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Prediction Of Compressive Strength Of Concrete With Different Aggregate Binder Ratio Using ANN Model

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Abstract : Compressive strength mainly depends on the ingredients of concrete mix design. In this study , conventional methods used to find out the 28 and 90 days compressive strength of concrete, in which the cement content is replaced by 30%,40% and 50% of class C fly ash . The aggregate binder ratio was varies 1.50, 1.75 and 2.00 and the water binder ratio was vaired 0.35, 0.40, 0.45 and 0.50. Artificial neural network can be effectively adopted for predicting the compressive strength of fly ash concrete. MATLAB soft ware was used to predict the results using ANN. ANN has been trained with about 70% of the total data sets and tested with about 30% of the total data sets. It is observed that the predicted values of maximum load, facture energy, critical stress intensity factor are in good agreement with those of the experimental values.

Key words : Compressive strength- Class C fly ash- Aggregate binder ratio- ANN

1. Introduction

An artificial neural network (ANN) is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network (NN) consists of group of artificial neurons interconnected to each other, and it processes information by using a connectionist approach to computation. They are mostly used to model complex relationships between inputs and outputs or to find patterns in data.

According to Rumelhart et al[1]. there are eight components of a parallel distributed processing model in neural network. These eight components are the processing units or neurons, the activation function, the output function, the connectivity pattern, the propagation rule, the activation rule, the learning rule and the environment in which the system operates. Neural networks are a series of interconnected artificial neurons which are trained by using available data to understand the underlying pattern. They consist of a series of layers with a number of processing elements within each layer. The layers can be divided into input layer, hidden layer and output layer. Information is provided to the network through the input layer, the hidden layer processes the information by applying and adjusting the weights and biases and the output layer gives the output Karna and Breen[2]. Each layer will have a number of processing units called neurons. The inputs are weighted to determine the amount of influence it has on the output, input signals with larger weights influence the neurons to a higher extend. An activation function is then applied to the weighted inputs, to produce an output signal by transforming the input. The input can be a single node or it may be multiple nodes depicting different parameters where each of the input nodes acts as an input to the hidden layer. The hidden layer consists of a number of neurons/nodes which calculate the weighted sum of the input data. Zong, Gung and Yun[3] utilized an automatic knowledge acquisition system, based on neural networks, to design concrete mixtures. In a later work, Gung and Zong proposed a method to predict 28-day compressive strength by using multi layer feed forward neural networks.. Yeh [4] was developed a strength based Artificial Neural Network (ANN) model, which was found to be more accurate than the one based on regression analysis. It was also discovered that his ANN model gave the detailed effects of the proportions of each variable from the concrete mixtures. Lai and Serra[5] were developed a model, based on neuro computing, for prediction of the compressive strength of cement conglomerates. Dias and Pooliyadda[6] were used back propagation neural network models to predict the strength and slump of ready mixed ordinary concrete and high strength concrete, in which chemical admixtures were used.

2.Experimental work

2.1Materials used

Cement*:* Ordinary Portland cement of 53 grade available in local market was used. The specific gravity and fineness of cement were 3.14 and 97% respectively.

Coarse Aggregate**:** Crushed angular granite of 12 mm size from a local source was used as coarse aggregate. The values of specific gravity and fineness modulus of coarse aggregate were 2.68 and 7.66 respectively.

Fine Aggregate**:** River sand available in local source comprising of zone-III was used as fine aggregate. The fine aggregate having specific gravity of 2.61 and fineness modulus 2.51 respectively.

Fly ash: Fly ash was procured from Neyveli Lignite Corporation Limited, Neyveli Tamilnadu. The fly ash was collected from this plant fall under Class C category. The fly ash was used to replace in various percentages of weight portion of cement content. The specific gravity of fly ash is 2.52

Water **:** Potable water was utilized for casting of all concrete specimens.

2.2Concrete Mix Design : Absolute volume method was used to find out the concrete mix proportions. Absolute volume proportioning method is accurate method and involves use of specific gravity values for all the ingredients of mix to calculate the absolute volume, each will occupy in a unit volume of concrete.

2.3**Compressive strength :** Compression strength test was conducted on hardened concrete at the ages of 28 and 90 days of curing. The cubes were taken from the curing tank and air dry for half an hour before testing of specimens. The cubical specimens were placed under the compression testing machine of capacity 2000 kN and tested available in the structural engineering lab.

3.Artificial Neural Network based Analysis

The purpose of this investigation is to check the applicability of the ANN –based methodology to predict the compressive strength. MATLAB software is used in developing the ANN robust models.

3. 1 Input and Output : Experimental studies indicated that the strength is influenced by age, water binder ratio, aggregate binder ratio and % of fly ash replacement. These four parameters are used as input terminals in the input layer. The outputs of the ANN are compressive strength (f_{ck}), Totally 145 data sets obtained from the concrete mixes.

3.2 Architecture on ANN: Back – propagation ANN architecture is used in the present study. The first hidden layer consists of four/five neurons and the second hidden layer consists of three neurons. Thus, three individual models have been developed for three outputs ((f_{ck}). In the present study, four layers have been used that includes one input layer, two hidden layers and one output layer. The transfer functions 'tansig' is used in between the input and first hidden layers; 'logsig' is used in between the first hidden layer and second hidden layer; 'logsig' is again used in between second hidden layer and output layer. The transfer functions and the number of nodes in all the layers remain same for all the four models. The algorithm of the transfer functions used in MATLAB for tan and log sigmoidal functions are given in equations 1 and 2 respectively (Demuth et al.,[7])

Tansig (n) = 2/(1+exp(-2*n))-1 (1)

Logsig(n) = 1 / (1 + exp(-n)) (2)

3.3 Transfer Function: Depending upon the type of input data and the output required, there are five types of activation functions used to transform input signal into output viz., linear function, threshold function, sigmoid function, hyperbolic tangent function and radial basis function (Roshan,[8]). For the following sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurones than do linear or threshold units, but all three must be considered rough approximations. The sigmoid function transforms the input into a value between 0 and 1. The log sigmoid function transforms any value of the input data from positive infinity and negative infinity to a value between zero and one

$$f(s) = \frac{1}{(1+\exp(-s)} \tag{3}$$

where, s is the weighted sum of the inputs from the previous layer to a particular neuron/node obtained from equation and *f(s)* is the log sigmoidal function. The function logsig generates outputs between zero and one as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks can use the tan-sigmoid transfer function tansig (Demuth et al) .

4.Training of ANN : About 70% of the total data sets are presented to ANN for training and remaining data sets are used for the validation of the trained model. Thus, 102 data sets are used for training and 43 for testing. The architecture of ANN is shown in Fig. 1 for compressive strength

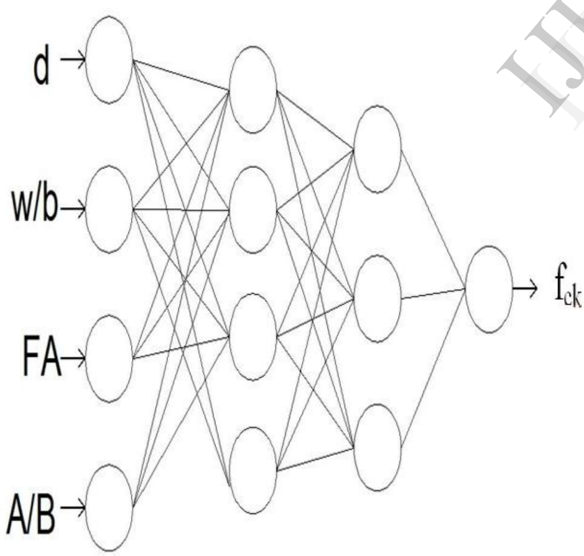

Fig. 1 ANN Architecture for Compressive strength

The data that form an input vector have different quantitative limits as shown in Table 6.1. Normalization of the data is to be carried out before presenting the input patters to ANN. Equation .3 is used for the linear normalization of the data to the values between 0 and 1.

$$x_i^n = \frac{x_i^a - x_i^{\min}}{x_i^{\max} - x_i^{\min}} \tag{4}$$

where, x_i^a and x_i^n are the ith components of the input vector before and after normalization, respectively, and $x_i^{\max}$ and $x_i^{\min}$ are the maximum and minimum values of all the components of the input vector before the normalization.

The training phase of ANN is converged at about 200 iterations or epochs forv (f_{ck}) 600 epochs in case of (σ_a) and (σ_b). The variation of the mean square error aginst the number of iterations for the training models are shown in Figs. 4.8 to 4.10.

Table 1 : Test Data

S.No	Age (days)	W/b ratio	% Fly ash	A/B ratio	Comp.strength (MPa)
1	28	0.35	30	1.5	50.4
2	28	0.35	30	1.5	53.58
3	28	0.4	30	1.5	43.32

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4	28	0.4	30	1.5	50.8
5	28	0.5	30	1.5	43.52
6	28	0.5	30	1.5	40.34
7	90	0.35	30	1.5	60
8	90	0.35	30	1.5	72
9	90	0.4	30	1.5	58.63
10	90	0.4	30	1.5	57.62
11	90	0.5	30	1.5	43.2
12	90	0.5	30	1.5	48.9
13	28	0.35	40	1.5	49.89
14	28	0.35	40	1.5	45.94
15	28	0.4	40	1.5	43.16
16	28	0.4	40	1.5	41.27
17	28	0.5	40	1.5	33.4
18	28	0.5	40	1.5	41.47
19	28	0.5	40	1.5	40.32
20	90	0.35	40	1.5	59.7
21	90	0.4	40	1.5	61.3
22	90	0.4	40	1.5	62.5
23	90	0.5	40	1.5	51
24	90	0.5	40	1.5	52.03
25	28	0.35	50	1.5	40
26	28	0.35	50	1.5	47.73
27	28	0.4	50	1.5	33.4
28	28	0.4	50	1.5	42.6

29	28	0.4	50	1.5	39.16
30	28	0.5	50	1.5	34.31
31	28	0.5	50	1.5	39.53
32	90	0.35	50	1.5	48.5
33	90	0.35	50	1.5	46
34	90	0.35	50	1.5	49.3
35	90	0.4	50	1.5	52.4
36	90	0.4	50	1.5	52.86
37	90	0.5	50	1.5	49
38	90	0.5	50	1.5	49.54
39	28	0.35	30	1.75	41.1
40	28	0.35	30	1.75	42.08
41	28	0.35	30	1.75	38.85
42	28	0.4	30	1.75	29.71
43	28	0.4	30	1.75	35.63
44	28	0.5	30	1.75	33.6
45	28	0.5	30	1.75	31.68
46	28	0.5	30	1.75	30.72
47	90	0.35	30	1.75	69.12
48	90	0.35	30	1.75	65.28
49	90	0.4	30	1.75	56.6
50	90	0.4	30	1.75	68.13
51	90	0.4	30	1.75	64.27
52	28	0.35	40	1.75	36.7
53	28	0.35	40	1.75	32.55

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54	28	0.35	40	1.75	35.7
55	28	0.4	40	1.75	35.7
56	28	0.4	40	1.75	39.6
57	28	0.4	40	1.75	34.68
58	28	0.5	40	1.75	28.71
59	28	0.5	40	1.75	30.45
60	28	0.5	40	1.75	28.56
61	90	0.35	40	1.75	56.6
62	90	0.4	40	1.75	59.4
63	90	0.4	40	1.75	56.1
64	90	0.5	40	1.75	56.73
65	90	0.5	40	1.75	60.39
66	28	0.35	50	1.75	27.9
67	28	0.35	50	1.75	29.7
68	28	0.35	50	1.75	32.4
69	28	0.4	50	1.75	34.41
70	28	0.4	50	1.75	37.74
71	28	0.4	50	1.75	38.85
72	28	0.5	50	1.75	26.25
73	90	0.35	50	1.75	51.28
74	90	0.35	50	1.75	56.16
75	90	0.4	50	1.75	54.94
76	90	0.4	50	1.75	57.42
77	90	0.4	50	1.75	61.64
78	90	0.5	50	1.75	39.1

79	28	0.4	50	2.00	43.9
80	28	0.4	50	2.00	46.73
81	28	0.4	50	2.00	51
82	28	0.45	40	2.00	37.2
83	28	0.45	40	2.00	39.7
84	28	0.45	40	2.00	43.2
85	90	0.35	40	2.00	55
86	90	0.35	40	2.00	48.4
87	90	0.4	40	2.00	54.6
88	90	0.4	40	2.00	59.6
89	90	0.4	40	2.00	51.4
90	90	0.45	40	2.00	40
91	90	0.45	40	2.00	46.5
92	90	0.45	40	2.00	42.6
93	90	0.5	40	2.00	41.5
94	90	0.5	40	2.00	44.2
95	28	0.4	50	2.00	34.4
96	28	0.4	50	2.00	36.4
97	28	0.4	50	2.00	40
98	28	0.45	50	2.00	28
99	28	0.45	50	2.00	30.6
100	28	0.5	50	2.00	24.75
101	28	0.5	50	2.00	27
102	28	0.5	50	2.00	23.5
103	90	0.35	50	2.00	38.8

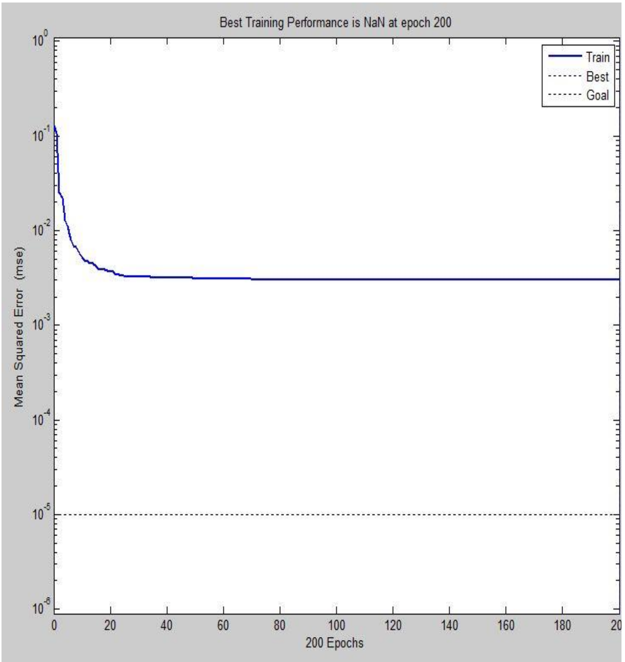

Fig. 2 Training performance for f_{ck}

By considering this minimum error, it can be concluded that predictions by ANN model is very good and it is able to establish the relationship between the input parameters and the output parameters ((f_{ck}).

5.Testing of ANN

On successful completion of ANN training with 103 datasets, the model is verified with remaining 43 testing datasets. The results are presented in Table 2. The output vector obtained from ANN model is a normalized data and hence, the normalized data is reverted to its actual value by using of equation 5.

$$x_i^a = x_i^n\left(x_i^{\max} - x_i^{\min}\right) + x_i^{\min} \tag{5}$$

where, x_i^n is the normalized result obtained after the test for the ith component. x_i^a is the actual result obtained for ith componenet, and $x_i^{\max}$ and $x_i^{\min}$ are the maximum and minimum values of all the compoents of the corresponding input vector before the normalization.

The value of coefficient of correlation (R) is determined by using the following formula

$$R = \frac{\sum_{i=1}^{n}\left(E_{ai} - \overline{E}_a\right)\left(E_{pi} - \overline{E}_p\right)}{\sqrt{\sum_{i=1}^{n}\left(E_{ai} - \overline{E}_a\right)}\sqrt{\sum_{i=1}^{n}\left(E_{pi} - \overline{E}_p\right)}} \tag{6}$$

where, E_{ai} and E_{pi} are the actual and predicted values, respectively, $\overline{E}_a$ and $\overline{E}_p$ are mean of actual and predicted E values corresponding to n patterns.

From Fig.3, it can be observed that the predicted values of maximum load, facture energy, stress intensity factor and critical crack tip opening displacement are in good agreement with those of the experimental values. The result is converged at 1000 epochs in all cases with error value of 5.44e-5, 0.000198, 1.90e-5 and 0.000105 for P_{max}, G_F, K_{Ic} and $CTOD_C$ respectively. The coefficient of determination, R^2 is 0.99908 for P_{max}, 0.99676 for G_F, 0.99539 for K_{IC} and 0.99503 for $CTOD_C$.

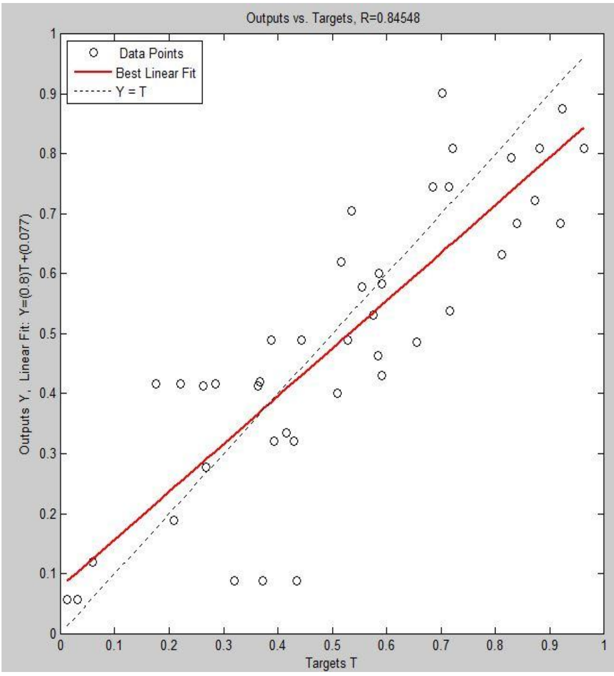

Fig. 3 Predicated vs experimental ((f_{ck}) (R =0.8455)

Table 2 Test Data/predicted for Compressive strength

S. No	Age (days)	W/b ratio	% FA	A/B ratio	Compressive strength (MPa)	
					Actual	Predicted
1	28	0.35	30	1.5	58.27	39.15
2	28	0.5	30	1.5	36.27	30.19
3	90	0.4	30	1.5	62.85	45.73
4	28	0.5	30	1.5	41.1	30.19
5	90	0.35	30	1.5	68.3	63.18
6	90	0.5	30	1.5	51.84	33.79
7	28	0.35	40	1.5	52.17	31.46
8	28	0.4	40	1.5	43.7	24.56
9	90	0.35	40	1.5	58.2	53.85
10	90	0.35	40	1.5	56.7	53.85
11	90	0.4	40	1.5	63.7	57.37
12	90	0.5	40	1.5	50.4	41.89
13	28	0.35	50	1.5	41.28	30.62
14	28	0.5	50	1.5	36.53	20.44
15	90	0.4	50	1.5	51.9	43.53
16	90	0.5	50	1.5	51.4	38.59
17	28	0.4	30	1.75	33.66	34.19
18	90	0.5	30	1.75	58.5	58.48
19	90	0.5	30	1.75	70.2	58.48
20	90	0.5	30	1.75	66.3	58.48
21	90	0.35	40	1.75	68.13	49.51
22	90	0.35	40	1.75	64.27	49.51
23	90	0.4	40	1.75	49.5	51.02
24	28	0.5	50	1.75	25.01	24.78
25	28	0.5	50	1.75	24.12	24.78
26	90	0.35	50	1.75	48.56	44.92
27	90	0.5	50	1.75	42.58	23.55
28	90	0.5	50	1.75	44.36	23.55
28	28	0.35	40	2.00	42.3	35.58
29	28	0.35	40	2.00	45	35.58
30	28	0.35	40	2.00	49.14	35.58
31	28	0.5	40	2.00	39	36.97

32	28	0.5	40	2.00	41.59	38.97
33	28	0.5	40	2.00	44.6	46.97
34	90	0.35	40	2.00	52.2	42.36
35	90	0.5	40	2.0	48.2	39.32
36	28	0.35	50	2.0	34.2	30.40
37	28	0.35	50	2.0	37.3	34.40
38	28	0.35	50	2.0	32	30.40
39	28	0.45	50	2.0	26.4	29.25
40	90	0.35	30	1.75	57.6	64.95
41	28	0.4	30	1.5	55.28	35.35
42	90	0.5	40	1.75	65.88	52.26

6.Conclusions

1) Towards development of ANN model, back-propagation training technique has been employed for updating the weights of each layer based on the error in the network output. The ANN architecture consists of one input, one output and two hidden layers. The sigmoidal transfer functions are used for squashing the weights between the layers.
2) Levenberg-Marquardt algorithm has been used for feed-forward back-propagation. Four ANN models have been developed by using MATLAB software for training and prediction of the three fracture parameters.
3) ANN has been trained with about 70% of the total data sets and tested with about 30% of the total data sets. It is observed that the predicted values of maximum load, facture energy, critical stress intensity factor and critical crack tip opening displacement are in good agreement with those of the experimental values.

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