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Artificial Neural Networks for the Prediction of Compressive Strength of Concrete

Palika Chopra[a*], Rajendra Kumar Sharma[a], and Maneek Kumar[b]

[a]*School of Mathematics and Computer Applications, Thapar University*, Patiala, India
[b]*Department of Civil Engineering, Thapar University*, Patiala, India

Abstract: In the paper, an artificial neural network (ANN) model is proposed to predict the compressive strength of concrete. For developing the ANN model the data bank on concrete compressive strength has been taken from the experiments conducted in the laboratory under standard conditions. The data set is of two types; in one dataset 15% cement is replaced with fly ash and the other one is without any replacement. Several training algorithms, like Quasi-Newton algorithm with Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update (BFG), Fletcher-reeves conjugate gradient algorithm (CGF), Polak-Ribiere conjugate gradient algorithm (CGP),Powell-Beale conjugate gradient algorithm (CGB), Levenberg–Marquardt (LM), Resilient backpropagation (RP), Scaled conjugate gradient backpropagation (SCG), One step Secant backpropagation (OSS) along with various network architectural parameters are experimentally investigated to arrive at the most suitable model for predicting the compressive strength of concrete. It is found that Levenberg–Marquardt (LM) with tan-sigmoid activation function is best for the prediction of compressive strength of concrete. In-situ concrete compressive strength data, based on varying mix proportions, have been taken from one of the research paper present in literature for the validation of the model. It is also recommended that ANN model with the training function, Levenberg–Marquardt (LM) for the prediction of compressive strength of concrete is one of the best possible tool for the purpose.

Keywords: Artificial neural network; prediction of compressive strength; concrete.

1. Introduction

Concrete is, by far, the most used construction material all over the world. It is known for its high compressive strength, durability, impermeability, fire resistance and abrasion resistance. Having the capability to be formed into any shape and size, it has formed the background of many appealing structures. From a simple material easily formed by just adding coarse aggregates, sand, cement and water in desired proportions. Concrete development for varying needs has been the topic of interest of many researchers. By playing around with its basic ingredients, researchers have been able to develop concretes which not only have very high compressive strength, but have good durability properties as well. The results of compressive strengths vary not only for different concrete mixtures, but for the same mixture as well, which has been attributed to various factors (ACI214R-02). Statistical procedures provide tools of considerable value when evaluating the results of strength tests. Information derived from such

* Corresponding author; e-mail: palika.chopra@thapar.edu

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procedures is also valuable in refining design criteria and specifications. Statistical methods also have the added attraction that once fitted they can be used to perform predictions quickly. In the construction industry, strength is a primary criterion in selecting a concrete for a particular application. Concrete used for construction gains a significant component of its strength during the initial 3 to 4 weeks, but continues to do so over a long period of time after pouring. The characteristic strength of concrete is defined as the compressive strength of a sample that has been cured for 28 days. However, to hasten the construction progress we must be able to predict the concrete strength based upon the early strength data. Therefore, rapid and reliable prediction for the strength of concrete would be of great significance. For example, it could provide a chance to make the necessary adjustments in the mix proportions used to avoid situation where concrete does not reach the required design strength or by avoiding concrete that is unnecessarily strong and also for more economic use of raw material and fewer construction failures, hence reducing construction cost [1]. Prediction of concrete strength, therefore, has been an active area of research and a considerable number of studies have been carried out. A significant number of studies have been carried out in this area [1-7]. Many attempts have been made to obtain a suitable mathematical model that is capable of predicting the strength of concrete at various ages with good accuracy [8-11]. In order to obtain concrete of desired and suitable strength, technical personnel often try several mix proportions, which is a time consuming process, resulting in wastage of material and the cost of concrete production. Thus, for the sake of saving time and decreasing the design cost, help of artificial neural network (ANN) is taken to develop models, so that the knowledge extracted from these neural network models, can be utilized to predict the strength of concrete. The basic strategy for developing a neural network based model for predicting concrete compressive strength is to train a neural network on the results of a series of experiments, thus, minimizing the absolute difference between the target (desired) outputs and the actual outputs, thereby, resulting in approximate optimal solutions [12].

2. Materials and Methods

Data for the present work has been taken from the experiments conducted by Kumar [13]. For generating a reliable data bank on concrete compressive strength, Kumar [13] considered five parameters, namely, water-cementitious material ratio, cementitious content, water content, workability, and curing ages in his experiments. The experiments were performed in controlled laboratory conditions. Table 1 shows the variations in the values of parameters as taken by Kumar [13].

Table 1. Range of values of various parameters

Water-cementitious ratio	0.42 – 0.55
Cementitious content	350 – 475 @ 25 kg/m^3
Water content	180-230 @ 10 kg/m^3
Workability	Medium and high
Curing ages, days	28, 56, 91

A set of 15 cubes for each of the mixes so proportioned were cast and tested after 28, 56 and 91 days of curing. Thus, an extensive data bank for analyzing the compressive strength of concrete had been generated and the same has been used in the present work. The physical properties of the materials used in the study are shown in Table 2.

Table 2. Physical Properties of Materials

Materials	Properties
Ordinary Portland Cement (OPC)	Grade: 43, as per IS:8112-1989 Specific Gravity: 3.12 7 days compressive strength: 35.50 MPa 28 days compressive strength: 46.50 MPa
Fine aggregates (FA)	Zone: III Fineness modulus: 2.09 Specific Gravity: 2.54
Coarse Aggregates – I (CA1) 20mm size	Specific Gravity: 2.61
Coarse Aggregates – I (CA2) 10mm size	Specific Gravity: 2.63

Ordinary Portland Cement (OPC) of 43 grade (as per IS: 8112-1989) was used. It had a specific gravity of 3.12 and attained a compressive strength of 46.50MPa after 28 days of curing. The fine aggregates used had a specific gravity of 2.54 and belonged to zone – II of the grading zones as per IS: 383-1970. Two types of coarse aggregates, one with size 20 mm (CA1) and other of 10 mm (CA2) size, were used in varying proportions, depending upon the requirements for a particular mix. The 20 mm coarse aggregates had a specific gravity of 2.61 and the 10 mm aggregates had a specific gravity of 2.63. The details of the mix proportions using different proportions of coarse aggregates (20 mm and 10 mm) are shown in Table 3 (without any replacement of cement with fly ash) and Table 4 (with 15% replacement of cement with fly ash). The compressive strength test was performed and the value was evaluated in accordance with IS: 519. Specimens were immersed in water until the day of testing at 28, 56 and 91 days. Table 5 and Table 6 show results of compressive strength at ages 28, 56 and 91 days.

2.1 Artificial Neural Network

The basic structure of a neural network consists of artificial neurons. The neurons are also sometimes referred to as processing elements (PEs), nodes, neurodes, units, *etc.*, and are analogous to biological neurons in the human brain, which are grouped into layers. The most common neural network structure consists of an input layer, one or more hidden layers and an output layer [14]. The basic strategy for developing a neural network model for material behavior is to train a neural network on the results of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the trained neural network will contain sufficient information about material behavior to qualify as a material model. Training a network with few data tuples often lead to early convergence. Apart from increasing the number of training data tuples, decreasing the error and increasing the number of epochs can be done to obtain more accuracy [15].

Table 3. Details of proportions for concrete mixes without fly ash

S.No.	Mix designation	w/cm ratio	Mix proportions (C: FA: CA)	Cement content, Kg/m^3
1	MD-1	0.53	1:1.58:3.05	375
2	MD-2	0.50	1:1.43:2.82	400
3	MD-3	0.53	1:1.54:2.99	400
4	MD-4	0.47	1:1.28:2.58	425
5	MD-5	0.49	1:1.39:2.77	425
6	MD-6	0.44	1:1.14:2.35	450
7	MD-7	0.47	1:1.25:2.54	450
8	MD-8	0.42	1:1.05:2.19	475
9	MD-9	0.44	1:1.19:2.46	475
10	MD-10	0.53	1:1.58:3.05	375
11	MD-11	0.50	1:1.43:2.82	400
12	MD-12	0.53	1:1.54:2.99	400
13	MD-13	0.47	1:1.28:2.58	425
14	MD-14	0.49	1:1.39:2.77	425
15	MD-15	0.51	1:1.51:2.95	425
16	MD-16	0.44	1:1.14:2.35	450
17	MD-17	0.47	1:1.25:2.54	450
18	MD-18	0.49	1:1.37:2.73	450
19	MD-19	0.42	1:1.05:2.19	475
20	MD-20	0.44	1:1.19:2.46	475
21	MD-21	0.46	1:1.23:2.51	475
22	MD-22	0.52	1:1.43:2.02	425
23	MD-23	0.49	1:1.29:1.86	450
24	MD-24	0.51	1:0.39:1.98	450
25	MD-25	0.46	1:1.18:1.72	475
26	MD-26	0.48	1:1.26:1.83	475
27	MD-27	0.51	1:1.39:3.26	350
28	MD-28	0.54	1:1.49:3.42	350
29	MD-29	0.48	1:1.25:2.99	375
30	MD-30	0.51	1:1.35:3.19	375
31	MD-31	0.45	1:1.10:2.70	400
32	MD-32	0.48	1:1.21:2.92	400
33	MD-33	0.42	1:0.98:2.47	425
34	MD-34	0.45	1:1.09:2.68	425
35	MD-35	0.42	1:0.98:2.45	450
36	MD-36	0.54	1:1.49:3.42	350
37	MD-37	0.51	1:1.35:3.19	375
38	MD-38	0.48	1:1.21:2.92	400
39	MD-39	0.45	1:1.09:2.68	425
40	MD-40	0.42	1:0.98:2.45	450
41	MD-41	0.53	1:1.47:2.41	375
42	MD-42	0.50	1:1.32:2.21	400
43	MD-43	0.53	1:1.44:2.36	400
44	MD-44	0.47	1:1.19:2.03	425
45	MD-45	0.49	1:1.29:2.18	425
46	MD-46	0.44	1:1.07:1.86	450
47	MD-47	0.47	1:1.17:2.00	450
48	MD-48	0.42	1:0.95:1.68	475
49	MD-49	0.44	1:1.06:1.84	475

Table 4. Details of proportions for concrete mixes with fly ash

S.No.	Mix designation	w/cm ratio	Mix proportions (C: FA: CA)	Cement content, Kg/m3
1	MD-1	0.45	1:1.10:2.70	340.0
2	MD-2	0.42	1:0.98:2.46	361.3
3	MD-3	0.48	1:1.09:2.68	361.3
4	MD-4	0.47	1:1.28:2.58	361.3
5	MD-5	0.42	1:0.98:2.45	382.5
6	MD-6	0.44	1:1.14:2.35	382.5
7	MD-7	0.47	1:1.25:2.54	382.5
8	MD-8	0.42	1:1.05:2.19	403.8
9	MD-9	0.44	1:1.19:2.46	403.8
10	MD-10	0.45	1:1.09:2.68	361.3
11	MD-11	0.47	1:1.28:2.58	361.3
12	MD-12	0.42	1:0.98:2.45	382.5
13	MD-13	0.44	1:1.14:2.35	382.5
14	MD-14	0.47	1:1.25:2.54	382.5
15	MD-15	0.49	1:1.37:2.73	382.5
16	MD-16	0.42	1:1.05:2.19	403.8
17	MD-17	0.44	1:1.19:2.46	403.8
18	MD-18	0.46	1:1.23:2.51	403.8
19	MD-19	0.47	1:1.19:2.03	361.3
20	MD-20	0.44	1:1.07:1.86	382.5
21	MD-21	0.47	1:1.17:2.00	382.5
22	MD-22	0.49	1:1.29:1.86	382.5
23	MD-23	0.51	1:1.39:1.98	382.5
24	MD-24	0.42	1:0.95:1.68	403.8
25	MD-25	0.44	1:1.06:1.84	403.8
26	MD-26	0.46	1:1.17:1.72	403.8
27	MD-27	0.48	1:1.26:1.83	403.8

2.1.1 Construction of Neural Network Models

ANN modeling technique was found out to have many favorable features such as efficiency, generalization and simplicity, which make it an attractive choice for modeling of complex systems [16]. A successful application of a neural network for the prediction of compressive strength of concrete requires a good comprehension of the effect of several internal parameters. For a feed-forward back-propagation network structure and training process, the important internal parameters include data preprocessing and presentation, initial synaptic weights, learning rate, number of hidden layers and number of neurons in each hidden layer, activation functions for hidden layers and output layers and the number of training epochs [17].

In this work, a three layer feed-forward back-propagation neural network is developed through experimental investigation of various internal parameters to predict the compressive strength of concrete.

In the Figure 1, x_1, x_2, x_3,..., x_n are the input variables, where for the problem in hand, x_1 is the w/cm (water-cement ratio), x_2 is fa/cm(fine aggregate-cement ratio), and x_3 is ca/cm (coarse aggregate-cement ratio). For the prediction of 28 days compressive strength, three inputs (x_1, x_2, x_3) are used and y (output) is the 28 days compressive strength of concrete. In case of prediction of 56 days compressive strength of concrete, four inputs (x_1, x_2, x_3, x_4) are used where x_4 is the 28 days compressive strength and y is the 56 days compressive strength of concrete. For the

Table 5. Details of compressive strength of concrete without fly ash for curing days of 28, 56 and 91 days.

S.No.	Mix designation	w/cm ratio	28 Days Curing Mean, MPa (CS28)	56 Days Curing Mean, MPa (CS56)	91Days Curing Mean, MPa (CS91)
1	MD-1	0.53	36.8	40.9	44.5
2	MD-2	0.50	43.1	50.2	51.9
3	MD-3	0.53	38.6	45.5	47.5
4	MD-4	0.47	47.2	51.3	54.3
5	MD-5	0.49	45.1	50.7	52.9
6	MD-6	0.44	49.6	54.5	58.0
7	MD-7	0.47	47.4	51.3	55.3
8	MD-8	0.42	54.0	57.9	60.2
9	MD-9	0.44	50.1	55.7	58.3
10	MD-10	0.53	37.8	43.5	47.6
11	MD-11	0.50	44.1	50.9	52.6
12	MD-12	0.53	40.9	46.6	51.1
13	MD-13	0.47	47.5	52.9	54.5
14	MD-14	0.49	45.3	51.5	53.1
15	MD-15	0.51	42.5	49.1	51.2
16	MD-16	0.44	52.0	56.3	59.2
17	MD-17	0.47	48.7	53.4	55.0
18	MD-18	0.49	46.6	53.2	53.7
19	MD-19	0.42	54.5	58.7	63.1
20	MD-20	0.44	53.1	56.7	62.6
21	MD-21	0.46	49.2	54.0	57.1
22	MD-22	0.52	40.0	46.9	48.5
23	MD-23	0.49	45.3	50.4	53.1
24	MD-24	0.51	42.7	48.5	49.6
25	MD-25	0.46	48.7	53.5	56.5
26	MD-26	0.48	45.5	50.9	53.6
27	MD-27	0.51	39.5	43.3	46.1
28	MD-28	0.54	31.7	37.2	43.9
29	MD-29	0.48	42.7	48.2	52.2
30	MD-30	0.51	40.7	44.5	46.4
31	MD-31	0.45	47.9	52.9	55.5
32	MD-32	0.48	44.9	51.2	53.9
33	MD-33	0.42	51.3	57.6	59.5
34	MD-34	0.45	49.1	54.1	57.4
35	MD-35	0.42	53.7	57.8	59.9
36	MD-36	0.54	36.6	43.5	46.6
37	MD-37	0.51	41.6	46.8	50.0
38	MD-38	0.48	46.2	52.6	53.1
39	MD-39	0.45	50.4	56.0	58.3
40	MD-40	0.42	54.1	58.5	62.3
41	MD-41	0.53	37.3	43.5	46.6
42	MD-42	0.50	44.0	50.5	52.6
43	MD-43	0.53	39.6	46.1	48.2
44	MD-44	0.47	47.4	51.3	54.8
45	MD-45	0.49	44.7	50.7	52.8
46	MD-46	0.44	50.9	55.7	59.1
47	MD-47	0.47	48.1	52.6	55.6
48	MD-48	0.42	54.1	58.2	61.1
49	MD-49	0.44	51.3	56.4	59.5

Table 6. Details of compressive strength of concrete with fly ash for curing days of 28, 56 and 91 days

S. No.	Mix designation	w/cm ratio	28 Days Curing Mean, MPa (CS28)	56 Days Curing Mean, MPa (CS56)	91Days Curing Mean, MPa (CS91)
1	MD-1	0.45	39.0	47.7	52.2
2	MD-2	0.42	45.1	50.2	55.8
3	MD-3	0.45	41.1	48.7	52.7
4	MD-4	0.47	38.4	43.3	50.4
5	MD-5	0.42	46.1	51.0	56.5
6	MD-6	0.44	42.5	49.2	53.1
7	MD-7	0.47	39.6	44.0	51.1
8	MD-8	0.42	47.3	52.3	57.7
9	MD-9	0.44	43.6	49.8	53.8
10	MD-10	0.45	42.0	49.7	53.4
11	MD-11	0.47	38.9	44.9	50.5
12	MD-12	0.42	47.3	51.9	57.2
13	MD-13	0.44	43.1	50.3	53.7
14	MD-14	0.47	40.3	45.3	51.6
15	MD-15	0.49	37.2	44.5	48.1
16	MD-16	0.42	48.4	53.6	58.2
17	MD-17	0.44	44.0	51.8	54.1
18	MD-18	0.46	40.7	45.9	52.1
19	MD-19	0.47	38.9	43.2	50.5
20	MD-20	0.44	43.2	49.9	53.6
21	MD-21	0.47	39.9	44.6	51.4
22	MD-22	0.49	36.9	41.3	47.3
23	MD-23	0.51	35.2	40.1	46.1
24	MD-24	0.42	47.9	53.1	57.8
25	MD-25	0.44	43.9	50.5	54.4
26	MD-26	0.46	40.3	45.6	52.4
27	MD-27	0.48	37.7	42.3	48.6

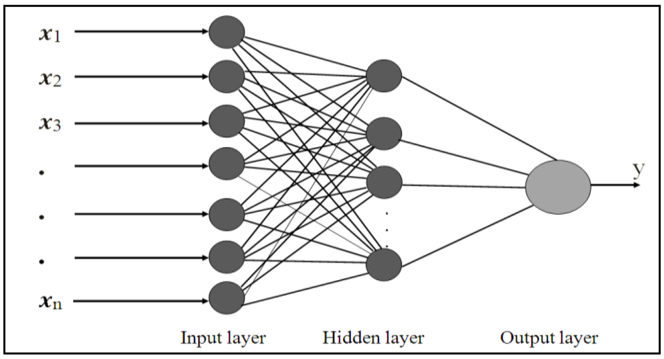


Figure 1. Structure of ANN model

prediction of 91 compressive strength of concrete, five inputs (x_1, x_2, x_3, x_4, x_5) are used where x_4 is the 28 days curing compressive strength and x_5 is the 56 days curing compressive strength and y is the 91 days compressive strength of concrete.

The preliminary experimentation is initiated with certain arbitrarily selected network architecture on the basis of the knowledge gathered through the literature review. The trail and error' approach is used to arrive at optimum parameter values that would produce the most accurate predictions. In the beginning, several variants of the standard back-propagation training algorithm based on some heuristics as well as standard numerical optimization techniques [18-20] are empirically explored for neural network performance optimization. The details of the training algorithms used are tabulated in Table 7.

In the Figure 2, x_1, x_2, x_3,…, x_n are the input variables; w_i are the weights assigned to each connection which can be adjusted in such a manner when a set of inputs is given to the network, the associated connection will produce the desired output; $(net)_j$ is the weighted sum of the j^{th} neuron for the input received from the preceding layer with n neurons; and w_{ij} is the weight between the j^{th} neuron and the i^{th} neuron in the preceding layer. The output of the j^{th} neuron o_j is calculated with activation function. Figure 3 shows the flow of all the steps of algorithm for the developed ANN model. Table 8 shows all the parameters used for ANN model to predict the compressive strength.

Table 7. List of training algorithms and their brief description [21]

Algorithm	Description
trainbfg	BFGS quasi-Newton method (BFG) algorithm. It requires storage of appropriate Hessian matrix and has more computation, in each iteration, than conjugate gradient algorithms, but usually converges in less iteration.
traincgp	Polak-Ribiere conjugate gradient (CGP) algorithm. It has faster convergence on some problems, but has larger storage requirements.
traincgb	Powell-Beale conjugate gradient (CGB) algorithm. Generally, it converges very fast and has slightly larger storage requirements.
traincgf	Fletcher-Reeves conjugate (CGF) algorithm. It has smaller storage requirements than CGP and CGB.
trainlm	Levenberg-Marquardt (LM) algorithm. It is the fastest training algorithm for the network of moderate size. It has memory reduction feature for the use when the training set is large.
trainrp	Resilient back-propagation (RP) algorithm. It is the simple batch mode training algorithm with convergence and minimal storage requirements.
trainscg	Scaled conjugate gradient (SCG) algorithm. It is the only conjugate gradient algorithm that requires no line search. A very good general purpose training algorithm.
trainoss	One step secant (OSS) algorithm. The OSS training algorithm requires less storage and computation per epoch than the BFG. It requires slightly more storage and computation per epoch than the conjugate gradient algorithms. Thus, the OSS method can be considered a compromise between full quasi-Newton algorithms and conjugate gradient algorithms.

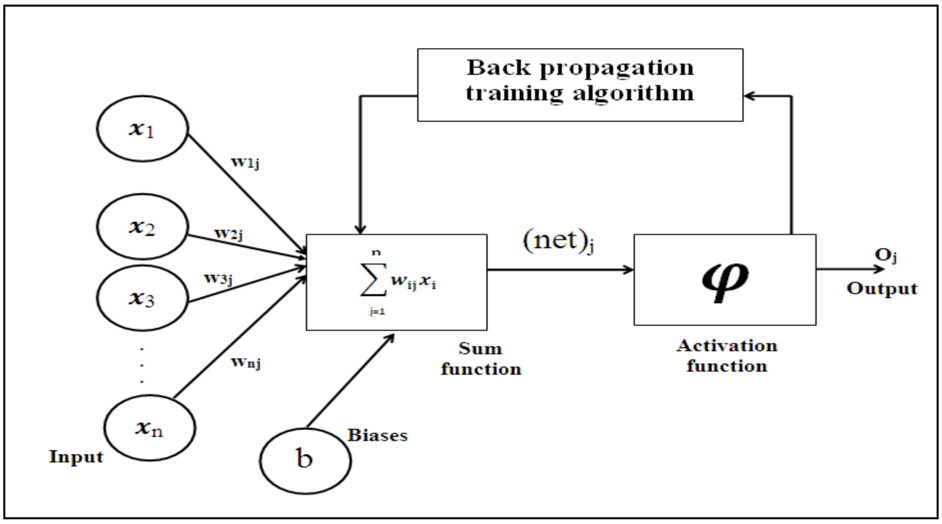


Figure 2. Architecture of the developed ANN model

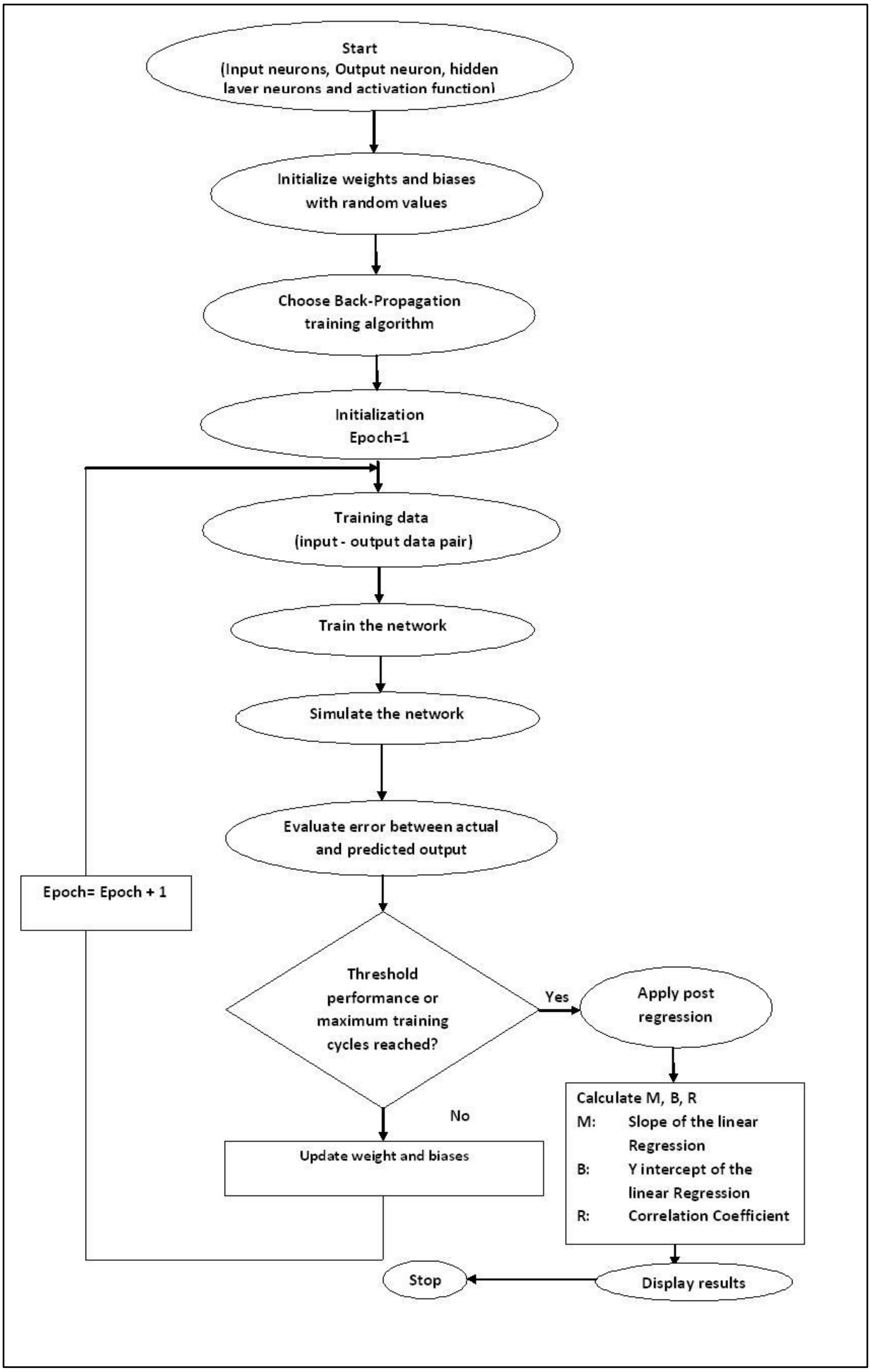


Figure 3. A plot to demonstrate the algorithm of ANN model

Table 8. Parameters used to develop ANN architecture

Parameters	**Values**	**Description**
Input	w/cm, fa/cm, ca/cm	Water-cement ratio, fine aggregate-cement ratio, coarse aggregate-cement ratio respectively.
Output	CS28,CS56,CS56	Compressive strength of 28 curing days compressive strength of 56 curing days, compressive strength of 91 curing days respectively.
Data set1	49	Without flyash (no any cement replacement)
Dataset2	27	With flyash (15% of the cement is replaced with flyash)
Activation function1 (at input layer)	tansig(x)	tansig(x)=$\frac{2}{1+e^{-2x}}$ -1
Activation function2 (at input layer)	logsig(x)	logsig(x)=$\frac{1}{1+e^{-x}}$
Activation function3 (at output layer)	purelin(x)	Purelin(x)=x
Performance function	mse	Performance function
Net.trainparam.lr	0.01	Learning rate
Net.trainfcn	trainbfg, traincgp, traincgb, traincgf, trainlm, trainrp, trainscg, trainoss	Quasi-Newton algorithm with Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update (BFG), Polak-Ribiere conjugate gradient algorithm (CGP),Powell-Beale conjugate gradient algorithm (CGB), Fletcher-reeves conjugate gradient algorithm (CGF), Levenberg–Marquardt (LM), Resilient backpropagation (RP), Scaled conjugate gradient (SCG), One step Secant backpropagation (OSS)
Net.trainparam.epochs	10000	Maximum number of epochs to train
Net.trainparam.goal	0.000001	Performance goal
Net.trainparam.show	15	Epochs between displays
Number of hidden layer neurons	50	Number of neurons in the hidden layer
Number of output layer neurons	01	Number of neurons in the output layer

3. Results and Discussions

The optimum dataset of the representative concrete mix proportion is used for developing the ANN model to predict the compressive strength of concrete. Eight different neural network models are developed based on the eight different training algorithms; each neural network model is trained with the same architectural parameter settings. During experiments, it is found that the LM is the best possible training function with R (correlation) equal to or greater than 95% on an average and after LM, BFG is another possible training function with the same architectural parameters having correlation equal to or above 93%. The results of each simulation experiment of data without fly ash are given in Table 9 and with fly ash in Table 10 and further data sets are partitioned according to the compressive strength curing days after 28 days, 56 days and 91 days. The ANN models are repeated with activation functions, *viz.*, tangent sigmoid and log sigmoid functions are applied to the hidden layer neurons. The predictions of the best ANN model are graphically depicted in Figure 4 to Figure 7.

In Figure 4 (a) ANN model output training data for 28 days without fly ash and Figure 4 (b) 56 days without fly ash using tangent-sigmoid function and trainlm training algorithm having correlation of 96.9% (used only 07 epochs) and 100% used (only 05 epochs) respectively. In Figure 4 (c) ANN model output training data for 91 days without fly ash and Figure 5 (a) 28 days with fly ash using tangent-sigmoid function and trainlm training algorithm having correlation of 95.7% (used only 04 epochs) and 98.9% (used only 03 epochs) respectively. In Figure 5 (b) ANN model output training data for 56 days with fly ash and Figure 5 (c) 91 days with fly ash using tangent- sigmoid function and trainlm training algorithm having correlation of 98.3% (used only 04 epochs) and 99.6% (used only 08 epochs) respectively. In Figure 6 (a) ANN model output training data for 28 days without fly ash and Figure 6 (b) 56 days without fly ash using log-sigmoid function and trainlm training algorithm having correlation of 95.8% and 93.5% (both of these used only 03 epochs) respectively. In Figure 6 (c) ANN model output training data for 91 days without fly ash and Figure 7 (a) 28 days with fly ash using log- sigmoid function and trainlm training algorithm having correlation of 92.2% (used only 03 epochs) and 98% (used only 04 epochs) respectively. In Figure 7 (b) ANN model output training data for 56 days with fly ash and Figure 7 (c) 91 days with fly ash using tangent- sigmoid function and trainlm training algorithm having correlation of 95.4% (used only 02 epochs) and 100% (used only 03 epochs) respectively. All the experiments are carried out with the ANN tool available in matlab and graphs (Figure4 to Figure 7) are generated by tool available in the software only.

3.1 Validation using Namyong's in-situ concrete strength data based on [9]

Once the weights are adjusted the performance of the trained network was validated and tested with the finite element analyses, which were never used in the training process. Validation set is a part of the data used to tune the network topology or network parameters other than weights. It is used to define the number of hidden units to detect the moment when the predictive ability of neural network started to deteriorate [22].

The best ANN model for the prediction of compressive strength of concrete for 28 days *i.e.*, Levenberg-Marquardt (LM) training algorithm with tangent-sigmoid activation function achieves correlation of 96.9%. The compressive strength of concrete at age 28 days in Table 11 is used for the validation purposes, in-situ data that is gathered from literature [9], where CS28/CM is the ratio of compressive strength of concrete at 28 days of curing compressive and cement (MPa-m^3/kg). W/cm, FA/cm and CA/cm are the ratios of contents of water, fine aggregates and coarse aggregates, respectively, with cement content and are unit-less quantities. The comparison between ANN model output and experimental output is in Figure 8 shows that the predicted values using ANN is in very good correlation and representation with the experimental dataset.

4. Conclusion

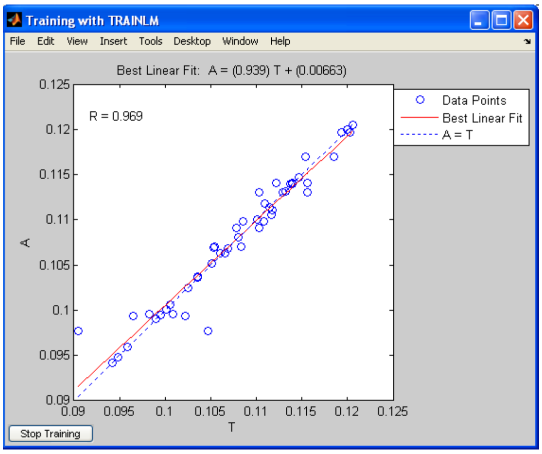
In this paper, an ANN model has been proposed to predict the compressive strength of concrete. In the development of this model, several variants of training algorithms are experimentally investigated for network optimization. Also, we empirically investigated different architectural parameters such as the number of hidden neurons, learning rate, activation functions, performance goal, epochs for the fine tuning of neural network. It is deduced that the best training algorithm is 'Levenberg-Marquardt' algorithm that attains more than 95% on average prediction accuracy. In view of the outcome of this study, it is inferred that the ANN approach has definite application potential for prediction of the compressive strength of concrete.

Table 9. Prediction performances of various ANN models trained using eight different algorithms to the data set of 49 tuples without fly ash

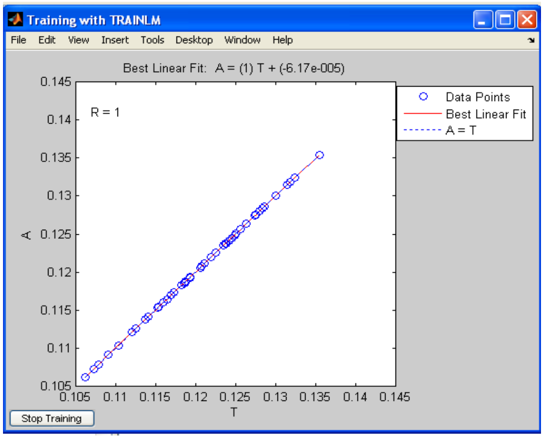
Without Fly ash				
Activation function= tansig (x)				
No. of curing days	Training function	R(%) (Correlation)	Epochs	Best linear fit given by post-regression (A=predicted strength, T=target strength)
28	BFG	91.2	94	A=(0.907)T+(0.00984)
	CGP	86.7	252	A=(0.936)T+(0.00685)
	CGB	91.6	303	A=(0.976)T+(0.00248)
	CGF	86.3	252	A=(0.904)T+(0.0106)
	LM	96.9	07	A=(0.939)T+(0.00663)
	RP	91.0	8457	A=(0.927)T+(0.00782)
	SCG	91.2	478	A=(0.939)T+(0.00658)
	OSS	91.6	612	A=(0.926)T+(0.00759)
56	BFG	91.5	79	A=(1.02)T+(-0.00256)
	CGP	80.1	302	A=(0.952)T+(0.00589)
	CGB	91.3	227	A=(1.02)T+(-0.00265)
	CGF	90.6	551	A=(0.975)T+(0.0031)
	LM	100	05	A=(1)T+(-6.17e-005)
	RP	90.8	21325	A=(0.991)T+(0.00105)
	SCG	90.5	441	A=(0.968)T+(0.00376)
	OSS	90.8	961	A=(0.989)T+(0.00138)
91	BFG	91.1	109	A=(1)T+(-0.000634)
	CGP	90.5	413	A=(0.971)T+(0.00353)
	CGB	91.1	295	A=(1)T+(-0.000207)
	CGF	88.3	604	A=(1.01)T+(-0.00099)
	LM	95.7	04	A=(1.04)T+(-0.0044)
	RP	90.8	4698	A=(0.991)T+(0.0011)
	SCG	90.8	464	A=(0.989)T+(0.00131)
	OSS	90.1	1556	A=(0.913)T+(0.0104)
Activation function=logsig (x)				
28	BFG	90.9	118	A=(0.896)T+(0.0112)
	CGP	73.4	252	A=(0.924)T+(0.00834)
	CGB	87.4	237	A=(0.926)T+(0.00788)
	CGF	85.3	506	A=(0.882)T+(0.0127)
	LM	95.8	03	A=(0.903)T+(0.0106)
	RP	90.9	4607	A=(0.922)T+(0.00839)
	SCG	91.1	493	A=(0.933)T+(0.00717)
	OSS	90.9	1208	A=(0.905)T+(0.0102)
56	BFG	87.9	112	A=(0.872)T+(0.0154)
	CGP	73.4	252	A=(0.878)T+().0147)
	CGB	89.8	279	A=(0.916)T+(0.0101)
	CGF	89.3	392	A=(0.87)T+(0.0157)
	LM	93.5	04	A=(0.858)T+(0.0163)
	RP	89.4	4294	A=(0.887)T+(0.0136)
	SCG	89.7	483	A=(0.911)T+(0.0108)
	OSS	89.7	1037	A=(0.914)T+(0.0103)
91	BFG	89.6	79	A=(0.849)T+(0.0191)
	CGP	85.4	408	A=(0.861)T+(0.0178)
	CGB	89.4	252	A=(0.865)T+(0.0171)
	CGF	77.1	257	A=(0.883)T+(0.015)
	LM	92.2	08	A=(0.832)T+(0.02)
	RP	89.7	3615	A=(0.903)T+(0.0123)
	SCG	89.8	318	A=(0.894)T+(0.0134)
	OSS	89.4	1062	A=(0.864)T+(0.0172)

Table 10. Prediction performances of various ANN models trained using eight different algorithms with the data set of 27 tuples with fly ash

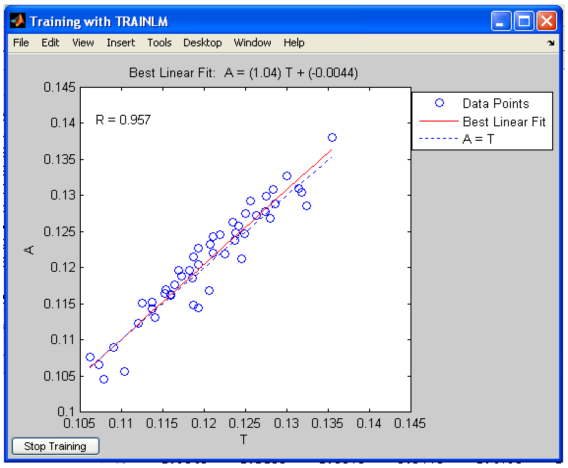
With Fly ash				
Activation function= tansig(x)				
No. of curing days	Training functions	R (%) Correlation	Epochs	Best linear fit given by post-regression (A=predicted strength, T=target strength)
28	BFG	92.0	73	A=(0.988)T+(0.00095)
	CGP	91.7	186	A=(0.962)T+(0.00356)
	CGB	92.7	116	A=(1.01)T+(-0.000917)
	CGF	92.5	135	A=(0.959)T+(0.00427)
	LM	98.9	03	A=(1)T+(-0.000852)
	RP	92.3	821	A=(1.02)T+(-0.00156)
	SCG	92.3	120	A=(1)T+(-0.000125)
	OSS	92.3	151	A=(0.939)T+(0.00553)
56	BFG	95.3	52	A=(0.965)T+(0.00433)
	CGP	93.8	202	A=(0.989)T+(0.00108)
	CGB	94.1	231	A=(1.01)T+(-0.000687)
	CGF	94.1	245	A=(1.01)T+(-0.00088)
	LM	98.3	03	A=(1.03)T+(-0.0048)
	RP	93.9	2548	A=(0.995)T+(0.00052)
	SCG	93.7	202	A=(0.979)T+(0.00227)
	OSS	94.9	223	A=(1.02)T+(-0.00235)
91	BFG	93.0	38	A=(0.989)T+(0.00115)
	CGP	92.9	226	A=(1.02)T+(-0.00218)
	CGB	92.6	145	A=(0.995)T+(0.000598)
	CGF	92.2	273	A=(0.974)T+(0.00294)
	LM	99.6	03	A=(1.05)T+(-0.00568)
	RP	92.2	1347	A=(0.973)T+(0.00315)
	SCG	92.4	150	A=(0.969)T+(0.00322)
	OSS	92.4	204	A=(0.993)T+(0.000851)
Activation function= logsig(x)				
28	BFG	93.6	41	A=(1.04)T+(-0.00358)
	CGP	92.0	164	A=(0.977)T+(0.00205)
	CGB	92.8	177	A=(1.04)T+(-0.00366)
	CGF	92.5	212	A=(1.02)T+(-0.00238)
	LM	98.0	04	A=(1.11)T+(-0.00815)
	RP	92.1	896	A=(1)T+(-0.00037)
	SCG	91.2	130	A=(0.926)T+(0.00686)
	OSS	91.5	443	A=(0.925)T+(0.00719)
56	BFG	94.0	73	A=(0.963)T+(0.004)
	CGP	94.1	240	A=(1.01)T+(-0.00117)
	CGB	94.0	146	A=(0.995)T+(0.000551)
	CGF	94.1	246	A=(1)T+(-7.79e-005)
	LM	95.4	02	A=(0.985)T+(0.000663)
	RP	93.9	2384	A=(0.997)T+(0.000285)
	SCG	93.7	243	A=(0.976)T+(0.00235)
	OSS	93.9	497	A=(0.993)T+(0.00055)
91	BFG	92.5	66	A=(1)T+(-8.58e-005)
	CGP	92.5	228	A=(0.995)T+(0.000631)
	CGB	92.7	130	A=(1)T+(-0.000284)
	CGF	92.4	338	A=(0.99)T+(0.000891)
	LM	100	03	A=(1)T+(3.73e-005)
	RP	92.2	3713	A=(0.979)T+(0.00244)
	SCG	91.9	147	A=(0.952)T+(0.00566)
	OSS	93.1	500	A=(1.03)T+(-0.00406)



(a) 28 days

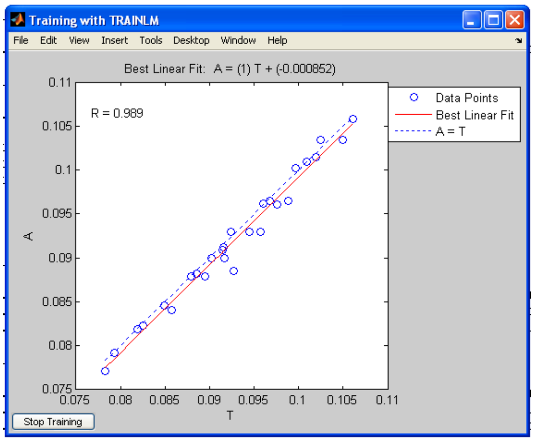


(b) 56 days

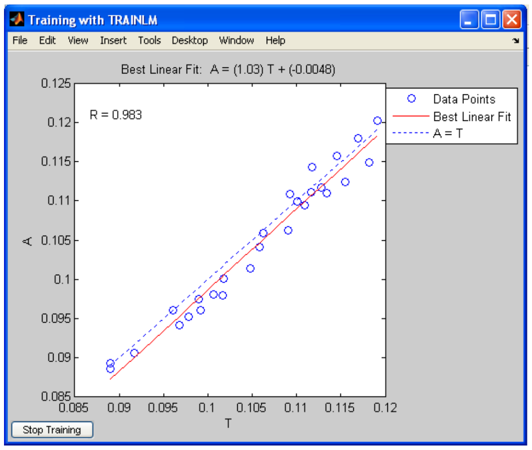


(c) 91 days

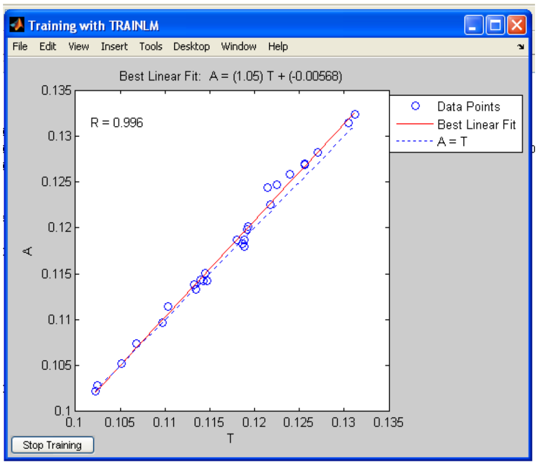
Figure 4. ANN model output training data for (a) 28days; (b) 56 days; and (c) 91 days strength of concrete without fly ash using tan-sigmoid and trainlm



(a) 28 days

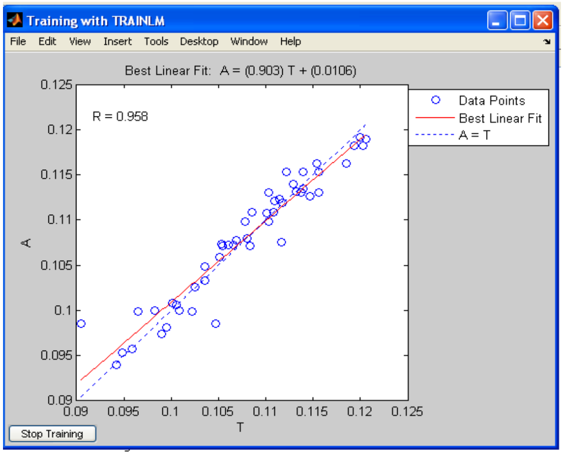


(b) 56 days

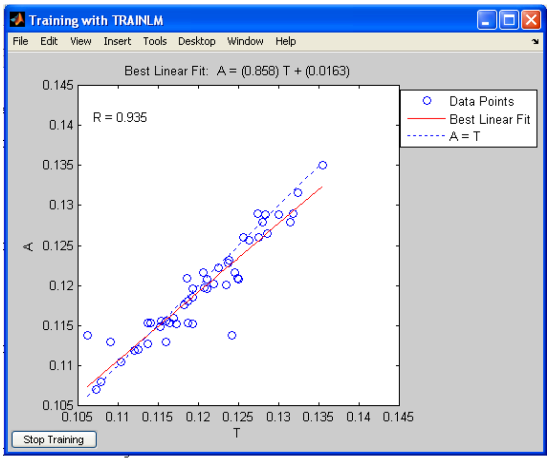


(c) 91 days

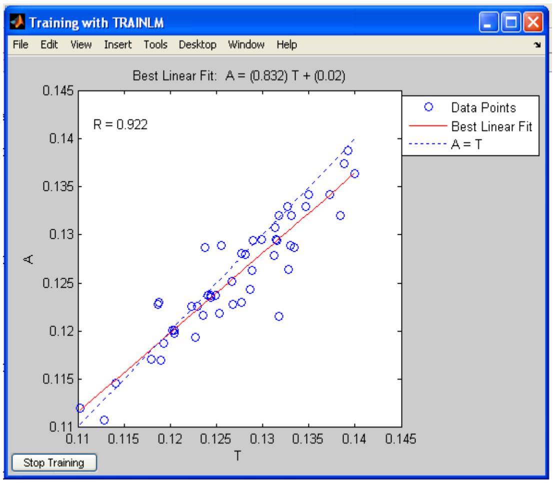
Figure 5. ANN model output training data for (a) 28 days; (b) 56 days; and (c) 91 days strength of concrete with fly ash using tangent-sigmoid activation function and trainlm



(c) 28 days

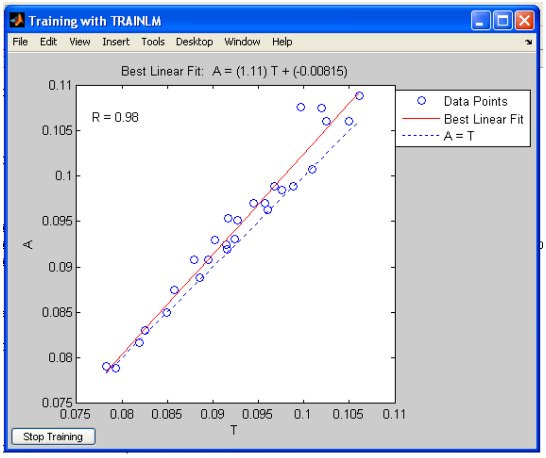


(d) 56 days

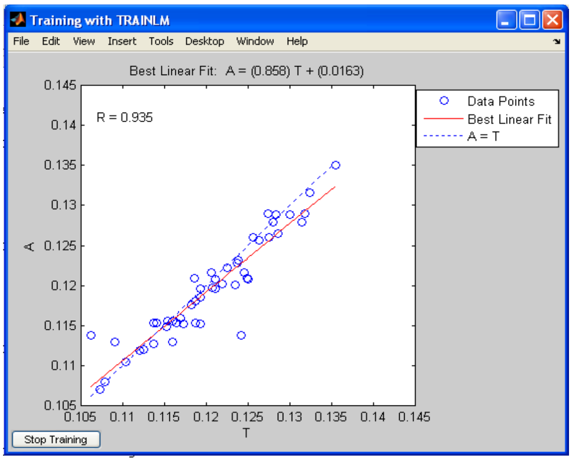


(c) 91 days

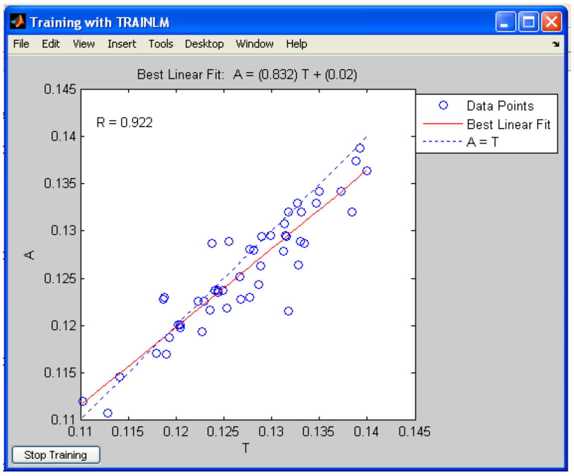
Figure 6. ANN model output training data for (a) 28 days; (b) 56 days; and (c) 91 days strength of concrete without fly ash and using log-sigmoid and trainlm



(a) 28 days



(b) 56 days



(c) 91 days

Figure 7. ANN model output training data for (a) 28 days; (b) 56 days; and (c) 91 days strength of concrete with fly ash using log-sigmoid and trainlm

Table 11. 28days compressive strength Data from literature [9]

W/CM	FA/CM	CA/CM	CS28/CM ($MPa\text{-}m^3/kg$)
0.60	3.23	3.11	0.07
0.59	3.01	2.79	0.08
0.61	3.07	2.85	0.08
0.57	3.19	2.87	0.09
0.60	2.87	2.74	0.08
0.61	2.95	2.78	0.07
0.59	2.66	3.16	0.07
0.50	2.70	2.87	0.11
0.50	2.70	2.87	0.11
0.48	2.19	2.68	0.07
0.49	2.38	2.54	0.09
0.52	2.47	2.74	0.08
0.44	2.18	2.69	0.07
0.45	2.31	2.56	0.08
0.49	2.53	2.59	0.09
0.49	2.34	2.39	0.08
0.50	2.59	2.67	0.09
0.49	2.53	2.59	0.09
0.49	2.34	2.39	0.08
0.50	2.59	2.67	0.09
0.49	2.34	2.39	0.09
0.50	2.59	2.67	0.09
0.49	2.38	2.40	0.09
0.45	2.09	2.24	0.08
0.45	1.99	2.37	0.08
0.47	1.93	2.49	0.08
0.50	2.29	2.73	0.09
0.47	2.00	2.47	0.07
0.47	2.00	2.47	0.07
0.48	2.11	2.41	0.07
0.48	2.13	2.39	0.07
0.48	2.16	2.44	0.07
0.48	2.10	2.39	0.07
0.47	2.21	2.36	0.08
0.47	2.40	2.37	0.07
0.47	2.29	2.25	0.07
0.44	2.28	2.38	0.08
0.48	2.13	2.51	0.07
0.45	2.14	2.47	0.07
0.48	2.13	2.44	0.07
0.46	1.88	2.44	0.08
0.49	2.09	2.48	0.08
0.47	2.29	2.25	0.07
0.44	2.28	2.38	0.08
0.46	2.25	2.32	0.07
0.48	2.21	2.68	0.08
0.46	1.77	2.29	0.08
0.46	1.78	2.31	0.07
0.43	1.86	2.20	0.07
0.41	1.58	2.17	0.07
0.41	1.56	2.18	0.07

Table 11. 28days compressive strength Data from literature (Cont'd) [9]

W/CM	FA/CM	CA/CM	CS28/CM ($MPa\text{-}m^3/kg$)
0.42	1.84	2.04	0.07
0.44	1.92	2.08	0.07
0.44	1.87	2.19	0.07
0.44	1.89	2.23	0.07
0.44	1.92	2.23	0.07
0.41	1.98	2.28	0.08
0.42	1.92	2.10	0.07
0.44	1.89	2.31	0.07
0.48	1.94	2.17	0.08
0.45	1.98	2.13	0.07
0.44	1.89	2.18	0.08
0.44	1.89	2.21	0.08
0.39	1.70	2.17	0.07
0.44	1.85	2.29	0.07
0.42	1.92	2.10	0.07
0.41	1.85	2.22	0.07
0.44	1.97	2.48	0.08

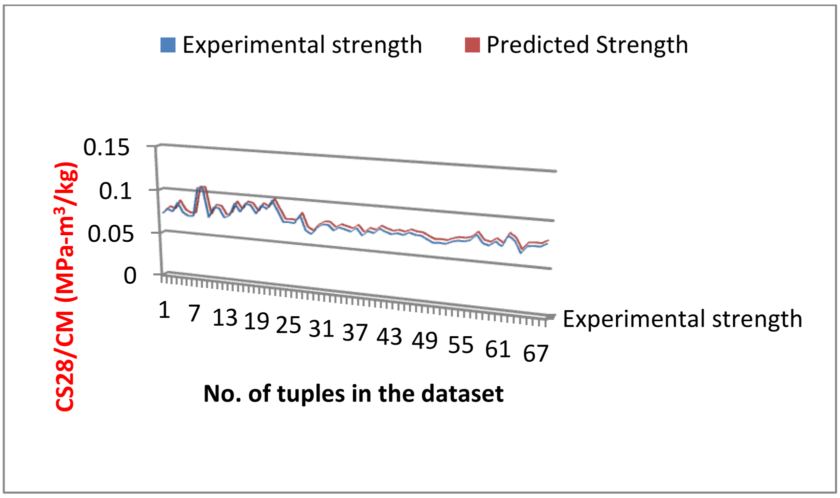


Figure 8. Validation of ANN model using 28 days compressive strength data from literature [9]

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