

# Strength Prediction of High Early Strength Concrete by Artificial Intelligence

Panga Narasimha Reddy, Javed Ahmed Naqash

**Abstract:** The evaluation of the combined effect of alccofine, chemical admixture and curing age to compressive strength prediction of High early strength concrete (HESC) in view of its increasing application in construction industries, is a novelty. Concrete is generally a mixture of different materials and it is a difficult task to predict the strength of HESC. However, it seems that a soft computing could save time and money. In this study, fuzzy logic (FL) and artificial neural network (ANN) models were developed to predict the strength of High Early Strength Concrete. This research paper presents the effect on strength of the concrete with alccofine (i.e. 25%) as a constant replacement of cement for all concrete mixes and several non-chloride hardening accelerator ratios (0-1.8) for different water to binder contents (i.e. 0.38, 0.4 and 0.45). The compressive strength was evaluated at 3, 7 and 28 days resulting in a total of 36 data sets that were used in FL and ANN. The results of the measured compressive strength were compared to values predicted from FL and ANNs. The results showed that ANN can be used successfully to strength prediction of high early strength concrete wherein the ANN model performed better than the FL model. The extrapolation capacity of FL and ANN was satisfactory.

**Index Terms:** high early strength concrete, artificial neural network, fuzzy logic, compressive strength, non-chloride hardening accelerator, prediction

## I. INTRODUCTION

Design of HESC requires more knowledge as well as material experience the normal strength concrete as far as physical properties and chemical compounds are considered [1]. Generally, any of the following method can be used to accelerate the hardening of concrete: (a) utilization of type III cement (ASTM C 150), (b) use of supplementary cementitious material, (c) reduction of water-cement ratio, (d) application of heat for plastic concrete, (e) employing insulation forms and (f) addition of chemical admixtures [2]. A complex design procedure can conduct to more trails to determine whether the desired properties can be achieved or not thereby not only involving the risk of material wastage but also a lot of manpower and time loss leading to higher concrete costs. Hence, few methods are in artificial intelligence i.e. ANN and FL are very useful in predicting the compressive strength of concrete that contributes to minimize the no. of trials. ANN is a one of the tool in artificial intelligence has been used in recent years to solve difficulties in civil engineering. Akkurt.et.al (2004) have used fuzzy logic and ANN to predict the cement strength at

28 days with input data as total alkali content, SO<sub>3</sub>, Blaine surface area and C<sub>3</sub>S [3]. Noorzai.et.al (2007) concentrated on developing artificial neural networks to predict strength of concrete. He used six inputs (i.e. cement, water, silica fume, plasticizers, coarse and fine aggregate) to predict the strength by using ANN. The results showed that ANNs have strong potential as a feasible method to predict strength of the concrete. Atici.et.al (2009) calculated the concrete strength contains blast furnace slag and fly-ash by using an ANN and multiple regression analysis (MRA). The results showed that ANNs performed better than MRA. Sakshigupta.et.al (2013) used an ANN to predict the concrete strength with Nano-silica. He concluded that the strength of concrete can be predicted by using ANN without experiments in a short time with acceptable error [4]. Duan.et.al (2013) used an ANN to predict the concrete strength using 14 input parameters of recycled aggregate concrete. He investigated that the artificial neural network had good potential as a compressive strength prediction tool.

There are many studies on high early strength concrete. In addition, there are many studies on the effect of alccofine and chemical admixtures on compressive strength, but a predict model for high early strength concrete has not been investigated. The aim of the research is to develop models of FL and ANN for the prediction of compressive strength of HESC mixes with chemical admixture and curing age. The results obtained from compression tests were compared to the predicted results.

## II. MATERIALS

### A. Cement

The cement used was 43 grade of OPC with a specific gravity of 3.11 and it has been tested according to Indian specification [5].

### B. Alccofine

Alccofine is a micro-fine material and easy to mix in the concrete. Alccofine 1203 was used conforming to ASTM C989-1999.

### C. Calcium nitrite (Non-chloride accelerator)

In the present research, Master set AC100 composed primarily of calcium nitrate was used as Non-chloride hardening accelerator conforming to ASTM C494: Type C.

### D. Aggregate

Crushed rock passing through 20 mm sieve confirming BIS: 383-2016 was used as a coarse aggregate. Locally available river sand, passing through a sieve of 4.75 mm was used as a fine aggregate under grading Zone II conforming BIS: 383-1970 [6].

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## III. EXPERIMENTAL WORK

Cube specimens of size 15 cm were prepared and cured at 23° C in water up to the test age. Three different W/B ratios employed were 0.38, 0.40 and 0.45. The compressive strength of HESCs mainly depend upon several factors i.e. the dosage of chemical admixtures, temperature, the mixing process, water-cement ratio, type of cement and curing condition. In this study, the replacement of cement with alccofine was 25% for all mixes and the varying proportion of Non-chloride accelerator was added to the concrete mixes in order to evaluate the strength of cubes at 3, 7 and 28 Days for different water to binder ratios (i.e. 0.38, 0.4 and 0.45) as shown in Table 1. From results, it was clearly seen that the strength of concrete enhanced with the addition of non-chloride accelerator at different water to binder ratios.

TABLE 1

Compressive strength data of HESC mixes

W/B	%NCHA	Compressive Strength (MPa)		
		3 Days	7 Days	28 Days
0.45	0	13.42	19.52	35.67
	0.65	17.29	21.67	35.92
	0.85	19.06	23.18	36.97
	1.05	18.96	22.64	36.72
0.40	0	16.20	26.89	45.82
	1.00	20.49	32.02	47.65
	1.25	22.90	35.24	46.79
0.38	1.50	22.57	34.00	46.46
	0	23.98	32.82	51.73
	1.60	30.23	36.52	55.61
0.38	1.70	31.72	37.28	54.53
	1.80	28.50	37.43	53.75

## IV. DEVELOPMENT OF FUZZY LOGIC MODEL

The theory of fuzzy logic, developed by Zadeh, has been applied to a variety of construction and scientific research fields. Fuzzy logic produces outputs for certain inputs on membership functions through mathematical operations and rules with IF preconditions and THEN consequences [7]. It only needs to set up a simple control system based on expert knowledge. Since there are no complicated mathematical analysis and system delay time in the process of operation is reduced, its impact on the control effects can be expected to be reduced [8]. Moreover, as the fuzzy control method is easy to understand and it can be adapted to the current scenario [9].

The fuzzy component forms fuzzy sets for variables of input-output using the membership function. The membership functions of fuzzy may take many forms, but there are two types of membership function in practical applications: (a) Triangular and (b) Gaussian. From the past,

researchers have commonly used triangular membership functions. The benefit of the triangular membership function is that it can be easily implemented in the MATLAB toolbox [10].

The developed fuzzy logic model was used in this part of the study to predict the concrete strength data from experiments. For this study, the fuzzy rules were written. From the Figure 1 fuzzy model has been developed using the fuzzy logic toolbox in MATLAB

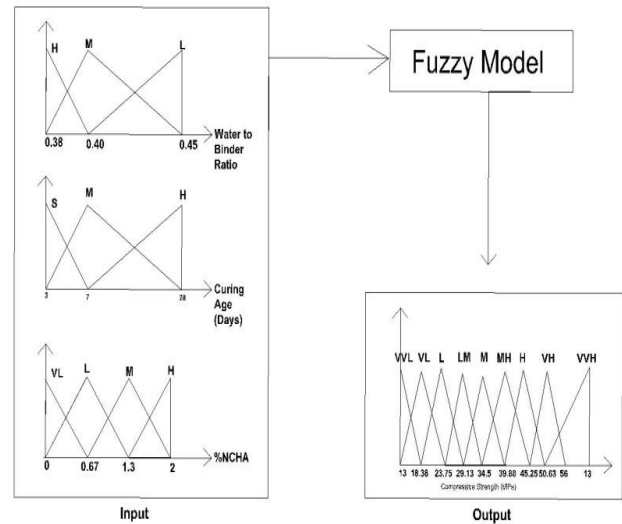


Fig. 1. Membership functions

The fuzzy logic model had three inputs and one output parameter. The input parameters were water to binder ratio, percentage of non-chloride hardening accelerator and curing age. The compressive strength was the model output variable. Figure 1 shows the membership functions used for the output and input parameters in the FL modeling. Fuzzy rules for predicting compressive strength were written which are shown in Table 2 below.

TABLE 2  
The Fuzzy rule sets

Rule	W/B	%NCHA	Age	CS
------	-----	-------	-----	----

1	L	VL	S	VVL
2	L	VL	M	VL
3	L	VL	L	M
4	L	L	S	VL
5	L	L	M	L
6	L	L	L	M
7	Not H	L	L	M
8	Not H	M	S	LM
9	Not M	M	M	M
10	L	M	L	H
11	L	H	S	L
12	Not H	H	M	M
13	Not H	H	L	H
14	M	VL	Not L	L
15	M	L	S	L
16	M	L	M	LM
17	M	M	S	M
18	M	M	M	MH
19	Not M	M	L	MH
20	M	Not L	S	VL
21	M	Not L	M	M
22	M	Not L	L	H
23	M	Not H	L	H
24	H	VL	S	L
25	H	VL	M	M
26	H	VL	L	VH
27	H	L	L	VH
28	H	H	M	H
29	H	VL	Not L	L
30	H	H	L	VH
31	H	H	L	VVH
32	H	Not H	L	VVH

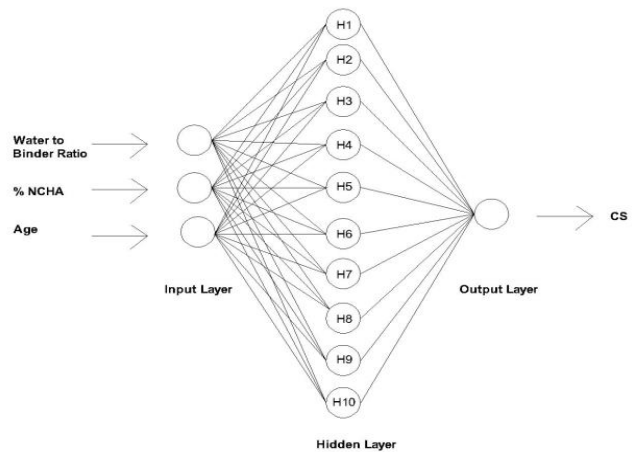
**V. DEVELOPMENT OF ANN MODEL**

Using the Artificial Neural Network, developed model will be able to predict the compressive strength of high early strength concrete. The Artificial neural network contains a set of well-arranged elements called neurons, which generate output from a few inputs. Feedforward networks are commonly named as multilayer network model. The multilayer network model consists of an input layer, a hidden layer followed by an output layer [11]. Input patterns of neuron are received from external environment and further transferred to the first layer of neuron [12]. The input layer of neuron is multiplied by their respective weights depending on the liking of neuron to the hidden layer. Summation of weighted is carried out in hidden layer.

A combined input value like hyperbolic tangent or sigmoid is passed through a non-linear transfer function to obtain the

neuron output. These output values are input to the neurons on the next layer. The output layer neurons finally generate the network model for getting optimum values [13].

The artificial neural network model is presented in this study to predict the effect of non-chloride hardening accelerator on the strength of concrete. The problem is suggested with three input parameters and one output parameter for network models. The parameters such as water to binder ratio, percentage of the non-chloride accelerator and curing age have been chosen as input parameters. The compressive strength of concrete was the output variable. The number of inner neuron layers was determined by the trial and error method. The selected model architecture is shown in Figure 2.



**Fig. 2. The selected model architecture**

It is very important to determine the optimum number of hidden layer neurons plays a crucial role to estimate a parameter with the help of artificial neural networks. However, it is very difficult to find out number of hidden layer neurons should be employ to solve a particular problem with the help of literature. The most excellent process to calculate the number of hidden layer neurons is to begin the process starting from adding a few numbers of neurons and then increases accordingly [14]. The complete process must be monitored in order to check network model performance for every hidden layer neuron with the predefined performance. The same procedure continues till the error become too small or insignificant. The parameter values used in ANN model can be outlined as one output layer neutrons, three input layer neurons, ten hidden layer neurons and one hidden layer.

**VI. CROSS-VALIDATION**

In this research, statistical analysis involving the mean square error (MSE), the mean absolute relative error (MARE) and the coefficient of correlation (R) were conducted for cross-validation of the model as shown in Equations (1), (2) and (3) respectively [15]. Lesser Mean square error represents accurate estimation.

$$MSE = \frac{|\sum_{i=1}^N (CS_{Experimental} - CS_{Predicted})|}{N} \dots(1)$$



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$$MARE = \frac{1}{N} \sum_{i=1}^N \frac{(CS_{Experimental} - CS_{Predicted})}{CS_{Experimental}} * 100 \quad \dots(2)$$

$$MSE = \frac{\sum_{i=1}^N (CS_{Experimental}) * (CS_{Predicted})}{\sqrt{\sum_{i=1}^N CS_{Experimental}^2} * \sqrt{\sum_{i=1}^N CS_{Predicted}^2}} \quad \dots(3)$$

## VII. RESULTS AND DISCUSSION

As stated earlier, FL and ANN are used extensively as a part of artificial intelligence technique, to predict the strength of HESC mixes containing non-chloride accelerator. Comparison of predicted and experimental strengths of HESC versus data samples for testing, training and validation are shown in Figure 4. However, Figure 4 shows that the network model predicts the strength of non-chloride concrete with R<sup>2</sup> of 0.985, 0.999 and 0.922 respectively, in which training, validation and test data were compiled against predicted strength data with the ANN model. In addition, Figure 5 shows that the FL model predicts compressive strength of HESC with R<sup>2</sup> at 0.992.

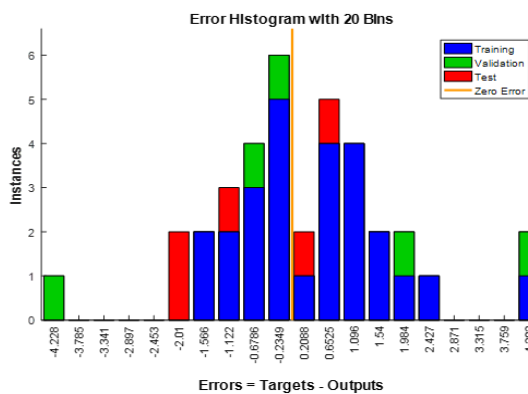
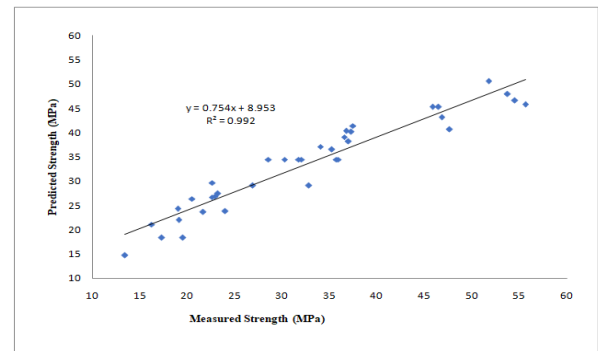
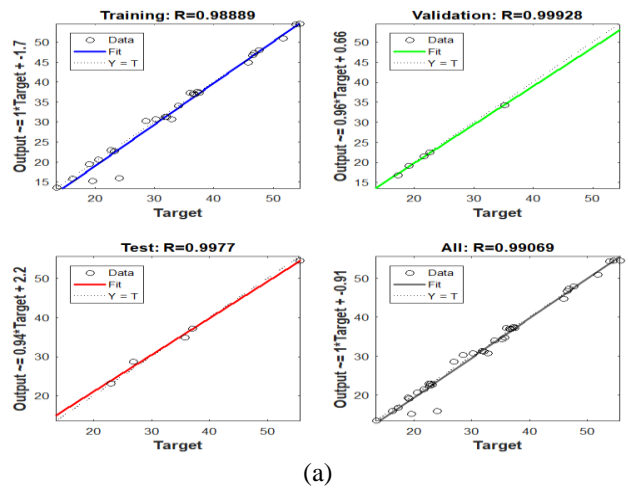


Fig. 3. The instances Vs Error results between targets and outputs (ANN)

The error ranged from -4.228 to 4.202 for input variables in testing, training and validation. Moreover, the values used for testing, training and validation with errors are more important than the other values shown in Figure 3.

Comparison of Figures 4 and 5 shows that for artificial neural network model had R-value slightly higher than the fuzzy logic model, indicating a better prediction by the artificial neural network than the fuzzy logic model.

For objective comparison of model performance error, MSE, MARE and R are shown in Table 3 for each prediction method.



(a) Training, Validation, test and all results of ANN;  
(b) Correlation of the predicted and measured strength for FL modeling

TABLE 3  
Summary of coefficients for the prediction models

Model	MSE	MARE	R
FL	0.967	6.335	0.992
ANN	0.338	1.450	0.998

In this study, an attempt has been made to demonstrate the influence of non-chloride accelerator on the strength of concrete versus time using the FL and ANN models. Table 4. shows the predicted and measured strength values by FL and ANN. Wherein ANN shows better results in comparison to FL. Since the model developed using ANN model predicts accurately the compressive strength of HESC containing a non-chloride accelerator, hence it can be used to evaluate the effects of non-chloride hardening accelerator on the compressive strength of HESC [16].

## VIII. CONCLUSION

The following conclusions were drawn from this study FL and ANN can be an alternative approach for the evaluation of the effect of non-chloride hardening accelerator on the compressive strength of HESC.

FL and ANN models are efficient for predicting the compressive strength of high dosage alccofine concrete with non-chloride hardening accelerator. R<sup>2</sup> comparison between FL and ANN model showed that ANN results better than FL results. FL and ANNs models have a good capacity of extrapolation in predicting compressive strength of High dosage alccofine concrete.

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TABLE 4. Comparison of predicted and measured strength results by ANN and FL

W/B Ratio	NCHA	Measured Values			ANN Model Values			FL Model Values		
		3	7	28	3	7	28	3	7	28
0.45	0	13.42	19.52	35.67	13.56	15.58	34.87	14.70	18.40	34.50
	0.65	17.20	21.67	35.92	16.82	21.50	37.27	18.40	23.60	34.50
	0.85	19.00	23.18	36.97	19.17	22.69	37.15	22.00	27.40	38.20
	1.05	18.90	22.60	36.72	19.42	22.47	36.89	24.30	29.70	40.40
0.40	0	16.20	26.89	45.82	15.87	28.65	44.80	21.10	29.10	45.30
	1.00	20.49	32.02	47.65	20.62	31.17	47.90	26.40	34.50	40.70
	1.25	22.90	35.24	46.79	23.05	35.32	47.27	26.90	36.50	43.20
	1.50	22.57	34.00	46.46	22.97	34.05	46.73	26.70	37.10	45.30
0.38	0	23.98	32.82	51.73	15.98	30.73	50.89	23.80	29.10	50.60
	1.60	30.23	36.52	55.61	30.71	37.10	54.54	34.50	39.10	45.80
	1.70	31.72	37.28	54.53	31.31	37.53	54.49	34.50	40.20	46.60
	1.80	28.50	37.43	53.75	30.28	37.31	54.44	34.50	41.40	48.00

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