

Concrete Mix Design Using Artificial Neural Network

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Abstract

Concrete mix design is a process based on sound technical principles for proportioning of ingredients in right quantities. This paper demonstrates the applicability of Artificial Neural Networks (ANN) Model for approximate proportioning of concrete mixes. For ANN a trained back propagation neural network is integrated in the model to learn experimental data pertaining to predict 7, 14 and 28-day compressive strength which have been loaded into a model, containing 55 concrete mixtures. The ANN model proposed is based on 5 input parameters such as cement, sand, coarse aggregate, and water and fineness modulus. The proposed concrete mix proportion design is expected to reduce the number of trials in laboratory as well as field, saves cost of material as well as labor and also saves time as it provides higher accuracy. The concrete designed is expected to have higher durability and hence is economical.

Keywords: concrete mix, artificial neural network (ANN), 7-days strength, 14-days strength, 28-days compressive strength, fineness modulus, activation function, modeling.

INTRODUCTION

Concrete is the most widely used construction material because of its flowability in most complicated form i.e. its ability to take any shape while wet, and its strength development characteristics when it hardens. Concrete production is a complex process that involves the effect of several processing parameters on the quality control of concrete pertaining to workability, strength etc. These parameters are all effective in producing a single strength quantity of compressive strength.

Artificial intelligence has proven its capability in simulating and predicting the behaviour of the different physical phenomena in most of the engineering fields. Artificial intelligence is receiving greater attention from the building industry to aid in the decision-making process in areas such as diagnostics, design, and repair and rehabilitation. In civil engineering, design of concrete mix is difficult and sensitive. The classical way for the determination of concrete mix design is based on uncertainty and depends on expert ideas.

Concrete is essentially a mixture which comprises of paste and aggregates. In concrete mix design and quality control, the uniaxial compressive strength of concrete is considered as the most valuable property, which in turn is

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influenced by a number of factors. The concrete mix design is based on the principles of workability of fresh concrete, desired strength and durability of hardened concrete which in turn is governed by water-cement ratio law. The strength of the concrete is determined by the characteristics of the mortar, coarse aggregate, and the interface. For the same quality mortar, different types of coarse aggregate with different shape, texture, mineralogy, and strength may result in different concrete strengths. There are various types of mixes such as nominal mix, standard mix and design mix. Nominal mixes are mixes of fixed cement-aggregate ratio which ensures adequate strength. However, due to the variability of mix ingredients the nominal concrete for a given workability varies widely in strength. The nominal mixes of fixed cement-aggregate ratio (by volume) vary widely in strength and may result in under- or over-rich mixes. For this reason, the minimum compressive strength has been included in many specifications. These mixes are termed standard mixes. In designed mixes the performance of the concrete is specified by the designer but the mix proportions are determined by the producer of concrete, except that the minimum cement content can be laid down. The common method of expressing the proportions of ingredients of a concrete mix is in the terms of parts or ratios of cement, fine and coarse aggregates. For e.g., a concrete mix of proportions 1:2:4 means that cement, fine and coarse aggregate are in the ratio 1:2:4 or the mix contains one part of cement, two parts of fine aggregate and four parts of coarse aggregate. The proportions are either by volume or by mass which provides two design methods. The concrete mix design can be carried out using IS standard code or US system of units. The tests for compressive strength are generally carried out at about 7, 14 or 28 days from the date of placing the concrete. The testing at 28-days is standard and therefore essential and at other ages can be carried out, if necessary.

ANNs have been applied to many civil engineering applications with some degree of success. ANNs have been applied to geotechnical problem like prediction of settlement of shallow foundations [1]. Many researchers have used ANN in structural engineering developing various neural network models [2-14].

Artificial Neural Network (ANN)

Neural networks are networks of many simple processes, which are called units, nodes, or neurons, with dense parallel interconnections. The connections between the neurons are called synapses. Each neuron receives weighted inputs from other neurons and communicates its outputs to other neurons by using an activation function. Thus, information is represented by massive cross-weighted

interconnections. Neural networks might be single-or multi layered. The single-layer neural networks present processing units of the neural networks, which take input from the outside of the networks and transmit their output to the outside of the networks; otherwise, the neural networks are considered multi layered. The basic methodology of neural networks consists of three processes: Network training, testing, and implementation. The connection weights of the neural network are adjusted through the training process, while the training effect is referred to as learning. Training of neural networks usually involves modifying connection weights by means of a learning rule. The learning process is done by giving weights and biases computed from a set of training data or by adjusting the weights according to a certain condition. In other words, neural networks learn from examples and exhibit some capability for generalization beyond the training data. Then, other testing data are used to check the generalization. The initial weights and biases joining nodes of an input layer, hidden layers, and an output layer are commonly assigned randomly. The weights and biases are changed for the output of networks to match required data values. As input data are passed through hidden layers, sigmoidal activation functions are generally used. During the training procedure, the data are selected uniformly. A specific pass is completed when all data sets have been processed. Generally, several passes are required to attain a desired level of estimation accuracy. The final sets of weights and biases comprise the long-term memory, or synapses, of respective events. Consequently, learning corresponds to determining the weights and biases associated with the connections in the networks. The back-propagation networks were used in this study. The learning mechanism of the back-propagation networks is a generalized delta rule that performs a gradient descent on the error space to minimize the total error between the actual calculated values and the desired ones of an output layer during modification of connection weights. In other words, a least mean square procedure is carried out to find the values of the connection weights that minimize the error function by using a gradient descent method.

Artificial neural networks (ANNs) are multi-layered, data driven, trainable systems. They have been successfully used to predict various concrete properties. Their prediction ability, however, depends, to a large extent, on the completeness and accuracy of the experimental database used in the training process. The multi-layer perceptron networks (MLP) are the most widely used ANNs in engineering applications due to their ability to implement nonlinear transformations for functional approximation problems and to map a given input(s) into a desired output(s). The main objective in building an ANN-based model is to train a specific network architecture using a comprehensive database to search for an optimum set of weights (connection strengths

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between its processing units) for which the trained ANN can predict accurate values of outputs for a given set of inputs from within the range of the training data. A neural network model requires no functional relationship among the variables, as is the case with most of other regression analysis techniques. A neural network based modelling algorithm requires setting up of different learning parameters (like learning rate, momentum), the optimal number of nodes in the hidden layer and the number of hidden layers so as to have a less complex network with a relatively better generalization capability.

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The use of ANN offers the following useful properties and capabilities:

- Non-linearity
- Input-output mapping
- Adaptivity
- Contextual information
- Uniformity of analysis and design

In this study, multilayer perceptron (MLP): a feed forward artificial neural network model is implemented. A large test database has been extensively surveyed and collected. It is then carefully examined to establish the input vectors and the desired output vectors. Finally, a new model is proposed based on ANN and then verified against experimental data which has been collected from different sources.

Materials used and Database

The main ingredients are given below which form a part of the input data along with fineness modulus:

- Cement
- Sand
- Coarse Aggregates
- Water

The success of the model to predict the 7, 14 and 28-days compressive strength depends upon the magnitude of the training data. A database of about 55 mixes was retrieved from various literatures to predict the results from ANN models. The predicted results obtained from neural network were compared with the experimental values obtained experimentally. The training of ANNs was carried out using pair of input vector and output vector. The complete list of data is given in the Table 1 for the inputs and Table 2 for the actual outputs. The ranges for the various parameters for ANN modeling have been listed in Table 3.

Table 1: Input data for the ANN modeling

S.No.	Cement (kg/m ³)	Sand(kg/m ³)	Coarse aggregates (kg/m ³)	Water (mL)	Fineness Modulus
1	462.5	721.5	1022.25	185	2.6
2	475	665	1054.5	190	2.4
3	475	698.25	1021.25	190	2.6
4	462.5	689.12	1031.38	185	2.4
5	462.5	721.5	1022.12	185	2.6
6	475	665	1054.5	190	2.4
7	475	698.25	1021.25	190	2.6
8	440.47	713.56	1057.13	185	2.4
9	440.47	739.99	1021.89	185	2.6
10	452.4	683.12	1054.09	190	2.4
11	452.4	764.56	1022.42	190	2.6
12	440.47	713.56	1057.13	185	2.4
13	440.47	739.99	1021.89	185	2.6
14	452.4	683.12	1054.09	190	2.4
15	452.4	764.56	1022.42	190	2.6
16	420.45	731.58	1055.33	185	2.4
17	420.45	765.22	1021.69	185	2.6
18	431.82	703.87	1057.96	190	2.4
19	431.82	742.73	1023.41	190	2.6
20	420.45	731.58	1055.33	185	2.4
21	420.45	765.22	1021.69	185	2.6
22	431.82	703.87	1057.96	190	2.4
23	431.82	742.73	1023.41	190	2.6
24	402.17	752.06	1065.75	185	2.4
25	402.17	780.21	985.32	185	2.6
26	413.04	726.95	1057.38	190	2.4
27	413.04	760	1024.34	190	2.6
28	402.17	752.06	1065.75	185	2.4
29	402.17	780.21	985.32	185	2.6
30	413.04	726.95	1057.38	190	2.4
31	413.04	760	1024.34	190	2.6

S.No.	Cement (kg/m ³)	Sand(kg/m ³)	Coarse aggregates (kg/m ³)	Water (mL)	Fineness Modulus
32	385.42	766.99	1056.05	185	2.4
33	385.42	796.82	1021.36	185	2.6
34	395.83	744.16	1056.87	190	2.4
35	395.83	775.83	1021.24	190	2.6
36	385.42	766.99	1056.05	185	2.4
37	385.42	796.82	1021.36	185	2.6
38	395.83	744.16	1056.87	190	2.4
39	395.83	775.83	1021.24	190	2.6
40	370	780.7	1054.5	185	2.4
41	370	821.4	1021.2	185	2.6
42	380	760	1056.4	190	2.4
43	380	790.4	1022.2	190	2.6
44	370	780.7	1054.5	185	2.4
45	370	821.4	1021.2	85	2.6
46	380	760	1056.4	190	2.4
47	380	790.4	1022.2	190	2.6
48	355.77	796.93	1056.64	185	2.4
49	355.77	825.39	1021.06	185	2.6
50	365.38	774.61	1055.94	190	2.4
51	365.38	807.49	1023.06	190	2.6
52	355.77	796.93	1056.64	185	2.4
53	355.77	825.39	1021.06	185	2.6
54	365.38	774.61	1055.94	190	2.4
55	365.38	807.49	1023.06	190	2.6

Table 2: Actual Output data for modeling

S.No.	7 days Strength	14 days Strength	28 days Strength
1	27.68	32.71	38.4
2	24.66	26.68	29.88
3	27.35	28.68	35.88
4	24.75	27.66	29.77
5	27.42	34.95	39.37

S.No.	7 days Strength	14 days Strength	28 days Strength
6	23.15	29.51	31.48
7	23.55	32.4	34.86
8	18.04	26.17	24.64
9	19.86	28.91	27.68
10	24.33	30.6	30.66
11	26.15	32.62	34.2
12	19.9	27.22	27.82
13	25.73	30.51	32.55
14	26.02	35.35	37.4
15	27.82	37.6	39.22
16	17.55	21.95	24.77
17	20.64	22.46	26.95
18	23.77	27.11	34.68
19	27.35	31.71	34.68
20	20	21.53	25.97
21	22.8	28.42	34.8
22	24.6	29.88	31.35
23	26	36.48	38.86
24	18.97	22.02	23.84
25	19.22	25.55	28.55
26	22.33	25.82	25.97
27	23.48	26.42	28.97
28	18.62	24.24	25.33
29	19.64	26.42	28.97
30	19.98	26.75	29.32
31	26.2	29.13	34.6
32	14.44	19.06	23.06
33	20.8	24.75	31.95
34	16.11	21.77	26.84
35	20.4	22.73	32.55
36	14.08	17.91	19.53
37	26	29.77	27.64
38	15.71	18.57	25.57

S.No.	7 days Strength	14 days Strength	28 days Strength
39	17.66	23.88	28.57
40	13.91	17.93	21.82
41	21.6	21.82	24.88
42	16.11	21.77	26.84
43	20.4	22.73	32.55
44	14.08	17.91	19.53
45	26	29.77	25.64
46	15.71	18.57	25.57
47	17.66	23.88	28.57
48	15.08	20.26	24.84
49	17.13	23	28
50	17.82	23.2	25
51	24.31	27.57	28.9
52	13.84	17.8	25.6
53	15.66	20.4	29.3
54	16.91	20.13	25.97
55	19.57	29.46	29.77

Table 3: Range of parameters in database

S.No.	Parameters	Range
1.	Cement	355.77-475.00
2.	Sand	665.00-825.39
3.	Coarse aggregates	985.32-1065.75
4.	Water	185-190
5.	Fineness modulus	2.4-2.6

Application of ANN

The multilayer perceptron approach has been used for developing of model. In the study the neural network is using back propagation training algorithm in this study. Back propagation is common method of training artificial neural networks so as to minimize the objective function. It is a supervised learning method and a generalization of the Delta rule. The activation function used is the log-sigmoidal function. A sigmoid curve is produced by

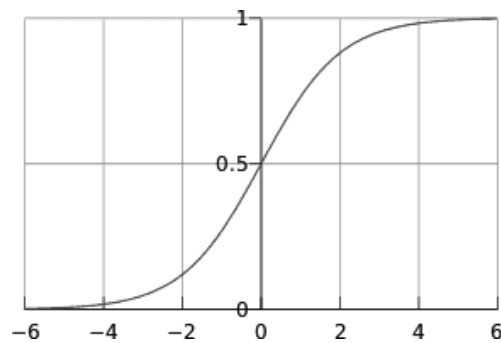


Figure 1: Logistic Curve

a mathematical function having an “S” shape. Often, sigmoid function refers to the special case of the logistic function shown below (Fig. 1) and defined by the formula:

$$S(t) = 1 / (1 + e^{-t})$$

The procedure for determining the output from the inputs is as given:

1. Sum up weighted inputs, i.e.

$$\text{Nod}_j = \sum_{i=1}^{\text{IN}} (\text{W}_{ij} x_i)$$

Where; Nod_j is summation for j th-hidden node,
 IN is total number of input nodes,
 W_{ij} is connection weight i th input and j th hidden node,
 x_i is normalized input at i th input node.

2. Transform the weighted input:

$$\text{Out}_j = 1 / (1 + e^{-\text{Nod}_j})$$

Where; Out_j is output from j th hidden node.

3. Sum up the hidden node outputs:

$$\text{Nod}_k = \sum_{j=1}^{\text{HN}} (\text{W}_{jk} \text{Out}_j)$$

Where; Nod_k is summation for k th output node,
 HN is total number of hidden nodes,
 W_{jk} is connection weight between j th hidden and k th output node.

4. Transform the weighted sum:

$$\text{Out}_k = 1 / (1 + e^{-N_{odj}})$$

Where; Out_k is output at k th output node.

Back propagation method of training of ANN has been done. From a desired output, the network learns from many inputs. It is a supervised learning method, and is a generalization of the delta rule. The learning rate is a common parameter in many of the learning algorithms, and affects the speed at which the ANN arrives at the minimum solution. In back propagation, the learning rate is analogous to the step-size parameter from the gradient-descent algorithm. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. The values of learning rate (L) and momentum (M) used in the study are 0.2 and 0.1 respectively. The training time (T) for each network is 400.

The normalization of the data had been done by using the software WEKA used in carrying out the ANN analysis. In the pre-process, the minimum, maximum, mean and standard deviation for each feature is computed and used in the sigmoidal function transformation. This maintains the resolution of most values that are within a standard deviation of the mean. Thus, it puts the normalized data in a range of 0 to 1. The cross-validation technique with 20 folds has been carried out which is a standard tool in analytics and is an important feature for helping one developed and fine-tune the data mining models.

Results and Analysis

The acceptance or rejection of the model developed is determined by its ability to predict the 7, 14 and 28 days compressive strength of concrete mix used. The correlation coefficient (C_c), root mean square error (RMSE), and mean absolute error (MAE) is used to judge the performance of the neural network approach in predicting the results. Since the neural networks are trained on actual test data, they are trained to deal with inherent noisy or imprecise data. As new data become available, the neural network model can be readily updated by retraining with patterns which include these new data.

Table 4 give the actual, predicted values along with error for 7, 14 and 28 days compressive strength. Table 5 gives the summary of Correlation Coefficient, Mean Absolute Error and Root Mean Square Error obtained to predict the 7, 14 and 28 days compressive strength. To compare the performance of models, graphs between actual and predicted strengths are plotted as shown in Figures 2, 3 and 4 for 7, 14 and 28 days compressive strength respectively.

Table 4: Actual v/s Predicted values with errors for 7, 14 and 28 days compressive strength.

7-days compressive strength			14-days compressive strength			28-days compressive strength		
Actual	Predicted	Error	Actual	Predicted	Error	Actual	Predicted	Error
26.02	27.245	1.225	37.4	33.258	-4.142	37.4	34.32	-3.08
15.66	15.128	-0.532	29.3	26.055	-3.245	29.3	25.388	-3.912
13.91	13.728	-0.182	21.82	22.123	0.303	21.82	21.422	-0.398
24.66	22.677	-1.983	29.88	30.605	0.725	29.88	30.872	0.992
26.2	23.739	-2.461	34.6	32.808	-1.792	34.6	32.193	-2.407
19.22	17.684	-1.536	28.55	26.979	-1.571	28.55	28.503	-0.047
19.86	25.163	5.303	27.68	30.079	2.399	27.68	27.919	0.239
27.68	26.608	-1.072	38.4	40.276	1.876	38.4	36.085	-2.315
24.75	22.277	-2.473	29.77	28.844	-0.926	29.77	29.305	-0.465
18.97	17.855	-1.115	23.84	25.474	1.634	23.84	24.391	0.551
25.73	26.129	0.399	32.55	35.424	2.874	32.55	34.806	2.256
13.84	13.545	-0.295	25.6	21.227	-4.373	25.6	22.222	-3.378
17.82	16.821	-0.999	25	26.685	1.685	25	26.913	1.913
23.77	23.339	-0.431	34.68	28.638	-6.042	34.68	29.428	-5.252
26.15	25.845	-0.305	34.2	35.451	1.251	34.2	33.967	-0.233
15.71	16.025	0.315	25.57	23.907	-1.663	25.57	23.986	-1.584
17.66	21.865	4.205	28.57	30.255	1.685	28.57	30.358	1.788
20.4	20.57	0.17	32.55	29.64	-2.91	32.55	30.751	-1.799
23.55	24.974	1.424	34.86	34.042	-0.818	34.86	34.316	-0.544
19.57	22.943	3.373	29.77	29.651	-0.119	29.77	30.525	0.755
19.9	22.264	2.364	27.82	26.511	-1.309	27.82	27.011	-0.809
24.31	21.251	-3.059	28.9	28.633	-0.267	28.9	26.004	-2.896
27.35	24.341	-3.009	35.88	34.279	-1.601	35.88	32.805	-3.075
21.6	15.64	-5.96	24.88	27.956	3.076	24.88	28.242	3.362
14.44	16.158	1.718	23.06	20.104	-2.956	23.06	21.639	-1.421
27.35	25.584	-1.766	34.68	36.31	1.63	34.68	35.557	0.877
16.91	15.401	-1.509	25.97	24.67	-1.3	25.97	25.361	-0.609
24.6	24.349	-0.251	31.35	30.88	-0.47	31.35	31.517	0.167
18.62	19.652	1.032	25.33	25.67	0.34	25.33	26.793	1.463

19.98	22.111	2.131	29.32	28.95	-0.37	29.32	30.561	1.241
23.48	21.862	-1.618	28.97	30.236	1.266	28.97	32.606	3.636
14.08	14.783	0.703	19.53	24.597	5.067	19.53	20.68	1.15
20	18.474	-1.526	25.97	25.702	-0.268	25.97	23.669	-2.301
22.8	25.994	3.194	34.8	28.057	-6.743	34.8	26.71	-8.09
15.71	15.025	-0.685	25.57	25.437	-0.133	25.57	24.787	-0.783
23.15	25.536	2.386	31.48	32.206	0.726	31.48	30.409	-1.071
20.64	21.077	0.437	26.95	31.089	4.139	26.95	25.378	-1.572
27.82	27.125	-0.695	39.22	43.334	4.114	39.22	38.375	-0.845
20.8	22.784	1.984	31.95	30.928	-1.022	31.95	30.718	-1.232
26	15.228	-10.772	25.64	27.398	1.758	25.64	25.877	0.237
26	27.539	1.539	38.86	39.488	0.628	38.86	37.115	-1.745
14.08	14.32	0.24	19.53	22.524	2.994	19.53	22.053	2.523
22.33	19.098	-3.232	25.97	30.024	4.054	25.97	28.878	2.908
16.11	18.144	2.034	26.84	26.071	-0.769	26.84	24.919	-1.921
20.4	20.486	0.086	32.55	31.097	-1.453	32.55	29.781	-2.769
26	22.227	-3.773	27.64	30.365	2.725	27.64	30.551	2.911
16.11	17.283	1.173	26.84	23.751	-3.089	26.84	26.398	-0.442
17.66	20.137	2.477	28.57	27.641	-0.929	28.57	31.634	3.064
18.04	21.205	3.165	24.64	24.717	0.077	24.64	26.53	1.89
27.42	28.008	0.588	39.37	36.487	-2.883	39.37	42.729	3.359
15.08	17.479	2.399	24.84	23.735	-1.105	24.84	23.246	-1.594
24.33	25.831	1.501	30.66	33.825	3.165	30.66	34.193	3.533
17.13	20.783	3.653	28	28.324	0.324	28	28.427	0.427
19.64	20.765	1.125	28.97	28.993	0.023	28.97	29.635	0.665
17.55	19.207	1.657	24.77	23.561	-1.209	24.77	24.057	-0.713

Table 5: Summary of the coefficients for ANN models

S.No.	Parameter	Correlation coefficient	Mean absolute error	Root mean square error
1	7-days compressive strength	0.8926	1.8111	2.286
2	14-days compressive strength	0.8540	1.8512	2.4848
3	28-day compressive strength	0.8787	1.8402	2.3434

The results suggest that most of the points are lying within $\pm 10\%$ of the line of perfect agreement, which suggest that neural network, can effectively be used to predict the strengths.

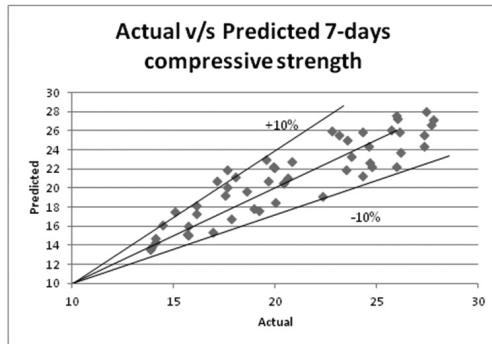


Figure 2: Actual v/s Predicted 7-days compressive strength

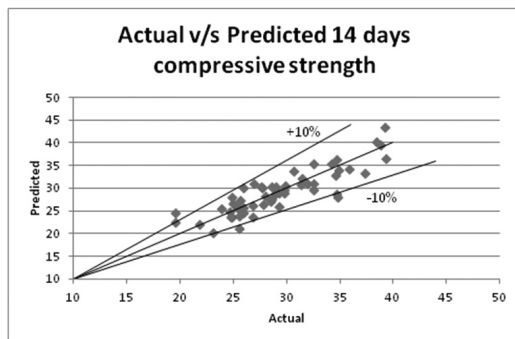


Figure 3: Actual v/s Predicted 14-days compressive strength

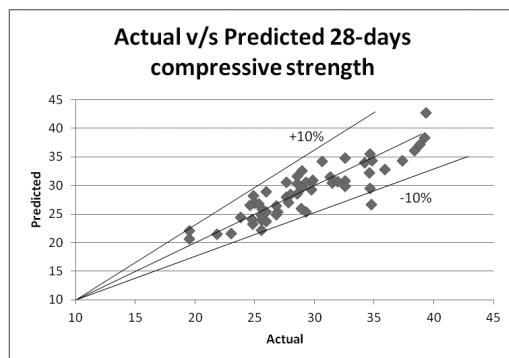


Figure 4: Actual v/s Predicted 28-days compressive strength

CONCLUSIONS

Concrete is a highly complex material, and prediction of the accurate compressive strength of concrete is quite a difficult task to model. The proposed ANN Artificial intelligence models will save time, reduce the waste of material and the design cost. In the study, Artificial intelligence controller was proposed for determination of the Compressive strengths at various ages 7, 14 and 28 days. The graphs show a marginal difference between the actual and predicted values. This difference is acceptable as the method is approximate. From the end user (engineers) point of view, outcome of the model is significant on following counts; it provides a way to capture inherent vagueness in the design. It offers flexibility for the mix design expert to decide appropriate value for parameters like 7, 14 and 28 compressive strength. Successful prediction of the outputs was done by all the methods, which indicated that ANN could be useful modeling tool for engineers and research scientists in the area of cement and concrete.

The correlation coefficients (C_c) for 7, 14 and 28 days is 0.8926, 0.8540 and 0.8787 respectively. The ANN model helps to capture experimental data and to use it expeditiously during the design of fresh batches of trial mixes. The analysis demonstrates the feasibility of using neural networks for capturing non-linear interactions between various parameters in complex civil engineering systems. Thus, it can be concluded that the application of ANN is more user-friendly and more explicit model can be made which help the concrete industry to avoid the risk of faulty or deficient concrete that often entails durability and safety problems.

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