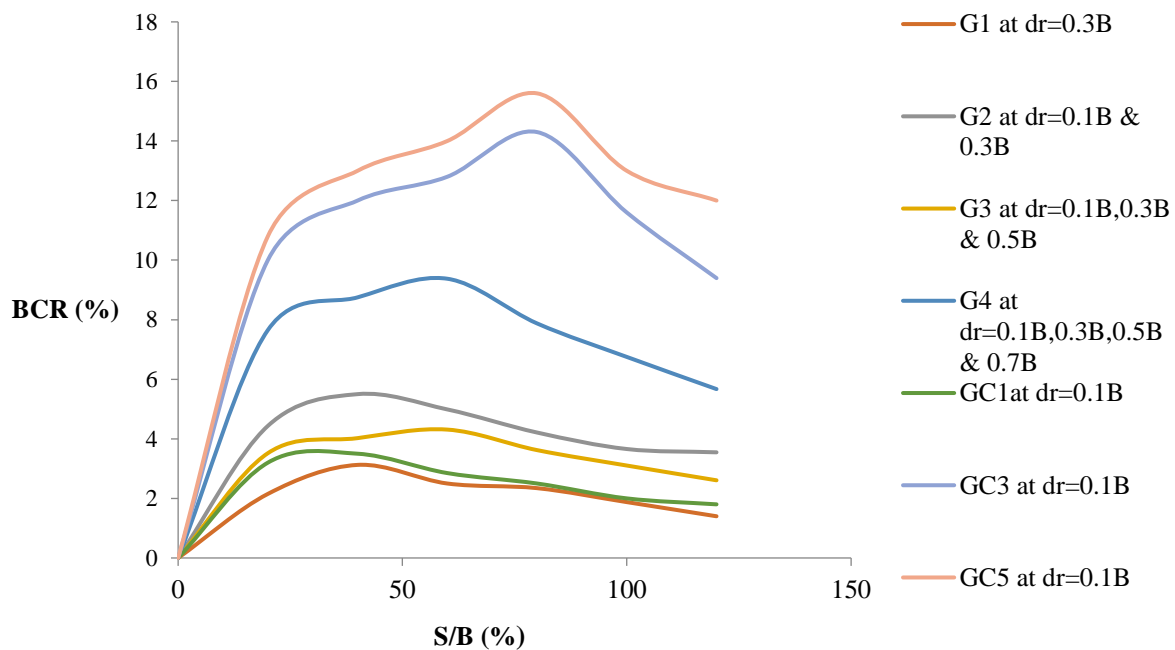
(b) Pattern of BCR for RF-R-Gr and RF-R-Gc at RD = 70%
Fig. 9. Effect of relative density on reinforced foundation

3.3. Effect of Reinforcement's Top Spacing for Geogrid and Geocell reinforced foundation

In case of R$_F$-R-G$_r$, the distance of first layer of reinforcement from the base of footing shall mobilize the tensile forces developed which are directly proportional to the depth of the reinforcement. As the

depth of reinforcement below the raft increases, these tensile forces decrease. From Figure 10a it could be inferred that for R_F-R-G_r the optimal results were achieved at u/B = 0.3 and the maximum improvement in BCR was obtained at S/B = 20%.

From test results, it is observed that R_F-R-G_c provides better performance than U-R_F and R_F-R-G_r in all cases. This improvement in performance is owing to interface friction developed between soil and 3-dimensional geocell which developed the confinement effect. From Figures 10b it is inferred that for R_F-R-G_{c1} the optimal results were achieved at U_g/B = 0.15 and the maximum improvement in BCR was obtained at S/B = 30%

3.4. Effect of Number of Layers

For R_F-R-G_r the maximum significant improvement in BCR was achieved when three layers were used as in test series G_3. Therefore, it can be concluded that further addition of number of geogrid layers does not affect the bearing capacity of soil significantly, while in case of R_F-R-G_c best results were obtained at test series GC3 as

shown in Figure 11.

3.5. Neural Models

The final topology for any neural model is obtained after finalizing the parameters like activation function, neurons in middle hidden layer, stopping criteria etc. The connections between the layers were logsigmoid and purelin. The first connection was logsigmoid and purelin was a successive function. Least Root Mean Square Error (RMSE) during testing was used for neurons selection in middle layer. Therefore, for R_F-R-G_r the topology was 7-12-1 and for R_F-R-G_c it was 5-11-1 as shown in Figure 12.

3.5.1. Performance of Neural Model

For identifying the performance of ANN, different performance variables (Kumar and Kumar, 2018) as shown in Table 2 were calculated. The performance variables help in deciding the goodness of developed neural models. The predicted results from the model are shown in Figure 13.
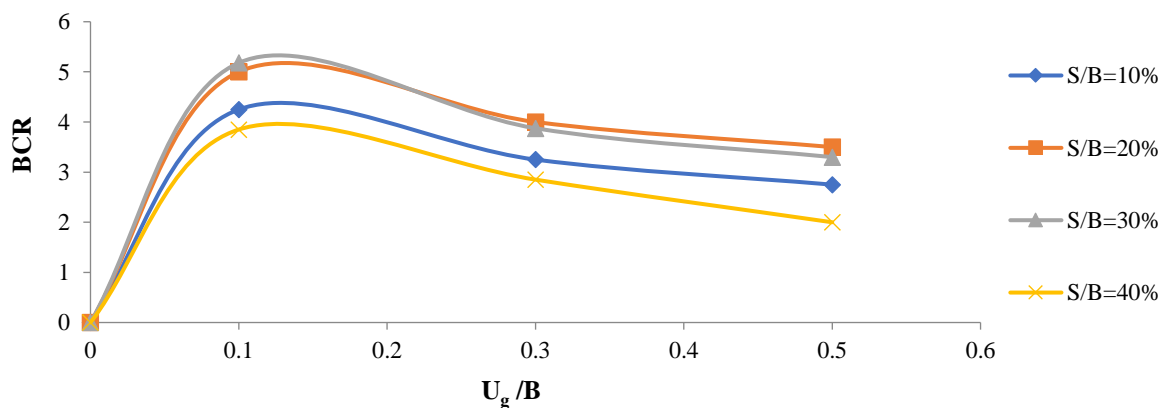
(a) BCR versus u/B for test series G1 at RD = 40%
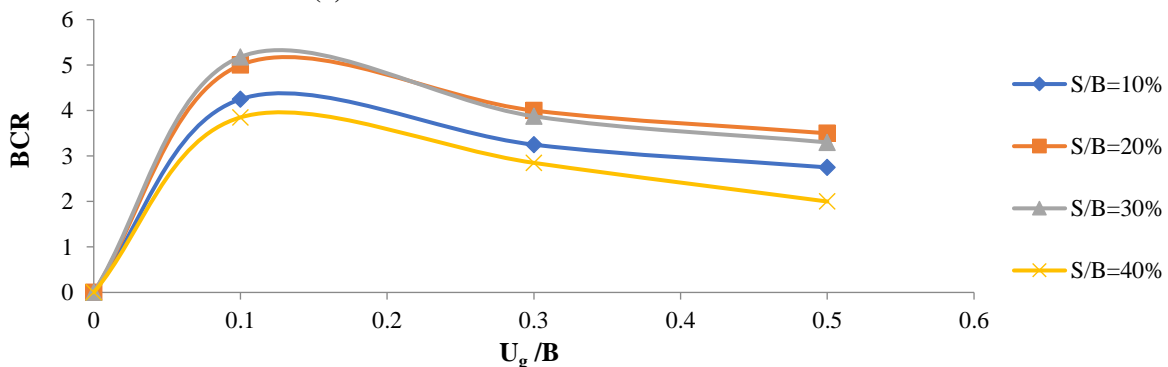
b)   BCR versus Ug/B at RD = 70% for test series GC1
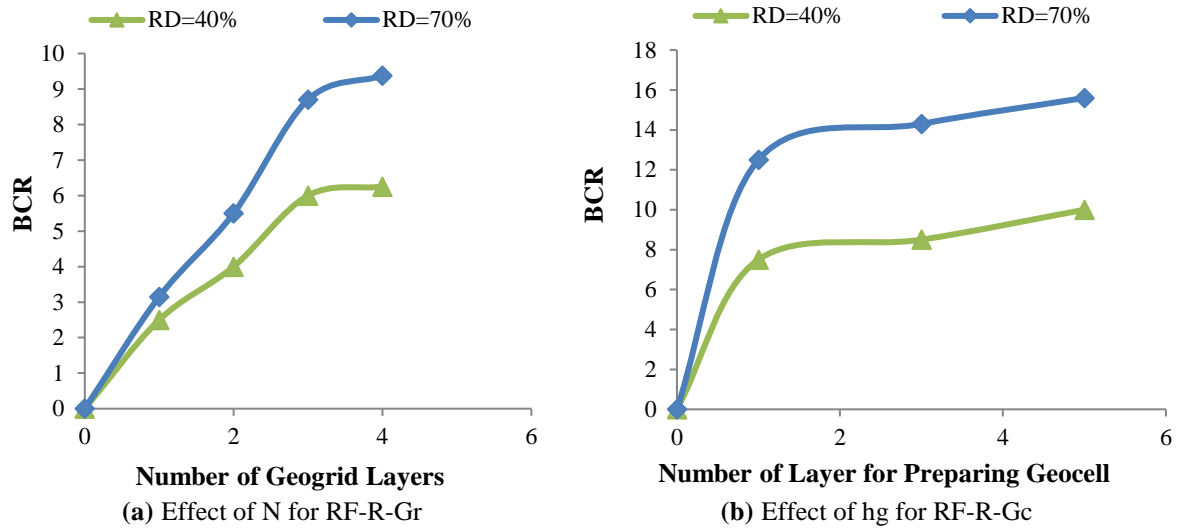**Fig. 10.** Effect of reinforcement top spacing on reinforced foundation

(a) Effect of N for RF-R-Gr

(b) Effect of hg for RF-R-Gc

Fig. 11. Effect of reinforcement layer
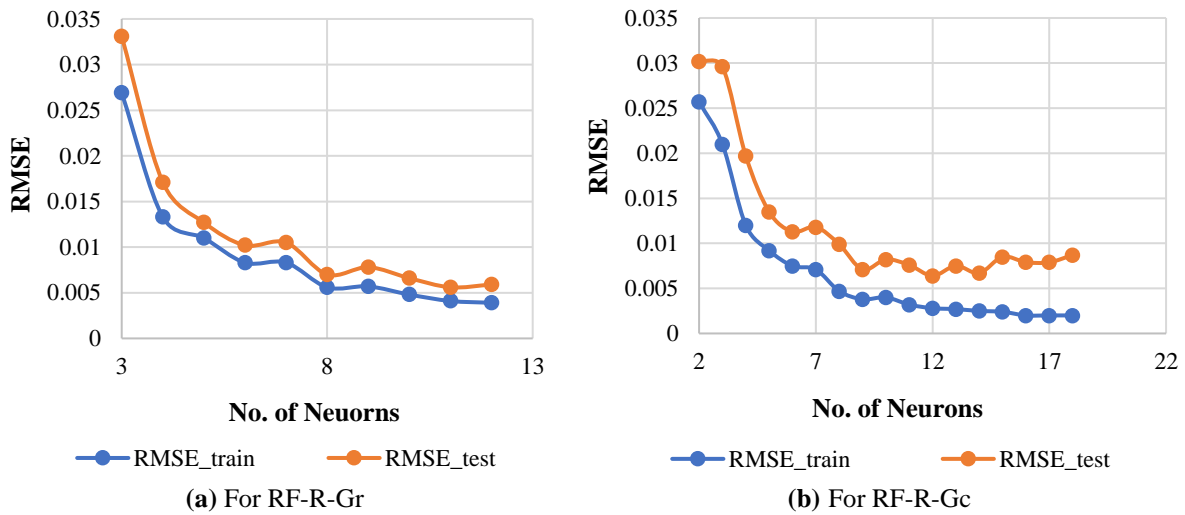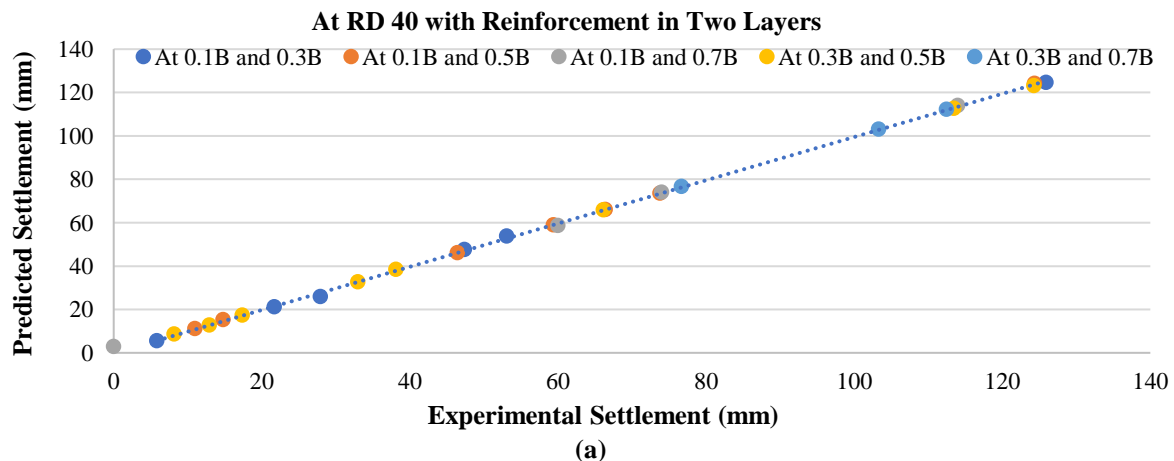

(a) For RF-R-Gr

(b) For RF-R-Gc

Fig. 12. Pattern of RMSE during training and testing

Table 2. Assessment of performance variables for Geogrid and Geocell

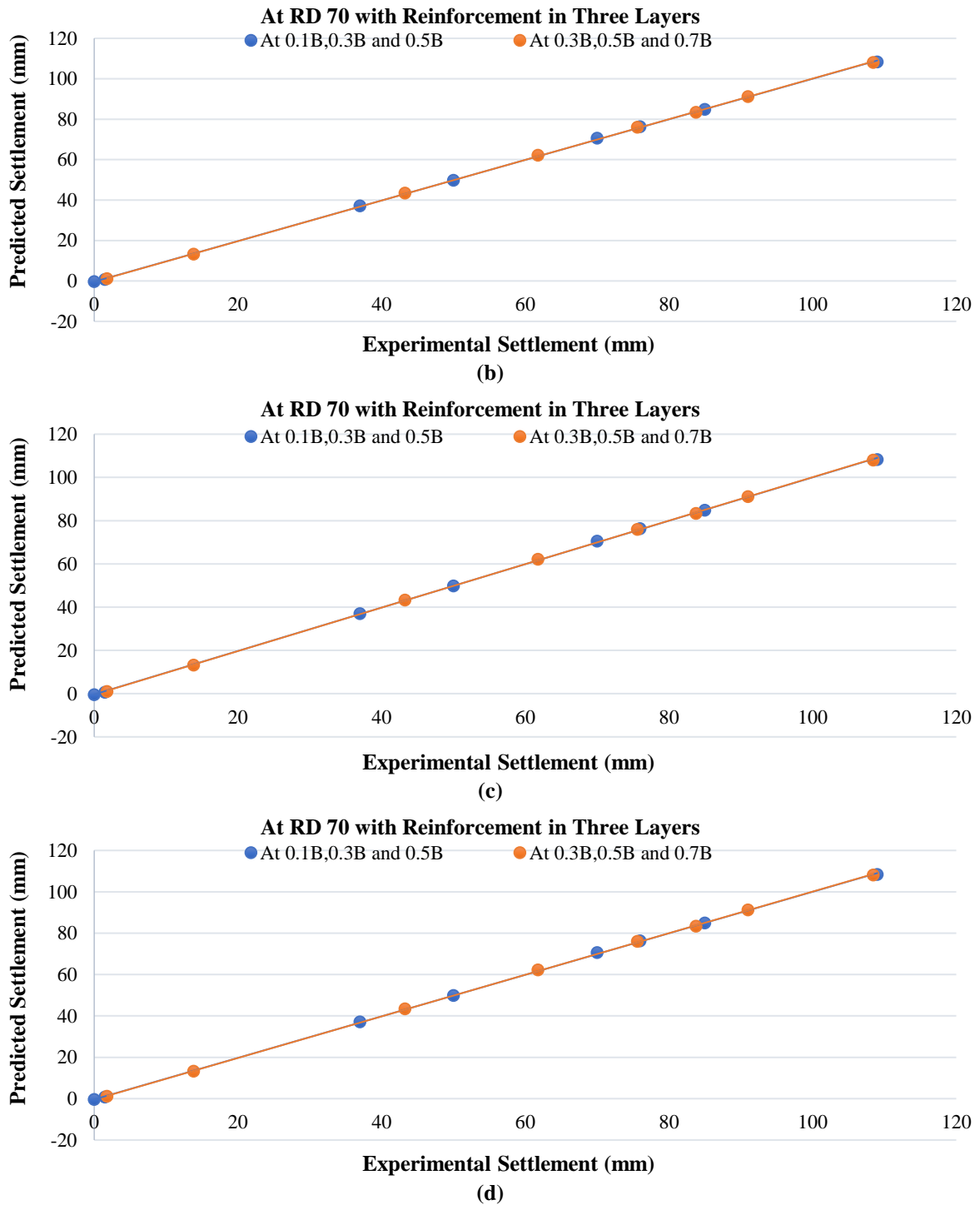|	MAE	RMSE	CF	r
Geogrid				
Training	0.002	0.003	0.999	0.9998
Testing	0.004	0.006	0.999	0.9996
Geocell				
Training	0.003	0.004	0.999	0.9997
Testing	0.004	0.005	0.999	0.9995

At RD 40 with Reinforcement in Two Layers

(a)

At RD 70 with Reinforcement in Three Layers

(b)

At RD 70 with Reinforcement in Three Layers

(c)

At RD 70 with Reinforcement in Three Layers

(d)

Fig. 12. Pattern of RMSE during training and testing

For R_F-R-G_r, the optimal architecture was obtained as 7-12-1 to predict settlement (S). The weights and biases obtained from trained model for geogrid are shown in Table 3. The Eq. (2) gives output (settlement) by using all input parameters (i.e. Loads (L), Relative Density (RD), dr1, dr2, dr3, dr4 and No. of layers (Nlp).

For raft reinforced with geocell the optimal architecture obtained was 5-11-1 to predict settlement (S). The weights and biases obtained from trained model for geocell had been shown in Table 4.

The normalized value of settlement (S) can be calculated using following equation.

$$Settlement = f_{sig}\{b_o + \sum_{k=1}^{h}[w_k f_{sig}(b_{hk} + \sum_{i=1}^{m} w_{ik}X(input)_i]\} \quad (2)$$

Table 3. Connection weights and biases for calculating settlement (Ygc) i.e. for raft reinforced with Geogrid

Hidden neuron	Weights									Bias		
	w_{ik}								w_k	b_{hk}	b_o
	Inputs								Output	Hidden layer	Output layer
(k = 1 to 12)	Load (L)	Relative density (RD)	dr1	dr2	dr3	dr4	No. of layers (N_{lp})	Settlement (S)			
1	2.8042	3.4678	2.1315	3.0136	3.8188	-0.2099	-3.0085	0.5280	-0.6778	0.0120
2	-8.4476	-4.2540	-4.0283	0.6813	-0.1670	-1.3368	7.3752	-0.0794	3.9817	
3	-2.4716	-8.1776	-14.7238	-0.0437	4.5439	0.7352	-11.6633	0.5249	-5.3355	
4	2.1153	-0.3233	0.3523	-2.9803	-3.7383	0.4669	3.2740	1.1401	-4.4261	
5	-1.7771	0.7992	-6.0401	-0.8943	-0.3476	0.6638	4.6114	1.2843	-3.0169	
6	2.1295	-0.2827	0.2917	0.2573	0.0546	0.6708	-1.7831	2.8495	2.2199	
7	1.9098	-0.3136	-0.0572	0.7825	0.1691	0.5006	-1.5603	4.6961	-0.9630	
8	1.2493	-0.5264	-1.3923	0.4040	-2.2094	4.4762	5.6170	-2.8879	2.4666	
9	-0.9754	0.1731	2.8333	0.4662	2.2984	-4.3208	4.5377	2.8611	0.8589	
10	0.7209	-0.5175	-2.4152	-0.7004	-1.3631	-4.1193	2.7417	-4.4829	-0.5241	
11	0.5201	0.7982	2.9534	0.5987	2.1740	0.5332	-1.4558	-1.8853	0.6765	
12	0.4852	-1.6963	3.8710	-7.8275	-0.2785	1.3689	7.4323	-1.3636	-3.5628	

where f_{sig}: represent the transfer function (here is log-sigmoid), b_o: is bias at output layer, w_k: is weight connection between 'k' of the hidden layer and the single output neuron, b_{hk} is bias at neuron 'k' of the hidden layer (k = 1, h), w_{ik}: is weight connection between input variable i and neuron k of the hidden layer and $X(input)_i$: is the input parameter.

4. Conclusions

Study showed the effectiveness of using planar reinforcement and geocell as settlement reduction measure with the rafts. In general, the extra strength was observed due to geocell-reinforcement which is to be dependent on the number of the geocell layers and thickness of geocell used to reinforce the soil. The BCR for R_F-R-G_r was typically six times higher than that of U-R_F while for R_F-R-G_c was eleven times than that of U-R_F. It was observed that relative density plays a significant role in improving the bearing capacity of soil. The effect of reinforcement was almost double in case of reinforced raft as compared to U-R_F. The optimal depth for placement of geogrid was obtained as 0.3B and for geocell it was 0.15B. In case of reinforced raft, it was observed that with increase in number of layers of geogrid, load intensity was found to be increased at RD 70% more than that for RD 40% however, this effect was observed to be insignificant after an optimum number of reinforcement layers. The lower values of the order of 10^{-3} for MAE and RMSE shows that the neural models are well trained and tested and can be used for solving complex geotechnical problems.

Table 4. Connection weights and biases for calculating settlement (Ygc) i.e. for raft reinforced with geocell

Hidden neuron	Weights					Bias		
	w_{ik} Inputs					w_k Output	b_{hk}	b_o
(k = 1 to 11)	Load (L)	Relative density (RD)	dr	Height of Geogrid (h_g)	No. of layers (N_{lg})	Settlement (S)	Hidden layer	Output layer
1	4.6619	-0.1100	0.3989	-0.5677	-1.4156	0.7687	-2.9583	2828.9116
2	-0.9584	-0.0199	1.4175	1.6667	-0.3249	-2829.0547	10.1704	
3	-1.6689	2.6778	-1.6870	-2.6193	-1.1327	-0.6833	1.0955	
4	1.0102	1.5909	0.7418	2.0951	0.3838	-153.4224	1.3146	
5	-1.6498	0.2736	-2.5507	1.0150	-0.5241	0.3931	-1.2418	
6	-5.1185	9.4275	-6.9803	-4.9604	-4.1751	0.1176	1.1746	
7	-2.6048	-1.5796	2.1554	-2.3718	-2.0127	0.2284	0.3234	
8	-1.2315	0.3857	30.4316	15.1914	16.4570	0.8228	37.0194	
9	1.0003	1.5870	0.7434	0.4169	2.0675	152.8009	1.2982	
10	-2.0663	0.0789	-0.2321	-0.4019	1.5601	-2.0521	-0.2065	
11	2.3428	2.1446	0.5364	1.4305	-0.0262	1.0644	2.2043	

5. References

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