A COMPARATIVE STUDY ON DIFFERENT PROPAGATIONS FOR DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK MODEL TO STUDY THE BEHAVIOUR OF CST (COMPOSITE STEEL TUBES) UNDER COMPRESSION

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Abstract

In this research work, the present study is emphasized on the behavior of Composite Steel Tubes filled with concrete under monotonic loading. The prime factors considered to get ultimate axial load and corresponding axial shortening under axial compression are cross-sectional area, wall thickness of the steel tube, strength of infilled concrete. Also this study focuses on the development of Artificial Neural Network architecture for the prediction of ultimate load carrying capacity of CST infilled with different grades of concrete. Artificial Neural Network for different propagations- Feed forward backdrop, Cascade backdrop, Elman backdrop, Time delay, Layer recurrent are developed. The developed ANN models were verified with the experimental results conducted on Composite Steel Tubes. The compressive strength of composite steel tubes was modeled as a function of Eight variables: Diameter, Thickness, Length, Grade on concrete, Yield strength of steel, Epoxy, L/D ratio, D/T ratio. The effects of each parameter on networks were studied for different propagations. The cascade forward back propagation performed better than other propagations. The error in the Cascade backdrop propagation almost subsidized to 0.932594% and is approximately providing results coinciding with Experimental values.

Keywords: *Artificial Neural Network, Composite Steel Tubes, Feed Forward Back Propagation, Cascade Back Propagation, Elman Propagation, Time Delay Propagation, Layer Recurrent Propagation.*

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1. INTRODUCTION

At the present time, concrete filled steel tube columns are widely used in construction. Nowadays, this type of structural elements is favored in practice because of its small cross sectional area to load carrying capacity ratio. Hence Mega concrete columns in tall buildings lower floors can be substituted by smaller sections of CST columns. Moreover, CST elements can be used as piers for bridges at congested areas. Therefore, such structural elements should be thoroughly investigated before used in critical structures. CST columns use combine action of steel and concrete when carrying compression loads and moments showing in ideal structural performance. While the steel tube confined the concrete core enhancing its compressive strength, the concrete core prevents the steel section from experiencing local buckling. Due to that, the use of CST columns has increased, becoming very popular in the last years.

Columns occupy a vital place in structural system. Weakness or failure of a column destabilizes the entire structure. Structure and ductility of steel columns need to be ensured through adequate strengthening, repair & rehabilitation techniques to maintain adequate structural performance.

One way of including specimen irregularities in the model is to use the results of the available experiments to predict the behavior of composite tubes subjected to different loading. ANN is a technique that uses existing experimental data to predict the behavior of the same material under different testing conditions. Using this method details regarding bonding properties between fiber matrix, strength variation of fibers and any manufacturing included imperfections are implicitly incorporated within the input parameters fed to the neural network.

2. STRUCTURAL BEHAVIOUR

The bond between the steel tubes and the concrete core is the integral factor for understanding the behavior of concrete filled steel tubes columns. Since, steel and concrete are two different materials they have different stress strain properties.

Hence it is difficult to determine the effective structural property. The important parameters affecting the load deformation behavior, ultimate strength and the failure mechanism of CFT's under a given loading condition are

a) The geometric parameters like shape of the cross section, the member size, thickness of steel tube, L/D ratio of the breadth.
b) Grades of concrete and steel
c) Type and rate of application of loading and boundary conditions

3. ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN) is a computational model which is designed to perform the complex pattern recognition tasks such as pattern classification, pattern mapping, pattern association. Thus a neural network can be characterized as a computing architecture, which consists of a large number of simply highly interconnected data processing elements called neurons, designed to resemble the learning and storing capability of human brain for performing the task of pattern to learn & acquire knowledge and to make that knowledge available for use.

When the signals received are strong enough, the neuron is activated and emits a signal through the axon. The signal might be sent to another synapse and might activate other neurons. The complexity of real neurons is highly abstracted, hence modeling artificial neurons. These basically consist of inputs which are multiplied by weights and then computed by a mathematical function which determines the activation of the neuron. Another function computes the output of the artificial neuron. ANN's combines artificial neurons in order to process information.

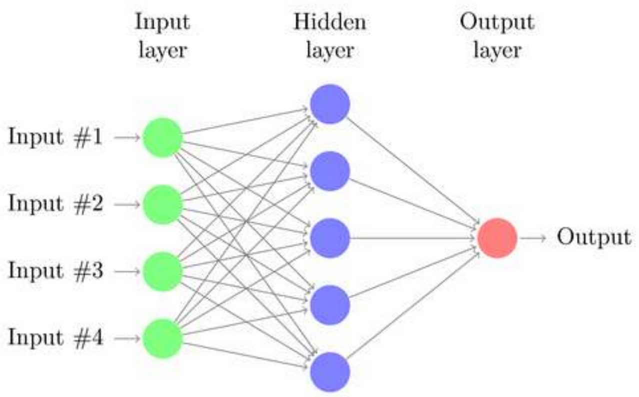


Fig-1: Neural Network Architecture

4. WORKFLOW

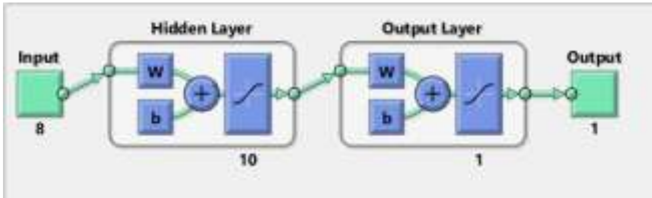
The workflow for the general neural network design process has seven primary steps

- Collect the data
- Create the network
- Configure the network
- Initialize the weights and biases
- Train the network
- validate the network
- use the network to predict the results

4.1 Feed Forward Back Propagation

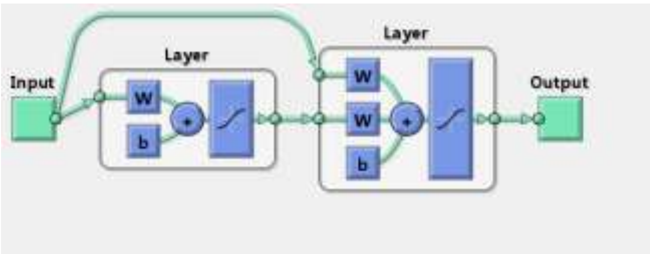
The back propagation algorithm has used in layered feed forward ANN's. this means that the artificial neurons are organized in layers and sends their signals "forward" and then the errors are propagated backwards. The network receives inputs by neurons in the input layer and the output of the network is given by the neurons on an output layer. There may be one more intermediate hidden layer.

The back propagation algorithm uses supervised learning, which means that we proved the algorithm with examples of the inputs and outputs we want the network to compute and then the error is calculated. The idea of back propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights and the goal is to adjust them so that the error will be minimal.



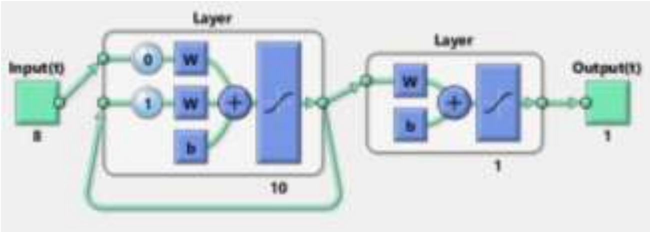
4.2 Cascade Backdrop Propagation

Cascade backdrop propagation is similar to the feed forward networks, but includes a weight connection from the input to each layer and from each layer to the successive layers. While two layered feed forward networks can potentially learn virtually any input output relationship, feed forward networks with more layers might learn complex relationships more quickly. Cascade forward back propagation ANN model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, but the main symptom of this network is that layer of neurons related to all layer of neurons.



4.3 Elman Back Propagation

Elman back propagation is a two layer back propagation network in which a recurrent connection exists from the output of the hidden layer to its input. Network is trained with gradient descent back propagation with adaptive learning rate.

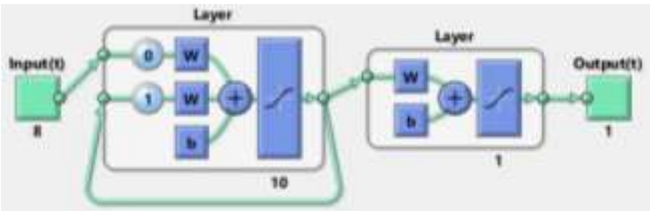


4.4 Time Delay Propagation

Time delay networks are similar to the feed forward networks, except that the weight has a tap delay line associated with it. This allows the network to have a finite dynamic response to time series input data. This network is also similar to the distributed time delay which has delays on the layer weights in addition to the input weight.

4.5 Layer Recurrent Propagation

Layer recurrent neural networks are similar to feed forward networks, except that each layer has a recurrent connection with a tap delay associated with it. This allows the network to have infinite dynamic response to time series input data. This network is similar to the time delay and distributed delay neural networks which have finite input responses.



5. NETWORK PROPERTIES

- Training (70%) Validation (15%) Testing (15)
- Lavenberg Marquartd Algorithm
- LEARNGDM adaption learning function
- MSE performance function
- TANSIG transfer function

5.1 Train the Network

Once the network weights and biases are initialized, the network is ready for training. The multilayer feed forward network can be trained for function approximation or pattern recognition. The training process requires a set of examples of proper network behavior, network inputs & network outputs.

5.2 Lavenberg Marquartd Algorithm

In mathematics and computing the Lavenberg Marquartd algorithm also known as the damped least squares method is used to solve non linear least squares problems.

5.3 Learngdm Adaption Learning Functions

LEARNGDM calculates the weight change dW for a given neuron from the neuron's input and error, the weight w, learning rate LR and momentum constant MC, according to gradient descent with momentum.

5.4 Mean Square Error (MSE)

The performance function in Artificial neural network is mean square error between the network output and the target.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Yi - \widetilde{Yi})^2$$

5.5 Tansig Transfer Function

TANSIG is a transfer function. Transfer functions calculate layer's output from its net input.

6. PREDICTION AND EXPERIMENTAL RESULTS

From the experiment it is evident that Ultimate load value of CST increases with increase in the diameter of the tubes, decrease in L/D ratio and increase in grade of concrete as shown in the graphs given below.

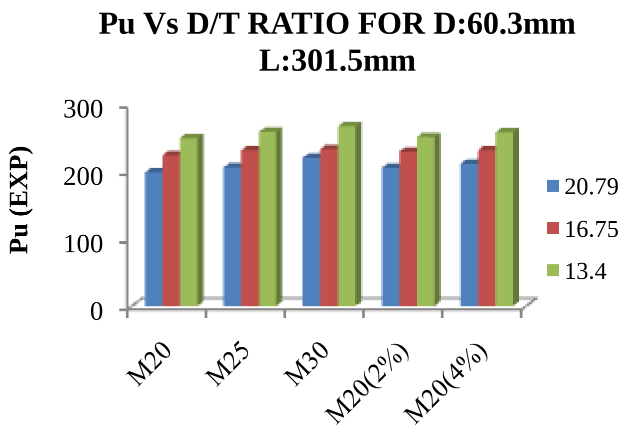


Fig 2: Pu Vs D/T ratio

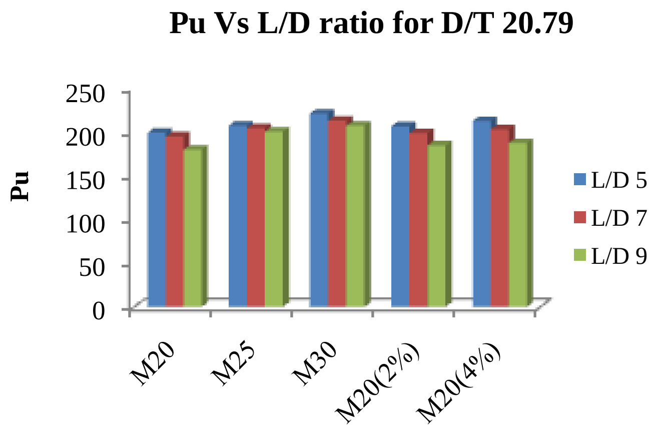


Fig 3: Pu Vs L/D ratio

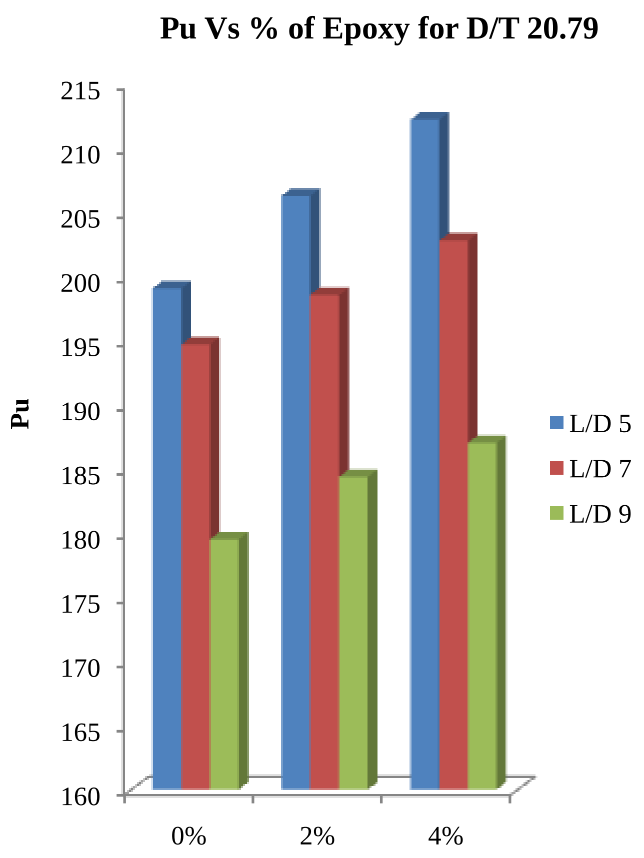


Fig 4: Pu Vs % of epoxy

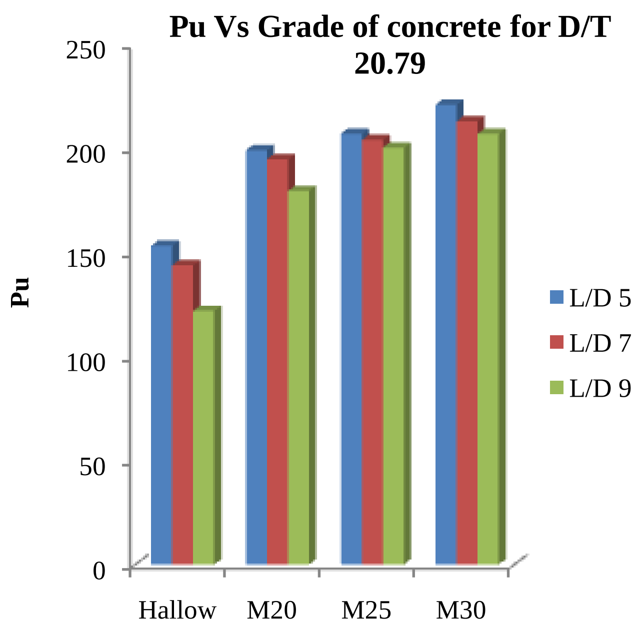


Fig 5: Pu Vs Grade of concrete

Depicts the various propagations used to create the artificial neural network model and train the network, the output parameter is trained separately for different propagations for predicting the ultimate load of CST infilled with concrete. The best values of prediction are obtained for ***Cascade Backdrop propagation*** with 11 hidden layers and 10 neurons in each hidden layer (8-10-11-1) & TANSIG as the transfer function.

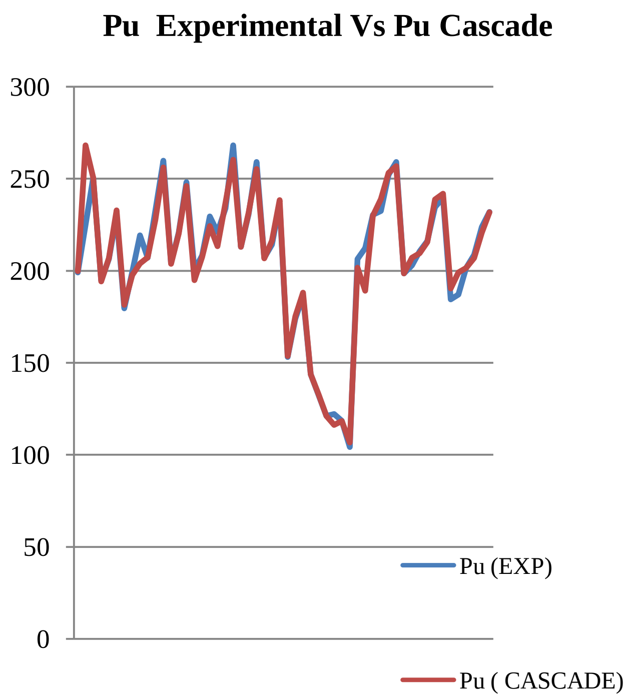


Fig 6: Pu Experimental Vs Pu Cascade

The results which were obtained from the experiments were given as the desired outputs to the various propagations in the Artificial neural network, the developed networks were used to predict the output values and are in good agreement with the experimental values. The ultimate load carrying capacity predicted by ANN's are detailed below in the table no.2

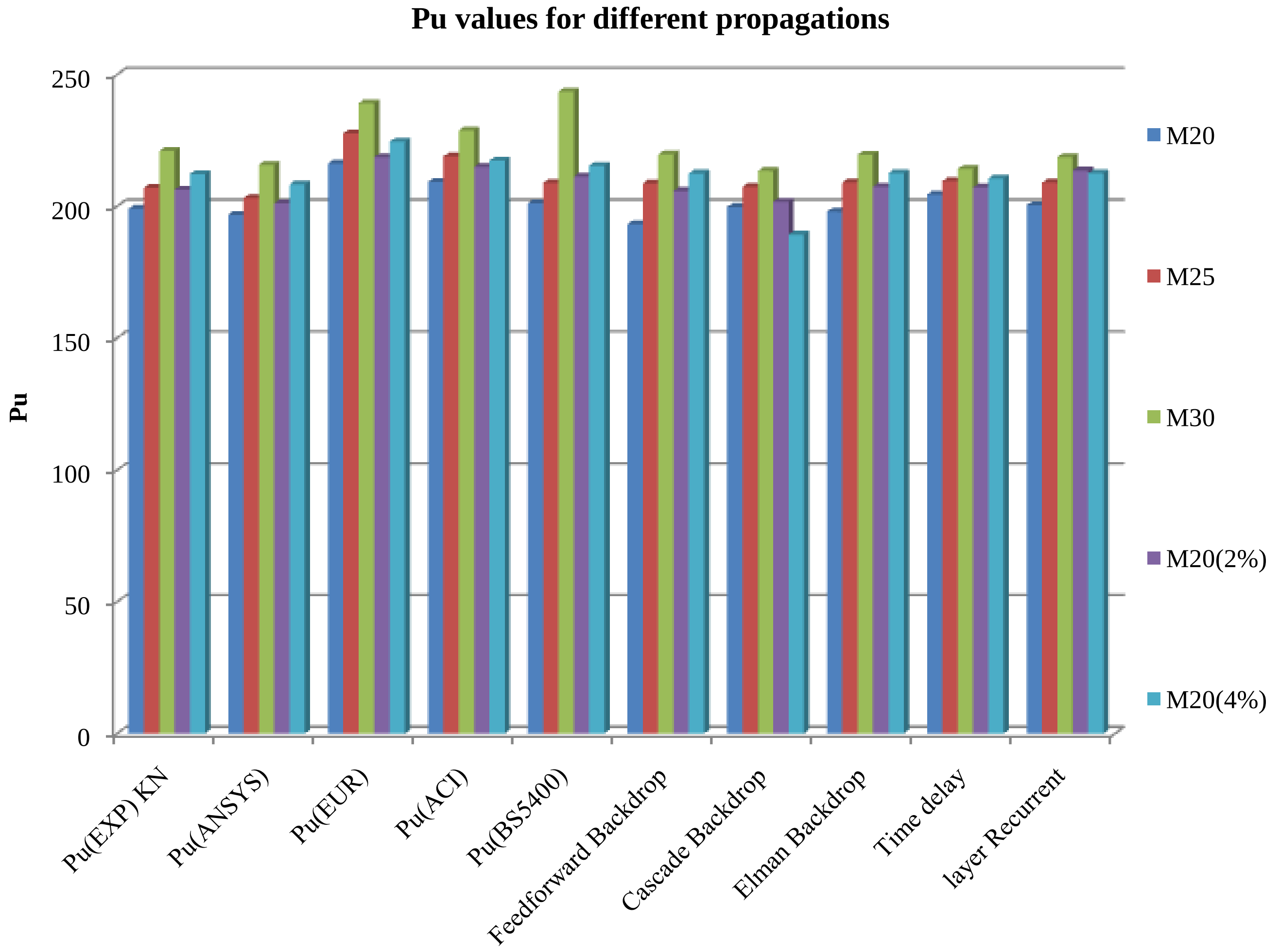


Fig 7: Pu for different propagations

The experimental values are obtained and verified for ultimate axial load. The ultimate axial load's average deviations are tabulated in the table no: 2. the best result is obtained for 11 layers with 10 hidden neurons, Cascade backdrop propagation as per Kolmogorov's principle and this is verified in the ultimate axial load deviation histogram for all propagations.

The predicted data is obtained after training the model to 1000 number of epochs and assigning the transfer function to TANSIG with the given inputs and output values. The input is trained using Lavenberg Marquardt algorithm. This performance is measured using MEAN SQUARE ERROR performance function. The experimental inputs are tested to different propagations and it is verified that the deviation for CASCADE backdrop propagation gives the best result with Tansig training function, also the best REGRESSION.

The various plots obtained after the computational analysis are given below.

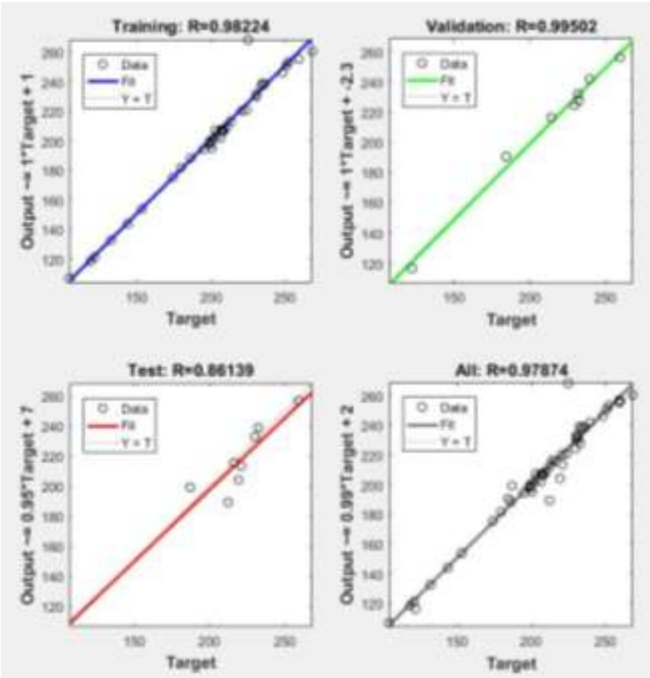


Fig 8: Regression plot

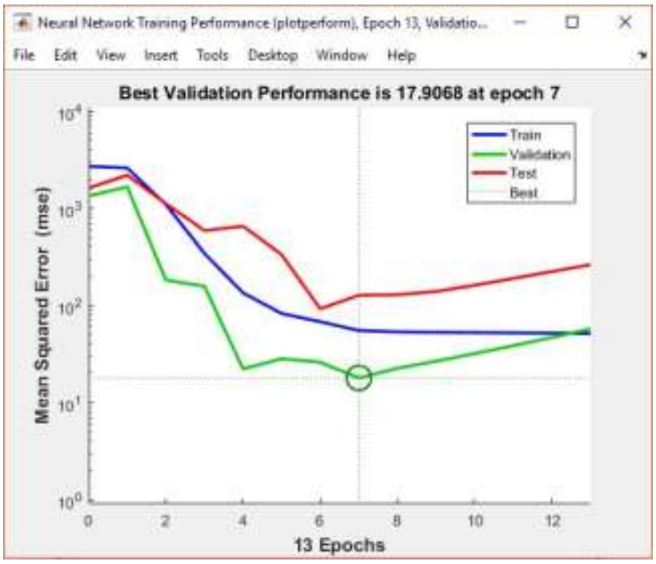


Fig 9: Performance plot

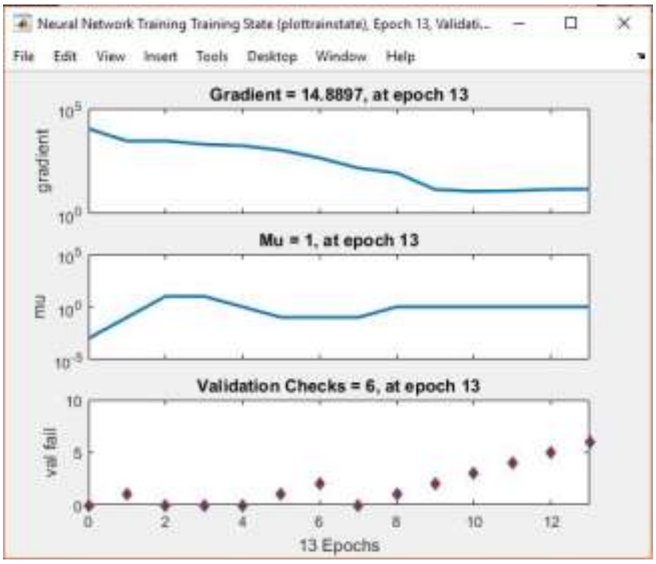


Fig 10: Training state

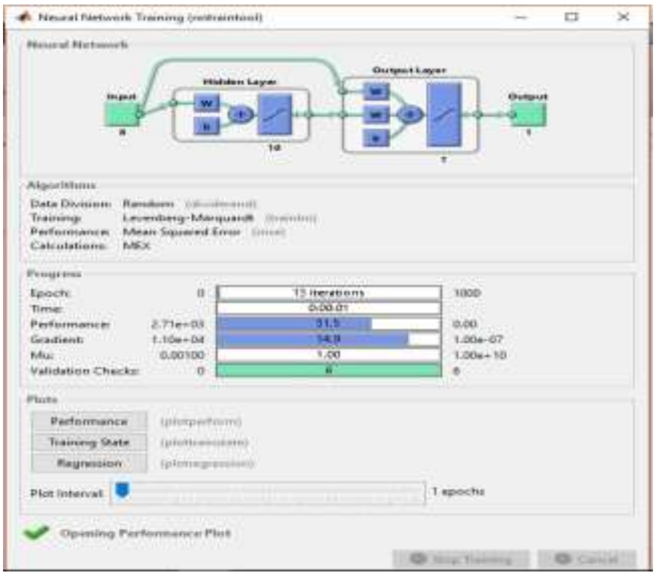


Fig 11: Neural network train tool

7. RESULTS AND DISCUSSIONS

The ANN is one way of including specimen irregularities in the model using the results of the available experiments to predict the behavior of composite tubes subjected to monotonic loading.

Input layer consist of 8 factors and the outer layer represents one neuron representing the ultimate axial load. Cascade backdrop propagation network shows the excellent performance with very much less errors.

The predicted results obtained show that Cascade backdrop propagation with 11 hidden layers and 10 neurons consistently provide the best prediction of the experimental results.

8. CONCLUSION

- ANN neural network architecture of (8-11-10-1) satisfies the requirement of determining ultimate load of CST infilled with different grades of concrete
- The percentage deviation is *0.932594%* obtained yields best fit results compared with experimentally obtained values as given in the table no 3
- ANN network architecture can be used to predict the different values in Civil Engineering.
- The performance of Cascade backdrop propagation is well with small data sets. For larger data sets, Feed forward backdrop propagation proves to be better.
- As the increase in the grade of concrete, the ultimate load carrying capacity of a structure increases.
- With the increase in Diameter and decrease in length, the load carrying capacity of the CST columns increases.
- The results are compared with Ansys, EURO CODE, ACI, BS5400 and are proved to be consistent

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Table: 1 Gives the data used to perform experiment

Dia (mm)	T(mm)	L(mm)	D/T ratio	L/D ratio	Grade	f_y n/mm^2	% of epoxy	Pu (EXP)Kn
60.3	2.9	301.5	20.79	5	20	310	-	199.10
60.3	3.6	301.5	16.75	5	20	310	-	224.82
60.3	4.5	301.5	13.4	5	20	310	-	250.63
60.3	2.9	422.1	20.79	7	20	310	-	194.72
60.3	3.6	422.1	16.75	7	20	310	-	206.31
60.3	4.5	422.1	13.4	7	20	310	-	230.12
60.3	2.9	542.7	20.79	9	20	310	-	179.52
60.3	3.6	542.7	16.75	9	20	310	-	199.40
60.3	4.5	542.7	13.4	9	20	310	-	219.20
60.3	2.9	301.5	20.79	5	25	310	-	207.07
60.3	3.6	301.5	16.75	5	25	310	-	232.63
60.3	4.5	301.5	13.4	5	25	310	-	259.82
60.3	2.9	422.1	20.79	7	25	310	-	204.13
60.3	3.6	422.1	16.75	7	25	310	-	220.73
60.3	4.5	422.1	13.4	7	25	310	-	248.09
60.3	2.9	542.7	20.79	9	25	310	-	200.41
60.3	3.6	542.7	16.75	9	25	310	-	208.33
60.3	4.5	542.7	13.4	9	25	310	-	229.51
60.3	2.9	301.5	20.79	5	30	310	-	221.03
60.3	3.6	301.5	16.75	5	30	310	-	233.92
60.3	4.5	301.5	13.4	5	30	310	-	268.16
60.3	2.9	422.1	20.79	7	30	310	-	213.01

60.3	3.6	422.1	16.75	7	30	310	-	230.53
60.3	4.5	422.1	13.4	7	30	310	-	259.12
60.3	2.9	542.7	20.79	9	30	310	-	207.02
60.3	3.6	542.7	16.75	9	30	310	-	214.15
60.3	4.5	542.7	13.4	9	30	310	-	236.22
60.3	2.6	301.5	20.79	5	hallow	310	-	153.12
60.3	3.6	301.5	16.75	5	hallow	310	-	174.01
60.3	4.5	301.5	13.4	5	hallow	310	-	186.12
60.3	2.9	422.1	20.79	7	hallow	310	-	143.71
60.3	3.6	422.1	16.75	7	hallow	310	-	132.17
60.3	4.5	422.1	13.4	7	hallow	310	-	121.12
60.3	2.9	542.7	20.79	9	hallow	310	-	122.03
310	3.6	542.7	16.75	9	hallow	310	-	118.53
60.3	4.5	542.7	13.4	9	hallow	310	-	104.17
60.3	2.9	301.5	20.79	5	20	310	2	206.31
60.3	2.9	301.5	20.79	5	20	310	4	212.26
60.3	3.6	301.5	16.75	5	20	310	2	230.34
60.3	3.6	301.5	16.75	5	20	310	4	232.40
60.3	4.5	301.5	13.4	5	20	310	2	252.17
60.3	4.5	301.5	13.4	5	20	310	4	259.11
60.3	2.9	422.1	20.79	7	20	310	2	198.59
60.3	2.9	422.1	20.79	7	20	310	4	202.82
60.3	3.6	422.1	16.75	7	20	310	2	210.49
60.3	3.6	422.1	16.75	7	20	310	4	216.18
60.3	4.5	422.1	13.4	7	20	310	2	234.51
60.3	4.5	422.1	13.4	7	20	310	4	239.60
60.3	2.9	542.7	20.79	9	20	310	2	184.39
60.3	2.9	542.7	20.79	9	20	310	4	187.03
60.3	3.6	542.7	16.75	9	20	310	2	201.53
60.3	3.6	542.7	16.75	9	20	310	4	208.67
60.3	4.5	542.7	13.4	9	20	310	2	223.72
60.3	4.5	542.7	13.4	9	20	310	4	232.01

*Experimental results are carried out at R&D laboratory, Department of Civil Engineering, Ghousia College of Engineering.

Table: 2 Comparison of the Experimental results with different propagations

Pu (EXP)	ANSYS	EURO code	ACI method	BS5400 method	Feed forward	Cascade	Elman	Time delay	Layer recurrent
199.10	196.77	216.19	209.33	201.20	193.25	199.75	197.93	204.49	200.41
224.82	219.08	242.95	236.31	228.57	224.83	268.16	236.76	224.48	223.36
250.63	245.88	285.73	279.53	272.30	250.53	250.63	250.13	249.81	246.72
194.72	189.68	216.19	209.33	201.20	192.83	194.30	195.44	195.00	195.02
206.31	203.29	242.95	236.31	228.57	204.33	206.99	207.03	208.22	203.27
230.12	225.53	285.73	279.53	272.30	227.63	232.83	229.26	232.92	225.91
179.52	175.42	216.19	209.33	201.20	180.91	181.58	192.63	182.94	188.63
199.40	193.35	242.95	236.31	228.57	199.06	197.71	197.25	193.04	198.47
219.20	215.12	285.73	279.53	272.30	220.21	204.01	206.68	207.70	216.08
207.07	203.1	227.70	218.96	208.87	208.74	207.34	209.05	209.62	208.99
232.63	225.02	254.02	245.78	236.08	230.08	227.63	231.68	233.14	224.08
259.82	256.5	296.06	288.16	279.27	260.63	256.19	257.69	254.77	257.94
204.13	201.2	227.70	218.96	208.87	206.76	203.83	206.10	202.68	208.42
220.73	215.93	254.02	245.78	236.08	224.46	220.22	217.69	218.96	220.14
248.09	242.17	296.06	288.16	279.27	243.24	246.12	242.95	244.05	246.16
200.41	196.49	227.70	218.96	208.87	198.78	194.91	200.46	196.42	199.83

208.33	205.73	254.02	245.78	236.08	214.33	207.36	207.41	208.66	210.33
229.51	224.15	296.06	288.16	279.27	232.52	224.34	226.27	228.68	232.60
221.03	215.78	239.14	228.76	216.65	219.69	213.41	219.60	214.21	218.68
233.92	230.8	265.09	255.12	243.50	236.78	236.99	236.53	240.01	235.74
268.16	262.61	306.39	279.09	286.24	262.95	260.34	261.91	257.97	263.13
213.01	210.9	239.14	228.76	216.65	212.24	213.06	214.30	208.15	210.97
230.53	226.18	265.09	255.12	243.50	229.12	231.49	225.24	227.57	226.51
259.12	254.86	306.39	297.09	286.24	246.29	255.22	250.10	251.05	255.27
207.02	201.19	239.14	228.76	216.65	206.78	206.78	206.57	205.43	201.11
214.15	210.59	265.09	255.12	243.50	215.44	216.24	214.79	219.73	214.48
236.22	230.75	306.39	297.09	286.24	234.65	238.35	237.00	241.79	242.48
153.12	150.11	175.05	170.05	170.05	153.06	153.72	153.67	159.94	155.13
174.01	168.14	198.68	198.68	198.68	174.33	175.25	169.63	167.44	173.17
186.12	181.91	204.42	204.42	204.42	185.69	188.22	186.04	180.83	187.53
143.71	138.37	170.05	170.05	170.05	143.11	143.79	143.98	133.21	135.45
132.17	127.26	198.68	198.68	198.68	133.71	132.64	131.28	133.30	131.66
121.12	115.07	204.42	204.42	204.42	122.83	121.18	122.19	130.93	129.78
122.03	115.2	170.05	170.05	170.05	123.21	116.27	140.66	118.74	114.82
118.53	112.35	198.68	198.68	198.68	113.31	118.46	118.88	116.46	116.38
104.17	101.48	204.42	204.42	204.42	109.91	106.73	106.23	112.85	117.33
206.31	201.17	218.68	215.03	206.35	205.83	201.76	207.47	207.20	213.58
212.26	208.32	224.56	217.35	211.23	212.49	189.24	212.62	210.58	212.51
230.34	224.21	223.12	218.39	215.36	230.24	229.90	229.30	228.70	228.70
232.40	228.92	225.96	221.78	219.87	252.73	238.97	234.33	232.23	234.41
252.17	248.23	249.89	245.91	241.43	255.13	253.17	255.18	252.39	255.55
259.11	255.18	253.43	254.68	250.89	259.23	256.77	259.44	254.13	258.72
198.59	193.65	193.12	188.61	185.64	199.39	198.58	197.83	197.97	199.15
202.82	197.12	196.87	191.32	187.84	204.13	207.14	197.01	201.00	204.36
210.49	206.94	205.48	201.55	198.45	208.89	209.51	212.45	213.22	211.08
216.18	211.03	209.56	205.38	202.52	229.10	215.57	215.79	217.61	216.28
234.51	228.35	229.65	225.91	223.63	235.89	238.70	234.41	239.19	239.72
239.60	236.55	233.75	229.54	225.18	241.77	241.81	239.16	243.19	239.72
184.39	178.63	178.41	175.25	172.33	183.90	190.39	184.95	186.21	184.39
187.03	182.33	184.15	181.47	178.68	187.17	199.09	172.58	188.10	187.57
201.53	196.84	196.16	190.71	187.89	200.47	201.53	201.00	201.28	200.23
208.67	202.21	198.02	194.62	191.52	213.62	206.90	204.87	206.90	206.00
223.72	219.48	218.19	214.86	213.86	224.79	220.70	223.36	221.91	222.07

Table: 3 Shows the percentage deviation from experimental values

FEED FORWARD	CASCADE	ELMAN	TIME DELAY	LAYER RECURRENT
5.84751	-0.65947	1.168447	-5.39336	-1.31701
-0.01079	-43.34	-11.9482	0.335674	1.453605
0.09403	-0.00548	0.493571	0.814103	3.906903
1.885707	0.412735	-0.72342	-0.2806	-0.30565
1.977341	-0.68812	-0.72964	-1.9167	3.038485
2.48149	-2.71198	0.853749	-2.80794	4.202694
-1.39212	-2.06826	-13.1186	-3.42553	-9.11601
0.336965	1.682935	2.143046	6.350212	0.92348
-1.0177	15.18008	12.5107	11.49024	3.110663
-1.67718	-0.27068	-1.98776	-2.55788	-1.9241
2.542891	4.999546	0.947491	-0.51188	8.549421
-0.81922	3.626217	2.126593	5.046554	1.875392

-2.63215	0.293489	-1.97341	1.44947	-4.29391
-3.73959	0.508698	3.036791	1.768886	0.580201
4.841923	1.966234	5.139046	4.032014	1.927078
1.630025	5.500017	-0.05325	3.986057	0.572155
-6.00225	0.96533	0.915145	-0.33033	-2.00622
-3.01588	5.162602	3.231128	0.820862	-3.09877
1.331456	7.613066	1.423144	6.818246	2.345673
-2.86513	-3.07108	-2.61116	-6.09641	-1.82202
5.208966	7.819567	6.245551	10.18259	5.023893
0.764823	-0.05671	-1.29608	4.855364	2.03721
1.404257	-0.95911	5.286604	2.951468	4.013726
12.82406	3.894354	9.014355	8.068285	3.845336
0.237045	0.236431	0.440311	1.588995	5.906154
-1.29345	-2.09197	-0.64374	-5.58479	-0.33612
1.568698	-2.13741	-0.78733	-5.57741	-6.26802
0.057252	-0.60636	-0.55391	-6.82587	-2.0105
-0.32362	-1.24549	4.37428	6.56009	0.836934
0.420663	-2.10519	0.076611	5.286261	-1.41623
0.591673	-0.08803	-0.27846	10.49084	8.254918
-1.54555	-0.47183	0.881759	-1.13793	0.508001
-1.71875	-0.06293	-1.07881	-9.81341	-8.66801
-1.18889	5.751928	-18.6327	3.280227	7.201209
5.21292	0.060721	-0.35313	2.06837	2.140182
-5.74629	-2.56291	-2.06952	-8.6869	-13.1618
0.474	4.545509	-1.16699	-0.89982	-7.27922
-0.23019	23.01587	-0.36601	1.674442	-0.25763
0.099843	0.437531	1.030388	1.637247	1.631631
-20.3389	-6.57397	-1.93892	0.168376	-2.01216
-2.96368	-1.00396	-3.01542	-0.2234	-3.38387
-0.12328	2.339761	-0.33142	4.97888	0.388343
-0.80623	0.002045	0.751617	0.6122	-0.56249
-1.31634	-4.32132	5.804311	1.817275	-1.54225
1.591768	0.971356	-1.9634	-2.73276	-0.59022
-12.9241	0.600804	0.381216	-1.43203	-0.10732
-1.38061	-4.19296	0.096388	-4.83823	-0.28032
-2.17949	-2.2164	0.43731	-3.59269	-0.12935
0.484061	-6.00483	-0.56324	-1.82938	-0.00451
-0.1434	-12.0644	14.44698	-1.07196	-0.54169
1.051937	-0.00699	0.526915	0.248748	1.296299
-4.95102	1.761832	3.791271	1.769503	2.669765
-1.07594	3.01191	0.354517	1.808501	1.649969
4.905111	0.159901	-0.75518	2.297788	3.225109
-23.5554	**0.932594**	**18.98962**	**37.69054**	**10.679**

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