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Analytical Studies on Composite Circular Re-Cycled Concrete filled Steel Columns using Artificial Neural Networks

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ABSTRACT

In this research work, Artificial Neural Network Model(ANN) for the composite circular steel tubes- with re-cycled concrete infill with three different grades of concrete(M20,M40 and M60) are tested for ultimate load capacity and axial shortening , under axial monotonic loading for compression has been developed. Steel tubes are compared for different lengths, cross sections and thickness, and specimens were tested separately. In this paper, authors have developed a suitable artificial neural network model using feed forward back propagation network having verified it for 11 hidden layers as per Kolmogorov's theorem. The developed ANN model has been verified with the experimental results conducted on composite steel columns (axial load) using Tagauchi's model. Being a flexible building method, the ANN is an ideal tool to construct the complex relationship between the input and the output parameters accurately. The ANN technique is used to predict the crushing behavior of axial shortening and ultimate axial load in composite circular steel columns. Effects of parameters such as network architecture and number of hidden layer neurons are considered. Predictions are compared to experimental results and are shown to be in good agreement.

1. Introduction

Columns occupy a vital place in the structural system. Weakness or failure of a column destabilizes the entire structure. Strength & ductility of steel columns need to be ensured through adequate strengthening, repair & rehabilitation techniques to maintain adequate structural performance. Recently, composite columns are finding a lot of usage for seismic resistance. In order to prevent shear failure of RC column resulting in storey collapse of buildings, it is essential to make ductility of column larger. Recently, most of the buildings utilize this CFT concept as primary for lateral load resisting frames. The concrete used for encasing the structural steel section not only enhance its strength and stiffness, but also protects it from fire damages. Recycled aggregate concrete is used as an infill in order to achieve economy.

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 and matrix, strength variation of fibers and any manufacturing –induced imperfections are implicitly incorporated within the input parameters fed to neural network. In the current work, the prediction of the load-carrying capacities for axially-loaded rectangular composite tubes is evaluated using ANN. To test the validity of using ANN in determining the crushing behavior of these tubes, the study will compare the predictions obtained to the experimental results using the neural network tool in MATLAB v7.12 (R2011a).

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2. Artificial Neural Network

2.1 Introduction

ANN have emerged as a useful concept from the field of artificial intelligence, and has been used successfully over the past decade in modeling engineering problems in general, and specifically those relating to the mechanism behavior of fiber-reinforced composite materials.

ANN generally consists of a number of layers: the layer where the patterns are applied is called input layer. This layer could typically include the properties of the composite material under consideration, its layup, the applied load, the tube aspect ratio etc. The layer where the output is obtained is the output layer which could, for example, contain the resulting deformation of this tube under the given loading conditions. In addition, there may be one or more layers between the input and output layers called hidden layers, which are so named because their outputs are not directly observable. The addition of hidden layers enables the network to extract high-order statistics which are particularly valuable when the size of the input is very large. Neurons in each layer are interconnected to preceding and subsequent layer neurons with each interconnection having an associated weight.

A training algorithm is commonly used to iteratively minimize a cost function with respect to the interconnection weights and neuron thresholds. The training process is terminated either when the mean square error(MSE) between the observed data and the ANN outcomes for all elements in the training set has reached a pre-specified threshold or after the completion of a pre-specified number of learning epochs[1-4].

2.2 Kolmogorov's Theorem:

- Any continuous real-valued functions f (x1, x2, ..., xn) defined on [0, 1]n, $n \geq 2$, can be represented in the form

$$f(x1, x2, ..., xn) = \sum_{j=1}^{2n+1} g_j\left(\sum_{i=1}^{n} \phi_{ij}(x_i)\right)$$

where the gj's are properly chosen continuous functions of one variable, and the ij's are continuous monotonically increasing functions independent of *f*.

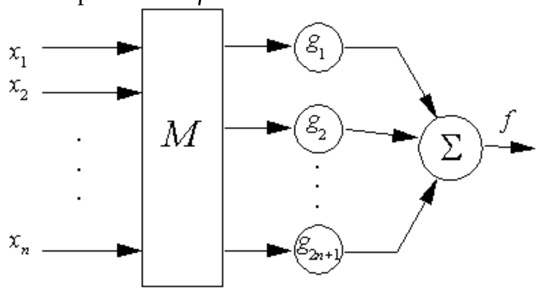


Fig1: Block diagram of feed forward network

Given any function $\phi : I^n \rightarrow R^m, \phi(x) = y$, where I is the closed unit interval [0,1], can be implemented exactly by a three layer neural network with n input nodes, 2n+1 hidden layer neurons and m output layer neurons, as represented in fig.1.

2.3 Multilayer Neural Network Architecture

2.3.1 Neuron Model

An elementary neuron with R inputs is shown below. Each input is weighted with an appropriate w. The sum of the weighted inputs and the bias forms the input to the transfer function f. Neurons can use any differentiable transfer function f to generate their output.

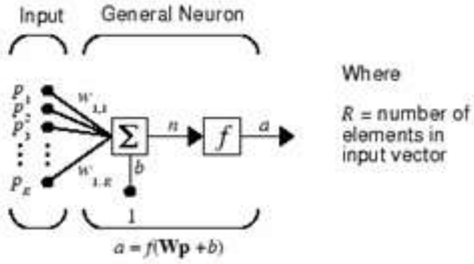
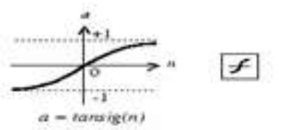
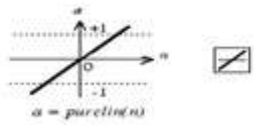


Fig 2.Neuron model

Fig.3a **Fig.3b**





Multilayer networks represented in fig.2, can use the tan-sigmoid transfer function tansig as shown in fig.3a. Sigmoid output neurons are often used for pattern recognition problems, while linear output neurons are used for function fitting problems. The linear transfer function purelin as shown in fig.3b.

2.4 Train the Network

Once the network weights and biases are initialized, the network is ready for training. The multilayer feedforward network can be trained for function approximation (nonlinear regression) or pattern recognition. The training process requires a set of examples of proper network behavior—network inputs p and target outputs t.

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function net.performFcn. The default performance function for feedforward networks is mean square error mse—the average squared error between the network outputs a and the target outputs t. It is defined as follows:

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

There are two different ways in which training can be implemented: *incremental mode* and *batch mode*. In incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In batch mode, all the inputs in the training set are applied to the network before the weights are updated. This chapter describes batch mode training with the train command. Incremental training with the adapt command is discussed in Incremental Training with adapt and in Adaptive Filters and Adaptive Training. For most problems, when using the Neural Network Toolbox software, batch training is significantly faster and produces smaller errors than incremental training.

For training multilayer feedforward networks, any standard numerical optimization algorithm can be used to optimize the performance function, but there are a few key ones that have shown excellent performance for neural network training.

These optimization methods use either the gradient of the network performance with respect to the network weights, or the Jacobian of the network errors with respect to the weights.

The gradient and the Jacobian are calculated using a technique called the backpropagation algorithm, which involves performing computations backward through the network. The backpropagation computation is derived using the chain rule of calculus.

2.5 Network Properties

The network type is feed forward backpropagation. The training function is levenberg-marquardt algorithm. The performance function is mean square error. The transfer function is tan-sigmoidal and purelin(Fig.4).

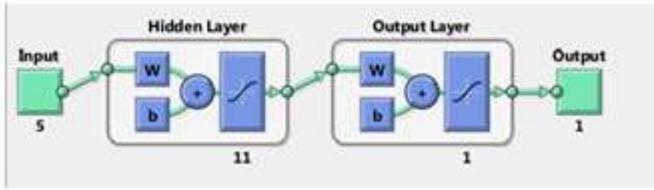


Fig.4. Network Model

3. Work Flow

The work flow for the general neural network design process has seven primary steps:

1. Collect data
2. Create the network
3. Configure the network
4. Initialize the weights and biases
5. Train the network
6. Validate the network (post-training analysis)
7. Use the network

4. Prediction and Experimental Results

Fig.4 depicts the Linear-Sigmoidal (linsig) and Tan-Sigmoidal (tansig) functions used to build the model and train the network. The output is trained separately for both ultimate load and axial shortening load. Also the best values of prediction are obtained for 11 layers.

The experimental results which are obtained are given as the desired outputs to the feed forward backpropagation network (Fig.5). These results were used to predict the output values and were in good agreement with the Kolmogorov's theorem. The output values and the deviations are obtained were tested and validated from 3 hidden layers to 14 hidden layers.

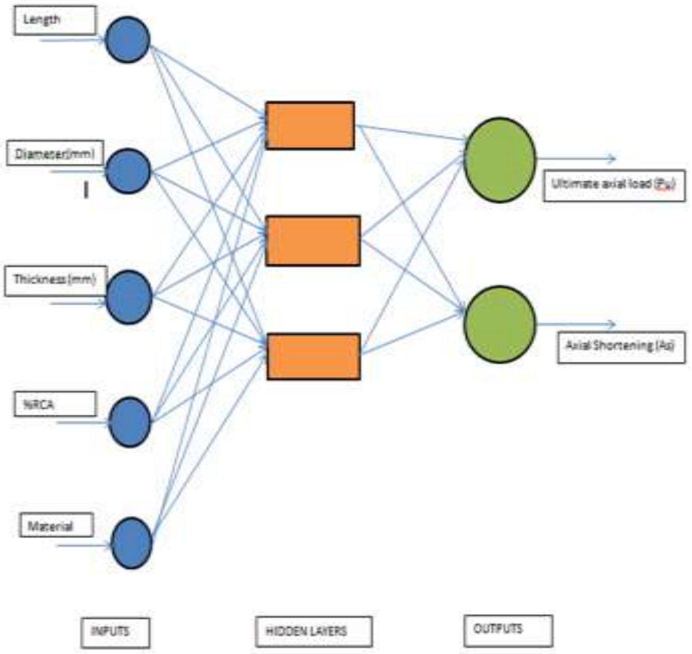


Fig.5 Block diagram of data obtained is implemented in feed forward network

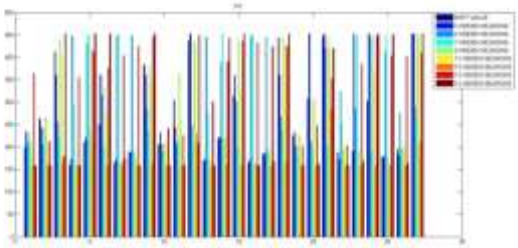


Fig.6a. Ultimate axial load prediction

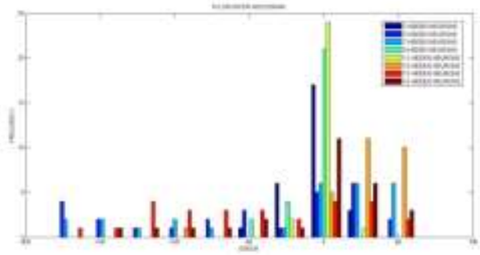


Fig.6b. Ultimate axial load deviation histogram

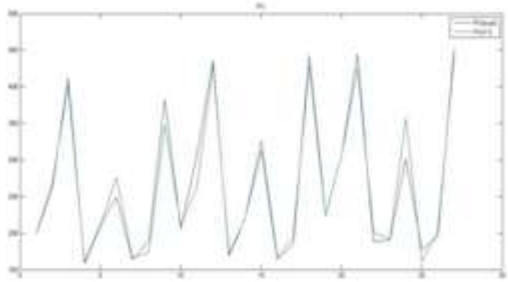


Fig.6c. Ultimate axial load for 11 hidden layers

The experimental values are obtained and verified for ultimate axial load (Table-1). The ultimate axial load's average deviations are tabulated in Table-2. The best result is obtained for 11 layers as per Kolmogorov principle and this is verified in the ultimate axial load deviation histogram for all the layers (Fig.6b).The comparison of the best result(11 hidden layers) and the experimental data are represented in fig.6c. A *histogram* is "a representation of a frequency distribution by means of rectangles whose widths represent class intervals and whose areas are proportional to the corresponding frequencies." The experimental data are obtained after training the model to 1000 number of epochs and assigning the transfer function as tansig with the given inputs and predicted values. The input is trained using Lavenberg-Marquardt algorithm. The performance is measured

using mean square error (MSE).The predicted values are tested, validated and plotted to obtain the best values on the curve fit. The experimental inputs are tested from 3 hidden layers to 14 hidden layers and it is verified that the deviations obtained for the 11 hidden layers gives the best result, also with the best regression fit.

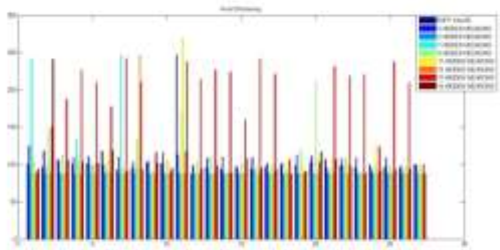


Fig.7a. Axial Shortening prediction

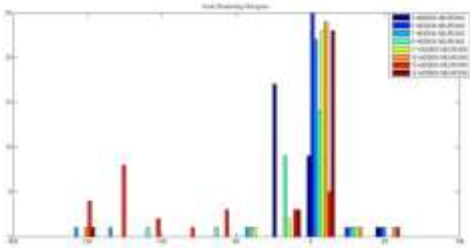


Fig.7b. Axial shortening deviation histogram

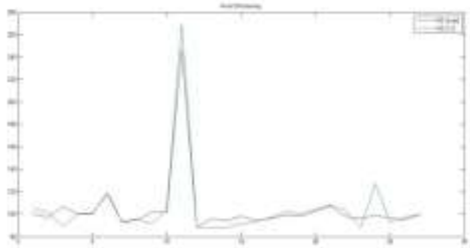


Fig.7c. Axial shortening for 11 hidden layers

The experimental values are obtained and verified for axial shortening load (Fig.7).The values are tabulated in Table-3. The deviations are also tabulated to choose the the best results (Table-4). Again it can be seen that the results obtained for 11as the number of hidden layers as per Kolmogorov's theorem and this is verified again with axial load shortening .The deviation is also represented in the histogram(Fig.7b). The comparision of the experimental results and the predicted ultimate axial load for 11 hidden layers are shown in fig.7c. The same procedure is repeated for axial shortening; The experimental data are obtained after training the model to 1000 number of epochs and assigning the transfer function as tansig with the given inputs and predicted values. The input is trained using Lavenberg-Marquardt algorithm. The performance is measured using mean square error (MSE).The predicted values are tested, validated and plotted to obtain the best values on the curve fit.

Table 1: Ultimate Load Predicted Values

		PU PREDICTED VALUES						
actual	3 (predicted)	5(predicted)	7(predicted)	9(predicted)	11(predicted)	12(PREDICTED)	13(PREDICTED)	14(PREDICTED)
199	233.6306	211.8325	206.9884	234.0382	199.1686	159.0001	363.7933	159.0009
262	243.2424	204.8739	238.4452	264.7444	266.6815	159.0001	211.9805	159.0038
412	360.0972	255.5873	218.67	439.781	402.4654	164.231	179.0743	451.9993
159	172.8064	447.9101	295.8314	159.8968	160.832	159	355.7929	159
210	220.7485	430.7538	451.0193	239.5384	211.4296	416.9132	412.2523	451.9954
249	360.0972	315.9174	201.0688	331.7902	276.1102	159.0005	376.1374	451.9975
164	172.8064	447.8504	451.2845	164.044	166.4306	162.8696	404.7779	174.0791
189	189	448.8279	187.0119	189.4613	173.73	159	425.0487	159
383	360.0971	284.1186	236.0635	379.1775	347.8355	162.4306	444.4275	451.998
206	233.4752	205.8147	188.4331	206.28	211.5537	159.0001	241.3338	159.0003
305	243.2419	207.3034	213.3534	362.6051	261.0242	159	225.3156	159.6789
436	452.172	247.3623	209.2823	436.1859	430.7385	230.4	208.7419	449.1042
169	172.8064	444.6967	275.1211	169.663	172.4796	159	300.4453	159
220	220.6634	389.7538	450.6073	218.9508	219.5619	161.9234	390.338	442.5326
314	360.0972	301.5798	195.8646	440.1926	326.8279	159.0012	435.8169	452
164	172.8064	445.8301	451.2105	164.0919	165.8605	160.9675	431.7476	159.0321
185	185.0025	444.964	193.3496	184.0121	195.5469	159	424.3452	168.3617
443	360.0971	267.4389	236.6314	441.7104	429.124	165.7788	424.1639	451.9988
225	233.3178	202.2298	177.7021	226.0659	224.1006	159.0001	202.8527	159
307	452	212.7628	196.1536	305.9693	307.2524	159.0002	247.5257	162.1663
445	452	419.9855	201.8259	445.0992	424.9833	283.0069	352.4627	419.2114
188	172.8065	325.0678	253.2737	191.3797	201.1591	159	203.0059	159.0183
191	452	286.5271	449.5074	190.8547	191.6071	159.8556	385.2445	169.3221
302	452	442.566	191.8932	450.8003	357.5315	159.0023	445.4359	452
178	178.001	412.3017	450.5187	177.7664	161.856	159.484	403.1332	450.273
195	181.7283	277.495	196.4267	195.1604	202.8715	159	401.532	163.0621
452	452	289.6754	238.798	450.6812	443.6997	211.716	409.3699	452

Table 2 : Deviation Values (Pu)

				PU DEVIATION				
	3%deviation	5%deviation	7%deviati	9%deviati	11%deviat	12%deviat	13%devia	14%deviation
	-14.82280147	-6.4484925	-4.01427	-17.6071	-0.08472	20.10045	-82.8107	20.10005025
	7.711484511	21.803855	8.990382	-1.04748	-1.78683	39.31294	19.09141	39.31152672
	14.41355279	37.9642476	46.92476	-6.74296	2.314223	60.13811	56.53536	-9.708567961
	-7.989518907	-181.70447	-86.0575	-0.56403	-1.1522	0	-123.769	0
	-4.869115758	-105.12086	-114.771	-14.0659	-0.68076	-98.5301	-96.3106	-115.2359048
	-30.85200329	-26.874458	19.24948	-33.2491	-10.8876	36.14438	-51.0592	-81.5251004
	-5.096107552	-173.07951	-175.173	-0.02683	-1.48207	0.689268	-146.816	-6.145792683
	0	-137.47508	1.051905	-0.24407	8.079365	15.87302	-124.893	15.87301587
	6.360201179	25.8175979	38.36462	0.998042	9.181332	57.58992	-16.0385	-18.0151436
	-11.76793081	0.08995146	8.527621	-0.13592	-2.69597	22.81549	-17.1523	22.81538835
	25.38958132	32.0316721	30.04807	-18.8869	14.4183	47.86885	26.12603	47.6462623
	-3.576515131	43.2655275	51.99947	-0.04264	1.206766	47.15596	52.12342	-3.005550459
	-2.202696196	-163.13414	-62.7936	-0.39231	-2.05893	5.91716	-77.7783	5.917159763
	-0.300638892	-77.160818	-104.822	0.476909	0.199136	26.39845	-77.4264	-101.1511818
	-12.80132142	3.95547771	37.62274	-40.1887	-4.08532	49.36268	-38.7952	-43.94904459
	-5.096107552	-171.84762	-175.128	-0.05604	-1.13445	1.849085	-163.261	3.029207317
	-0.001351333	-140.52108	-4.5133	0.534	-5.70103	14.05405	-129.376	8.993675676
	23.02237369	39.6300451	46.58433	0.291106	3.13228	62.57815	4.251941	-2.031331828
	-3.565008756	10.1200889	21.02129	-0.47373	0.399733	29.33329	9.843244	29.33333333
	-32.07964602	30.6961564	36.10632	0.335733	-0.08221	48.2084	19.37274	47.17710098
	-1.548672566	5.62123596	54.64587	-0.02229	4.498135	36.40294	20.7949	5.795191011
	8.792203997	-72.908404	-34.7201	-1.79771	-6.99952	15.42553	-7.98186	15.41579787
	-57.74336283	-50.014188	-135.344	0.076073	-0.31785	16.30597	-101.699	11.34968586
	-33.18584071	-46.545033	36.45921	-49.2716	-18.3879	47.35023	-47.4953	-49.66887417
	-0.000561795	-131.63017	-153.1	0.131236	9.069663	10.40225	-126.479	-152.9623596
	7.30304526	-42.305128	-0.73164	-0.08226	-4.03667	18.46154	-105.914	16.37841026
	0	35.9125221	47.16858	0.29177	1.83635	53.16018	9.431438	0
SUM	-134.5067582	-1239.8611	-566.405	-181.763	-7.23882	684.3682	-1317.48	-294.2630463
AVG	**-4.981731787**	**-45.92078**	**-20.978**	**-6.73195**	**-0.2681**	**25.34697**	**-48.7957**	**-10.89863134**

Table 3 : Axial Shortening Predicted Values

			AXIAL SHORTENING PREDICTED VALUES					
actual	3(predicted)	5(predicted)	7(predicted)	9(predicted)	11(predicted)	12(predicte	13(predic	14(predicted)
100.32	125.0807	88	241.7927	101.7269	104.9689	88	89.8282	94.2782
97.02	118.09404	88	96.0686	147.0969	101.8107	88	149.8828	240.8159
106.54	105.1405	88	88.5917	112.7783	88.8206	88	187.4439	105.4284
100.57	109.4811	88	133.2868	106.9964	100.0808	88	226.0198	103.669
100.85	110.5635	88	99.4819	99.9512	100.2558	88	209.7908	101.8322
117.97	99.9005	88	91.4675	102.5711	119.192	88	177.7678	118.7075
92.83	109.9376	88	246.6489	95.2437	93.3722	88.0001	242.1165	91.4277
94.99	103.8446	88	95.1734	132.3399	95.2063	246.65	210.5453	92.9475
102.1	105.0006	88	88	90.0949	91.4792	88	116.1634	102.2478
101.34	116.3533	88	88.2966	106.2393	104.7751	88	89.9007	95.2578
146.65	113.4058	88	88.0216	170.3404	142.34	88	117.7788	237.5746
88	98.581	88	88.0001	102.9253	88.2966	88	213.895	94.3213
95.87	108.7307	88.0001	88.0486	110.764	88.5227	88	226.7062	98.8209
94.1	109.9058	88	88.0001	91.8793	88.0088	88	224.2319	88.144
98.16	95.1827	88	88	101.693	91.3978	88	159.3727	107.1012
94.22	109.5208	92.1038	88.002	99.6071	93.5214	88	241.7589	95.0605
96.38	101.2871	88	88.3476	102.1451	96.9822	88	221.0557	92.6627
99.05	102.4905	88	88	93.2286	102.135	88	106.2636	88.1107
98.41	112.5405	88.0003	88	119.0012	100.266	88	89.3452	91.1834
102.61	110.8497	88	88	210.9246	104.8154	88	103.1278	116.946
107.18	95.3462	88	88.0002	94.1283	107.8825	88	231.0928	107.3228
98.03	107.9152	99.4063	88.0874	108.5946	103.3665	88	218.5586	97.4436
95.87	109.5436	88	88	90.0727	88.1191	88	220.4565	88.2045
99.05	92.3513	88	88	98.7962	127.0825	88	124.0614	91.8838
96.54	109.2001	88	88	98.2164	93.0588	88	237.4611	92.2688
95.11	98.3242	88	88.5379	94.49	97.1397	88	209.0603	94.2739
99.94	99.5636	88	88	96.9274	99.6647	88	100.4911	88.0491

Table 4 : Deviation Values(As)

				AXIAL SHORTENING DEVIATION				
	3%deviation	5%deviation	7%deviation	9%deviation	11%deviation	12%deviation	13%deviatio	14%deviation
	-24.6817185	12.2807018	-141.02143	-1.4024123	-4.634070973	12.28070175	10.4583333	6.022527911
	-21.7213358	9.29705215	0.98062255	-51.615028	-4.937847866	9.297052154	-54.4864976	-148.2126366
	1.313591139	17.4019148	16.8465365	-5.8553595	16.63168763	17.40191477	-75.9375821	1.043363995
	-8.86059461	12.4987571	-32.531371	-6.3899771	0.486427364	12.49875708	-124.738789	-3.081435816
	-9.63163114	12.7416956	1.35656916	0.89122459	0.589191869	12.74169559	-108.022608	-0.973921666
	15.31702975	25.4047639	22.4654573	13.0532339	-1.035856574	25.40476392	-50.6889887	-0.625158939
	-18.4289562	5.20305936	-165.69956	-2.6001293	-0.584078423	5.202951632	-160.817085	1.510610794
	-9.3216128	7.35866933	-0.193073	-39.319823	-0.22770818	-159.658911	-121.649963	2.15022634
	-2.84094025	13.8099902	13.8099902	11.7581783	10.40235064	13.80999021	-13.774143	-0.144760039
	-14.8147819	13.1636077	12.8709295	-4.8345175	-3.389678311	13.16360766	11.2880403	6.001776199
	54.02156902	64.3219136	64.3131563	30.9384148	4.31	64.32191364	52.2486114	3.679464829
	-12.0238636	0	-0.0001136	-16.960568	-0.337045455	0	-143.0625	-7.183295455
	-13.4147283	8.20892876	8.15833942	-15.535621	7.663815584	8.209033066	-136.472515	-3.078022322
	-16.7968119	6.48246546	6.48235919	2.35993624	6.473113709	6.482465462	-138.291073	6.329436769
	3.033109209	10.3504482	10.3504482	-3.5992258	6.888956805	10.35044825	-62.3601263	-9.108801956
	-16.2394396	2.24601995	6.5994481	-5.7175759	0.741456166	6.601570792	-156.58979	-0.892061134
	-5.09140901	8.69474995	8.33409421	-5.9816352	-0.624818427	8.694749948	-129.358477	3.856920523
	-3.47349823	11.1559818	11.1559818	5.87723372	-3.114588592	11.15598183	-7.28278647	11.04422009
	-14.358805	10.5778884	10.5781933	-20.92389	-1.885987196	10.57819327	9.21125902	7.343359415
	-8.03011402	14.2383783	14.2383783	-105.5595	-2.149303187	14.23837833	-0.50462918	-13.97134782
	11.04105244	17.8951297	17.8949431	12.1773652	-0.655439448	17.89512969	-115.611868	-0.133233812
	-10.0838519	-1.40395797	10.1424054	-10.776905	-5.443741712	10.23156177	-122.950729	0.598184229
	-14.2626473	8.20903307	8.20903307	6.04704287	8.084802336	8.209033066	-129.953583	7.995723375
	6.762948006	11.1559818	11.1559818	0.25623423	-3.234	11.15598183	-25.2512872	7.234931853
	-13.1138388	8.84607417	8.84607417	-1.7364823	3.605966439	8.846074166	-145.971722	4.424280091
	-3.37945537	7.47555462	6.90999895	0.65187677	-2.134055304	7.475554621	-119.808958	0.879087373
	0.376625976	11.9471683	11.9471683	3.01440865	0.275465279	11.9471683	-0.55143086	11.89803882
SUM	-148.704109	329.56197	-55.799439	-211.7835	31.76501417	178.5357613	-2060.93089	-105.3925229
AVG	-5.50755958	12.2059989	-2.0666459	-7.8438333	1.176482006	6.612435605	-76.3307736	-3.903426775

Table-5: Experimental results from which the ANN model has developed by the authors

Length(mm)	Diameter(mm)	Thickness (mm)	% RCA	Pu (20)	Pu(40)	Pu(60)(kN)	As (20)(mm)	As(40)
300	42.4	2.9	0	199	206	225	100.32	101.34
300	48.3	3.2	50	262	305	307	97.02	246.65
300	60.3	4	100	412	436	445	106.54	88
500	42.4	3.2	100	159	169	188	100.57	95.87
500	48.3	4	0	210	220	191	100.85	94.1
500	60.3	2.9	50	249	314	302	117.97	98.16
600	42.4	4	50	164	164	178	92.83	94.22
600	48.3	2.9	100	189	185	195	94.99	96.38
600	60.3	3.2	0	383	443	452	102.1	99.05

Pu(20)- Ultimate axial load of steel tubes in filled with M20
Pu(40)- Ultimate axial load of steel tubes in filled with M40
Pu(60)- Ultimate axial load of steel tubes in filled with M60
As(20)- Axial shortening at ultimate point of steel tubes in filled with M20
As(40)- Axial shortening at ultimate point of steel tubes in filled with M40
As(60)- Axial shortening at ultimate point of steel tubes in filled with M60

The experimental inputs are tested from 3 hidden layers to 14 hidden layers and it is verified that the deviations obtained for the 11 hidden layers gives the best result, also with the best regression fit.

5. Conclusion

The experimental behavior and corresponding ANN predictions of circular composite tube subjected axial compressive load were presented and discussed. The ANN has been shown to successfully predict the crushing behavior of wide range of circular tubes. The predicted results obtained, are showed that the feed forward back propagation network with 11 hidden neurons consistently provided the best predictions of the experimental data. From the current work it can be concluded that ANN techniques can be used to effectively predict the response of ultimate axial load and axial shortening on composite tubes.

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References

[1] B. Yegnanarayana, Artificial Neural Networks, PHI Learning Pvt. Ltd., 01-Aug-2004.
[2] Simon S. Haykin, Neural Networks, Macmillan.
[3] Jacek M. Zurada, Introduction to Artificial Neural Systems,West.
[4]Freeman,Neural Networks: Algorithms, Applications, And Programming Techniques, Pearson Education India.
[4] Dr N.S.Kumar, Sameera Simha T.P., Experimental Investigation on Composite Circular Steel Columns - Taguchi's Approach , International journal of, Applied Mechanics and Materials Vols. 105-107 (2012) pp 1742-1750
[5] H. Ravi Kumar, K.U.Muthu and N.S.Kumar ,Concrete filled steel tubular columns-a critical review,International journal of , *N.S.Kumar/ Elixir Cement & Con. Com. 48 (2012) 9656-9662*
[6] Shams M saadeghavaziri MA. State of art concrete filled tubular columns ACI Struct J1997;94(5)558-7.
[7] Liu Dalin , Gho wie- Min , Yuan Jie. Ultimate capacity of high-strength rectangular concrete-filled steel hollow section stubcolumns. Jconstrsteelres 2003; 59: 1499-515
[8] Elremaily Ahmed, Azizinamini Atorod. Behavior and strength of circular concrete-filled tube columns. J constr steel res 2002;58:1567-91.
[9] Tao zhong, Han Lin-Hai, Wang Dong-ye. Strength and ductility of stiffened thin -walled hollow steel structural stub columns filled with concrete. Thin Walled struct 2008;46:1113-28.
[10] IS 10262-1982.India standard recommended guidelines for concrete mix design. Bureau of Indian Standards, New Delhi, India.
[11] Eurocode 4. Design of composite steel and concrete structures, part 1.1:general rules for buildings. Commission of European communities, British standards institution;1994
[12] Douglas montgomery, design and analysis of experiments 5th ed.New York: John Wiley& sons (ASIA) pvt. Ltd.; 2004.
[13] Schneider SP. Axially loaded concrete-filled steel tubes.J struct eng, ASCE 1998;124(10):1125-38.
[14] American Institute of steel construction (AISC). Manual of steel construction: load and resistance factor design (LRFD),2ND ed. Chicago;1994.
[15]D.S.Ramachandra Murthy,et.al., "Seismic resistance of the reinforced concrete beam-column joints with TMT and CRS bars", ICI Journal, vol.1,July-Sep.2000,no.2, pp.19-26.
[16] Schneider,S.P., "Axially loaded concrete-filled steel tubes",JournalofStructuralEngineering,ASCE,vol.124,no.10,Oct. 1998,pp.1125-1138.
[17] Kilpatrick, A.E., and Rangan,B.V., "Tests on high-strength concrete-filled steel tubular columns", ACI Structural Journal, vol.96,no.2,Mar/Apr.1999,pp.268-274.
[18] Zhang, W., and Shahrooz, B.M., "Strength of short and long concrete-filled tubularcolumns", ACI Structural Journal, vol.96, no.2,Mar/Apr-1999., pp 230-238.www.efunda.com/formulae/solid_mechanics/columns/intro.cfm.
[19] Michel Bruneau, and Julia Marson - Siesmic Design of concrete-Filled Circular Steel Bridge Piers, Journal of Bridge Engineering, ASCE ,vol.9,no.1,Jan-2004.pp 24-34.

[20] Picard,A., and Beaulieu,D.(1997),"Resistance of concrete-filled hollow structural sections." Can.J.Civ.Eng.,24,785-789.
[21] Prion,H., and Boehme ,J.(1994)."Beam-Column behaviour of Steel tubes filled with high strength concrete."Can.J.Civ.Eng.,21(2),207-218.
[22]Saatcioglu,M., and Razvi,S.R.(1992)."Strengthand ductility of confined concrete."J.Struct.Eng.,118(6).1590-1607.
[23]Viest,I.M.,Colaco,J.P.,Furlong,R.W.,Griffis,L.G.,Leon,R.T., and Wyllie,L.A.,Jr.(1997). Composite Construction design for buildings,ASCE,McGraw-Hill,New York.
[24] Intro. to ANN using Matlab6.0 --- Shivanandam , sumathie and s.n.deepa, Mc.Graw Hill compamies, 2012.
[25] Design and analysis of experiments by R.Panneerselvam , EEE ,PHI, 2012