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Prediction of Compressive Strength of High Performance Concrete using Artificial Neural Network (ANN) Models

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Abstract - *Concrete is the most versatile construction material because it can be designed to withstand harshest environments. Nowadays, most concrete mixture contains supplementary cementitious materials (SCM) which form a part of the cementitious component. The main benefits of SCMs are their ability to replace certain amount of cement and still be able to display cementitious property, thus reducing the cost of using Portland cement. The fast growth in industrialization has resulted in tons and tons of by-product or waste materials such as Fly Ash, Silica Fume, Ground Granulated Blast Furnace Slag, Steel fibers, etc., which can be used as SCMs in concrete. In the present work, a model has been developed using Artificial Neural Network (ANN) and Multiple Regression Analysis (MRA for the prediction of compressive strength of concrete with SCMs like Fly Ash, Silica Fume and Ground-Granulated Blast Furnace Slag (GGBFS). Experimental data published by various authors have been used for training, validation and testing process in the model development. The mix contents like cement, flyash water cement ratio, GGBS, silicafume are taken as the input parameters and cube compressive strength of the concrete was considered as the target output parameter. The data sets were modelled using both MRA and ANN and their results were compared. Three types of algorithms, Bayesian Regularization Algorithm, Levenberg-Marquardt Method and Scaled Conjugate Gradient Method were used in the study. The models using Bayesian Regularization Algorithm and Levenberg-Marquardt Method are found to be optimum model with the regression coefficients of 0.97 and 0.94 respectively. The model developed using Multiple Regression Analysis has a regression value (R) of 0.74 and does not give accurate results and hence this method is discarded.*

Key Words: Supplementary cementitious materials, Artificial Neural network, Multiple regression analysis.

1. INTRODUCTION

High-Performance Concrete (HPC) refers to the type of concrete mixture which has adequate workability, develops high strength and possesses excellent durability properties throughout its intended service life. To ensure eco-friendly and sustainable development, several industrial by-products such as Fly ash, Silica fume, GGBS, Fibers etc., are being utilized in concrete manufacturing as a substitute for either cement or fine aggregate or as an admixture. The mineral materials, when used in HPC, can enhance either or both the physical and durability properties of concrete. Concretes with these cementitious materials are used extensively throughout the world. Some of the major users are power, gas, oil and nuclear industries. The applications of such concretes are increasing with the passage of time due to their excellent performance, low influence on energy utilisation and environment friendliness.

In order to minimize the experimental task for concrete mix design, probabilistic models are generally constructed using Artificial Neural Networks (ANN) and Multiple Regression Analysis (MRA) and constitutive equations are derived. Multiple Regression Analysis (MRA) is one of the traditional methods used to forecast the compressive strength of concrete, by implementing linear or non-linear method. MRA is based on the least-squares fit approach. It is a statistical technique to examine the relationship between one or more independent variables and a dependent variable.

Neural networks are networks of many simple processes, which are called units, nodes, or neurons, with dense parallel interconnections. The connections between the neurons are called synapses. Each neuron receives weighted inputs from other neurons and communicates its outputs to other neurons by using an activation function. Thus, information is represented by massive cross-weighted inter-connections. Neural networks might be single-or multi layered. The single-layer neural networks present processing units of the neural networks, which take input from the outside of the networks and transmit their output to the outside of the networks; otherwise, the neural networks are considered multi layered. The basic methodology of neural networks consists of three processes: Network training, testing, and implementation.

In this study, multilayer preceptor (MLP): a feed forward artificial neural network model is implemented. A large test database has been extensively surveyed and collected. It is then carefully examined to establish the input vectors and the desired output vectors. Finally, a new model is proposed based on ANN and then verified against experimental data which has been collected from different sources.

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. In the current study, the compressive strength of High Performance

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Concrete is taken as the dependent variable, whereas, the mix constituents and age of the specimen form the independent variables.

Bhanja and Sengupta (2005) worked on Influence of silica fume on the tensile strength of concrete. Extensive experimentation was carried out over water–binder ratios ranging from 0.26 to 0.42 and silica fume–binder ratios from 0.0 to 0.3. For all the mixes, compressive, flexural and split tensile strengths were determined at 28 days.**A. Elahi *et al,*** carried out investigation to evaluate the mechanical and durability properties of High Performance Concrete (W/B = 0.3) containing supplementary cementitious materials (Silica Fume, Fly Ash, Ground Granulated Blast Furnace Slag) in binary and ternary systems. Portland cement was replaced with fly ash upto 40%, silica fume upto 15% and GGBS upto a level of 70%. The ternary mixes containing GGBS or Fly Ash (50%) and Silica Fume (7.5%) performed the best amongst all the mixes to resist the chloride diffusion. Silica fume (7.5%) performs better than other supplementary cementitious materials for the strength development.**B. K. Raghu Prasad *et al,*** proposed an artificial neural network (ANN) to predict 28 days compressive strength of high performance concrete. The high values of R^2 demonstrated that the proposed ANN model was suitable for predicting the compressive strength values very closely with the experimental values. **K. E. Hassan *et al,*** carried laboratory study on the properties of super-plasticized high performance concrete by using SF and FA (10%, 30% by weight of cement). The SF concrete showed similar strength development to that of the Ordinary Portland Cement concrete but slight higher values at all tested ages (1, 3, 7, 28, 365 days). FA concrete gave lowest compressive strength at early ages, same at 28 days and higher at 365 days than OPC concrete.**Vaishali G Ghorpade** performed tests on four mixes of concrete with 0%, 0.5%, 1.0% and 1.5% by volume fraction of glass fiber, silica fume (0%, 10%, 20%, 30% by weight of cement) with W/B ratio = 0.35, aggregate/binder = 2.0 and super-plasticizer 1% of the weight of cement. The optimum percentage recommended as 1% fiber volume with 10% silica fume for achieving maximum benefits in compressive strength, split tensile strength and flexural strength.

2. OBJECTIVES

The objective of this study is to construct probabilistic models for the prediction of compressive strength of High Performance Concrete with Fly ash, Silica fume and GGBS as partial cement replacement.

3. INPUT AND OUTPUT DATA FOR ANN MODELLING

The details on the materials used in various mixes like cement, fine aggregate (FA), Coarse aggregate (CA), water-cement (w/c) ratio and supplementary cementing materials such as flyash , slicafume and ground granulated blast furnace slag (GGBS) used in experimental works and the compressive strength (fc) obtained from various literature collected for this work are given through Table 1 to Table 6.

4. CREATION OF ALGORITHM FOR ANN

In order to develop ANN architecture, 466 samples of concrete data on 7th, 28th, 56th and 90th day of compressive strength of concrete were collected. In the present work, training data set comprises 326 data entries, and the remaining data entries (140) are divided between the validation and testing sets. To test the reliability of the neural network model, 70 samples were randomly selected as the test set and 70 samples as the validation set. The dividing process was carried out randomly between the three sets and each dataset has been statistically examined to ensure that it covers the range of input parameters. In a neural network if the area for data is more, learning is better.

Table 7 – Maximum and Minimum values of data used in ANN Model

Components	Data	
	Minimum	Maximum
Cement (kg/m^3)	100.5	650
Fine Aggregate (kg/m^3)	502	835
Coarse Aggregate (kg/m^3)	853	1848
Fly ash (kg/m^3)	0	227
Silica fume (kg/m^3)	0	147
GGBS (kg/m^3)	0	325
Compressive strength (MPa)	14.2	119

Table 8 – Parameters used in ANN Model

Number of input layer neurons	8
Number hidden layer	1
Number of hidden layer neurons	30
Number of output layer neutron	1

4.1 Training of Network

Feed-Forward Neural Network (FFNN) consists of at least three layers of neurons: an input layer, at least one intermediate hidden layer, and an output layer. Typically, neurons are connected in a feed-forward fashion with input units fully connected to neurons in the hidden layer and hidden neurons fully connected to neurons in the output layer. Back propagation is the traditional training method for FFNN during which the neurons adapt their weights to acquire new knowledge.

Learning in FFNN with back propagation occurs during the training phase in which each input pattern from the training set is applied to the input layer and then propagates forward. The pattern of activation arriving at the output layer is then compared with the correct (associated) output pattern to calculate an error signal. The error signal for each such target output pattern is then back propagated from the output layer to the input neurons in order to adjust the weights in each layer of the network. After the training phase during which the NN learns the correct classification for a set of inputs, it can be tested on a second (test) set of samples to see how well it classifies new patterns. Thus, an important consideration in applying back propagation learning is how well the network makes the generalization.

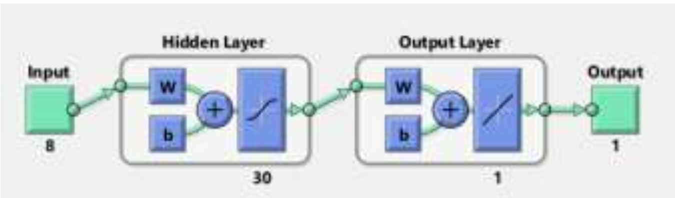

Figure.1 Feed Forward Neural Network Diagram

4.2 Construction of Neural Network Model

The architecture of a network describes how many layers a network has, the number of neurons in each layer, each layer's activation function, and how the layers connect to each other. In the present study there are eight inputs and compressive strength of concrete is output. For this reason, the initial structure of neural network is illustrated Figure 1.

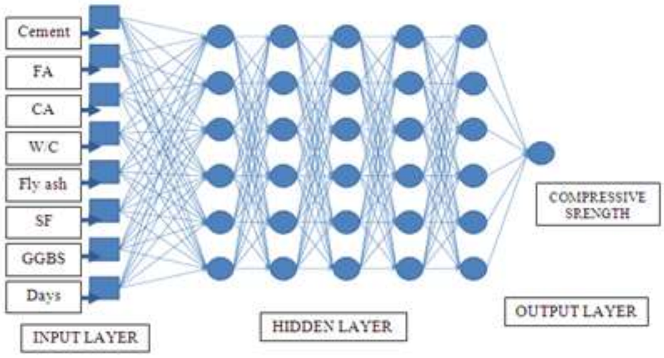

Figure 2: Architecture of Neural network developed

4.3 Selection of Training Algorithm

Training of datas can be done by choosing an algorithm. There are three types of algorithms.

i. Levenberg-Marquardt
ii. Bayesian Regularization
iii. Scaled Conjugate Gradient

i) Levenberg-Marquardt Method

This algorithm typically takes more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation sample.

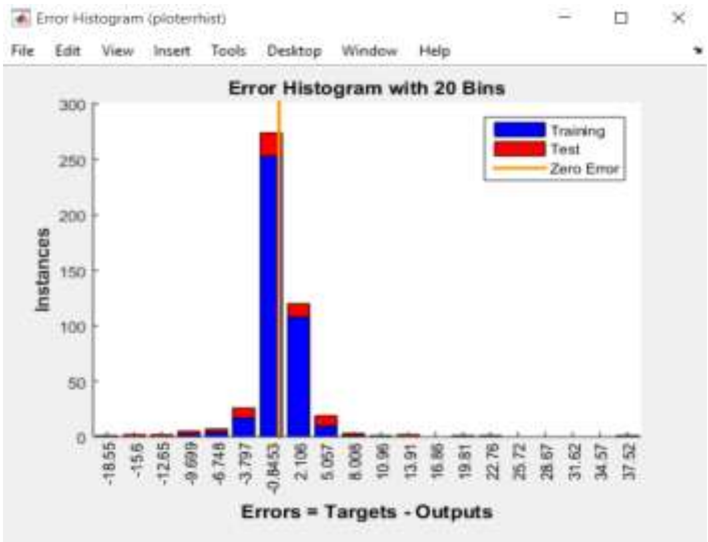

Figure .3 Plot Error Histogram for Levenberg-Marquardt Method

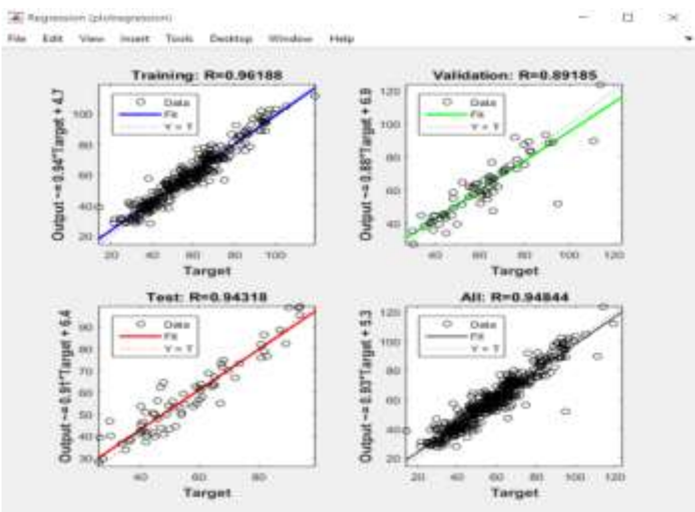

Figure.4 Plot Regression for Levenberg-Marquardt Method

ii) Bayesian Regularization Method

This algorithm typically takes more time, but can result in good generalization for difficult, small or noisy datasets. Training stops according to adaptive weight minimization (regularization).

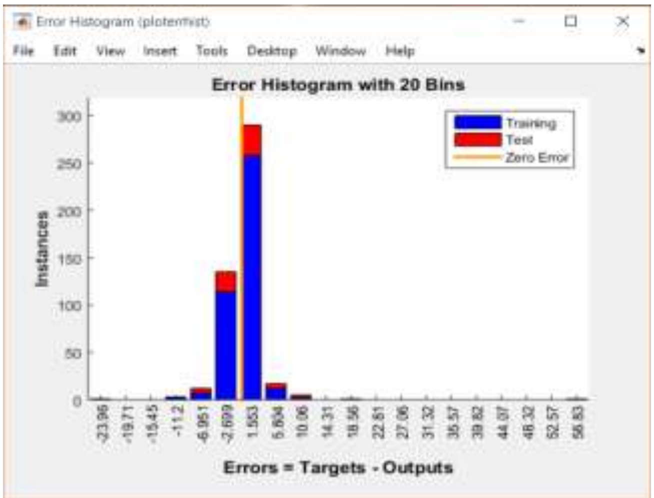

Figure.5 Plot Error Histogram for Bayesian Regularization Method

i) Scaled Conjugate Gradient Method

This algorithm takes less memory. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation sample.

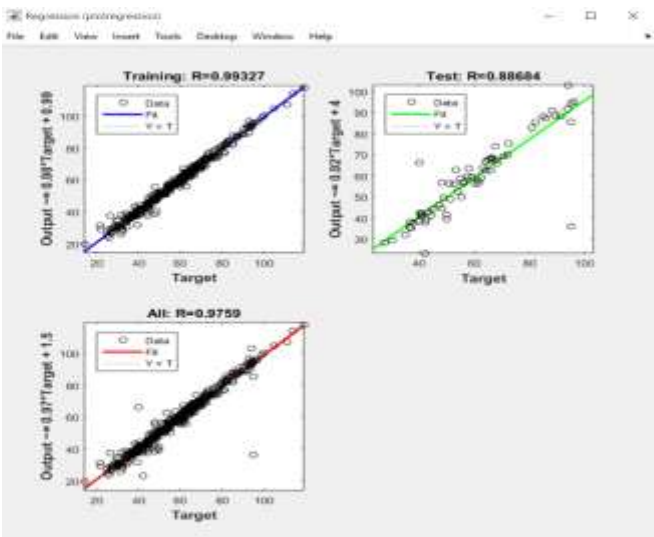

Figure.6 Plot Regression for Bayesian Regularization Method

5. RESULTS OF ANN MODEL

The input data sets for ANN model were trained under the category of 70% training, 15% validation and 15% testing. Some of the above mentioned input data sets are chosen for the prediction of compressive strength using ANN model. From observing the above three algorithms, Bayesian Regularization Algorithm yields the best fit results with least number of errors and Regression value (R) of 0.97, while Levenberg-Marquardt Method has a Regression value (R) of 0.94 and Scaled Conjugate Gradient Method has a Regression value (R) of 0.12. Hence, by training the inputs by Bayesian Regularization Algorithm the compressive strength of the concrete mixes is predicted by using ANN model.

6. DEVELOPMENT OF MODEL USING MRA

Building a model is rarely a simple or straightforward process. Analysts must have a prior knowledge of the variables to identify as independent variables to be included in the model. The independent variables can be first-order or second-order terms, interaction terms, and dummy variables. The variable screening methods, stepwise regression and all-possible-regressions selection procedure, can help analysts to select the most important variables that contribute to the response variable.

1) Stepwise Regression determines the independent variable(s) added to the model at each step using t-test.

2) All-Possible-Regressions Selection Procedure gives all possible models at each step with the suggested independent variable(s). One drawback of adding more independent variables in the model will increase eventually to 1. Adjusted or MSE Criterion takes into account the sample size and the number of parameters in the model increases only if MSE decreases. The largest or smallest MSE indicates the best fit of the model. A small value indicates that the total mean square error and the regression bias are minimized.

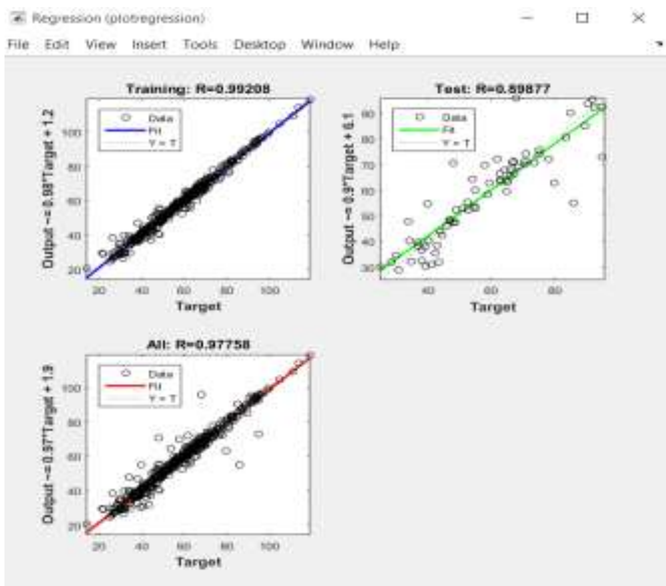

Figure.7 Maximum Regression value curve

5.1 Results of Multiple Regression Analysis

Next to the ANN model, Regression value is found using Multiple Regression Analysis. The Regression value (R) obtained here is 0.74.

6. CONCLUSIONS

From the above results and test data, it is found that Artificial Neural Network model is best suited for the prediction of compressive strength of High Performance Concrete using Supplementary Cementitious Materials, when compared to Multiple Regression Analysis. The graph shows a marginal difference between actual and predicted values. Therefore, compressive strength values of concrete can be predicted in ANN models without attempting any experiments in a quite short period of time with marginal errors.

Thus, it can be concluded that the application of ANN is more user friendly and more explicit model can be made which help the concrete industry to avoid the risk of faulty or deficient concrete that often entails durability and safety problems.

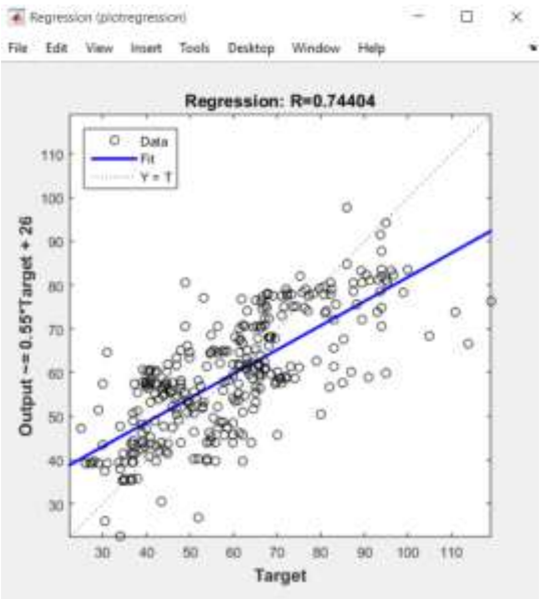

Figure.8 Regression value curve of MRA

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Table 1 - Mix Proportions containing Fly ash

INPUT						OUTPUT
SOURCE	Cement (kg/m³)	FA (kg/m³)	CA (kg/m³)	w/c ratio	Flyash kg/m³	f_c (28 days) MPa
Peter et.al 2009	454	593	1848	0.35	80	94
	428	593	1848	0.31	106	95
	401	593	1848	0.4	135	94
	374	593	1848	0.3	160	86
Subbiah Karthick et.al	318	745	952	0.37	136	47
	280	768	953	0.42	120	43
	250	820	939	0.47	107	37
	227	662	950	0.37	227	40
	200	685	982	0.42	200	37
	179	703	1008	0.47	179	30

Table 2 - Mix Proportions containing Silica fume

INPUT						OUTPUT
SOURCE	Cement (kg/m³)	FA (kg/m³)	CA (kg/m³)	w/c ratio	Silica fume kg/m³	f_c (28 days) Mpa
Uma et.al	532.35	672	1149.8	0.34	13.8	60
	512.51	672	1149.8	0.34	27.59	61
	492.66	672	1149.8	0.34	41.39	65
	472.5	672	1149.8	0.34	55.19	60
	453.6	672	1149.8	0.34	68.98	60
Venkate-swarao et.al	509.2	737	1044.0	0.32	26.8	65.77
	482.4	737	1044.0	0.32	53.6	68
	455.6	737	1044.0	0.32	80.4	65.33
	494	667	1146.0	0.26	26	93
	468	667	1146.0	0.26	52	92
	442	667	1146.0	0.26	78	95
	416	667	1146.0	0.26	104	92.5
	390	667	1146.0	0.26	130	85
Sengupta et.al	484.5	653	1122.5	0.3	25.5	75
	459	653	1122.5	0.3	51	78
	433.5	653	1122.5	0.3	76.5	82
	408	653	1122.5	0.3	102	85
	382.5	653	1122.5	0.3	127.5	81
	475	640	1100.0	0.34	25	64
	450	640	1100.0	0.34	50	70
	425	640	1100.0	0.34	75	72
	400	640	1100.0	0.34	100	75
	375	640	1100.0	0.34	125	73
	465.5	628	1078.0	0.38	24.5	59

	441	628	1078.0	0.38	49	63
	416.5	628	1078.0	0.38	73.5	64
	392	628	1078.0	0.38	98	65
	367.5	628	1078.0	0.38	122.5	66
	343	628	1078.0	0.38	147	64
	456	616	1058.0	0.42	24	49
	432	616	1058.0	0.42	48	55
	408	616	1058.0	0.42	72	56
	384	616	1058.0	0.42	96	57
	360	616	1058.0	0.42	120	60
	336	616	1058.0	0.42	144	48
Venkata Reddy et. al	486	773	1044.0	0.29	25.55	62.67
	461	773	1044.0	0.29	51.1	65.33
	436	773	1044.0	0.29	76.65	71.11
	411	773	1044.0	0.29	102.2	67.33
	386	773	1044.0	0.29	127.75	63.11
Vivek, et.al	491.61	683.24	1108.13	0.32	12.6	55.24
	478.99	683.24	1108.13	0.32	25.21	58.54
	466.39	683.24	1108.13	0.32	37.81	62.12
Vishnuram et.al	543.31	599.81	1171.47	0.3	28.58	55
	529.01	594.58	1171.47	0.3	42.87	61.33
	514.72	589.35	1171.47	0.3	57.16	56.33
	543.31	599.81	1171.47	0.32	28.58	63
	529.01	594.58	1171.47	0.32	42.87	66
	514.72	589.35	1171.47	0.32	57.16	60
Sanjeewa et.al	522.5	543	1088.0	0.3	27.5	66.1
	495	543	1088.0	0.3	55	69.7
	481.3	543	1088.0	0.3	68.8	69.9
	467.5	543	1088.0	0.3	82.5	64.4
Suresh kumar et.al	420	663	1082	0.4	21	60
	542.99	610.27	1171.8	0.45	28.58	55
	514.41	610.27	1171.8	0.45	57.16	61.33
	485.83	610.27	1171.8	0.45	85.74	56.33

Table 3 - Mix Proportions containing GGBS

INPUT						OUTPUT
SOURCE	**Cement (kg/m^3)**	**FA (kg/m^3)**	**CA (kg/m^3)**	**w/c ratio**	**GGBS kg/m^3**	**f_c (28 days) MPa**
N.Venkateswarao et.al	482.4	737	1044	0.32	53.6	64.88
	428.8	737	1044	0.32	107.2	66.22
	375.2	737	1044	0.32	160.8	68.44
	321.6	737	1044	0.32	214.4	65.33
	375.2	737	1044	0.32	160.8	65.77

Subbiah Karthick et.al	318	762	946	0.37	136	48
	280	783	972	0.42	120	42
	250	835	956	0.47	107	39
	227	760	943	0.37	227	50
	200	780	969	0.42	200	45
	179	832	853	0.47	179	40

Table 4 – Mix Proportions containing Fly ash and Silica fume

INPUT							OUTPUT
SOURCE	Cement (kg/m³)	FA (kg/m³)	CA (Kg/m³)	w/c ratio	Flyash kg/m³	Silicafume kg/m³	f_c (28 days) MPa
Kanta-Rao, et.al	570	502	1060	0.32	30	60	82.1
	540	502	1060	0.32	60	60	85
	510	502	1060	0.32	90	60	91
	480	502	1060	0.32	120	60	87
	450	502	1060	0.32	150	60	83
	420	502	1060	0.32	180	60	79
Vara Lakshmi, et.al	495.91	601.55	1151.06	0.26	58.34	29.17	67
	481.33	601.55	1151.06	0.26	58.34	43.75	71
	466.74	601.55	1151.06	0.26	58.34	58.34	81
	452.16	601.55	1151.06	0.26	58.34	72.92	77
Ankit Kumar	389.7	625	1164	0.43	8.66	34.64	41
	389.7	625	1164	0.43	17.32	25.98	39
	389.7	625	1164	0.43	21.65	21.65	37
	389.7	625	1164	0.43	25.98	17.32	36.5
	389.7	625	1164	0.43	34.64	8.66	36.5
Sanjeewa et.al	495	543	1088	0.3	27.5	27.5	71.1
	467.5	543	1088	0.3	55	27.5	70.8
	440	543	1088	0.3	82.5	27.5	66.4
	412.5	543	1088	0.3	110	27.5	62.9
	467.5	543	1088	0.3	27.5	55	70.6
	440	543	1088	0.3	55	55	68.7
	412	543	1088	0.3	82.5	55	67.4
	385	543	1088	0.3	110	55	65.6
	453.8	543	1088	0.3	27.5	68.8	72.1
	426.3	543	1088	0.3	55	68.8	70.1
	398.8	543	1088	0.3	82.5	68.8	65.8
	440	543	1088	0.3	27.5	82.5	65.8
	412.5	543	1088	0.3	55	82.5	63
	385	543	1088	0.3	82.5	82.5	61.2
Suresh kumar	485.83	610.2	1171.8	0.45	57.16	28.58	58.67
	457.26	610.2	1171.8	0.45	57.16	57.16	57.64
	428.68	610.2	1171.8	0.45	57.16	85.74	55.34

Table 5 - Mix Proportions containing Fly ash and GGBS

INPUT							OUTPUT
SOURCE	CEMENT (kg/m^3)	FA (Kg/m^3)	CA (Kg/m^3)	W/C RATIO	FLY ASH	GGBS	f_c (28 Days) MPa
Kavitha Chandrakar, et.al	419.99	585	1205	0.45	46.66	46.66	52
	335.99	585	1205	0.45	83.99	46.66	54
	326.66	585	1205	0.45	139.99	46.66	56
	279.99	585	1205	0.45	186.66	46.66	60
	419.99	585	1205	0.45	46.66	93.33	54
	335.99	585	1205	0.45	83.99	93.33	56
	326.66	585	1205	0.45	139.99	93.33	60
	279.99	585	1205	0.45	186.66	93.33	62
	419.99	585	1205	0.45	46.66	139.99	54
	335.99	585	1205	0.45	83.99	139.99	62
	326.66	585	1205	0.45	139.99	139.99	64
	279.99	585	1205	0.45	186.66	139.99	70
	419.99	585	1205	0.45	46.66	186.66	51
	335.99	585	1205	0.45	83.99	186.66	52
	326.66	585	1205	0.45	139.99	186.66	54
	279.99	585	1205	0.45	186.66	186.66	62
Afroz Khan, et.al	390	695	981	0.2	104	156	93.13
	390	695	981	0.2	117	143	96.7
	390	695	981	0.2	130	130	100
	357.5	695	981	0.2	117	175.5	91.25
	357.5	695	981	0.2	131.63	160.87	90.45
	357.5	695	981	0.2	146.25	146.25	96.23
	325	695	981	0.2	130	130	95.15
	325	695	981	0.2	146.25	146.25	94

Table 6 – Mix Proportions containing Silica fume and GGBS

INPUT							OUTPUT
SOURCE	Cement (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	w/c ratio	Silica fume kg/m^3	GGBS kg/m^3	f_c (28 days) MPa
Vivek, et.al	375.2	683	1060	0.32	26.8	160.8	68.44
	375.2	683	1060	0.32	53.6	160.8	70.66
	375.2	683	1060	0.32	80.4	160.8	68.88
Venkata Reddy	348.4	737	1044	0.32	26.8	160.8	68.44
	321.6	737	1044	0.32	53.6	160.8	70.66
	294.8	737	1044	0.32	80.4	160.8	68.88
Gorav Gupta, et.al	395.6	650	1130	0.4	12.9	21.5	32.01
	374.1	650	1130	0.4	12.9	43	38.55
	352.6	650	1130	0.4	12.9	64.5	37.25
	331.1	650	1130	0.4	12.9	86	38.55
	391.3	650	1130	0.4	17.2	21.5	40.3

	369.8	650	1130	0.4	17.2	43	42.04
	348.3	650	1130	0.4	17.2	64.5	44.22
	326.8	650	1130	0.4	17.2	86	38.12
	387	650	1130	0.4	21.5	21.5	48.15
	365.5	650	1130	0.4	21.5	43	26.4
	344	650	1130	0.4	21.5	64.5	35.91
	322.5	650	1130	0.4	21.5	86	35.07

Table 8– Comparison of experimental results with ANN model results

CEMENT (kg/m^3)	FINE AGGREGATE (Kg/m^3)	COARSE AGGREGATE (Kg/m^3)	W/C RATIO	FLY ASH	SILICA FUME	COMPRESSIVE STRENGTH (28 DAYS)	
						Experimental data	Prediucted value
570	502	1060	0.32	30	60	82.1	87.1
540	502	1060	0.32	60	60	85	87.5
510	502	1060	0.32	90	60	91	86.4
480	502	1060	0.32	120	60	87	87.4
450	502	1060	0.32	150	60	83	86.8
420	502	1060	0.32	180	60	79	79.3
495.91	601.55	1151.06	0.26	58.34	29.17	67	74.6
481.33	601.55	1151.06	0.26	58.34	43.75	71	74.7
466.74	601.55	1151.06	0.26	58.34	58.34	81	74.4
452.16	601.55	1151.06	0.26	58.34	72.92	77	73.7
389.7	625	1164	0.43	8.66	34.64	41	38.4
389.7	625	1164	0.43	17.32	25.98	39	38.3
389.7	625	1164	0.43	21.65	21.65	37	38.4
389.7	625	1164	0.43	25.98	17.32	36.5	38.5
389.7	625	1164	0.43	34.64	8.66	36.5	38.6
495	543	1088	0.3	27.5	27.5	71.1	72.8
467.5	543	1088	0.3	55	27.5	70.8	71.6
440	543	1088	0.3	82.5	27.5	66.4	66.9
412.5	543	1088	0.3	110	27.5	62.9	63.5
467.5	543	1088	0.3	27.5	55	70.6	70.4
440	543	1088	0.3	55	55	68.7	68.7
412	543	1088	0.3	82.5	55	67.4	65.7
385	543	1088	0.3	110	55	65.6	64.3
453.8	543	1088	0.3	27.5	68.8	72.1	68.8
426.3	543	1088	0.3	55	68.8	70.1	67.2
398.8	543	1088	0.3	82.5	68.8	65.8	64.3
440	543	1088	0.3	27.5	82.5	65.8	67.1
412.5	543	1088	0.3	55	82.5	63	65.4