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Research Paper

Prediction of unconfined compressive strength of geopolymer stabilized clayey soil using Artificial Neural Network

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ABSTRACT

Viability of Artificial Neural Network (ANN) in predicting unconfined compressive strength (UCS) of geopolymer stabilized clayey soil has been investigated in this paper. Factors affecting UCS of geopolymer stabilized clayey soil have also been reported. Ground granulated blast furnace slag (GGBS), fly ash (FA) and blend of GGBS and FA (GGBS + FA) were chosen as source materials for geo-polymerization. 28 day UCS of 283 stabilized samples were generated with different combinations of the experimental variables. Based on experimental results ANN based UCS predictive model was devised. The prediction performance of ANN model was compared to that of multi-variable regression (MVR) analysis. Sensitivity analysis employing different methods to quantify the importance of different input parameters were discussed. Finally neural interpretation diagram (NID) to visualize the effect of input parameters on UCS is also presented.

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1. Introduction

Geopolymer technology is a recent field of research interest in concrete science and engineering and is gaining increasing attention for utilization of industrial by products such as FA and GGBS. Any pozzolanic material containing source of silica and alumina that is readily dissolved in the alkaline solution acts as a source of geopolymer precursor species and lends itself to geopolymerization [1]. Geopolymerization involves the poly-condensation reaction of geopolymeric precursors i.e. alumino-silicate oxide with alkali polysiliates yielding polymeric Si–O–Al bond as shown below [2–4].

$$M_n[-(Si-O_2)_z-Al-O]_n.wH_2O$$

where M is the alkaline element, z is 1, 2 or 3 and n is the degree of poly-condensation [4]. It is worthwhile to mention that the micro-structure of the end product formed after geopolymerization is totally different from that of pozzolanic reactions since pozzolanic reaction yields calcium silicate hydrate and/or calcium alumino-silicate [5].

Review of literature reveals that limited research have been carried out on soil stabilization by geopolymer binder. In recent past, FA based geopolymer was successfully used by some researchers for improvement of clayey soil [6–9]. However, in most of the cases, the specimens were cured either at elevated temperature or at ambient temperature for a prolonged period, sometimes up to one year. Zhang et al. [10] studied the feasibility of metakaolin based geopolymer as a next generation soil stabilizer. GGBS-based geopolymer binder shows very high strength within hours and yet doesnot require elevated temperature curing [11,12]. Till date, rare literatures are reported on the effectiveness of GGBS-based geopolymer soil stabilization. Only recently, Yaolin et al. [13] investigated the effect of several alkali activators on the stabilization efficacy of GGBS treated marine soft clay. Detail investigation on role of parameters such as binder content, alkali to binder ratio and molar strength of alkali affecting mechanical properties of GGBS based geopolymer stabilized soil is yet to be explored.

In the present study, an effort has been made to stabilize clayey soil by GGBS based geopolymer. Source materials such as FA and blend of GGBS + FA were also incorporated in the present study to compare the stabilization efficacy among them and were reported via 28 day UCS. For optimal and effective stabilization, ANN based UCS predictive model was developed. Prediction efficacy of developed ANN model was compared with that of MVR model. Sensitivity analysis was employed to understand the effect and to quantify the importance of different input geopolymer mix parameters on the predicted UCS of stabilized specimens.

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Table 1
Engineering properties of clayey soils.

Soil type	Liquid limit	Plastic limit	Plasticity index	MDD[a] in kN/m^3	OMC[b]	d10 in micron	d50 in micron	d90 in micron	Classification	
									USCS	AASTHO
S1	116.27	27.81	88.46	14.112	23.89	0.835	1.568	2.505	CH	CH
S2	82.15	25.69	56.46	15.288	19.26	6.473	9.245	18.34	CH	CH
S3	37.68	23.61	14.07	16.562	19.05	54.889	51.475	66.59	CL	CL

[a] Maximum dry density.
[b] Optimum moisture content.

2. Experimental procedure

2.1. Material used

Three different types of soil designated as S_1, S_2 and S_3 in the present study were undertaken. The soils were collected from three different locations in Silchar city within 2 m of the ground surface. The engineering properties of the soils conforming to relevant Indian Standard Code of Practice are presented in Table 1. Commercially available ultra-fine GGBS and ASTM class F fly ash collected from thermal power plant at Farakka (India) was used as source material. The chemical and physical characteristics of GGBS and FA are presented in Table 2. Sodium hydroxide was chosen in the present study as alkali activator because of its greater capacity to liberate silicate and aluminate monomers [14]. Commercial grade sodium hydroxide (NaOH) pallets with purity 98%, specific gravity 2.13 and molecular weight 40 were used in the present study. Sodium silicate is often used along with sodium hydroxide for alkali activation as the presence of sodium silicate in sodium hydroxide is believed to enhance the reaction kinetics of geopolymerization [15]. In the present study, sodium silicate (Na_2SiO_3) combined with sodium hydroxide was used only in few cases to produce variations in some of the experimental variables, details of which will be dealt in subsequent sections. Sodium silicate used in the study had a specific gravity of 1.5, 97% purity and a molecular weight ($Na_2SiO_3.5H_2O$) equal to 212. The alkali solution was prepared with tap water one day prior to use.

2.2. Methodology

The requisite quantity of clay soil weighed to the nearest gram was oven dried for 24 h at 110 ± 5 °C and then thoroughly mixed with source materials in a kitchen appliance until a uniform mix was obtained. Amount of binder were varied as a percentage of dry weight of soil solids from 4–50% for GGBS, 4–20% for FA and blend GGBS + FA. Molar concentration of alkali solution (M) used in the present study were 4 M, 8 M, 10 M, 12 M and 14.5 M. Alkali solution was added to the mix and the mixing was continued for 15 min. In literature, a mixing time of 10–20 min is reported for obtaining a homogeneous mix with the same alkali solution [10,13,16]. Ratio of alkali solution to binder by weight (A/B) was also selected as an experimental variable and the values of A/B were 0.45, 0.65 and 0.85. Review of literature reveals that researchers had considered A/B ratio in the range of 0.25–0.66 for geopolymer synthesis [16–18]. However, in the present study values of A/B ratio were varied from 0.45 to 0.85 to achieve wide variation in Na/Al ratio for geopolymer synthesis. Samples were compacted manually at a consistency of plastic limit with a tempting rod to eliminate air voids in PVC molds having diameter 38 mm and height 76 mm. Since the samples were compacted manually, it was found that at a consistency of plastic limit, desired workability for homogeneous compaction was possible. The prepared samples in molds were kept in laboratory for 24 h and then cured continuously in water for 28 days. After curing, samples were air dried at room temperature for one hour before testing. The 28 day UCS of the specimens was determined according to IS: 2720 (Part 10) [19]. Average test results of three specimens were reported as the UCS of the specimen.

Table 2
Chemical and physical properties of source materials.

Source material	CaO	Al_2O_3	Fe_2O_3	SO_3	MgO	SiO_2	Specific surface area in m^2 /kg
GGBS	34	20	2	0.8	8	35	800
FA	0.67	22.63	5.3	0.41	0.16	66.39	300

2.3. Na/Al and Si/Al ratios

Previous research on geopolymer reveals that reaction kinetics of geopolymer synthesis are controlled by the atomic ratio of Na to Al (Na/Al) and Si to Al (Si/Al) in the mix and governs the strength of the product formed after geopolymerization [4,5,20,21]. Therefore, in the present study Na/Al and Si/Al for individual mixes were considered as experimental variables. Source of Na is NaOH and Na/Al ratio increases with increase in M and A/B in the mix. GGBS and FA are the source of Si and Al and Si/Al is constant for a particular binder. Again, for a particular binder, Na/Al ratio is independent of the binder percentage in the mix (but depends upon the relative proportion of the binders in a blended mix i.e. GGBS + FA). An example of calculation procedure of Na/Al and Si/Al is briefly explained in Appendix A. Calculated values of Na/Al and Si/Al of mixes with various combinations of M and A/B are presented in Tables 3 and 4. To examine the role of variation in Si/Al value on UCS, sodium silicate along with sodium hydroxide as secondary source of Si in the form of alkali activator was introduced in some mixes while maintaining a constant Na/Al ratio. Three different Na/Al ratios were chosen and for each value of Na/Al, variation in Si/Al was done accordingly as shown in Table 5.

2.4. Experimental results

28 day UCS of stabilized soil specimens with various combinations of the experimental variables are presented in Appendix B. Experimental results indicated the potential role of all the

Table 3
Calculated Na/Al and Si/Al ratios at different M and A/B for GGBS and FA.

Molar concentration, M	Alkali to binder ratio, A/B	Na/Al		Si/Al	
		GGBS	FA	GGBS	FA
4	0.45	0.39	0.34	1.49	2.49
8	0.45	0.69	0.61	1.49	2.49
12	0.45	0.93	0.82	1.49	2.49
14.5	0.45	1.05	0.93	1.49	2.49
12	0.65	1.34	1.18	1.49	2.49
14.5	0.65	1.52	1.34	1.49	2.49
12	0.85	1.75	1.55	1.49	2.49
14.5	0.85	1.98	1.75	1.49	2.49

Table 4
Calculated Na/Al and Si/Al ratios at different M and A/B for blended mix, GGBS + FA.

Relative proportion in the blended mix (GGBS + FA)		Molar concentration, M	Alkali to binder ratio, A/B	Na/Al	Si/Al
%GGBS	%FA				
80	20	14.5	0.65	1.18	1.7
80	20	12	0.65	1.04	1.7
60	40	14.5	0.65	0.86	1.92
60	40	12	0.65	0.76	1.92
40	60	14.5	0.65	0.56	2.12
40	60	12	0.65	0.49	2.12
20	80	14.5	0.65	0.27	2.31
20	80	12	0.65	0.24	2.31

Table 5
Variation in Si/Al at different Na/Al with NaOH replacement by Na_2SiO_3.

Replacement of NaOH by sodium silicate	0%	5%	10%	15%	20%	25%	40%	55%	65%	75%
Na/Al = 1.34 (12M, A/B-0.65)	1.49	1.52	1.55	1.58	1.62	1.65	1.75	1.85	1.92	1.99
Na/Al = 1.52 (14.5M, A/B-0.65)	1.49	1.52	1.56	1.6	1.64	1.67	1.79	1.9	1.98	2.06
Na/Al = 1.54 (10M, A/B-0.85)	1.48	1.52	1.56	1.6	1.64	1.68	1.8	1.91	1.99	2.06

Table 6
Statistical parameters of training and testing data of ANNG model.

Model variable		LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al	UCS
Standard deviation	Training data	32.46	30.76	12.94	4.74	2.65	0.15	0.45	0.36	6.52
	Testing data	32.56	30.86	12.96	4.49	2.63	0.14	0.43	0.33	6.47
Mean	Training data	63.78	38.84	15.83	2.24	12.45	0.62	1.16	1.71	5.79
	Testing data	63.74	38.8	16.06	1.84	12.06	0.62	1.19	1.67	5.72
Maximum	Training data	116.27	88.46	50	20	14.5	0.85	1.98	2.49	23.48
	Testing data	116.27	88.46	50	20	14.5	0.85	1.98	2.49	24.26
Minimum	Training data	37.68	14.07	0	0	4	0.45	0.24	1.49	0
	Testing data	37.68	14.07	0	0	4	0.45	0.24	1.49	0
Range	Training data	78.59	74.39	50	20	10.5	0.4	1.74	1	23.48
	Testing data	78.59	74.39	50	20	10.5	0.4	1.74	1	24.26

variables in influencing the UCS but not in a same manner, both in magnitude and their resulting effect (direct or inverse).

3. Predictive model development

3.1. ANN model development

ANN has been widely used in solving various geotechnical engineering problems [22–28]. Therefore for the sake of brevity the detail discussion of ANN is refrained in the present study and can be found in literature [29–34]. An ANN based predictive model designated as ANNG (ANN model for geopolymer) was developed. ANNG has liquid limit (LL), plasticity index (PI), percentage GGBS (%S), percentage FA (%FA), molar concentration (M), alkali to binder ratio (A/B), Na/Al and Si/Al as input parameters and 28 day UCS in MPa as output parameter. ANN modeling was implemented in MATLAB R2013a environment with neural network toolbox. In order to obtain a statistically consistent training and testing data, data division of ANN model is carried out as suggested by Shahin et al. [23]. 70% of the experimental data were used for training the model and rest 30% for testing the trained model. Statistical parameters of training and testing data are given in Table 6. As a part of pre-processing, the input and output variables were normalized to fall in the range [−1, 1]. A feed-forward multilayer perceptron neural network with one hidden layer was adopted. Number of neurons in the hidden layer was varied to find the optimum architecture. The performance of ANNG model was reported in terms of three statistical parameters namely, mean squared error (MSE), mean absolute percentage error (MAPE) and linear correlation coefficient (R). Optimum architecture of ANNG model was characterized by nine neurons in hidden layer with tan-sigmoid (hyperbolic tangent) transfer function and a pure linear transfer function at output layer. Bayesian regularization back propagation training algorithm is used for its better generalization to the training data.

3.2. MVR model development

In the present study, a multi-variable regression analysis (MVR) was also conducted to predict the UCS of geopolymer stabilized soil. Similar to ANNG model, 70% of total data were used for developing the MVR model. Rest 30% data were used to evaluate the prediction efficacy of the model. The generalized linear relationship between the dependent variable and independent variables takes the form

$$Y = a_0 + a_1X_1 + a_2X_2 + \ldots\ldots\ldots\ldots\ldots + a_pX_p \pm e \quad (1)$$

where Y is dependent variable, a_0 is the Y intercept. a_1, a_2 and a_p are the slopes associated with X_1, X_2 and X_p. X_1, X_2 and X_p are the values of independent variables, e is the error. "a" values are obtained via least square optimization of error. MVR model was developed with

UCS as dependent variable and LL, PI, %S, %FA, M, A/B, Na/Al and Si/Al as independent variables.

4. Results and discussion of ANN& MVR model

Statistical performance of developed ANNG & MVR model is summarized in Table 7. MSE, MAPE and *R* value of ANNG model for training and testing data were 3.65, 0.34 and 0.9959 & 8.34, 1.50 and 0.9823 respectively while for MVR model these values were found to be 19.20, 7.24 and 0.910 & 19.26, 8.04 and 0.899 respectively. The statistical values in Table 7 suggest that compared to MVR model, ANNG model learnt and predicted the experimental data very well. The regression plot of predicted UCS (Y) against the experimental UCS (T) of testing data of ANNG model is presented in Fig. 1. The best fitting line with $R = 0.9823$, showed a great agreement with line of equality (defined as locus of all the points where Y is equal to T). In Fig. 1 upper bound and lower bound corresponds to 99% confidence interval and refers to the likelihood of predicted values to lie in the region bounded by them over a range of experimental values. From Fig. 1, it may be observed that almost all the data points lie well within the 99% confidence interval band. Tables 8 and 9 shows the analysis of variance (ANOVA) and statistical information of predictor variables of MVR model.

Interpretation of regression analysis data in Tables 8 and 9 were made with the aid of *F*-test and *t*-test at 95% confidence level. From Table 8, it may be observed that *P* value (3.43901E−68) is very low, which suggest that with confidence level $(1-P)$ almost 100%, at least one of the coefficients of MVR model is significant. However, this *F*-test is not sufficient to identify which coefficients are significant in the MVR model. Furthermore, *t*-tests were conducted to identify significance of individual coefficients. Table 9 gives the *t*-stat and corresponding *P* value of individual coefficients. It is observed that *P* values of coefficients of LL, PI, M, A/B and Si/Al corresponds to pretty low confidence levels $(1-P < 0.95)$ and are not significant for the model MVR. On the other hand *P* values of %S, %FA and Na/Al are fairly low with high confidence level $(1-P > 0.95)$ and suggest that these coefficients are significant for MVR model. Table 9 also shows the lower and upper limit of 95% confidence interval. The fact that with 95% probability zero falls in this interval of LL, PI, M, A/B and Si/Al is consistent with the insignificance obtained from *t*-tests of these parameters. Confidence intervals of %S, %FA and Na/Al do not include zero and hence agrees with the significance of *t*-tests. Notably MVR model failed to generalize the geopolymer stabilization mechanism as it rejected the significance of LL, PI, M, A/B and Si/Al in UCS prediction.

Table 7
Performance of ANNG & MVR model.

Model	Dataset	Statistical parameter		
		R	MSE	MAPE (%)
ANNG	Training data	0.996	0.34	3.65
	Testing data	0.982	1.50	8.34
MVR	Training data	0.910	7.24	19.20
	Testing data	0.899	8.04	19.26

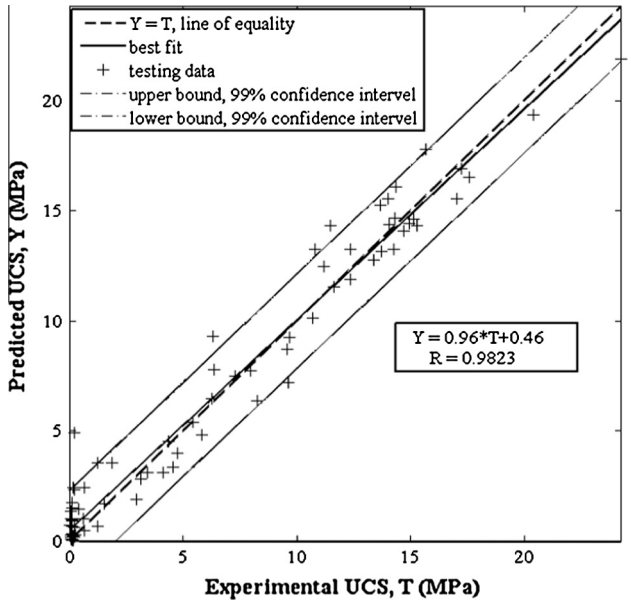

Fig. 1. Regression plot of predicted UCS against experimental UCS of ANNG model.

5. Sensitivity analysis

ANN has often been labeled as "black box" because it does not provide any meaningful insight into the relative influence of input variables in the prediction process. However, methods such as Garson's algorithm and Connection weight approach have been successfully used by some researchers for assessing variable contribution in geotechnical engineering problems [22,24,26,27]. In the present study, aforesaid two methods have been used to identify important input variables in UCS prediction. Both the methods use optimized weight vector to identify important input variables, details of which are available elsewhere [35,36]. Optimized weight vectors of the ANNG model are presented in Table 10. Based on the weights listed in Table 10 the importance and relative ranking of different input variables of ANNG using Garson's algorithm and Connection weight approach is shown in Table 11. It may be observed from Table 11 that both the methods ranked %S as most important parameter and PI, LL as least important. Ranking given by Connection weight approach seems to be more realistic and acceptable due to following reasons:

Table 8
Analysis of variance (ANOVA) of MVR model.

Source	Df[a]	SS[b]	MS[c]	F	P
Regression	8	6934.78	866.847	114.247	3.44E−68
Residual	189	1434.03	7.58748		
Total	197	8368.81			

[a] Degrees of freedom.
[b] Sum square.
[c] Mean square.

Table 9
Statistical information of predictor variables of MVR model.

Predictor variable	Coefficient	St. Error[a]	*t* Stat	*P*-value	Lower 95%	Upper 95%
Intercept	−19.383	37.314	−0.519	0.604	−92.988	54.223
LL	0.677	1.653	0.410	0.683	−2.584	3.938
PI	−0.803	1.746	−0.460	0.646	−4.246	2.641
%S	0.446	0.019	23.522	0.000	0.408	0.483
%FA	−0.159	0.075	−2.128	0.035	−0.307	−0.012
M	0.010	0.093	0.104	0.917	−0.173	0.192
A/B	1.559	2.337	0.667	0.506	−3.051	6.168
Na/Al	1.929	0.835	2.310	0.022	0.282	3.576
Si/Al	1.835	1.133	1.619	0.107	−0.400	4.070

[a] Standard error.

Table 10
Weights and biases of ANNG model.

Hidden neuron	1	2	3	4	5	6	7	8	9
Weights									
LL	0.3628841	0.5419326	−0.2937444	−0.2116877	0.2653603	−0.1853607	−0.3097787	0.0075196	0.0204999
PI	0.369377	0.5369191	−0.2245446	−0.2318771	0.2738614	−0.2184916	−0.3115534	−0.0538415	0.0185486
%S	0.5897703	−0.7615235	1.1981799	0.927121	−0.8416281	2.3030705	0.6571431	−0.4821696	−3.0940908
%FA	−0.7323973	−0.2151186	−0.1192431	0.6972916	0.0437981	−0.1492126	−0.3636751	−0.5134436	−0.6653426
M	0.0459346	−1.3432356	0.2324142	−0.0029854	−0.25607	0.3956939	0.3794025	−0.4053115	−0.6236945
A/B	0.3968692	0.1144805	−0.714601	1.4446369	0.4706329	0.5180817	−0.948128	−0.5417032	−0.4761987
Na/Al	−0.2166143	0.0985487	−0.6259914	0.7770202	−0.5654682	−0.0393934	−0.5098167	−0.2473717	0.0039087
Si/Al	−0.8783382	−0.2924284	0.8183638	−1.0704382	0.9229966	−1.1520773	−0.0449366	0.3899406	0.4866911
UCS	0.6853775	−0.2436421	0.9247476	0.7800804	−0.7024167	−1.3515494	−0.7118643	1.2871627	−1.0579425
Biases									
Hidden layer	−0.2315256	−0.030465	−0.4300668	0.3754885	0.3755988	0.1207328	−0.1433123	−1.35863	−0.4448306
Output layer	−1.0629781								

Table 11
Sensitivity analysis results.

Model variable name		LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al
Connection weight approach	Importance	−0.05	−0.03	2.08	0.46	0.08	0.16	0.35	0.32
	Relative ranking	8	7	1	2	6	5	3	4
Garson's algorithm	Importance	0.5536	0.5682	2.45414	0.8804	0.9393	1.37442	0.7808	1.4491
	Relative ranking	8	7	1	5	4	3	6	2

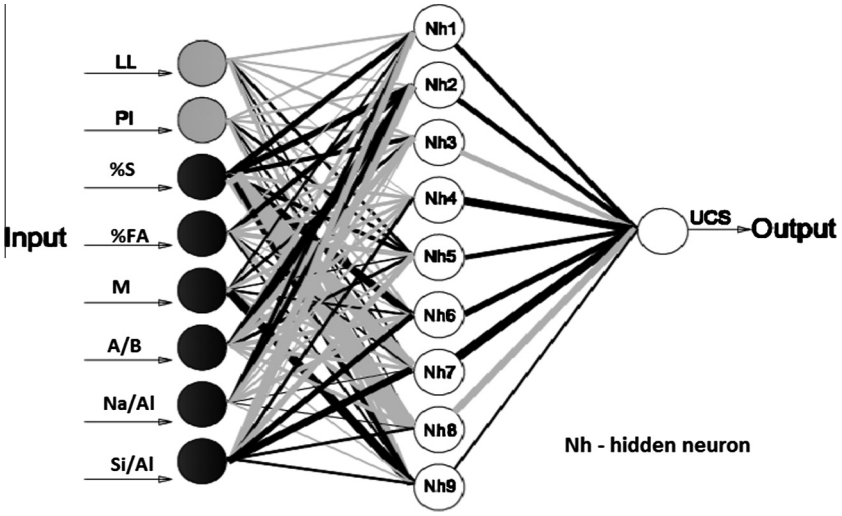

Fig. 2. Neural interpretation diagram of ANNG model.

- As the amount of binder (i.e. %S or %FA) in the mix increases, more binder is available to bind relatively lesser amount of soil, resulting in higher value of UCS. Therefore Connection weight approach ranking of %S and %FA as the most important parameters confirmed the critical effect of source material on UCS.
- Na/Al and Si/Al ratios of each specimen were independent of %S and %FA in the mix and variation of these two parameters were done by changing M, A/B and replacing NaOH with in different dosages of Na_2SiO_3. Connection weight approach ranked Na/Al and Si/Al as most important parameters after %S and %FA. Role played by Na/Al and Si/Al in the present study is in good agreement with Duxson et al. [20] and Rees [21] for geopolymer synthesis.
- The relative importance given by Connection weight approach of %S is approximately 4.5 times of that of %FA, which is quite evident from experimental results. UCS of GGBS treated soil is much higher than that of FA stabilized soil under identical mix proportions. GGBS is highly reactive compared to FA and dissolution extent of Si and Al element of GGBS is much higher than that of FA in geopolymer environment [5,37].

6. Neural interpretation diagram (NID)

Neural interpretation diagram (NID) is a method for visual interpretation of connection weights among the neurons [38]. Using the weights given in Table 10, a NID is presented in Fig. 2 where grey line signifies negative connection weight and black line signifies positive connection weight. Thickness of the line represents the relative magnitude of connection weight. Grey circle and black circle indicates inverse effect and direct effect respectively. It may be observed from Fig. 2 that LL and PI have inverse effect on UCS which is a justified physical representation of the stabilization mechanism.

7. Conclusions

The following general conclusions may be derived from the present study:

1. GGBS-based geopolymer stabilization is an effective method for treating clayey soil and yields much higher strength than FA-based geopolymer stabilized samples under identical mix proportions.
2. ANNG model with MLP feed-forward network and Bayesian Regularization back propagation training algorithm outperformed MVR model in predicting 28 day UCS of geopolymer stabilized clayey soil with LL, PI, %S, %FA, M, A/B, Na/Al and Si/Al as input parameters.
3. MVR model showed that %S, %FA and Na/Al are the significant parameters for UCS prediction.
4. Compared to Garson's algorithm, Connection weight approach is capable of identifying the true importance of input variables in UCS prediction.
5. According to Connection weight approach, %S is the most important parameter influencing UCS prediction followed by %FA, Na/Al, Si/Al, A/B, M, LL and PI.
6. NID demonstrated the negative or inverse effect of LL and PI on the UCS of treated soil.
7. The superiority of ANNG model over MVR model in UCS prediction can be attributed to its flexibility and adaptability in generalizing the data.

Appendix A. Example showing calculation procedure of Na/Al and Si/Al

Example

In a certain mix, let us assume that total amount of dry soil taken is $\boldsymbol{x}$ gm. Binder percentage is S, molarity is M and alkali to binder ratio is A/B

Therefore amount of binder present in the mix in gm = $(S/100) * \boldsymbol{x}$

Amount of alkali solution present in the mix in gm = $(S/100) * \boldsymbol{x} * (A/B)$

Again 1 molar NaOH solution contains = 40 gm NaOH in 1 l (1000 gm) water

M molar NaOH solution contains = $40 * M$ gm NaOH in 1 l (1000 gm) water.

Therefore $(1000 + 40 * M)$ gm alkali solution contains = $40 * M$ gm of NaOH

So, $(S/100) * \boldsymbol{x} * (A/B)$ gm alkali solution contains = $\frac{40*M}{(1000+40*M)} * (S/100) * \boldsymbol{x} * (A/B)$ gm of NaOH

Now 40 gm NaOH contains = 23 gm of Na

$\frac{40*M}{(1000+40*M)} * (S/100) * \boldsymbol{x} * (A/B)$ gm NaOH contains = $\frac{23}{40} * \frac{40*M}{(1000+40*M)} * (S/100) * \boldsymbol{x} * (A/B)$ gm of Na

Again, from Avogadro's No

23 gm Na contains = $6.023 * 10\text{^}23$ No. of Na atoms

$\frac{23}{40} * \frac{40*M}{(1000+40*M)} * (S/100) * \boldsymbol{x} * (A/B)$ gm Na contains = $\frac{\left(\frac{S}{100}\right)*\boldsymbol{x}*\left(\frac{A}{B}\right)*\mathbf{M}}{(\mathbf{1000}+\mathbf{40}*\mathbf{M})} * \mathbf{6.023} * \mathbf{10\text{^}23}$ No. of Na atoms

Now percentage of Al_2O_3 and SiO_2 in GGBS are 20% & 35% respectively

Therefore amount of Al_2O_3 present in binder = $(S/100) * \boldsymbol{x} * 0.20$ gm

Therefore amount of SiO_2 present in binder = $(S/100) * \boldsymbol{x} * 0.35$ gm

Now 102 gm Al_2O_3 contains = 54 gm of Al

$(S/100) * \boldsymbol{x} * 0.20$ gm Al_2O_3 contains = $\frac{54}{102} * (S/100) * \boldsymbol{x} * 0.20$ gm of Al

Again 27 gm Al contains = $6.023 * 10\text{^}23$ No. of Al atoms

Therefore $\frac{54}{102} * (S/100) * \boldsymbol{x} * 0.20$ gm of Al contains = $\frac{\mathbf{1}}{\mathbf{51}} * \mathbf{(S/100)} * \boldsymbol{x} * \mathbf{0.20} * \mathbf{6.023} * \mathbf{10\text{^}23}$ No. of Al atoms

Similarly,

It can be shown that No. of Si atoms present in the mix = $\frac{\mathbf{1}}{\mathbf{60}} * \mathbf{(S/100)} * \boldsymbol{x} * \mathbf{0.35} * \mathbf{6.023} * \mathbf{10\text{^}23}$

$$\mathbf{Na/Al} = \frac{\frac{\left(\frac{S}{100}\right)*\boldsymbol{x}*\left(\frac{A}{B}\right)*\mathbf{M}}{(\mathbf{1000}+\mathbf{40}*\mathbf{M})} * \mathbf{6.023} * \mathbf{10\text{^}23}}{\frac{\mathbf{1}}{\mathbf{51}} * (\mathbf{S/100}) * \boldsymbol{x} * \mathbf{0.20} * \mathbf{6.023} * \mathbf{10\text{^}23}} \quad (1)$$

And

$$\mathbf{Si/Al} = \frac{\frac{\mathbf{1}}{\mathbf{60}} * (\mathbf{S/100}) * \boldsymbol{x} * \mathbf{0.35} * \mathbf{6.023} * \mathbf{10} \wedge \mathbf{23}}{\frac{\mathbf{1}}{\mathbf{51}} * (\mathbf{S/100}) * \boldsymbol{x} * \mathbf{0.20} * \mathbf{6.023} * \mathbf{10} \wedge \mathbf{23}} \quad (2)$$

e.g., say S = 20, $\frac{A}{B}$ = 0.65, M = 14.5, putting these values in Eqs. (1) & (2), we get

Na/Al = 1.52

Si/Al = 1.49

Appendix B. Details of experimental variables and test results

Sl. No	Soil type	LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al	28 day UCS (MPa)	Sl. No	Soil Type	LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al	28 day UCS (MPa)
1	S1	116	88.46	20	0	4	0.45	0.39	1.49	0.0595	143	S3	37.7	14.07	0	12	14.5	0.65	1.34	2.49	0.18
2	S1	116	88.46	16	0	4	0.45	0.39	1.49	0.0616	144	S3	37.7	14.07	0	8	14.5	0.65	1.34	2.49	0.127
3	S1	116	88.46	12	0	4	0.45	0.39	1.49	0.0551	145	S3	37.7	14.07	0	4	14.5	0.65	1.34	2.49	0
4	S1	116	88.46	8	0	4	0.45	0.39	1.49	0.0494	146	S3	37.7	14.07	0	20	14.5	0.85	1.75	2.49	0.189
5	S1	116	88.46	4	0	4	0.45	0.39	1.49	0.0484	147	S3	37.7	14.07	0	16	14.5	0.85	1.75	2.49	0.17
6	S1	116	88.46	20	0	8	0.45	0.69	1.49	0.1784	148	S3	37.7	14.07	0	12	14.5	0.85	1.75	2.49	0.163
7	S1	116	88.46	16	0	8	0.45	0.69	1.49	0.1044	149	S3	37.7	14.07	0	8	14.5	0.85	1.75	2.49	0.12
8	S1	116	88.46	12	0	8	0.45	0.69	1.49	0.0542	150	S3	37.7	14.07	0	4	14.5	0.85	1.75	2.49	0
9	S1	116	88.46	8	0	8	0.45	0.69	1.49	0.0638	151	S3	37.7	14.07	8	12	12	0.65	0.49	2.12	5.855
10	S1	116	88.46	4	0	8	0.45	0.69	1.49	0.0553	152	S3	37.7	14.07	6	10	12	0.65	0.49	2.12	2.597
11	S1	116	88.46	20	0	12	0.45	0.93	1.49	1.836	153	S3	37.7	14.07	5	7	12	0.65	0.49	2.12	0.12
12	S1	116	88.46	16	0	12	0.45	0.93	1.49	1.5198	154	S3	37.7	14.07	3	5	12	0.65	0.49	2.12	0.097
13	S1	116	88.46	12	0	12	0.45	0.93	1.49	0.442	155	S3	37.7	14.07	2	2	12	0.65	0.49	2.12	0.053
14	S1	116	88.46	8	0	12	0.45	0.93	1.49	0.0738	156	S3	37.7	14.07	8	12	14.5	0.65	0.56	2.12	4.899
15	S1	116	88.46	4	0	12	0.45	0.93	1.49	0.0557	157	S3	37.7	14.07	6	10	14.5	0.65	0.56	2.12	3.41
16	S1	116	88.46	20	0	12	0.65	1.34	1.49	3.8335	158	S3	37.7	14.07	5	7	14.5	0.65	0.56	2.12	0.604
17	S1	116	88.46	16	0	12	0.65	1.34	1.49	2.5293	159	S3	37.7	14.07	3	5	14.5	0.65	0.56	2.12	0.096
18	S1	116	88.46	12	0	12	0.65	1.34	1.49	1.5138	160	S3	37.7	14.07	2	2	14.5	0.65	0.56	2.12	0.074
19	S1	116	88.46	8	0	12	0.65	1.34	1.49	0.4841	161	S3	37.7	14.07	12	8	12	0.65	0.76	1.92	7.346
20	S1	116	88.46	4	0	12	0.65	1.34	1.49	0	162	S3	37.7	14.07	10	6	12	0.65	0.76	1.92	6.191
21	S1	116	88.46	20	0	12	0.85	1.75	1.49	4.0932	163	S3	37.7	14.07	7	5	12	0.65	0.76	1.92	0.348
22	S1	116	88.46	16	0	12	0.85	1.75	1.49	3.0047	164	S3	37.7	14.07	5	3	12	0.65	0.76	1.92	0.144
23	S1	116	88.46	12	0	12	0.85	1.75	1.49	1.2701	165	S3	37.7	14.07	2	2	12	0.65	0.76	1.92	0.045
24	S1	116	88.46	8	0	12	0.85	1.75	1.49	0.5495	166	S3	37.7	14.07	12	8	14.5	0.65	0.86	1.92	9.562
25	S1	116	88.46	4	0	12	0.85	1.75	1.49	0.3633	167	S3	37.7	14.07	10	6	14.5	0.65	0.86	1.92	8.595
26	S1	116	88.46	20	0	15	0.45	1.05	1.49	3.7829	168	S3	37.7	14.07	7	5	14.5	0.65	0.86	1.92	0.971
27	S1	116	88.46	16	0	15	0.45	1.05	1.49	2.4024	169	S3	37.7	14.07	5	3	14.5	0.65	0.86	1.92	0.14
28	S1	116	88.46	12	0	15	0.45	1.05	1.49	1.2396	170	S3	37.7	14.07	2	2	14.5	0.65	0.86	1.92	0.054
29	S1	116	88.46	8	0	15	0.45	1.05	1.49	0.2017	171	S3	37.7	14.07	4	16	12	0.65	0.24	2.31	2.687
30	S1	116	88.46	4	0	15	0.45	1.05	1.49	0.064	172	S3	37.7	14.07	3	13	12	0.65	0.24	2.31	0.65
31	S1	116	88.46	20	0	15	0.65	1.52	1.49	4.7478	173	S3	37.7	14.07	2	10	12	0.65	0.24	2.31	0.199
32	S1	116	88.46	16	0	15	0.65	1.52	1.49	3.1467	174	S3	37.7	14.07	2	6	12	0.65	0.24	2.31	0.109
33	S1	116	88.46	12	0	15	0.65	1.52	1.49	1.6606	175	S3	37.7	14.07	1	3	12	0.65	0.24	2.31	0.037
34	S1	116	88.46	8	0	15	0.65	1.52	1.49	0.5452	176	S3	37.7	14.07	4	16	14.5	0.65	0.27	2.31	3.127
35	S2	116	88.46	4	0	15	0.65	1.52	1.49	0.0513	177	S3	37.7	14.07	3	13	14.5	0.65	0.27	2.31	0.615
36	S2	116	88.46	20	0	15	0.85	1.98	1.49	3.1376	178	S3	37.7	14.07	2	10	14.5	0.65	0.27	2.31	0.134
37	S2	116	88.46	16	0	15	0.85	1.98	1.49	2.6131	179	S3	37.7	14.07	2	6	14.5	0.65	0.27	2.31	0.142
38	S2	116	88.46	12	0	15	0.85	1.98	1.49	1.4259	180	S3	37.7	14.07	1	3	14.5	0.65	0.27	2.31	0
39	S2	116	88.46	8	0	15	0.85	1.98	1.49	0.635	181	S3	37.7	14.07	16	4	12	0.65	1.04	1.7	10.53
40	S2	116	88.46	4	0	15	0.85	1.98	1.49	0.0656	182	S3	37.7	14.07	13	3	12	0.65	1.04	1.7	7.492
41	S2	82	56.46	20	0	4	0.45	0.39	1.49	0.0575	183	S3	37.7	14.07	10	2	12	0.65	1.04	1.7	0.656
42	S2	82	56.46	16	0	4	0.45	0.39	1.49	0.0568	184	S3	37.7	14.07	6	2	12	0.65	1.04	1.7	0.24
43	S2	82	56.46	12	0	4	0.45	0.39	1.49	0.0617	185	S3	37.7	14.07	3	1	12	0.65	1.04	1.7	0
44	S2	82	56.46	8	0	4	0.45	0.39	1.49	0.0724	186	S3	37.7	14.07	16	4	14.5	0.65	1.18	1.7	10.56

(*continued on next page*)

Appendix B (*continued*)

Sl. No	Soil type	LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al	28 day UCS (MPa)	Sl. No	Soil Type	LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al	28 day UCS (MPa)
45	S2	82	56.46	4	0	4	0.45	0.39	1.49	0.0761	187	S3	37.7	14.07	13	3	14.5	0.65	1.18	1.7	9.61
46	S2	82	56.46	20	0	8	0.45	0.69	1.49	2.6153	188	S3	37.7	14.07	10	2	14.5	0.65	1.18	1.7	1.323
47	S2	82	56.46	16	0	8	0.45	0.69	1.49	0.7228	189	S3	37.7	14.07	6	2	14.5	0.65	1.18	1.7	0.176
48	S2	82	56.46	12	0	8	0.45	0.69	1.49	0.081	190	S3	37.7	14.07	3	1	14.5	0.65	1.18	1.7	0.04
49	S2	82	56.46	8	0	8	0.45	0.69	1.49	0.0815	191	S1	116	88.46	25	0	12	0.45	0.93	1.49	5.012
50	S2	82	56.46	4	0	8	0.45	0.69	1.49	0.0611	192	S1	116	88.46	30	0	12	0.45	0.93	1.49	6.644
51	S2	82	56.46	20	0	12	0.45	0.93	1.49	4.7157	193	S1	116	88.46	35	0	12	0.45	0.93	1.49	7.278
52	S2	82	56.46	16	0	12	0.45	0.93	1.49	0.9838	194	S1	116	88.46	40	0	12	0.45	0.93	1.49	8.696
53	S2	82	56.46	12	0	12	0.45	0.93	1.49	0.1699	195	S1	116	88.46	50	0	12	0.45	0.93	1.49	10.35
54	S2	82	56.46	8	0	12	0.45	0.93	1.49	0.092	196	S1	116	88.46	25	0	12	0.65	1.34	1.49	5.423
55	S2	82	56.46	4	0	12	0.45	0.93	1.49	0.1138	197	S1	116	88.46	30	0	12	0.65	1.34	1.49	6.251
56	S2	82	56.46	20	0	12	0.65	1.34	1.49	6.3339	198	S1	116	88.46	35	0	12	0.65	1.34	1.49	8.13
57	S2	82	56.46	16	0	12	0.65	1.34	1.49	5.499	199	S1	116	88.46	40	0	12	0.65	1.34	1.49	9.384
58	S2	82	56.46	12	0	12	0.65	1.34	1.49	2.9055	200	S1	116	88.46	50	0	12	0.65	1.34	1.49	11.18
59	S2	82	56.46	8	0	12	0.65	1.34	1.49	0.3208	201	S1	116	88.46	25	0	14.5	0.45	1.05	1.49	3.484
60	S2	82	56.46	4	0	12	0.65	1.34	1.49	0.1083	202	S1	116	88.46	30	0	14.5	0.45	1.05	1.49	4.605
61	S2	82	56.46	20	0	12	0.85	1.75	1.49	6.5492	203	S1	116	88.46	35	0	14.5	0.45	1.05	1.49	6.519
62	S2	82	56.46	16	0	12	0.85	1.75	1.49	5.612	204	S1	116	88.46	40	0	14.5	0.45	1.05	1.49	8.7
63	S2	82	56.46	12	0	12	0.85	1.75	1.49	4.5196	205	S1	116	88.46	50	0	14.5	0.45	1.05	1.49	10.35
64	S2	82	56.46	8	0	12	0.85	1.75	1.49	1.0488	206	S1	116	88.46	25	0	14.5	0.65	1.52	1.49	4.951
65	S2	82	56.46	4	0	12	0.85	1.75	1.49	0.0826	207	S1	116	88.46	30	0	14.5	0.65	1.52	1.49	5.471
66	S2	82	56.46	20	0	15	0.45	1.05	1.49	6.9624	208	S1	116	88.46	35	0	14.5	0.65	1.52	1.49	6.285
67	S2	82	56.46	16	0	15	0.45	1.05	1.49	4.4171	209	S1	116	88.46	40	0	14.5	0.65	1.52	1.49	7.956
68	S2	82	56.46	12	0	15	0.45	1.05	1.49	1.0497	210	S1	116	88.46	50	0	14.5	0.65	1.52	1.49	10.92
69	S2	82	56.46	8	0	15	0.45	1.05	1.49	0.1081	211	S2	82.2	56.46	25	0	12	0.45	0.93	1.49	6.304
70	S2	82	56.46	4	0	15	0.45	1.05	1.49	0.0969	212	S2	82.2	56.46	30	0	12	0.45	0.93	1.49	11.62
71	S2	82	56.46	20	0	15	0.65	1.52	1.49	7.8573	213	S2	82.2	56.46	35	0	12	0.45	0.93	1.49	13.87
72	S2	82	56.46	16	0	15	0.65	1.52	1.49	6.0593	214	S2	82.2	56.46	40	0	12	0.45	0.93	1.49	15.55
73	S2	82	56.46	12	0	15	0.65	1.52	1.49	3.5162	215	S2	82.2	56.46	50	0	12	0.45	0.93	1.49	18.53
74	S2	82	56.46	8	0	15	0.65	1.52	1.49	0.3799	216	S2	82.2	56.46	25	0	12	0.65	1.34	1.49	10.69
75	S2	82	56.46	4	0	15	0.65	1.52	1.49	0.1194	217	S2	82.2	56.46	30	0	12	0.65	1.34	1.49	12.35
76	S2	82	56.46	20	0	15	0.85	1.98	1.49	6.9127	218	S2	82.2	56.46	35	0	12	0.65	1.34	1.49	13.26
77	S2	82	56.46	16	0	15	0.85	1.98	1.49	5.7791	219	S2	82.2	56.46	40	0	12	0.65	1.34	1.49	13.66
78	S2	82	56.46	12	0	15	0.85	1.98	1.49	4.3611	220	S2	82.2	56.46	50	0	12	0.65	1.34	1.49	15.69
79	S2	82	56.46	8	0	15	0.85	1.98	1.49	1.9891	221	S2	82.2	56.46	25	0	14.5	0.45	1.05	1.49	10.08
80	S2	82	56.46	4	0	15	0.85	1.98	1.49	0.0786	222	S2	82.2	56.46	30	0	14.5	0.45	1.05	1.49	12.59
81	S3	38	14.07	20	0	4	0.45	0.39	1.49	0.0724	223	S2	82.2	56.46	35	0	14.5	0.45	1.05	1.49	13.45
82	S3	38	14.07	16	0	4	0.45	0.39	1.49	0.0778	224	S2	82.2	56.46	40	0	14.5	0.45	1.05	1.49	15.12
83	S3	38	14.07	12	0	4	0.45	0.39	1.49	0.0713	225	S2	82.2	56.46	50	0	14.5	0.45	1.05	1.49	15.36
84	S3	38	14.07	8	0	4	0.45	0.39	1.49	0.0445	226	S2	82.2	56.46	25	0	14.5	0.65	1.52	1.49	8.791
85	S3	38	14.07	4	0	4	0.45	0.39	1.49	0.0301	227	S2	82.2	56.46	30	0	14.5	0.65	1.52	1.49	10.95
86	S3	38	14.07	20	0	8	0.45	0.69	1.49	0.2017	228	S2	82.2	56.46	35	0	14.5	0.65	1.52	1.49	12.02
87	S3	38	14.07	16	0	8	0.45	0.69	1.49	0.1687	229	S2	82.2	56.46	40	0	14.5	0.65	1.52	1.49	14.26
88	S3	38	14.07	12	0	8	0.45	0.69	1.49	0.1089	230	S2	82.2	56.46	50	0	14.5	0.65	1.52	1.49	17.04
89	S3	38	14.07	8	0	8	0.45	0.69	1.49	0.0869	231	S3	37.7	14.07	25	0	12	0.45	0.93	1.49	15.86

90	S3	38	14.07	4	0	8	0.45	0.69	1.49	0.0985	232	S3	37.7	14.07	30	0	12	0.45	0.93	1.49	18.92
91	S3	38	14.07	20	0	12	0.45	0.93	1.49	10.089	233	S3	37.7	14.07	35	0	12	0.45	0.93	1.49	19.46
92	S3	38	14.07	16	0	12	0.45	0.93	1.49	5.8037	234	S3	37.7	14.07	40	0	12	0.45	0.93	1.49	22.03
93	S3	38	14.07	12	0	12	0.45	0.93	1.49	0.1173	235	S3	37.7	14.07	50	0	12	0.45	0.93	1.49	23.48
94	S3	38	14.07	8	0	12	0.45	0.93	1.49	0.0676	236	S3	37.7	14.07	25	0	12	0.65	1.34	1.49	17.25
95	S3	38	14.07	4	0	12	0.45	0.93	1.49	0.1071	237	S3	37.7	14.07	30	0	12	0.65	1.34	1.49	18.98
96	S3	38	14.07	20	0	12	0.65	1.34	1.49	10.786	238	S3	37.7	14.07	35	0	12	0.65	1.34	1.49	20.72
97	S3	38	14.07	16	0	12	0.65	1.34	1.49	9.5833	239	S3	37.7	14.07	40	0	12	0.65	1.34	1.49	22.38
98	S3	38	14.07	12	0	12	0.65	1.34	1.49	2.5673	240	S3	37.7	14.07	50	0	12	0.65	1.34	1.49	24.26
99	S3	38	14.07	8	0	12	0.65	1.34	1.49	0.0693	241	S3	37.7	14.07	25	0	14.5	0.45	1.05	1.49	14
100	S3	38	14.07	4	0	12	0.65	1.34	1.49	0.0257	242	S3	37.7	14.07	30	0	14.5	0.45	1.05	1.49	17.14
101	S3	38	14.07	20	0	12	0.85	1.75	1.49	10.042	243	S3	37.7	14.07	35	0	14.5	0.45	1.05	1.49	20.41
102	S3	38	14.07	16	0	12	0.85	1.75	1.49	9.6476	244	S3	37.7	14.07	40	0	14.5	0.45	1.05	1.49	21.89
103	S3	38	14.07	12	0	12	0.85	1.75	1.49	8.2621	245	S3	37.7	14.07	50	0	14.5	0.45	1.05	1.49	22.71
104	S3	38	14.07	8	0	12	0.85	1.75	1.49	0.1486	246	S3	37.7	14.07	25	0	14.5	0.65	1.52	1.49	11.46
105	S3	38	14.07	4	0	12	0.85	1.75	1.49	0.0337	247	S3	37.7	14.07	30	0	14.5	0.65	1.52	1.49	14.33
106	S3	38	14.07	20	0	15	0.45	1.05	1.49	10.809	248	S3	37.7	14.07	35	0	14.5	0.65	1.52	1.49	16.58
107	S3	38	14.07	16	0	15	0.45	1.05	1.49	9.8781	249	S3	37.7	14.07	40	0	14.5	0.65	1.52	1.49	18.08
108	S3	38	14.07	12	0	15	0.45	1.05	1.49	0.2692	250	S3	37.7	14.07	50	0	14.5	0.65	1.52	1.49	18.64
109	S3	38	14.07	8	0	15	0.45	1.05	1.49	0.1788	251	S3	37.7	14.07	20	0	10	0.85	1.54	1.49	11.58
110	S3	38	14.07	4	0	15	0.45	1.05	1.49	0.0567	252	S3	37.7	14.07	20	0	10	0.85	1.54	1.52	11.61
111	S3	38	14.07	20	0	15	0.65	1.52	1.49	11.033	253	S3	37.7	14.07	20	0	10	0.85	1.54	1.56	12.16
112	S3	38	14.07	16	0	15	0.65	1.52	1.49	8.187	254	S3	37.7	14.07	20	0	10	0.85	1.54	1.6	12
113	S3	38	14.07	12	0	15	0.65	1.52	1.49	3.5342	255	S3	37.7	14.07	20	0	10	0.85	1.54	1.64	12.47
114	S3	38	14.07	8	0	15	0.65	1.52	1.49	0.099	256	S3	37.7	14.07	20	0	10	0.85	1.54	1.68	12.62
115	S3	38	14.07	4	0	15	0.65	1.52	1.49	0.0382	257	S3	37.7	14.07	20	0	10	0.85	1.54	1.8	13.05
116	S3	38	14.07	20	0	15	0.85	1.98	1.49	8.6611	258	S3	37.7	14.07	20	0	10	0.85	1.54	1.91	13.37
117	S3	38	14.07	16	0	15	0.85	1.98	1.49	7.9992	259	S3	37.7	14.07	20	0	10	0.85	1.54	1.99	14.32
118	S3	38	14.07	12	0	15	0.85	1.98	1.49	7.754	260	S3	37.7	14.07	20	0	10	0.85	1.54	2.06	15.57
119	S3	38	14.07	8	0	15	0.85	1.98	1.49	1.2167	261	S3	37.7	14.07	20	0	10	0.85	1.54	2.14	17.55
120	S3	38	14.07	4	0	15	0.85	1.98	1.49	0.0708	262	S3	37.7	14.07	20	0	10	0.85	1.54	2.22	18.33
121	S3	38	14.07	0	20	12	0.45	0.82	2.49	0.1174	263	S3	37.7	14.07	20	0	10	0.85	1.54	2.26	18.31
122	S3	38	14.07	0	16	12	0.45	0.82	2.49	0.1099	264	S3	37.7	14.07	20	0	12	0.65	1.34	1.49	12.35
123	S3	38	14.07	0	12	12	0.45	0.82	2.49	0.0849	265	S3	37.7	14.07	20	0	12	0.65	1.34	1.52	13.03
124	S3	38	14.07	0	8	12	0.45	0.82	2.49	0.0169	266	S3	37.7	14.07	20	0	12	0.65	1.34	1.55	13.6
125	S3	38	14.07	0	4	12	0.45	0.82	2.49	0	267	S3	37.7	14.07	20	0	12	0.65	1.34	1.58	14.24
126	S3	38	14.07	0	20	12	0.65	1.18	2.49	0.2107	268	S3	37.7	14.07	20	0	12	0.65	1.34	1.62	14.7
127	S3	38	14.07	0	16	12	0.65	1.18	2.49	0.197	269	S3	37.7	14.07	20	0	12	0.65	1.34	1.65	15.01
128	S3	38	14.07	0	12	12	0.65	1.18	2.49	0.1689	270	S3	37.7	14.07	20	0	12	0.65	1.34	1.75	14.93
129	S3	38	14.07	0	8	12	0.65	1.18	2.49	0.1103	271	S3	37.7	14.07	20	0	12	0.65	1.34	1.85	15.27
130	S3	38	14.07	0	4	12	0.65	1.18	2.49	0	272	S3	37.7	14.07	20	0	12	0.65	1.34	1.92	14.72
131	S3	38	14.07	0	20	12	0.85	1.55	2.49	0.2293	273	S3	37.7	14.07	20	0	12	0.65	1.34	1.99	13.38
132	S3	38	14.07	0	16	12	0.85	1.55	2.49	0.2241	274	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.49	12.57
133	S3	38	14.07	0	12	12	0.85	1.55	2.49	0.1868	275	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.52	13.54
134	S3	38	14.07	0	8	12	0.85	1.55	2.49	0.1555	276	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.56	13.38
135	S3	38	14.07	0	4	12	0.85	1.55	2.49	0	277	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.6	13.73
136	S3	38	14.07	0	20	15	0.45	0.93	2.49	0.1954	278	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.64	13.7
137	S3	38	14.07	0	16	15	0.45	0.93	2.49	0.1232	279	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.67	14.01
138	S3	38	14.07	0	12	15	0.45	0.93	2.49	0.08	280	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.79	14.06

(*continued on next page*)

Appendix B (*continued*)

Sl. No	Soil type	LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al	28 day UCS (MPa)	Sl. No	Soil Type	LL	PI	%S	%FA	M	A/B	Na/Al	Si/Al	28 day UCS (MPa)
139	S3	38	14.07	0	8	15	0.45	0.93	2.49	0.039	281	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.9	14.03
140	S3	38	14.07	0	4	15	0.45	0.93	2.49	0	282	S3	37.7	14.07	20	0	14.5	0.65	1.52	1.98	14.65
141	S3	38	14.07	0	20	15	0.65	1.34	2.49	0.1852	283	S3	37.7	14.07	20	0	14.5	0.65	1.52	2.06	14.82
142	S3	38	14.07	0	16	15	0.65	1.34	2.49	0.1819											

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