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MODELING AND PREDICTION OF FLEXURAL STRENGTH OF HYBRID MESH AND FIBER REINFORCED CEMENT-BASED COMPOSITES USING ARTIFICIAL NEURAL NETWORK (ANN)

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ABSTRACT: In this paper, Artificial Neural Network (ANN) has been used to predict the equivalent flexural strength of hybrid mesh and fiber reinforced cement-based composites (HMFRCBC). Three ANN models (Models 1, 2 and 3) were developed for predicting the flexural strength of cement-based composites. Model 1 used 48 data of the previously published data of the present authors and Model 2 used 48 data (out of the 75 ANN validated data) from previous studies related to mesh reinforced cement-based composites. Model 3 with 98 data (combined data sets of Model 1 and Model 2) employed seven input parameters, namely the width and depth of slab, cylinder compressive strength, mesh ultimate strength, mesh volume fraction, fiber volume fraction, fiber ultimate strength, and an output, the ultimate flexural strength of mesh and fiber reinforced cement based composites. Hidden layer was fixed based on 5 trial runs for Models 1 and 2, and 10 trial runs for Model 3. All the three models (Models 1, 2 and 3) were trained with 80% of the data, and tested with balance 20% of the data. For Models 1, 2 and 3, the Lowest Individual Error (LIE) of 11.18%, 6.95% and 11.56% (respectively) is achieved in Trial Run No.1.4 (with I-H-O, Input-Hidden Neurons-Output of 5-6-1), Trial Run No.2.2 (5-4-1) and Trial Run No.3.7 (7-10-1) respectively. Also, the lowest absolute average deviation (AAD%) of 4.81%, 3.51% and 4.58% (respectively); lowest Root Mean Square Error (RMSE) of 0.86, 0.76 and 0.99 (respectively); and highest R^2 of 0.933, 0.988 and 0.975 (respectively) are seen for these trials 1.4, 2.2, 3.7 in Models 1, 2 and 3 respectively. All the three ANN models were found to be in good agreement with actual results, and these three ANN models can serve as simple but reliable predictive tools in determination of flexural strength of HMFRCBC.

Keywords: Bending, Experimental, Ferrocement, Simulation, Validation

1. INTRODUCTION

Steel Mesh Reinforced Cement-Based Composite (SMRCC) (traditionally known as ferrocement) is made up of hydraulic cement mortar embedded with small diameter steel wires [1]. As there are some limitations in increasing the thickness of SMRCC slab elements (>25 mm) as well as number of reinforcing mesh layers, a novel method of adding fibers (mild or stainless steel fibers, mineral—glass or asbestos fibers, synthetic organic—carbon, cellulose or polymeric fibers) [2] as additional reinforcement to mesh-reinforced cement-based composites has been suggested by several authors [3]-[6].

Accordingly, the present authors have previously conducted experimental investigation [7] under four-point bending tests to determine the equivalent flexural strength of 12.5 mm, 18.75 mm and 25 mm thick hybrid mesh and fiber reinforced cement based composites (HMFRCBC). Also, several other experimental studies of the present authors [8]-[11] have determined the flexural and impact strength of HMFRCBC, which used variables such as steel mesh layers (3, 4 and 5 layers), fiber volume fraction (0 to 2.5% with 0.5% interval), and fiber-type (polyolefin and stainless steel fibers). But there is a need to develop a holistic model from the available experimental data of the present authors and also from related studies to predict the strength parameters of HMFRCBC. This is because rational and ready-made or easy-to-use equations are not available in design codes to accurately predict the properties of hybrid composites [12]. Even, the numerical modeling methods are static and cannot be generalized well on datasets outside those for which they were designed [13].

Artificial Neural Network (ANN) is a powerful prediction tool that rapidly processes the information without any need for standard experimental design or assumptions or any specific equation to build such a model (which is normally a pre-requisite in parametric approach) [14]. ANN captures the numerical relationship between its nodes and no formal formula is utilized within the model; ANNs are trained based on guidelines and relationships between data [15]. ANN has the universal capability of approximating almost all kinds of non-linear functions including quadratic functions without any need for prior specification of suitable fitting function [16]. ANN replaces or substitutes autocorrelation, multivariable regression, linear regression, trigonometric and other statistical analysis and techniques [17]-[18].

ANN operates in an emulation of biological nervous system that is made up of several layers of neurons (nodes) interconnected by links [13], [19]. ANN resembles the functioning of the human brain, demonstrating the ability to learn, recall and standardizes from training patterns or data [19] through interconnected computing elements [20]-[23]. ANN adapts to experimental test results, empirical data or theoretical results [24], tolerates approximate or imprecise data, gets continuously trained (or retrained), solves complex problems and provides accurate predictive solutions [19], [22]-[23], [25]-[27]. ANN learns from historical or previously measured data, captures unknown data better than traditional statistical methods and solves new problems with no prior idea on the nature of these interactions [12], [28].

Therefore, this study has made an attempt to develop ANN models to predict the flexural strength of hybrid mesh and fiber reinforced cement-based composites (HMFRCBC) using the previously published results of the present authors (Sakthivel et al., 2014a [7]; Sakthivel et al., 2015a, b) [9]-[10] and data from similar studies, as described in detail in Section 3.

2.0 PREVIOUS STUDIES

2.1 ANN Prediction & Modeling Studies

Many researchers have solved a wide variety of problems in civil engineering applications relating to validation of new experimental studies or previously measured data, and developed new trustworthy models using ANN [29]. ANN has been helpful in solving structural engineering [30] and construction engineering related problems [21]. This includes structural analysis and design [31], [32], prediction of load-deflection of CFRF strengthened RC slabs [15]; prediction of shear capacity of concrete beam [27], [33]-[36], and shear strength of steel-fiber reinforced high strength concrete deep beams [24], prediction of moment capacity of ferrocement members [19], detection of structural damage [37]-[38], identification of structural system identification [39]-[40], modeling of material behavior, structural optimization [41] and structural dynamics and control [42].

ANN has been used to predict concrete mix proportions [43] and compressive strength of concrete with different properties, subjected to various tests [25]; [44]-[46] and model the compressive strength of recycled aggregate concrete [47]. The workability of concrete with metakaolin and flyash [48-49], mechanical behavior of concrete at high temperatures [50]; and concrete strength [51-54] have also been ascertained.

Kaklauskas et al. (1999) [55] have used a large number of stress-strain curves (with strain of tensile concrete as input and the corresponding stress as input) for tensile concrete to train a neural network material model; and 14 beams were tested under a four point loading system which gave a constant moment zone of 1.2 m. Karahan et al. (2008) [28] have used ANN and employed six input variables (amount of cement, fly ash replacement, sand aggregate, gravel aggregate, steel fiber, and age of samples) and two output parameters (compressive and flexural strength of concrete), after normalizing the original data. Similarly, Prasad et al. (2009) [21] have used ANN to predict a 28-day compressive strength of a normal and high strength self-compacting concrete (SCC) and high performance concrete (HPC) with high volume fly ash. Also, Liu et al. (2011) [56] have shown that ANN can predict the compressive strength and Altun et al. (2008) [57] have presented an ANN model for compressive strength of lightweight concrete containing steel fiber.

Parichatprecha and Nimityongskul (2009) [12] have analyzed the influence of the content of water and cement, water-binder ratio, and the replacement of fly ash and silica fume on the durability of high performance concrete For developing ANN models, they have used 86 data from previous studies [58] on high strength concrete. The mean absolute percentage error of predicted test results was found to be 13.88% and the absolute fraction of variance (R^2) was 0.9741. The results indicated that the developed ANN model is reliable and accurate.

In another study, Khan et al. (2013) [59] have predicted the compressive strength of plain concrete confined with ferrocement using ANN, with 8 inputs, namely the cylinder and core dimensions, number of mesh layers, yield strength, wire diameter, wire spacing, unconfined compressive strength and experimental confined compressive strength, and one output, the theoretical confined compressive strength with 16 neurons as hidden variables. Out of 55 experimental results, 19 were selected for training of multi-layer feed forward neural network. The ANN predicted compressive strength (output) estimated by ANN predictive model was very close to the experimental results than existing theoretical models.

Rashid et al. (2012) [60] have studied the behavior of ferrocement beam sections (I, rectangular, channel and box) and ferrocement slab section, reinforced with different percentage of tensile reinforcements with different sizes. A database of 43 tests on ferrocement members is developed from the review of literature and some new tests are used for training and testing of this model. 4 input variables, section, loading type, load and length of the beam, and 2 outputs, shear force and bending moment were used. The theoretical predictions are made and mathematical models developed to predict the shear force and bending moment capacity of ferrocement beams and slabs using ANN; and the predicted results were in close agreement with experimental results.

In the study of Tavakoli et al. (2014) [61], they have predicted the combined effects of nano-silica particles (0 to 6% replacement of cement content) and three fiber types (steel, polypropylene and glass) on the mechanical properties (compressive, tensile and flexural strength) of reinforced self-compacting concrete (SCC) using ANN. The experimental data was used to train ANN, and two input variables (percentage of nano particles and fiber) and three outputs (flexural tensile strength, tensile strength behavior and compressive strength) were used. Before training procedure, the data set was normalized to their mean value and standard deviation. 25 out of 28 input-output data pairs are used to train the neural network with one hidden layer, and the remaining 3 data pairs were employed to test the network performance. The comparison revealed that the obtained ANN results are in good agreement with the experimental ones.

Imam et al. (2015) [13] have developed four different ANN models; a model each to directly predict the residual flexural strength of corroded RC beams with the diameter of reinforced steel and corrosion activity index as input variables. Imam et al. (2015) [13] used the experimental data of Azad et al. (2010) [62] consisting of 48 RC beams of different cross sections and reinforcements; the beams were made of three different depths, viz., 215 mm, 265 mm and 315 mm, two different diameters of tension bars, viz., 16 and 18 mm, and different durations of corrosion; out of the 48 beams, 36 beams were subjected to accelerated corrosion; both the corroded and un-corroded beams were tested on four-point bending to find their load carrying capacity using a span length of 900 mm and a flexural span of 200 mm. The data was divided into training and testing subsets in the ratio of 70:30 respectively. ANN models with randomized data stratification have resulted in better predictions than those with fixed stratification. ANN models are thus simpler, adaptive and more reliable for the prediction of flexural strength of corroded RC beams.

Naik and Kute (2013) [24] have predicted the shear strength of high-strength steel fiber-reinforced concrete deep beams (output) using ANN, with eight input nodes that represent width, effective depth, volume fraction, fiber aspect ratio and shear span-to-depth ratio, longitudinal steel, compressive strength of concrete, and clear span-to-overall depth ratio. 20 neurons were used in the hidden layer. 80% of the data was trained. The values used were normalized within the values of 0 and 1. The results predicted by the developed ANN matches with previous research studies.

Sudarsana Rao et al. (2012) [22] have used back-propagation neural networks for predicting the ultimate flexural strength of ferrocement elements (the output variable), employing 3 input variables, namely the span to depth ratios (3, 6, 9 and 11.45), number of mesh layers (0, 1, 3, and 5) and percentage replacement of silica fume (0, 5, 10, 15, 20, and 25). The hidden layer used 10 neurons. The network was trained with experimental data and the network model learned the relationship for predicting the ultimate flexural strength in 300 training epochs, and after successful learning, the model predicted the ultimate flexural strength satisfying all the constraints with accuracy of 95%.

3. ANN MODEL DEVELOPMENT STAGES OF THE PRESENT STUDY

The following steps are followed to develop the three ANN Models, as proposed in this study:

Step No.1: ANN Inputs and Output

1. Back-propagation neural network model has been used in this study, and the network is trained by feeding a set of mapping data with input and output (target) variables. For Models 1 and 2, the data of 5 inputs and 1 output data are given in Tables 1 and 2 respectively, as explained in Step No.2. For Model No.3, the data of two models 1 and 2 are combined and presented in Step No.2.

2. Next, the number of neurons for the hidden layers has to be fixed for all the models. This is important as the hidden layers does all the pre-processing functions and gives the output based on the sum of the weighted values from the input layer, modified by a sigmoid transfer function (transig) at the hidden layer, and a linear transfer function (purelin) as output [63].

3. But there are no fixed guidelines to determine the exact number of neurons for the hidden layer, and the thumb-rule or trial-and-error method has to be used [12]. To fix the number of hidden neurons, several arbitrary architectures are tried, and the trial which has given the best performance was selected [14]. The number of hidden-layer nodes should be at least greater than the square root of the sum of the number of the components in the input and output vectors; or the number of nodes in the hidden layer is between the sum and the average of the number of nodes in the input and output layers [32], [64]-[65].

Step No.2. Data Sets for Modeling

ANN Model No.1: Model 1 used 49 published data sets (see Table 2) of experimental work of present authors [7], [9-10] on HMFRCBC.

Table 1.Data Sets for ANN Model No.1

Data No.	d	f'$_c$	M. V_r	F. V_f	F.UTS	EUFS	Ref
	mm	N /mm^2	%	%	N /mm^2	N/ mm^2	
1	12.50	25.48	0.98	0.0	0	10.56	1
2	12.50	30.57	0.98	0.5	640	11.52	1
3	12.50	33.12	0.98	1.0	640	13.44	1
4	12.50	35.67	0.98	1.5	640	17.28	1
5	12.50	38.22	0.98	2.0	640	19.20	1
6	18.75	25.48	0.66	0.0	0	8.10	1
7	18.75	30.57	0.66	0.5	640	9.38	1
8	18.75	33.12	0.66	1.0	640	11.09	1
9	18.75	35.67	0.66	1.5	640	12.79	1
10	18.75	38.22	0.66	2.0	640	17.06	1
11	25.00	25.48	0.49	0.0	0	5.28	1
12	25.00	30.57	0.49	0.5	640	6.96	1
13	25.00	33.12	0.49	1.0	640	9.36	1
14	25.00	35.67	0.49	1.5	640	10.56	1
15	25.00	38.22	0.49	2.0	640	11.76	1
16	25.00	48.41	0.49	2.5	640	12.48	1
17	25.00	25.48	0.74	0.0	0	7.68	2
18	25.00	30.57	0.74	0.5	640	8.88	2
19	25.00	33.12	0.74	1.0	640	10.56	2
20	25.00	35.67	0.74	1.5	640	12.48	2
21	25.00	38.22	0.74	2.0	640	12.72	2
22	25.00	48.41	0.74	2.5	640	12.96	2
23	25.00	25.48	0.98	0.0	0	9.84	2
24	25.00	30.57	0.98	0.5	640	12.48	2
25	25.00	33.12	0.98	1.0	640	13.44	2
26	25.00	35.67	0.98	1.5	640	15.36	2
27	25.00	38.22	0.98	2.0	640	15.60	2
28	25.00	48.41	0.98	2.5	640	16.56	2
29	25.00	25.48	1.23	0.0	0	12.72	2
30	25.00	30.57	1.23	0.5	640	13.44	2
31	25.00	33.12	1.23	1.0	640	17.04	2
32	25.00	35.67	1.23	1.5	640	17.28	2
33	25.00	38.22	1.23	2.0	640	17.76	2
34	25.00	48.41	1.23	2.5	640	15.84	2
35	25.00	30.14	0.74	0.5	1353	8.64	3
36	25.00	31.00	0.74	1.0	1353	8.88	3
37	25.00	33.54	0.74	1.5	1353	9.84	3
38	25.00	36.52	0.74	2.0	1353	11.04	3
39	25.00	38.22	0.74	2.5	1353	12.48	3
40	25.00	30.14	0.98	0.5	1353	10.32	3
41	25.00	31.00	0.98	1.0	1353	13.20	3
42	25.00	33.54	0.98	1.5	1353	14.64	3
43	25.00	36.52	0.98	2.0	1353	12.24	3
44	25.00	38.22	0.98	2.5	1353	12.96	3
45	25.00	30.14	1.23	0.5	1353	14.64	3
46	25.00	31.00	1.23	1.0	1353	15.36	3
47	25.00	33.54	1.23	1.5	1353	17.04	3
48	25.00	36.52	1.23	2.0	1353	16.80	3
49	25.00	38.22	1.23	2.5	1353	16.32	3

Note: Ref.1- Sakthivel et al., 2014a [7]; 2 – Sakthivel et al., 2015a [9]; 3 – Sakthivel et al., 2015b [10] for data 1-49, d=depth; f'$_c$=cylinder compressive strength, M.V_r=Mesh Volume fraction; F.V_f=Fiber Volume fraction; F.UTS=Fiber Ultimate Tensile Strength; Constant width (b)=200 mm, Constant Mesh Ultimate Tensile Strength (M.UTS)=512 N/mm^2; EUFS–Equivalent Ultimate Flexural Strength

Table 1 shows that 5 variables have been used in this model as inputs, namely the depth (d=12.5-25 mm) of specimen, cylinder compressive strength of mortar (f'$_c$=25.48-48.41 N/mm^2), Steel Mesh Volume of Reinforcement (M.V_r=0.49-1.23%), Fiber Volume Fraction (F.V_f=0-2.5%, Fiber Ultimate Tensile Strength (F.UTS=0-1353 N/mm^2). Since Model 1 has used constant width, b=200 mm, and M.UTS=512 N/mm^2 for dataset no. 1-49, they are not included as inputs. Model No.1 has used single output, Equivalent Ultimate Flexural Strength (EUFS) with values ranging from 5.28-19.20 N/mm^2. From the number of hidden neurons (3 to 7), the best performance of the hidden neurons was determined from 5 trial runs, Trial Nos. 1.1, 1.2, 1.3, 1.4 and 1.5 with input variables-hidden neurons-output variables (I-H-O) of 5-3-1, 5-4-1, 5-5-1, 5-6-1 and 5-7-1 respectively, as shown in Tables 3 and 4.

ANN Model No.2: Development of ANN Prediction Model, choosing 49 data sets (at random) (as in Table 3) from 75 validated data sets of Mashrei et al. (2010) [19] on ultimate moment of ferrocement elements. Model 2 has used five inputs variables, namely the width (b=76-400 mm) and depth of specimen (d=13-100 mm), cylinder compressive strength (f'$_c$=8.06-39.68 N/mm^2), Steel Mesh Ultimate Tensile Strength (M.UTS=371-979 N/mm^2) and Mesh Volume of reinforcement (M.V_r=0.50-8.25 N/mm^2) (as shown in Table 1). Since Model 2 has not used fibers in the experiments under dataset no.50-98, Fiber Volume fraction (F.V_f) and Fiber Ultimate Tensile Strength (F.UTS) are not used as inputs. One output, Equivalent Ultimate Flexural Strength (EUFS) with range of 5.74-43.18 N/mm^2. From the varying number of hidden neurons (3 to 7), the best performance of the hidden neurons was determined from 5 trial runs (Trial Nos. 2.1, 2.2, 2.3, 2.4 and 2.5 with I-H-O of 5-3-1, 5-4-1, 5-5-1, 5-6-1 and 5-7-1 respectively), as in Tables 5 and 6.

Originally, Mashrei et al. (2010) [19] have used 75 data to predict the moment capacity of ferrocement elements, consisting of 16 own data sets and 59 data from previous studies [66]-[73]. Mashrei et al. (2010) [19] used five input variables with ranges: width of specimen (76-400 mm), depth of specimen (13-80 mm), cube compressive strength of ferrocement matrix (12.5-62 N/mm^2), ultimate strength of wire mesh (371-850 N/mm^2) and volume fraction of wire mesh (0.164-6.64%), and one output, the ultimate moment capacity of ferrocement elements**.** Mashrei et al., 2010 [19] has split the 75 data sets into 61 back-propagation training sets (80%) and 14 test data sets (20%).

From Mashrei et al. (2010) [19], the cylinder compressive strength has been calculated as 80% of cube compressive strength; and the equivalent ultimate flexural strength is converted from the actual ultimate moment values, as in Table 2.

Table 2. Data Sets for ANN Model 2

Data No.	b	d	f'$_c$	M. UTS	M. V_r	EUFS	Ref
	mm	mm	N/mm^2	N/mm^2	%	N/mm^2	
50	400	75	8.06	371	0.80	9.20	4
51	400	75	8.06	371	1.20	14.38	4
52	400	50	8.06	371	1.20	11.61	4
53	400	50	27.33	600	0.50	6.00	5
54	200	80	32.00	600	1.03	10.16	5
55	300	50	31.42	600	0.50	5.74	5
56	300	50	32.00	600	1.30	16.01	5
57	100	20	19.14	533	3.62	26.40	6
58	100	40	19.14	533	3.62	25.87	6
59	100	60	19.14	533	3.62	20.67	6
60	100	100	19.14	533	3.62	20.25	6
61	100	20	19.14	500	3.92	25.65	6
62	100	30	19.14	500	3.92	23.40	6
63	100	40	19.14	500	3.92	23.10	6
64	100	60	19.14	500	3.92	24.38	6
65	100	100	19.14	500	3.92	23.62	6
66	100	25	32.00	371	2.10	13.20	7
67	100	35	32.00	371	1.48	9.31	7
68	100	25	32.00	371	3.01	19.44	7
69	100	35	32.00	371	2.22	13.96	7
70	100	25	32.00	371	4.18	22.8	7
71	100	35	32.00	371	2.96	17.39	7
72	100	25	28.80	371	1.72	12.00	8
73	100	25	28.80	371	2.28	13.92	8
74	100	25	28.80	371	2.86	16.32	8
75	130	13	39.68	513	2.22	11.74	9
76	130	13	39.68	513	4.44	24.44	9
77	130	13	39.68	513	6.64	35.67	9
78	130	13	39.68	714	4.44	29.14	9
79	130	13	39.68	714	6.64	42.41	9
80	130	13	39.68	562	4.62	25.45	9
81	100	26	15.49	383	0.70	6.75	10
82	100	26	15.49	383	1.38	7.96	10
83	100	26	15.49	383	2.85	14.95	10
84	100	26	15.49	383	4.09	18.61	10
85	100	26	15.49	383	5.48	22.22	10
86	100	26	15.49	383	6.82	23.98	10
87	100	26	15.49	383	8.25	26.05	10
88	200	25	18.11	979	1.62	9.18	11
89	200	25	18.11	979	2.43	15.53	11
90	76	50	23.04	628	1.85	23.19	12
91	76	50	23.04	628	2.50	30.61	12
92	76	50	23.04	628	3.12	33.16	12
93	76	50	23.04	628	4.98	43.18	12
94	76	50	23.04	628	2.52	27.48	12
95	76	50	23.04	628	5.04	34.61	12
96	76	50	23.04	628	1.68	23.19	12
97	76	50	23.04	628	2.36	26.59	12
98	76	50	23.04	628	3.40	31.94	12

(Reference 4 - Paramasivam et al., 1985 [66]; 5 - Mashrei et al. 2010 [19]; 6 - Mansur, 1988 [67]; 7 - Paramasivam and Ravindarajah, 1988 [68]; 8 - Mansur and Paramasivam, 1986 [69]; 9 - Balaguru et al., 1977 [70]; 10 - Alwash, 1974 [71]; 11- Desayi and Reddy, 1991 [72]; 12 - Logan and Shah, 1973 [73]); b=width and d=depth of specimens; f'$_c$=cylinder compressive strength, M.UTS=Mesh Ultimate Tensile Strength; M.V_r=Mesh Volume Fraction; Fiber Volume Fraction (F.V_f)=0%; and Constant Fiber Ultimate Tensile Strength (F.UTS)=0 (N/mm^2) for data set no. (Runs)=50-98; EUFS-Equivalent Ultimate Flexural Strength

ANN Model No.3: For Model 3, 98 data sets were used from 48 data sets of Model 1 (as in Table 2) and 48 data sets of Model 2 (as in Table 3). Seven inputs (with their ranges) are width (b=76-400 mm) and depth (d=12.5-100 mm) of specimens, cylinder compressive strength (f'$_c$=8.06-48.41 N/mm^2) of plain/ fibrous mortar, Steel Mesh Ultimate Tensile Strength (M.UTS=371-979 N/mm^2), Mesh Volume of Reinforcement (M.V_r=0.49-8.25%); Fiber Volume Fraction (F.V_f=0-2.5%; and Fiber Ultimate Tensile Strength (F.UTS=0-1353 N/mm^2) are used to develop this model.

Model No.3 has used single output, Equivalent Ultimate Flexural Strength (EUFS) with values ranging from 5.28-43.18 N/mm^2. From the varying number of hidden neurons (4 to 13), the best performance of the hidden neurons was determined from 10 trial runs, i.e., Trial Nos. 3.1, 3.2, 3.3, 3.4, 3.5 with I-H-O of 7-4-1, 7-5-1, 7-6-1, 7-7-1 and 7-8-1 (respectively), as shown in Tables 7A and 8A, and Trial Nos. 3.6, 3.7, 3.8, 3.9 and 3.10 with I-H-O of 7-9-1, 7-10-1, 7-11-1, 7-12-1 and 7-13-1 (respectively), as shown in Tables 7B and 8B.

Step No.3. Splitting the Training and Testing Data:

For testing purposes, separate data sets were used that are not part of the training phase [55], [63]-[74]. The data used in the network was split into training and testing in the proportion of 80:20.

In Models 1 and 2, out of 49 data sets, 80% (38 nos.) have been chosen at random for training purposes, and the balance 20% (10 nos.) utilised for test purposes. Similarly, out of the total 98 data sets under Model 3, 78 data sets (80%) were selected at random for training the network and the balance 20 data sets (20%) for testing purposes.

Particularly, the randomization process was employed to split training and test data, as each sample will get an equal chance of being selected for training or testing; and there will be good mix of the data and all experimental cases will be represented in each subset [13]. In order to interpolate data very well, patterns which are chosen for training cover upper as well as lower boundaries and a sufficient number of samples representing particular feature over the entire training domain [75]. On completion of training, the neural network model is used to predict the target value, with the given input data in normalized form.

The testing was done for 5 trials for Model No. 1 (Trial Nos. 1.1 to 1.5), as shown in Tables 3 and 4, and Model No.2 (Trial Nos. 2.1 to 2.5), as shown in Tables 5 and 6. Similarly, 10 Trials (Trial Nos. 3.1 to 3.10) for Model No.3 done are shown in Tables 7A, 7B, 8A and 8B. The ANN simulation was carried out using Neural Network Toolbox of MATLAB mathematical software (MATLAB, R2014a).

Step No.4. Normalization of Data:

As it can be seen in the input data, large difference in the actual values of the data is seen, which cannot be directly fed into the neural system without any normalization process. Generally, the values are normalized to a uniform/ specified range or same order of magnitude, before they are used in the neural network for fast convergence, to avoid premature saturation of hidden nodes which is responsible for impeding the learning process, and to predict the output in a manner suiting the functioning of the network. Thus, the input values are normalized for the data shown in Tables 1 and 2 separately for Models 1 and 2, and in a combined manner for Model No.3 to avoid floating-point overflow problems and prevent large numbers from overriding smaller ones, and to obtain the minimal root mean square error (RMSE) [12], [63].

In this study, the input values in the three models shown in Tables 1 and 2 were normalized from 0 to 1 using formula given in Eq.(1) by Pal Pandian et al. (2013) [76]:

$$X_{cr} = (X_{AC} - X_{\min})\frac{X_{N\max} - X_{N\min}}{X_{\max} - X_{\min}} \quad ..(1)$$

Where $X_{AC=}$ Actual value of the variable before normalization; $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the variable X.

For example, the inputs (b, d, f'$_c$, M.UTS, SM.V$_r$, F.V$_f$ and F.UTS) were normalized to values X_{Nmin} and X_{Nmax} such that $0 < X_{\text{Nmin}} < X_{\text{Nmax}} < 1$. For example, in Model 3, from these 98 data sets, the minimum and maximum values for input variable, width (b) are $X_{\min}$ = 76 mm and $X_{\max}$= 400 mm. Using Eq.(1), X_{Nmin} = 0 and X_{Nmax} = 1, and the range 76 to 400 is mapped between 0 and 1.

Step No.5. Performance Checks:

The following are the statistical checks used:

RMSE indices are calculated to analyze the prediction efficiency of the ANN models that are developed [18]. The main intention of using RMSE is to measure the spread of the actual x values around the average of the predicted y values; and RMSE computes the average of the squared differences between each predicted value and its corresponding actual value. The formula to calculate RMSE is given in Eq. (1) by Imam et al. (2015) [13]; Aggarwal et al. (2013) [14] Shanmugaprakash and Sivakumar (2013) [63]; Khan et al, (2013) [59]; Tavakoli et al. (2014) [61]; Fakhim et al. (2013) [77]; and the lowest RMSE coefficient is recommended.

The coefficient of determination (R^2) is to test the goodness of fit of ANN predicted responses, and is calculated using Eq. (3) of Parichatprecha and Nimityongskul (2009) [12]; Yilmaz nd Kaynar (2011) [18]; Khan et al. (2013) [59].

The AAD (%) for ANN models is calculated to learn the accuracy of the models, and AAD% is calculated using Eq. (3) of Shanmugaprakash and Sivakumar, 2013 [63]; Fakhim et al. (2013) [77].

$$\text{RMSE}=\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(X_{PRED.} - X_{ACT.})^2\right)} \quad ..(2)$$

$$R^2= 1-\left(\frac{\sum_i^n (X_{PRED.}-X_{ACT.})^2}{\sum_i^n (X_{ACT.}-X_{ACT.AV.})^2}\right) \quad .(3)$$

$$\text{AAD (\%)} = \left(\frac{1}{n}\sum_{i=1}^{n} \left| \left(\frac{X_{PRED.}-X_{ACT.}}{X_{ACT.}}\right) \right|\right) \times \mathbf{100} \quad ..(4)$$

Where X_{PRED}= Predicted Data; $X_{ACT.}$ = Actual (Measured) Value; $X_{ACT.AV}$ = Actual Average of Actual Values; and n is the number of data

4. RESULTS AND DISCUSSION

This study has predicted the ultimate flexural strength of HMFRCBC, and the following are related to developing three ANN Models:

1. Five trials were conducted for Models 1 and 2 to fix the neurons for the hidden layer, and presented in Tables 3, 4, 5 and 6 and Figs. 1 and 4. For Model 3, the results of 10 trials are presented in Tables 7A, 7B, 8A and 8B. 5 input variables and 1 output for Models 1 and 2, and 7 inputs and 1 output for model 3 have been used. Fig. 10 gives the ANN predicted error for all the three models.
2. Tables 3, 5 and 7A-7B and Figs. 1,4 and 7 show that the actual values match with predicted ANN values for all the three models (Models 1, 2 and 3) (respectively). Accordingly, it is seen from Tables 4, 6 and 8A-8B that the best results in choosing the hidden neurons are seen in Trial No.1.4 (I-H-O of 5-6-1), Trial No.2.2 (5-4-1) and Trial No.3.7 (7-10-1) for Models 1, 2 and 3 respectively. The higher performance of these trials for each model is evidenced in Fig.10 by the LIE (%) of 11.18%, 6.95% and 11.56%. The present authors opine that one of the criteria for selecting the hidden layer should be based on lowest individual error, analyzed from trial runs.
3. Model 1 (Table 4), Model 2 (Table 6), Model 3 (Tables 8A and 8B) show that the lowest AAD (%) of 4.81%, 3.51% and 4.58% is achieved in trial run nos. 1.4 (I-H-O of 5-6-1), 2.2 (5-4-1) and 3.7 (7-10-1) respectively. Accordingly, the lowest RMSE of 0.86, 0.76 and 0.99 are observed for Models 1, 2 and 3 respectively. The low values of AAD% and RMSE represent that the flexural

strength of HMFRCBC predicted by all ANN Models are in good agreement with actual results.

4. The goodness of fit of the three models was confirmed by the coefficient of determination (R^2), which showed 0.933, 0.988 and 0.975 for Model Nos. 1, 2 and 3, and R^2 value closer to 1 indicates that the ANN models are accurate in predicting the ultimate flexural strength of HMFRCBC. For Models 1, 2 and 3, R^2 of 93.3%, 98.8% and 97.5% demonstrates that the measured data of HMFRCBC are compatible with the data predicted by Trials 1.4, 2.2 and 3.7 (respectively), and only 6.7%, 1.2% and 2.5% of the total variations (respectively) are not explained by the models.

5. For Models 1, 2 and 3, Figs. 2, 5 and 8 show that the best training performance for Trial No.1.4, 2.2 and.3.7 is achieved at 226, 695 and 372 epochs respectively. Fig. 3, 6 and 9 related to training sets of models 1, 2 and 3 (respectively) with co-efficient of high correlation (R) values of 0.994, 0.991 and 0.994 for Models 1, 2 and 3 respectively indicate that the network is well-trained and the output has deviated a little from the desired values.

Table 3. ANN Predicted Ultimate Flexural Strength (Model No.1)

No	Act. Data (in N/ mm²)	ANN Predicted Ultimate Flexural Strength (in N/mm²) (Model No.1)				
		Trial No. 1.1 5-3-1	Trial No. 1.2 5-4-1	Trial No. 1.3 5-5-1	Trial No. 1.4 5-6-1	Trial No. 1.5 5-7-1
4	17.28	17.65	17.97	17.38	17.14	17.75
8	11.09	10.00	10.24	11.37	10.33	10.74
14	10.56	10.60	10.40	10.94	10.45	9.93
18	8.88	9.39	9.93	9.06	9.01	9.07
22	12.96	13.41	12.60	13.21	13.95	11.67
28	16.56	14.92	13.36	14.47	14.86	12.14
33	17.76	17.71	17.62	17.83	17.75	17.44
38	11.04	10.11	11.39	11.38	9.81	11.67
46	15.36	17.09	17.64	16.44	16.52	17.51
48	16.80	17.15	16.23	17.30	17.02	16.23

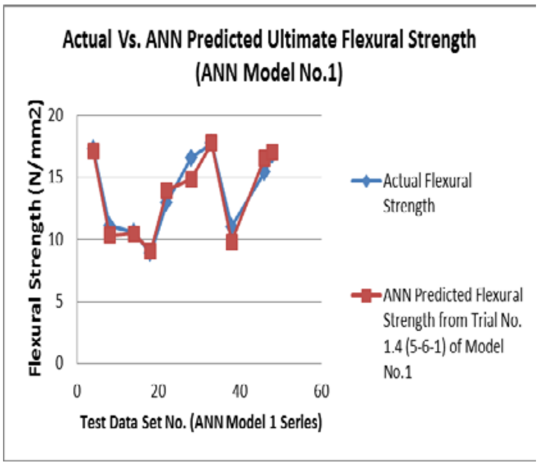

Fig. 1. Actual Vs. ANN Predicted Ultimate Flexural Strength (ANN Model No.1)

Table 4.ANN Predicted Error for Model No.1

Test Data No.	ANN Prediction Error (%) (Model No.1)				
	Trial No. 1.1 5-3-1	Trial No. 1.2 5-4-1	Trial No. 1.3 5-5-1	**Trial No. 1.4 5-6-1**	Trial No. 1.5 5-7-1
4	2.14	4.00	0.57	0.80	2.73
8	9.80	7.65	2.52	6.85	3.2
14	0.33	1.49	3.62	1.05	5.95
18	5.70	11.88	2.07	1.48	2.16
22	3.49	2.80	1.92	7.63	9.93
28	9.93	19.32	12.60	10.29	26.72
33	0.26	0.77	0.41	0.04	1.78
38	8.41	3.13	3.08	**11.18**	5.71
46	11.23	14.86	7.03	7.52	13.98
48	2.10	3.38	2.96	1.29	3.41
LIE %	11.23	19.32	12.60	**11.18**	26.72
AAD%	5.34	6.93	3.68	**4.81**	7.31
RMSE	0.92	1.36	0.79	**0.86**	1.65
R^2	0.925	0.823	0.937	**0.933**	0.764

Note: LIE (%)-Lowest Individual Error (in percentage); AAD (%)-Absolute Average Deviation (in percentage); RMSE-Root Mean Square Error; R^2-Coefficient of Determination

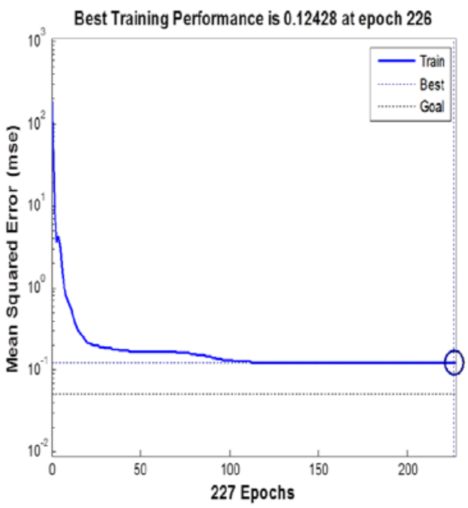

Fig. 2 Best Training Performance for Training Data (Trial No.1.4, 5-6-1) (ANN Model No.1)

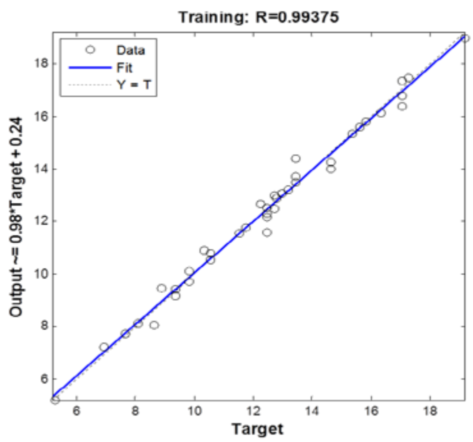

Fig. 3. Predicted Output Vs. Target for Training Data (Trial No.1.4, 5-6-1) (ANN Model No.1)

Table 5. ANN Predicted Ultimate Flexural Strength (Model No.2)

No	Act. Data	ANN Predicted Ultimate Flexural Strength (in N/mm^2) (Model No.2)				
		Trial No. 2.1 5-3-1	Trial No. 2.2 5-4-1	Trial No. 2.3 5-5-1	Trial No. 2.4 5-6-1	Trial No. 2.5 5-7-1
57	26.40	25.73	27.29	28.34	28.17	27.96
63	23.10	24.14	23.80	23.64	23.10	23.09
66	13.20	13.47	13.44	15.20	13.74	13.74
69	13.96	13.50	13.07	13.11	13.44	13.48
72	12.00	11.02	11.17	11.40	10.75	10.93
76	24.44	23.98	23.81	23.87	24.04	24.17
85	22.22	21.81	21.64	21.86	20.93	21.09
90	23.19	24.44	23.38	23.76	23.85	23.75
92	33.16	31.61	32.02	31.84	31.81	31.81
96	23.19	23.57	22.23	22.74	22.86	22.73

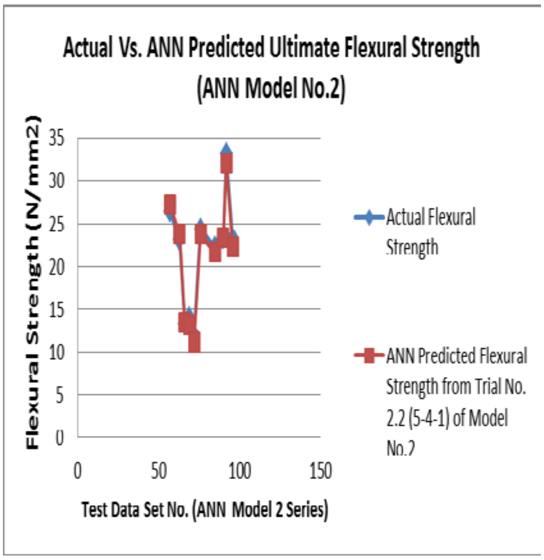

Fig. 4. Actual Vs. ANN Predicted Ultimate Flexural Strength (ANN Model No.2)

Table 6. ANN Prediction Error for Model No.2

Test Data No.	ANN Prediction Error (%) (Model No.2)				
	Trial No. 2.1 5-3-1	**Trial No. 2.2 5-4-1**	Trial No. 2.3 5-5-1	Trial No. 2.4 5-6-1	Trial No. 2.5 5-7-1
57	2.54	3.39	7.36	6.70	5.90
63	4.48	3.01	2.34	0.00	0.06
66	2.04	1.82	15.14	4.09	4.12
69	3.27	6.39	6.12	3.70	3.47
72	8.15	**6.95**	5.01	10.39	8.92
76	1.90	2.57	2.33	1.62	1.13
85	1.83	2.63	1.61	5.80	5.10
90	5.40	0.81	2.46	2.83	2.44
92	4.66	3.44	3.97	4.08	4.07
96	1.65	4.14	1.93	1.40	1.99
LIE(%)	8.15	**6.95**	15.14	10.39	8.92
AAD(%)	3.75	**3.51**	4.83	4.13	4.05
RMSE	0.85	**0.76**	1.09	0.97	0.88
R^2	0.982	**0.988**	0.970	0.978	0.982

Note: LIE (%)-Lowest Individual Error (in percentage); AAD (%)-Absolute Average Deviation (in percentage); RMSE-Root Mean Square Error; R^2-Coefficient of Determination

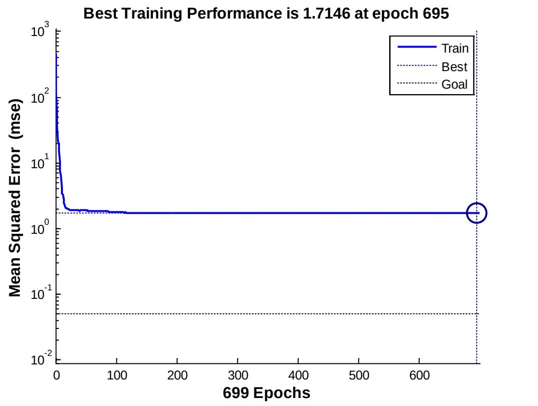

Fig. 5 Best Training Performance for Training Data (Trial No.2.2, 5-4-1) (ANN Model No.2)

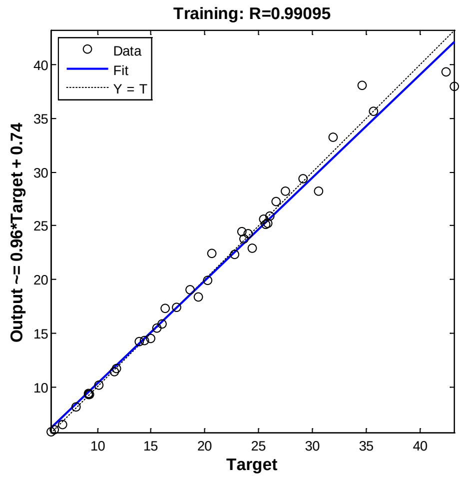

Fig. 6. Predicted Output Vs. Target for Training Data (Trial No.2.2, 5-4-1) (ANN Model No.2)

Table 7A. ANN Prediction of Ultimate Flexural Strength (Model No.3)

No	Act. Data (in N/mm^2)	ANN Predicted Ultimate Flexural Strength (in N/mm^2) (Model No.3)				
		Trial No. 3.1 7-4-1	Trial No. 3.2 7-5-1	Trial No. 3.3 7-6-1	Trial No. 3.4 7-7-1	Trial No. 3.5 7-8-1
4	17.28	16.40	16.00	15.55	15.82	15.87
8	11.09	10.74	10.88	11.18	11.20	10.96
14	10.56	10.09	10.51	10.37	10.29	10.57
18	8.88	9.38	9.21	9.34	9.26	9.32
22	12.96	13.50	13.45	13.26	13.59	13.47
28	16.56	14.42	14.51	14.28	14.64	14.52
33	17.76	16.61	17.15	18.13	17.90	17.70
38	11.04	10.42	10.48	10.30	10.44	10.67
46	15.36	17.04	17.89	17.26	17.01	17.15
48	16.80	15.56	15.87	15.98	15.78	15.92
57	26.40	27.68	26.19	28.00	27.47	26.90
63	23.10	22.84	23.49	23.42	24.02	24.09
66	13.20	13.15	14.15	13.94	14.40	14.03
69	13.96	12.95	13.35	12.56	13.73	13.67
72	12.00	10.84	11.47	11.49	11.33	10.96
76	24.44	23.85	24.39	22.70	22.96	23.38
85	22.22	22.53	21.65	21.52	21.58	21.67
90	23.19	25.51	24.62	24.89	24.44	24.64
92	33.16	31.17	31.46	31.33	31.59	31.51
96	23.19	24.45	23.06	23.41	22.75	23.16

Table 7B. ANN Prediction of Ultimate Flexural Strength (Model No.3)

No	Act. Data (in N/ mm^2)	ANN Predicted Ultimate Flexural Strength (in N/mm^2) (Model No.3)				
		Trial No. 3.6 7-9-1	Trial No. 3.7 7-10-1	Trial No. 3.8 7-11-1	Trial No. 3.9 7-12-1	Trial No. 3.10 7-13-1
4	17.28	16.65	16.70	16.49	15.90	16.49
8	11.09	10.51	11.03	10.91	11.01	10.78
14	10.56	10.56	10.40	10.55	10.45	10.76
18	8.88	9.33	9.19	9.22	9.29	9.22
22	12.96	13.88	13.48	13.60	13.52	13.38
28	16.56	14.90	14.65	14.71	14.52	14.45
33	17.76	17.27	17.46	18.46	17.91	17.27
38	11.04	10.42	10.83	10.27	10.70	10.74
46	15.36	17.20	17.09	16.69	17.05	16.69
48	16.80	15.73	16.25	16.04	15.97	16.05
57	26.40	28.19	27.80	27.88	26.94	27.99
63	23.10	24.63	24.18	23.04	24.19	23.35
66	13.20	14.49	14.63	14.85	14.35	13.99
69	13.96	13.11	13.94	13.65	13.70	13.47
72	12.00	11.35	11.07	11.52	10.95	11.14
76	24.44	24.29	23.75	23.65	23.82	23.97
85	22.22	21.34	21.26	21.46	21.67	21.63
90	23.19	24.50	24.00	24.24	24.21	24.90
92	33.16	30.97	31.60	31.20	31.64	31.34
96	23.19	22.55	22.03	22.27	22.45	23.59

Table 8A. ANN Prediction Error for Model No.3

Test Data No.	ANN Prediction Error (%) (Model No.3)				
	Trial No. 3.1 7-4-1	Trial No. 3.2 7-5-1	Trial No. 3.3 7-6-1	Trial No. 3.4 7-7-1	Trial No. 3.5 7-8-1
4	5.09	7.40	10.02	8.47	8.15
8	3.12	1.88	0.84	1.02	1.15
14	4.50	0.49	1.79	2.57	0.10
18	5.63	3.70	5.13	4.32	4.97
22	4.14	3.77	2.35	4.85	3.90
28	12.92	12.39	13.78	11.59	12.34
33	6.47	3.43	2.11	0.80	0.36
38	5.59	5.04	6.67	5.44	3.36
46	10.92	16.47	12.35	10.75	11.64
48	7.39	5.51	4.87	6.06	5.26
57	4.86	0.78	6.07	4.07	1.89
63	1.14	1.70	1.37	3.98	4.29
66	0.39	7.23	5.62	9.10	6.32
69	7.22	4.34	10.04	1.66	2.11
72	9.66	3.38	4.26	5.58	8.70
76	2.40	0.18	7.12	6.06	4.32
85	1.40	2.55	3.15	2.86	2.49
90	10.02	6.18	7.32	5.39	6.25
92	6.00	5.13	5.52	4.75	4.97
96	5.44	0.56	0.95	1.88	0.13
LIE %	12.92	16.47	13.78	11.59	12.34
AAD %	5.71	4.60	5.57	5.06	4.63
RMSE	1.18	1.03	1.20	1.03	1.00
R^2	0.968	0.974	0.965	0.973	0.975

Note: LIE (%)-Lowest Individual Error (in percentage); AAD (%)-Absolute Average Deviation (in percentage); RMSE-Root Mean Square Error; R^2-Coefficient of Determination

Table 8B. ANN Prediction Error for Model No.3

Test Data No.	ANN Prediction Error (%) (Model No.3)				
	Trial No. 3.6 7-9-1	**Trial No. 3.7 7-10-1**	Trial No. 3.8 7-11-1	Trial No. 3.9 7-12-1	Trial No. 3.10 7-13-1
4	3.67	3.37	4.55	7.97	4.55
8	5.22	0.53	1.63	0.70	2.81
14	0.04	1.51	0.13	1.08	1.91
18	5.02	3.50	3.79	4.65	3.79
22	7.10	4.00	4.95	4.36	3.22
28	10.00	**11.56**	11.18	12.30	12.71
33	2.76	1.68	3.93	0.85	2.74
38	5.63	1.89	7.02	3.10	2.74
46	11.98	11.24	8.65	11.03	8.67
48	6.34	3.29	4.54	4.96	4.47
57	6.78	5.30	5.59	2.04	6.02
63	6.62	4.70	0.26	4.72	1.09
66	9.79	10.80	12.48	8.71	5.99
69	6.11	0.11	2.21	1.86	3.51
72	5.39	7.77	3.98	8.76	7.16
76	0.63	2.84	3.23	2.52	1.92
85	3.95	4.33	3.40	2.49	2.63
90	5.64	3.49	4.52	4.39	7.36
92	6.60	4.69	5.92	4.60	5.48
96	2.76	5.00	3.96	3.17	1.74
LIE %	11.98	**11.56**	12.48	12.30	12.71
AAD %	5.60	**4.58**	4.80	4.71	4.52
RMSE	1.14	**0.99**	1.00	0.97	0.98
R^2	0.968	**0.975**	0.975	0.977	0.976

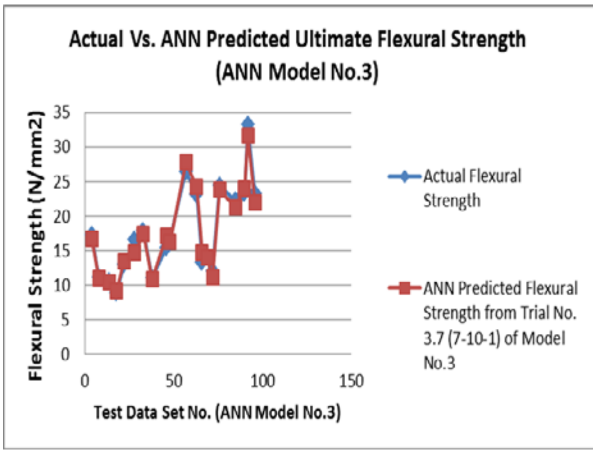

Fig. 7. Actual Vs. ANN Predicted Ultimate Flexural Strength (ANN Model No.3)

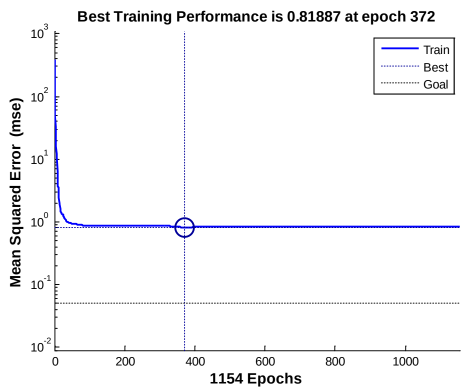

Fig. 8 Best Training Performance for Training Data (Trial No.3.7, 7-10-1) (ANN Model No.3)

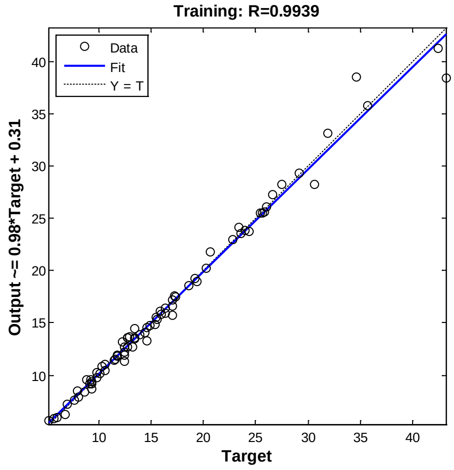

Fig. 9. Predicted Output Vs. Target for Training Data (Trial No.3.7, 7-10-1) (ANN Model No.3)

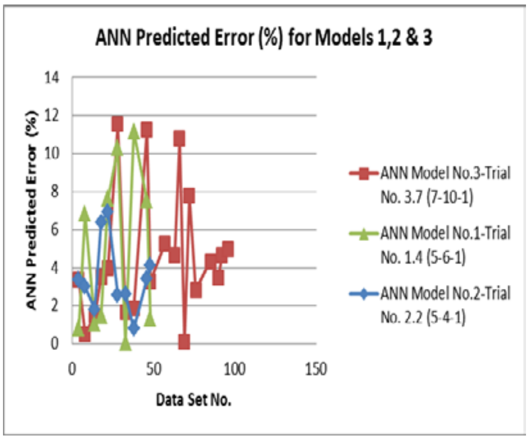

Fig. 10. ANN Predicted Error for all Models

5. CONCLUSION

In this study, the flexural strength of hybrid mesh and fiber reinforced cement based composite (HMFRCBC) slab elements have been predicted using Artificial Neural Network (ANN). Three ANN models were developed, and based on various trials, the number of neurons for hidden layers was determined. Based on Lowest Individual Error (LIE %), lowest Absolute Average Deviation (AAD %), lowest Root Mean Square Error (RMSE) and the highest co-efficient of correlation (R^2), the best trial run have been finalized for all the three models in fixing the hidden neurons. The best trial run for Models 1, 2 and 3 shows LIE (%) of 11.18%, 6.95% and 11.56%, lowest AAD (%) of 4.81%, 3.51% and 4.58%, lowest RMSE of 0.86, 0.76 and 0.99, and highest R^2 of 0.933, 0.988 and 0.975 respectively. Thus, ANN can be an effective technique in predicting the values from previous experimental studies or empirical or theoretical data, thus saving time and cost in conduct of new experiments.

6. ACKNOWLEDGEMENTS

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