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RESEARCH ARTICLE

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PREDICTION OF STRENGTH CHARACTERISTICS OF FLY ASH CONCRETE USING ARTIFICIAL NEURAL NETWORKING

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ABSTRACT

An exhaustive literature survey shows that a little effort has been done towards artificial neural network (ANN) approach in the area of concrete technology. In the present investigation, development of ANN approach to predict strength characteristics of fly ash concrete in lieu of conventional laboratory approach. The traditional lab approach attracts some drawbacks such as manual involvement, time consuming, chances of creeping of human errors, uncertain prediction and always invasive in nature. Hence to reduce above drawbacks, this study is undertaken to develop an ANN between concrete mix ingredients and compressive, tensile, shear, flexure strength of mix. The work deals with collection of huge input data's by conducting experiments, ANN's training and its testing are adopted to fix appropriate weighted matrix which in turn predict strength characteristics of fly ash concrete.

Keywords: ANN, Fly ash concrete, Prediction, Performance, Topology.

INTRODUCTION

Fly ash is a by-product from burning pulverized coal in electric power generating plants. During combustion, mineral impurities in the coal (clay, feldspar, quartz, and shale) fuse in suspension and float out of the combustion chamber with the exhaust gases. As the fused material rises, it cools and solidifies into spherical glassy particles called fly ash. It is generally observed that a partial substitution of Portland cement by fly ash in a mortar or concrete mixture reduces that water requirement for obtaining a given consistency. Good fly ash can act as a super plasticizing admixture when used in high-volume. The phenomenon is attributable to three mechanisms. First, fine Particles of fly ash get absorbed on the oppositely charged surfaces of cement particles and prevent them from flocculation. The cement particles are thus effectively dispersed and will trap large amounts of water means that the system will have a reduced water requirement to achieve a given consistency. Secondly, the spherical shape and the smooth surface of fly ash particles help to reduce the inter-particle friction and thus facilitate mobility. Thirdly, the “particle packing effect” is also responsible for the reduced water demand in plasticizing the system. It may be noted that both Portland cement and fly ash contribute particles that are mostly in the 1 to 45µ size range, and therefore serve as excellent fillers for the void space within the aggregate mixture. In fact, due to its lower density and higher volume per unit mass, fly ash is a more efficient void-filler than Portland cement.

IS: 10262-2009 the code recommended by the Bureau of Indian standards to design a concrete mix proportions, because of its complex graphs, tables, it requires high knowledge of interpolation, graph reading and so on. At last it also requires a more human resource involvement and time consuming. This is very tedious and uneconomical for small and moderate projects. In the present work, an attempt is made to eliminate those difficulties by adopting ANN approaches which is basically data driven approach rather than equation. The basic philosophy of ANN is that it learns by known examples and results are stored as experienced knowledge in the form of weighted matrix. This weighted matrix is used for future prediction for unknown examples. This basic concept is used in this study to estimate the strength characteristics of fly ash concrete.

ARTIFICIAL NEURAL NETWORKING THEORY

An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes or learns, in a sense - based on that input and output. ANNs are considered nonlinear statistical data modeling tools where the complex relationships between input and outputs or modeled or patterns are found ANN is also known as a neural network. ANN is used as a random function approximation tool. These types of tools help estimate the most cost-effective and ideal methods for arriving at solutions while defining computing functions or distributions. ANN takes data samples rather than entire data sets to arrive at solutions, which saves both time and money. ANNs are considered fairly simple mathematical models to enhance existing data analysis technologies.

ANNs have three layers that are interconnected. The first layer consists of input neurons. Those neurons send data on to the second layer, which in turn sends the output neurons to the third layer. Training an artificial neural network involves choosing from allowed models for which there are several associated algorithms. The general computational ANN model is always represented by a 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 numbers of output or target variables. The number of hidden layers and neurons in hidden layer are fixed during the training process.

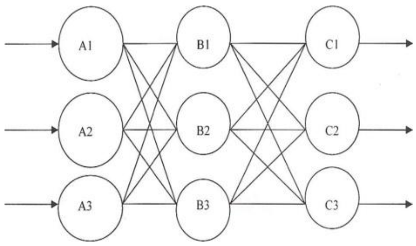

Fig.1 Structure of neural network

Learning and training

A network can learn when training is used or the network can learn also in the absence of training. Two barrowed categories of the network learning are supervised and unsupervised learning. Supervised learning provides the outputs to compare, while unsupervised does not. During supervised training, external prototypes are used as target output and the network is given a learning algorithm to follow and calculate new connection weights and bring the output closer to the target output.

Methodology

1) Casting of specimens, 2) Curing of specimens, 3) Testing of specimens, 4) Collection of test results, 5) Training, testing, validation were done using ANN to generate weighted matrix and 6)

Predicted values were compared with the experimental values.

Topology of ANN model used for predicting strength of fly ash concrete

The network architecture used in this study is 8-5-1, where the 1st digit is the number of inputs, 2nd digit is the number of hidden neurons and 3rd digit is the number of outputs.

- The maximum number of training epochs, which is chosen as 1000 to achieve the specified error tolerance. Once this number is attained the program is terminated even if the error tolerance is not met.
- Among the total number of data, 85% of the total data used for training and remaining 15% for testing.
- A learning rate is set to 0.7.
- Levenberg-Marquardt algorithm is used.

Performance of ANN model is based on Mean Squared Error.

Table 1 Input and output data used in prediction of compressive strength of fly ash concrete

Training input data									Training output data
Fly ash (%)	Slump (mm)	Coarse aggregate in kG	Fine aggregate in kG	Cement in kG	Water in kG	W/C	Fly ash in kG	No. of days	Compressive strength N/mm^2
0	50	4.65	2.7	1.50	0.75	0.5	0.00	7	30.22
10	50	4.65	2.7	1.35	0.75	0.5	0.15	7	30.36
20	50	4.65	2.7	1.20	0.75	0.5	0.30	7	30.51
30	50	4.65	2.7	1.05	0.75	0.5	0.45	7	29.92
40	50	4.65	2.7	0.90	0.75	0.5	0.60	7	29.64
50	50	4.65	2.7	0.75	0.75	0.5	0.75	7	29.22
0	50	4.65	2.7	1.50	0.75	0.5	0.00	28	35.10
10	50	4.65	2.7	1.35	0.75	0.5	0.15	28	35.25
20	50	4.65	2.7	1.20	0.75	0.5	0.30	28	35.40
30	50	4.65	2.7	1.05	0.75	0.5	0.45	28	34.80
40	50	4.65	2.7	0.90	0.75	0.5	0.60	28	34.51
50	50	4.65	2.7	0.75	0.75	0.5	0.75	28	34.07

Graphical representation of predicted compressive strength of fly ash concrete

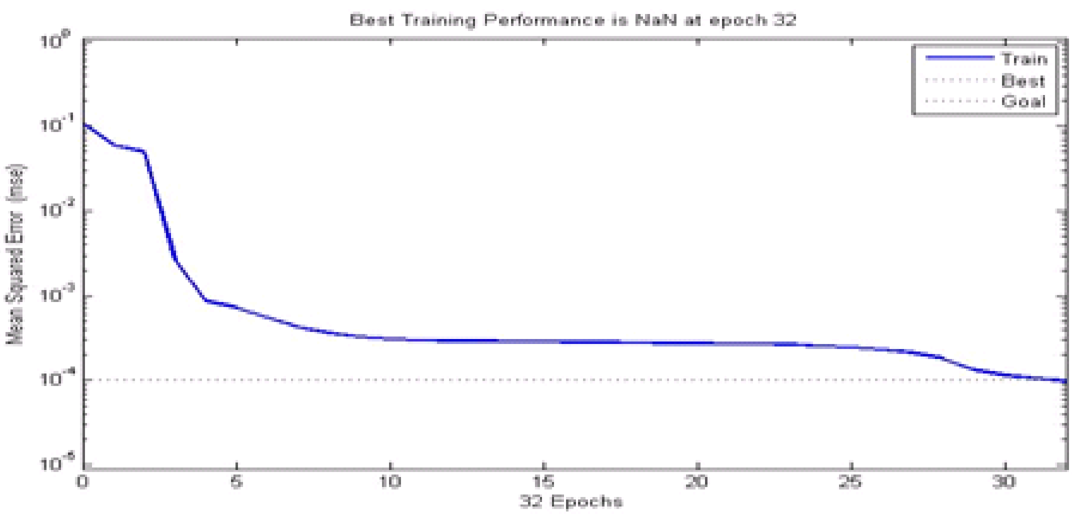

Fig.2 Training performance of ANN (Levenberg-Marquardt Algorithm)

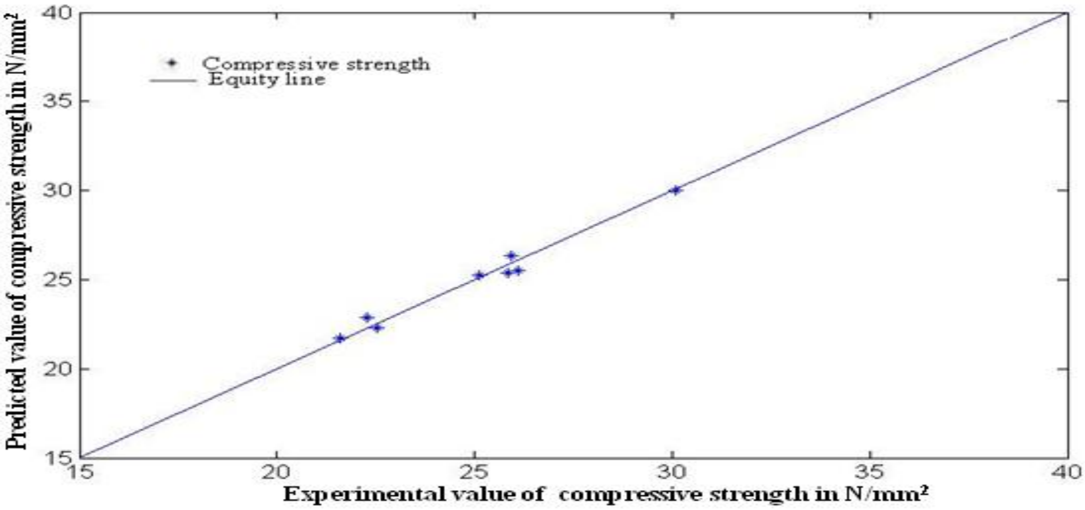

Fig.3 Experimental value v/s predicted value of compressive strength in training

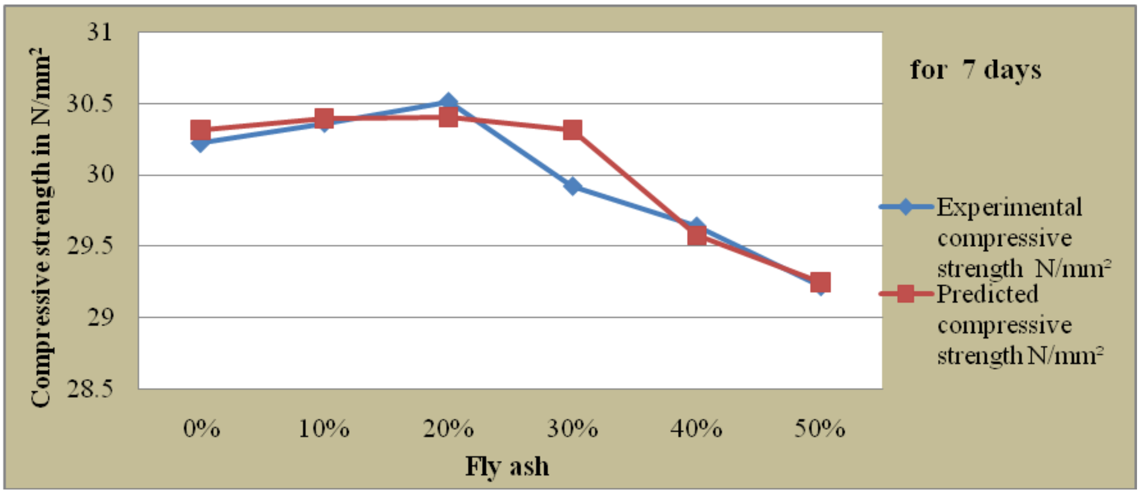

Fig.4 Comparison of experimental and predicted values of 7 days compressive strength

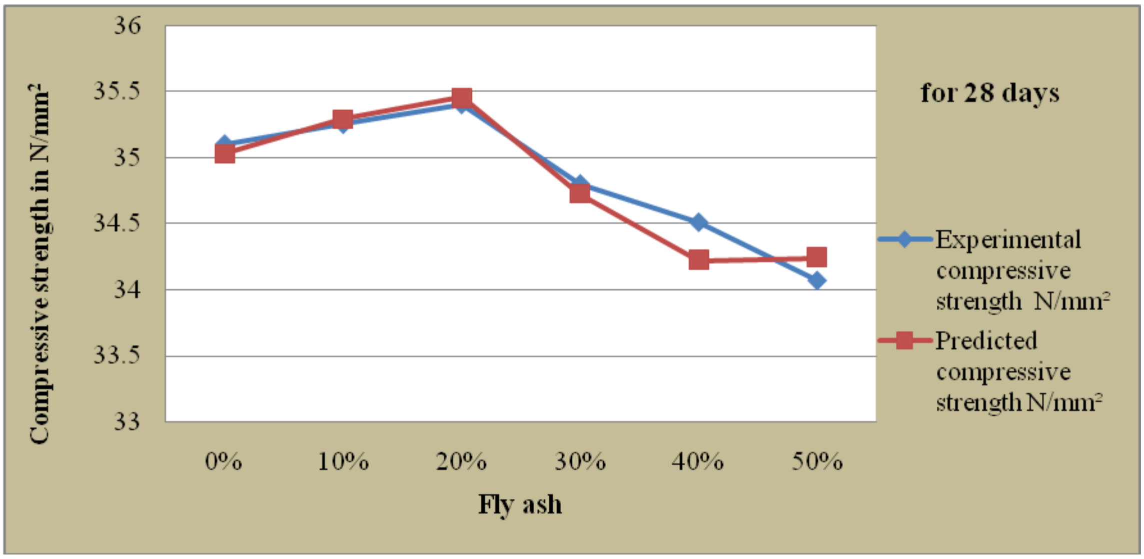

Fig.5 Comparison of experimental and predicted values of 28 days compressive strength

Table 2 Training input and output data used in prediction of tensile strength of fly ash concrete

Training input data									Training output data
Fly ash in %	Slump (mm)	Coarse aggregate in kG	Fine aggregate in kG	Cement in kG	Water in kG	W/C	Fly ash in kG	No. of days	Tensile strength N/mm^2
0	50	7.30	4.24	2.33	1.17	0.5	0.000	7	2.40
10	50	7.30	4.24	2.12	1.17	0.5	0.235	7	2.49
20	50	7.30	4.24	1.88	1.17	0.5	0.471	7	2.58
30	50	7.30	4.24	1.65	1.17	0.5	0.707	7	2.44
40	50	7.30	4.24	1.41	1.17	0.5	0.943	7	2.35
50	50	7.30	4.24	1.17	1.17	0.5	1.179	7	2.21
0	50	7.30	4.24	2.33	1.17	0.5	0.000	28	2.82
10	50	7.30	4.24	2.12	1.17	0.5	0.235	28	2.92
20	50	7.30	4.24	1.88	1.17	0.5	0.471	28	3.01
30	50	7.30	4.24	1.65	1.17	0.5	0.707	28	2.87
40	50	7.30	4.24	1.41	1.17	0.5	0.943	28	2.77
50	50	7.30	4.24	1.17	1.17	0.5	1.179	28	2.63

Graphical representation of predicted tensile strength of fly ash concrete

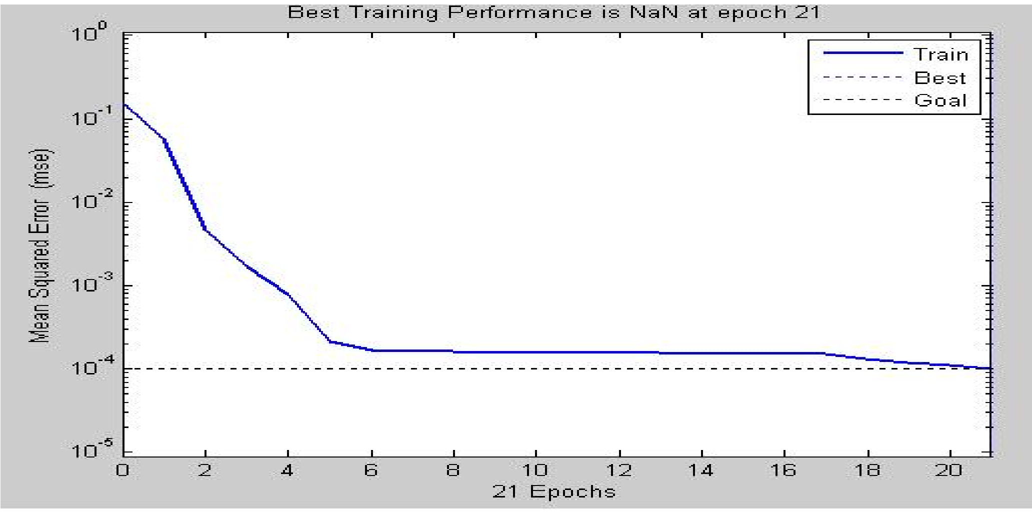

Fig.6 Training Performance of ANN (Levenberg-Marquardt Algorithm)

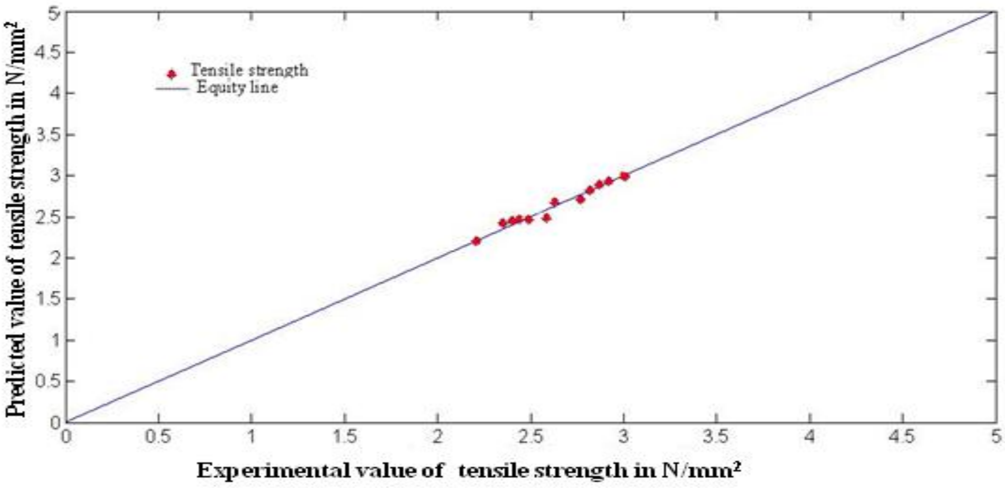

Fig.7 Experimental value v/s predicted value of tensile strength in training

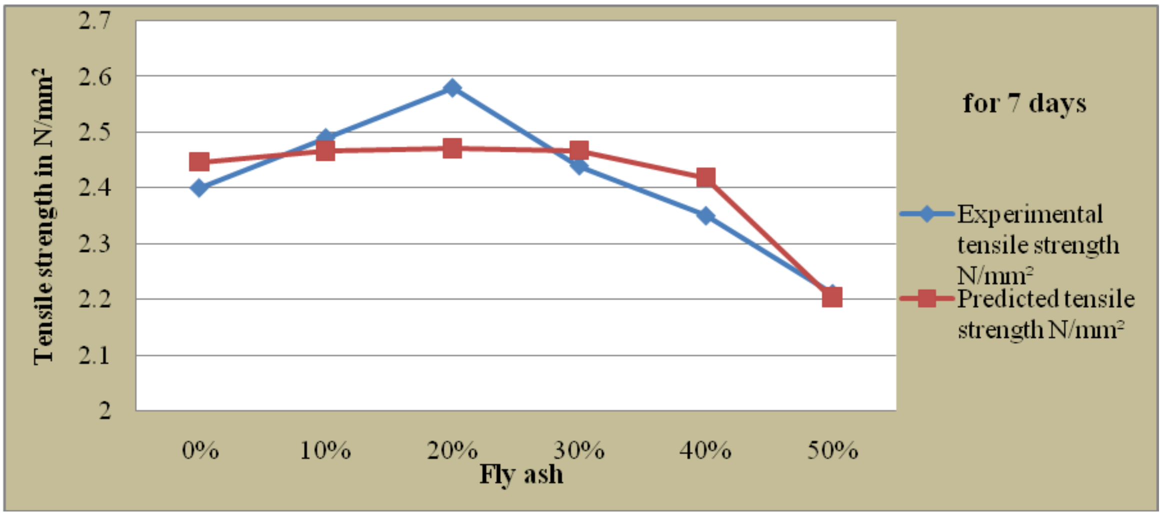

Fig.8 Comparison of experimental and predicted values of 7 days tensile strength

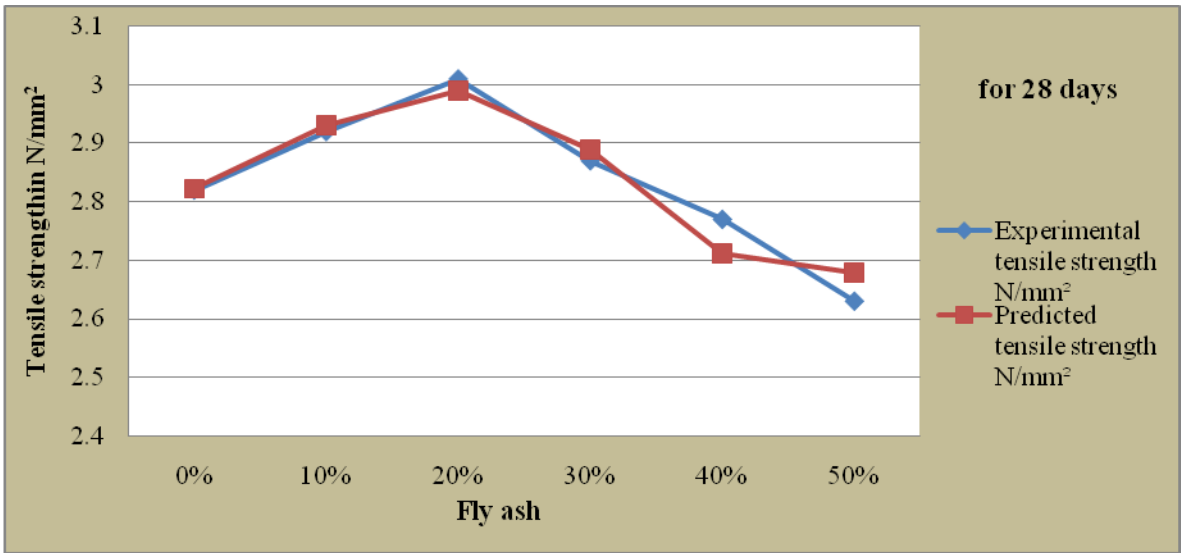

Fig.9. Comparison of experimental and predicted values of 28 days tensile strength

Table 3 Training input and output data used in prediction of shear strength of fly ash concrete

Training input data									Training output data
Fly ash in %	Slump (mm)	Coarse aggregate in kG	Fine aggregate in kG	Cement in kG	Water in kG	W/C	Fly ash in kG	No. of days	Shear strength N/mm^2
0	50	3.537	2.05	1.464	0.57	0.5	0.000	7	2.77
10	50	3.537	2.05	1.350	0.57	0.5	0.114	7	2.95
20	50	3.537	2.05	0.912	0.57	0.5	0.228	7	3.14
30	50	3.537	2.05	0.798	0.57	0.5	0.342	7	2.58
40	50	3.537	2.05	0.684	0.57	0.5	0.456	7	2.03
50	50	3.537	2.05	0.570	0.57	0.5	0.570	7	1.84
0	50	3.537	2.05	1.646	0.57	0.5	0.000	28	3.33
10	50	3.537	2.05	1.350	0.57	0.5	0.114	28	3.48
20	50	3.537	2.05	0.912	0.57	0.5	0.228	28	3.64
30	50	3.537	2.05	0.798	0.57	0.5	0.342	28	3.14
40	50	3.537	2.05	0.684	0.57	0.5	0.456	28	2.59
50	50	3.537	2.05	0.570	0.57	0.5	0.570	28	2.41

Graphical representation of predicted shear strength of fly ash concrete

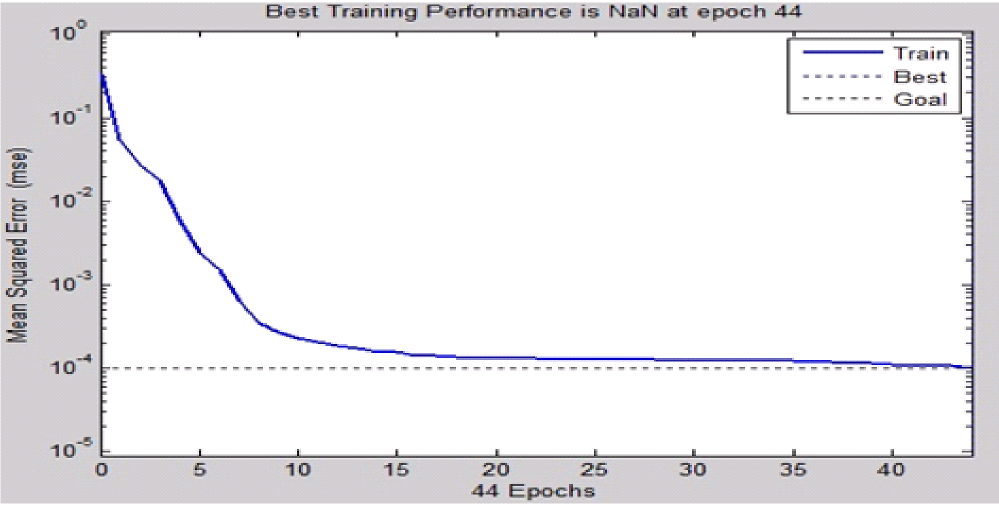

Fig.10 Training Performance of ANN (Levenberg-Marquardt Algorithm)

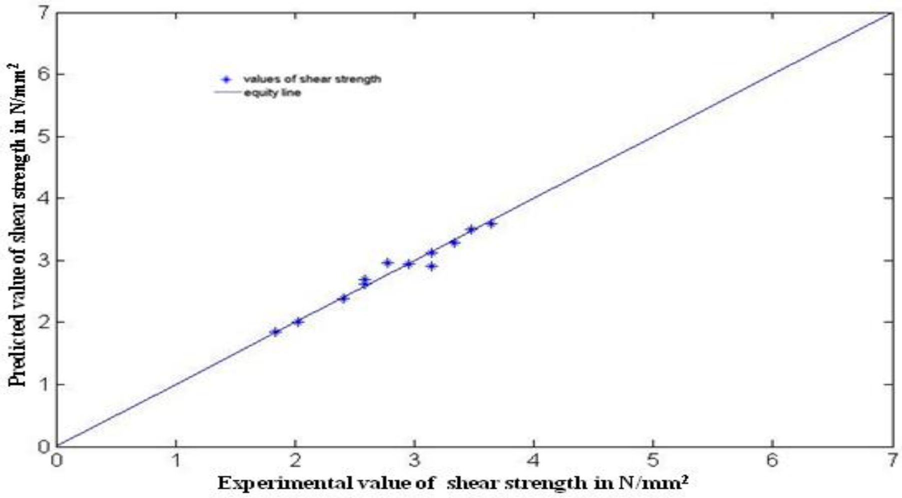

Fig.11 Experimental value v/s predicted value of shear strength in training

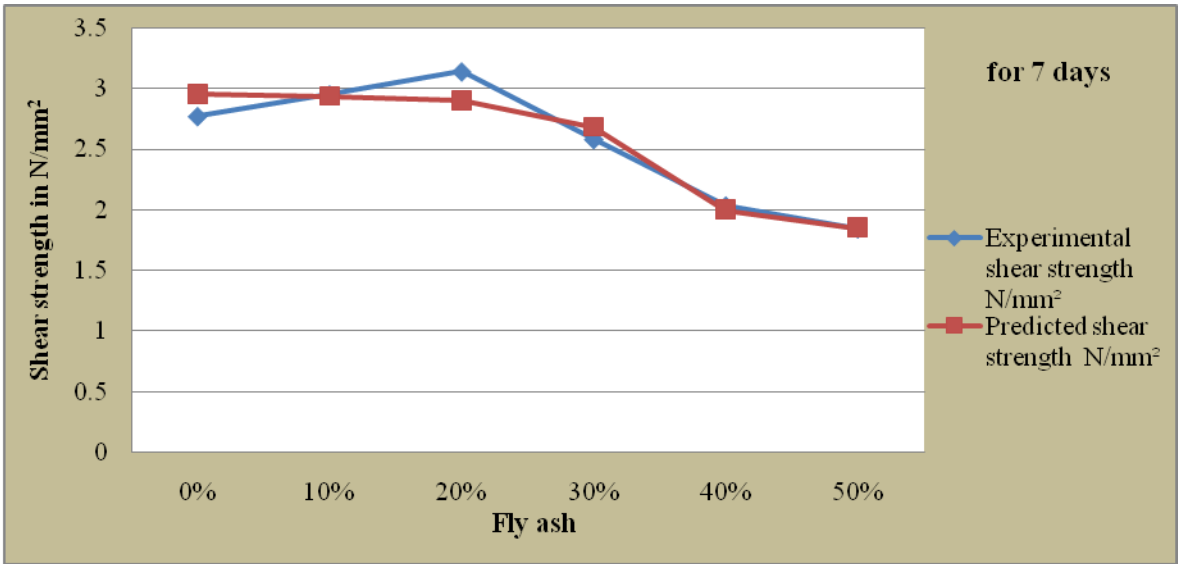

Fig.12 Comparison of experimental and predicted values of 7 days shear strength

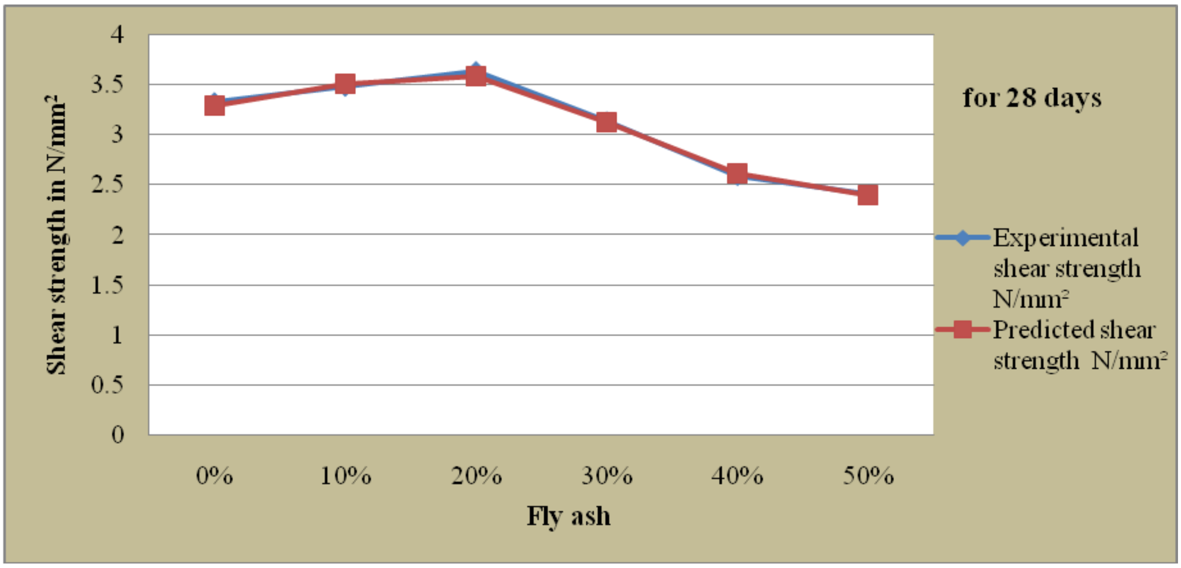

Fig.13 Comparison of experimental and predicted values of 28 days shear strength

Table 4 Training input and output data used in prediction of flexure strength of fly ash concrete

Training input data									Training output data
Fly ash in %	Slump (mm)	Coarse aggregate in kG	Fine aggregate in kG	Cement in kG	Water in kG	W/C	Fly ash in kG	No. of days	Flexure strength N/mm^2
0	50	6.94	4.0	2.24	1.112	0.5	0.000	7	7.50
10	50	6.94	4.0	2.02	1.112	0.5	0.224	7	7.83
20	50	6.94	4.0	1.79	1.112	0.5	0.448	7	8.00
30	50	6.94	4.0	1.57	1.112	0.5	0.672	7	7.66
40	50	6.94	4.0	1.34	1.112	0.5	0.896	7	7.33
50	50	6.94	4.0	1.12	1.112	0.5	1.120	7	7.00
0	50	6.94	4.0	2.24	1.112	0.5	0.000	28	9.00
10	50	6.94	4.0	2.02	1.112	0.5	0.224	28	9.40
20	50	6.94	4.0	1.79	1.112	0.5	0.448	28	9.50
30	50	6.94	4.0	1.57	1.112	0.5	0.672	28	9.16
40	50	6.94	4.0	1.34	1.112	0.5	0.896	28	8.83
50	50	6.94	4.0	1.12	1.112	0.5	1.120	28	8.50

Graphical representation of predicted flexure strength of fly ash concrete

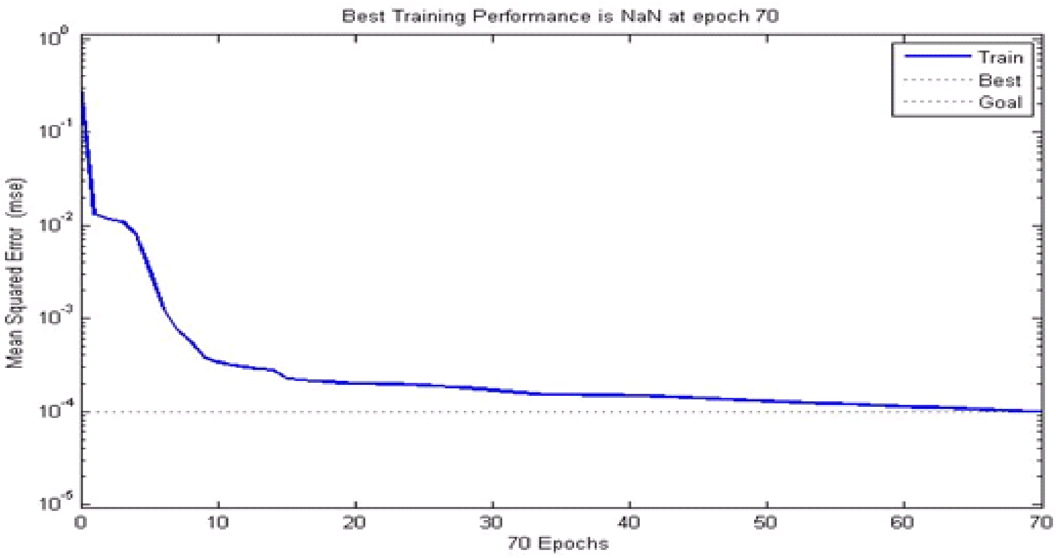

Fig.14 Training Performance of ANN (Levenberg-Marquardt Algorithm)

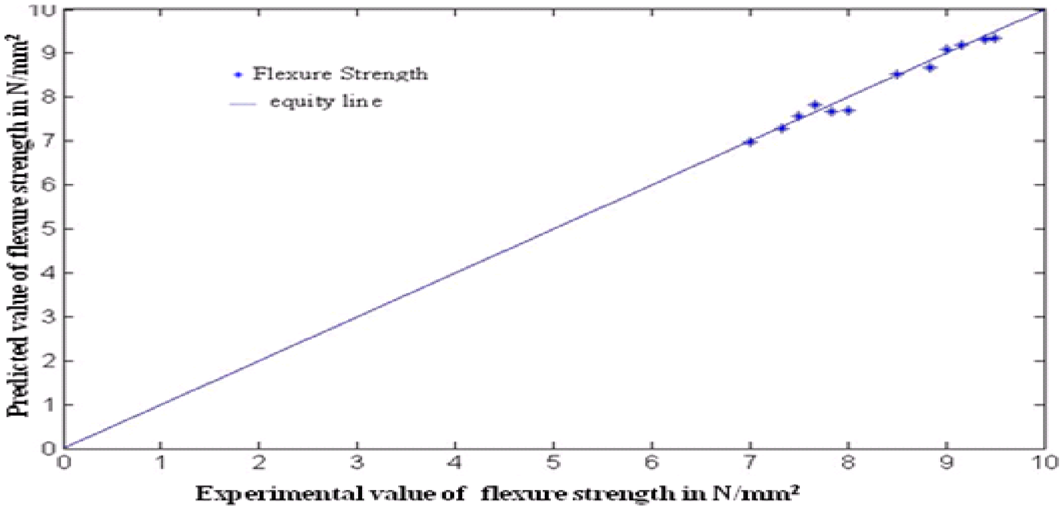

Fig.15 Experimental value v/s predicted value of flexure strength in training

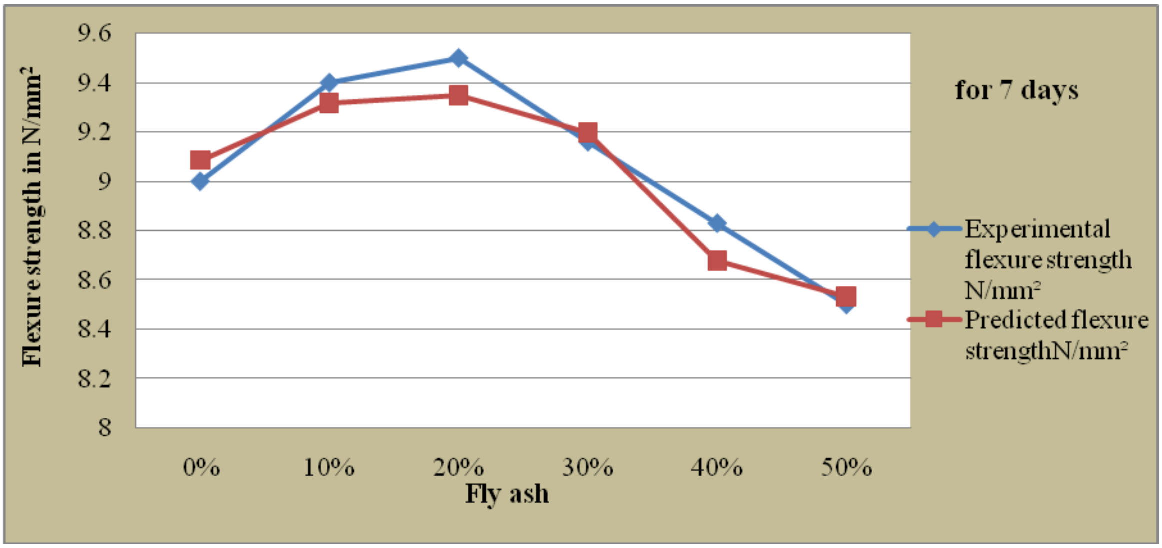

Fig.16 Comparison of experimental and predicted values of 7 days flexure strength

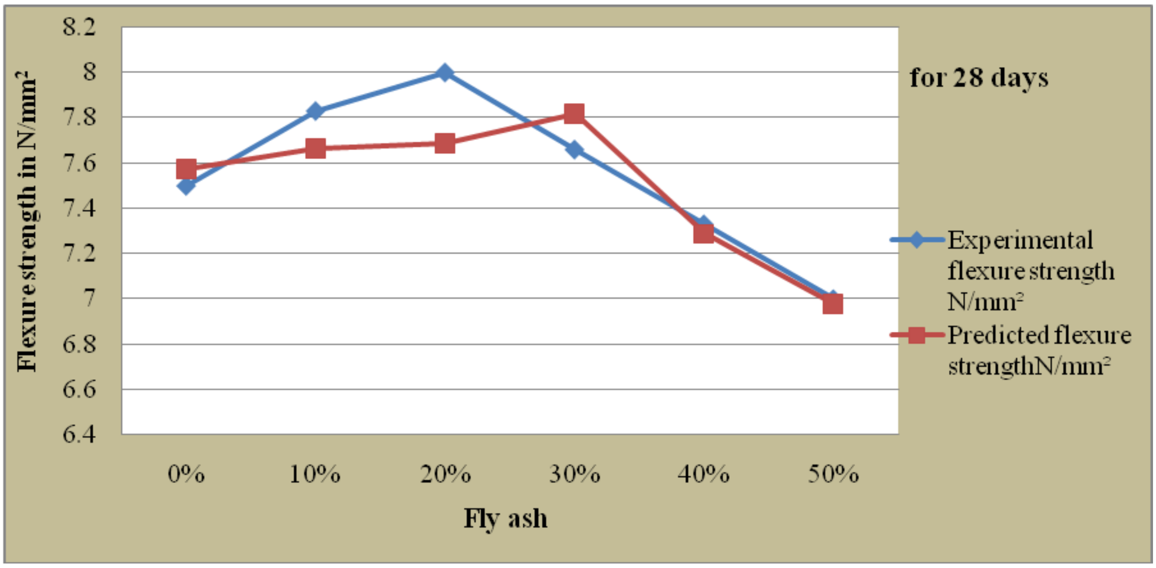

Fig.17 Comparison of experimental and predicted values of 28 days flexure strength

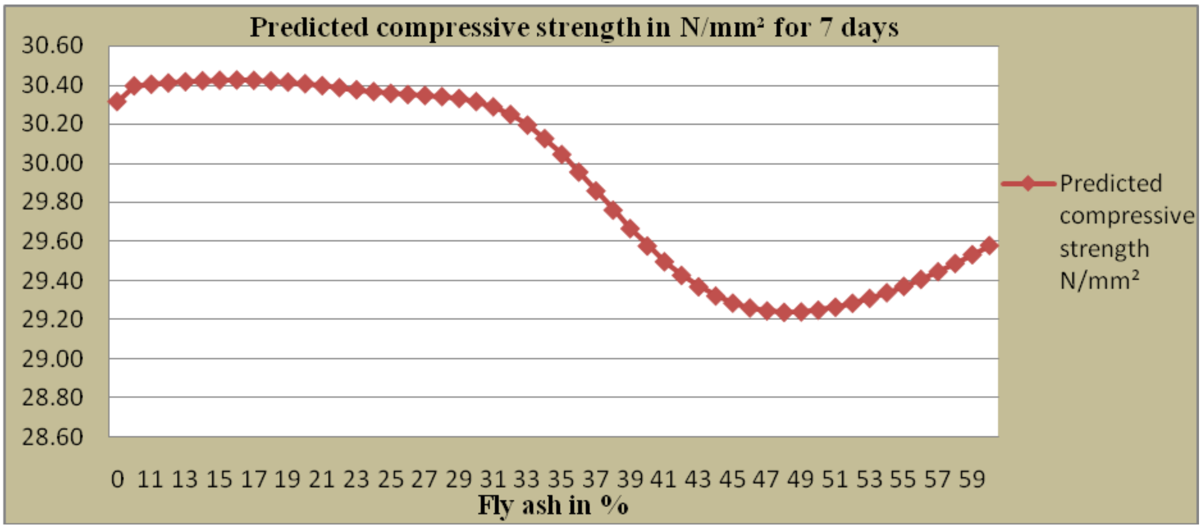

Fig.18 Predicted values of compressive strength of fly ash concrete for 7 days

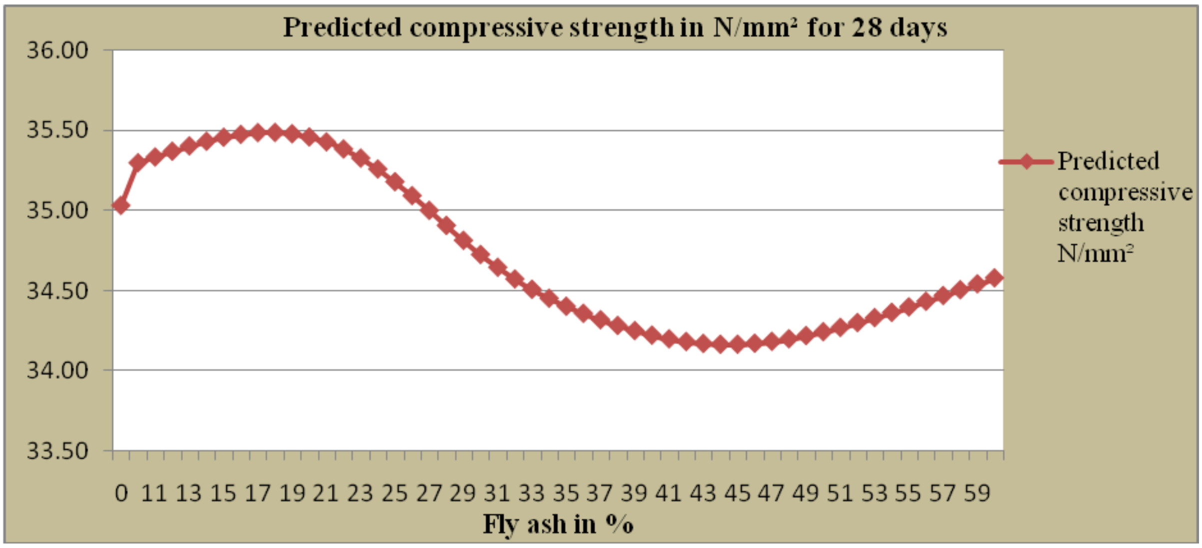

Fig.19 Predicted values of compressive strength of fly ash concrete for 28 days

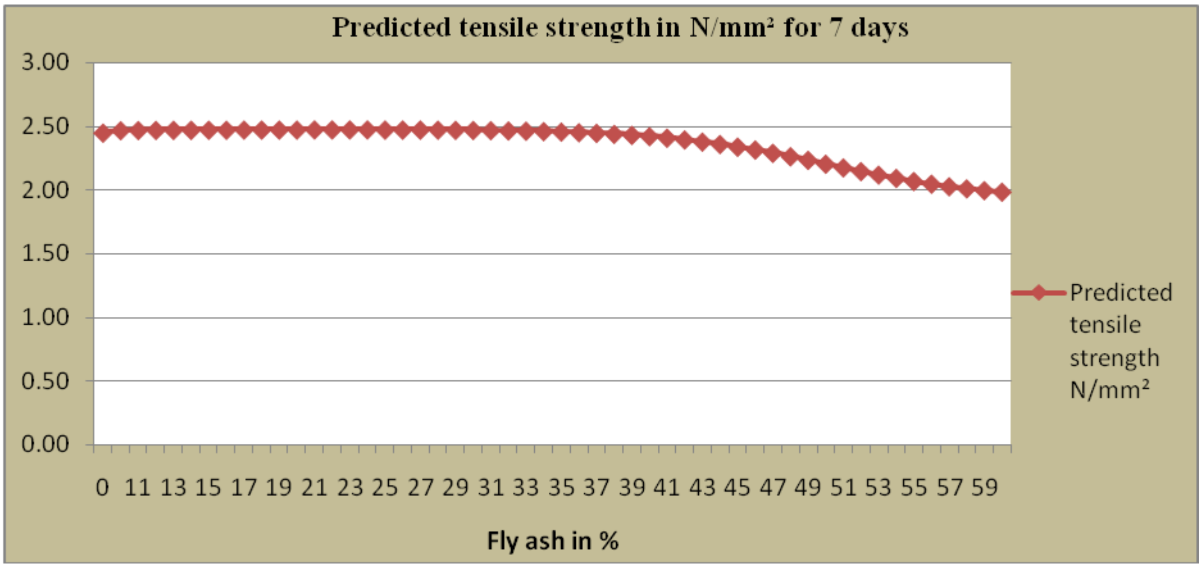

Fig.20 Predicted values of tensile strength of fly ash concrete for 7 days

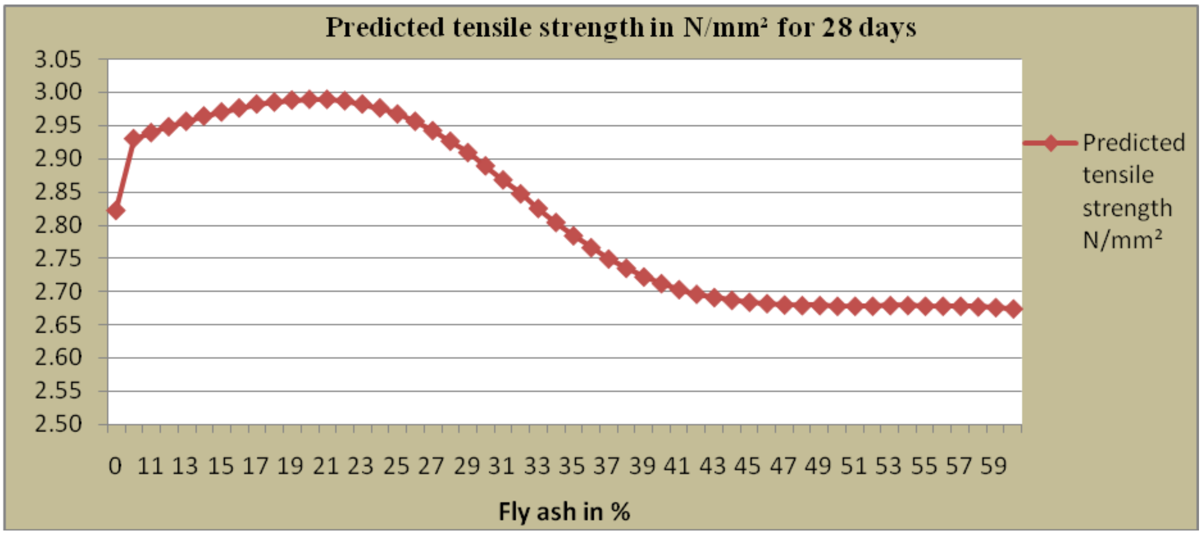

Fig.21 Predicted values of tensile strength of fly ash concrete for 28 days

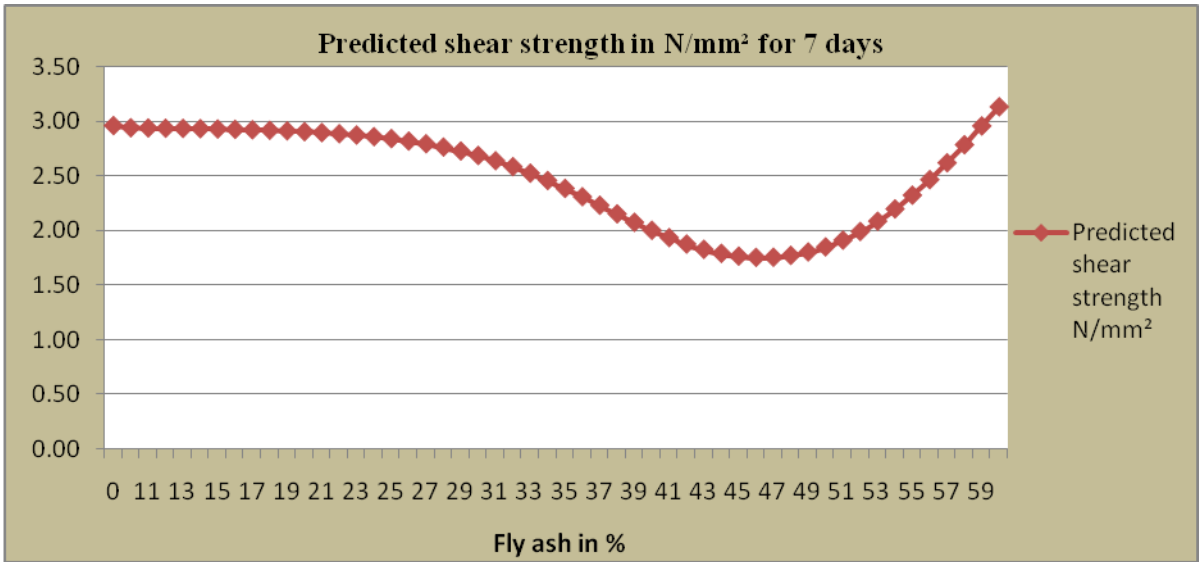

Fig.22 Predicted values of shear strength of fly ash concrete for 7 days

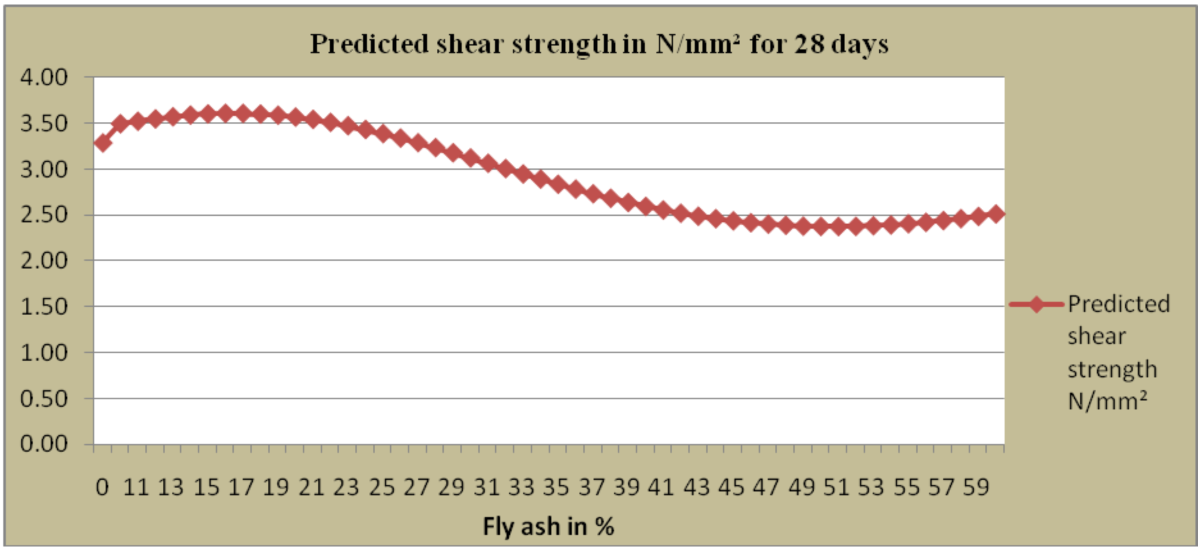

Fig.23 Predicted values of shear strength of fly ash concrete for 28 days

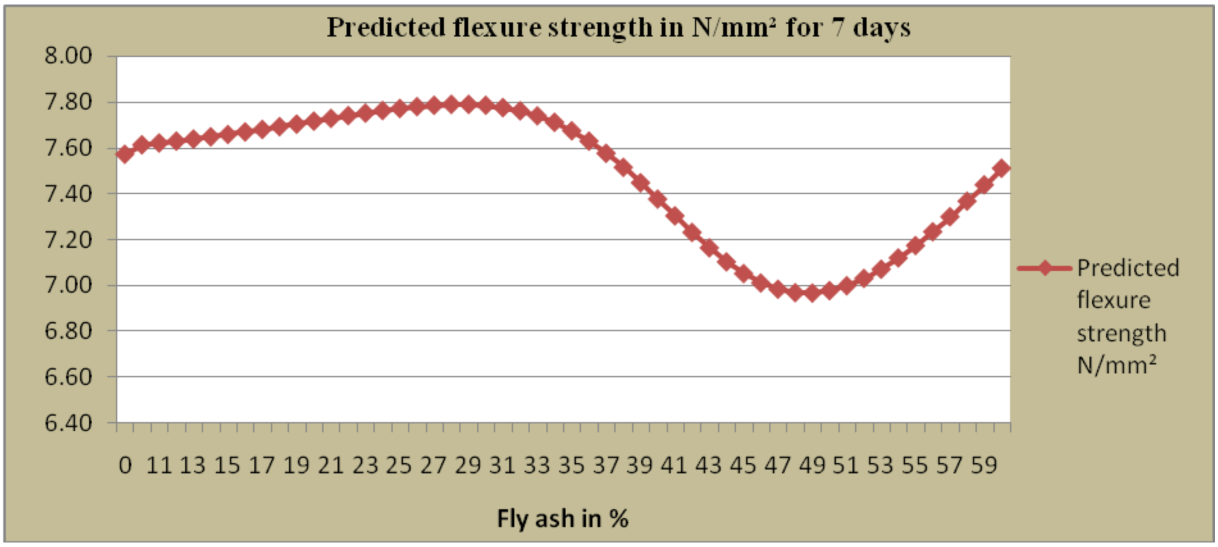

Fig.24 Predicted values of flexure strength of fly ash concrete for 7 days

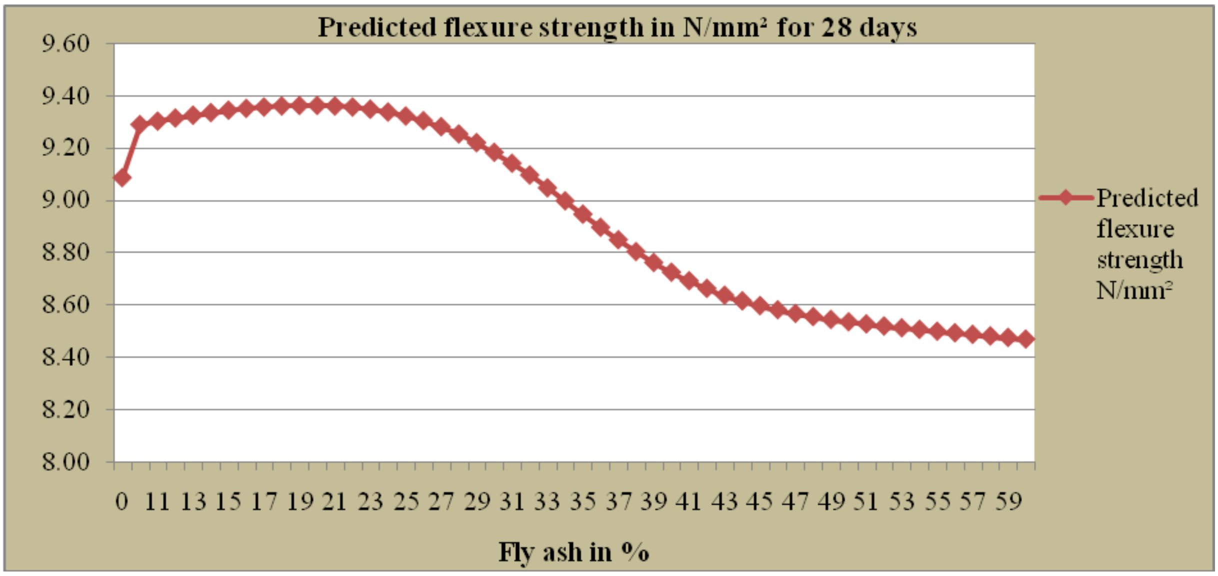

Fig.25 Predicted values of flexure strength of fly ash concrete for 28 days

CONCLUSIONS

1. ANN approach avoids memorization of equations and generalizes the problem domain.
2. The predicted compressive, tensile, shear, and flexure strength of fly ash concrete show lesser error.
3. The present dissertation work demonstrates that all the predicted values of compression, tensile, shear and flexure strength of fly ash concrete are well within permissible limit.
4. The developed ANN model will guide to get the values of compression, tensile shear, and tensile strength of fly ash concrete without using complicated equations and laboratory experiments.

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