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Prediction on Flexural Strength of Over-Reinforced Concrete Beams Using Artificial Neural Networks

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ABSTRACT: In this study Artificial Neural Network (ANN) models are constructed to predict the flexural behavior of over-reinforced Concrete containing hybrid fibers, confinement of stirrups and GGBS as partial cement replacement respectively. Four different volume fractions (0.5%, 1.0%, 1.5%, and 2%) of hybrid fibre with 20% GGBS (as a replacement of cement) were used in this investigation. A total of 13 numbers of beams of size 120mm x 200mm x 2100mm was casted and tested. From the test results, the ultimate deflection, ductility index, peak load and flexural rigidity were calculated. These values has been taken for the training of models and testing results have shown that artificial neural networks have strong potential for predicting the ultimate deflection, ductility index, peak load and flexural rigidity values of hybrid fiber concretes containing GGBS. Artificial Neural Network models demonstrated more accuracy and had higher correlation. It is found that the models predicted the number of cycles to failure and the corresponding values were very close to the experimental values. It can be concluded that the models are found to be robust and reliable for cement based strengthening systems also.

KEYWORDS: Prediction, Matlab, Artificial Neural Neural.

I. INTRODUCTION

Minimization of experimental task leads to the development of software which will predict the properties of the concrete in recent years. Models have been created using these software and equations were also derived to predict the engineered properties. Generating of models by Regression analysis is one of the traditional methods involved in model generation. Simplest and quickest prediction was the major advantage of regression analysis. Multiple regression will be performed for the accuracy of the model. By performing multiple regression the accuracy of the model can be enhanced. Increase in number of independent variables will result in the decrease in the accuracy of regression analysis. In such complex cases, the use of methods like Artificial Neural Networks, adaptive neuro fuzzy inference systems, factorial design, genetic based algorithms, model tree and fuzzy logic are employed to improve the accuracy of the predicted models.

The human brain is similar to a computer which is highly complex, non-linear and parallel. The structural components of human brain are the neurons, which are interconnected in a complex way. Based on the human brain the neural network has been developed which consists of large parallel interconnections. The idea of neural network has been derived from the human brain and hence the neural network consists of large parallel interconnections.

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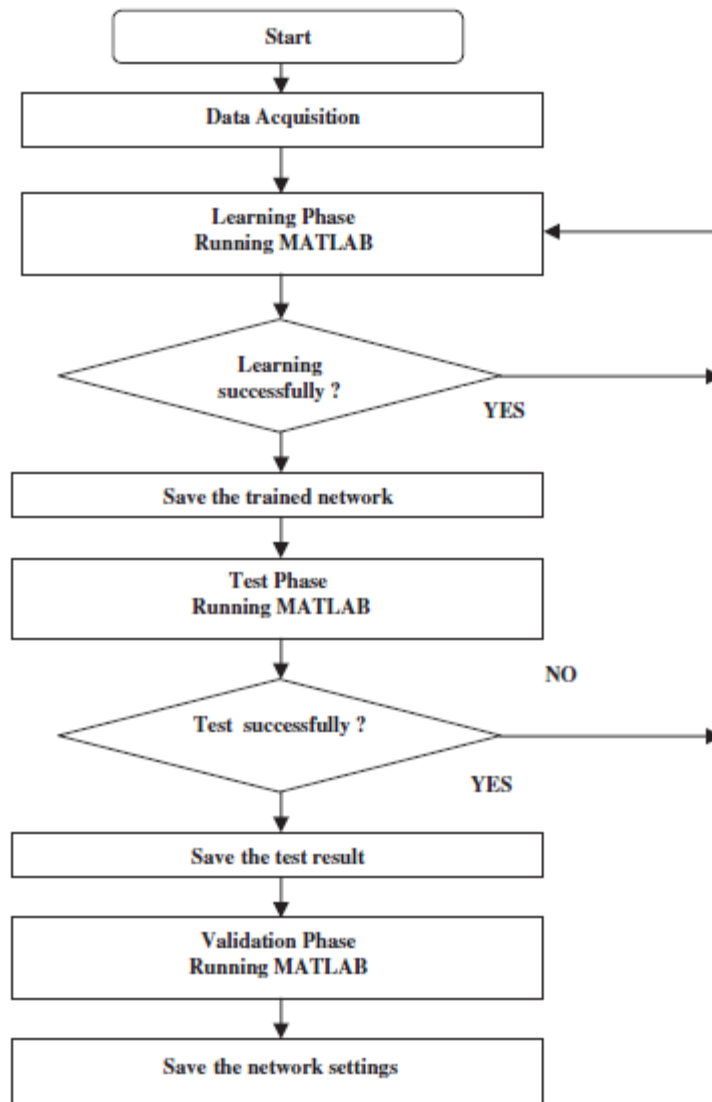


Fig.1. Overview of ANN

Artificial Neural Network (ANN) is similar to the natural neural system, which can be operated using computer software and electronic components, subject to certain restrictions which was shown in Fig.1. In order to improve these studies, reducing the amount of material, testing, time and cost, models based on experimental data can predict with an acceptable error range, the influence of hybrid fiber with GGBS in the concrete behavior. Some of these models are based on ANN, which is an artificial intelligence technique that can be applied to tasks where there is a database of a problem and the ANN model learns by example. According to Braga, modeling is performed through the use of input and output variables, without many restrictions on the amount of input. ANN has the tendency to exploit non-linearity, predict input–output relationship, adapt to the changes in the free parameters and has sufficient fault tolerance. It also provides evidential results with reliability.

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II. LITERATURE REVIEW

Artificial neural networks (ANNs) are based on the present understanding of biological nervous system, though much of the biological detail is neglected. Of the many ANN paradigms, the multi-layer back propagation network (MLP) is by far the most popular. Artificial neural networks (ANN) are an information processing techniques that is inspired by the way biological nervous systems, such as the brain, process information. The fundamental concept of neural networks is the structure of the information processing system. Even an ANN quite simple and small in size when compared to the human brain, has some powerful characteristics in knowledge and information processing due to its similarity to the human brain. Therefore, an ANN can be a powerful tool for engineering applications. In recent years, ANN have been applied to many civil engineering problems with some degree of success. In civil engineering, neural networks have been applied to the detection of structural damage, structural system identification, modeling of material behavior, structural optimization, structural control, ground water monitoring, prediction of experimental studies, and concrete mix proportions.

Consequently, it is seen that ANN was the widespread method for predicting concrete and mortar properties. In training of the models, the age of specimen (AS), Portland cement (PC), GGBFS, water (W) and aggregate (A) were entered as input; while f_c values were used as outputs. The models were trained with 52 data of experimental input and results, and then remainders were used as only experimental input values for testing and values similar to the experimental data were obtained. In the current study, the flexural behavior of normal Concrete is taken as the dependent variable, whereas, the mix constituents and age of the specimen form the independent variables. The objective of this study is to construct probabilistic models for the prediction of ultimate deflection, ductility index, peak load and flexural rigidity of Hybrid fiber Concrete with GGBS as partial cement.

III. MATERIALS AND METHODOLOGY

Ordinary Portland Cement (OPC) 43 grade conforming to IS 12269-1987 with a specific gravity of 3.08 was used in concrete mixtures. River sand passing through 4.75 mm IS sieve conforming to grading zone II of IS 383:1970 and having a specific gravity of 2.45 was used in this work. Crushed aggregate available from local sources with a maximum size of 20 mm and conforming to IS 2386:1963 was used as coarse aggregate in this study. Steel fiber having length a_f of 30mm with diameter of 0.75mm and glass fiber having a length of 25mm with diameter of 0.5mm were used. The aspect ratio of 80 for steel fiber and 50 for glass fiber were kept constant. Four different volume fractions (0.5%, 1.0%, 1.5%, and 2%) of hybrid fiber with 20% GGBS (as a replacement of cement) were used in this investigation which is given in the Table1.

Table -1 Mixing proportion for 1m³

Mix	W/C	Water Kg/m ³	Cement Kg/m ³	Fine Aggregate Kg/m ³	Coarse Aggregate Kg/m ³	Volume Fraction V_f	Steel fiber content Kg/m ³	Glass fiber content Kg/m ³	GGBS (20% Replacement) Kg/m ³
Ref	0.5	195	390	712.64	1105.68	0	0	0	0
SC-0.5-100	0.5	195	312	712.64	1105.68	0.5	12.01	0	78
HC-0.5-80-20	0.5	195	312	712.64	1105.68	0.5	9.61	2.40	78
HC-0.5-60-40	0.5	195	312	712.64	1105.68	0.5	7.20	4.81	78
SC-1-100	0.5	195	312	712.64	1105.68	1.0	24.03	0	78
HC-1-80-20	0.5	195	312	712.64	1105.68	1.0	19.22	4.81	78
HC-1-60-40	0.5	195	312	712.64	1105.68	1.0	14.42	9.61	78
SC-1.5-100	0.5	195	312	712.64	1105.68	1.5	36.05	0	78

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HC-1.5-80-20	0.5	195	312	712.64	1105.68	1.5	28.84	7.21	78
HC-1.5-60-40	0.5	195	312	712.64	1105.68	1.5	21.63	14.42	78
SC-2-100	0.5	195	312	712.64	1105.68	2.0	48.06	0	78
HC-2-80-20	0.5	195	312	712.64	1105.68	2.0	38.44	9.62	78
HC-2-60-40	0.5	195	312	712.64	1105.68	2.0	28.83	19.23	78

Artificial Neural Network

In this study, a multilayered feed forward neural network with a feed forward back propagation algorithm was adopted which was shown in Fig.2. Back propagation algorithm, as one of the most well-known training algorithms for the multilayer perceptron, is a gradient descent technique to minimize the error for a particular training pattern in which it adjust the weights by a small amount at a time. The nonlinear sigmoid function was used in the hidden layers and the cell outputs at the output layer. In training and testing of the neural network model AG, C, W, S, A, RA, SP and SF were entered as input; while ultimate deflection, ductility index, peak load and flexural rigidity values were used as outputs. Herein, 52 data of experiment results were used for training and testing. The limit values of input and output variables used in ANN model are listed in Table 2. the detailed information of the learning rate, momentum rate and layer details was given in Fig. 4. Two hidden layers were used in the architecture of multilayer neural network due to its minimum absolute percentage error values for training and testing sets which was shown in Fig.5. The neurons of neighboring layers are fully interconnected by weights. Finally, the output layer neurons produce the network prediction as a result. Momentum rate and learning rate values were determined and the model was trained through iterations. The trained model was only tested with the input values and the results found were close to experiment results.

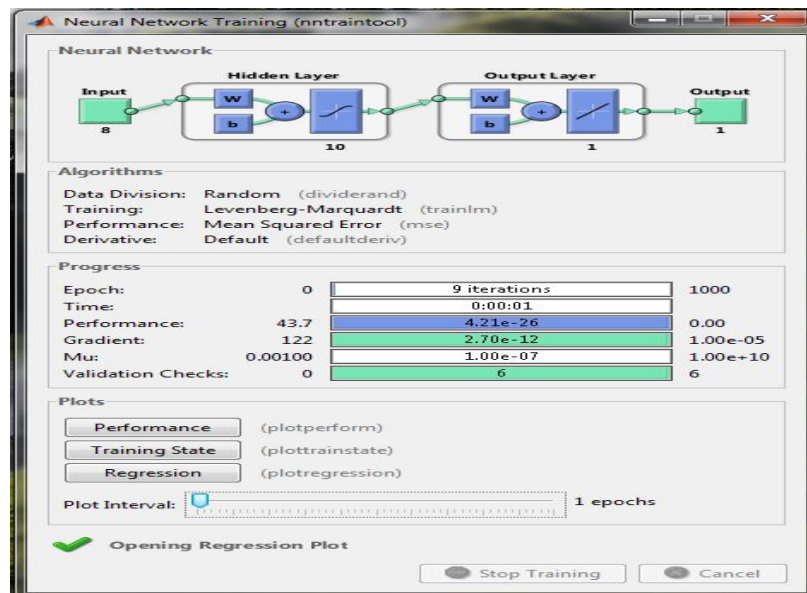


Fig.2 ANN tool

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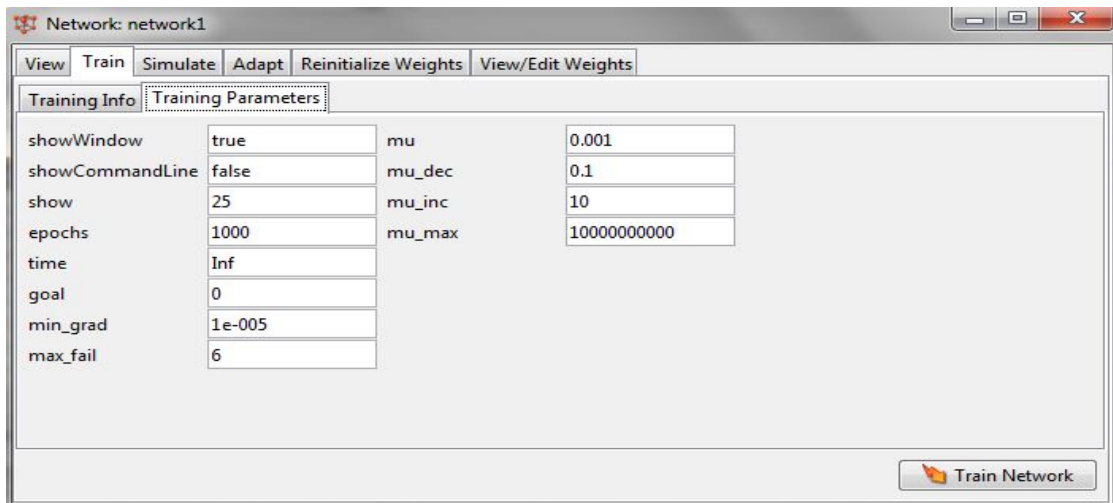


Fig.3. ANN Training Parameters

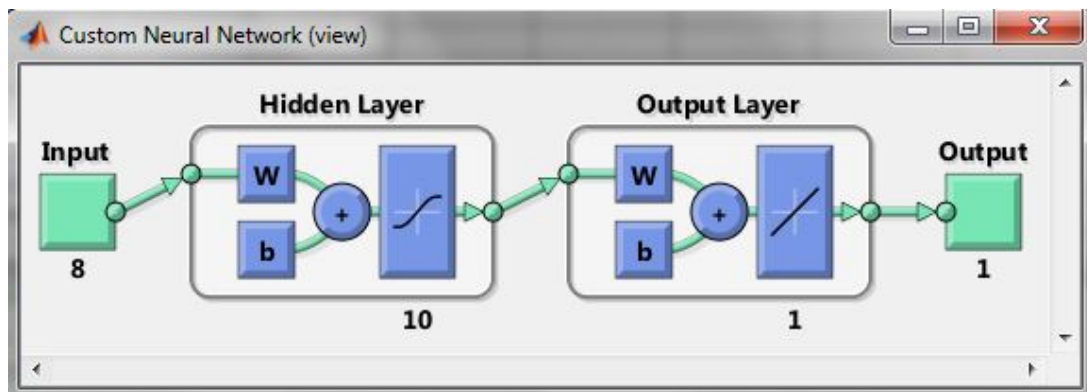


Fig.4. Custom Neural Network

IV. RESULT

Results of flexural behaviour of confined concrete with admixtures predicted by ANN model and estimated models has been summarised in Table 2. Results flexural behaviour of confined concrete with admixtures predicted by ANN model and has been plotted from Figure 5 to Figure 8 for comparison in terms of closeness to the experimental results. Results showed that ANN model is more efficient than existing mathematical models by comparing the statistical regression value (R), root mean square error (RMS) and absolute fraction of variance (V).

As mentioned by authors models proposed by ANN estimates the flexural properties of confined concrete very efficiently and more accurately to the experimental results, than other existing mathematical models, However in current research, in spite of using parameters of the data of 13 specimens for training purpose, ANN predictive model exhibited more promising results than all mathematical models .

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Table 2. Comparison of fc experimental data with training results obtained from models

Mix	ULTIMATE DEFLECTION		PEAK LOAD		FLEXURAL RIGIDITY		DUCTILITY INDEX	
	EXP	PRE	EXP	PRE	EXP	PRE	EXP	PRE
Ref	5.76	5.57	72	72	80.02	74.98	1.40	0.24
SC-0.5-100	7.12	9.60	96	96.45	131.88	194.78	1.34	0.18
HC-0.5-80-20	11.23	11.37	104	103.97	225.34	263.47	2.05	0.16
HC-0.5-60-40	11.16	14.19	112	114.05	241.16	357.70	1.84	0.16
SC-1-100	10.78	9.33	100	96.13	207.99	184.26	2.02	1.22
HC-1-80-20	10.53	12.53	108	109.05	219.42	301.05	2.14	1.23
HC-1-60-40	16.26	16.98	132	132.45	414.11	424.39	2.22	1.33
SC-1.5-100	10.92	11.49	108	108.17	227.54	243.20	1.76	1.43
HC-1.5-80-20	12.35	14.98	116	116.90	276.40	364.23	2.30	1.56
HC-1.5-60-40	15.36	13.97	120	119.92	355.62	343.91	2.25	1.67
SC-2-100	12.83	12.44	112	112.06	277.24	272.42	2.09	1.47
HC-2-80-20	14.29	16.39	120	108.95	330.85	358.17	2.01	1.71
HC-2-60-40	16.38	11.83	124	105.56	391.88	275.05	2.08	1.85

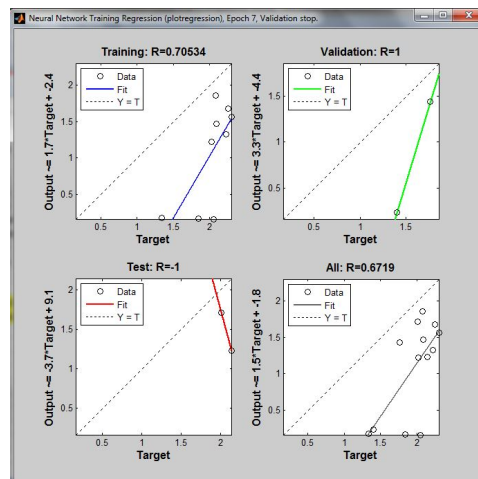


Fig.5. Ductility Index Model

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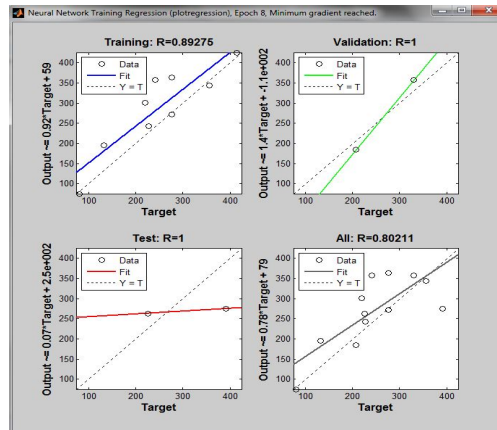


Fig.6. Flexural Rigidity Model

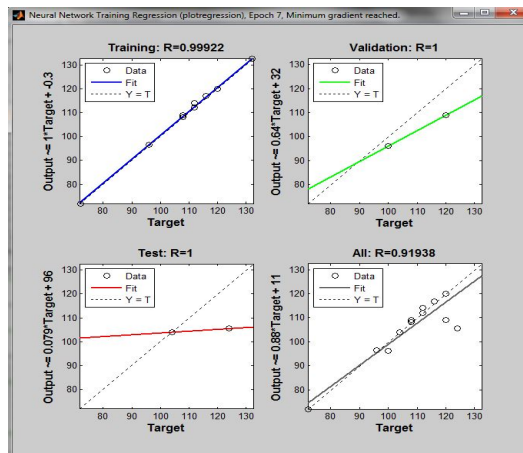


Fig.7. Peak Load Model

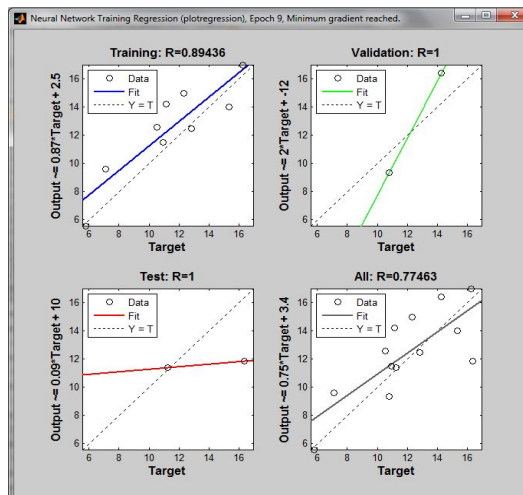


Fig.8. Ultimate Deflection Model

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V. CONCLUSION

In the models constructed in ANN, a multilayered feed forward neural network with a back propagation algorithm was used respectively. The models were trained with input and output data. Using only the input data in trained models the ultimate deflection, ductility index, peak load and flexural rigidity values of confined concrete with admixtures were found. The values are very closer to the experimental results obtained from training and testing for in artificial neural networks models. As a result, the flexural properties of the confined concrete containing hybrid fibers and admixtures can be predicted in the models in artificial neural networks with comparing the experimental datas in a quite short period of time with tiny error rates. The obtained conclusions have shown that artificial neural networks was practicable method for predicting the ultimate deflection, ductility index, peak load and flexural rigidity values. It is found that the models predicted the number of cycles to failure and the corresponding values were very close to the experimental values. It can be concluded that the models are found to be robust and reliable for cement based strengthening systems also.

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