INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING Int. J. Optim. Civil Eng., 2018; 8(3):453-467



ANN BASED MODELING FOR HIGH STRENGTH CONCRETE BEAMS WITH SURFACE MOUNTED FRP LAMINATES

K. Suguna^{*,†}, P.N. Raghunath, J. Karthick and R. Uma Maheswari Department of Civil and Structural Engineering, Annamalai University, India

ABSTRACT

This study focuses on using an artificial neural network (ANN) based model for predicting the performance of high strength concrete (HSC) beams strengthened with surface mounted FRP laminates. Eight input parameters such as geometrical properties of the beam and mechanical properties of FRP laminates were considered for this study. Back propagation network with Lavenberg-Marquardt algorithm has been chosen for the proposed network, which has been implemented using the programming package MATLAB. In the present study, comparison has been made between the experimental results and those predicted through neural network modeling. The amount of MAPE and RMSE were predicted and were found to be acceptable range. The statistical indicators such as correlation co-efficient (r) and co-efficient of determination (\mathbb{R}^2) were also predicted to estimate the accuracy of results obtained through ANN modeling. The results predicted through ANN modeling exhibit good correlation with the experimental results.

Keywords: ANN; FRP; beams; high strength concrete; static.

Received: 20 September 2017; Accepted: 12 November 2017

1. INTRODUCTION

Now-a-days, strengthening of high strength concrete members with surface mounted fibre reinforced polymer laminates (FRP) has proved to be an effective and appropriate technique to improve their performance under service loads or ultimate loads [1]. This technique has several advantages because of the inherent characeteristics of FRP material such as high strength-to-weight ratio, low maintenance cost and higher corrosion resistance [2]. Fibre-reinforced polymer (FRP) is a composite material made of a polymer matrix reinforced with fibres. FRP composites are becoming an alternative material for rehabilitation and retrofitting projects around the world [3]. Depending on the design objectives, these

^{*}Corresponding author: Department of Civil and Structural Engineering, Annamalai University, India sugunaraghunath@gmail.com (K. Suguna)

materials can be used to improve one or more of the structural member characteristics such as load capacity, ductility and durability [4,5]. Design of structural strengthening applications using surface mounted FRP composites is usually based on conventional design approaches with improvements to account for the presence and characteristics of the FRP material. In the meantime, soft computing and artificial intelligence techniques like artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and optimization algorithms (GA) have also been used in various civil engineering applications. An effort has been taken by some researchers in the area of soft computing and artificial intelligence techniques [5-8]. Shanmugavelu et al [5] proposed an ANN based model for predicting the performance characteristics of reinforced concrete beams strengthened with glass fibre reinforced polymer laminates. The model was developed using general regression neural network (GRNN) to predict different target parameters such as yield load, deflection at yield load, ultimate load, deflection at ultimate load and ductility ratio respectively. The authors reported that the proposed artificial neural network based model performed well to predict the target parameters. Metwally [6] predicted the flexural capacity of reinforced concrete beams using artificial neural network. The feed-forward back-propagation neural network was applied to predict the flexural load capacity. The author reported that the proposed ANN model provides accurate results in calculating the ultimate flexural load. Amani and Moeini [7] predicted the shear strength of reinforced concrete (RC) beams using ANN and ANFIS based model. Back-Propagation (BP) algorithm was used to predict the shear strength of RC beams. The authors reported that the ANN based model was better than that of ANFIS based model and the two models provide better prediction when compared to ACI and ICI empirical codes. Pannirselvam et al [8] developed an ANN based model for predicting the effectiveness of glass fibre reinforced polymer laminates on the performance of RC beams. The results of fifteen reinforced concrete beams with an ANN based model were reported in this study. The authors reported that the ANN based model provided a reasonable prediction of the target parameters. The predicted results are in good agreement with the experimental results. This study has been taken up for predicting the performance of high strength concrete (HSC) beams strengthened with surface mounted FRP laminates using an artificial neural network (ANN) based model.

2. MATERIALS AND METHODS

2.1 Artificial neural network (ANN)

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems such as brain and process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. There are other ANNs which are adaptive systems used to model things such as environments and population. The ANN attempts to recreate the computational mirror of the biological neural network, although it is not comparable since the number and complexity of neutrons used in a biological neural network is many times more than those in an artificial neutral network. An ANN is comprised of a network of artificial neurons (also known as "nodes"). These nodes are

454

connected to each other and the strength of their connection to one another is assigned a value based on their strength: inhibition (maximum being -1.0) or excitation (maximum being +1.0). If the value of the connection is high, then it indicates that there is a strong connection. Within each node's design, a transfer function is built in. There are three types of neutrons in an ANN, input nodes, hidden nodes, and output nodes. The neural network architecture is shown in Fig. 1.



Figure 1. Architecture of Neural Network

2.2 Human nervous system versus artificial neural network

Artificial neuron is a basic building block of every artificial neural network. Its design and functionalities are derived from observation of a biological neuron that is basic building block of biological neural networks (systems) which includes the brain, spinal cord and peripheral ganglia. Similarities in design and functionalities can be seen in Fig. 2. Fig. 2(a) represents a biological neuron with its soma, dendrites and axon and Fig. 2(b) represents an artificial neuron with its inputs, weights, transfer function, bias and outputs.



In case of biological neuron, information comes into the neuron via dendrite; soma processes the information and passes it on via axon. In case of artificial neuron, information comes into the body of an artificial neuron via inputs that are weighted (each input can be individually multiplied with a weight). The body of an artificial neuron then sums the weighted inputs, bias and "processes" the sum with a transfer function. At the end, an artificial neuron passes the processed information via output(s).

2.3 Data used in ANN modeling

The geometrical properties of the beam such as length (L), breadth (B) and depth (D) of the section, reinforcement ratio (ρ), characteristic compressive strength of concrete (f_{ck}) and the mechanical properties of FRP laminates such as tensile strength (f_{frp}) and elasticity modulus (E_{frp}) were considered as the input parameters. The experimental results of all the test beams such as yield load (P_y), deflection at yield load (Δ_y), service load (P_s), deflection at service load (Δ_s), ultimate load (P_u), deflection at ultimate load (Δ_u) and deflection ductility (DD) were considered as the target parameters. The input and target parameters for ANN modeling are presented through Tables 1 and 2.

Table 1: Input parameters for ANN modeling

Beam	L	В	D	Т	$f_{\rm frp}$	E _{frp}	ρ _s	f_{ck}
designation	(mm)	(mm)	(mm)	(mm)	(MPa)	(GPa)	(%)	(MPa)
RA	3000	150	250	0.00	0.0	0.00	0.419	64.0
RAC3	3000	150	250	3.00	126.2	7.47	0.419	64.0
RAC5	3000	150	250	5.00	156.0	11.39	0.419	64.0
RAU3	3000	150	250	3.00	446.9	13.97	0.419	64.0
RAU5	3000	150	250	5.00	451.5	17.37	0.419	64.0
RB	3000	150	250	0.00	0.00	0.00	0.628	64.0
RBC3	3000	150	250	3.00	126.2	7.47	0.628	64.0
RBC5	3000	150	250	5.00	156.0	11.39	0.628	64.0
RBU3	3000	150	250	3.00	446.9	13.97	0.628	64.0
RBU5	3000	150	250	5.00	451.5	17.37	0.628	64.0

Table 2: Target parameters for ANN modeling

Beam designation	$P_{y}(kN)$	$\Delta_{\rm y}({\rm mm})$	$P_s(kN)$	$\Delta_{\rm s}({\rm mm})$	$P_u(kN)$	$\Delta_{\mathrm{u}} \left(\mathrm{mm} \right)$	DD
RA	29.42	7.91	27.79	14.03	41.68	21.05	2.66
RAC3	36.77	9.02	34.32	22.31	51.48	33.46	3.70
RAC5	46.58	10.10	44.13	31.21	66.19	46.81	4.63
RAU3	51.48	11.42	47.39	35.50	71.09	53.26	4.66
RAU5	53.70	10.74	52.30	38.14	78.45	57.21	5.32
RB	39.22	8.11	35.95	20.85	53.93	31.28	3.86
RBC3	51.48	11.35	40.86	24.15	61.29	36.23	3.19
RBC5	53.24	12.41	42.49	37.94	63.74	56.91	4.59
RBU3	58.80	12.85	58.83	40.69	88.25	61.04	4.75
RBU5	63.00	12.69	67.00	43.73	100.51	65.59	2.66

456

ANN BASED MODELING FOR HIGH STRENGTH CONCRETE BEAMS WITH ... 457

2.4 Steps involved in ANN modeling

In this stage, the input data are divided into three groups which are train data, validate data and test data. The step-wise procedure for ANN modeling is presented through Figs. 3 to 10.

2.4.1 Building the network

This stage, specifies the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function and performance function as shown in Figs. 3 and 4.



Figure 3. Architecture of proposed NN model

📣 MATLAB R2013a					e X
HOME PLOTS APP		Liikise D	 Search Documer 	ntation	≖ م
New New Open Compare Information	Neural Network Fitting Tool (ntbool) Network Architecture Set the number of neurons in the fitting network's hidden layer.	- 8 2			
← → 🔄 🖾 🗼 + C: → Program Files	- Viddae I war	Personmendation			- p
Current Folder		A CONTRACTOR			• <
Name A	Define a fitting neural network. (fitnet)	Return to this panel and change the number of neurons if the network does not netform well after training.	alue	Min	Max
🗉 📗 m3iregistry	Number of Hidden Neurons: 10		x18 double>	29.4200	130.66
E registry			x18 double>	0	230000
e win32				0	0
both has & vi.mat					
data.mat					
doba.m					
error_file.mat					
📃 ffffffffffff.mat					
📩 hashmi.mat	Restore Defaults				
harmi arulti mat					
insttype.ini	- Neural Network				_
📄 Icdata.xml					۲
lcdata.xsd	Hidden Layer	Output Layer			^
Icdata_utf8.xml	Input	Output	1:53 AM%		
matlab.exe			sat')		
🔠 matlab2.mat					
📩 matlab 45.mat	8		:52 FM%		
iii matlab first data.mat	10	1			
matab wk spinat					
i mcc.bat			126 PH		
MemShieldStarter.bat	Channe settions if desired then slick (Next) to continue		1-37 EM		
S mex.bat	- Change seconds in dealers, then circle [next] to containe.				
both has & vi.mat (IIAT File)	Reural Network Start 144 Welcome	Sack Next Cancel	s & vi.mat')		•
					_
👌 🏉 🔕 📜	👹 📉 🕄 🖉 🔺	S 🖆 🖪 🔒 🤅) 🖗 🖯 🏼 🖗 () Ia _	7:43 PM 1/24/2016
	Element Manual mar	treve ula e un la ita eta un			

Figure 4. Neural network architecture

2.4.2 Training the network

Back propagation algorithms are used to developing the artificial neural network. The training processes are shown through Figs. 5 and 6. The weights are adjusted to make the actual outputs (predicted) close to the target (measured) outputs of the network.



Figure 5. Training Network Wizards

📣 MATLAB R2013a	(
HOME PLOTS APP	ঙ	Neural Network Training (nntraintool)	BHARLDCE	😧 Search Documentation 🛛 🔎 🗖
🛃 🕂 🗀 🕞 Find Files 🕹	A Neural Network Fitting Tool (nftoo	Neural Network Hidden Output		
New New Open Compare Import Script • • Data FILE	Train Network Train the network to fit	Input W + Compared W + Compared 1		- 0
Current Folder	I rain Network	10 1		() <
Name &	Train using Levenberg-Marquardt	Algorithms	🖻 MSE 🖉 R	tu tu ta
A militarity			8.94452e-0 9.97114e-1	Nue Min Max or
		Data Division: Random (dividerand)	04.61457e-0 9.93499e-1	x18 double> 29.4200 130.00
🗉 🍈 util		Training: Levenberg-Marquardt (trainim) Reformance: Mean Sourced Error (mca)	964.50634e-0 -9.17629e-1	0 0
🗉 🎍 win32		Derivative: Default (defaultderiv)		
both has & vi.mat				
data.mat	Training automatically stops when	Progress	ror Histogram	
a deploytool.bat	indicated by an increase in the me	Epoch: 0 12 iterations 1000	sion	
error_file.mat	samples.	Time: 0:00:02		
🔢 ffffffffff.mat	Notes	Performance: 835ex03 699 000		
🖶 hashmi.mat	Training multiple times will a	Gradient 183e-04 886 100e-07	and difference	
hasmi df du results.mat	to different initial conditions	Max 0.00100 100 100 100 100 100 100 100 100	ues are better. Zero	
hasmi results.mat		Validation Checker 0 6		
 Insuppermi Indata vml 		validation checks.	Constant and	۲
Icdata.xsd		Plots	and a close	A
Cdata_utf8.xml				1:53 BM*
🚳 matlab.bat		Performance (plotperform)		nat 1)
🔺 matlab.exe		Training State (plottrainstate)		
matlab2.mat		For the second s		1152 PM
matlab 45.mat		(plotermist)		
matlab w/c co mat		Regression (plotregression)		
Muild.bat		Fit (olotfit)		1.06 TM 8
🚳 mcc.bat		direction of the second		120 PA
MemShieldStarter.bat	<u>→</u>	Plot Interval: 1 epochs		
🚳 mex.bat	Open a plot, retrain, or clid			1:37 PM8
hath has find and (ULT The)	Reural Network Start		Next 🙆 Cancel	-
both has & vilmat (MA1 Hie)		Validation stop.		s & vi.mat')
🕑 🍐 💽 📋	🧶 🕅 🚱		8 🗳 🖪 🗈	🕕 🚰 🎖 🎿 🖓 🔪 🐚 7746 PM 11/24/2016
		() Y		

Figure 6. Neural Network Training

2.4.3 Test performance of model

The fitness of the developed model is shown through Figs. 7 to 10. At this stage, unseen data are exposed to the model.



Figure 7. Neural Network Regression Plot



Figure 8. Neural Network Training Performance Plot



Figure 9. Neural Network Training State



Figure 10. Neural Network Error Histogram State

2.5 Data used for validating the ANN results

The experimental results pertinent to this problem from other researchers published work were used for the purpose of validating the ANN model. Data such as length of the section (L), breath of the section (B), depth of the section (D), thickness of FRP laminates ($t_{\rm frp}$), tensile strength of FRP laminates ($f_{\rm frp}$), elasticity modulus of FRP laminates ($E_{\rm frp}$), reinforcement ratio (ρ) and characteristic strength of concrete at 28 days (f_{ck}) taken from the research works [] are presented through Tables 3 to 4.

Table 3: Input parameters for ANN modeling

Authors name	Beam	L (mm)	B (mm)	D (mm)	T (mm)	f_{frp}	E_{frp}	ρ_s	f_{ck}
		3000	150	250				0 107	(IVII a) 77.0
	Anu	3000	150	230	0.00	0.0	0.00	0.107	//.0
	AH1	3000	150	250	0.05	3850.0	230.00	0.107	77.0
	AH4	3000	150	250	0.18	3850.0	230.00	0.107	77.0
Hashemi et al.	ACG3	3000	150	250	0.48	3850.0	230.00	0.107	77.0
(2009)	BHO	3000	150	250	0.00	0.0	0.00	0.203	77.0
	BH1	3000	150	250	0.05	3850.0	230.00	0.203	77.0
	BH4	3000	150	250	0.18	3850.0	230.00	0.203	77.0
	BCG3	3000	150	250	0.48	3850.0	230.00	0.203	77.0
	SAB1	3000	150	250	0.00	0.0	0.00	0.565	66.7
Phalguni	FS1	3000	150	250	2.50	786.5	152.70	0.565	53.3
Mukhopadhyaya	FS2	3000	150	250	3.50	786.5	229.00	0.565	54.0
et al.	FS3	3000	150	250	3.50	786.5	229.00	0.565	66.5
(1998)	FS4	3000	150	250	3.50	786.5	229.00	0.565	79.7
	FS5	3000	150	250	3.50	786.5	229.00	0.565	66.6

Pabinovith									
Additiovitii	A 1	2500	200	200	0.00	0.0	0.00	0 482	763
(2003)	AI	2300	200	200	0.00	0.0	0.00	0.462	70.5
(2003)	Δ2	2500	200	200	1 20	2800.0	165.00	0.482	763
	A2 A3	2500	200	200	1.20	2800.0	165.00	0.482	76.3
	R1	2500	200	200	0.00	2800.0	0.00	0.482	76.3
	B1 B2	2500	200	200	1.20	2800.0	165.00	0.482	76.3
Grace et al	D2	2300	200	200	1.20	2000.0	105.00	0.402	70.5
(2002)	С	2744	152	254	0.00	0.0	0.00	0.521	65.2
	C-1	2744	152	254	0.13	2413.0	231.00	0.521	65.2
	C-2	2744	152	254	1.30	2413.0	231.00	0.521	65.2
	C-3	2744	152	254	1.90	2413.0	231.00	0.521	65.2
	H-50-2	2744	152	254	1.00	1324.0	379.00	0.521	65.2
	H-75-2	2744	152	254	1.50	1324.0	379.00	0.521	65.2
Mahfuz ud darain									
et al. (2016)	CB	3300	125	250	0.00	0.0	0.00	0.724	60.5
(2010)	CBC8P1	3300	125	250	0.17	4900.0	230.00	0 724	60 5
	CBC8P2	3300	125	250	0.34	4900.0	230.00	0.724	60.5
	CBC10P1	3300	125	250	0.17	4900.0	230.00	0.724	60.5
	CBC10P2	3300	125	250	0.34	4900.0	230.00	0.724	60.5
	CBC10PA	3300	125	250	0.34	4900.0	230.00	0.724	60.5 60.5
Maghsoudi et al. (2009)	AH0	3000	150	250	0.00	0.0	0.00	1.200	77.0
et ul. (2007)	AHE	3000	150	250	0 94	2800.0	165.00	1 200	77.0
	AHD	3000	150	250	0.67	2800.0	165.00	1.200	77.0
	BH0	3000	150	250	0.00	0.0	0.00	2400	77.0
	BHE	3000	150	250	0.00	2800.0	165.00	2.400 2 400	77.0
	BHD	3000	150	250	0.67	2800.0	165.00	2.100 2 400	77.0
Fanning et al.	F1	3000	155	240	0.00	0.0	0.00	0.912	80.0
(2001)	F2	2000	155	240	0.00	0.0	0.00	0.012	80.0
	Г2 Е2	2000	155	240	1.20	2400.0	0.00	0.912	80.0
	ГЭ Е4	2000	155	240	1.20	2400.0	155.00	0.912	80.0
	F4 E5	2000	155	240	1.20	2400.0	155.00	0.912	80.0
	F5 EC	2000	155	240	1.20	2400.0	155.00	0.912	80.0
	F0 F7	2000	155	240	1.20	2400.0	155.00	0.912	80.0
		3000	155	240	1.20	2400.0	155.00	0.912	80.0
	F8	3000	155	240	1.20	2400.0	155.00	0.912	80.0
Gopinathan et al. (2016)	CBHSC	3000	150	250	0.00	0.0	0.00	0.603	67.0
	C3HSC	3000	150	250	3.00	126.2	7.47	0.603	67.0
	C5HSC	3000	150	250	5.00	156.0	11.39	0.603	67.0
	W3HSC	3000	150	250	3.00	147.4	6.86	0.603	67.0
	W5HSC	3000	150	250	5.00	178.1	8.99	0.603	67.0
	U3HSC	3000	150	250	3.00	446.9	13.97	0.603	67.0

ANN BASED MODELING FOR HIGH STRENGTH CONCRETE BEAMS WITH ... 461

Author	am	ad	at id	ad	at ad		at 1)	_
	st Be	eld Lo (kN)	lection eld Loa (mm)	vice Lo (kN)	lection vice Lo	Jltimate ad (kN	lection Iltimate ad (mm	eflection
	Te	Yi	Y:	Ser)ef Ser	ΓC	Lo	D D
	A 110	63.03	21.00	54.17	68.00	81.25	102.00	1 35
	AH1	69.50	13.00	59.93	33.61	89.90	102.00 50.42	3.88
	ΔH4	64 70	9.83	78.20	21.90	117 30	32.85	3.30
Hashemi et	ACG3	67 33	10.37	69.33	17.70	104.66	26.20	2 53
a1(2009)	BH0	122 22	13 33	99.68	63.80	149 52	20.20 95 70	2.33 7.18
ul.(2007)	BH1	130.00	14 11	100.00	42 16	150.00	63 24	4 48
	BH4	118.00	12.86	111 33	20.61	167.00	30.92	$\frac{1.40}{240}$
	BCG3	130.66	13.80	108.22	17 33	162.33	26.00	2.40
	SAB1	170.50	22 17	133.26	19.07	102.55	20.00	1.00
	FS1	190.25	22.17	140.93	18.32	211.40	28.00	1.27
Phalouni et	FS2	179.00	30.60	131 27	20.61	196.90	30.91	1.00
a1 (1008)	FS2	100 00	27.14	1/6 53	20.01	210.20	33.07	1.10
al. (1770)	FS4	215 35	27.14	155 53	22.01 26.40	217.00	39.60	2.16
	FS5	213.33	19.20	154.6	20.40 24.2	233.30	36.36	1.58
	Δ1	65.00	9.90	50 28	27.2	231.90 75.42	50.00	5.05
	Δ2	140.00	10.50	104 40	11 33	156.60	17.00	1.62
Rabinovith	Δ3	135.00	11.00	118 67	12.67	178.00	19.00	1.02
et al. (2003)	R1	109.00	12.00	73 33	32.67	110.00	49.00	4.04
	B2	155.00	11.50	124.93	12.67	187.40	19.00	1.65
	C D2	82 30	14.00	63.80	33.00	95 70	49 52	3 55
	C-1	85.90	13.20	67.93	18.93	101.90		2.15
Grace et	C-2	132.60	16.00	88.40	10.55	132.60	16.00	1.00
a1(2002)	C-3	107 70	13.50	89.60	14.73	132.00 134.40	22 10	1.00
al.(2002)	H_50_2	97.90	15.30	76 53	23 73	11/ 80	35.60	1.0+ 2.33
	H-75-2	113.90	13.20	87.20	19 47	130.80	29.20	2.55
	CB	36.00	15.70	26.00	22.87	39.00	34 30	2.15
	C8P1	50.00	14.90	20.00 47 33	22.07	71.00	39.70	2.27
Mahfuz ud	C8P2	55.00	15.20	51 33	20.47	77.00	31.30	2.00
darain et al.	C10P1	54.00	16.60	54.67	20.07	82.00	43 30	2.00
(2016)	C10P2	69.00	23 70	58.00	20.07	87.00	42 70	2.00
	$C10P2\Delta$	80.00	23.70 24 70	70.00	31.93	105.00	47.90	1.00
	F1	53.00	12 18	45 53	31.33	68 30	47.00	3.86
	F2	53.50	12.10	45.33	30.00	67.90	45.00	3.00
	F3	82.90	11.05	73.93	14 67	110.90	22.00	1.84
Fanning et	F4	83.60	12 50	79.00	16.00	118.50	22.00 24.00	1.04
a1(2001)	F5	85.60	10.96	66 67	11.33	100.00	17.00	1.52
ul.(2001)	F6	85.60	12.73	68.67	13 33	103.00	20.00	1.55
	F7	83 70	12.75	65.07	12.00	97 50	18.00	1.37
	F8	78 30	13.10	54 67	10.67	82.00	16.00	1.77
Maghson di	AHO	63 73	11 89	54 17	48.00	81 25	72.00	6.05
et al. (2009)	AHF	76.70	11.13	68.67	15.49	103.00	23.23	2.08
Hashemi et al. (2009) Phalguni et al. (1998) Rabinovith et al. (2003) Grace et al. (2002) Mahfuz ud darain et al. (2016) Fanning et al. (2001) Maghsou di et al. (2009)	AH0 AH1 AH4 ACG3 BH0 BH1 BH4 BCG3 SAB1 FS1 FS2 FS3 FS4 FS5 A1 A2 A3 B1 B2 C C-1 C-2 C-3 H-50-2 H-75-2 CB C8P1 C10P2 C10P1 C10P2 C10P2A F1 F2 F3 F4 F5 F6 F7 F8 AH0 AHF	$\begin{array}{c} 63.93\\ 69.50\\ 64.70\\ 67.33\\ 122.22\\ 130.00\\ 118.00\\ 130.66\\ 170.50\\ 190.25\\ 179.00\\ 199.90\\ 215.35\\ 214.70\\ 65.00\\ 140.00\\ 135.00\\ 109.00\\ 135.00\\ 109.00\\ 155.00\\ 82.30\\ 85.90\\ 132.60\\ 107.70\\ 97.90\\ 113.90\\ 36.00\\ 55.00\\ 54.00\\ 69.00\\ 55.00\\ 54.00\\ 69.00\\ 55.00\\ 54.00\\ 69.00\\ 80.00\\ 53.50\\ 82.90\\ 83.60\\ 85.60\\ 83.70\\ 78.30\\ 63.73\\ 76.70\\ \end{array}$	$\begin{array}{c} 21.00\\ 13.00\\ 9.83\\ 10.37\\ 13.33\\ 14.11\\ 12.86\\ 13.80\\ 22.17\\ 25.92\\ 30.60\\ 27.14\\ 20.63\\ 19.24\\ 9.90\\ 10.50\\ 11.00\\ 12.00\\ 11.50\\ 14.00\\ 13.20\\ 16.00\\ 13.50\\ 15.20\\ 13.70\\ 15.20\\ 15.20\\ 13.70\\ 15.2$	$\begin{array}{c} 54.17\\ 59.93\\ 78.20\\ 69.33\\ 99.68\\ 100.00\\ 111.33\\ 108.22\\ 133.26\\ 140.93\\ 131.27\\ 146.53\\ 155.53\\ 154.6\\ 50.28\\ 104.40\\ 118.67\\ 73.33\\ 124.93\\ 63.80\\ 67.93\\ 88.40\\ 89.60\\ 76.53\\ 87.20\\ 26.00\\ 47.33\\ 51.33\\ 54.67\\ 58.00\\ 70.00\\ 45.53\\ 45.27\\ 73.93\\ 79.00\\ 66.67\\ 68.67\\ 65.00\\ 54.67\\ 54.17\\ 68.67\\ \end{array}$	$\begin{array}{c} 68.00\\ 33.61\\ 21.90\\ 17.47\\ 63.80\\ 42.16\\ 20.61\\ 17.33\\ 19.07\\ 18.32\\ 20.61\\ 22.61\\ 26.40\\ 24.2\\ 33.33\\ 11.33\\ 12.67\\ 32.67\\ 12.67\\ 33.00\\ 18.93\\ 10.67\\ 14.73\\ 23.73\\ 19.47\\ 22.87\\ 26.47\\ 20.87\\ 28.87\\ 28.47\\ 31.93\\ 31.33\\ 30.00\\ 14.67\\ 16.00\\ 11.33\\ 13.33\\ 12.00\\ 10.67\\ 48.00\\ 15.49\end{array}$	81.25 89.90 117.30 104.66 149.52 150.00 167.00 162.33 199.90 211.40 196.90 219.80 233.30 231.90 75.42 156.60 178.00 110.00 187.40 95.70 101.90 132.60 134.40 132.60 134.40 130.80 39.00 71.00 77.00 82.00 87.00 105.00 68.30 67.90 110.90 118.50 100.00 97.50 82.00 81.25 103.00	$\begin{array}{c} 102.00\\ 50.42\\ 32.85\\ 26.20\\ 95.70\\ 63.24\\ 30.92\\ 26.00\\ 28.60\\ 27.48\\ 30.91\\ 33.92\\ 39.60\\ 36.36\\ 50.00\\ 17.00\\ 19.00\\ 49.00\\ 19.00\\ 49.00\\ 19.00\\ 49.52\\ 28.40\\ 16.00\\ 22.10\\ 35.60\\ 29.20\\ 34.30\\ 39.70\\ 31.30\\ 43.30\\ 42.70\\ 47.90\\ 47.00\\ 45.00\\ 22.00\\ 24.00\\ 17.00\\ 22.00\\ 24.00\\ 17.00\\ 20.00\\ 18.00\\ 16.00\\ 72.00\\ 23.23\\ \end{array}$	$\begin{array}{c} 4.3:\\ 3.8:\\ 3.3:\\ 2.5:\\ 7.1:\\ 4.4:\\ 2.4:\\ 1.2:\\ 1.0:\\ 1.5:\\ 5.0:\\ 1.6:\\ 5.0:\\ 1.6:\\ 5.0:\\ 1.6:\\ 5.0:\\ 1.6:\\ 2.1:\\ 1.0:\\ 1.6:\\ 3.5:\\ 2.1:\\ 1.0:\\ 1.6:\\ 3.5:\\ 2.1:\\ 1.0:\\ 1.6:\\ 3.5:\\ 2.1:\\ 1.0:\\ 1.6:\\ 3.5:\\ 2.1:\\ 1.0:\\ 1.6:\\ 3.5:\\ 2.1:\\ 1.0:\\ 1.6:\\ 3.5:\\ 2.1:\\ 1.5:\\ 1.4:\\ 1.2:\\ 6.0:\\ 2.0:\\ 2.0:\\ 1.0:\\ 1.5:\\ 1.4:\\ 1.2:\\ 6.0:\\ 2.0:\\ 1.0:\\ 1.5:\\ 1.4:\\ 1.2:\\ 6.0:\\ 2.0:\\ 1.0:\\ 1.5:\\ 1.4:\\ 1.2:\\ 6.0:\\ 2.0:\\ 1.0:\\ 1.5:\\ 1.4:\\ 1.2:\\ 6.0:\\ 2.0:\\ 1.0:\\ 1.5:\\ 1.4:\\ 1.2:\\ 6.0:\\ 2.0:\\ 1.0:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\ 1.5:\\ 1.4:\\ 1.2:\\ 1.5:\\$

Table 4: Source Data used for Validation of Predicted Results

	AHD	71.30	10.15	67.33	13.31	101.00	19.96	1.97
	BHF	122.00	13.04	89.93	38.00	134.90	57.00	4.28
	BHD	124.00	12.18	107.33	16.25	161.00	24.38	1.87
	CBHSC	35.00	2.34	108.76	16.70	163.30	25.05	2.07
	C3HSC	40.00	3.09	36.67	4.69	55.00	7.03	3
Coningthan	C5HSC	45.00	3.78	43.33	5.97	65.00	8.95	2.89
Gopinathan	W3HSC	45.00	3.91	60.00	8.00	90.00	12.00	3.17
et al. (2010)	W5HSC	50.00	4.17	46.67	6.29	70.00	9.44	2.414
	U3HSC	68.00	4.32	66.67	8.55	100.00	12.82	3.07
	U5HSC	76.00	4.46	80.00	10.75	120.00	16.13	3.73

ANN BASED MODELING FOR HIGH STRENGTH CONCRETE BEAMS WITH ... 463

3.0 RESULTS AND DISCUSSION

The proposed Artificial Neural Network (ANN) based model was performed well for predicting the performance parameters of FRP strengthened high strength concrete beams such as yield load, deflection at yield load, service load, deflection at service load, ultimate load, deflection at ultimate load, and deflection ductility. To ascertain the accuracy of the models, scatter plots were drawn between the experimental results and those results predicted through ANN model as shown in Fig. 11.

The predicted versus experimental value for the yield load and deflection at yield load are shown through Figs. 11(a) and (b). The ANN predictions for the yield load resulted in a MAPE of 5.23%, a RMSE of 6.375, a correlation co-efficient of 0.934 and a co-efficient of determination of 0.981 was observed at 50 epochs. For the deflection at yield load, the ANN resulted in a correlation co-efficient of 0.926, a co-efficient of determination of 0.966, a RMSE of 1.055 and a MAPE of 5.31% was observed at 30 epochs.

The predicted versus experimental value for the service load and deflection at service load are presented through Figs. 11(c) and (d). For the service load, the ANN yields a correlation co-efficient of 0.918, co-efficient of determination of 0.968, a RMSE of 6.621 and a MAPE of 5.99% was observed at 37 epochs. The ANN predictions for the deflection at service load resulted in a correlation co-efficient of 0.927, a co-efficient of determination of 0.980, a RMSE of 1.786 and a MAPE of 6.07% was observed at 17epochs.

The ANN prediction for the ultimate load resulted in a correlation co-efficient of 0.953, a co-efficient of determination of 0.960, a RMSE of 9.542 and a MAPE of 5.85% was observed at 60 epochs. The ANN resulted in a correlation co-efficient of 0.937, a co-efficient of determination of 0.974, a RMSE of 3.121 and a MAPE of 6.93% was observed at 40epochs in the prediction of deflection at ultimate load. Good convergence was observed between the experimental results and predicted results for ultimate load and deflection at ultimate load as shown through Figs. 11 (e) and (f).

The predicted versus experimental value for the deflection ductility is shown in Fig. 11 (g). The ANN resulted in a correlation co-efficient of 0.966, a co-efficient of determination of 0.988, a RMSE of 6.352 and a MAPE of 9.54% was observed at 18epochs in the prediction of deflection ductility. Good convergence was observed between the experimental results and the predicted results. The summary of performance evaluation of ANN model is reported in Table 5.

The results of ANN model have been validated using other researcher's results to improve its accuracy. The input and target parameters considered for the validation of results are presented in Tables 3 and 4. The results predicted through ANN modeling are presented through Fig. 11 (a) to (g) in the form of scatter plots. From Fig. 11 (a) to (g), it can be observed that most of the points fall along the diagonal line for the ANN prediction model. It shows that the results predicted through ANN model are in very good agreement with the experimental results.





(g) Deflection Ductility Figure 11. Comparison of Experimental and Predicted Results

Table 5: Performance evaluation of ANN model	
--	--

S.NO	Output parameters	r	RMSE	MAPE	\mathbf{R}^2
1	Yield load (kN)	0.934	6.375	5.230	0.981
2	Deflection at Yield load (mm)	0.925	1.055	5.310	0.966
3	Ultimate load(kN)	0.954	9.542	5.850	0.960
4	Deflection at ultimate load(mm)	0.938	3.121	6.930	0.974
5	Service load(kN)	0.918	6.624	5.990	0.968
6	Deflection at service load (mm)	0.927	1.786	6.070	0.980
7	Deflection ductility	0.966	0.351	9.540	0.938

4. CONCLUSIONS

This main aim of this study focuses on using an artificial neural network (ANN) based model for predicting the performance of high strength reinforced concrete (HSC) beams strengthened with surface mounted FRP laminates. The performances of the models were evaluated and the results predicted through ANN modeling were compared with the experimental results. The results predicted through ANN modeling exhibited better convergence with the experimental results. Also the results show that ANN modeling is a more accurate and reliable tool for evaluating the performance of high strength concrete beams strengthened with FRP laminates under static loading condition. This is evident from the values of correlation co-efficient (r), RMSE, MAPE and R², which are global, more realistic and meaningful error types. It can be seen from the obtained results that the lowest RMSE and MAPE and the highest r and R². A correlation co-efficient of 0.918 to 0.966 and a co-efficient of determination of 0.938 to 0.981 was observed for HSC beams strengthened with FRP laminates while predicting the convergence through scatter plots.

REFERENCES

- 1. Gopinathan TK, Raghunath PN, Suguna K. Static and cyclic performance of HSC beams with GFRP laminates, *Asian J Eng Technol* 2016; **4**: 2321-2462.
- 2. Gopinathan TK, Raghunath PN, Suguna K. Regression model for static and cyclic performance of HSC beams with GFRP laminates, *Indian J Sci Technol* 2016; **9**: 974-80.
- 3. Parthiban B, Suguna K, Raghunath PN. Hybrid fibre reinforced concrete beams strengthened with externally bonded GFRP laminates, *Asian J Eng Technol* 2014; **2**: 2319-39.
- 4. Rajeshguna R, Suguna K, Raghunath PN. Steel fibre reinforced concrete beams with externally bonded FRP laminates, *Asian J Eng Technol* 2014; **2** 2321-24.
- 5. Shanmugavelu VA, Ramachandran N, Raghunath PN, Suguna K. Experimental and analytical studies on reinforced concrete beams with GFRP laminates, *Int J Appl Eng Res* 2016; **1**: 1950-53.
- 6. Ibrahim M. Intelligent predicting system for modelling of reinforced concrete of flexurally strengthened beams with CFRP laminates, *Build Res J* 2014; **61**: 25-42.
- 7. Amani J, Moeini R. Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network, *Sci Iran Trans A; Civil Eng* 2012; **19**: 242-48.
- 8. Pannirselvam N, Nagaradjane V, Chandramoul, Ravindrakrishna M. Artificial neural network model for performance evaluation of RC rectangular beams with externally bonded glass fibre reinforced polymer reinforcement, *ARPN J Eng Appl Sci* 2010; **5**: 77-85.
- 9. Hashemi SH, Rahgozar R, Maghsoudi AA. Flexural testing of high strength reinforced concrete beams strengthened with CFRP sheets, *IJE Transact B: Applicat* 2009; **22**: 131-40.
- 10. Phalguni M, Narayan Swamy, and Cyril L. Optimizing structural response of beams strengthened with GFRP plates, *J Compos Construct* 1998; **2**: 87-95.
- 11. Rabinovitch O, Frostig Y. Experiments and analytical comparison of RC beams strengthened with CFRP composites, *J Compos: part B* 2003; **34**: 663-77.
- 12. Grace F, George AS, Ragheb F. An innovative ductile composite fabric for strengthening concrete structures, *ACI Struct J* 2002; **99**: 692-700.

- 13. Mahfouz Ud Darain, Mohd Zamin Jumaat, Ahmad Azim Shurkri, Obaydullah M, Nazmul Huda, Akterhosen, Nursat Hoque. Strengthening of RC beams using externally bonded reinforcement combined with near surface mounted technique, *Polym* 2016; **8**: 261-67.
- 14. Paul Fanning Oliverkelly. Ultimate response of rc beams strengthened with cfrp plates, *J Compos Construct* 2001; **5**: 122-27.