USE OF ARTIFICIAL INTELLIGENCE FOR PREDICTING DIFFERENT PROPERTIES OF CONCRETE

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RECOMMENDATION CERTIFICATE

It is hereby certified that this thesis **"USE OF ARTIFICIAL INTELLIGENCE FOR PREDICTING DIFFERENT PROPERTIES OF CONCRETE"** has been prepared by **SUMANTA MANDAL (Class Roll No.-002010402003)** who has carried out this assignment work under my supervision and guidance.

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ABSTRACT

In the present study an effort has been made to predict different concrete properties using five different machine learning techniques - Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP). For this purpose, two hundred numbers of concrete mixtures data have been considered by varying the level of key ingredients- cement, water, fine aggregate, coarse aggregate and size of coarse aggregate along with their strength and workability. Among these eighty five percent data have been used for training purpose and fifteen percent data have been used for testing purpose in all the five machine learning methods. Furthermore, for validation of the five networks, experimental investigation have been carried out for fifteen numbers of different concrete mixes. It is to be mentioned that all the five methods yields satisfactory results for predicting compressive strength and slump value in both testing and validation. However, ANFIS yields best result among all the five methods for predicting the same in testing and validation. In addition to that, multi objective optimisation and robust optimisation have been carried out using the basis equations obtained from GEP to determine the proportions of concrete mixtures for maximum concrete strength and workability at lowest cost. The results corroborates that present methods can be used successfully for predicting concrete property using different ingredients. Moreover, the optimisation procedure and result can be used for obtaining accurate number of mix proportions with desired compressive strength, and workability at minimum cost.

Chapter 1
INTRODUCTION

1.1 GENERAL

Concrete plays major role in our construction industries. Traditionally, concrete mix has been designed on the basis of codal provision and by using trial batches in the laboratory as well as in the field to ensure they meet specified requirements for strength, workability, durability, etc. Indian codal (IS 10262:2019) provisions meet the needs for concrete mixture design in India and its neighbouring country. However, it is important to note that concrete is heterogeneous material and prediction of different properties of concrete is very difficult. Several researches were conducted to predict the concrete properties using different machine learning techniques (SVM, ANN, ANFIS, FIS, GA). In addition to that different costly admixture enhances the performance of concrete, but simultaneously cost of concrete increases substantially. Thus, it is very difficult to design mixture proportion for getting maximum performance at low cost. Therefore, it is necessary to optimize the concrete mix proportions to obtain the maximum performance of concrete without using the admixtures, after establishing the multidimensional nonlinear relationship between the raw material and desired performance.

The development of various machine learning and optimisation tools may make easier for predicting and optimising concrete properties.

1.2 NEED FOR PRESENT STUDY

Concrete is the most used material in the world after water. It needs an accurate method for predicting concrete properties which will be beneficial for construction industry. Nowadays, various machine learning algorithm like Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) Genetic Expression Programing (GEP) etc have been used for prediction purpose and it can be used for estimating concrete properties. Further, in concrete obtaining higher strength and higher slump simultaneously at lowest cost are very difficult. Thus, optimisation technique must be carried out for getting the concrete mix proportion to achieve maximum strength and workability at lowest cost. Further, due to heterogeneity concrete properties may yield inconsistency value. Thus robust optimisation should also be conducted considering the uncertainty.

1.3 OBJECTIVE & SCOPE OF WORK

The objective of this study is to predict concrete properties from different concrete ingredients and optimisation of concrete.

The scope of work measure the following parameters in concrete are

a) To predict concrete compressive strength by different machine learning techniques (Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP)).
b) To predict concrete workability by different machine learning techniques (Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP).
c) To conduct multi objective optimisation and find mixture proportion of concrete for obtaining maximum strength and workability at lowest cost.
d) To carry out robust optimisation and find mixture proportion of concrete for obtaining maximum strength and workability at lowest cost considering the uncertainty of results.

1.4 ORGANIZATION OF THESIS

The thesis has been divided into five chapters. The table and figures have been presented in a sequence as they appear in the text.

In **Chapter 1** an attempt has been made to introduce the problem along with need for present research, scope and objectives of the work and organization of thesis.

Chapter 2 furnishes a detailed literature review on the relevant topic .

Chapter 3 presents collection of data, experimental program and prediction methodlogy and result obtained by different machine learning techniques.

Chapter 4 describes the deterministic multi objective optimisation conducted.

Chapter 5 reveals robust optimisation carried out.

Chpter 6 depicts the concluding remarks along with major findings, draw backs and future study.

References is furnished at the end.

Chapter 2

LITERATURE REVIEW

2.1 GENERAL :

Use of different machine learning techniques Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP) have been discussed for the purpose of predicting concrete compressive strength and slump. Further, past literature has been conversed on use of these techniques for estimating the different properties of concrete. Furthermore, optimisation technique are briefly reviewed .

2.2 DIFFERANT MACHINE LEARNING TECHNIQUES

2.2.1 Support Vector Machine (SVM)

SVM was first introduced by Vapnik .A support vector machine (SVM) is a supervised machine learning model that uses classification algorithms for two-group classification problems. After giving an SVM model sets of labeled training data for each category, they're able to categorize new text.Compared to newer algorithms like neural networks, they have two main advantages: higher speed and better performance with a limited number of samples (in the thousands). This makes the algorithm very suitable for text classification problems, where it's common to have access to a dataset of at most a couple of thousands of tagged samples. SVM has been used in many civil engineering applications, and in recent years, it has often been used to predict concrete compressive strength. The support vector regression, which is a variation of SVM, is used to build an input-output model from concrete. SVM uses an objective function that allows the function estimation process to occur . When nonlinear space occurs, the kernel radial-based function (RBF) is selected as a kernel function in SVM because it can provide better results than the other kernels.

In this model underlies the functional relationship between one or more independent variables with the response variable:

$$y(A) = wT\,\phi(A) + B \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where *A Є R, y Є R, and ϕ(A): Rn*is the process of mapping to higher dimensional feature space.

2.2.2 Artificial Neural Network (ANN)

Artificial neuron is a computational model inspired by natural neurons. Natural neurons receive signals through synapses found in the dendrites membrane of neurons. When signals are found strong enough, the neuron activates and releases the signal to the axon. This signal can be sent to another synapse, and it may activate other neurons. ANN solves various problems in pattern recognition, predictive performance, memory-related memory. As it has the ability to automatically learn from a given training pattern, ANN can solve the map problem by finding the approximate limitations of the input data associated with the output data, and such a feature separates it from other conventional specialist systems. The ANN computing system is made up of synthetic neurons, which play the role of vital units and mimic a parallel process of brain biology for response. The behaviour of the ANN network is influenced by the communication pattern of the neurons, which determine the class of the network as well. As mentioned earlier, training the network to improve network performance is thought. In precise terms, the structure and weights of the network connection change iteratively so that the error that refers to the entire node of the output layer is minimal.

The trained neural network assists as an analytical tool for qualified predictions of the results, for any sets of input data which are not involved in the learning process of the network. Their functions are practically simple and easy, nevertheless correct and precise. In the present study total, 200 numbers of concrete samples have been prepared in the laboratory using different proportions of water, cement, fine aggregate, coarse aggregate . Their slump value and 28 days compressive strength have been measured. Artificial Neural Network (ANN) has been used to predict the slump value and compressive strength value from different mix proportions of concrete. The neural network is composed of numerous mutually connected neurons grouped in layers. The complicity of the network is determined by the number of layers. Besides the input (first) and the output (last) layer, a network can have one or a few hidden layers. The purpose of the input layer is to accept data from the surroundings. Those data are processed in the hidden layers and sent into the output layer. The final results from the network are the outputs of the neurons from the last network layer and that is the solution for the Analized problem. The basic rule is that for each data must have only one input value.

2.2.3 Fuzzy Inference System (FIS)

Input → Fuzzy elements → Fuzzy sets → Fuzzy rules → Fuzzy implications → Fuzzy system → Output

In fuzzy we can take intermediate value like high, medium ,low, very low .FL is a multi-valued logic which permits intermediary values to be defined between conventional assessments like true/false, yes/no, high/low, etc. Ideas like pretty tall or very fast can be expressed mathematically and processed by computational systems, to apply a more human-like thinking procedure in the computers programming. The term "fuzzy" was first presented by Zadeh(D'urso and Gil 2017)in his research paper on fuzzy sets. In this research a new mathematical discipline namely fuzzy logic which was based on the theory of fuzzy sets, was introduced. The aim of the logic was for supporting the presentation and consideration of rough idea by fuzzy sets. The imprecision is to be understood as a grouping of set members into classes, the boundaries of which are not sharply defined. It was expected that the theory of fuzzy sets should become a novel methodology suitable enough to help formulate and solve complex problems in engineering and science that are difficult to handle using "precise" crisp logic, such as binary logic, where the variables can be either true or false. The theory of fuzzy sets allows the concept of partial belongingness of an object or a variable in a fuzzy set and, therefore, allows a gradual transition from full membership to a totally non-membership. Thereby, in fuzzy logic an object or a variable within a domain may partially belong to several fuzzy sets in the same domain simultaneously and, thus, it provides a framework for a multi-valued logic. This is essential for capturing the vagueness in a natural linguistic description of any system. Moreover, the underlying fuzzy logic incorporates a variety of rules with the premises containing fuzzy propositions generally defined using linguistic terms, such as low and high (temperature, pressure, flow, frequency, voltage, etc.), old, older, very old (person, engine, sensor, measured value, etc.). The related linguistic rules are of IF-THEN art.

Successful prediction by the model in various study in the past indicates that fuzzy logic could be a useful modelling tool for engineers and research scientists in the area of cement and concrete.The study has been conducted to predict the strength and slump of concrete using the fuzzy logic toolbox .The purpose of making this logic to decision making ,understanding, problem solving , planning etc .

2.2.4 Adaptive Neural Fuzzy Inference System (ANFIS)

Neuro-fuzzy modeling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modeling or to a fuzzy inference system (FIS). The basic structure of a FIS consists of three conceptual components: a rule-base, which contains a selection of fuzzy rules; a data-base which defines the membership functions (MF) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output. FIS implements a nonlinear mapping from its input space to the output space. This mapping is accomplished by several fuzzy if-then rules, which each describes the local behavior of the mapping. The parameters of the if-then rules (antecedents or premises in fuzzy modeling) define a fuzzy region of the input space, and the output parameters (also consequents in fuzzy modeling) specify the corresponding output. Hence, the efficiency of the FIS depends on the estimated parameters. However, the selection of the shape of the fuzzy set (described by the antecedents) corresponding to input is not guided by any procedure. But the rule structure of a FIS makes it possible to incorporate human expertise about the system being modeled directly into the modeling process to decide on the relevant inputs, number of MFs for each input, etc. and the corresponding numerical data for parameter estimation. In the present study, the concept of the adaptive network, which is a generalization of the common back-propagation neural network, has been employed to tackle the parameter identification problem in a FIS. An adaptive network is a multi-layered feed-forward structure whose overall output behavior is determined by the value of a collection of modifiable parameters. More specifically, the configuration of an adaptive network is composed of a set of nodes connected through directional links, where each node is a processing unit that performs a static node function on its incoming signal to generate a single node output. The node function is a parameterized function with modifiable parameters. It may be noted that links in an adaptive network only indicate the flow direction of signals between nodes and no weights are associated with these link.

In the present study, three ANFIS model have been developed to predict the concrete compressive strength, slump and dry density. For all the three models water, cement, fine aggregate, coarse aggregate have been used as input variable. All the models have been developed by a grid partition fuzzy interference system using 3 linear membership functions.

Neural network can predict any kind of network but can not take proper decision. FUZZY is weakness for learning.

Neural network + FUZZY = ANFIS

It has highly generalization capability and high strength as a neural network. The only limitations are computational cost is very high due complex structure and not suitable for large inputs.

2.2.5 GENETIC EXPRSSION PROGRAMMING (GEP)

In the present study an effort has been made to determine the optimum proportion of concrete mixtures through experimental data. For this purpose 99 numbers of concrete mixtures have been considered by varying the level of key ingredients- cement, water, fine aggregate and coarse aggregate. Using the experimental data equations have been proposed of compressive strength and slump as a function of cement, water, fine aggregate and coarse aggregate by Genetic Expression Programing (GEP).

In case of single objective function , one objective function is used. However, in case of multi objective function more than one number of the objective function can be used for the same constraints. This objective function can be determined successfully by GEP using software GeneXproTools. In this process, the first human chromosomes were initially randomly generated by software. In the next step, the chromosomes are transferred and the suitability of the individual population is assessed. Then, when considering eligibility, individuals are selected randomly, leaving a seed with new traits. In the new generation one finds the same process - genetic predisposition, hostility, and reproduction through evolution. For a certain number of generations or until a specific solution is reached, this process continues.

a) Mainly focus on optimization to get better results.
b) Solve complex problem.
c) Based on “Survival of the fittest” (Darwinian Theory).

In the GA method at first, the chromosomes of the initial population are randomly generated by this software. Subsequently, the chromosomes are conveyed and fitness of each individual population is assessed. After that, considering the fitness, individual populations are chosen with mutation, leaving offspring with new characters. In the new generation the individual undergoes same process- presentation of the genomes, hostility of the selection environment, and reproduction with mutation. For a specific number of generations or until a certain solution has been reached, this process is continued. In order to express compressive strength, slump and dry density separately as a function of water, cement, fine aggregate, coarse aggregate, small plastic, big plastic; GeneXpro Tools 5.0 (www.genexprotools.soft112.com/)

was used in the current study. In all cases the 30 number chromosomes, each containing the three-dimensional genes have been used in the calculation.

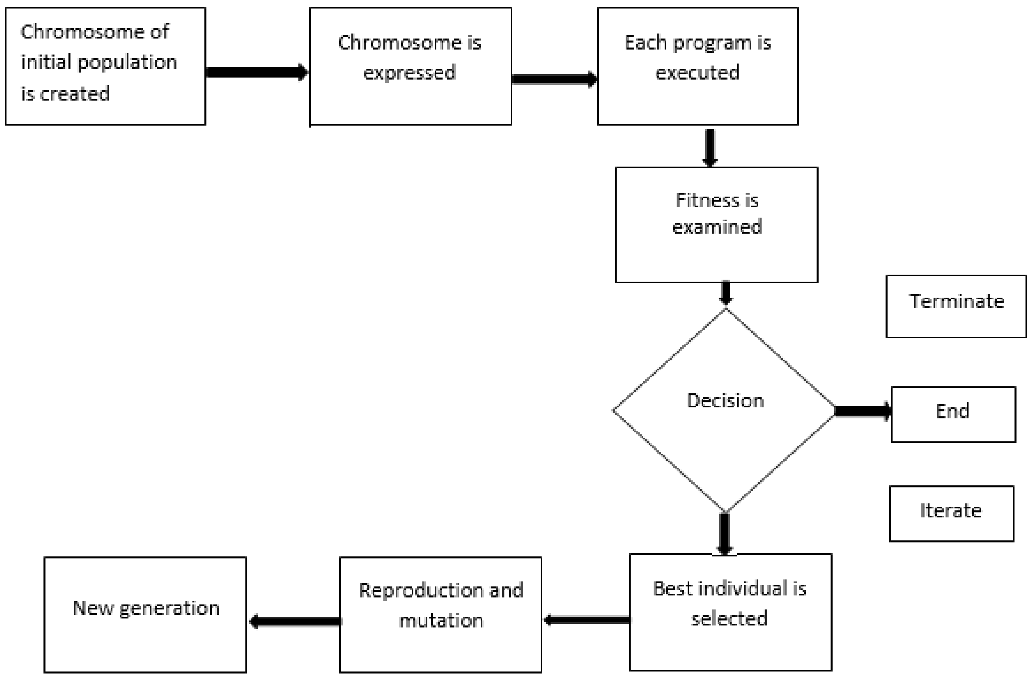

Fig. 2.1

2.3 LITERATURE REVIEW ON PRDICTION OF DIFFERENT PROPERTIES OF CONCRETE

Warren McCulloch and Walter pits in 1943[48],the first work with AI . They proposed a model of artificial neurons and opened the subject by creating a computational model for neural networks Donald Hebb demo started in 1949[48] an updating rule for modifying the connection strength between neurons. His rule is now called Hebbianlearning. The Alan Turing in 1950[48] ,who was an English mathematician and pioneered Machine learning . Alan Turing publishes Computing Machinery and Intelligence in which he proposed a test. The test can check the machine's ability to exhibit intelligent behaviour equivalent to human intelligence, called a Turing test.

Rao (2012)[18] successfully used ANN for prediction of concrete compressive strength for different binder ratio. Mustapha and Mohamed (2017)[3] estimated compressive strength of high performance concrete by using Support Vector Machine (SVM). SFS and ANN were used by Abuodeh et al. (2019)[6] for interpretation of ultra-high performance concrete compressive strength. Armaghani and Asteris (2021)[14] carried out a comparative study of

ANN and ANFIS models for the estimation of cement-based mortar materials compressive strength. Danial Jahed Armaghani et al. (2020) conducted comparative investigation of ANN and ANFIS models for the prediction of cement-based mortar materials compressive strength.

R. Mustapha and E. A. Mohamed in 2017[3] proposed the High-Performance Concrete Compressive Strength Prediction Based Weighted Support Vector Machines.In comparison with SVMs, the accuracy of the proposed SVM was significantly better for different evaluation measurements.

O. Abuodeh, J. A. Abdalla, and R. A. Hawileh in 2019[6] proposed Prediction of Compressive Strength of Ultra-High Performance Concrete using SFS and ANN . D. J. Armaghani and P. G. Asteris in 2021[14] proposed A comparative study of ANN and ANFIS models for predicting the strength of cement-based compression. The ANFIS model achieves the highest performance prediction, the best model, capable of defining CS-based cement-based behavior, in fact. ANN model and subsequently, presented as the best predictable model in this study. DanialJahed Armaghani, Panagiotis G. Asteris in 2020 [14] proposes a comparative study of ANN and ANFIS models to estimate the compressive strength of cement-based cement .

2.4 LITERATURE REVIEW ON CONCRETE OPTIMIZATION

Traditionally, concrete mix design is carried out on the basis of codal provision and by using trial batches in the laboratory as well as in the field to ensure they meet specified requirements for strength, workability and durability. Indian codal (IS 10262:2019) provisions meet the needs for concrete mixture design in India and its neighbouring country. Different costly admixture augments the performance of concrete, but simultaneously cost of concrete increases substantially. Moreover, It is very challenging job to optimise concrete mixture.

In past several researches were carried out to optimize the concrete mixture design using different methodologies. Abbasi et al. (1987)[43] carried out an experimental method of optimizing concrete mixture for a given workability and compressive strength. Shilstone and James (1990)[33] suggested a quantitative technique for optimizing proportions of aggregate and carrying out adjustments during progress of the work. Chang ( ) proposed densified mixture design algorithm methodology to yield optimum high-performance concrete having high workability and good durability. Using locally available ingredients, Kasperkiewicz

(1994)[46] applied analytical techniques of concrete mix design to attain optimal composition of concrete at lowest cost. Soudki et al. (2001)[42] produced statistical analysis results by full factorial experiment which was aimed to optimize a concrete mix proportions for hot climates. Ahmad (2007)[39] proposed a laboratory trial procedure for optimum design of concrete mixes having minimum cost of concrete. Yeh (2007)[36] used several analytical methods like ANN, nonlinear programing, GA to obtain the optimum mixture of concrete composition for required performance with the lowest cost. Lee et al. (2009)[37] adopted GA, ANN and convex hull as an optimum technique to determine minimum cost of concrete under a given strength requirement. Yeh (2009)[37] optimized concrete mixture proportions by a flattened simplex - Centroid mixture design and ANN. Jayram et al. (2009)[13] developed elitist GA models for the optimization of high volume fly ash concrete mix. Self-consolidating high strength concrete was optimized by Akalin et al. (2010)[32] using D-optimal design. By applying the PSO for design of high performance concrete mixtures. Xiaoyong and Wendi (2011)[40] presented an optimum approach to concrete mixtures design which was based upon experimental and orthogonal method to identify the main influencing factors on compressive strength of concrete in mix proportion. Nunes et al. (2013) used robust mix design methodology in self-compacting concrete. M.A.Jayaram, M.C.Nataraja, C.N.Ravikumar (2015)[13] demonstrated the possibilities of adapting elitism-based PSO models to optimize the high volume fly ash concrete mixes and found that by applying the PSO for design of high performance concrete mixtures, the number of trial mixtures, with desired properties in the field can be reduced. R. Ghiamat-M. Madhkhanand Bakhshpoori (2019) proved that cost optimization with the optimal combination of genetic operators leads to a 13% reduction in the construction cost and weight of this bridge superstructure, mostly due to the reduction in required pre-stressing tendons. Hamed Naseri (2019)[24] reported that, PSO is better than GA as it finds better solution in concrete mix proportions. As per the investigation carried out by Sobhani , PSO yields faster and better result than GA. Feng-Mohammadi and MehrabiIt (2021)[10] presented that metaheuristic algorithms, especially the PSO technique, are able to cover the prediction problems of non-linear data and the best performance of hybrid models was obtained for ANFIS-PSO, ANFIS-ACO and ANFIS-DEO, respectively. A.Shiuly, and k Moulick (2019)[31] presented An efficient robust cost optimization procedure for rice husk ash concrete mix. Soumy Bhattacharjya, Ph.D.-Datta, S.M.ASCE2; and HariGovind Surya Dutta Aravapalli (2022)[16] reported that the RDO yields marginally higher optimal construction cost than the conventional ASCE or British code-based design.

In past several researches have been carried out to optimize the concrete mixture design using different methodologies. S .Bhattacharrjya, A.Shiuly, and k Moulick (2019)[31] presented An efficient robust cost optimization procedure for rice husk ash concrete mix . Conventional Reliability Based Design Optimization for dealing optimization under uncertainty as expressed by Abbasnia et al. (2014)[48] brings specified target reliability of desired performance; but the design may be still sensitive to input parameter variations. Moreover, when the probability density function is unavailable and stochastic parameters are model as uncertain but bounded type, Robust Optimization becomes an attractive alternate to RBDO. The RO is fundamentally concerned with minimizing the effect of uncertainty in the uncertain parameters to the variation of performance function and constraints. The RO has been successfully implemented in the recent past for stochastic mechanical systems (Beyer and Sendhoff, 2007[51]; Cheng et al., 2017)[50] . Thus, in the present paper, the RDO is applied for cost optimization of Concrete mix under uncertainty which is abbreviated here as Robust Cost Optimization (RCO) approach .

2.3 CRITICAL APPRAISAL OF LITERATURE

On the basis of above literature survey following observations may be made.

a) Vast study has not been carried out in concrete mix design for predicting concrete properties using Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP).
b) Multi objective optimisation using GA has not carried out for achieving maximum strength and workability at minimum cost.
c) Robust optimisation using GA has not carried out for achieving maximum strength and workability at minimum cost considering uncertainity .

Chapter 3

PRDEICTION OF CONCRETE PROPERTIS BY DIFFERENT MACHINE LEARNING TECHNIQUES

3.1 GENERAL

Concrete is heterogeneous materials used hugely in construction industry. The prediction of its properties is very difficult. In the present chapter predict different concrete properties using five different machine learning techniques - Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP). Here, two hundred numbers of concrete mixtures data have been considered by varying the level of key ingredients- cement, water, fine aggregate, coarse aggregate and size of coarse aggregate along with their compressive strength and slump value. 170 numbers of data has been used for training purpose and 30 numbers of data have been used for testing. In addition to that experiments has been conducted in laboratory considering 15 numbers of different mix proportions and their strength and slump value has been obtained.

3.2 EXPERIMENTAL PROGRAM

For developing the optimization procedure of concrete mixture design, extensive experimental program has been conducted. Arbitrarily chosen 15 concrete trial mixes have been carried out in this programme. The OPC cement has been used in the experiment. The crushed stone particles obtained from a local hill have been used as coarse aggregate and local river sand has been used as fine aggregate. Both this aggregate confirms to IS 383-1970. Potable water has been used for mixing the constituents of all the tests. However, chemical admixture has not been used in these experiments. Total 15X3=45 number of cubes of dimension 150X150X150 mm has been casted for obtaining compressive strength of concrete. After 24 hours the cubes have been removed from the mould and cured for 28 days in a curing tank under normal temperature. After that, the compressive strength of the specimens have been determined with standard compressive testing machine. The average compressive strength of the three cube samples prepared from the same concrete mixture design has been marked as compressive strength of that mixture. Average 28-day compressive strength test results for all 15 concrete mixtures along of each mixture per 1 cubic meter are presented in Table 3.1. Table 3.1 Summary of measured compressive strength and corresponding the mixture proportions.

Fig. 3.1 Experimental programme for the purpose of validation

Table 3.1 Experimental mixture design data along with measured compressive strength and slump.

Max agg size	Cement O.P.C (Kg/m3)	Water Content (Kg/m^3)	**Fine Aggregate (Kg/m^3)**	**Coarse Aggregate (Kg/m^3)**	compressive strength(Mpa)	Slump(mm)
20	400	215	590	1195	47.2	110
20	380	175	675	1150	47.3	120
20	375	190	695	1190	45.5	110
40	375	180	665	1180	43.4	120
20	375	190	680	1205	43.9	150
40	375	180	630	1215	46.5	120
40	400	200	585	1235	40.1	125
20	385	195	685	1165	40.8	90
20	390	215	715	1125	50.4	120
40	350	160	720	1170	50.6	60
20	380	180	695	1135	50.3	200
20	360	170	748	1122	32.8	190

20	375	225	760	1130	33.2	160
40	385	180	635	1180	31.3	110
40	375	180	665	1180	36	120

3.3 DIFFERENT PREDICTION METHODS

3.3.1 Support Vector Machine (SVM)

In the present study coarse Gaussian SVM has been used. Each network consists five input parameters, namely coarse aggregate size, cement, sand, coarse aggregates. The output parameter for the this networks are 28 days compressive strength and slump. Prediction Speed was 5200 obs/sec and Training time is 1.1814 sec. The actual verses predicted curve for compressive strength and slump for testing is presented in Fig. 3.2 and 3.3 respectively. Further, Fig. 3.4 and 3.5 denotes the compressive strength and slump for validation respectively.

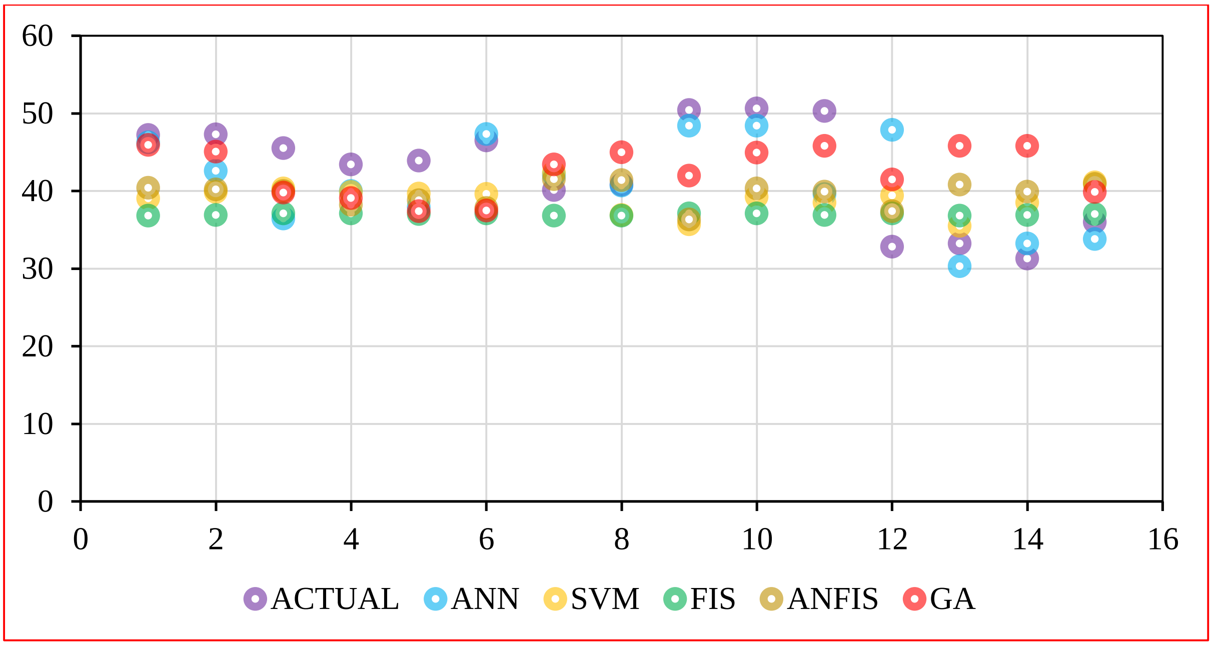

Fig.3.2 Actual vs predicted curve for testing data for compressive strength by different method.

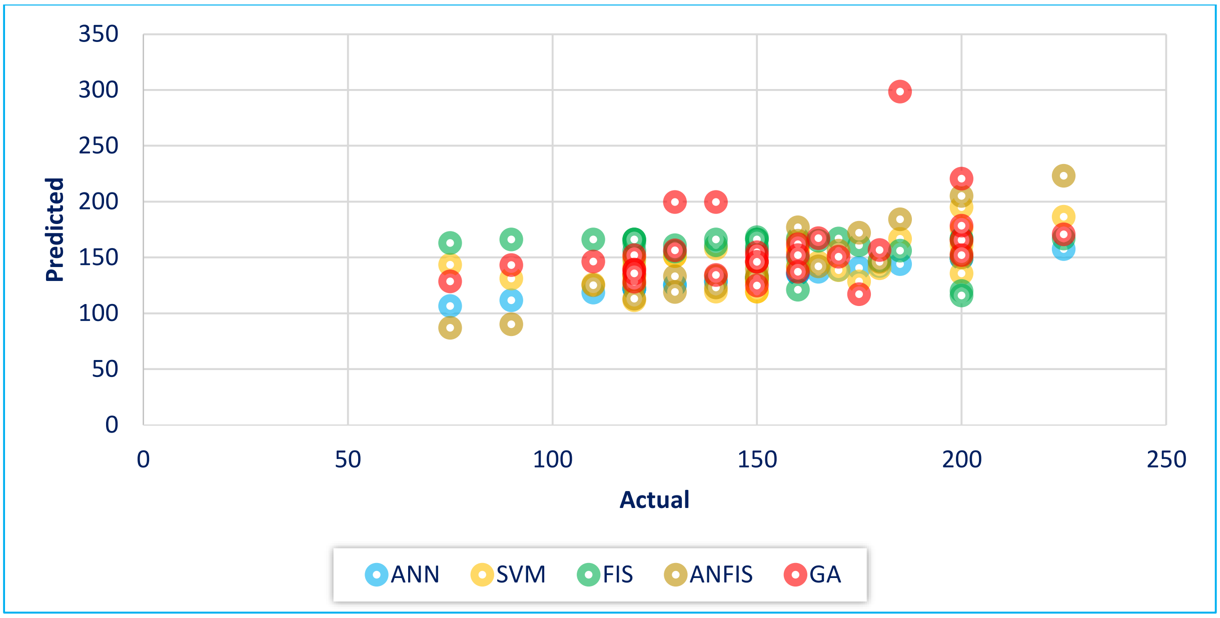

Fig.3.3 Actual vs predicted curve for testing data for slump by different method.

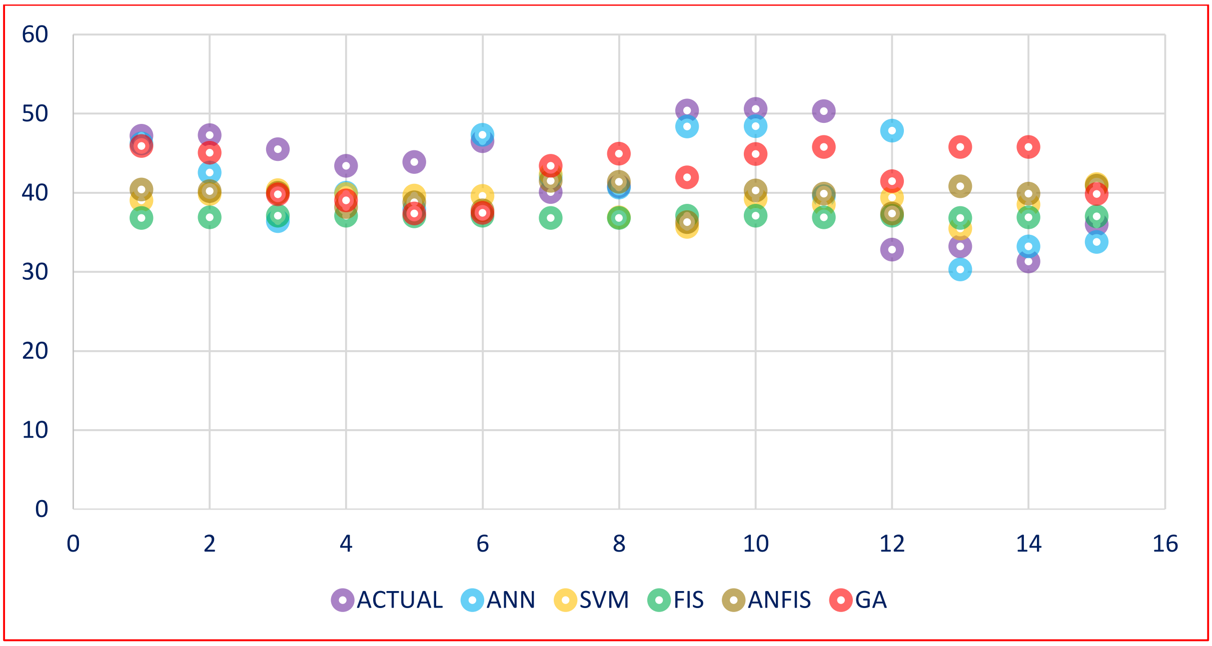

Fig.3.4 Actual vs predicted curve for validation data for compressive strength by different method.

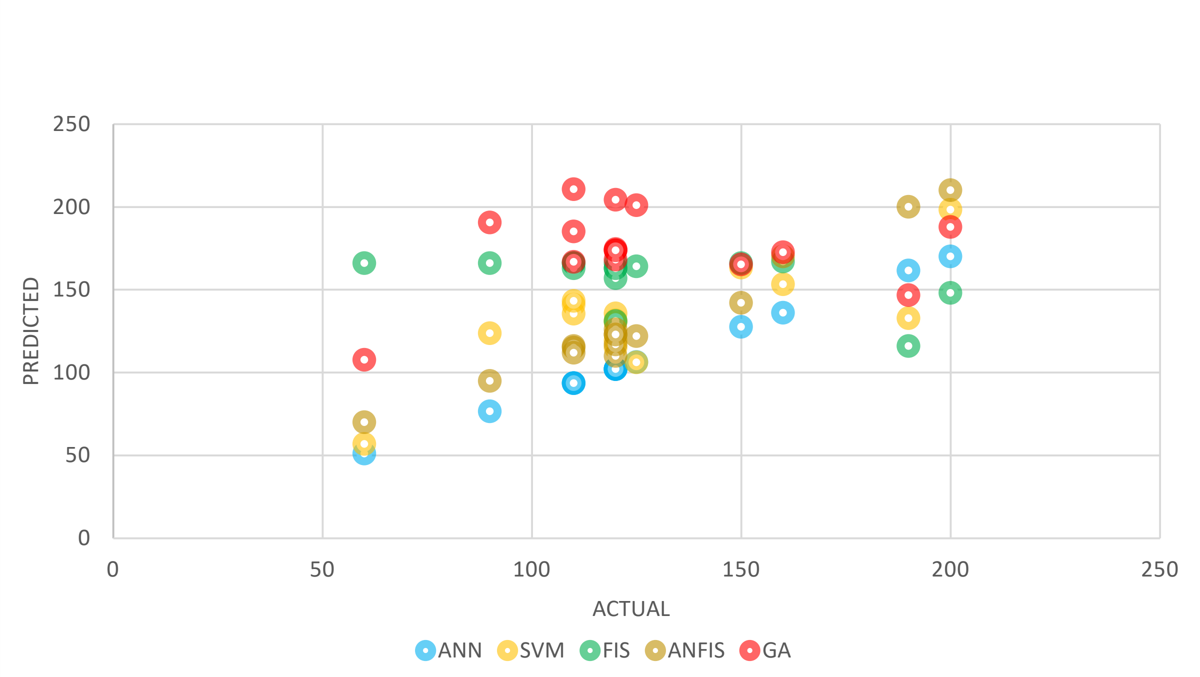

Fig.3.5 Actual vs predicted curve for validation data for slump by different method.

3.3.2 Artificial Neural Network (ANN)

In the present study three ANN algorithm has been used. Each network consists five input parameters, namely coarse aggregate size, cement, sand, coarse aggregates. The output parameter for the three networks are 28 days compressive strength and slump. The MATLAB ANN toolbox (Demuth and Beale 2002) was used to perform the current process. To search the most appropriate network for a given set of training data, trial methods and errors were used. In this study, the most efficient network is selected with a correlation coefficient (*R*) whose value varies from -1 to +1. *R* a value close to 1 and -1 means a strong positive and negative relationship respectively and a close to 0 means no relationship. In the performance function used is Mean Square Error (MSE). The trial and error procedure has been adopted for selecting the best two networks. Table 3.1 and Table 3.2 spectaculates shows the trial and error procedure adopted for selecting finest network of estimating compressing strength. The finest network has been presented in pictorial form for compressive strength and slump are presented in Fig. 3.6 and Fig. 3.7. Table 3.2 and Table 3.3 spectaculates the finest network details for predicting strength and slump respectively. The correlation coefficient reveals that the present method can be used to predict compressive strength and slump. The actual vs. predicted curve for strength, slump are presented in Fig. 3.2 – Fig. 3.3 respectively for training data and Fig.3.4 – Fig.3.5 respectively for validation.

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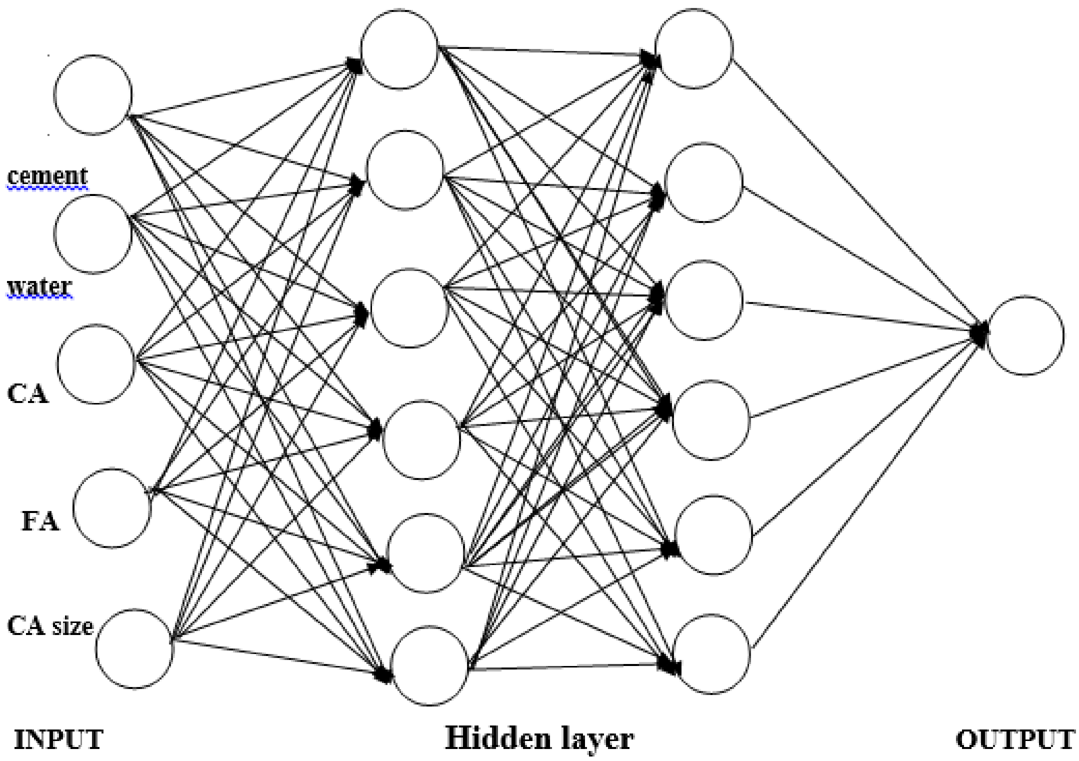


Fig. 3.6 Network used in ANN for predicting compressive strength.

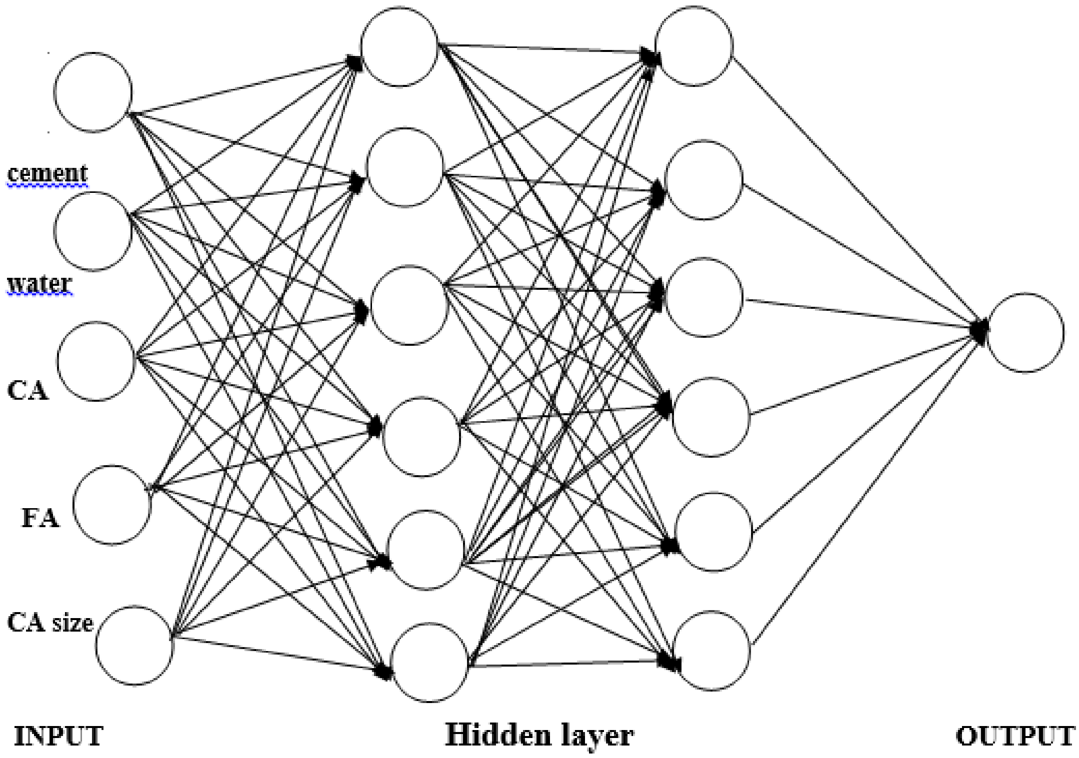


Fig. 3.7 Network used in ANN for predicting compressive slump.

Table 3.2 Trial used to find finest network in ANN for predicting compressive strength.

Trial	Neurons	R(Training)	R(validation)	Test	R(all)	Training function	Transfer function	No of layer	performance function	Adapting learning function	Epoch
1	4	0.5755	0.54304	0.52424	0.56123	TRAINLM	TANSIG	2	MSE	LEARNGDM	18
2	5	0.53843	0.57408	0.52499	0.54408	TRAINLM	TANSIG	2	MSE	LEARNGDM	15
3	6	0.61333	0.55849	0.53889	0.59166	TRAINLM	TANSIG	2	MSE	LEARNGDM	21
4	7	0.53318	0.53458	0.47466	0.52014	TRAINLM	TANSIG	2	MSE	LEARNGDM	10
5	16	0.63021	0.36438	0.32553	0.54215	TRAINLM	TANSIG	2	MSE	LEARNGDM	17
6	9	0.36193	0.41979	0.47102	0.38749	TRAINLM	TANSIG	2	MSE	LEARNGDM	7
7	10	0.58997	0.35712	0.36777	0.52939	TRAINLM	TANSIG	2	MSE	LEARNGDM	12
8	11	0.46379	0.39542	0.39557	0.44109	TRAINLM	TANSIG	2	MSE	LEARNGDM	14
9	11	0.58801	0.49513	0.38029	0.54021	TRAINLM	TANSIG	3	MSE	LEARNGDM	28
10	11	0.51522	0.5344	0.08594	0.460921	TRAINLM	TANSIG	4	MSE	LEARNGDM	13
11	8	0.5662	0.33933	0.49892	0.52059	TRAINLM	TANSIG	3	MSE	LEARNGDM	15

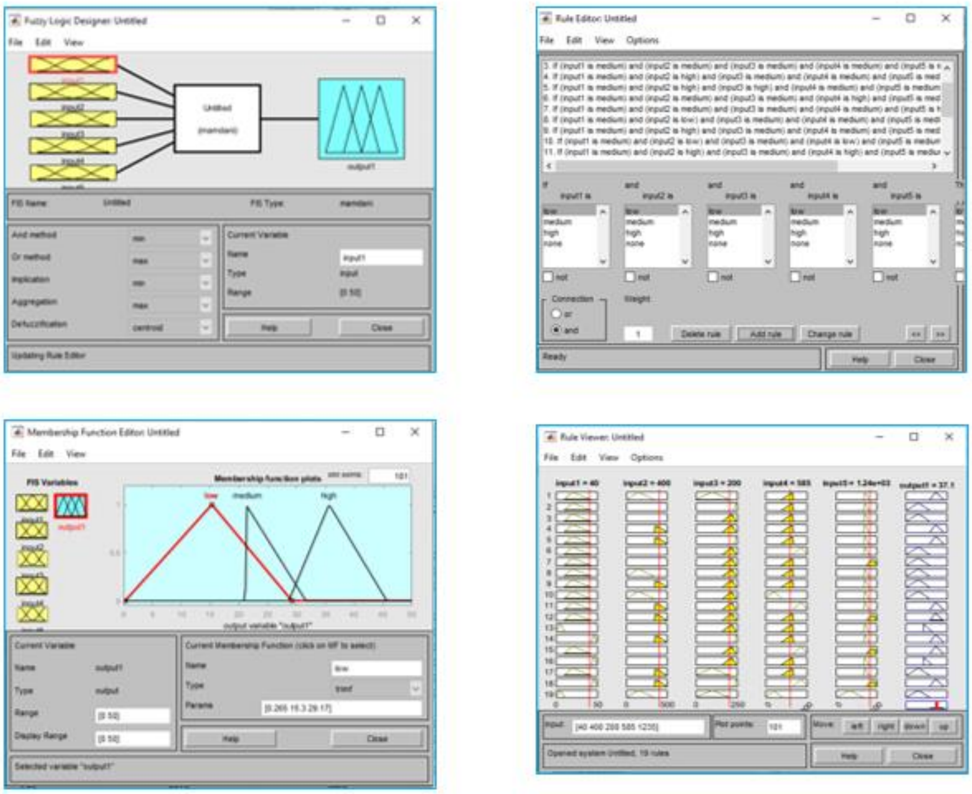
12	8	0.30836	0.49761	0.38569	0.33004	TRAINLM	TANSIG	4	MSE	LEARNGDM	8
13	8	0.59536	0.56019	0.56091	0.58133	TRAINLM	TANSIG	2	MSE	LEARNGD	33
14	8	0.55445	0.52395	0.43916	0.5325	TRAINLM	TANSIG	2	MSEREG	LEARNGDM	11
15	8	0.6269	0.50297	0.42546	0.57966	TRAINLM	TANSIG	2	MSEREG	LEARNGD	23
16	9	0.76117	0.40788	0.33172	0.38736	TRAINLM	TANSIG	2	MSE	LEARNGD	11
17	9	0.57784	0.65355	0.52334	0.57188	TRAINLM	TANSIG	2	MSEREG	LEARNGD	22
18	8	0.61866	0.4632	0.59067	0.59179	TRAINLM	LOGSIG	2	MSE	LEARNGDM	26
19	8	0.42499	0.48084	0.53431	0.45179	TRAINLM	PURELIN	2	MSE	LEARNGDM	12
20	9	0.53121	0.54093	0.57889	0.5363	TRAINLM	LOGSIG	2	MSE	LEARNGDM	13
21	14	0.64298	0.42538	0.40738	0.57413	TRAINLM	TANSIG	2	MSE	LEARNGDM	15
22	10	0.837672	0.74246	0.807672	0.61814	TRAINLM	TANSIG	2	MSE	LEARNGDM	16

Table 3.3 Trial used to find finest network in ANN for predicting slump.

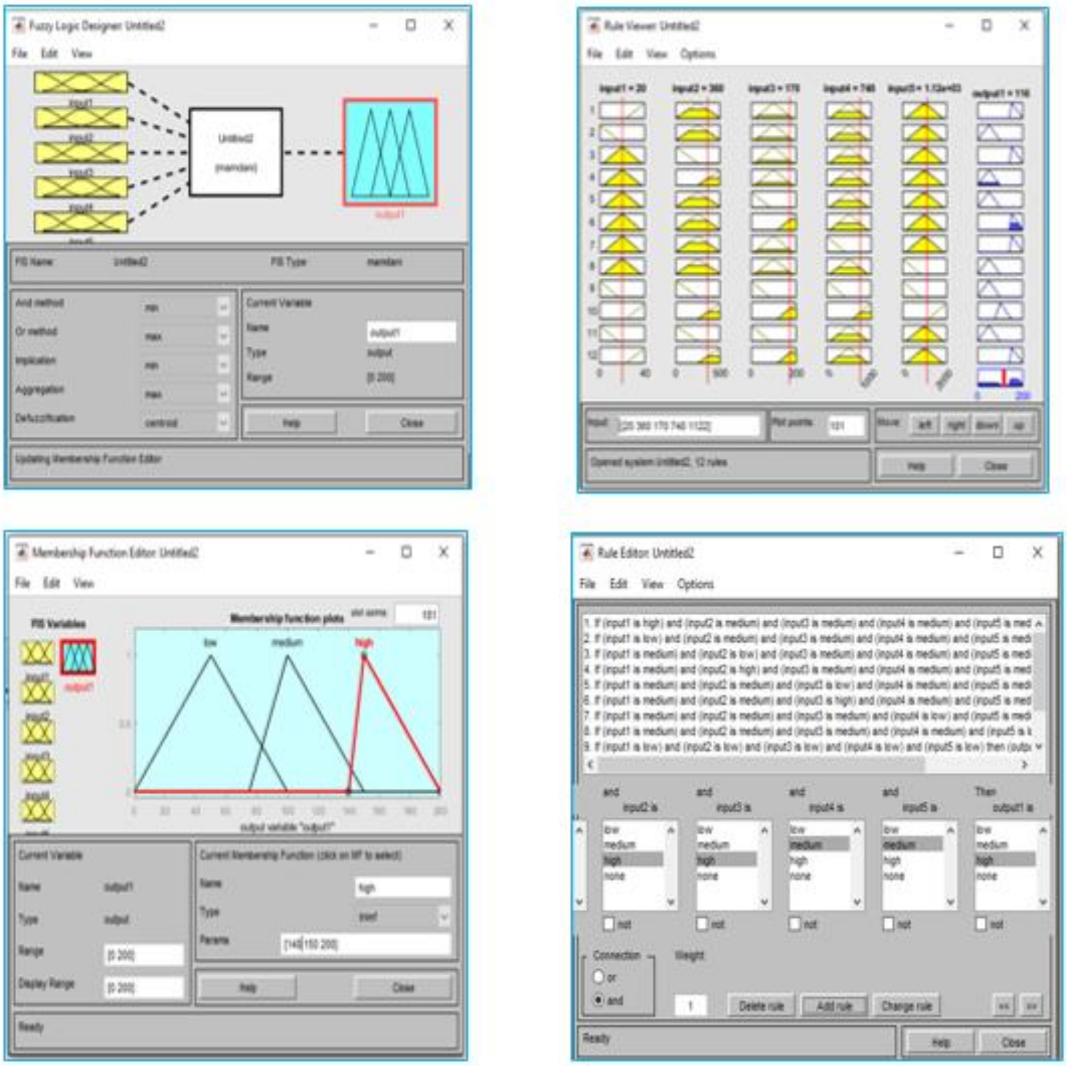
Trial	Neurons	R(Training)	R(validation)	Test(R)	R(all)	Training function	Transfer function	No of layer	function	Adapting learning function	Epoch
1	4	0.68378	0.36291	0.48221	0.46763	TRAINLM	TANSIG	2	MSE	LEARNGDM	13
2	5	0.54357	0.58904	0.25103	0.36543	TRAINLM	TANSIG	2	MSE	LEARNGDM	8
3	6	0.72322	0.48841	0.47556	0.50573	TRAINLM	TANSIG	2	MSE	LEARNGDM	23
4	7	0.69716	0.32346	0.47662	0.46616	TRAINLM	TANSIG	2	MSE	LEARNGDM	10
5	8	0.70815	0.20995	0.51324	0.46457	TRAINLM	TANSIG	2	MSE	LEARNGDM	9
6	9	0.66744	0.39786	0.39427	0.44039	TRAINLM	TANSIG	2	MSE	LEARNGDM	9
7	10	0.86702	0.48147	0.2485	0.56917	TRAINLM	TANSIG	2	MSE	LEARNGDM	14
8	11	0.85374	0.36257	0.30015	0.5678	TRAINLM	TANSIG	2	MSE	LEARNGDM	18
9	12	0.86702	0.48147	0.2485	0.56917	TRAINLM	TANSIG	2	MSE	LEARNGDM	10
10	12	0.88207	0.69505	0.60804	0.71696	TRAINLM	TANSIG	2	MSE	LEARNGDM	17
11	12	0.82726	0.30682	0.25757	0.58771	TRAINLM	LOGSIG	2	MSE	LEARNGDM	22
12	12	0.60804	0.2598	0.64171	0.3323	TRAINLM	PURELIN	2	MSE	LEARNGDM	8

3.3.3 Fuzzy Inference System (FIS)

Successful prediction by the model in various study in the past indicates that fuzzy logic could be a useful modeling tool for engineers and research scientists in the area of cement and concrete. Here also, the study has been conducted to predict the strength and slump of concrete using the FIS toolbox where coarse aggregate size , amount of cement, water, coarse aggregate, fine aggregate have been used as the input variables while strength and slump have been used as the output variable in the two networks of the FIS. The number of Membership functions for input and output parameters used for fuzzy modeling is 15 and the type of membership function is chosen as 'trimf' (triangular membership function) (Fig. 3.8). The membership functions and the number of subsets have been decided by considering the avilable data. Fig. 3.10 reveals the pictorial form of FIS network used in the study. Fig. 2 and Fig. 3 represents the actual vs. predicted curve for strength, and slump for training data and Fig. 4 and Fig.5 represents and actual vs. predicted curve for strength, and slump for validation data respectively.



(a) FIS network used for predicting compressive strength.

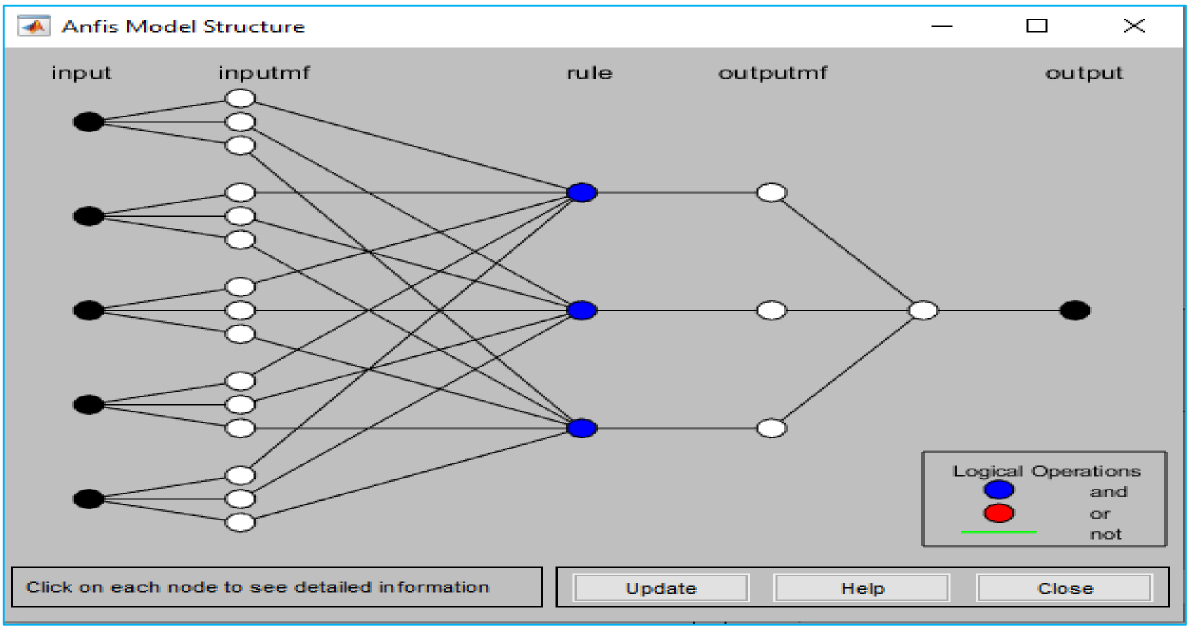


(b) FIS network used for predicting slump strength.

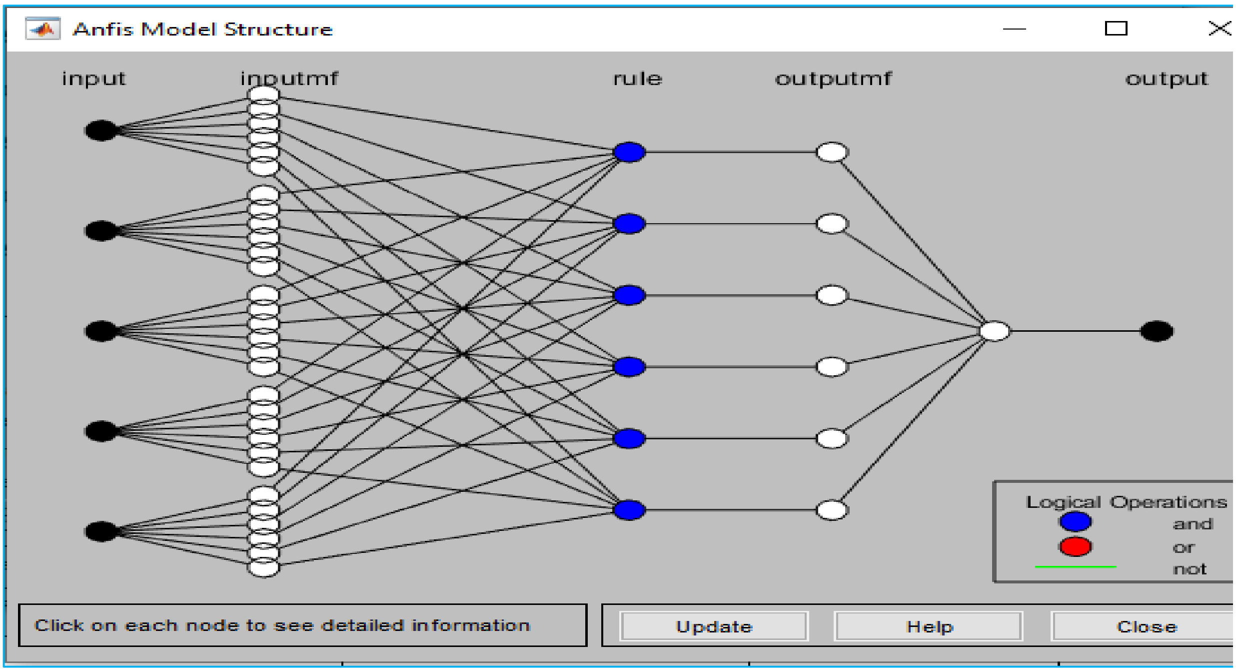
Fig. 3.8 FIS network used in the study.

3.3.4 Adaptive Neuro Fuzzy Inference System (ANFIS)

In the present study, three ANFIS model have been developed to predict the concrete compressive strength and slump. For all the two models coarse aggregate size, cement, sand, coarse aggregates have been utilised as input variable. All the models have been developed by a grid partition fuzzy interference system. The ANFIS model for predicting compressive strength has been presented in Fig. 3.9. Further, the output model has been presented in Fig. 3.10. The actual vs. predicted curve for training data set of strength and slump using ANFIS model for training and validation data are Fig.3.2 –Fig.3.3 and Fig. 3.4 -Fig. 3.5 respectively.

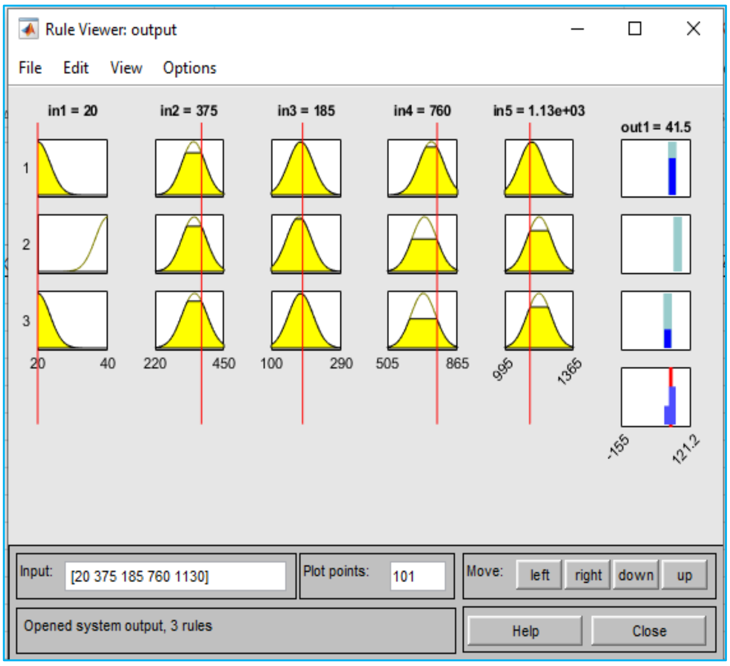


(a) ANFIS network for compressive strength



(b) ANFIS network for slump

3.9 The network used in ANFIS



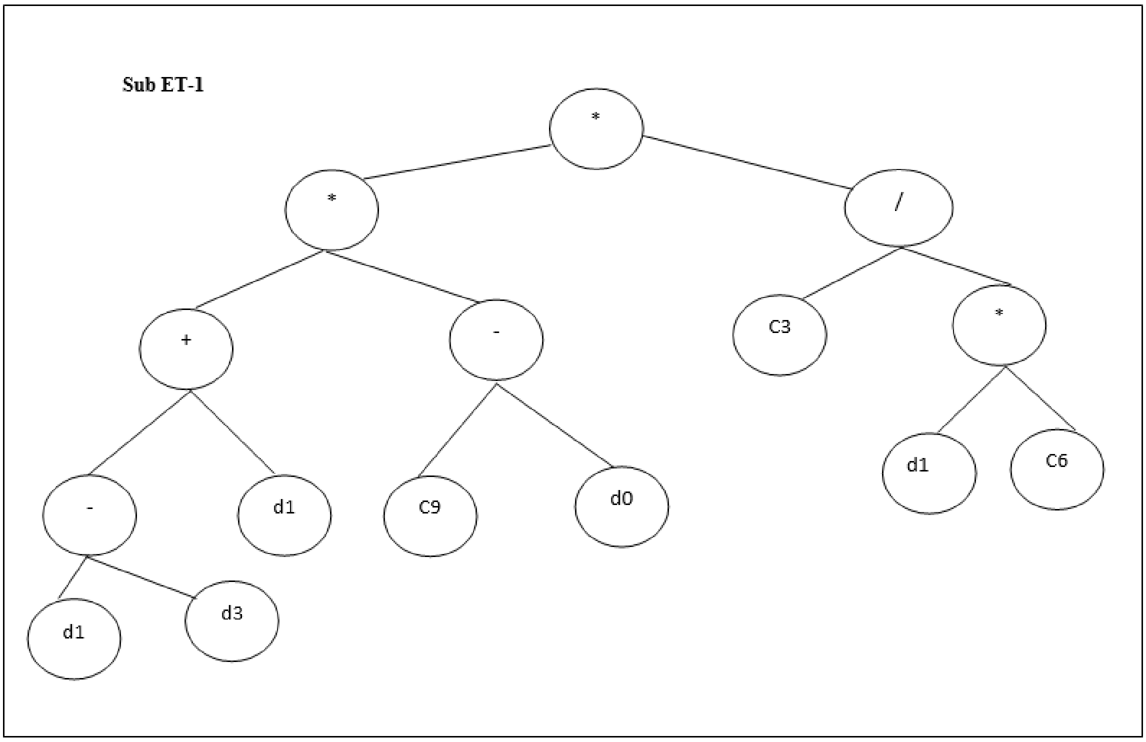
(a) Compressive strength

(b) Slump

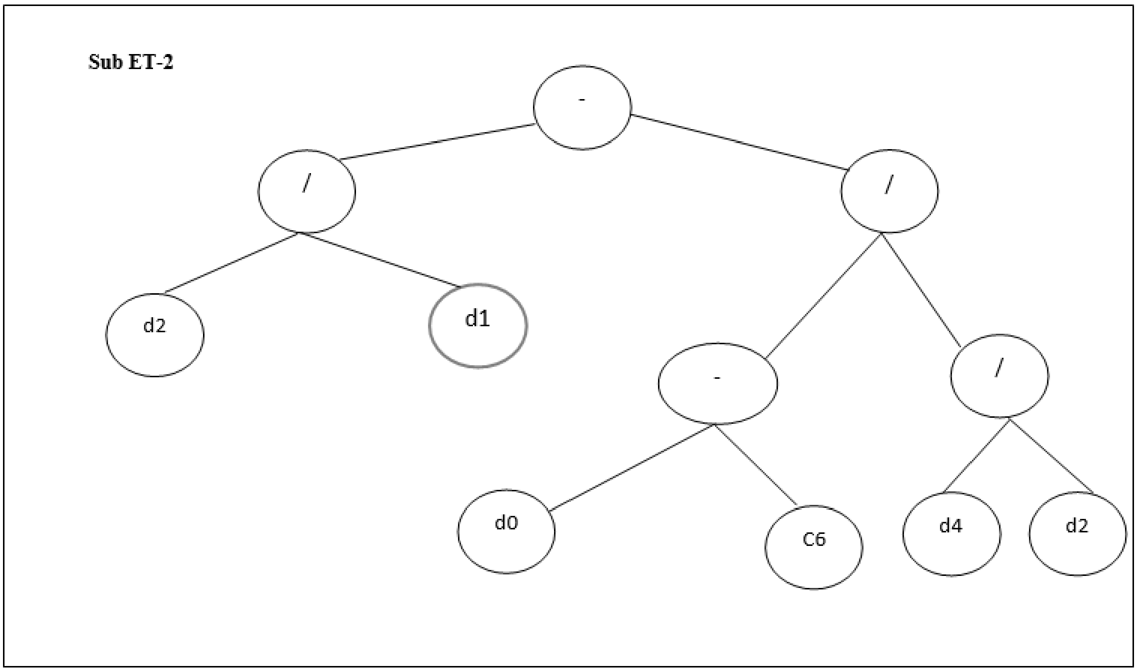
Fig. 3.10 the output models in ANFIS network.

3.3.5 Genetic Expression Programing (GEP)

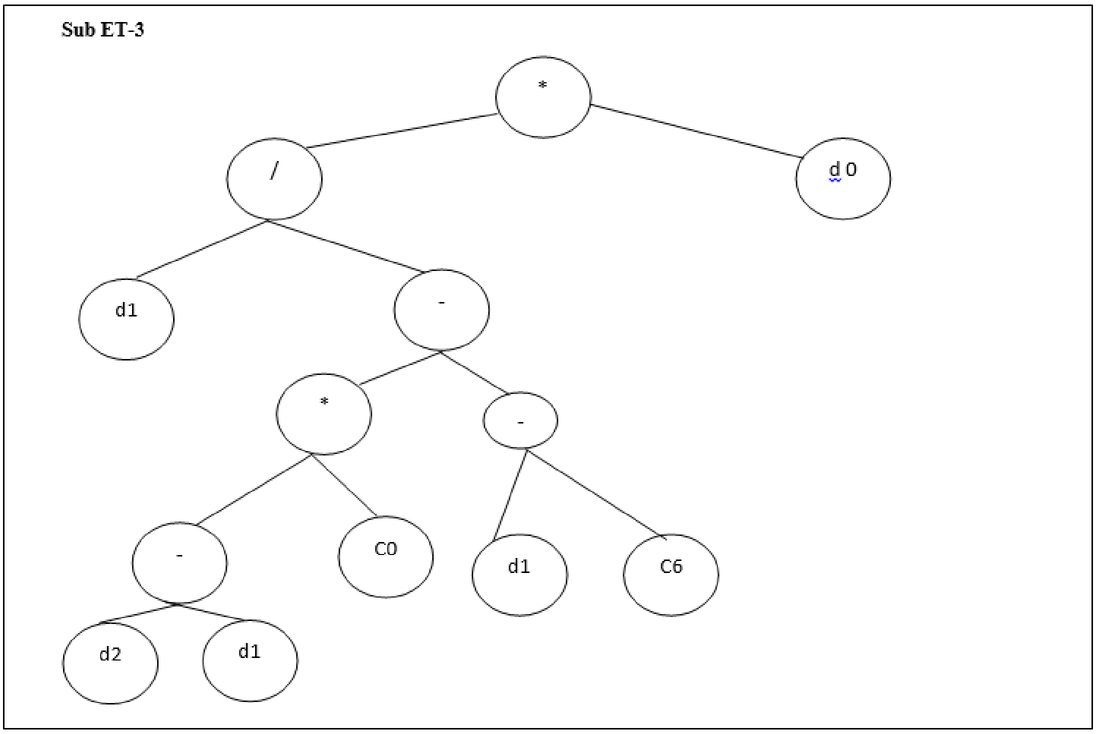
To produce compressive strength, slump and dry density is a function of coarse size, cement, sand, coarse aggregates; GeneXpro Tools 4.0 (www.genexprotools.soft112.com/) was used in the current study. In all cases the 30 number chromosomes, each containing the three-dimensional genes of the head size eight are used in the calculation. "Addition" is used as a link function to predict compressive strength and slump.. For the maximum correlation coefficient obtained for estimating the strength, slump are 96565 and 122349 iteration respectively. The genetic algorithm trees for compressive strength and slump are presented in Fig. (). The equations for compressive strength and slump are presented in Equation 3.11 and 3.12 respectively. Further the equations are presented in Equation 3.1 and 3.2 respectively. Further, these two figures are very useful in predicting the above-mentioned features of concrete. Moreover, it may be used as basis function in optimisation procedure.



(a) Chromosome 1



(b) Chromosome 2



(c) Chromosome 3

3.11 Generated GEP tree for strength.

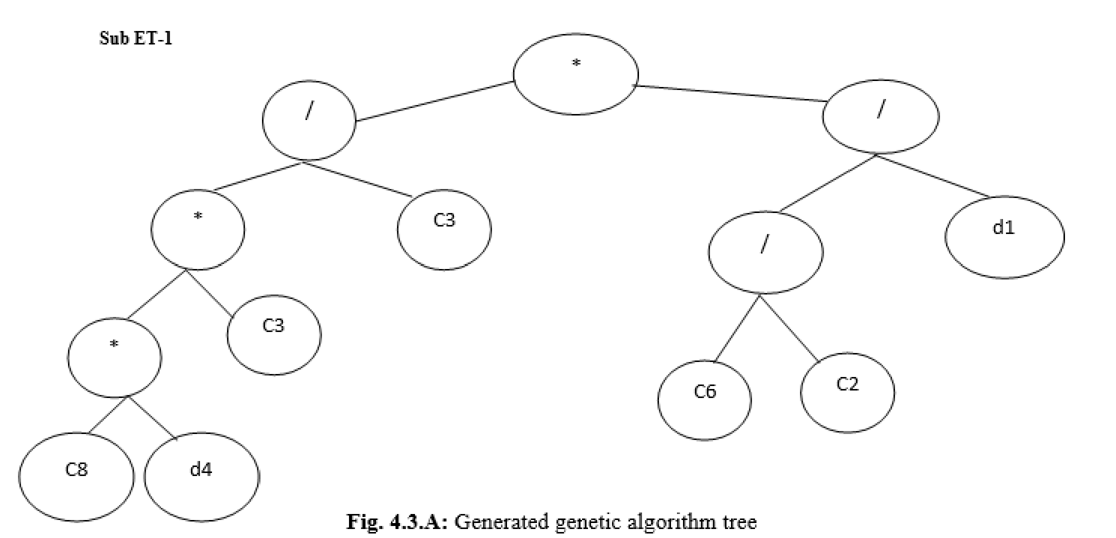
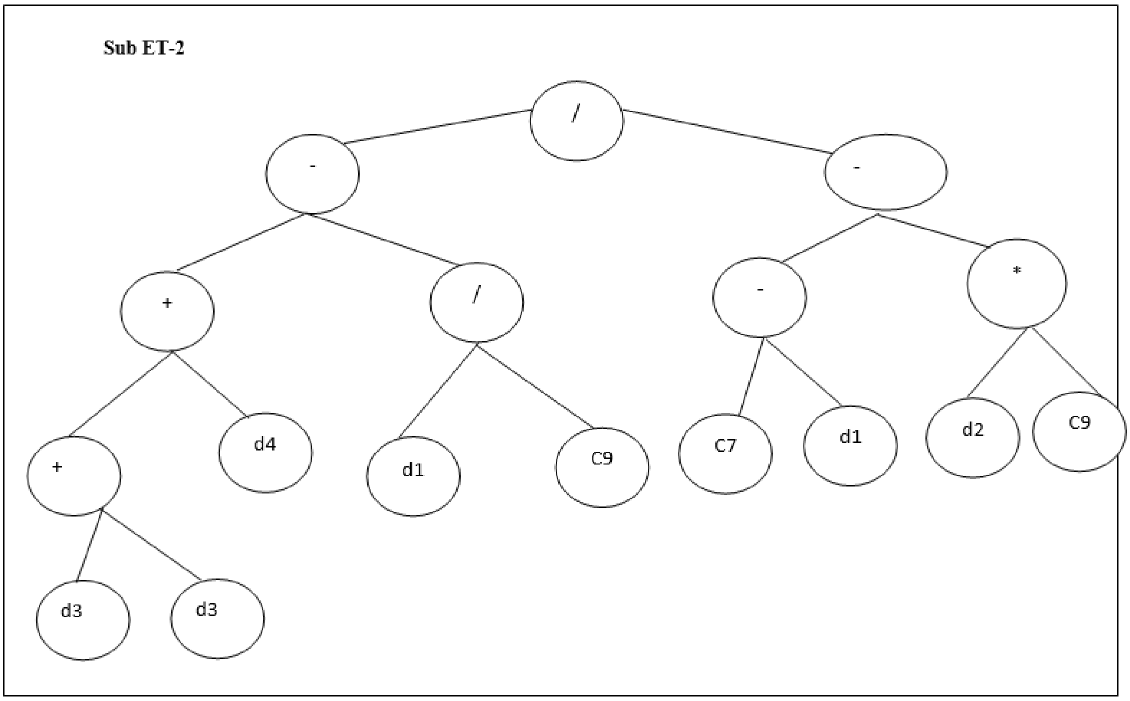
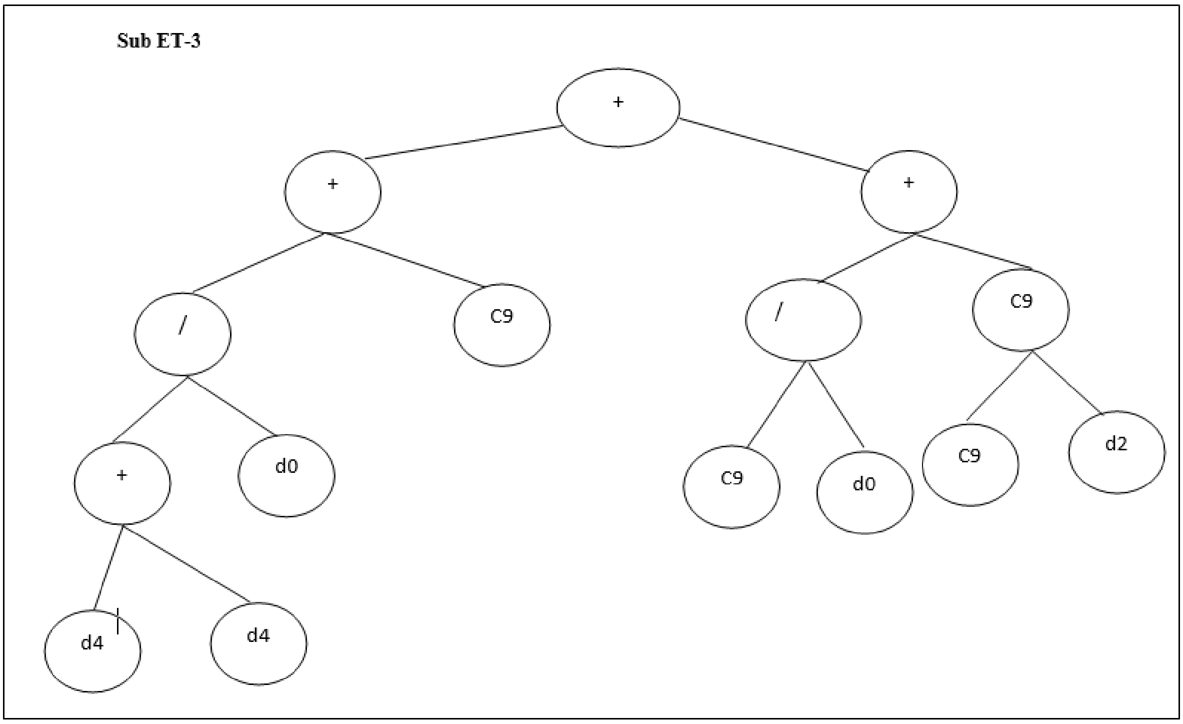


Fig. 4.3.A: Generated genetic algorithm tree

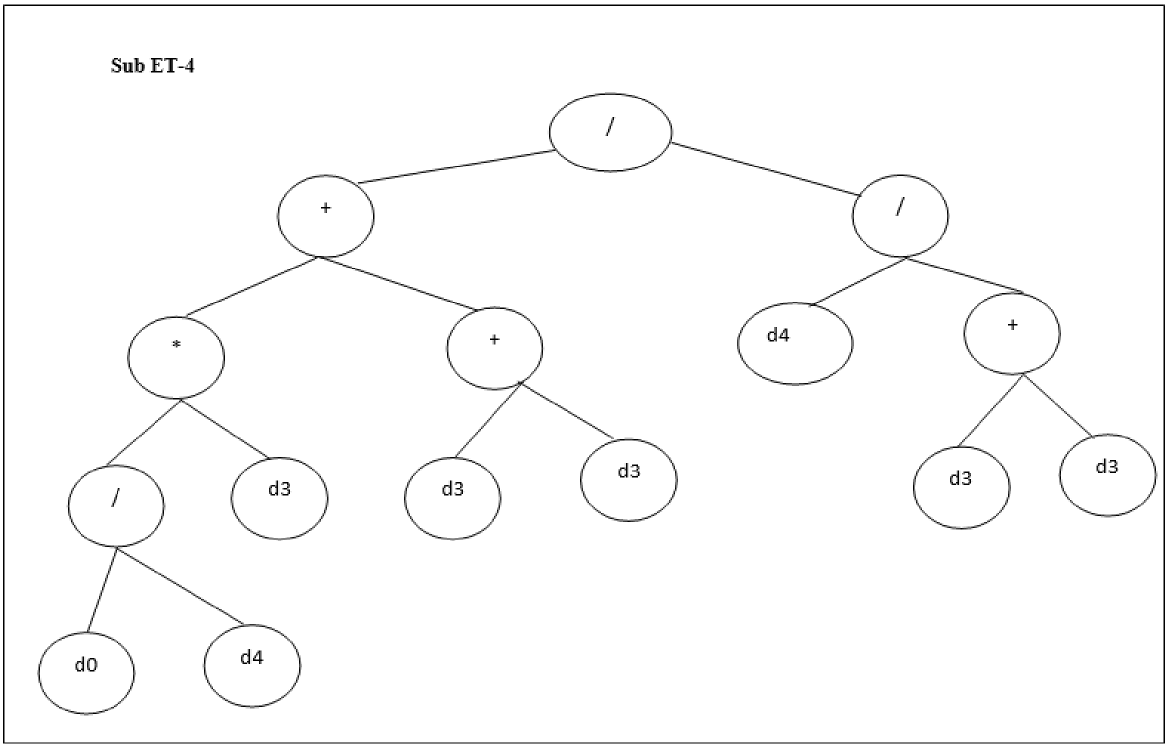
(a) Chromosome 1



(b) Chromosome 2



(c) Chromosome 3



(d) Chromosome 4

3.12 Generated GEP tree for slump.

$y(1) = \left[\{(d(2)-d(4))+d(2)\} * \{(-46.3750570834068)-d(1)\} * \{\frac{3.87863402806583}{((d(2) * 10.8301795938042)}\}\right] + \left[\frac{\{(d(2)-d(1))-d(3)\}}{\{\frac{d(4)}{d(3)}\}}\right] - \left[\frac{(d(1)-(-16.1558986905887))}{\{\frac{d(5)}{d(3)}\}}\right] + \left[\left\{\frac{d(2)}{((d(3)-d(2)) * (-7.89030981708951)) - (d(2)-(-31.3645369854215}\right. * d(1)\right]$	(Eq. 3.1)
$y(2) = \left[\left\{\frac{((0.450301792461842 * d(5)) * 7.89544358653523)}{7.89544358653523}\right\} * \left\{\frac{(\frac{(-11.0172670250786)}{2.18198406609944})}{d(2)}\right\}\right] + \left[\frac{\{((d(4)+d(4))+d(5)) - \frac{d(2)}{(-2.63698393180232)}\}}{\{((-21.2197122639063)-d(2)) - (d(3) * (-2.63698393180232)))\}}\right] + \left[\left\{\frac{(d(5)+d(5))}{d(1)}\right\} + (-10.3960394115875) + \left\{\frac{(-10.3960394115875)}{d(1)} + (-10.3960394115875)\right\}\right] + \left[\frac{\left[\left\{\frac{d(1)}{d(5)} * d(4)\right\} + \{(-6.20188909573656)+d(1)\}\right]}{\left\{\frac{d(5)}{(d(4)+d(4))}\right\}}\right]$	Eq (3.2)

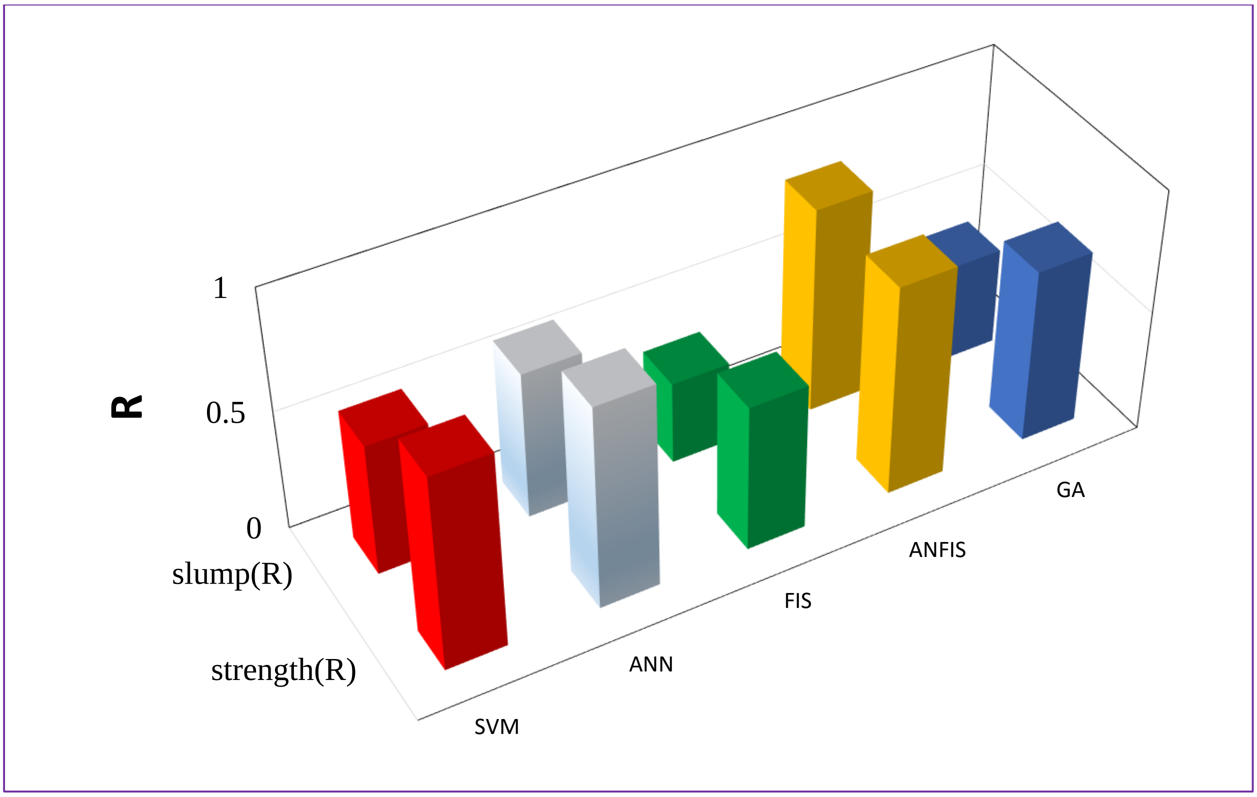


Fig.3.13 R-value comparison by different method for predicting compressive strength & slump for training.

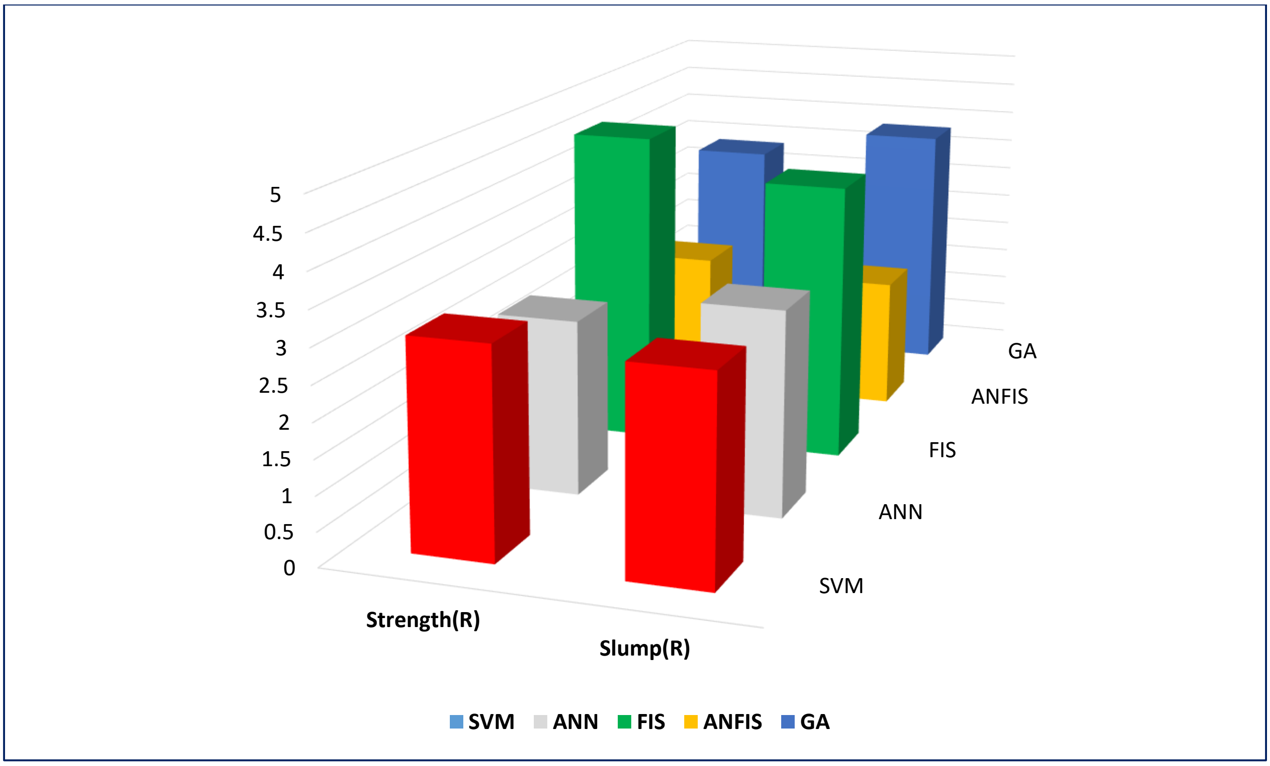


Fig.3.14 RMSE value comparison by different method for predicting compressive strength & slump for training.

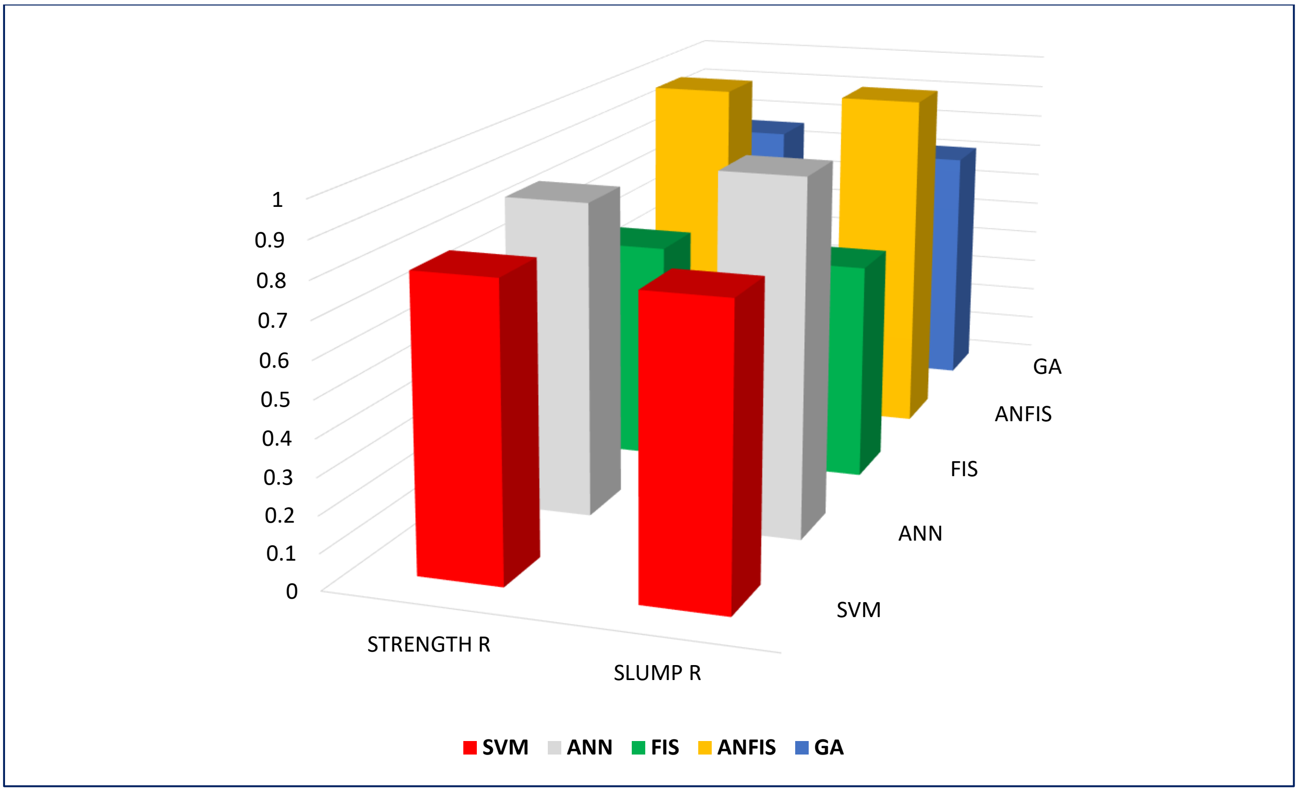


Fig.3.15 R-value comparison by different method for predicting compressive strength & slump for validation.

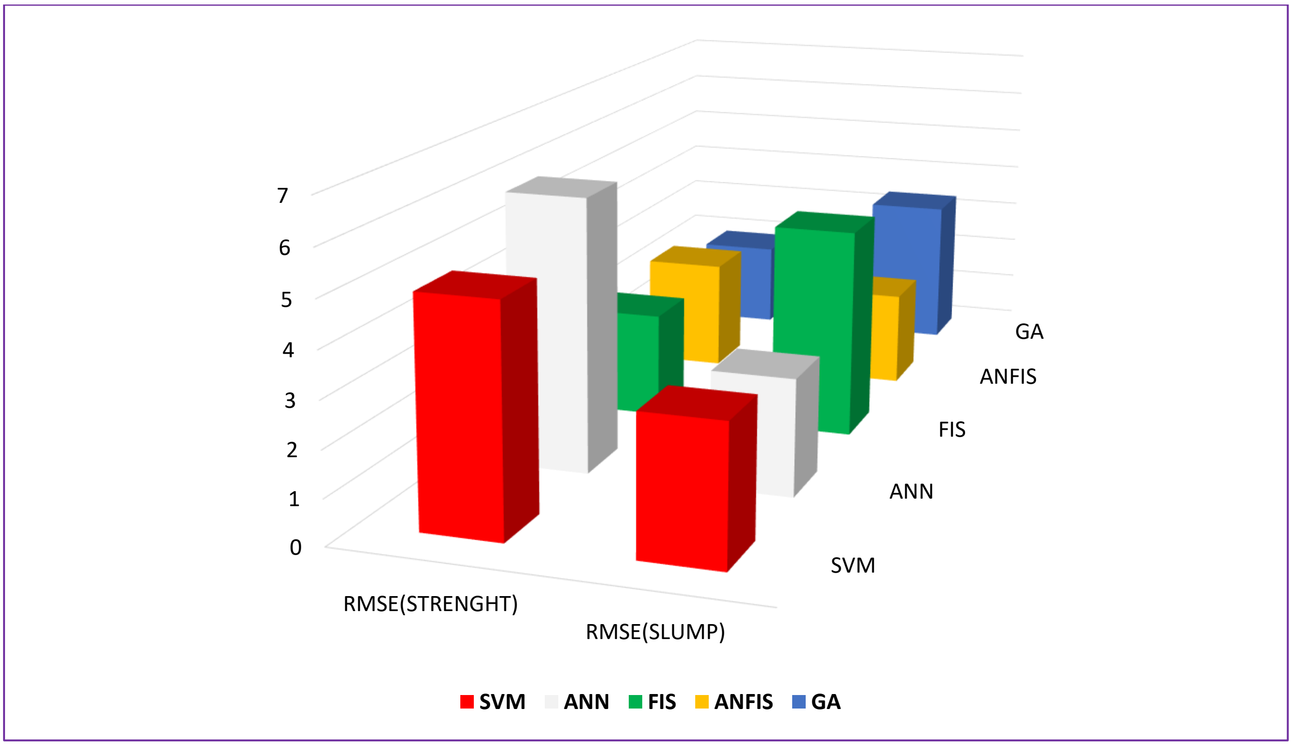


Fig.3.16 RMSE -value comparison by different method for predicting compressive strength & slump for validation.

3.4 ANALYSIS OF THE PREDICTED RESULT

In order to compare the accuracy of prediction of all the five methods R value and RMSE value has been computed and presented in Fig. 3.13 and Fig. 3.14 respectively for training and Fig. 3.15 and Fig. 3.16 respectively for validation. The results clearly signifies that ANFIS yiled best results among all the five methods. Thus, it can be used successfully for predicting concrete compressive strength and slump using available data. However, GEP generate equations which is very much helpful for others. Further, the generated equations can be used as basis equation in optimisation process.

Chapter 4

DETERMINISTIC OPTIMIZATION OF CONCRETE MIXTURE

4.1 GENERAL

In the present study an effort has been made to determine the optimum proportion of concrete mixtures through available data. For this purpose 200 numbers of concrete mixtures have been considered by varying the level of key ingredients- aggregate size, cement, water, fine aggregate and coarse aggregate. As discussed previous, using the data equations have been proposed of compressive strength and slump as a function of aggregate size, cement, water, fine aggregate and coarse aggregate by Genetic Expression Programing (GEP). These equations are very much useful for predicting compressive strength and workability of concrete for particular ingredients. In this chapter, mathematical multi objective optimization has been conducted by Genetic Algorithm (GA) using these equations as basis functions and optimum content of aggregate size, cement, water, fine aggregate and coarse aggregate have been determined for obtaining maximum compressive strength, maximum slump at lowest cost. Thus, by implementing the present results more accurate number of mix proportions with desired compressive strength, and slump can be obtained at minimum cost.

4.2. OPTIMIZATION METHODOLOGY

Design variable and design parameters are the basis of the performance of an optimal design. In an optimization process design variables needs to be optimized. Though design parameters are present in optimization, but they cannot be controlled in optimization process. The main objective of an optimization is to evaluate the design variable for expected optimization design. Design objectives are normally presented by performance function accompanying with a set of equal and unequal constraints. The optimization process mathematically can be expressed as: Minimize $f_n(\mathbf{y})$

Subjected to $(y) \leq 0 \forall_j \boldsymbol{\epsilon J}$

$g_j(y) \leq x_i \leq x_i^u \forall_j \boldsymbol{\epsilon}$k

Where, $f_n(\mathbf{y})$is the objective function, $g_j($$y$represents jth constraint, $\mathbf{y}$ = [$\mathbf{x}$, $\mathbf{z}$] is a n dimensional vector composed of both design variable vector ($\mathbf{x}$ = $[x_1 , x_2 , \dots , x_k]^T$) and design parameter vectors (z = [$z1$, $z1$,… , zK] T), xiL and xiU are the lower bound and upper bound of ith design variable respectively. In the case of a single objective function, one objective function is used. However, in the case of multi-objective function more than one number of objective functions can be applied to the same constraints.This objective function can be determined successfully by GEP using software GeneXproTools. In this process, the first human chromosomes were initially randomly generated by software. In the next step, the chromosomes are transferred and the suitability of the individual population is assessed. Then, when considering suitability, individuals are selected randomly, leaving a seed with new traits. In the new generation one finds the same process - genetic predisposition, hostility, and reproduction with mutation. For a certain number of generations or until a specific solution is reached, this process continues. A detailed procedure is shown in Fig.2.1.

4.3 OPTIMIZATION OF CONCRETE MIX DESIGN

The data shown in Table 1, have been used for generation of basis function by GEP to examine the significance of the mixture proportions and subsequently to obtain equations for compressive strength and slump as a function of cement, sand, coarse aggregate and water. In order to determine objective function in this present process, which estimates compressive strength as a function of aggregate size, cement, water, fine aggregate and coarse aggregate, GeneXpro Tools 5.0 (www.genexprotools.soft112.com/) has been used which is described in previous chapter. Another objective function, which predicts the cost of mixture is constructed from the cost of material taken from the USA market. This is presented in equation 3. The cost of cement, sand coarse aggregate and water per kg are Rs 0.124, 0.006, 0.0075 and 0.000013 respectively.

$y(3) = 0.124 * d(2) + 0.006 * d(3) + 0.0075 * d(4) + 0.000013 * d(5)$	(Eq. 4.1)

In order to maximize the strength of concrete, slump and minimize the cost (ie to minimize (1/$strength$) ,(1/$slump$) and ($cost$)) equation 1-3 has been minimized the present study for the given constraints.

Available range constraint

1) CA_{max}<Size of CA<CA_{min}
2) $Cemax<Ce<Cemin$
3) $FAmax<FA<FAmin$
4) $CAmax<CA<CAmin$
5) $Wamax<Wa<Wamin$

These values of lower [20 350 130 505 1015]and upper limit[40 410 195 865 1365]have been taken by the minimum and maximum values of the size of CA ,weight of cement,water, fine aggregate and coarse aggregate used (Table 1).

2) Ratio constraint

According to Indian code the water cement ratio is minimum 0.35. Therefore the following constraint has been introduced $Wa/Ce > 0.37$

3) Absolute weight constraint

All the weight has been converted with respect of total volume of mixture as $1m^3$. Therefore weight constraint is

$0.124 * d(2) + 0.006 * d(3) + 0.0075 * d(4) + 0.000013 * d(5) = 1$	(Eq. 4.2)

4.4 RESULTS

The optimisation result is presented in Table 4.1. It will be very much helpful to obtain the maximum strength and slump at minimum cost.

Table 4.1 Value obtained by multi objective optimisation maximization of strength, slump and minimization cost.

Table 4.1 Optimisation of slump and strength

cost(USD)	strength(Mpa)	slump(mm)	size of CA (mm)	Cement O.P.C (Kg/m3)	Water Content (Kg/m^3)	**Fine Aggregate (Kg/m^3)**	**Coarse Aggregate (Kg/m^3)**
47.9807	38.77843	21.2816	20	350	130	505	1015
54.79562	53.88439	143.879	21.20653	401.7528	184.5748	514.0126	1209.92991
47.99215	38.7453	21.3418	20.00919	350.0062	130.0014	506.4167	1018.64229
54.79577	53.88387	143.8873	21.20765	401.7542	184.5672	514.0145	1209.93107
53.98078	49.40462	218.5364	23.25992	395.2565	165.6198	527.9417	1207.24925
47.99411	39.06105	4.313755	20.05094	350.0052	131.9693	505.1095	1025.29605
49.07454	42.48581	153.2789	21.32339	356.5155	161.7349	517.4125	1200.9722
52.94997	48.77516	6446.089	20.83439	388.4254	155.4855	511.629	1160.63078

CHAPTER 5

ROBUST OPTIMIZATION OF CONCRETE MIXTURE

5.1 GENERAL

Present study proposes a Robust Cost Optimization procedure for concrete mix , which minimizes such unwanted deviation due to uncertainty and provides guarantee of achieving maximum strength and workability with minimum possible cost .This study an effort has been made to determine the minimum cost. Using the equations generated by GEP and equation 4.1 the present study has been carried out. by Genetic Algorithm (GA) This model provides sufficiently accurate results . Its also shown that the uncertainty of estimated coefficient values has a statistically insignificant effect on concrete strength, confirming the reliability of the proposed model.

5.2. OPTIMIZATION METHODOLOGY

Design variable and design parameters are the basis for optimal design performance. In the process of optimization, design variables require optimization. Although design parameters exist in optimization, they cannot be controlled by the process of optimization. The main purpose of the optimization is to evaluate the design variable to find the design for the expected optimization. Design objectives are often articulated in a performance function that accompanies a set of equal and unequal constraints. The process of mathematically performing can be illustrated by Minimize $f_n(\mathbf{y})$

A generic mathematical programming problem is of the form:

$$\text{Min} \quad y_0$$

$$y_0 \in \mathrm{R},\ \mathrm{y} \in \mathrm{Rn}$$

$$f_0\ (\mathrm{y},\zeta) < x_0$$

$$f_i\ (\mathrm{y},\zeta) < 0$$

where I =1,…………………………………….,m .

where y in the *design vector*, the functions f0 (objective function) and f1,… ,fm are *structural elements* of the problem, and ζ stands for the *data* specifying a particular problem instance. This notation is quite general, as the functions could be linear or nonlinear.

5.2.1 Development of the Robust cost optimization

Minimize the cost satisfying compressive strength and slump requirement criteria as

$$\text{F(a.b): cost} \qquad \text{(Eq. 5.1)}$$

$$\text{Subjected to} \quad h_1\text{(a,b)} : \sigma_c^t - \sigma(a,b) \leq 0$$

$$\text{Subjected to} \quad h_2\text{ (a,b)} : \delta_c^t - \delta(a,b) \leq 0$$

$$a_i^L \leq a_i \ll a_i^L$$

$$where\ i = 1,2 \dots \dots \dots \dots \dots \dots \dots \dots \dots n$$

In the above, a_i^L and a_i^U are the lower and the upper bounds of the i^{th} DV, respectively., σ_c^t $\sigma(a,b)$, δ_c^t and $\sigma(a,b)$ are the target compressive strength, obtained compressive strength, the target slump and obtained slump, respectively. It can be noted here that the Deterministic optimisation problem as described by above equation does not consider the effect of uncertainty in **[a b]**. But, the performance function and the constraints are the function of **[a b]**. Thus, the uncertainty in [**a b]** is expected to propagate at the system level, influencing the performance function and the constraints of the related optimization problem. The Robust Cost Optimisation approach under uncertainty is discussed in the next section.

5.2.2 Robustness of the Objective Function

The robustness of the objective function is generally expressed in terms of the dispersion of the performance function from its mean value. The objective of an ideal design is to achieve the optimal performance as well as less sensitivity of the performance function with respect to the variation in the design variable and design parameter due to uncertainty. Thus, one needs to optimize the objective function as well as its dispersion (standard deviation for normal random parameters).Hence, the Robust Design Optimisation problem is posed as the minimization problem of the mean and standard deviation of the objective function, leading to a two criteria Robust Design Optimisation problem which can be expressed as:

$$\text{Find x, to minimize } [\alpha j, \beta j] \qquad \text{(Eq. 5.2)}$$

In the above, $\alpha j\ and\ \beta j$ are the mean and the standard deviation of the performance function respectively. Normally, minimization of the mean and variance of the performance are sought leading to a set of Pareto-optimal solution as shown by Deb et al. **(2002)** [52]**.** The Weighted

Sum Method (WSM) is an easy, computationally efficient and popular way to deal with the trade-offs between conflicting objectives (Doltsinis et al., 2005[53]) and is adopted in the present study. Applying the WSM the multi objective function is converted to an equivalent single objective function as,

$$\omega(v) = (1-\epsilon)\alpha j/\alpha j^{*} \quad + \quad \varepsilon\mu j/\mu j^{*} \qquad \text{(Eq. 5.3)}$$

where, $\omega(v)$ is a new objective function, called desirability function and the parameter ϵ serves as a weighting factor; $\mu j^{*}$and $\alpha j^{*}$are the optimal values of the mean and the standard deviation obtained for α equals to 0.0 and 1.0, respectively. The maximum robustness will be achieved when α becomes 1.0. In the present case, two types of uncertain variables are involved in the RCO, i.e. normal random and UBB. Let us denote **u** = **[a b**]. By using first order perturbation approach, the mean and standard deviation of objective function can be obtained for normal random parameters as (Doltsinis et al., 2005)[53] ,

$$\vartheta_{g1}(u) \approx g_1(u*)\,, \sigma_{g1}^2 \;\approx\; \sum_{j=1}^{n}(\frac{\partial g1}{\partial u_j})^2\, \sigma_{ui}^2 \qquad \text{(Eq. 5.4)}$$

Similarly, for UBB uncertainty, using worst case propagation concept, the nominal value $\bar{f}$ (i.e. mean for normal random case) and dispersion Δf (i.e. standard deviation for normal random case) can be obtained as (Lee and Perk, 2001[54]**)**

$$\bar{f}_2 = f(\bar{\mathbf{u}}) \qquad \Delta f_2 = \sum_{i=1}^{N} \left|\partial f/\partial u_i\right| \Delta u_i \qquad \text{(Eq.5.5)}$$

In the above, $\bar{\mathbf{u}}$ denotes nominal value of **u,** i.e. $\bar{\mathbf{u}} = (\mathbf{u}^L+\mathbf{u}^U)/2$. Finally, for a mixed system of UBB and random parameters, the resulting nominal value and dispersion of objective function can be obtained as,

$$\mu f = \mu f_1 + f_2 \qquad \varphi f = \emptyset f_1 + \nexists f_2 \qquad \text{(Eq.5.6)}$$

The formulation presented above is valid for comparatively smaller levels of uncertainty in the **u**. However to deal with non-normal variables, the Monte Carlo Simulation (MCS) approach may be used in estimating mean and standard deviation values.

5.3. EXPERIMENTAL PROGRAM

Now,

$$Min\ y\ [\left\{\frac{y(1)*\alpha}{y1[(d(1),d(2),d(3),d(4),d(5)]}+\frac{y(2)*\beta}{y2[(d(1),d(2),d(3),d(4),d(5)]}+\frac{y(3)*\gamma}{y3[(d(1),d(2),d(3),d(4),d(5)]}\right\}*\varepsilon+\left\{\frac{\sigma_{y(1)}*\alpha}{\sigma_{y(1)}[(d(1),d(2),d(3),d(4),d(5)]}+\frac{\sigma_{y(2)}*\beta}{\sigma_{y(2)}[(d(1),d(2),d(3),d(4),d(5)]}+\frac{\sigma_{y(3)}*\gamma}{\sigma_{y(3)}[(d(1),d(2),d(3),d(4),d(5)]}\right\}*(1-\varepsilon)]$$

……….(Eq.5.7)

Where α= β= γ=0.33 and ε=0.5

$$\sigma_{y(1)}=[\{\frac{\partial y_1}{\partial d_1}*0.09*d(1)\}^2+\{\frac{\partial y_1}{\partial d_2}*0.22*d(2)\}^2+\{\frac{\partial y_1}{\partial d_3}*0.16\ d(3)\}^2+\{\frac{\partial y_1}{\partial d_4}*0.67\ d(4)\}^2+\{\frac{\partial y_1}{\partial d_5}*0.62*d(5)\}^2]^{0.5}$$

……….(Eq.5.8)

$$\sigma_{y(2)}=[\{\frac{\partial y_2}{\partial d_1}*0.09*d(1)\}^2+\{\frac{\partial y_2}{\partial d_2}*0.22*d(2)\}^2+\{\frac{\partial y_2}{\partial d_3}*0.16\ d(3)\}^2+\{\frac{\partial y_2}{\partial d_4}*0.67\ d(4)\}^2+\{\frac{\partial y_2}{\partial d_5}*0.62*d(5)\}^2]^{0.5}$$

……….(Eq.5.9)

$$\sigma_{y(3)}=[\{\frac{\partial y_3}{\partial d_1}*0.09*d(1)\}^2+\{\frac{\partial y_3}{\partial d_2}*0.22*d(2)\}^2+\{\frac{\partial y_3}{\partial d_3}*0.16\ d(3)\}^2+\{\frac{\partial y_3}{\partial d_4}*0.67\ d(4)\}^2+\{\frac{\partial y_3}{\partial d_5}*0.62*d(5)\}^2]^{0.5}$$

…………(Eq.5.10)

$.\frac{1}{y(1)} =$

$0.004*\Big[\{(d(2)-d(4))+d(2)\}*\{(-46.3750570834068)-d(1)\}*$

$\{\frac{3.87863402806583}{((d(2)*10.8301795938042)}\}\Big] + \left[\frac{\{(d(2)-d(1))-d(3)\}}{\{\frac{d(4)}{d(3)}\}}\right] - \left[\frac{(d(1)-(-16.1558986905887))}{\{\frac{d(5)}{d(3)}\}}\right] +$

$\left[\left\{\frac{d(2)}{((d(3)-d(2))*(-7.89030981708951))-(d(2)-(-31.3645369854215))}\right\}*\right.$

$\left.d(1)\right]+0.001*\left[\left\{\frac{((0.450301792461842*d(5))*7.89544358653523)}{7.89544358653523}\right\} * \left\{\frac{(\frac{(-11.0172670250786)}{2.18198406609944})}{d(2)}\right\}\right] +$

$\left[\frac{\{((d(4)+d(4))+d(5))-\frac{d(2)}{(-2.63698393180232)}\}}{\{((-21.2197122639063)-d(2))-(d(3)*(-2.63698393180232)))\}}\right] + \left[\left\{\frac{(d(5)+d(5))}{d(1)}\right\} +\right.$

$\left.(-10.3960394115875) + \left\{\frac{(-10.3960394115875)}{d(1)} + (-10.3960394115875)\right\}\right] +$

$\left[\frac{\left[\left\{\frac{d(1)}{d(5)}*d(4)\right\}+\{(-6.20188909573656)+d(1)\}\right]}{\left\{\frac{d(5)}{(d(4)+d(4))}\right\}}\right]+0.003*\{0.124*d(2)+0.006*d(3)+0.0075*$

$d(4)+0.000013*d(5)\}+$

$0.057*[\{(\frac{(-0.35813*(2*d(2)-d(4))}{d(2)} - \frac{d(3)}{d(4)} - \frac{d(3)}{d(5)}) + \frac{d(2)}{((-7.89*d(3))+6.89*d(2)+31.36))}) * (0.09 *$

$d(1))\}^2 + \{(\frac{(0.35813*d(1)*(46.37-d(1)))}{d(2)*d(2)} + \frac{d(3}{d(4)} +$

$\frac{(7.89*d(1)*d(3))+31.36*d(1))}{(-7.89*d(3))+6.89*d(2)+31.36)*(-7.89*d(3))+6.89*d(2)+31.36)}) * (0.22*d(2))\}^2 +$

$\{(\frac{(-2*d(3)-d(1)-d(2))}{d(4)}) - \frac{d(1)+16.15}{d(5)} +$

$\frac{(7.89*d(1)*d(2)}{(-7.89*d(3))+6.89*d(2)+31.36)*(-7.89*d(3))+6.89*d(2)+31.36)}) * (0.16*d(3))\}^2 +$

$\{(\frac{(-0.35818*(-46.375-d(1))}{d(2)} - \frac{(d(3)*d(2)-d(3)*d(1)-d(3)*d(1))}{(d(4)*d(4))}) * (0.67*d(4))\}^2 +$

$\{(\frac{(d(3)*d(1)+16.15*d(3))}{(d(5)*d(5))}) * (0.62*d(5))\}^2]^{0.5}$

$+0.0098*[\{(\frac{10.39-2*d(5)}{d(1)*d(1)} + \frac{2*d(4)*\{d(4)+d(5)\}}{d(5)*d(5)}) * (0.09*d(1))\}^2 + \{(\frac{2.27*d(5)}{d(2)*d(2)}) +$

$\frac{2*d(1)+d(5)+0.99*d(3)-8.03}{(-21.21-d(2)+2.63*d(3))*(-21.21-d(2)+2.63*d(3))}) * (0.22*d(2))\}^2 +$

$\{(\frac{-2.63*(2*d(1)+d(5)+0.379*d(2))}{(-21.21-d(2)+2.63*d(3))*(-21.21-d(2)+2.63*d(3))}) * (0.16*d(3))\}^2) +$

$\{(\frac{2}{(-21.21-d(2)+2.63*d(3))} + \frac{(-12.4*d(5)+4*d(1)*d(4)+2*d(1)*d(5))}{d(5)*d(5)}) * (0.67*d(4)\}^2 + \{((\frac{-2.27}{d(2)}) +$

$(\frac{1}{(-21.21-d(2)+2.63*d(3)}) + (\frac{2}{d(1)}) + \frac{(-4*d(4)*d(1)*d(4)+12.4*d(4)*d(5)-2*d(1)*d(4)*d(5))}{(d(5)*d(5)*d(5))}) * (0.62*$

$d(5)\}^2]^{0.5}+0.023*[\{0.124*0.124*0.22*0.22*d(2)*d(2)\} + \{0.006*0.006*0.16*$

$0.16 * d(3) * d(3)\} + \{0.0075 * 0.0075 * 0.67 * 0.67 * d(4) * d(4)\} + \{0.000013 * 0.000013 * 0.62 * 0.62 * d(5) * d(5)\}]^{0.5}$

.... (Eq.5.11)

Where d(1),, d(2), d(3), d(4) and d(5) are size of coarse aggregate, amount of cement, water, fine aggregate and coarse aggregate respectively.

In order to minimize the cost ,equation (4) has been minimized the present study for the given constraints. The constraint function has been used as mentioned in Chapter 4.

Available range constraint

1) CA_{max}<Size of CA<CA_{min}
2) $Cemax<Ce<Cemin$
3) $FAmax<FA<FAmin$
4) $CAmax<CA<CAmin$
5) $Wamax<Wa<Wamin$

These values of lower [20 350 130 505 1015]and upper limit[40 410 195 865 1365]have been taken by the minimum and maximum values of the size of CA ,weight of cement, water, fine aggregate and coarse aggregate used .

5.4 RESULTS

Table 5.1 Obtained Robust Optimisation result.

Max agg size	Cement O.P.C (Kg/m3)	Water Content (Kg/m^3)	Fine Aggregate (Kg/m^3)	Coarse Aggregate (Kg/m^3)	Desired strength(Mpa)	Desired slump(mm)	Cost (USD)
40	367.62	183.33	864.99	1364.97	45.02	147.90	53.12

Using the experimental data, Robust optimization by Genetic Algorithm (GA) has been carried out by MATLAB 2014. The mixture design has been evaluated at maximum strength, maximum slump with lowest cost, which is presented in above Table . The optimisation result has been presented in Table 5.1. This is very much helpful to obtain optimum mix proportion for finding maximum strength and workability at lowest cost considering all the uncertainty.

Chapter 6

CONCLUDING REMARKS

6.1 GENERAL

In the present study concrete compressive strength and workability in terms of slump has been predicted by adopting - Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP) by considering two hundred of concrete mix design data.. having coarse aggregate size, cement, water, fine aggregate and coarse aggregate. Among these eighty five percent data have been used for training purpose and fifteen percent data have been used for testing purpose in all the five machine learning methods. In addition to that, for validation of the five methodologies, experimental investigation have been conducted for fifteen numbers of different concrete mixes. In addition to that In addition to that, multi objective optimisation and robust optimisation have been carried out using the basis equations obtained from GEP to determine the proportions of concrete mixtures for maximum concrete strength and workability at lowest cost. The major findings from the present study are as follows

6.2 MAJOR FINDINGS

1) The R value obtained for Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP) are 0.80,0.83,0.60,0.86,0.71 for compressive strength and for slump 0.54,0.60,0.33,0.85,0.40 respectively for training & 0.80,0.87,0.62,0.99,0.76 for strength and for slump 0.80,0.98,0.61,0.99,0.71 respectively for validation. It clearly depicts ANFIS yield best results among all the five methods.
2) The RMSE value obtained for Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS) and Genetic Expression Programing (GEP) are 3.02, 2.56, 4.65, 2.11, 3.36 for compressive strength and for slump 2.96, 2.99, 4.1, 1.95, 3.82 respectively for training & for compressive strength and 3.01,2.56,4.65,2.11,3.66

4.94,6.01,2.34,2.49,1.94 for slump respectively for validation which clearly signifies that ANFIS is best predictive models.

3) Study demonstrates that the deterministic optimization of concrete design mix using Genetic Algorithm (GA) can be carried out successfully by using basis functions generated by Genetic Expression Programing (GEP) for obtaining optimum concrete mix proportion to determine maximum compressive strength and slump at lowest cost.
4) The study also reveals that robust optimization of concrete design mix by considering all the uncertainty using Genetic Algorithm (GA) depending on the basis functions generated by Genetic Expression Programing (GEP), can be used to predict the maximum compressive strength and slump at lowest cost.

6.3 DRAW BACK OF THE PRESENT STUDY

1) The study has been carried out using less number of data.

2) In concrete mix proportion admixture has not used.

3) Gradation of coarse and fine aggregate has not been considered.

6.4 FUTURE SCOPE

1) More number of data should be used

2) Most advanced prediction method if any may be used any future.

3) Gradation, concrete admixture should be incorporated in future work.

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