Modelling of soil shear strength using neural network approach

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ANN based Prediction of Shear Strength of Soil from their index properties

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Abstract: Shear strength of soil (expressed in terms of 'cohesion' and friction angle 'Φ') is significant in designing of civil engineering structures and for solving many geotechnical problems. The conventional method of determining shear strength parameter by using laboratory experiments is both time consuming and cumbersome. An attempt has been made to develop models for the prediction of cohesion 'c' and friction angle 'Φ' using artificial neural network. The input variables used for developing the model are index properties such as (water content (w), Liquid Limit(LL), Plastic Limit(PL), Plasticity index(PI), Dry Density (DD), Bulk density(BD), Gravel %(GP), Sand %(SP), Silt%(STP), and Clay%(CP) of soil which is collected from the city of Ranchi in Jharkhand. Models consisting of different combination of input parameters were studied by varying the number of hidden layers and number of epochs. Optimum architecture of neural network was identified and performance of developed models is evaluated using statistical parameters such as RMSE, NMSE, MB, FB and d. A low value of RMSE, NMSE, MB and FB values and, "d" value nearly equal to unity confirmed the efficiency of ANN in prediction of shear strength.

Keywords: *Cost prediction, artificial neural network, Factors affecting performance, ANN*

1. Introduction

A loaded soil mass fails when the shearing stress induced in it reaches to limiting value, causing the deformation of soil. Sinking of footing, movement of wedge soil behind a retaining wall or sliding in an earth embankment are some of the forms of failure. So prior to designing of foundation for structure or road embankment, retaining wall etc, determination of shear strength of soil is of utmost importance. Further**,** it is one of the most complex properties of soil, as obtaining undisturbed soil sample from the field and conducting no. of triaxial shear test in laboratory is both time consuming and needs careful supervision. Hence there is now a tendency in countries all over the world towards building up correlation equation between the soil properties and index properties of soil (Obasi and Anyaegbunam)(1)

Shear strength of soil is defined as the "the internal resistance per unit area that the soil mass can offer to resist failure and sliding along any plane inside it". It is generally considered to be a function of cohesion between soil particles and inter-granular friction. Jain et al., (2) explained that the angle of internal friction depends upon dry density, particle size distribution, shape of particles, surface texture, and water content. Cohesion depends upon size of clayey particles, types of clay minerals, valence bond between particles, water content, and proportion of the clay.

Many empirical and polynomial models have already been employed for estimating shear strength parameters. Using statistical and neural approach Goktepe et al. (3) analyzed relation between index properties and shear strength parameters of normally consolidated clays. The results indicated that the ANN-based model is more successful. Roy et.al (4) also correlated shear strength parameters with bulk density, dry density, natural moisture content, specific gravity, liquid limit, plastic limit, plasticity index using statistical models. Mousavi et al,(5) used Genetic Programming (GP) and orthogonal least squares algorithm to present a correlation between the internal friction angle and the physical properties of soils such as the fine and coarse content, density, and liquid limit. Other researchers (Gupte et.al,(6), Pradhan et. al,(7) and Vishal et. al,(8)) have also applied different numerical solution for investigating the dump slope stability.

ANNs have been found very successful in several areas of geotechnical engineering such as pile capacity prediction Ideris and Izzad(9), site characterization Samui and Sitharam(10) earth retaining structures Goh and Kulhawy (11), settlement of structures((Shahin et.al, (12). Models have also been developed for design of tunnels Leu et.al, (13), liquefaction Venkatesh et.al, (14), permeability (Sinha and Wang)(15) and compressive strength of rocks Singh et.al,(16)

Using ANN specifically, efforts have been made extensively for determining correlations between the shear strength parameters and soil index properties. Khanlari et al.(17) utilized the ANN approach to predict friction angle and cohesion of soils. The input layer consist of percentages of passing the Sieve No. 200 (≠ 200), 40 (≠ 40) and 4 (≠ 4), plasticity index, and bulk density. The results indicated that Multilayer Perceptron feed forward neural network model shows better performance rather than radial basis function neural network model.

Recently, Tizpa et al.(18) related compaction characteristics, permeability, and soil shear strength to soil index properties. In this study, six input variables were used for the ANN model for prediction of permeability coefficient are fineness modulus (FM), liquid limit (LL), gravel content (G_c), sand content (S_c), fine content (F_c), and compaction degree (C_d).

Also Kanungo et al (19) investigated the potential of ANN and regression tree (CART) technique for the indirect estimation of shear strength parameters. Models were developed using gravel %(GP), Sand %(SP), Silt %(STP), clay %(CP), dry density(DD) and plasticity index (PI) as input parameter.

2. Methodology

2.1. Study area

Fig 1 *Surroundings of Ranchi, Jharkhand*

The study area is Ranchi, Jharkhand (Fig 1).The soil samples were collected from in and around the areas of Ranchi, situated between latitude of 23^{o}22'10''N and longitude 85^{0}20'.58''E. Being the capital city of Jharkhand, the newly formed state in the year 2000, has witnessed construction of many high rise buildings in recent years. Every year the construction of dams, bridges, tunnels and retaining walls are also increasing rapidly.

The determination of cohesion "c" and friction angle "φ" and hence bearing capacity is essential for the construction of foundation of any building. As Jharkhand does not have enough testing equipment and trained manpower, a neural model as such will be able to satisfy this demand

2.2. Soil Properties

Soil characteristics are commonly assessed through soil testing which involves experimental measurements. Many engineering properties can be correlated. Sezer (20) proposed that strength of soil is related to shape of particle and grain size distribution Tsiambos et.al (21) justified the influence of the variation in clay mineral content on the residual strength of soils and attempted correlations with clay size fraction and plasticity index. Mousavi et al (5)and Tizpa et al(18)also confirmed and concluded the importance of bulk density on internal friction angle. Roopnarine et.al (22) showed strong and significant correlation of soil friction angle with clay and sand percent. Therefore all index properties have direct or indirect effect upon the shear strength of soil.

Based upon all these research work and literature review all the index properties have been considered for developing the ANN model. The soil samples were collected from the field and laboratory tests conducted to determine the index properties. A total number of 50 bore hole were explored using standard penetration test.

A total of 300 soil samples were collected which include both disturbed and undisturbed samples. Undisturbed samples were subjected to triaxial testing apparatus in unconsolidated undrained condition for quick determination of shear strength parameters of soil cohesion "c" and internal friction angle "φ".

These undisturbed samples were also subjected to a series of laboratory tests to determine the index properties of soil. These tests include Atterberg Limit test, Grain size distribution, Hydrometer test and Bulk density test . Tests were performed as per (IS:2720-Part IV, V and XXIX) for determination of Liquid limit (LL), plastic limit(PL), plasticity Index(PI), gravel% (GP), Sand%(STP), Silt%(SP), Clay%(CP), Bulk density(BD), Dry density(DD) and water content(w). The percentage of silt was found to be high in most of the soil collected.

Table1 shows the statistical analysis considering the maximum, minimum, mean, and standard deviation on the all the soil parameters to understand the nature of soil. It can be seen that mean and average value of each parameters are similar. It clearly indicates that the statistical distribution for each of the parameters of soil is normal. Maximum difference between mean and median values shown by percent of sand and silt is 9.75% and 8% respectively. It can also be seen from Table1 the soil samples considered for model development varies in nature, from fine grained soil to coarse grained soil.

Table 1*: Statistical analysis of all the soil parameters*

Parameter	L.L (%)	P.L (%)	P.I (%)	GP (%)	SP (%)	Silt (%)	Clay (%)	BD (g/cm^3)	DD (g/cm^3)	W (%)	C Kg/cm^2	Φ (^{0})
Maximum	58.3	33.46	36.15	16	90	78	39	2.35	1.986	25.2	1.51	35
Minimum	0	0	0	0	8	10	0	1.54	1.460	3.65	0	3
Mean	33.81	22.96	10.81	0.23	25.75	62.02	11.996	1.98	1.651	19.659	0.314	17.0
Median	37	25.6	11.2	0	16	70	14	1.98	1.64	20.4	0.36	14.5

2.3. Development of ANN model

Artificial Neural Network is the most widely used pattern recognition method. A neural network consists of simple synchronous processing elements, called neurons, which are inspired by biological nervous system. It discovers the inherent relationship between parameters through learning process and creates a mapping between input space and target space. The true power and advantage of neural network lies in its ability to represent both linear and non-linear relationship from the data being modeled (Lal and Tripathy) (23)

There are no hard and fast rules to determine the network architecture especially the number of hidden layers. The number of hidden layers was estimated by hit and trial method. The number of hidden layers depends upon the complexity of input output mapping, the amount of noise in the data and amount of training data available. The manner in which the database is used in training and testing has a significant effect on the result. Here the database was divided into several combination of training and testing sets until a robust representation of the whole population was achieved. Here various differentiable nonlinear functions (such as tan-sig and log-sig) are used as a transfer function. These functions were incorporated for mapping desired nonlinear input output relation. MLP utilizes a supervised learning technique called back propagation for training the network. A supervised training algorithm requires teacher for training purpose, implying a large no. of input and output sample to optimize the connection weights and bias of each node by iterative process Jain et.al,(2).

In the current research work architecture was developed with four layers of neurons connected by weights. The model developed for predicting the cohesion of soil (c) and internal friction angle (φ**)** are 10:18:8:1, 9:18:8:1, 8:18:8:1, 7:18:8:1 and 10:2:18:1, 9:2:18:1, 8:2:18:1, 7:2:18:1 respectively. Table 2 and Table 3 summarize the four models with different combination of input variable.

Table2*: Neural network Architecture of internal friction angle "φ" as output variables and varying input variable for different ANN models*

Model	Neural Network Architecture	Input variable
Model 1	7:2:18:1	LL,PL,PI,GP, SP,STP, CP
Model 2	8:2:18:1	LL,PL,PI,GP, SP,STP, CP, BP
Model 3	9:2:18:1	LL,PL,PI,GP, SP,STP, CP, BP,DD
Model 4	10:2:18:1	LL,PL,PI,GP, SP,STP, CP, BP,DD, w

Table3*: Neural network Architecture of cohesion "c" as output variables and varying input variable for different ANN model.*

Model	Neural Network Architecture	Input variable
Model 5	7:18:8:1	LL,PL,PI,GP, SP,STP, CP
Model 6	8:18:8:1	LL,PL,PI,GP, SP,STP, CP, BP
Model 7	9:18:8:1	LL,PL,PI,GP, SP,STP, CP, BP,DD
Model 8	10:18:8:1	LL,PL,PI,GP, SP,STP, CP, BP,DD, w

2.4. Normalization of Data

It may occur that input and output vectors contain data comprising of physical values often varying in order of magnitude. This may result in large amplitudes of the target solution surfaces and attract the training attention to the regions with the highest amplitudes. In such cases, it may be useful to transform the input and output vectors so that all variables would receive similar attention during training. All variables can be scaled dimensionless values falling into an interval (0, 1). Normalization is done with respect to the mean and standard deviation of the training set using equation (1)

$$X_{ni}=\frac{x_i-\min(X)}{\max(X)-\min(X)} \quad (1)$$

Flood and Kartam (24) stated that" two hidden layers provide the greater flexibility necessary to model complex-shaped solution surfaces, and are thus recommended as a starting point when developing a layered feed-forward network of sigmoidal neurons".

2.5. Statistical Parameters

The primary goal is to make a model that most accurately predicts the desired target value for *the new* data. There are many statistical parameters which give an indication whether the model developed has achieved the desired goal or not. The built models are evaluated using the statistical parameter like root mean square error (RMSE), index of agreement (d), Model (MB), Fractional Bias (FB) and normalized mean square error (NMSE).

If the value of index agreement is 1 and the values of RMSE, MB and FB values are minimum, it indicates that the model developed shows a strong correlation between the predicted and measured values (Lal and Tripathy)[23].

RMSE is one of the most popular measures of error. It has the advantage that large errors receive much greater attention than small errors. Lower RMSE value denotes a more precise model.

$$\mathbf{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \qquad (2)$$

Where P_i and O_i are Predicted and observed data points respectively. N is the number of data points

The d is descriptive statistical parameter that reflects the degree to which the observed variate is accurately measured or estimated by the simulated variable. It is measure of the degree to which model prediction are error free.

$$\mathbf{d} = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}[|P_i - \overline{O}| + |O_i - \overline{O}|]^2} \qquad (3)$$

Here $\overline{O}$ denotes the mean of the observed data points. Similarly $\overline{P}$ represents the mean of predicted data points.

Normalized mean square error (NMSE) is the statistics which emphasizes the scatter in the entire data set. The normalization by the product $\overline{p_i} * \overline{o_i}$ assures that the NMSE will not be biased towards models that over predict or under predict. Smaller values of NMSE denote better model performance. The expression for the NMSE is given by:

$$\mathbf{NMSE} = \frac{\overline{(P_i - O_i)^2}}{\overline{p_i} \cdot \overline{o_i}} \qquad (4)$$

Fractional Bias is normalized to make it non-dimensionless. This fractional bias (FB) varies between +2 and -2 and has a value of zero for an ideal model. It is written in symbolic form as:

$$\mathrm{FB} = 2 * \frac{\overline{P} - \overline{O}}{\overline{P} + \overline{O}} \qquad (5)$$

Model bias is the mean error that is defined as the observed value of concentration less than predicted value. It is given by:

$$\mathbf{MB} = \overline{P_i - O_i} \qquad (6)$$

3. Results and Discussion

In this research a dataset consisting of 300 number of soil samples were used for developing the models out of which, 180 number of soil data were used for training the neuron, and remaining 120 were subjected to testing and validating using the 60:40 distribution. Four models were developed each for prediction of shear strength parameter of soil internal friction angle "φ" and cohesion "c" separately. Furthermore, analysis was carried out by changing the number of epochs and the network which gave the least root mean square error was selected. The performance of Model-1 to Model-4 by changing the input for the prediction of cohesion "c" during generalization on the validation dataset are presented in Table 4 –Table 7.

Similar analysis was done for prediction of internal friction angle "φ". Performances of model 5 to model 8 containing 7, 8, 9 and 10 input neurons during generalization on the validation data set are presented in Table 8-Table 11. They describe the performance for each model having 7:2:18:2, 8:2:18:1, 9:2:18:1 and 10:2:18:1 neural network architecture.

***Table 4**: Estimates of the statistics for cohesion "c" during generalization of Model 1(seven input variables)*

No. of Epoch	D	NMSE	RMSE	M.B	F.B
50	0.91	0.0276	0.0364	0.0073	-0.03328
100	0.886	0.0375	0.042	0.0019	-0.0086
150	0.862	0.0437	0.0458	0.0048	-0.02214
200	0.857	0.0562	0.0513	0.0014	-0.0063
250	0.89	0.0342	0.0402	0.0020	-0.00919
300	0.80	0.063	0.0551	0.050	-0.02301
350	0.84	0.0517	0.0501	0.0063	-0.02892

***Table 5:** Estimates of the statistics for cohesion "c" during generalization of Model 2(eight input variables)*

No. of Epoch	d	NMSE	RMSE	M.B	F.B
50	0.877	0.0357	0.0413	0.0079	-0.0362
100	0.812	0.0491	0.0489	0.0117	-0.0528

150	0.914	0.0317	0.039	0.0075	-0.0340
200	0.896	0.0346	0.0402	0.0016	-0.0078
250	0.756	0.0823	0.0639	0.0116	-0.0524
300	0.8013	0.0729	0.0608	0.0155	-0.0695
350	0.835	0.0341	0.0405	0.0055	-0.0253

Table 6: *Estimates of the statistics for cohesion "c" during generalization of Model 3(nine input variables)*

No. of Epoch	d	NMSE	RMSE	M.B	F.B
50	0.943	0.0218	0.0314	-0.0039	0.0182
100	0.876	0.0502	0.0489	0.0090	-0.0421
150	0.921	0.0276	0.0364	0.0043	-0.0197
200	0.868	0.0576	0.0525	0.0049	-0.022
250	0.887	0.0476	0.0457	-0.0132	0.0634
300	0.736	0.0845	0.0632	0.0025	-0.0113
350	0.945	0.0218	0.0314	-0.0035	0.0183

Table 7: *Estimates of the statistics for cohesion "c" during generalization of Model 4(Ten input variables)*

No. of Epoch	d	NMSE	RMSE	M.B	F.B
50	0.984	0.0602	0.0166	-0.0012	0.0555
100	0.927	0.0502	0.0489	0.0090	-0.0421
150	0.974	0.0276	0.0364	0.0043	-0.0197
200	0.838	0.0531	0.0299	0.0055	-0.0253
250	0.931	0.0476	0.0457	-0.0132	0.0634
300	0.974	0.0091	0.0202	-0.0028	-0.0013
350	0.933	0.0221	0.0324	0.0056	-0.0256

Table8*: Estimates of the statistics for "φ" during generalization of Model 5(seven input variables)*

No. of Epoch	D	NMSE	RMSE	M.B	F.B
50	0.91	0.0238	0.0629	0.0019	-0.00472
100	0.907	0.0254	0.065	0.0024	-0.00578
150	0.926	0.0212	0.0598	0.011	-0.0270
200	0.913	0.027	0.0613	0.0087	-0.02118
250	0.907	0.0279	0.0685	0.0069	-0.01691
300	0.921	0.0243	0.0636	0.0100	-0.02432
350	0.914	0.0271	0.0673	0.0118	-0.02858

Table9: *Estimates of the statistics for "φ" during generalization of Model 6(Eight input variables)*

No. of Epoch	D	NMSE	RMSE	M.B	F.B
50	0.928	0.0197	0.0578	0.0134	-0.0325
100	0.921	0.0236	0.0631	0.0141	-0.0343
150	0.913	0.0248	0.0644	0.0039	-0.0095
200	0.914	0.0230	0.0625	0.0054	-0.0015
250	0.916	0.0234	0.0693	0.0045	-0.0051
300	0.912	0.0281	0.0692	0.0162	-0.0392
350	0.909	0.0267	0.0673	0.0119	-0.02881

Table10: *Estimates of the statistics for "φ" during generalization of Model 7(nine input variables)*

No. of Epoch	D	NMSE	RMSE	M.B	F.B
50	0.930	0.0233	0.0568	0.0007	-0.0017
100	0.919	0.0242	0.0641	0.0193	-0.0466
150	0.894	0.0322	0.074	0.0137	-0.0331
200	0.911	0.0269	0.0675	0.0122	-0.0296
250	0.866	0.0439	0.0858	0.0127	-0.0309
300	0.911	0.0256	0.0653	0.0034	-0.0084
350	0.871	0.0399	0.0812	-0.0012	0.0292

Table11: *Estimates of the statistics for "φ" during generalization of Model 8(Ten input variables)*

No. of Epoch	D	NMSE	RMSE	M.B	F.B
50	0.924	0.0232	0.0631	0.0178	-0.0430
100	0.917	0.0243	0.0639	0.0188	-0.0214
150	0.910	0.0283	0.0688	0.0106	-0.0258
200	0.922	0.0232	0.0621	0.0081	-0.0198
250	0.911	0.0273	0.0684	0.0110	-0.0268
300	0.913	0.0274	0.0682	0.0158	-0.0383
350	0.910	0.0276	0.0681	0.0079	-0.0193

In each model for prediction of cohesion "c", the epochs were varied and statistical parameters evaluated. The numbers of epochs corresponding to the least RMSE was selected as the best one for the particular model. Table-12 gives the summary of four models which gives least value of RMSE. Table-13 shows the performance statistics of the four models for the predictions of cohesion "c". Low RMSE values are obtained for model 4. Predicted cohesion (δp) and observed cohesion (δo) is minimum in model-4. Also the mean of the predicted cohesion ($\overline{p}$ =0.2143) is comparable with the observed mean ($\overline{o}$ =.2155). Hence model with ten input neurons, two hidden layer having eighteen and eight numbers of neurons respectively and one output neurons for cohesion parameters was selected as the best model. The d value of model-4 is 0.98, which is close to 1, and hence explains that the 98.4% of the model prediction are error free. Even though FB value is slightly higher for model-4(0.055), since the NMSE (0.0091) and MB (0.0055) values are closer to zero in model-4 as compared to other three models. Hence it can be concluded that the overall performance of model-4 is better than the other three models.

Similarly based on correlation analysis, Model-7 having 9:2:18:1 architecture has been selected as the best architecture for internal friction angle. This can be explained from Table15 as the difference between observed δp(0.118) and predicted δo(0.116) for prediction of φ value is minimum in model 7. The average deviation of model 7 is minimum(0.0339). The d value is .93 implying that more than 90% of predicted data is near the observed value. Table-14 gives the performance description of selected model and other three with their NMSE, MB, FB and d value. Although NMSE value is slightly higher than other three models, as the MB value (0.0007) and FB value (0.0017) closer to zero value model-7 can be chosen as the best model.

Table 12*: Summary of the statistical parameter of different models for prediction of cohesion "c"*

Model	Network Architecture	No. of Epoch	Learning rate	d	NMSE	RMSE	MB	FB
Model 1	7:18:8:1	50	0.05	0.913	0.0276	0.039	0.0073	-0.03328
Model 2	8:18:8:1	150	0.05	0.914	0.0317	0.0364	0.0075	-0.0340
Model 3	9:18:8:1	50	0.05	0.943	0.0218	0.0314	-0.0039	0.0182
Model 4	10:18:8:1	50	0.05	0.984	0.0091	0.0166	-0.0012	-0.0555

Table 13*: performance statistics of models for prediction of cohesion "c"*

$\overline{p}$	$\overline{o}$	δp	δo	RMSE	D	MB	Maximum deviation	Minimum deviation	NMSE	Average deviation
0.2144	0.2155	0.0494	0.0663	0.0276	0.913	0.0073	0.165	0.0002	0.0276	0.018
0.222	0.2155	0.0599	0.0663	0.0317	0.914	0.0075	0.206	0.0002	0.0317	0.021
0.2116	0.2155	0.0684	0.0663	0.0218	0.943	-0.0039	0.1123	0.001	0.0218	0.025
0.2143	0.2155	0.0676	0.0663	0.0202	0.974	-0.0012	0.0671	0.0001	0.0091	0.011

Table 14*: Summary of the statistical parameter of different models for prediction of internal friction angle "φ"*

Model	Network Architecture	No. of Epoch	Learning rate	d	NMSE	RMSE	MB	FB
Model 5	7:2:18:1	150	0.05	0.926	0.0212	0.0598	0.011	-0.0270
Model 6	8:2:18:1	50	0.05	0.928	0.0197	0.0578	0.0134	-0.0325
Model 7	9:2:18:1	50	0.05	0.930	0.0233	0.0568	0.0007	-0.0017
Model 8	10:2:18:1	200	0.05	0.922	0.0232	0.0621	0.0081	-0.0198

Table 15*: performance statistics of models for prediction of internal friction angle "φ"*

$\overline{p}$	$\overline{o}$	δp	δo	RMSE	d	MB	Maximum deviation	Minimum deviation	NMSE	Average deviation
0.4166	0.4054	0.112	0.116	0.0598	0.926	0.011	0.2398	0.0008	0.0212	0.0357
0.4188	0.4054	0.108	0.116	0.0578	0.928	0.0134	0.2524	0.001	0.0197	0.0361
0.4061	0.4054	0.118	0.116	0.0568	0.930	0.0007	0.2441	0.0006	0.0233	0.0339
0.4153	0.4054	0.106	0.116	0.0621	0.922	0.0081	0.2375	0.0001	0.0232	0.0382

The developed MLP model gave reliable estimate of the c and φ values. The results indicated that the proposed model has high potential to estimate the values of cohesion and internal friction angle since predicted values do not differ much from the observed value. Fig 2 and Fig 3 illustrates the Error Scatter of the models for cohesion, c. and internal friction angle. From this figure, it can be seen that more than 90% of the predicted data are in good agreement with observed values.

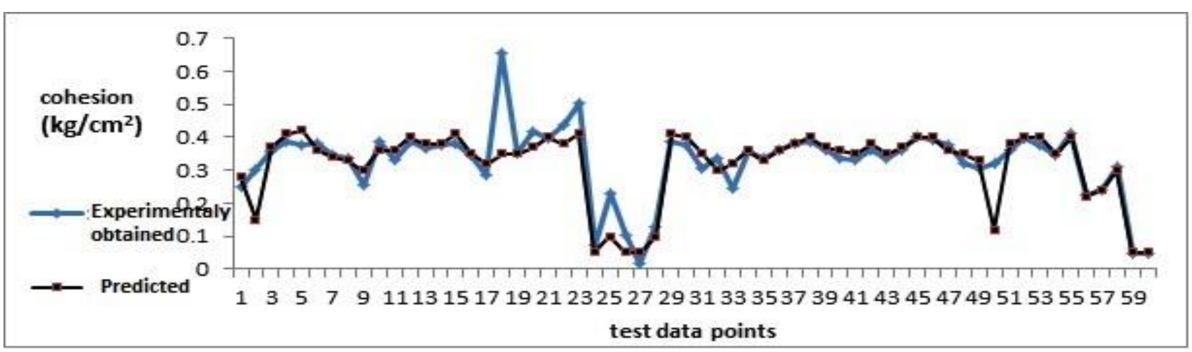

Fig2*: Plot showing comparison between observed and predicted values of cohesion for best selected Model 4*

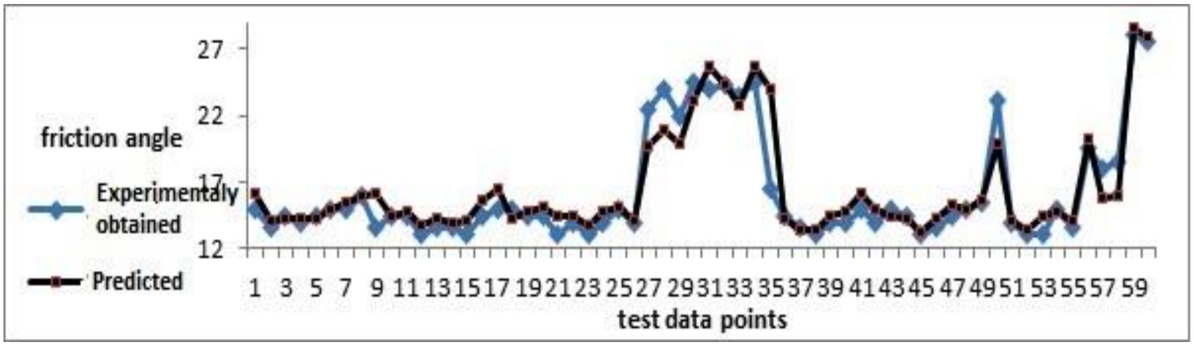

***Fig3**: Plot showing comparison between observed and predicted values of internal friction angle for best selected Model 7*

4. Conclusion

ANN based model is developed to predict the value of shear strength parameter of soil in the state of Jharkhand. It is observed that prediction model with all ten input parameters consisting of liquid limit (LL), Plastic limit(PL), plasticity index(PI), gravel%(GP), sand%(SP), silt%(STP), clay%(CP), bulk density(BD), dry density (DD)and water content(w) showed best performance for the prediction of cohesion "c". Similarly for the estimation of internal friction angle "φ", prediction model with nine input parameter i.e excluding water content showed the best performance on the test data.

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