

Development Of Genetic Algorithm Based Neural Network Model For Predicting Strength Of High Performance Concrete

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ABSTRACT

This paper presents an results of experimental investigation conducted to evaluate the possibilities of adopting Genetic Algorithm (GA) based Artificial Neural Networks (ANN) to predict the strength characteristics of High Performance Concrete (HPC) with different water-binder ratios (0.3, 0.325, 0.35, 0.375, 0.4, 0.425, 0.45, 0.475 & 0.5) and different aggregate binder ratios (2, 2.5 & 3) and different percentage replacement of cement by mineral admixtures such as Flyash, Metakaolin and Silicafume (0, 10, 20 & 30%) as input vectors. The network has been trained with experimental data obtained from laboratory experimentation. The Artificial Neural Network learned the relationship for predicting the Compressive strength, Tensile strength, Flexural strength and Young's Modulus of HPC in 2000 training epochs. After successful learning the GA based ANN model predicted the strength characteristics satisfying all the constraints with an accuracy of about 95%. The various stages involved in the development of genetic algorithm based neural network model are addressed at length in this paper.

KEYWORDS: Genetic Algorithm (GA), Artificial Neural Network (ANN), Back Propagation (BP), Root Mean Square Error (RMSE). Mineral Admixtures (MA) and Strength Characteristics (SC)

I. INTRODUCTION

High performance concrete is defined as a concrete which satisfies certain criteria proposed to overcome limitations of conventional concretes. The development of high performance concrete at improved strength has brought new opportunities to the construction industry. High performance concrete confirms to a set of standards of the most common applications but not limited to strength. Some of the standards are ease of placement, compaction without segregation, early age strength, permeability etc. The researchers have done considerable work in replacing the cement with Flyash, Silicafume, Metakaolin, blast furnace slag and chemical admixtures such as super plasticizers without affecting the strength \

characteristics. These mineral admixtures help in obtain both high performance and economy. These materials increase the long-term performance of the HPC through reduced permeability resulting in improved durability. Addition of such material has indicated the improvements in strength properties of HPC.

Flyash is the blended material for production of Portland pozzolana cement is normally obtained from thermal power plants. The quality of Flyash to be used in Portland Pozzolana cement is covered under IS 3812-1981. Silicafume is highly pozzolanic. The amount of silica fume present, the super fineness, the high specific surface area of 25000m³/kg are the main characters of Silicafume. Metakaolin is recently developed man made factory manufactured mineral admixture which has potential for use in the production of HPC. The mechanical and durability properties of high performance Metakaolin and silicafume concretes to their microstructure characteristics related by Poon et. al [2006]. The use of zeolitic admixtures, a natural pozzolana was examined by Feng et. Al [1990]. Metakaolin a reactive alumino-silicate pozzolana reported by Walters and Jones [1991]. The mechanical properties of super-plasticized Metakaolin concrete were presented by Wild et. al [1996]. Pore size distribution in Metakaolin paste and the large pores in the paste decreases with increase in Metakaolin content was studied and reported by Khatib and Wild [1996]. However the applications of HPC are hampered due to complicated mix design relations. Mix design relates both strength and strength to the macro-structural characteristics. Hence, strength is a very important property for HPC. Development of models using analytical approach to predict the strength parameters of HPC is difficult because of the complex multi parametric interaction between the various constituents of HPC. Very recently, it is established that neural networks and genetic algorithms have the ability to map this type of multi parametric interaction.

An artificial neural network is an information processing paradigm that is inspired by the way human brain processes information. In the recent years, ANNs have been gaining momentum as

effective strategies to provide control actions for wide diversity of applications. The main advantage is that one does not have to explicitly assume a model from which relationship of possibly complicated shape between input and output variables is generated by data points themselves. ANNs with this remarkable ability to derive meaning from complicated or imprecise data can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. ANNs are massively parallel distributed processor made of simple processing units, which has a natural propensity for strong experimental knowledge and making it available for use. ANNs are capable of learning from examples, generalizing the knowledge learnt and apply to new data; they are able to capture the complex relationships in a relatively easier way than other computational methods. Among all kinds of neural network algorithms, error back propagation (BP) network is the most typical delegate. The training of network by BP involves three stages; the feed forward of the input training pattern, the calculation and back propagation of the associate error, and the adjustments of the weights (neurons). But drawback of BP algorithm is slow training and numerous variations of back propagation have been required to improve the speed of the training process. Genetic algorithm (GA) on the other hand is adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. The basic concept of GA is designed to stimulate processes in natural system necessary for evolution, especially those that follow the principles first laid down by Charles Darwin of survival of fittest. As such they represent an intelligent exploration of a random search within a defined search space to solve the problem. GA is a method of "breeding" computer programs and solutions to optimization or search problems by means of stimulated evolution, processes based on natural selection, crossover, and mutation are repeatedly applied to a population of binary strings which represent potential solutions. Over time, the numbers of above average individuals are created, until a good solution to the problem at hand is found. However GA also has its own shortages such as lower local convergence speed inkling to premature convergence etc. It is evident that there is strong complementarity between BP and GA. Based on that complementarity a new hybrid evolution mode can be established. That is the relationship model is established by BP network, the connection weights and thresholds of BP are optimized by GA and then the precision of model is increased by BP. The GA is accomplished by the BP techniques such as training repetition; early stopping and complex regulation are employed to improve evolutionary process results. Moreover, it accelerates the convergence speed of the algorithms and overcomes the drawback of BP network that is

difficult to achieve a satisfactory model with few training samples. The purpose of this article is to provide a methodology for predicting the strength of high performance concrete which combines the features of genetic algorithms and back propagation and it is presented as an improved approach.

1.1 LITERATURE SURVEY

Serio Lai and Marzouk [1997] presented an ANN model for predicting strength of building materials. Tarkey Haggzy and Susan Tully [1998] employed an ANN for predicting the structural behavior of concrete slabs. Yeh [1998] adopted ANN methods for modeling the strength of high performance concrete. Savic et.al. [1999] developed software for the optimal design of general and systematic balanced laminates (or sandwich panels) with specified mechanical properties. Ni Hong-Guang, Wang Ji-Zong [2000] developed ANN model for predicting the strength of concrete. Nehdi et al. [2001] have developed Neural Network models for performance of cellular concrete mixtures. Sanad and Saka [2001] developed ANN for predicting ultimate shear strength of reinforced concrete deep slabs. Rajashekar and Ananda kumar [2001] proposed cellular genetic algorithms for the optimization of mix proportions for high performance concrete. Hadi [2002] developed neural nets for applications in concrete structures. Cengiz Toklu [2005] formulated an aggregate-blending as a multi-objective optimization problem and solved by using genetic algorithms. Noor Zaii and Hakim [2007] focused on development of ANN in prediction of compressive strength of concrete after 28 days. Sudarsana Rao and Ramesh babu [2007] employed ANN model for the design of beam subjected to bending and shear. Sudarsana Rao and Chandrasekhara Reddy [2008] have developed Artificial Neural Network based macro mechanical model for slurry infiltrated fibrous concrete using multi layer feed forward network with back propagation learning algorithm. Serkan and Subasi developed an ANN model for predicting the mechanical properties of class-C fly ash. Pratibha Agarwal [2011] presented an ANN model for predicting compressive strength of self compacting concrete with Fuzzy logic. Mohammed Iqbal Khan [2012] developed an ANN model for predicting properties of high performance concrete composite cementitious material system.

II. EXPERIMENTAL WORK

2.1 MATERIALS USED

Cement: The cement used in the experimentation was 53-grade ordinary port land cement and having a specific gravity of 3.15 which satisfies the requirements of IS: 12269-1987 specifications

Coarse aggregates: The crushed granite aggregate were collected from the local quarry. The quarry

aggregate was used in the experimentation were of 20MM and downsize aggregate and tested as per IS: 2386-1963 (I, II, and III) specifications.

Fine aggregates: Locally available sand collected from the bed of river Pandumeru was used as fine aggregate. The sand used was having fineness modulus of 2.96 and conformed to grading zone-III as per IS: 383-1970 specification.

Metakaolin: The mineral admixture Metakaolin was obtained from the 20 MICRON LIMITED company at Vadodara in Gujarat. The Metakaolin was in conformity with the general requirements of pozzolana.

Silica Fume: The Silica fume used in the present study was obtained from the Elkem India Pvt Limited, Mumbai in Maharashtra.

Fly Ash: Fly ash belonging to class-F obtained from Rayalaseema Thermal Power station (RTPS), Muddanuru was used in the present investigation.

Water: Ordinary portable water free from organic content turbidity and salts was used for mixing and for curing throughout the investigation.

Super Plasticizer: To impart the additional desired properties, a super plasticizer (Conplast SP-337) was used.

III. EXPERIMENTAL PROCEDURE

The main objective of this experimental investigation is to develop a neural network model for predicting the strength of high performance concrete. Experiments was conducted to determine the strength of High performance concrete after 28 days curing with various parameters like water-cement ratio (0.3, 0.325, 0.35, 0.375, 0.4, 0.425, 0.45,

0.475 & 0.5), aggregate-binder ratio (2, 2.5 & 3) and percentage replacement of mineral admixtures (0, 10, 20 & 30%). A total of 324 HPC mixes were cast in the laboratory. Out of these 324 data sets, 300 data sets (80% of total data) were used for training and the remaining 24 data sets were used for validation. A part of the training data set is presented in the Table 3.1

The following input vectors were selected to predict the values of compressive strength, tensile strength and flexural strength along with the value of young's modulus.

- a. Water-binder ratio (W/B)
- b. Aggregate binder ratio(A/B)
- c. Type of mineral admixture(Type of MA) and
- d. Percentage replacement of cement by admixture (% replacement)

Based on the input vectors selected, the network model was formulated as

IP = [W/B, A/B, Type of MA, % replacement]

The following output vectors were selected to predict from the network model such as

- a. Compressive Strength (CS),
- b. Tensile Strength (TS),
- c. Flexural Strength (FS) and
- d. Young's modulus (E).

Based on the output vectors selected the network model was formulated as

OP = {(CS), (TS), (FS) (E)}

IV. EXPERIMENTAL RESULTS

The following Table gives the details of the input vectors and output vectors, the following Table No 3.1 gives the strength test results of high performance concrete for various input vectors

Table No 3.1: Strength test results of high performance concrete for various input vectors

Sl. No	Input Vectors				Output Vectors (Strength in MPa)			
	W/B	A/B	Type of MA	% replacement	CS	TS	FS	E
1	0.3	2.0	1	2	74.3	5.31	6.39	45252
2	0.325	2.0	1	0	82.6	5.69	7.0	49523
3	0.35	2.0	1	3	63.3	4.68	5.11	40546
4	0.375	2.0	1	1	84.8	5.89	7.47	49094
5	0.4	2.0	1	2	69.6	4.89	5.97	44217
6	0.425	2.0	1	3	61.8	4.38	5.21	39964
7	0.45	2.0	1	1	80.7	5.56	7.12	48030
8	0.475	2.0	1	0	75.2	5.29	6.27	46891
9	0.5	2.0	1	2	65.9	4.59	5.49	42173
10	0.3	2.5	2	1	79.6	5.88	7.51	48346
11	0.325	2.5	2	3	59.8	4.4	5.31	43644
12	0.35	2.5	2	0	71.1	5.39	6.52	45454
13	0.375	2.5	2	1	71.3	5.39	6.98	46557
14	0.4	2.5	2	3	56.6	4.13	5.02	41488
15	0.425	2.5	2	2	60.7	4.34	5.46	41739
16	0.45	2.5	2	1	65.5	5.0	6.49	44209

17	0.475	2.5	2	2	56.2	4.14	5.28	40490
18	0.5	2.5	2	3	50.9	3.60	4.55	39494
19	0.3	3.0	3	0	63.3	5.42	6.56	42818
20	0.325	3.0	3	2	57.3	4.99	6.02	40524
21	0.35	3.0	3	3	51.1	3.89	5.59	38288
22	0.375	3.0	3	1	61.5	5.30	7.01	42462
23	0.4	3.0	3	0	53.8	4.78	5.89	39834
24	0.425	3.0	3	1	56.9	5.20	6.15	40957
25	0.45	3.0	3	2	50.0	4.21	5.5	37975
26	0.475	3.0	3	3	45.6	3.21	4.88	35230
27	0.5	3.0	3	1	51.3	4.67	5.58	37820

The input and output vectors have been normalized in the range (0, +1) using suitable normalization factors or scaling factors. The following Table No.3.2 gives the scaling factors for input and output vectors.

Table No. 3. 2: Details of scaling factors

Nature of vector	Parameter	Minimum Value	Maximum Value	Scale Factor
Input Vector	Water binder ratio (W/B)	0.3	0.5	0.7
	Aggregate binder ratio (A/B)	2	3	4
	Percentage replacement of admixture (% replacement)	0	30	35
Output Vector	Compressive strength (CS)	36.1	94.8	110
	Tensile strength(TS)	4.77	6.59	9
	Flexural strength(FS)	4.26	8.27	11
	Young's modulus(E)	23539	52962	55000

The network configuration is defined in terms of number, size, nodal properties, etc. of the input/output vectors and the intermediate hidden layers. Once the input and output vectors are decided to cater the present investigation requirements, the task of selecting a suitable configuration has been taken up. There is no direct method to select number of nodes in hidden layer. Generally a trial and error method is adopted for arriving at the network configuration. After doing a few trials, it is observed that the network with 24 neurons in one hidden layer is behaving well. Accordingly a configuration of (4-24-4) has been selected for this network model. The architecture is depicted in Figure No 1

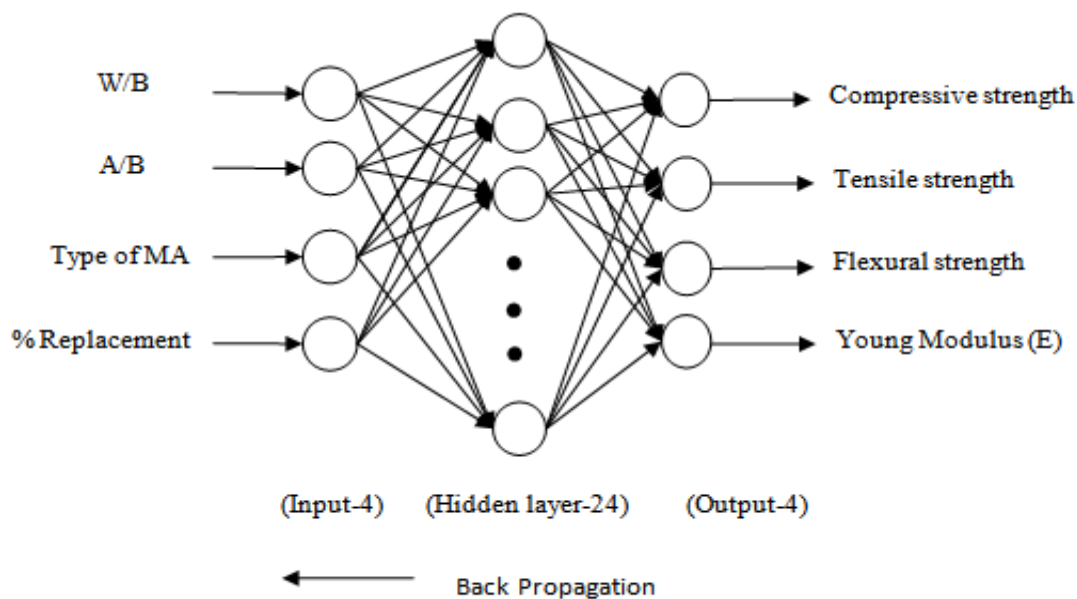


Fig No.1 Configuration of GA/ANN Model

Conventionally, a BPN determines its weights based on gradient search techniques and hence runs the risk of encountering local – minima. GA on the other hand is found to be good at finding ‘acceptably good’ solutions. The idea to hybridize the two networks has been successful to enhance the speed of training [Rajasekaran and Vijayalakshmi Pai, 2003]. In the present work, the weights for the BPN have been obtained by using GA. genetic Algorithms (GAs) which use a direct analogy of natural behavior, work with a population of individual strings, each representing a possible solution to the problem considered. Each individual string is assigned a fitness value which is an assessment of how good a solution is to a problem. The high-fit individuals participate in “reproduction” by cross-breeding with other individuals in the population. This yields new individual strings as offspring which share some features with each parent. The least-fit individuals are kept out from reproduction and so they “die out”. A whole new population of possible solutions to the problem is generated by selecting the high-fit individuals from the current generation. This new generation contains characteristics which are better than their ancestors. The parameters which represent a potential solution to the problem, genes, are joined together to form a string of values referred to as a Chromosome. A decimal coding system has been adopted for coding the chromosomes in the present work. The network configuration chosen for the present work is 4 – 24 - 4. Therefore, the numbers of weights (genes) that are to be

determined are $4 \times 24 + 24 \times 4 = 192$. With each gene being a real number, and taking the gene length as 5, the string representing the chromosomes of weights will have a length of $192 \times 5 = 960$. This string represents the weight matrices of the input hidden layer-output layers. An initial population of chromosomes is randomly generated. Weights from each chromosome have been extracted then using the procedure suggested by Rajasekaran & Vijayalakshmi Pai [2003]. The fitness function has been devised using FITGEN algorithm [Rajasekaran & Vijayalakshmi Pai, 2003]. A constant learning rate of 0.6 and a momentum factor of 0.9 have been adopted during the training. Satisfactory training has been obtained after just 2000 training cycles. The progress of the learning of the network is presented in Table No.3.3. It can be seen from Table No.3.3, that the RMS error after 2000 cycles is only 0.001192. Accordingly the performance of the network is acceptable. At this stage the training of the network is terminated to avoid over training. Such an overtraining may hamper the generalization capabilities of the network. The training of the network accepted at this stage is presented in Figure No.2 & 3. The figure is drawn only for twenty training examples selected at random. Though the figure is drawn for only twenty four examples the author has verified all the three hundred training examples and it is found that the network has predicted all the values to the good satisfaction. Thus it can be concluded that at this stage the network has learnt the relationship between input and output parameters successfully.

Table No 3.3: Learning progress of the network

Sl.No	No of Epochs	RMS Value
1	100	0.057025
2	200	0.001285
3	300	0.001204
4	400	0.001199
5	500	0.001197
6	600	0.001195
7	700	0.001195
8	800	0.001194
9	900	0.001194
10	1000	0.001194
11	1100	0.001194
12	1200	0.001193
13	1300	0.001193
14	1400	0.001193
15	1500	0.001193
16	1600	0.001193
17	1700	0.001192
18	1800	0.001192
19	1900	0.001192
20	2000	0.001192

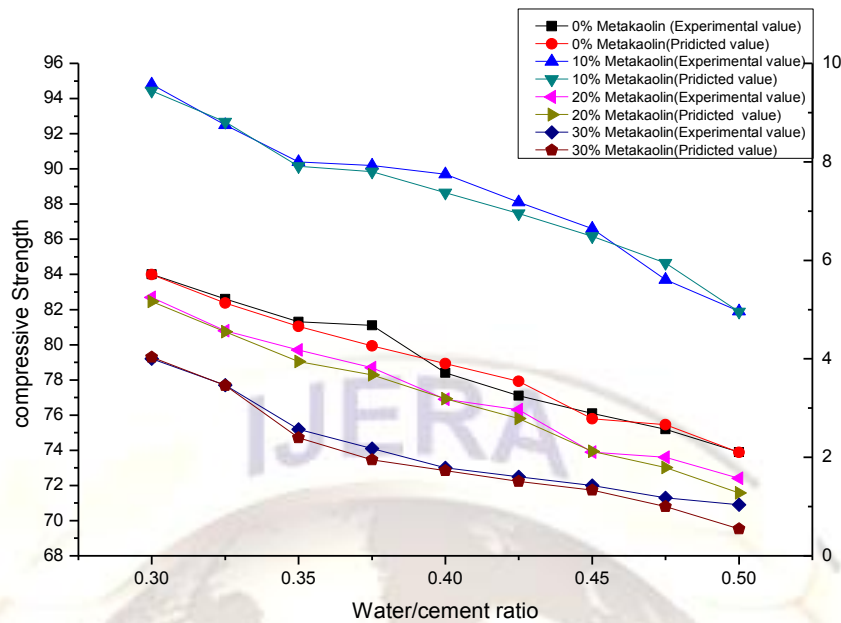


Fig. No. 2 Learning of GA/ANN Model for Compressive strength

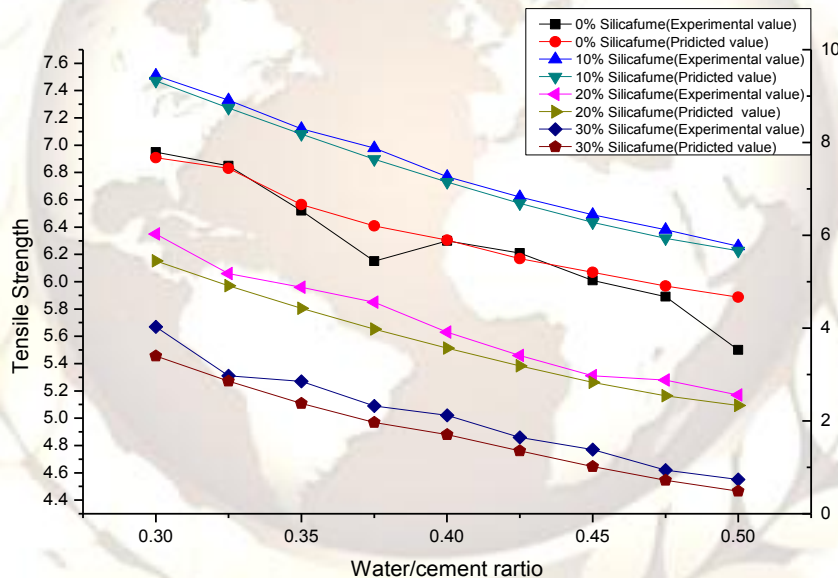


Fig No. 3 Learning of GA/ANN Model for Tensile strength

V. RESULTS AND DISCUSSIONS:

Validation of the network is to test the network for parameters that are not used in the training of the network. The network was asked to predict Compressive strength, Flexural strength, Tensile strength and Young's modulus for 24 new data sets which are not included in the training set. It can be observed that from the Figure No.4 & 5 the values predicted by hybrid model for new sets matches satisfactorily with the experimental results. Hence, the results of GA based ANN model can be used for the prediction of strength properties of high performance concrete.

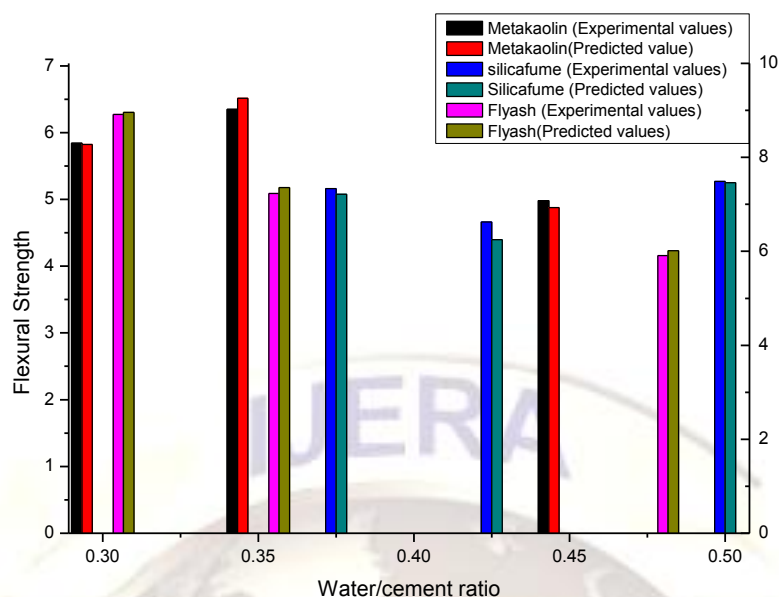


Figure No.4 Validation of GA/ANN Model for Flexural strength

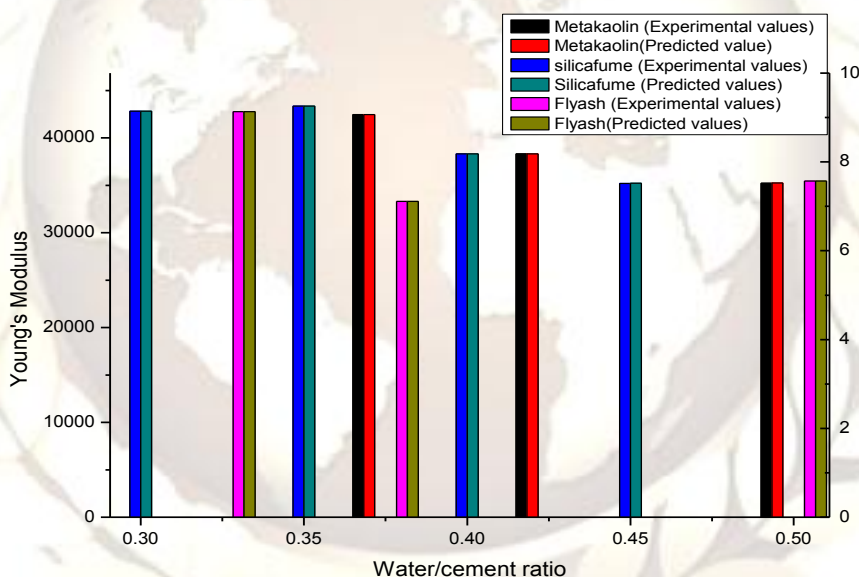


Figure No.5 Validation of GA/ANN Model for Young's Modulus

VI. CONCLUSIONS:

In this paper, the application of Genetic Algorithm based neural network model for predicting the Compressive strength, Tensile strength, Flexural strength and Young's modulus of High performance concrete has been demonstrated. The neural network model has been trained using 300 examples obtained from experimental results. The training examples are so chosen that they will cover all the variables involved in the problem. The weights for the network have been obtained using a genetic algorithm. The network could learn the strength prediction problem

with just 2000 training cycles. After successful training, the GA based neural network model is able to predict the Compressive strength, Tensile strength, Flexural strength and Young's modulus of High performance concrete satisfactorily for new problems with an accuracy of about 95%. Thus, it is concluded that the developed neural network model can serve as a macro-mechanical model for predicting the strength of high performance concrete.

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REFERENCES:

- [1] Cengiz Toklu.Y(2005) *Aggregate blending using Genetic algorithms*
- [2] Davis L (1991) *Hand book of genetic algorithms*, (New York: Van No strand Reinhold)
- [3] Hadi. N. (2000). *Neural network applications in Concrete Structures, Compute & Struct.* 8:373-38
- [4] I-Cheng Yeh (1999). *Design of High – Performance Concrete Mixture Using Neural Networks and Nonlinear Programming .Journal of Civil Engineering*, Vol.13, No.1.
- [5] Jamil.M,ZainM .F.M, Basri .H.B.(2009)*Neural Network Simulator Model for Optimization in High Performance Concrete Mix Design .European Journal of Scientific Research* Vol.34 No.1, pp.61-68
- [6] Jenkins W.M. (1992) *Plane frame optimum design environment based on genetic algorithm.*
- [7] M. Nehdi, Y. Djebbar and A.Khan, (2001). *Neural Network Model for Preformed-Foam Cellular Concrete*, ACI Materials Journal,
- [8] Mohammad Iqbal Khan (2012) *Predicting properties of high performance concrete containing composite cementitious material using neural networks* Automation in construction, volume 22.
- [9] Ni Hong-Guang, Wang Ji-Zong (2000) *Prediction of Compressive strength of concrete by neural networks* Cement and Concrete research -Cem. Concr. Res.volume 30:1245–1250.
- [10] Noorzaii. J, Wan, S. J. S. Hakim, M. S. Jafarand W. A. M. Thanoon(2007) *Development of artificial neural networks for predicting concrete compressive strength of concrete* International journal of Engineering and Technology.Vol.4, No.2, 2007, pp. 141-153.
- [11] Prathibha Aggarwal (2011) *Prediction of compressive strength of self compacting concrete with fuzzy logics* World Academy of Science, Engineering and Technology.
- [12] Rajasekaran, S. and Vijayalakshmi Pai, G. A. (2003). *Neural Networks, Fuzzy Logic and Genetic Algorithms*, (Prentice Hall of India, New Delhi).
- [13] Rajasekaran. S and R. Amalraj S. Anandkumar (2001). *Optimization of mix proportions for high Performance Concrete using cellular genetic algorithms* Proceedings of National Seminar on Concrete Technology for 21 Century Annamalainagar : Annamalai University
- [14] Sanad. A and Saka M.- (2001). *C Prediction of Ultimate shear strength of reinforced concrete deep beams using neural networks* , M.sc ThJ.Struct.Eng.,127(7),818-828.
- [15] Serio Lai and Mauro. (1997) *Concrete Strength Prediction by means of Neural Network Construction and Building Materials* Vol11. No. 2, pp:93-98
- [16] Serkan Subasi. D April (2009) *Prediction of mechanical properties of cement containing class C fly ash using artificial neural network and regression technique*, Academic Journals Vol.4 940 pp.289-297
- [17] Sudarsana Rao. H and Ramesh Babu. B (2007). *Hybrid neural network model for the design of beam subjected to bending and shear using Artificial Neural Networks*, ACI Materials Journal, Vol.98, No.5, pp. 394-401.
- [18] Sudarsna Rao. H,Vaishali. G and Beulah.(2012) *Development of Genetic algorithm based neural network model for predicting workability of high performance concrete* Vol.5,International Journal of Advances in Science and Technology
- [19] Tarek Hazey, susan tully, Hesham Marzouk (1998) *Prediction A neural network approach for predicting the structural behavior of concrete slabs* Canadian journal of Civil engineering, 25(4): 668-667, 10.1139/198-009. Vol.98, No.5, pp. 402-409.
- [20] Yeh. I. (1998). *Model of Strength of High Performance Concrete using Neural Networks*, Cem Conc. Rec., 28(12):1797 – 808.