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# Development of Genetic Algorithm based Neural Network Model for Predicting Workability and 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 workability and 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 Compaction factor, Vee-bee time, Compressive of HPC in 1300 training epochs. 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 models predicted the workability and 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 models are addressed at length in this paper.***

***Keywords: Artificial Neural Network (ANN), Back Propagation (BP), Genetic Algorithm (GA), Mineral Admixtures (MA), Root Mean Square Error (RMSE). Workability characteristics 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.

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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 $25000m^3/kg$ 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 prosperity 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.

## II. 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. Rajashekaran 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.

## III. EXPERIMENTAL WORK

### III.1 MATERIALS USED

**A. 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

**B. 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.

**C. 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.

**D. 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.

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

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

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

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

### III.2 EXPERIMENTAL PROCEDURE

The main objective of this experimental investigation is to develop a neural network models for predicting the workability and strength of high performance concrete. Experiments was conducted to determine the workability and 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 for workability and strength. Out of these 324 data sets, 300 data sets (80% of total data) for each for these models were used for training and the remaining 24 data sets were used for validation in both the models. A part of the training data sets is presented in the Table 3.1 & Table 3.2 The following input vectors were selected to predict the values of compaction factor, vee- bee time. However, the same input vectors were selected to predict the values of compressive strength, tensile strength, flexural strength and 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]

## IV. EXPERIMENTAL RESULTS

The following Tables gives the details of the input vectors and output vectors, the Table No 3.1 gives the workability test results of high performance concrete for various input vectors. Table No.3.2 gives the strength test results of high performance concrete for various input vectors.

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

a. Compaction Factor(CF),
b. VB Time (VB)

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

OP = {(CF), (VB)}

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 of strength 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)}

**Table No 3.1: Workability 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 | Compaction factor(CF) | VB Time |
| 1 | 0.3 | 2.0 | 1 | 2 | 0.778 | 10 |
| 2 | 0.325 | 2.0 | 1 | 0 | 0.835 | 6.8 |
| 3 | 0.35 | 2.0 | 1 | 3 | 0.805 | 8.7 |
| 4 | 0.375 | 2.0 | 1 | 1 | 0.853 | 6.9 |
| 5 | 0.4 | 2.0 | 1 | 2 | 0.835 | 7.8 |
| 6 | 0.425 | 2.0 | 1 | 3 | 0.812 | 8.8 |
| 7 | 0.45 | 2.0 | 1 | 1 | 0.895 | 5.8 |
| 8 | 0.475 | 2.0 | 1 | 0 | 0.929 | 4.8 |
| 9 | 0.5 | 2.0 | 1 | 2 | 0.896 | 6 |
| 10 | 0.3 | 2.5 | 2 | 1 | 0.781 | 9.7 |
| 11 | 0.325 | 2.5 | 2 | 3 | 0.72 | 12.1 |
| 12 | 0.35 | 2.5 | 2 | 0 | 0.843 | 6.8 |
| 13 | 0.375 | 2.5 | 2 | 1 | 0.828 | 7.6 |
| 14 | 0.4 | 2.5 | 2 | 3 | 0.758 | 10.8 |
| 15 | 0.425 | 2.5 | 2 | 2 | 0.825 | 8.5 |
| 16 | 0.45 | 2.5 | 2 | 1 | 0.826 | 7.5 |
| 17 | 0.475 | 2.5 | 2 | 2 | 0.832 | 7.6 |
| 18 | 0.5 | 2.5 | 2 | 3 | 0.804 | 8.7 |
| 19 | 0.3 | 3.0 | 3 | 0 | 0.815 | 8.3 |
| 20 | 0.325 | 3.0 | 3 | 2 | 0.686 | 12.2 |
| 21 | 0.35 | 3.0 | 3 | 3 | 0.66 | 13.8 |
| 22 | 0.375 | 3.0 | 3 | 1 | 0.731 | 9.2 |
| 23 | 0.4 | 3.0 | 3 | 0 | 0.855 | 7.1 |
| 24 | 0.425 | 3.0 | 3 | 1 | 0.766 | 7.9 |
| 25 | 0.45 | 3.0 | 3 | 2 | 0.739 | 9.2 |
| 26 | 0.475 | 3.0 | 3 | 3 | 0.719 | 10.6 |
| 27 | 0.5 | 3.0 | 3 | 1 | 0.905 | 5.8 |

**Table No 3.2: 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 | 0 | 63.3 | 5.42 | 6.56 | 42818 |
| 2 | 0.325 | 2.0 | 1 | 2 | 57.3 | 4.99 | 6.02 | 40524 |
| 3 | 0.35 | 2.0 | 1 | 3 | 51.1 | 3.89 | 5.59 | 38288 |
| 4 | 0.375 | 2.0 | 1 | 1 | 61.5 | 5.30 | 7.01 | 42462 |
| 5 | 0.4 | 2.0 | 1 | 0 | 53.8 | 4.78 | 5.89 | 39834 |
| 6 | 0.425 | 2.0 | 1 | 1 | 56.9 | 5.20 | 6.15 | 40957 |
| 7 | 0.45 | 2.0 | 1 | 2 | 50.0 | 4.21 | 5.5 | 37975 |
| 8 | 0.475 | 2.0 | 1 | 3 | 45.6 | 3.21 | 4.88 | 35230 |
| 9 | 0.5 | 2.0 | 1 | 1 | 51.3 | 4.67 | 5.58 | 37820 |
| 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 | 2 | 74.3 | 5.31 | 6.39 | 45252 |
| 20 | 0.325 | 3.0 | 3 | 0 | 82.6 | 5.69 | 7.0 | 49523 |
| 21 | 0.35 | 3.0 | 3 | 3 | 63.3 | 4.68 | 5.11 | 40546 |
| 22 | 0.375 | 3.0 | 3 | 1 | 84.8 | 5.89 | 7.47 | 49094 |
| 23 | 0.4 | 3.0 | 3 | 2 | 69.6 | 4.89 | 5.97 | 44217 |
| 24 | 0.425 | 3.0 | 3 | 3 | 61.8 | 4.38 | 5.21 | 39964 |
| 25 | 0.45 | 3.0 | 3 | 1 | 80.7 | 5.56 | 7.12 | 48030 |
| 26 | 0.475 | 3.0 | 3 | 0 | 75.2 | 5.29 | 6.27 | 46891 |
| 27 | 0.5 | 3.0 | 3 | 2 | 65.9 | 4.59 | 5.49 | 42173 |

The input and output vectors have been normalized in the range (0, +1) using suitable normalization factors or scaling factors. The following Table No.3.3 and Table No.3.4 give the scaling factors for input and output vectors of workability and strength.

Table No. 3. 3: Details of Scaling Factors for Workability

| Nature of vector | Parameter | Minimum Value | Maximum Value | Scale Factor |
|---|---|---|---|---|
| Input Vector | Water binder ratio (W/B) | 0.3 | 0.5 | 0.8 |
| | Aggregate binder ratio (A/B) | 2 | 3 | 4 |
| | Type of mineral admixture ( type of MA) | 1 | 3 | 3 |
| | Percentage replacement of admixture (% replacement) | 0 | 30 | 35 |
| Output Vector | Compaction Factor (CF) | 0.54 | 0.943 | 1 |
| | VB Time (VB) | 4.5 | 15.3 | 18.0 |

**Table No. 3. 4: Details of Scaling Factors for Strength**

| Nature of vector | Parameter | Minimum Value | Maximum Value | Scale Factor |
|---|---|---|---|---|
| Input Vector | Water binder ratio (W/B) | 0.3 | 0.5 | 0.8 |
| | Aggregate binder ratio (A/B) | 2 | 3 | 4 |
| | Type of mineral admixture( type of MA) | 1 | 3 | 3 |
| | 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 10 neurons in one hidden layer is behaving well for workability model and 24 neurons in one hidden layer is behaving well for strength model. Accordingly a configuration of (4-10-2) has been selected for the network model for workability and (4-24-4) for strength. The architecture is depicted in Figure No 1 & Figure No 2.

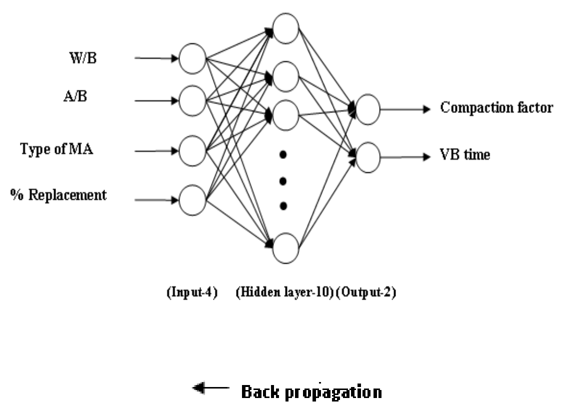



Figure 1.ConfigurationofGA/ANN Model of workability

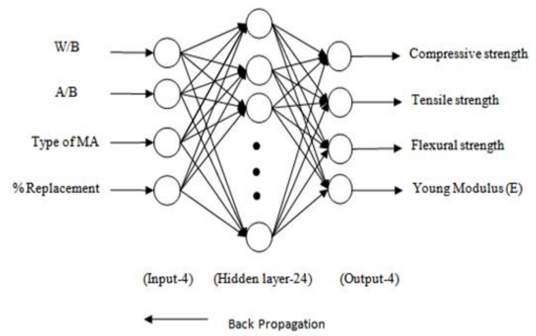



Figure 2.ConfigurationofGA/ANN Model of strength

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 – 10 – 2 and 4 – 24 - 4. Therefore, the numbers of weights (genes) that are to be determined are 4x10+10x2=60 and 4 x 24 + 24 x 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 60x5=300 and 192x5=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 and Table No.3.4. It can be seen from Table No.3.5 & Table No.3.6, that the RMS error after 1300cycles is 4.49264355 x$10^{-05}$ for workability2000 cycles is only 0.001192 for strength. 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.3, 4 & 5. 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 3.5: Learning progress of the network (Workability)**

| Sl.No | No of Epochs | RMS Value |
|---|---|---|
| 1 | 100 | 0.084939 |
| 2 | 200 | 8.847304194x$10^{-05}$ |
| 3 | 300 | 7.13414715 x$10^{-05}$ |
| 4 | 400 | 7.069323057 x$10^{-05}$ |
| 5 | 500 | 6.725693212 x$10^{-05}$ |
| 6 | 600 | 6.27169901 x$10^{-05}$ |
| 7 | 700 | 6.16183994 x$10^{-05}$ |
| 8 | 800 | 6.05495717 x$10^{-05}$ |
| 9 | 900 | 5.94416126 x$10^{-05}$ |
| 10 | 1000 | 5.77803725 x$10^{-05}$ |
| 11 | 1100 | 5.447092135 x$10^{-05}$ |
| 12 | 1200 | 5.17097158 x$10^{-05}$ |
| 13 | 1300 | 4.49264355 x$10^{-05}$ |

**Table No 3.6: Learning progress of the network (Strength)**

| 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 |

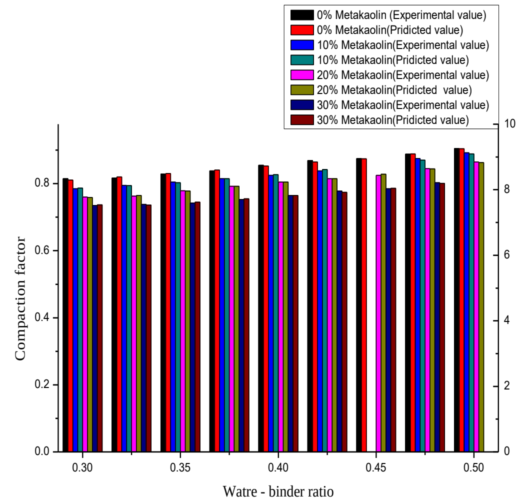



**Figure No. 3 Learning of GA/ANN Model for Compaction factor**

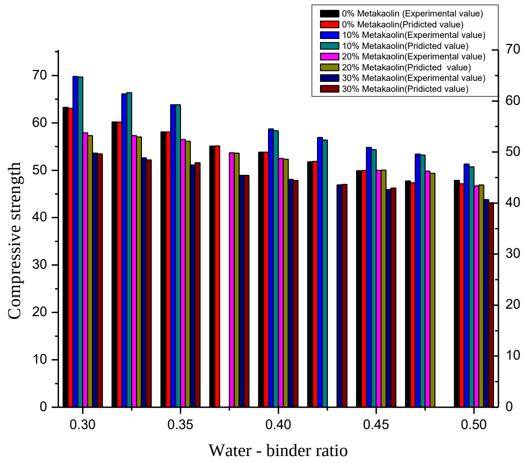



**Figure No. 4 Learning of GA/ANN Model for Compressive strength**

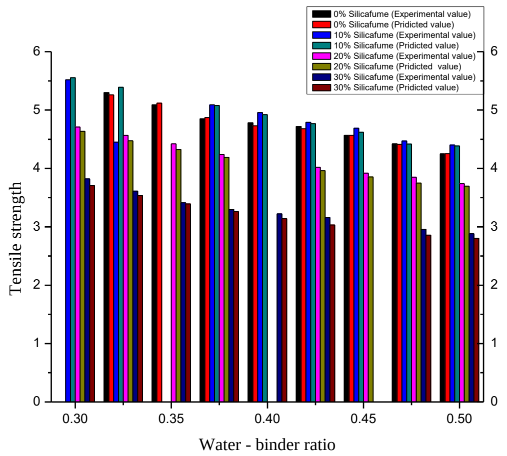



**Figure No. 5 Learning of GA/ANN Model for Tensile strength**

## V. RESULTS AND DISCUSSIONS

In case of workability and strength models, validation of the network is to test these networks for parameters that are not used in the training of these networks. The network was asked to predict Compaction factor, Vee bee time, 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.6, 7 & 8 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 workability and strength properties of high performance concrete.

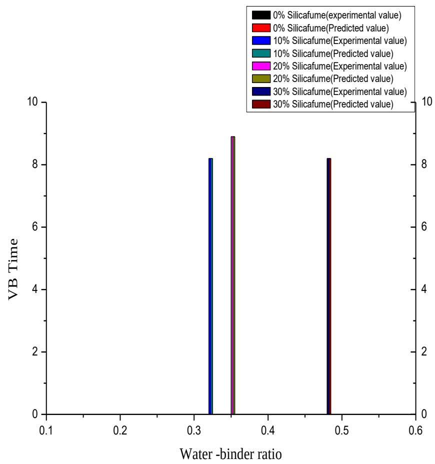



**Figure No.6 Validation of GA/ANN Model for VB Time**

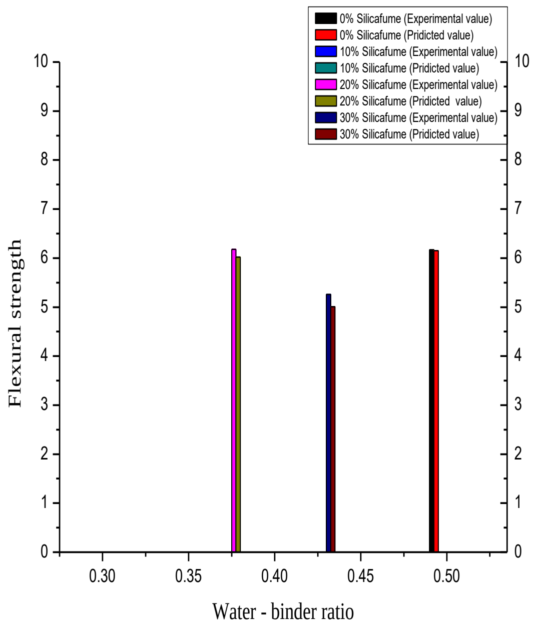
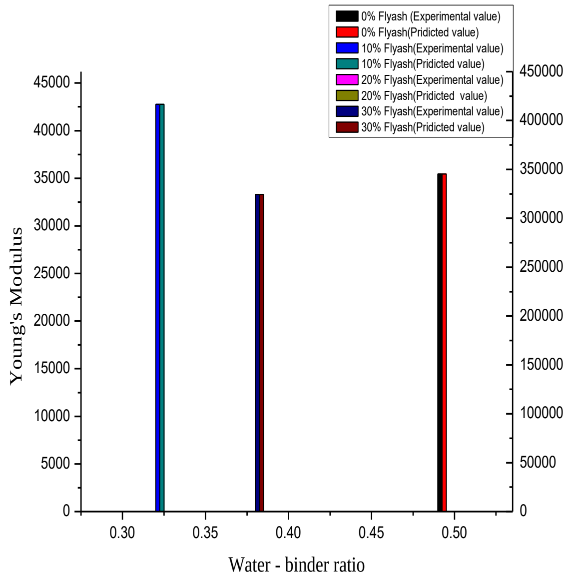



**Figure No.7 Validation of GA/ANN Model for Flexural strength**

Figure No.8 Validation of GA/ANN Model for Young's




Modulus

## VI. CONCLUSIONS

In this paper, the application of Genetic Algorithm based neural network models for predicting the Compaction factor, VB time and Compressive strength, Tensile strength, Flexural strength and Young's modulus of High performance concrete has been demonstrated. The neural network models have been trained using 300 examples for each model 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 workability prediction problem with just 1300 training cycles and the network could learn the strength prediction with 2000 training cycles . After successful training, the GA based neural network model is able to predict the compaction factor ,vee bee time, 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 workability and strength of high performance concrete.

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