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Prediction of unconfined compressive and Brazilian tensile strength of fiber reinforced cement stabilized fly ash mixes using multiple linear regression and artificial neural network

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Abstract. This paper presents the application of multiple linear regression (MLR) and artificial neural network (ANN) techniques for developing the models to predict the unconfined compressive strength (UCS) and Brazilian tensile strength (BTS) of the fiber reinforced cement stabilized fly ash mixes. UCS and BTS is a highly nonlinear function of its constituents, thereby, making its modeling and prediction a difficult task. To establish relationship between the independent and dependent variables, a computational technique like ANN is employed which provides an efficient and easy approach to model the complex and nonlinear relationship. The data generated in the laboratory through systematic experimental programme for evaluating UCS and BTS of fiber reinforced cement fly ash mixes with respect to 7, 14 and 28 days' curing is used for development of the MLR and ANN model. The data used in the models is arranged in the format of four input parameters that cover the contents of cement and fibers along with maximum dry density (MDD) and optimum moisture contents (OMC), respectively and one dependent variable as unconfined compressive as well as Brazilian tensile strength. ANN models are trained and tested for various combinations of input and output data sets. Performance of networks is checked with the statistical error criteria of correlation coefficient (R), mean square error (MSE) and mean absolute error (MAE). It is observed that the ANN model predicts both, the unconfined compressive and Brazilian tensile, strength quite well in the form of R, RMSE and MAE. This study shows that as an alternative to classical modeling techniques, ANN approach can be used accurately for predicting the unconfined compressive strength and Brazilian tensile strength of fiber reinforced cement stabilized fly ash mixes.

Keywords: artificial neural network (ANN); back propagation algorithm; multiple linear regression (MLR); fly ash; unconfined compressive strength (UCS); Brazilian tensile strength (BTS)

1. Introduction

The fly ash is obtained as a by-product during the combustion of pulverized coal. It is generally

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produced in large quantities by thermal power plants. The worldwide production of fly ash is growing every year. The disposal of fly ash is considered as one of the major environmental issues these days because of its potential to pollute the atmosphere and to contaminate the ground water. Even though the use of fly ash in cement and concrete industries has increased in last few years, bulk utilization of fly ash is possible only in geotechnical applications such as embankments, pavements, subgrades and backfills.

The unconfined compressive strength (UCS) and Brazilian (i.e., indirect) tensile strength (BTS) are some of the significant strength tests normally carried out in respect of geotechnical characterization of fly ash or fly ash based geotechnical materials. The engineering properties of fly ash depend on various factors such as coal source, degree of pulverization, design of boiler unit, loading and firing conditions, handling and storage methods, etc. Further, the compressive strength of the fly ash based mixes also depends on many parameters/index or geotechnical properties of the materials involved in it. The evaluation of these properties involves extensive laboratory investigation. Thereafter, certain period is required for curing prior evaluating the strength of the mix. In a nutshell, for evaluating the strength, considerable time and efforts are required.

The present practice is to perform laboratory investigations on fiber reinforced and cement stabilized fly ash mixes to determine the cement and fiber contents required for a given application. Contents. The evaluation of strength experimentally is a lengthy process as it involves the curing period. Under such circumstances, if the estimation of strength could be developed on the basis of the laboratory tests alone, without resorting to curing of the samples, it would be useful for the engineers. A predictive equation, which can accurately determine the gain in strength of fiber reinforced cement stabilized fly ash mixes would not only save a lot of time, but also result in an optimum and effective utilization of cement and fibers.

2. Review of applications of soft computing tools in geotechnical engineering

The engineering properties of soil and allied materials including pozzolonic along with the rock exhibit varied and uncertain behaviour due to complex and imprecise physical processes associated with the formation of these materials. This is in contrast to most other civil engineering materials, such as steel, concrete and timber, which exhibit far greater homogeneity and isotropy. In order to cope up with the complexity of geotechnical behaviour and spatial variability of these materials, traditional forms of engineering design models are justifiably simplified. An alternative approach, which has been shown to have some degree of success, is based on the data alone to determine the structure and parameters of the model. This technique is known as artificial neural networks (ANNs) and is well suited to model complex problems where relationship between the model variables is unknown (Hubick 1992). The ANNs find applications in various areas of the geotechnical engineering such as foundation engineering, material properties and behaviour, site characterization, liquefaction, earth retaining structures, slope stability, etc. Along similar lines, the statistical method called MLR analysis is also used either independently or in conjunction with ANNs. However, the present study deals with the prediction of strength of based on the properties of the materials in case of fiber reinforced cement stabilized fly ash as mixes and hence, some of the significant works related to use of artificial intelligence and statistical modelling based methods are presented in the subsequent paragraphs.

The properties of the geotechnical materials and its behaviour are the areas that have attracted many researchers to modelling using ANNs. Goh (1995) used neural networks to model the correlation between relative density and the cone resistance from cone penetration test (CPT). Ellis *et al*. (1995) developed an ANN model for sands based on grain size distribution and stress history. Najjar *et al.* (1996) showed that neural network based models can be used accurately to assess soil swelling and that neural networks models can provide significant improvements in prediction accuracy over statistical models. Penumadu and Jean-Lou (1997) used neural networks for representing the behaviour of sand and clay soils. Sidarta and Ghaboussi (1998) employed an ANN model within a finite element analysis to extract the geometrical constitutive behaviour from non-uniform material tests. Ghaboussi and Sidarta (1998) used neural networks for modelling the drained and un-drained behaviour of sandy soil subjected to triaxial compression type testing. Penumadu and Zhao (1999) also used ANNs to model the stress-strain and volume change behaviour of sand and gravel under drained triaxial compression test conditions. Shahin *et al.* (2001) presented the state of the art of the applications of ANNs in geotechnical engineering.

Kurup and Dudani (2002) used neural networks for profiling stress history of clays from PCPT data. Yoon and Kim (2004) presented regression analysis for predicting the compression index for Kwangyang marine clay. Yoon *et al.*(2004) proposed best regression models for predicting compression index using natural water content, liquid limit and void ratio for Korean coastal area. Narendra *et al.* (2006) carried out laboratory investigation on cement stabilized red earth (CL), brown earth (CH), and black cotton soil (CH); and presented a predictive model for unconfined compressive strength (UCS) using genetic programming (GP). The developed model comprised liquid limit, liquidity index, water content, curing period, pH and sodium ion concentrations as the input. However, the output was found to be more dependent on water cement ratio, cement contents and curing period rather than their soil properties. It was attributed to the fact that only three types of soil samples were considered. Ozer *et al.* (2008) used statistical models and neural networks to assess the compression index of clay-bearing soils. Das and Sabat (2008) used neural networks for predicting some of the properties of fly ash.

Isik (2009) developed the models using regression equations and artificial neural networks to estimate the swell index of fine grained soils. Subasi (2009) applied ANN for the prediction of mechanical properties of cement containing class C fly ash. Alavi *et al.* (2010) studied the application of artificial neural networks (ANN) to predict maximum dry density (MDD) and unconfined compressive strength (UCS) of soil and ANN was found to be a better prediction technique. Das *et al.* (2011) used ANN and support vector machine (SVM) to predict the MDD and UCS of cement stabilized soil based on soil plasticity, clay contents, sand contents, gravel contents, moisture content and cement contents as inputs. Sulewska (2011) presented some applications of ANNs in geo-engineering using the analysis of few geotechnical problems, related mainly to prediction and classification purposes. Yildirim and Gunaydin (2011) also estimated the California Bearing Ratio (CBR) of soils from different parts of Turkey using regression analysis and observed the satisfactory agreement in the predicted and the experimental values. Abasi *et al.* (2012) used regression analysis to predict the compression behaviour of normally consolidated fine grained soil and concluded that the proposed empirical models predict the compression index accurately as compared to that with the existing equations.

Akayuli and Ofosu (2013) developed the empirical models for estimating the compression index based on the physical properties of weathered Birimian Phyllites. The regression analysis was used. Viji *et al.* (2013) reported the application of regression analysis and ANN analysis for predicting the compaction characteristics of fly ashes. Borowiec and Wilk (2014) presented the application of ANNs and regression analysis for predicting the consistency parameters of fen soils.

Table 1 Chemical and physical properties of fly ash

Chemical composition			
Property	Value (%)	Property	Value (%)
Silica (SiO_2)	58.040	Titanium Oxide (TiO_2)	1.30
Alumina (Al_2O_3)	25.71	Magnesium Oxide (MgO)	1.589
Ferric Oxide (Fe_2O_3)	5.31	Sodium Oxide (Na_2O)	0.601
Sulphur Tri Oxide (SO_3)	0.677	Potassium Oxide (K_2O)	0.60
Calcium Oxide (CaO)	5.59		
Physical Properties			
Specific Gravity	2.13		
Liquid limit	-		
Shrinkage limit	30.42		
Loss of ignition	1.071		
Moisture (%)	0.267		

Table 2 Characteristics of polypropylene fibers

Property	Value	Property	Value
Length (mm)	60	Water absorbing capacity	Nil
Specific Gravity	0.91	Tensile Strength	450 MPa
Elongation	15%	Melting Point (℃)	165
Nature	Inert	Heat Resistance (℃)	<130

The prediction using ANNs were found in closer agreement with that observed experimentally as compared to the one using regression analysis. Bhatt and Jain (2014) dealt with the prediction of CBR of soils using ANN and regression analysis. Khan *et al*. (2015) developed prediction models for residual strength of clay using functional networks. Suman *et al.* (2016) developed models for predicting MDD and UCS of cement stabilized soil using artificial intelligence techniques such functional networks (FN) and multivariate adaptive regression splines (MARS).

3. Objective of the present study

However, the literature review indicates that the development of ANN and MLR models for predicting UCS and BTS of the cement stabilized and fibre reinforced fly ash mixes is not fully investigated. ANNs are proposed as an alternative method for solving certain difficult problems in selecting the best mix proportion for required characteristics where the conventional techniques have not achieved the desired speed, accuracy and efficiency. Therefore, the objective of the present study is to examine the potential of both, MLR and ANN, for predicting 7, 14 and 28 days' UCS and BTS with the data obtained experimentally (Chore and Vaidya 2015). The complex relationship between mixture proportions and engineering properties of fiber reinforced fly ash is generated based on the data obtained experimentally. It is aimed that both, MLR and ANN, can effectively predict UCS and BTS in spite of the intricate data and it can be used as a tool to support decision making, by improving the efficiency of the process. Hence, this paper deals with

Table 3 Characteristics of cement

Normal Consistency	
Required water for Normal Consistency	110 ml
% of Normal Consistency	27.5%
Setting Time	
Initial Setting Time	150 Min
Final Setting Time	225 Min
Specific Gravity	3.03
Specific Surface	310.83
Compressive Strength (MPa)	
3 Days	27
7 Days	37
28 Days	53

the application of MLR and ANN to correlate UCS and BTS obtained experimentally with other independent variables like cement and fibers along with the maximum dry density and optimum moisture contents.

4. Materials, experimental programme and methodology

4.1 Materials

In the experimental study, the materials, fly ash, Polypropylene fibers and ordinary Portland cement (OPC) were used.

4.1.1 Fly ash

The fly ash was supplied by M/s Dirk India Private Limited, Eklahare Nasik, Maharashtra, India (Source: Nasik Thermal Power Station). The chemical and physical properties of the fly ash were provided by the supplier and are shown in Table 1.

4.1.2 Polypropylene fibers

The polypropylene fibers used in the present investigation were supplied by M/s RMC Readymix (India) Pvt. Ltd., Ghatkopar, Mumbai, India. The fibers used in this investigation were modified virgin polypropylene. They were hydrophobic, non-corrosive and resistant to alkalis, chemicals and chlorides. The characteristics of the fibers were provided by the suppliers and are given in Table 2.

4.1.3 Ordinary portland cement (OPC)

The cement comprised ordinary Portland cement (ACC Cement of 53 Grade, i.e., the cement with characteristic compressive strength of 53 MPa after 28 days' curing) which was made available by M/s RMC Readymix (India) Pvt. Ltd., Ghatkopar, Mumbai, India. The characteristics of the cement were tested in the laboratory of the supplier in accordance with the specifications brought out by Bureau of Indian Standards (BIS) (IS: 4031-1988) and are given in Table 3.

5. Experimental programme and methodology

The experimental programme involved in the present investigation entailed various tests that, include Atterberg's limits (liquid limit and plastic limit) tests, standard Proctor tests (1965) for finding out OMC, MDD (IS: 2720-1965) and UCS (IS:2720-1973) and BTS tests (Bandopadhyay and Bhattacharjee 2010). These tests were carried out on various combinations of fiber reinforced fly ash- cement mixes.

The performance of a total 32 samples, stabilized fly ash mixes was investigated by varying the percentage of cement and polypropylene fibers. For each mix, two samples were prepared. The fly ash was replaced by cement contents of 5%, 10%, 15 %and 20%, respectively, on dry weight basis. Further, four values of fibers, i.e., zero, 0.5, 1 and 1.5 percent, were considered for each of these mixes. The specimens were cured in air for 7, 14 and 28 days using an air curing technique that entailed letting the samples remain at normal air temperature (28℃). Depending upon the mix proportions, the required amount of ingredient were mixed thoroughly in a dry state and the specimens were prepared in desiccators for humidity control curing. The stabilized fly ash, in actual practice, may be subjected to inundation in the field to assess the effect of soaking. In view of this, two series of tests were conducted on un-soaked and soaked specimens compacted at the optimum moisture content. For soaking, the specimens were immersed in water for 8 to 10 hours after curing.

6. Multiple linear regression (MLR) analysis

Multiple linear regression (MLR) is the simplest and well developed representation of a casual, time invariant relationship between an input function of time and corresponding output function. MLR models are considered as benchmark for comparison with other techniques for prediction or forecasting purpose. MLR attempts to model the relationship between two or more independent variables and dependent variables by fitting a linear regression equation to observed data. Every value of the independent variable 'x' is associated with a value of the dependent variable 'y'. If y is a dependent variable (expected value) and x_1, x_2,..., x_n are the independent variables, then the basic MLR model is given by

$$y = a + b_1x_1 + b_2x_2 + \cdots + b_nx_n \tag{1}$$

Where a, bi=regression constant determined using a least square method.

Every value of the independent variable is associated with a value of the dependent variable. For the least-squares model, the best-fitting equation for the experimental UCS and BTS data is calculated by minimizing the sum of the squares of the vertical deviations from each data point to the regression equation (if a data point lay on the fitted line exactly, then its vertical deviation was 0). In MLR, the physical properties served as the input variables. The SPSS (Version 16) software is used for performing the regression analysis wherein various formulae are developed by varying the input parameters to predict the strength of such stabilized mixes corresponding to 7, 14 and 28 days' curing.

Based on the laboratory results and using SPSS 16.0, statistical program, MLR models are developed which correlate the strength of cement stabilized fly ash and polypropylene fiber with four independent variables as cement (CEM), fibers (FB), maximum dry density (MDD) and optimum moisture content (OMC) and one dependent variable as UCS. Similarly, based on the data generated for evaluating BTS, the MLR equations are developed. The equations developed for

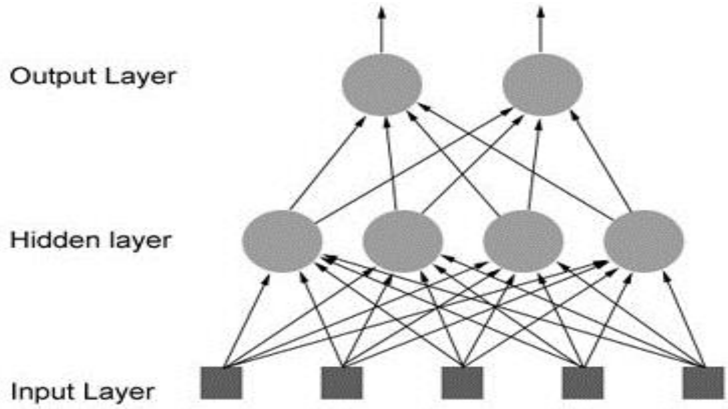

Fig. 1 Configuration of feed forward three-layer ANN with multi input and multi output

UCS and BTS are explained in result and discussion section.

7. Artificial neural network (ANN)

Artificial neural networks take their name from the networks of nerve cells in the brain. Although they represent a much simplified version of the human brain; yet these computational models inspired by biological neural network may provide new directions to solve problems arising in natural tasks. In contrast to digital computers, which offer sequential processing of information, ANNs' parallel processing inspired by working of a human brain gives computers an additional advantage to simultaneously process large volumes of data. The ANNs are well suited for problems whose solutions require knowledge that is difficult to specify; but for which there is enough data or observations (Chau *et al.* 2005).

Haykin (2009) has defined neural networks as 'a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use'. Neurons are the basic units used for computation in the brain and their simplified abstract models are the basic processing units of ANNs. In addition to the processing elements called 'neurons', the neural networks comprise of the connections between the processing elements. The connections carry a 'weight' parameter signifying importance of the link between the neurons. The synaptic weights store the knowledge of the neural networks and therefore, in the training phase with a continuous flow of information, there is a gradual a reorganization of weights within the neural network; and subsequent comparison of target and predicted values in an attempt to reduce the network error to a minimum. The continuous updating of synaptic weights is undertaken by a learning algorithm called error back-propagation. Back-propagation provides a computationally efficient method for changing the weights in a feed forward network with differentiable activation units to learn a training set of input-output examples (Castro 2007).

Generally, an ANN is made of an input layer of neurons, sometimes referred to as nodes or processing units, one or several hidden layer of neurons and output layer of neurons. The neighbouring layers are fully interconnected by weight. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation (Dutta and Rao 2007, 2009). The layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units (Wilmott and Matsuura 2005). According to the information stated above, an artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs. Fig. 1 shows a typical neural network with input layer, hidden layer and output layer.

8. ANN model development

For developing an ANN model, numbers of decisions have to be made, including the neural network type, network structure, methods of pre-and post-processing of input- output data sets, the training algorithm and the stopping criteria. There are no hard and fixed rules for developing an ANN model, even though a general framework can be followed based on previous successful applications in engineering. The goal of an ANN is to generalize a relationship of the form

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

Where, x^n is an n-dimensional input vector consisting of variables $x_1 \ldots x_i \ldots x_n$. y_m is an m-dimensional output vector consisting of the resulting variables of interest $y_{1\ldots} y_i \ldots, y_m$. In the present modelling, value of x_i is the inputs and y_i, one dependent variable as UCS and BTS.

The present work adopts feed forward supervised ANN model for prediction of UCS and BTS. The possible training parameters are number of iterations (epoch) learning rate, error goal and number of hidden layers. These parameters are varied until a good convergence of ANN training is obtained; and thereby, fixing the optimal training parameters. These optimal parameters are used for testing and validation process. The general computational ANN model is always represented by a term topology which represents number of neurons in input layer, hidden layer and output layer. However, the numbers of neurons in the input layer and output layer are determined based on the problem domain depending upon number of input variables and number of output or target variables. The number of hidden layers and neurons in hidden layer are fixed during the training process. The model success in predicting the behavior of UCS and BTS for various mixtures depends on availability of the training data. Availability of large variety of experimental data is required to develop the relationship between the mixture variables of UCS and BTS and its measured properties.

The basic parameters considered in this study are cement stabilized fly ash and polypropylene fiber with four independent variables as cement (CEM), fibers (FB) and maximum dry density(MDD) and optimum moisture content (OMC).A database of 32 mixes obtained experimentally is retrieved having mixture composition with comparable physical and chemical properties. The ANNs are designed using 32 pairs of input and output vectors for strength prediction, the predicted results obtained from neural network are compared with the values obtained experimentally. The training of ANNs is carried out using pair of input vector and output vector wherein 70% of data is used for training and 30% of the data is used for validation.Various networks were trained and tested by varying the number of hidden layers, neurons in the hidden layer and with various activation functions.

9. Performance measures

The following performance criteria’s are used to assess the performance of the models and equations and all the performance criteria are estimated based on the observed and predicted values (Srinivasulu and Jain 2006).

10. Coefficient of correlation (R)

The coefficient of correlation (R) measures the degree of linear association between the target and the realized outcome and it is a measure to know how far the trends in forecasted values follow those in actual observed values and it is a number between 0 and 1. Higher the correlation coefficient better is the model fit. The following formula is used to find the correlation coefficient (R)

$$R = \frac{\sum_{t=1}^{N}\left[St_{obs}(t) - \overline{St_{obs}}\right]\left[St_{est}(t) - \overline{St_{est}}\right]}{\sqrt{\sum_{t=1}^{N}\left[St_{obs}(t) - \overline{St_{obs}}\right]^2\left[St_{est}(t) - \overline{St_{est}}\right]^2}} \tag{3}$$

Where,

St_{obs} =Observed strength

$\overline{St_{obs}}$ = Mean strength,

St_{est} = Estimated Strength

$\overline{St_{est}}$ = Mean estimated Strength

The values of Rclose to 1.0 indicate good model performance.

11. Mean square error (MSE)

Mean square error (MSE) is defined as the average of the square of the difference between the actual observations and the response predicted by the model. It is a function of the quality of the actual observations and the response predicted by the model. It is a measure of the statistical dispersion of the predicted response with respect to the desired response. The value of MSE close to zero indicates better model performance.

$$MSE = \frac{\sum_{i=1}^{N}\left[St_{est}(t) - St_{obs}(t)\right]^2}{N} \tag{4}$$

12. Mean absolute error (MAE)

The mean absolute error (MAE) has the advantage that it does not distinguish between the over and underestimation and does not get too much influenced by higher values. It is generally engaged in addition to RMSE to get the average error without worrying about the positive or negative sign of the difference. Lower the value of MAE the better is the forecasting performance.

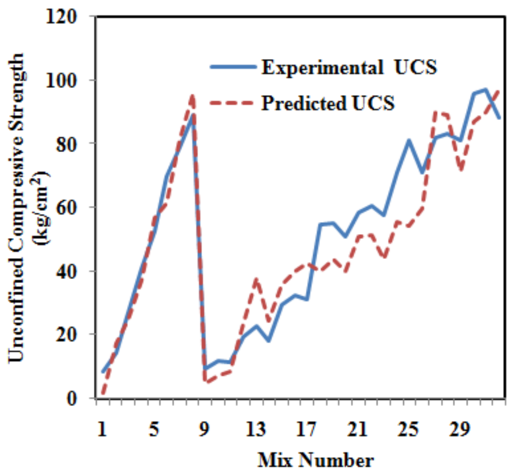

Fig. 2 Variation of experimental and predicted values of UCS for 28 days curing using MLR

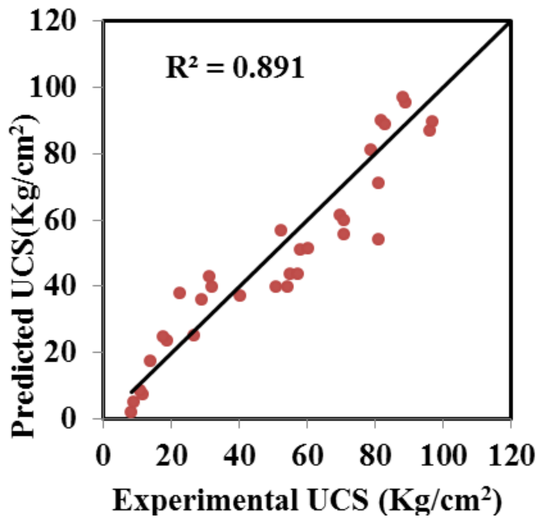

Fig. 3 Scatter plot for MLR (UCS)

The following formula is used to compute MAE

$$MAE = \frac{\sum_{i=1}^{N} \left| St_{est}(t) - St_{obs}(t) \right|}{N} \tag{5}$$

13. Results and discussion

Both the above tools (MLR and ANN) are applied to obtain the predicted UCS and BTS values and further, the relationship between experimental and predicted strength is established in the form of performance measures.

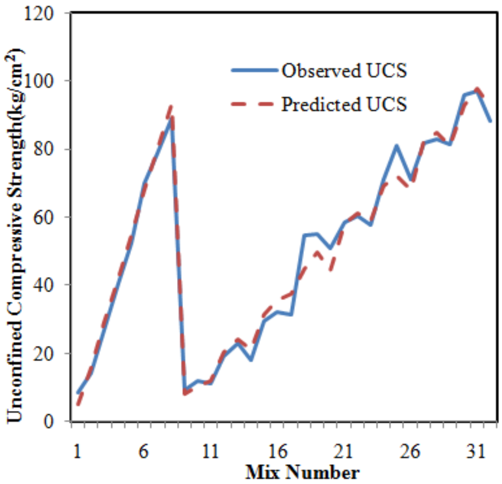

Fig. 4 Variation of experimental and predicted values of UCS for 28 days curing using ANN

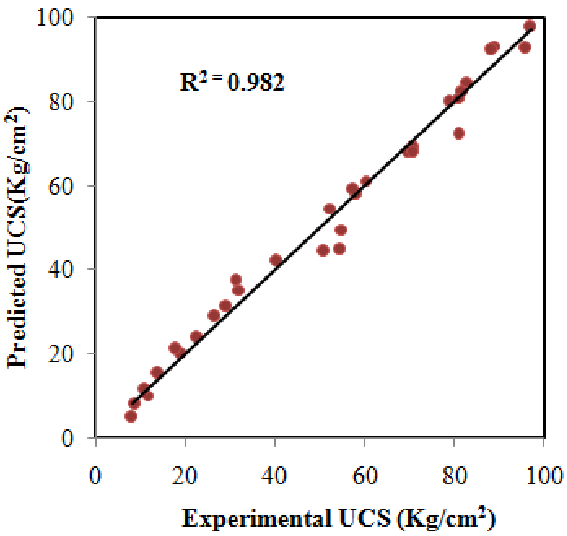

Fig. 5 Scatter plot for ANN (UCS)

The formulae, derived by the MLR, are applied on 32 trial mixes to predict UCS and BTSfor 7, 14 and 28 days curing period. The developed equations for UCS (Eqs. (6)-(8)) and BTS (Eqs. (9)-(11)) are given below.

$$UCS_7 = -197.993 + 1.39\,CEM + 1.49\,FB + 145.39\,MDD - 0354\,OMC \quad (6)$$

$$UCS_{14} = -290.186 + 2.73693\,CEM + 0.5369\,FB + 196.87\,MDD + 1.10\,OMC \quad (7)$$

$$UCS_{28} = -309.659 + 4.1038\,CEM + 2.571\,FB + 223.84\,MDD + 0.118\,OMC \quad (8)$$

$$BTS_7 = -50.57 + 0.421\,CEM + 0.581\,FB + 39.32\,MDD - 0.1878\,OMC \quad (9)$$

Table 4 Performance measures of MLR and ANN Models for UCS

Performance Criteria	MLR			ANN		
	7 days	14 days	28 days	7 days	14 days	28 days
R	0.79	0.93	0.94	0.98	0.95	0.98
MSE	54.62	50.17	43.48	3.08	5.21	12.67
MAE	6.29	6.06	8.81	1.38	1.63	2.69

Table 5 Performance measures of MLR and ANN Models for BTS

Performance Criteria	MLR			ANN		
	7 days	14 days	28 days	7 days	14 days	28 days
R	0.95	0.96	0.93	0.95	0.96	0.97
MSE	0.89	1.31	6.90	1.40	1.45	1.64
MAE	0.74	0.94	1.65	0.83	0.92	0.90

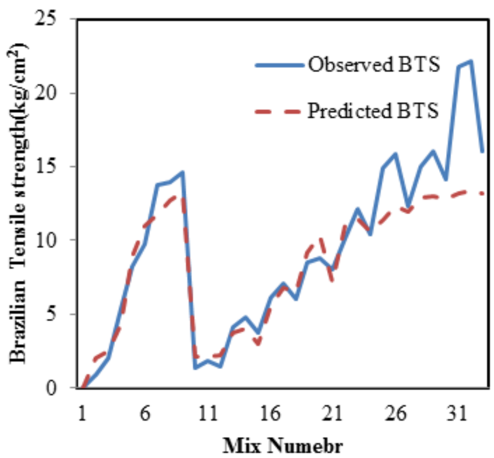

Fig. 6 Variation of experimental and predicted values of BTS for 28 days curing using MLR

$$BTS_{14} = -83.231 + 0.474\,CEM + 0.592\,FB + 61.17\,MDD - 0.042\,OMC \tag{10}$$

$$BTS_{28} = -94.88 + 0.735\,CEM + 0.769\,FB + 74.76\,MDD - 0.392\,OMC \tag{11}$$

The graphical variation of experimental and predicted strength and a scatter plot (a tool for analyzing relationships between the two variables) for both, MLR and ANN for 28 days curing, is shown in Figs. 2-3 and Figs. 4-5, respectively.

From Fig. 2, it is observed that in case of MLR, a fairly good agreement is seen between the observed and predicted strength. However, in respect of higher mixes, the MLR fails to predict the strength. The scatter plot (Fig. 3) shows that the predicted values are not aligned along the ideal line, which is deflected from the ideal line revealing under prediction as well over prediction of strength; but exhibit positive correlation. Fig. 4 shows the graphical plot indicating the variation of observed and predicted strength and Fig. 5 shows the scatter plot using ANN for 28 days curing. From Figs. 4-5, it is observed that the ANN shows a very good agreement between both, the

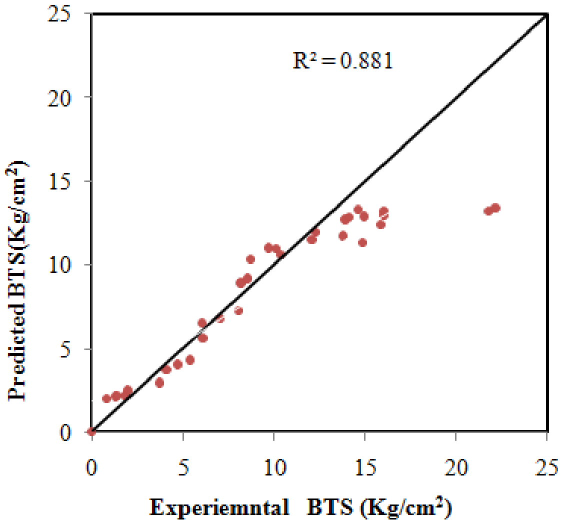

Fig. 7 Scatter plot for MLR (BTS)

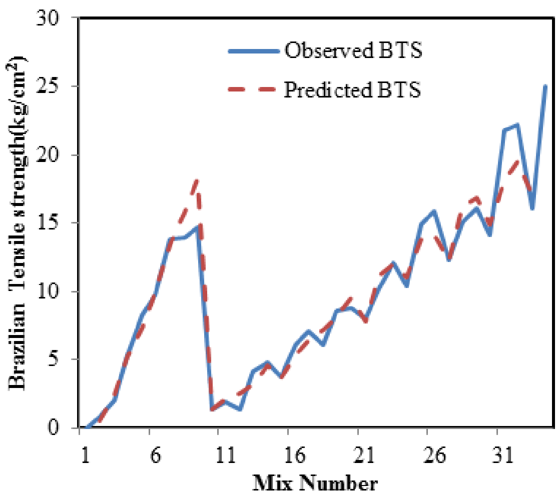

Fig. 8 Variation of experimental and predicted values of UCS for 28 days curing using ANN

observed and predicted strength, for all the mixes. The scatter plot (Fig. 5) reveals that most of the values are aligned parallel to straight ideal line which shows strong correlation.

Table 4 depicts the performance measures obtained by MLR and ANN in the form of R, MSE, and MAE for UCS which covers 7, 14 and 28 days' curing period from which it is observed that the performance of ANN is superior to MLR for all the performance measures. The ANN model has obtained best statistics, i.e., maximum of R, minimum of MSE; and minimum of MAE. The coefficient of correlation (R), which shows the measure of linear dependence and association between two variables, is a substantial higher value for ANN than MLR. The MSE, a measure of the statistical dispersion of the predicted response with respect to the desired response, is also quite less than MLR for ANN. The MAE value, which measures the average magnitude of the errors in a set of forecasts without considering their direction, is found to be less for ANN than MLR.

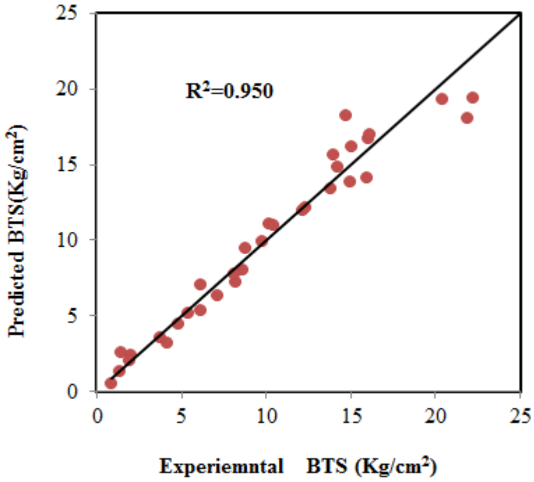

Fig. 9 Scatter plot for ANN (BTS)

Similarly, the graphical variation of the experimental and predicted strength with scatter plot for MLR and ANN is shown in Figs. 6-9. From Fig. 6, it is observed that in case of MLR, fairly a good agreement is seen between the observed strength and predicted strength; but for higher mixes, MLR fails to predict the value of BTS which is clearly shown in Fig. 6. The solid line shows the experimental data and the hidden line in the figure denotes the predicted values. The scatter plot (Fig. 7) shows that the values of strength are not aligned properly and deflected from the ideal line, particularly, for moderate and higher values revealing under prediction as well over prediction. Figs. 8-9 show that the ANN has mapped all the values and there is a close agreement between the observed and the predicted strength. Fig. 9 shows that almost all the strength values are aligned parallel to an ideal line and hence, the prediction is quite well.

Table 5 gives the summary of the values of performance criteria for the strength values corresponding to 7, 14 and 28 days' curing obtained by both the methods, MLR as well as ANN with respect to BTS. Table 5 again reveals ANN to have performed superior than MLR in respect of all performance measures.

14. Conclusions

In the present study, an attempt is made to develop the prediction models for both, the UCS and BTS of cement stabilized and fiber reinforced fly ash mixes using MLR and ANN. From the study, it may be concluded that the relationship between the dependent and independent variables can be captured very well by both the tools, i.e., MLR and ANN. These tools can also be effectively used for mapping the input and output data sets. The multiple regression analysis can be effectively used as a predictive tool in the present study because it gives explicit formula which can be directly used to predict the strength of the fiber reinforced cement stabilized mixes. The findings show that the predictions can be achieved with the best accuracy of coefficient of correlation (R), root mean squared error (RMSE) and mean absolute error (MAE) by artificial neural network. This indicates that the ANN is superior to MLR for the present study. ANN might have performed better than MLR in the present investigation owing to its inherent flexibility.

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