Validation of Buckling Capacity of SCC Infilled Composite Steel Tubes using ANN-R2016a

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ABSTRACT

In this present research, behavior of Self Compacting Concrete Filled Steel Tube (CFST) under cyclic loading is investigated. The parameters chosen for the study are geometry of specimen-circular section of dia 33.7, 42.4, 48.3, different grades of self compacting infill M20, M30, M40, different L/D ratios 6, 12, 16, different D/T ratios 10.5 & 13.3 and different lengths. Also this study focuses on development of Artificial Neural Network (ANNs) in prediction of ultimate load carrying capacity in order to validate experimental results. To predict ultimate load carrying capacity five input parameters are identified. In this paper authors have also developed a suitable artificial neural network model using *Feed forward back propagation* network having verified it for 13 hidden layers as per *LM algorithm*. The developed ANN model has been verified with the experimental results conducted on composite steel columns. The ANN technique is used to predict the crushing behavior of self compacting concrete steel tubes and ultimate axial load. Different parameters effecting are network architecture, no of hidden neurons, transfer function & error function are considered. Predictions are compared to experimental results and are shown to be in good agreement. From the experimental results it is indiacted that load carrying capacity increases by decrease in L/D ratio, increase in diameter of concrete, and increase in grades of concrete. It is concluded that 5-13-1 neural architecture provides perfect model to verify the above. Almost error is subsidized to 0.58% and is approximately providing results coinciding with experimental values.

Keywords: Artificial neural network, Self compaction concrete filled steel tubes, Feed forward back propagation, Transfer function, Tansigmoid.

INTRODUCTION

Columns occupy a vital place in structural system. Weakness or failure of a column destabilizes the entire structure. Structure & ductility of steel columns need to be ensured through adequate strengthening, repair & rehabilitation techniques to maintain adequate structural performance. Nowadays, composite columns are finding a lot of usage for seismic resistance in earthquake prone countries like Japan, New Zealand, Italy, etc. In order to prevent shear failure of RC columns resulting in collapsing of buildings, it is essential to make ductility of columns larger. Nowadays, most of the building construction adopt CFST concept for lateral load resisting frames.

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 neural network.

In the current work of the load carrying capacities for axially loaded SCC infilled circular steel tubes is evaluated using ANN. To predict validity of the data using ANN in determining the ultimate axial load values of these tubes, the study will compare the predictions obtained from the experimental results using the neural network tool in MATLAB (R2016a).

ARTIFICIAL NEURAL NETWORK

Study on artificial neural networks has been motivated right from its inception by the recognition that the brain computes in an entirely different way from the conventional digital computer. A neural network is massively parallel distributed processor that has a propensity for strong experimental knowledge & making it available for use. It resembles the brain in two respects

1. Knowledge is acquired by the network through a learning process.
2. Interneuron connection strengths known as synaptic weights are used to store the knowledge.

The procedure used to perform the learning process is called learning process. A neural network can be trained to perform a particular task. The approach is particularly attractive for hard to learn problems and when there is no formal underlying theory for the solution of the problem. The great majority of Civil Engineering application of neural network is based on the use of back propagation algorithm primarily because of its simplicity. Training of a neural network with a supervised learning algorithm su7ch as back propagation means finding weights of the links connecting the nodes using a set of training examples. An error function in the form of the sum of the squares of the errors between the actual outputs from the training set and the computed

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output is minimized iteratively. The learning rate or training rule specifies how the weights are modified in each neuron.

An artificial neuron is a computational model inspired in natural neurons. Natural neurons receive signals through synapses located on the dendrites or membranes of the neuron. 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 hen 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. ANNs combines artificial neurons in order to process information.

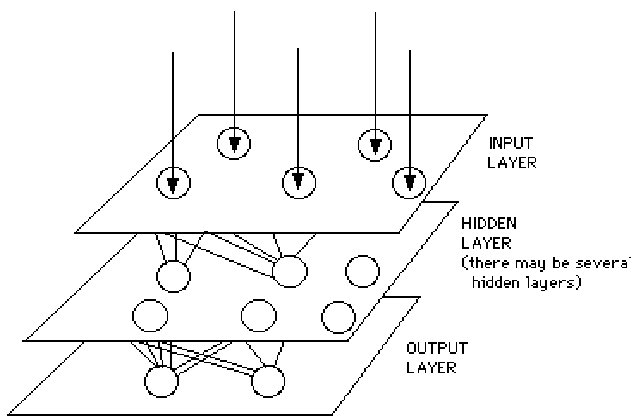

Fig. 1

The no of types of ANN and their uses are very high. Since the first neural model by McCulloch and Pitts (1943) there have been developed hundreds of different models considered as ANNs. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc. also there are many hybrid models where each neuron has more properties than the reviewing here. Because of matters of space we will present only an ANN which learns using back propagation algorithm for learning the appropriate weights, since it is one of the most common models used in ANNs and many others are based on it. Since the function of ANNs is to process information, they are mainly used in fields related to it. There are variety of ANNs that are used to model real neural networks, and study behavior and control in animals and machines, but also there are ANNs which are used for engineering processes, such as pattern recognition, forecasting and data comparison.

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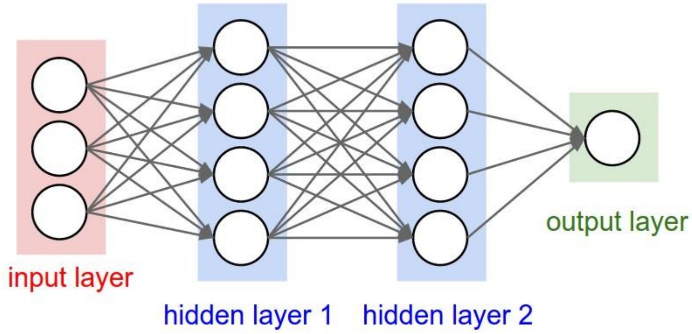

Fig. 2 Displays the Neural Network Architecture

TRAIN THE NETWORK

Network properties

- *Lavenberg-Marquardt* training algorithm
- Training (70%), Validation(15%), Testing(15%)
- *Feed forward* back propagation
- *TRAINLM* training function
- *LEARNGDM* adaption learning function
- *MSE* performance function
- *TANSIG* & *LOGSIG* transfer function

A. LAVENBERG-MARQUARTD TRAINING ALGORITHM

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

These minimization problems arise especially in least squares curve fitting.

The LMA is used in many software applications for solving generic curve fitting problems. However, as for many fitting algorithms, the LMA finds only a local minimum, which is not necessarily the global minimum. The LMA interpolates between the GAUSS NEWTON algorithm and the method of different descent. The LMA is more robust than GNA, which means that in many cases it finds solution even if it starts very far off the final min. for well behaved functions and reasonable functions and reasonable starting parameters, the LMA tends to be a bit slower than GNA. LMA can also be viewed as GAUSS-NEWTON using a trust region approach.

The algorithm was first published in 1944 by Kenneth Levenberg, while working at the Frankford Army Arsenal. It was rediscovered in 1963 by Donald Marquardt who worked as a statistician at DuPont and independently by Girard, Wynne and Morrison.

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B. FEED FORWARD BACK PROPAGATION

The back propagation algorithm is used in layered feed forward ANNs. This means that the artificial neurons are organized in layers, a11d 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 rando0m weights and the goal is to adjust them so that the error will be minimal.

WORK FLOW

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

- Collect Data
- Create the network
- Configure the network
- Initialize the weights and biases
- Train the network
- Validate the network
- Use the network

MULTILAYER NEURAL NETWORK ARCHITECTURE

An elementary neuron with R inputs is shown below. Each input is weighted with an appropriate weigth. The sum of the weighted inputs and the biases forms the inputs to the transfer function F. neurons can use any differentiable transfer function F to generate their output. Multilayer networks represented in Fig can use the TANSIG transfer function as shown in Fig below.

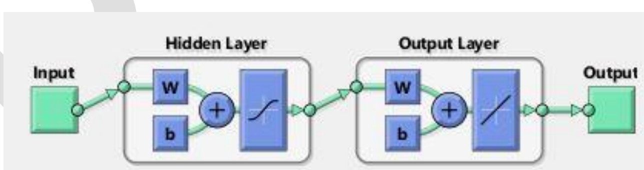

Fig.3 shows multilayer neural network architecture

The number of neurons in the hidden layers is calculated by the empirical formula given by WANG & LIU

No of neurons in hidden layers = m

m = √ (no of input parameters +no of output parameters) + a constant varies from 1-10

PREDICTION AND EXPERIMENTAL RESULTS

From the experiment it is indicated that ultimate load value of SSC infilled composite steel tubes increases with increase in the diameter of the tubes, decrease in L/D ratio, increase in the grade of concrete. Grade M30 concrete provides consistent values as shown in Fig.4

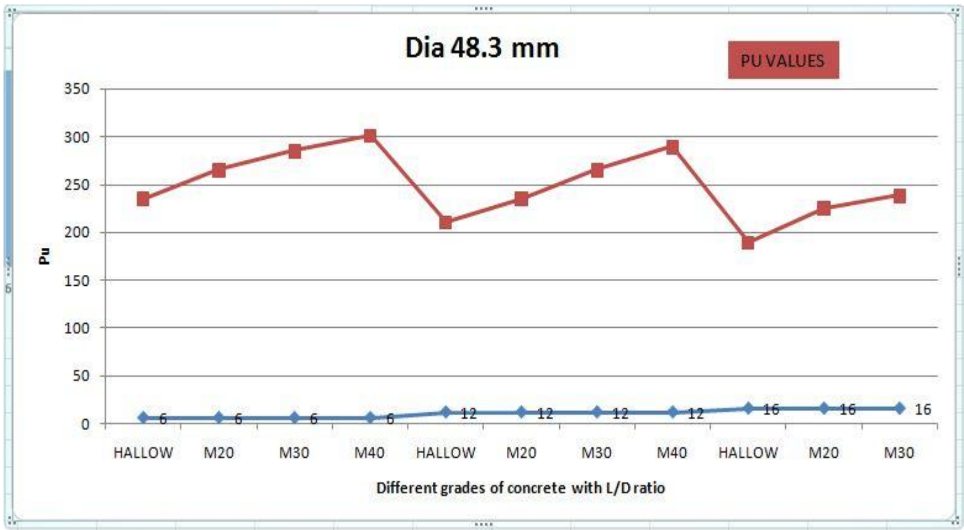

Fig.4 shows Pu_{exp} Vs L/D ratios

Depicts the LOG SIGMOIDAL and TAN SIGMOIDAL used to built the model and train the network. The output parameter is trained separately for both transfer functions (LOGSIG & TANSIG) for predicting the ultimate load of the self compacting concrete filled steel tubes.

Also the best value of prediction is obtained for 13 hidden layers and 10 hidden neurons with TANSIG as transfer function as given in the Table no. 3

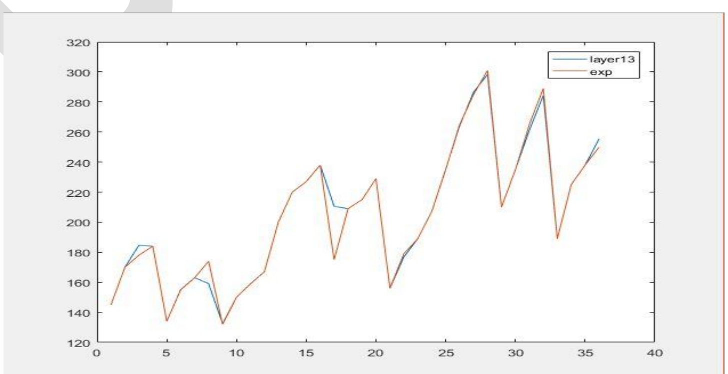

Fig. 5 shows graph for Pu experimental Vs Pu predicted(13layers)

The experimental results which are obtained are given as the desired outputs to the Feed Forward Back Propagation network. These networks were used to predict the output values and are in good agreement with Kolmogorov’s theorem. The output values obtained were tested, trained and validated from 1 to 14 hidden layers.

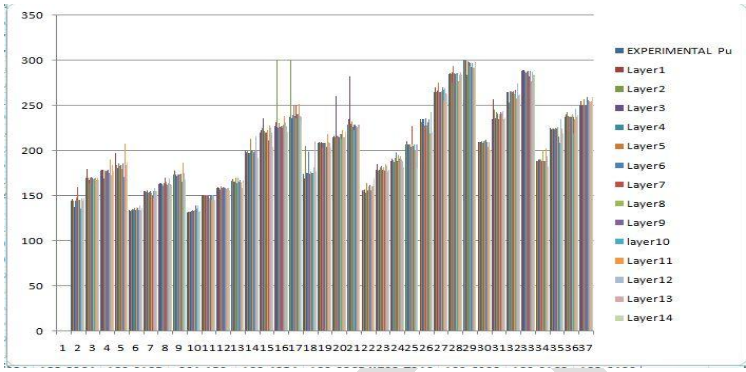

Fig. 6 *Histogram for Pu exp Vs Pu predicted(1-14)layers

The experimental values are obtained and verified for ultimate axial load. The ultimate axial load’s average deviations are tabulated in table2. The best result is obtained for 13 layers as per Kolmogorov’s principal and this is verified in the ultimate axial load deviation histogram for all the layers. The comparison of the best result and the experimental data are obtained & validated as below

Validation of predicted data			
		Regression	ANN
Exp Pu	**Output=0.96*target+8.1**	**Pu**	**Pu**
235	0.96*235+8.1	233.7	235.2334
265	0.96*265+8.1	262.5	264.202
285	0.96*285+8.1	281.7	286.5966
301	0.96*301+8.1	297.06	298.2899
210	0.96*210+8.1	209.7	209.9972
235	0.96*235+8.1	233.7	235.018

Table. 1 shows Validation of the predicted data

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 ouput values. The input is trained using Levenberg-Marquardt algorithm. This performance is measured using MEAN SQUARE ERROR (MSE). The output values are tested, trained and validated, plotted to obtain the best values on the curve fit. The experimental inputs are tested in 1 to 14 layers and it is verified that the deviation for 13 layers gives the best result with TANSIG training function, also the best REGRESSION fit.

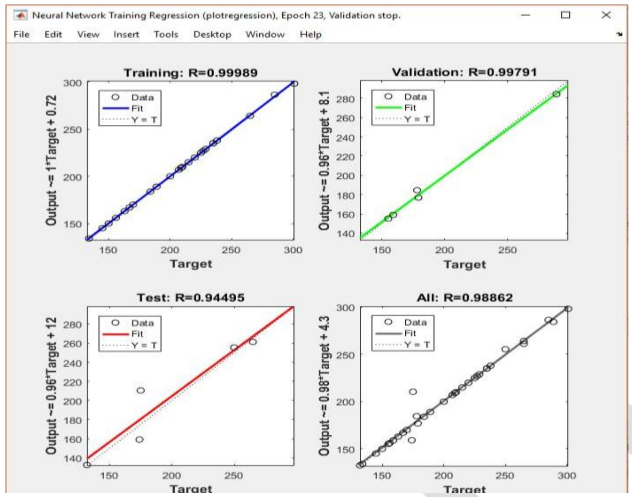

Fig. 7: *Regression Plot

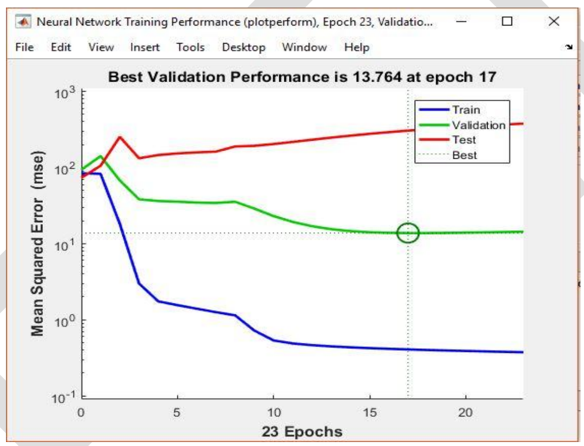

Fig. 8: *Epoch Vs MSE

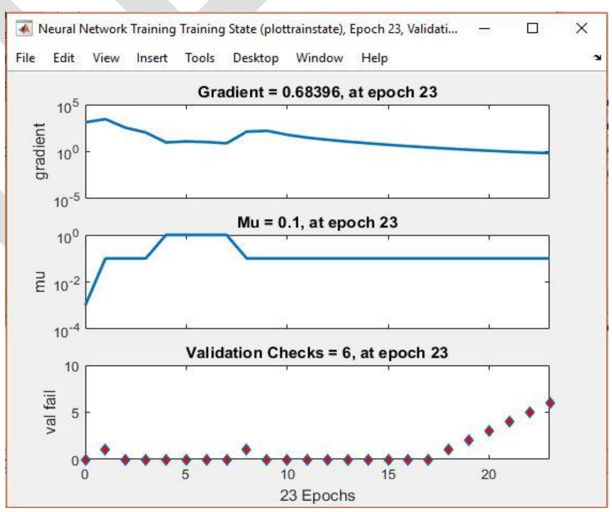

Fig. 9 shows graph for Epoch Vs Gra, Mu, Val

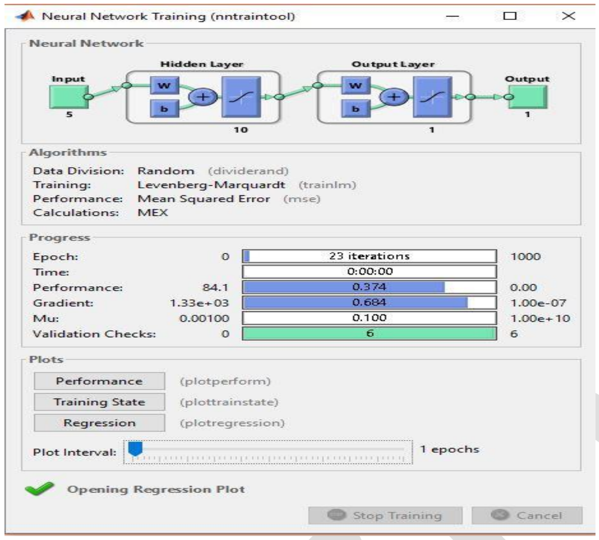

Fig. 10 shows NN train tool

DISCUSSION ON THE PREDICTED VALUES FROM ARTIFICIAL NEURAL NETWORK

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

The ANN has been shown to successfully predict the crushing behavior of wide range of circular composite steel tubes.

The predicted results obtained, are showed that *Feed Forward Back propagation* network and *Kolmogorov's* theorem with 13 hidden neurons consistently provided the best predictions of the experimental data.

CONCLUSION

- ANN model of 5-13-1 neural architecture satisfies the requirement of determining ultimate load (Pu).
- Percentage variation in MSE 0.58% obtained yields best fit results compared with experimentally obtained values.
- ANN model can be further modified using different number of hidden layers and more hidden neurons as per the Rule of Thumb Method.
- Results obtained from Regression Analysis also satisfy the target value of Ultimate Load (Pu).
- With the increase in grade of concrete the ultimate load value increases marginally by 4-5%. The M30 grade concrete is found to be consistent.
- As L/D ratio increases, the load carrying capacity of the composite tube decreases by 7-12%.

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BIOGRAPHIES

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Dr. N.S.Kumar, Involved in the Research field related to the behavior of composite steel column since a decade presently guiding 6 PhD scholars (research under VTU Belgaum) has more than 28 years of teaching experience & 6 years of research experience at Ghousia College of Engineering.

	% Deviation with Tansigmoid transfer function													
	layer1	layer2	layer3	layer4	layer5	layer6	layer7	layer8	layer9	layer10	layer11	layer12	layer13	layer14
	-1.889	0.039	7.0531	0.53	-3.062	0.17759	-14.39	-0.914	-0.62293	9.47203	2.0065	-2.075	0.0025	-2.728
	-9.584	-0.472	2.8888	5.7363	-0.541	-0.8235	0.0671	1.782	3.22	1.04181	0.2154	2.8609	-0.009	2.1169
	-0.581	0.7494	-1.009	8.3339	0.1882	1.14365	0.1652	0.7615	-0.99213	2.84796	-12.18	4.8822	-6.559	0.646
	-13.76	-0.339	3.4946	-1.706	0.7145	-0.3006	-0.148	4.4178	-1.76614	13.0584	-23.6	4.6238	0.0027	-3.462
	0.2618	-0.212	-0.817	-0.972	-2.518	-0.6156	-0.163	-2.213	-2.84947	-0.3289	-0.954	-5.47	0.0181	-2.527
	-0.395	0.4822	-0.835	1.2523	2.056	0.98744	-0.166	1.4352	4.64E+00	-6.47E-02	7.4414	-3.658	-0.13	-0.296
	-1.148	-0.625	-1.092	-0.177	1.4059	-1.2198	-7.338	-3.12	-0.06547	0.67619	-1.152	-6.685	-0.007	0.7008
	-3.725	0.3009	0.3431	1.6728	0.0141	0.65893	0.1299	0.8939	-0.42632	8.19473	-12.41	-1.843	14.878	5.9544
	-0.683	-0.129	-0.196	-1.23	-2.028	-1.07E+00	-1.259	-2.452	-7.1265	-3.7403	-2.372	-7.338	-0.488	-0.933
	-0.593	0.0026	0.3478	5.7712	-0.54	0.38761	0.394	2.8806	-8.93E-01	-2.71E-01	4.7769	-1.218	-0.007	4.2909
	-0.252	0.5939	0.5149	1.8071	-1.657	-0.1337	-0.457	-1.027	1.32E-01	-9.12E-02	1.0322	0.4417	0.0608	2.4944
	-1.718	-0.038	0.8171	1.0665	-2.773	2.90783	0.1362	-2.958	0.802565	-0.3304	2.4491	8.0001	-0.014	2.2208
	1.5236	-0.016	2.2424	2.7464	-12.76	-0.0061	0.0005	-0.061	1.45055	0.05747	-7.446	-15.79	0.0158	8.1087
	-2.612	-5.839	-16.14	0.0499	-2.103	-0.2201	-4E-04	-2.589	8.600031	1.11171	-7.707	-5.518	-0.007	16.042
	-4.693	-73.68	0.9275	1.9676	-3.406	0.4231	0.0529	-0.598	1.907532	-2.1951	-11.95	-4.508	-0.01	5.5524
	-2.848	-62.75	1.8617	-1.415	-12.27	-0.1643	-11.81	1.9292	-2.01036	-2.7258	-13.62	-0.58	-0.029	4.3159
	5.4708	-30.45	-0.04	-0.193	-0.964	-24.089	0.071	-2	-0.01475	-0.1707	-4.975	-6.645	-35.5	-2.396
	-0.464	0.0587	-0.6	0.3385	5.8512	0.08651	0.0423	-0.07	4.666157	14.8562	-9.16	-0.487	-0.046	5.1912
	-1.838	0.0076	-45.9	1.0361	-1.288	-0.9618	0.0307	-3.635	-3.44726	1.54191	-7.69	-0.258	0.036	-6.252
	-6.028	0.0022	-53.26	-0.502	-3.623	2.83113	-0.007	6.1824	-0.1825	1.53902	2.5718	0.3331	-0.03	4.1965
	0.0401	-0.175	-0.604	2.7058	-8.282	0.01566	-0.005	-4.299	-5.93882	0.20371	-4.328	-4.985	0.0217	-13.35
	-6.504	0.6586	0.1659	0.1418	-2.438	-4.222	0.3867	-2.505	8.97E-01	5.88E-01	-6.145	-4.188	2.1075	-0.135
	-2.345	-0.664	5.6264	1.3549	-3.327	-8.8918	0.0382	-6.71	-2.51283	-1.3081	-4.827	-1.27	-8E-04	7.7132
	-3.358	0.1202	-0.165	-0.013	-0.219	2.21823	-20.61	-0.116	1.359203	0.15828	6.2564	0.2919	0.0006	26.083
	3.4878	3.1188	0.3322	0.0037	6.9213	-1.1915	9.5006	7.293	3.132163	0.11777	15.266	-7.587	-0.233	14.549
	-4.874	0.0548	-1.295	-0.187	-10.03	0.21464	-0.016	-0.765	-5.12126	-2.6159	10.127	-4.568	0.798	2.0775
	-0.688	-0.034	-1.494	9.9801	-8.805	-1.1012	0.0757	-0.735	2.94E-01	-9.96E-01	7.5566	0.7097	-1.597	0.4074
	1.2215	0.1027	0.6063	16.734	1.6356	2.52112	3.8881	6.9163	7.77247	3.41568	8.6274	8.8409	2.7101	6.0957
	-0.082	-0.017	0.18	-0.581	1.4476	-0.1204	-0.001	-1.64	-2.70408	0.25906	5.9068	6.8339	0.0028	9.4045
	-21.58	-10.7	-0.695	0.5057	-7.569	-6.067	0.2395	-5.53	-8.30797	-1.0017	-6.236	-8.616	-0.018	-2.243
	-0.165	11.058	2.4059	-0.491	-0.801	0.12973	-0.513	1.5253	-2.39E+00	9.66E-01	6.7648	-9.395	3.7242	3.1521
	-0.887	30.614	-0.384	1.0926	2.8186	1.39598	0.5028	7.8602	6.62E+00	2.58E-01	11.834	1.366	4.6193	5.2031
	0.0481	-0.009	-1.091	-1.044	-1.248	0.1036	-0.019	-12.16	5.15E-01	-2.65E-02	-13.72	-4.7	-0.017	6.3534
	1.1018	0.0345	0.0377	1.1512	1.9116	-0.0319	0.5377	-0.879	9.11E+00	1.66E+01	3.0066	-9.963	0.0182	5.8192
	-2.522	-4.962	0.4632	-0.271	0.0789	0.43877	0.0808	-2.674	2.00E-01	1.83E+01	2.8075	-8.427	-0.024	-1.466
	-5.232	-0.044	0.2347	-0.493	-7.391	0.08794	-0.103	-6.457	-9.50E+00	-7.58E-01	-5.446	-4.765	-5.505	-10.01
SUM	-87.9	-143.1	-95.08	56.703	-74.6	-34.5	-40.66	-22.23	-1.55643	78.6071	-57.27	-91.35	-21.22	102.88
AVG	-2.442	-3.976	-2.641	1.575	-2.072	-0.9583	-1.129	-0.671	-4.32E-02	2.18E+00	-1.591	-2.537	-0.589	2.8578

Table. 2 shows the Mean Square Error for the predicted vales of ANN for (1-14) layers

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Grade	Exp Pu	Predicted Values of ANN for different layers													
		Layer1	Layer2	Layer3	Layer4	Layer5	Layer6	Layer7	Layer8	Layer9	layer1(	Layer1	Layer1	Layer1	Layer14
HALLOW	145	146.89	144.96	137.95	144.47	148.06	144.82	159.39	145.91	145.62	135.53	142.99	147.07	145	147.73
M20	170	179.58	170.47	167.11	164.26	170.54	170.82	169.93	168.22	166.78	168.96	169.78	167.14	170.01	167.88
M30	178	178.58	177.25	179.01	169.67	177.81	176.86	177.83	177.24	178.99	175.15	190.18	173.12	184.56	177.35
M40	184	197.76	184.34	180.51	185.71	183.29	184.3	184.15	179.58	185.77	170.94	207.6	179.38	184	187.46
HALLOW	134	133.74	134.21	134.82	134.97	136.52	134.62	134.16	136.21	136.85	134.33	134.95	139.47	133.98	136.53
M20	155	155.39	154.52	155.83	153.75	152.94	154.01	155.17	153.56	150.36	155.06	147.56	158.66	155.13	155.3
M30	163	164.15	163.62	164.09	163.18	161.59	164.22	170.34	166.12	163.07	162.32	164.15	169.68	163.01	162.3
M40	174	177.73	173.7	173.66	172.33	173.99	173.34	173.87	173.11	174.43	165.81	186.41	175.84	159.12	168.05
HALLOW	132	132.68	132.13	132.2	133.23	134.03	133.07	133.26	134.45	139.13	135.74	134.37	139.34	132.49	132.93
M20	150	150.59	150	149.65	144.23	150.54	149.61	149.61	147.12	150.89	150.27	145.22	151.22	150.01	145.71
M30	159	159.25	158.41	158.49	157.19	160.66	159.13	159.46	160.03	158.87	159.09	157.97	158.56	158.94	156.51
M40	167	168.72	167.04	166.18	165.93	169.77	164.09	166.86	169.96	166.2	167.33	164.55	159	167.01	164.78
HALLOW	200	198.48	200.02	197.76	197.25	212.76	200.01	200	200.06	198.55	199.94	207.45	215.79	199.98	191.89
M20	220	222.61	225.84	236.14	219.95	222.1	220.22	220	222.59	211.4	218.89	227.71	225.52	220.01	203.96
M30	227	231.69	300.68	226.07	225.03	230.41	226.58	226.95	227.6	225.09	229.2	238.95	231.51	227.01	221.45
M40	238	240.85	300.75	236.14	239.41	250.27	238.16	249.81	236.07	240.01	240.73	251.62	238.58	238.03	233.68
HALLOW	175	169.53	205.45	175.04	175.19	175.96	199.09	174.93	177	175.01	175.17	179.97	181.64	210.5	177.4
M20	209	209.46	208.94	209.6	208.66	203.15	208.91	208.96	209.07	204.33	194.14	218.16	209.49	209.05	203.81
M30	215	216.84	214.99	260.9	213.96	216.29	215.96	214.97	218.63	218.45	213.46	222.69	215.26	214.96	221.25
M40	229	235.03	229	282.26	229.5	232.62	226.17	229.01	222.82	229.18	227.46	226.43	228.67	229.03	224.8
HALLOW	156	155.96	156.17	156.6	153.29	164.28	155.98	156.01	160.3	161.94	155.8	160.33	160.99	155.98	169.35
M20	179	185.5	178.34	178.83	178.86	181.44	183.22	178.61	181.5	178.1	178.41	185.15	183.19	176.89	179.14
M30	189	191.35	189.66	183.37	187.65	192.33	197.89	188.96	195.71	191.51	190.31	193.83	190.27	189	181.29
M40	207	210.36	206.88	207.16	207.01	207.22	204.78	227.61	207.12	205.64	206.84	200.74	206.71	207	180.92
HALLOW	235	231.51	231.88	234.67	235	228.08	236.19	225.5	227.71	231.87	234.88	219.73	242.59	235.23	220.45
M20	265	269.87	264.95	266.3	265.19	275.03	264.79	265.02	265.76	270.12	267.62	254.87	269.57	264.2	262.92
M30	285	285.69	285.03	286.49	275.02	293.81	286.1	284.92	285.73	284.71	286	277.44	284.29	286.6	284.59
M40	301	299.78	300.9	300.39	284.27	299.36	298.48	297.11	294.08	293.23	297.58	292.37	292.16	298.29	294.9
HALLOW	210	210.08	210.02	209.82	210.58	208.55	210.12	210	211.64	212.7	209.74	204.09	203.17	210	200.6
M20	235	256.58	245.7	235.69	234.49	242.57	241.07	234.76	240.53	243.31	236	241.24	243.62	235.02	237.24
M30	265	265.16	253.94	262.59	265.49	265.8	264.87	265.51	263.47	267.39	264.03	258.24	274.39	261.28	261.85
M40	289	289.89	258.39	289.38	287.91	286.18	287.6	288.5	281.14	282.38	288.74	277.17	287.63	284.38	283.8
HALLOW	189	188.95	189.01	190.09	190.04	190.25	188.9	189.02	201.16	188.49	189.03	202.72	193.7	189.02	182.65
M20	225	223.9	224.97	224.96	223.85	223.09	225.03	224.46	225.88	215.89	208.44	221.99	234.96	224.98	219.18
M30	238	240.52	242.96	237.54	238.27	237.92	237.56	237.92	240.67	237.8	219.7	235.19	246.43	238.02	239.47
M40	250	255.23	250.04	249.77	250.49	257.39	249.91	250.1	256.46	259.5	256.11	255.45	254.76	255.5	260.01

Table no. 3 Shows the Predicted values of Ultimate load for different grades of concrete for (1-14) layers

for dia 33.7, L/D = 6, D/T = 10.5 and length = 202.2														
Pu = 170														
Grade M20														
	layer1	layer2	layer3	Layer4	layer5	layer6	layer7	layer8	layer9	layer10	layer11	layer12	layer13	layer14
Regression	170.86	173.5	174.8	169.5	170.068	170.6	172	171.2	170.6	171.6	173.8	172.2	166.9	168.9
ANN	179.5838	170.4717	167.1112	164.2637	170.5406	170.8235	169.9329	168.218	166.78	168.9582	169.7846	167.1391	170.009	167.8831
MSE	-9.58379	-0.47169	2.888809	5.736311	-0.5406	-0.82355	0.067078	1.781971	3.22	1.041808	0.21542	2.860876	-0.009	2.11692
Pu = 178														
Grade M30														
	layer1	layer2	layer3	Layer4	layer5	layer6	layer7	layer8	layer9	layer10	layer11	layer12	layer13	layer14
Regression	178.86	181.5	182.8	177.54	178.068	178.44	179.84	178.96	177.66	179.6	181.32	180.12	178.74	176.66
ANN	178.5811	177.2506	179.0095	169.6661	177.8118	176.8564	177.8348	177.2385	178.9921	175.152	190.1817	173.1178	184.559	177.354
MSE	-0.58114	0.749405	-1.00948	8.333886	0.188197	1.143649	0.165228	0.761496	-0.99213	2.847958	-12.1817	4.882225	-6.55899	0.646044
Pu = 184														
Grade M40														
	layer1	layer2	layer3	Layer4	layer5	layer6	layer7	layer8	layer9	layer10	layer11	layer12	layer13	layer14
Regression	184.86	187.5	188.8	183.22	184.068	184.32	185.72	184.78	184.32	185.6	186.96	186.06	184.62	182.48
ANN	197.7636	184.3392	180.5054	185.706	183.2855	184.3006	184.1476	179.5822	185.7661	170.9416	207.6015	179.3762	183.9973	187.4623
MSE	-13.7636	-0.33919	3.494552	-1.70599	0.714485	-0.30063	-0.14761	4.417842	-1.76614	13.05835	-23.6015	4.623813	0.002669	-3.46232

Table no. 4 shows the validation of data with the experimental results and ANN predicted results