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# Prediction of UCS and STS of Kaolin clay stabilized with supplementary cementitious material using ANN and MLR

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**Abstract.** The present study focuses on the application of artificial neural network (ANN) and Multiple linear Regression (MLR) analysis for developing a model to predict the unconfined compressive strength (UCS) and split tensile strength (STS) of the fiber reinforced clay stabilized with grass ash, fly ash and lime. Unconfined compressive strength and Split tensile strength are the nonlinear functions and becomes difficult for developing a predicting model. Artificial neural networks are the efficient tools for predicting models possessing non linearity and are used in the present study along with regression analysis for predicting both UCS and STS. The data required for the model was obtained by systematic experiments performed on only Kaolin clay, clay mixed with varying percentages of fly ash, grass ash, polypropylene fibers and lime as between 10-20%, 1-4%, 0-1.5% and 0-8% respectively. Further, the optimum values of the various stabilizing materials were determined from the experiments. The effect of stabilization is observed by performing compaction tests, split tensile tests and unconfined compression tests. ANN models are trained using the inputs and targets obtained from the experiments. Performance of ANN and Regression analysis is checked with statistical error of correlation coefficient (R) and both the methods predict the UCS and STS values quite well; but it is observed that ANN can predict both the values of UCS as well as STS simultaneously whereas MLR predicts the values separately. It is also observed that only STS values can be predicted efficiently by MLR.

**Keywords:** Kaolin clay; grass ash; unconfined compression test; split tensile test; artificial neural network; regression model

## 1. Introduction

Soils with high clay content prove to be problematic. Construction of any structure on such soils needs to be carefully designed. Kaolin clay though is a low swell-shrink clay but it has high compressibility and low strength (Alrubaye *et al*. 2016). The most suitable method of stabilization for clays is soil improvement using the chemical stabilization. Chemical stabilization is a guaranteed method for improving the properties of soils which transforms it into a stronger and stable material. Lime/cement has been used for soil stabilization since olden times. Recently industrial and agriculture wastes like Fly ash, silica fume, ground granulated blast furnace slag, baggese ash, rice husk ash etc. are also used for stabilization. These materials are difficult to dispose and also poses environmental issues as it pollutes the atmosphere as well as ground water. It is observed that these pozzolans proves very effective when it is mixed with concrete (for

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improving the workability) or soil (improving the strength). In the past, many researchers Amiralian *et al*. 2012; Bhuvaneshwari *et al*. 2005, Bandopadhyay and Bhattacharjee 2010, Sahoo *et al*. 2010, Jala and Goyal 2006, Brooks 2009, Mahajan and Saliq 2015, Hussain and Dash 2015, Mohanty *et al*. 2016, observed that fly ash alone and fly ash in combination with lime improves the workability of soil, helps in erosion control, improves the dry density, UCS, CBR, free swell index, liquid limit and plastic limit of soil. Fiber along with puzzolons is a good stabilizer. Fiber mixed with clay improves the strength and toughness of soil (Tang *et al*. 2007, Kumar *et al*. 2007, Ayyappan *et al*. 2010, Attom and Tamimi 2010, Malekzadeh and Bilsel 2012, Changizi and Haddad 2014, Li *et al*. 2014). Stabilization using combination of different puzzolons like rice husk ash, pond ash and silica fume with lime has been presented by many researchers, Gupta and Kumar (2016; 2017), Kumar and Gupta 2016, Karatai *et al*. 2017 and Alrubaye *et al*. 2017. Grass ash is used as a replacement in concrete (Cordeiro and Sales 2015). Amu *et al*. 2011 used sugarcane straw ash to enhance the geotechnical properties of lateritic soil. Grass ash is the residue left after burning of grass. Disposal of this residue is difficult and results in environmental pollution. Based on the detailed literature survey, it is observed that grass ash is rarely used as a stabilizing material and literature related to it is very limited.

In the present study emphasis has been made to mix grass ash which is easily available to kaolin clay along with other materials to observe its use as a stabilizing material.

Artificial neural network (ANN) mimics the human brain and learns from the examples presented to it. ANNs can model the complex behaviour of geotechnical properties. ANNs have been employed to predict the compressive strength of concrete, lateral loads as well as the uplift capacities of pile foundations, drilled shafts, estimating soil properties, liquefaction potential, retaining wall, geo-environmental engineering, aerospace engineering, environmental engineering etc. (Shahin and Jaksa 2005, Shahin and Jaksa 2006, Chen *et al*. 2006, Shahin *et al*. 2003, Kung *et al*. 2007, Shahin 2010, Choobbasti *et al*. 2015, Mahamaya *et al*. 2015, Asadollahfardi *et al*. 2016, Sunny *et al*. 2016, Chore and Magar 2017, Saha *et al*. 2017, Ayat *et al*. 2018). Unconfined Compressive strength and Split (indirect) tensile strength are some tests to determine the compressive and tensile strengths of clays and clays stabilized with supplementary cementitious materials. The tests are easier to conduct but to determine the UCS and STS of various mixes is time consuming. Prediction of UCS and STS from different percentage of clay, grass ash, fly ash, fiber, lime, maximum dry density (MDD) and optimum moisture content (OMC) using statistical model (ANN and regression analysis) as it can easily accommodate the nonlinear nature of UCS and STS. The objective of this study is to stabilize the kaolin clay with various combinations of grass ash, fly ash, lime and polypropylene fiber and develop an ANN model as well as regression analysis for predicting UCS and STS.

## 2. Experimental analysis

Properties of Kaolin clay as performed by Indian and American standards is presented in Table 1. Lime used for the study was locally procured. Polypropylene fibrillated fiber of 6 mm length (procured from Nina Concrete Systems Pvt Ltd) was used in the study and the properties are adopted from Kumar and Gupta (2016). The grass was acquired from school ground in Ferozepur, India. The grass was sun dried for 2 days and then burnt in a period of 3rd to 5th day. The burning of grass yields roughly 9% of black ash which can be easily transformed into powdered form. Fly ash (Class F) was obtained from Guru Gobind Singh super thermal power plant Ropar, Punjab. Fly ash passing from 425 micron sieve is used in this study.

(a) Kaolin Clay

(b) Fly Ash

(c) Lime

(d) Grass Ash

(e) Proctor Test

(f) UCS Test

Fig. 1 Materials used for Testing and various tests performed

The experiments conducted included Atterberg's limits test (liquid limit and plastic limit IS 2720 Part V, 1985), standard proctor tests (IS:2720 (part-VII) 2011), Unconfined compressive strength test (IS:2720-1973) and split tensile strength test (ASTM C496M-17). The Atterberg's limit test were only performed on clayey soil. It was observed that the Liquid limit was 43% and Plastic limit was 19%. Free Swell tests (IS:2720 Part XL, 1977) were also performed to confirm non swelling characteristics. The Atterberg's limit test and Free Swell tests were performed only to know the classification of clay and to observe the swelling characteristics and these values are not further used in development of the model. The tests like Standard Proctor test, unconfined Compressive strength and Split tensile strength were extended on various combinations of lime, fly ash, grass ash and fiber. Fig. 1 presents the different materials procured for testing and the tests performed in the laboratories.

Firstly optimum mixes of lime (L), fly ash (FA), Grass ash (GA) and Fiber (F) are determined. Percentage of lime is varied by 4% and 8% and from the test results 4% is found to be optimum amount of mix and similar mix is recommended by Lime Manual (2004). Fly Ash percentage is varied from 10% to 25% with an increment of 5%. From the various tests it is observed that 20% replacement of Fly Ash was optimum percentage and similar results were also reported by Shahu *et al*. (2013). Grass ash percentage is varied from 1% to 4% and the results recommend 4% replacement for optimum results. Polypropylene fiber percentage is varied from 0.5% to 1.5% and from the various results the optimum replacement was decided to be 1% as the results by replacement of 1.5% fiber demonstrated marginal improvement. These optimum mixes are further combined with each other to observe the improvement in the strength of clay. The total tests performed contributed to 21 samples including only Clay sample.

Combination of materials like lime, fiber, fly ash and grass ash with Kaolin clay (K) for determining different test results are presented in Table 1. It is observed that combination 71% K + 4% L + 4% GA + 20% FA + 1%F yields the maximum results for UCS as well as STS.

Table 1 Test Results for various combinations

| Mix | Combination | MDD (kN/m$^3$) | OMC (%) | UCS kPa | STS kPa |
|---|---|---|---|---|---|
| M1 | 100% K | 16.75 | 19.2 | 104.2 | 23.24 |
| M2 | 96% K + 4% L | 16.2 | 20.5 | 201 | 46.48 |
| M3 | 92% K + 8% L | 15.8 | 22.4 | 211 | 45.61 |
| M4 | 90% K + 10% FA | 16.9 | 18.2 | 155.6 | 33.9 |
| M5 | 85% K + 15% FA | 17.1 | 17.9 | 163.6 | 37.5 |
| M6 | 80% K + 20% FA | 17.2 | 17.3 | 175.6 | 46.27 |
| M7 | 75% K + 25% FA | 17.5 | 16.9 | 160.5 | 15.4 |
| M8 | 99.5 % K + 0.5 % F | 16.5 | 19.5 | 147 | 26.8 |
| M9 | 99% K + 1.0% F | 16.21 | 19.9 | 163.6 | 33 |
| M10 | 98.5% K + 1.5% F | 16 | 20.5 | 168.4 | 35.75 |
| M11 | 99% K + 1% GA | 16.68 | 19.4 | 117 | 24.95 |
| M12 | 98% K + 2% GA | 16.4 | 19.8 | 125.3 | 25.67 |
| M13 | 97% K + 3% GA | 16.1 | 20.4 | 149 | 29.32 |
| M14 | 96% K + 4% GA | 16 | 21 | 165 | 31.82 |
| M15 | 92% K + 4% L + 4% GA | 16.6 | 20.10 | 270.5 | 51.6 |
| M16 | 76% K + 4% L + 20% FA | 16.3 | 19 | 285.4 | 51.84 |
| M17 | 76% K + 4% GA + 20% FA | 16.8 | 17 | 247.5 | 43.12 |
| M18 | 72% K + 4%L + 4% GA + 20% FA | 16.15 | 20.5 | 347.5 | 60.12 |
| M19 | 75% K+ 4%L + 20% FA + 1% F | 15.6 | 18.6 | 356.5 | 66.15 |
| M20 | 91% K + 4%L + 4% GA + 1%F | 15.25 | 19.1 | 312 | 57.2 |
| M21 | 71% K + 4% L + 4% GA + 20% FA + 1%F | 15.7 | 19.5 | 415.7 | 71.2 |

## 3. Modelling using artificial neural network

In this section an ANN model using the NNtool in MATLAB (R2015a) has been developed. Neural networks are based on the biological nervous system. Neural networks learn by examples and can be trained. Neural networks are applied to the problems of pattern recognition, image processing, data compression, forecasting and optimization.

In the present study ANN model is developed to predict both the unconfined compressive strength as well as split tensile strength of Kaolin clay from the different percentages of kaolin clay, fiber, grass ash, fly ash, lime and the values of compaction (MDD and OMC). The data presented in Table 1 is normalized between 0 and 1. Normalization of data is required for having the same range of values which further helps in stable convergence, the normalized data using the normalization function in Eq.1. is presented in Table 2.

$$A = \left( \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \right) \tag{1}$$

Table 2 Consolidated Properties and their Normalized Values

| Norm (FA) | Norm (Kaolin Clay) | Norm (GA) | Norm (Fiber) | Norm (Lime) | Norm (STS) | Norm (MDD) | Norm (OMC) | Norm (UCS) |
|---|---|---|---|---|---|---|---|---|
| 0.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.09 | 0.67 | 0.42 | 0.00 |
| 0.00 | 0.98 | 0.00 | 0.33 | 0.00 | 0.16 | 0.56 | 0.47 | 0.14 |
| 0.00 | 0.93 | 0.00 | 0.67 | 0.00 | 0.00 | 0.43 | 0.56 | 0.19 |
| 0.00 | 0.91 | 0.00 | 1.00 | 0.00 | 0.33 | 0.33 | 0.75 | 0.21 |
| 0.00 | 0.86 | 0.00 | 0.00 | 0.50 | 0.53 | 0.42 | 0.65 | 0.31 |
| 0.00 | 0.72 | 0.00 | 0.00 | 1.00 | 0.52 | 0.24 | 1.00 | 0.34 |
| 0.40 | 0.66 | 0.00 | 0.00 | 0.00 | 0.29 | 0.73 | 0.24 | 0.17 |
| 0.60 | 0.48 | 0.00 | 0.00 | 0.00 | 0.36 | 0.82 | 0.18 | 0.19 |
| 0.80 | 0.31 | 0.00 | 0.00 | 0.00 | 0.53 | 0.87 | 0.07 | 0.23 |
| 1.00 | 0.14 | 0.00 | 0.00 | 0.00 | 0.41 | 1.00 | 0.00 | 0.18 |
| 0.00 | 0.97 | 0.25 | 0.00 | 0.00 | 0.12 | 0.64 | 0.00 | 0.04 |
| 0.00 | 0.93 | 0.50 | 0.00 | 0.00 | 0.14 | 0.51 | 0.53 | 0.07 |
| 0.00 | 0.90 | 0.75 | 0.00 | 0.00 | 0.21 | 0.38 | 0.64 | 0.14 |
| 0.00 | 0.86 | 1.00 | 0.00 | 0.00 | 0.25 | 0.33 | 0.75 | 0.20 |
| 0.00 | 0.72 | 1.00 | 0.00 | 0.50 | 0.63 | 0.60 | 0.58 | 0.53 |
| 0.80 | 0.17 | 0.00 | 0.00 | 0.50 | 0.63 | 0.47 | 0.38 | 0.58 |
| 0.80 | 0.17 | 1.00 | 0.00 | 0.00 | 0.43 | 0.69 | 0.02 | 0.46 |
| 0.80 | 0.03 | 1.00 | 0.00 | 0.50 | 0.77 | 0.40 | 0.65 | 0.78 |
| 0.80 | 0.14 | 0.00 | 0.67 | 0.50 | 0.90 | 0.16 | 0.31 | 0.81 |
| 0.00 | 0.69 | 1.00 | 0.67 | 0.50 | 0.73 | 0.00 | 0.40 | 0.67 |
| 0.80 | 0.00 | 1.00 | 0.67 | 0.50 | 1.00 | 0.20 | 0.47 | 1.00 |

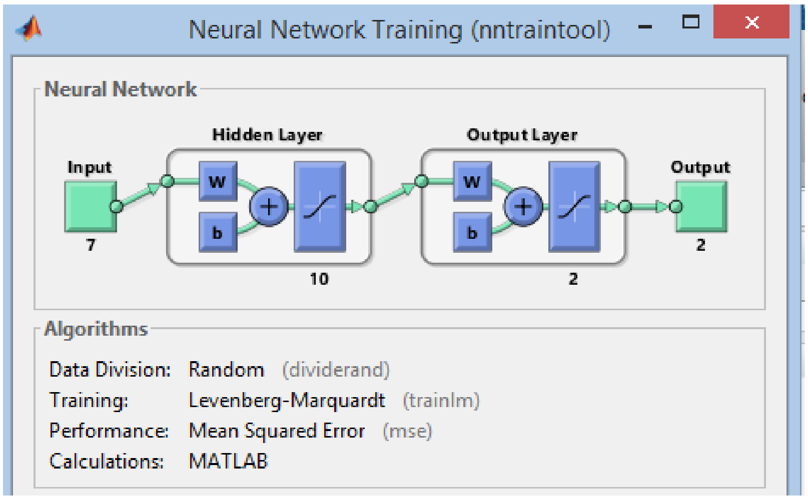


Fig. 2 Constructed neural network in MATLAB (R2015a)

The normalized values of Kaolin clay, fiber, grass ash, fly ash, lime, MDD and OMC (7 input parameterss) are entered as input variable in the NNtool of MATLAB and the normalized values of UCS and STS are entered as the target variable. ANN model aims to generate the relation in the form of

$$y^m = f(x^n) \tag{2}$$

where $x^n$ is an $n$-dimensional input vector consisting of variables, $x_1 \ldots x_i \ldots x_n$ and $y_m$ is an $m$ dimensional output vector consisting of the variables $y_1 \ldots . y_i .., y_m$. In the present study, value of $x_i$ is the inputs and $y_i$ is one dependent variable as UCS and STS (Chore and Magar 2017).

### *3.1 Network construction*

All the inputs are stored in one matrix viz. "*a*" and the targets are stored in another matrix, viz. "*b*". The matrices are recalled in the NNtool and stored as inputs and targets and the network is constructed. NNtool by default divides the training (70% values), validation and testing data (30% values). The network is trained using the network type Feed Forward Back Propagation as this network helps in reducing the error. The constructed network alongwith inputs, hidden layer and outputs is presented in Fig. 2.

Training function used is TrainLM, Performance function is MSE (mean squared error), number of neurons is 10 and transfer function considered is TANSIG that is Tan - Sigmoid transfer function. Transfer function calculates layer's output from net input. This function is well suited for neural networks as the speed is important. Levenberg-Marquardt optimization is the most widely used algorithm. It locates the minimum of sum of squares of non linear functions. LM is a combination of steepest descent and Gauss Newton method, where if the solution is far from correct it assumes the steepest descent form for guaranteed convergence and when the solution is close to correct one it assumes the Gauss Newton method (Lourakis 2005). The network is divided in two layers and the created network is presented in Fig. 3. It is observed from Fig. 2 that the overall $R^2$ is above 99% (0.99027) which indicates the network is trained well and can be used further for predicting unknown data.

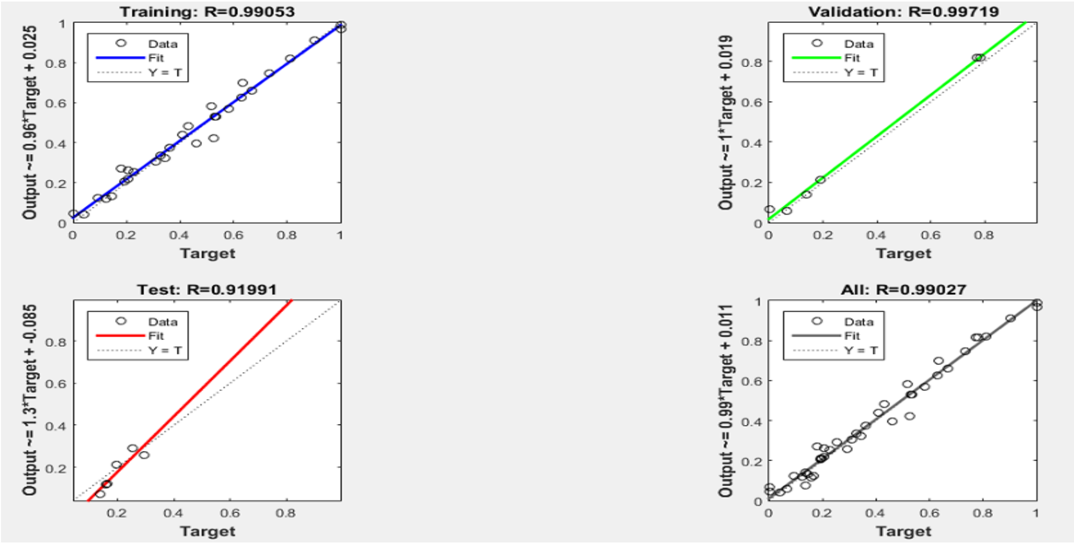
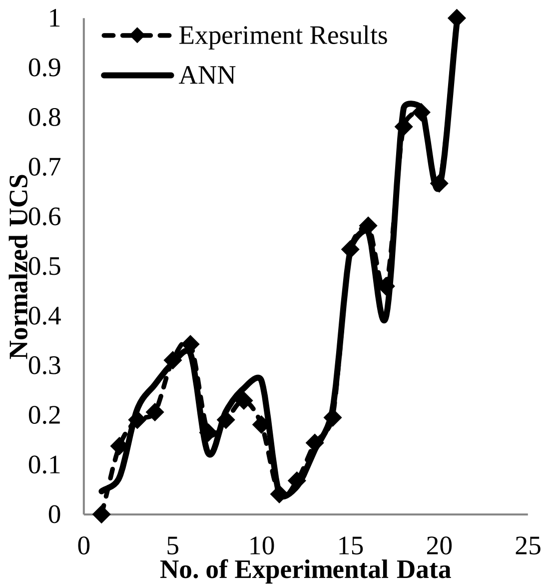



Fig. 3 ANN Results showing the $R^2$ values



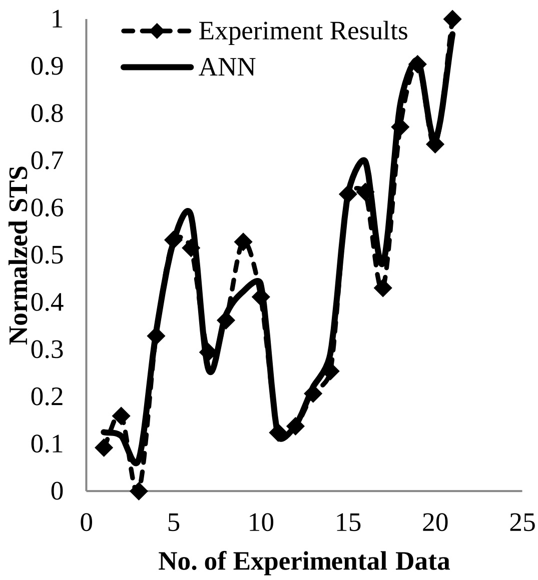




Fig. 4 Comparison of normalized UCS of Experimental and Predicted results using ANN

Fig. 5 Comparison of normalized STS of Experimental and Predicted results using ANN

Two different sets of outputs from the trained network are obtained for UCS and STS and are compared with the results of experimental data and the results are presented in Fig. 4 and 5.

It is observed from Figs. 3 and 4 that the network is trained well with the provided inputs of number of neurons, hidden layer properties and epoch value. The formula presented in Eq. 4. obtained from training the network can be used for renormalizing the target parameters of both UCS as well as STS.

$$output = 0.99 \times target + 0.011 \tag{4}$$

## 4. Modelling using multiple regression analysis

A multiple regression analysis is performed using MS Excel for predicting UCS and STS values. Regression analysis studies the relationship between the dependent variable and independent variables. If the regression function is linear then it is termed as linear regression model and if more than one independent variable is involved then it is termed as multiple linear regression (Orlov 1996). Regression analysis in the past has been employed by many researchers in the field of concrete, hydraulic structures, geotechnical engineering etc. (Yildirim and Gunaydin 2011, Abasi *et al*. 2012, Viji *et al*. 2013, Aktas and Ozerdem 2016, Altunisik *et al*. 2018)

The general formula for multiple linear regression model is presented in Eq. 5. This formula is derived from the intercepts obtained from performing the regression analysis as presented in Tables 3 and 4.

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots b_p x_p \tag{5}$$

where $b$ is the regression constant determined using least squares method

Table 3 Multiple regression analysis for UCS values

| *Regression Statistics* | | | | | | |
|---|---|---|---|---|---|---|
| Multiple R | 0.976421 | | | | | |
| R Square | 0.953398 | | | | | |
| Adjusted R Square | 0.928305 | | | | | |
| Standard Error | 23.43708 | | | | | |
| *ANOVA* | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | |
| Regression | 7 | 146090.5144 | 20870.07 | 37.994168 | 1.16396E-07 | |
| Residual | 13 | 7140.857939 | 549.2968 | | | |
| Total | 20 | 153231.3724 | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
| Intercept | -1551.82 | 3628.735485 | -0.42765 | 0.6759057 | -9391.230696 | 6287.582 |
| FA | 23.94893 | 33.60611915 | 0.712636 | 0.4886655 | -48.6526793 | 96.55053 |
| Kaolin | 19.64362 | 33.65717053 | 0.583638 | 0.5694519 | -53.06828074 | 92.35551 |
| GA | 37.01021 | 33.40384908 | 1.107962 | 0.2879567 | -35.15442242 | 109.1748 |
| Fiber | 85.29668 | 54.80951212 | 1.556239 | 0.1436529 | -33.11207403 | 203.7054 |
| LIME | 38.46986 | 32.93574703 | 1.168028 | 0.2637711 | -32.68349135 | 109.6232 |
| Dry Density | -15.7756 | 24.17947927 | -0.65244 | 0.5254882 | -68.01219277 | 36.46099 |
| OMC | -2.67775 | 6.69883259 | -0.39973 | 0.6958429 | -17.14969654 | 11.7942 |

Table 4 Multiple regression analysis for STS values

| *Regression Statistics* | | | | | | |
|---|---|---|---|---|---|---|
| Multiple R | 0.963436 | | | | | |
| R Square | 0.928208 | | | | | |
| Adjusted R Square | 0.889551 | | | | | |
| Standard Error | 4.859327 | | | | | |
| Observations | 21 | | | | | |
| ANOVA | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | |
| Regression | 7 | 3968.853 | 566.979 | 24.01125 | 1.82E-06 | |
| Residual | 13 | 306.9698 | 23.61306 | | | |
| Total | 20 | 4275.823 | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
| Intercept | -1741.43 | 752.3638 | -2.31461 | 0.037624 | -3366.82 | -116.049 |
| FA | 17.41773 | 6.967724 | 2.499773 | 0.0266 | 2.364878 | 32.47058 |
| Kaolin | 16.74268 | 6.978309 | 2.399246 | 0.03213 | 1.666959 | 31.8184 |
| GA | 18.60079 | 6.925787 | 2.685729 | 0.018696 | 3.638537 | 33.56304 |
| Fiber | 33.3371 | 11.36393 | 2.933589 | 0.011633 | 8.786823 | 57.88738 |
| LIME | 20.43716 | 6.828733 | 2.992819 | 0.010381 | 5.684579 | 35.18974 |
| Dry Density | 4.782729 | 5.013252 | 0.954017 | 0.357479 | -6.04774 | 15.6132 |
| OMC | 0.644545 | 1.388902 | 0.464068 | 0.650274 | -2.356 | 3.645086 |

It is observed from Tables 3 and 4 the $R^2$ for UCS is 0.95 and STS is 0.93. This indicates the model explains the variation in the data well. $R^2$ doesn't indicate whether one's model fits the data well or not, that is indicated by the *F significance* and *P-value*. The value of *F significance* for both the cases (UCS and STS) is less than 0.05 (5%). *P-value* for all the independent variables is above 0.05, which indicates weak evidence against null hypothesis i.e. the model explains about variation well but is not significant. In the case of STS results, *P-value* for independent variables like Fly ash, Kaolin clay, Grass Ash, Fiber and Lime is less than 0.05, indicating significance in fitting the data well whereas MDD and OMC values have higher *P-value* and are omitted from predicting the STS results and the new regression analysis is presented in Table 5 and using the coefficients for the Table, the formula for predicting STS (eliminating MDD and OMC values) using regression analysis is

$$STS = -1350 + 14.47 * FA + 13.75 * K + 15.32 * GA + 26.47 * F + 17.16 * L \tag{6}$$

The comparison of experimental results and predicted results from regression analysis are presented in Fig. 6 and 7. Though the results for UCS are satisfactory, the *P-value* for independent variables for UCS doesn't recommend the exact fitting and it is concluded that using the present independent variables of fiber, Kaolin clay, grass ash, lime, fly ash percentages, MDD and OMC for predicting UCS in regression analysis.

Table 5 Multiple regression analysis for STS values without MDD and OMC

| *Regression Statistics* | | | | | | |
|---|---|---|---|---|---|---|
| Multiple R | 0.960817 | | | | | |
| R Square | 0.923169 | | | | | |
| Adjusted R Square | 0.897559 | | | | | |
| Standard Error | 4.679857 | | | | | |
| Observations | 21 | | | | | |
| **ANOVA** | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | |
| Regression | 5 | 3947.307 | 789.4614 | 36.04672 | 7.67E-08 | |
| Residual | 15 | 328.5159 | 21.90106 | | | |
| Total | 20 | 4275.823 | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* |
| Intercept | -1350.55 | 543.3675 | -2.48553 | 0.025215 | -2508.71 | -192.394 |
| FA | 14.47289 | 5.408781 | 2.675813 | 0.017276 | 2.944344 | 26.00143 |
| Kaolin | 13.75491 | 5.440783 | 2.528113 | 0.023181 | 2.158159 | 25.35167 |
| GA | 15.32422 | 5.289326 | 2.897197 | 0.011057 | 4.05029 | 26.59815 |
| Fiber | 26.46919 | 7.911826 | 3.345523 | 0.004426 | 9.605535 | 43.33285 |
| LIME | 17.15688 | 5.292114 | 3.241972 | 0.005473 | 5.87701 | 28.43676 |

## 5. Conclusions

In the present study, compaction tests, split tensile tests and unconfined compression strength tests are performed on Kaolin clay stabilized with lime, grass ash, fly ash and fiber. Initially individual tests on each material were performed to determine the optimum percentages to be replaced in the kaolin clay. Later different tests on the combination of materials at their optimum replacement values with Kaolin were performed and was observed that combination of clay, Grass Ash (4%), Fly Ash (20%), Lime (4%) and Fiber (1%) yields the maximum result and this can be used as a light weight fill material in different structures like retaining wall, embankment and highway substructures.

The 21 numbers of test results are used for developing an ANN and multiple linear regression model for predicting UCS and STS results. UCS and STS are dependent variables and percentages of Kaolin clay, lime, fiber, Fly ash and Grass Ash along with MDD and OMC are the independent variables. It is observed that ANN predicted the UCS and STS results simultaneously and the $R^2$ obtained is 0.99 whereas it is observed that regression analysis model could predict the results for only one parameter at a time. Moreover it is also observed that the independent variables used for predicting UCS in regression analysis are not compatible and only STS could be predicted satisfactorily. The $R^2$ values obtained for both the models are above 0.9 which indicates a good fit. It is, therefore, concluded that ANN is a better method for prediction as it possesses inherent flexibility. A better result can be achieved for more number of mixes.

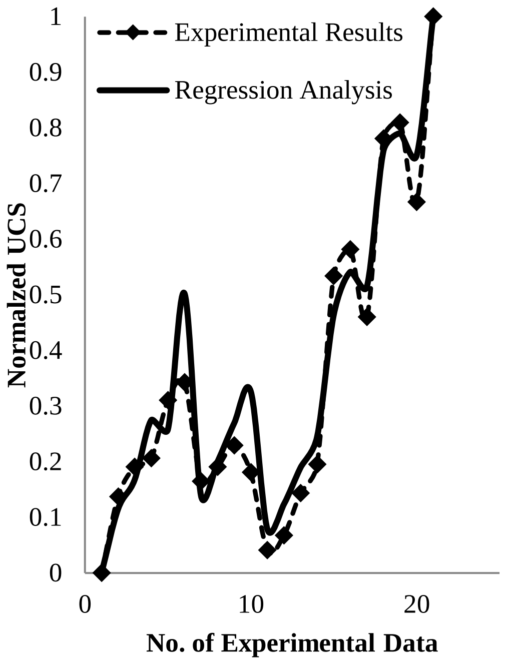



Fig. 6 Comparison of normalized UCS of Experimental and Predicted results using Regression Analysis

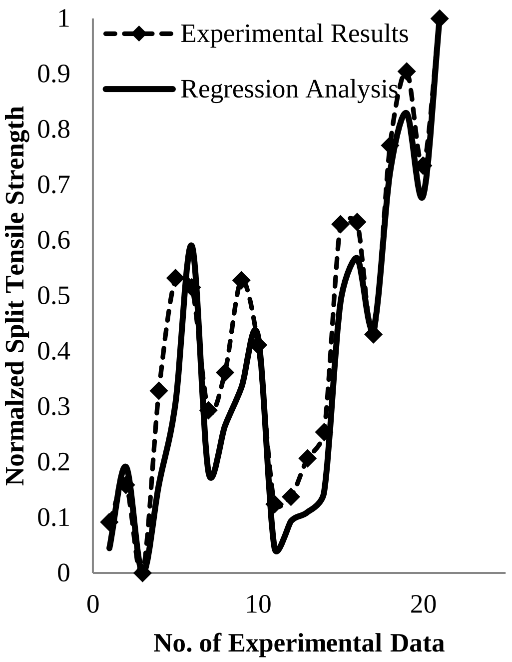



Fig. 7 Comparison of normalized STS of Experimental and Predicted results using Regression Analysis

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