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Analytical Investigation on SCC Infilled Composite Steel Tubes Using-Ann Approach

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Abstract: ***In this research, we are going to investigate the behavior of Self Compacting Concrete Filled steel tube (CFST). Composite Circular hallow steel tubes with infill of different grades of Self Compacting Concrete are tested for ultimate load capacity. Steel tubes are compared for different lengths, cross sections, thickness and grade. Specimens were tested separately. Experimental results were compared with American Concrete Institute (ACI), Euro Code-4(EC-4) and modeling was carried out using ANN (Artificial Neural Network) technique which is a soft tool in Matlab-R2016a. In ANN Feed forward back propagation network is used for verifying it for different hidden layers as per LM algorithm, to generate predicted ultimate load as part of static investigation. The developed ANN model has been verified with the experimental results conducted on composite steel columns. In that way, an alternative efficient method is aimed to develop for the solution of the present problem, which provides avoiding loss of time for computing some necessary parameters.***

Keywords: Artificial neural network, Self Compacting Concrete filled steel tubes, Static investigation, Feed forward back propagation, Transfer function, Tan sigmoid

1. Introduction

Column occupies a vital place in any civil engineering structural system. Weakness or failure of a column destabilizes the entire structure. Strength and ductility of steel columns need to be ensured through adequate strengthening, repair and rehabilitation techniques to maintain adequate structural performance. In India reinforced concrete members are mostly used in the framing system for most of the buildings since this is the most convenient & economic system for low-rise buildings. However, for medium to high rise buildings this type of structure is no longer economic because of increased dead load, high stiffness, span restriction and hazardous formwork.

Recently, composite columns are finding a lot of usage for seismic résistance. Composite members combine both steel and concrete, resulting in a member that has the beneficial qualities for both the materials. Steel members have the advantages of high tensile strength and ductility, while concrete members have the advantages of high compressive strength and stiffness. In order to prevent shear failure of RC column resulting in storey collapse of building, it is necessary to make ductility of column larger , recently , most of building utilizes this Concrete Filled Steel tubes (CFST) concept as primary for lateral load resisting frames. The concrete used for encasing the structural steel section not only enhances its strength & stiffness, but also protects it from fire damages.

1.1 Artificial Neural Network

A first wave of interest in neural networks emerged by McCulloch and Pitts (1943), after the introduction of simplified neurons. ANN is a technique that seeks to build an intelligent program using models that simulate the working network of the neurons in the human brain (Fig. 1). Unlike conventional computational programs, the ANN does not have exact data and provides outputs with respect to introduced data set. The data and the circumstances introduced to the program are put into process by the help of various methods of education and learnings. With the aid of the outputs of these transactions, the program assigns weights between the data and the neurotic structures. Afterward, when come up to different situations and data, the cases are commented and results are presented in accordance with previous learnings.

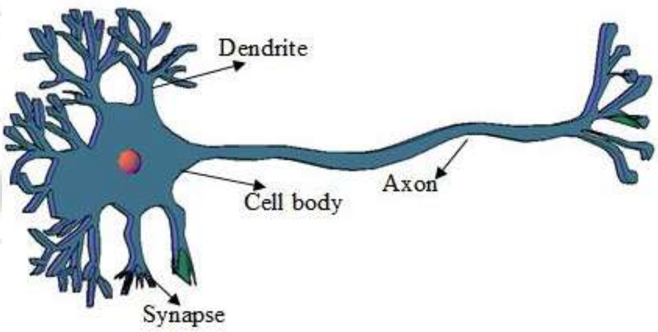


Figure 1: A biologic nerve cell structure

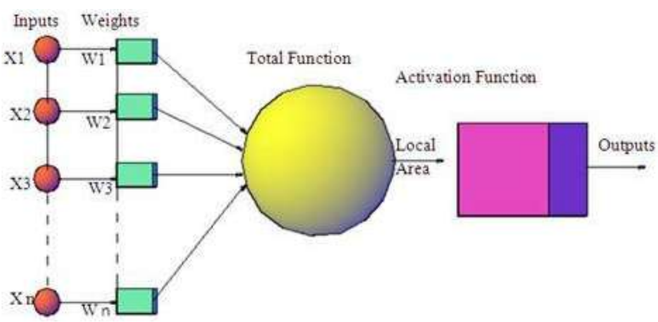


Figure 2: Artificial neural network sample

1.2 Composite Steel Column

A steel-concrete composite column is conventionally a compression member in which the steel element is a structural steel section. There are three types of composite columns used in practice which are Concrete Encased, Concrete filled, Battered Section.

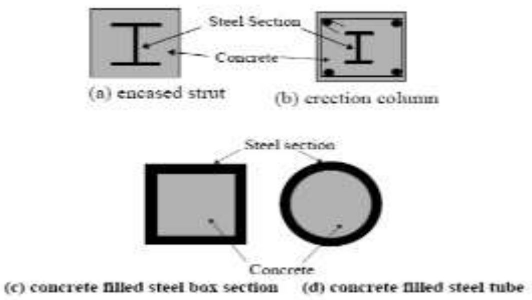


Figure 3: Different types of CFST

Advantages of composite structure:
1) Most effective utilization of materials viz. concrete in compression and steel in tension.
2) Steel can be deformed in a ductile manner without premature failure and can withstand numerous loading cycles before fracture. Such high ductility of steel leads to better seismic resistance of the composite section.
3) Steel component has the ability to absorb the energy released due to seismic forces.
4) Ability to cover large column free area. This leads to more usable space. Area occupied by composite column is less than the area occupied by RCC column.
5) Quality of steel is assured since it is produced under Control environment in the factory. Larger use of Steel in composite construction compare to RCC Option ensores better quality for the major part of the structure

1.3 Self-compacting concrete:

Self-compacting concrete is a high-performance concrete which is highly flowable or self-leveling cohesive concrete that can be easily placed in the tight reinforcement. It is also known as super workable concrete. As the name suggest, this concrete compacts by itself without the use of external vibrators. Some admixtures are used to reduce the yield stress in SCC such as HRWR (high range water-reducing admixture), and the viscosity is increased by using VMA (viscosity modifying admixture).

Advantages of SCC
1) Faster construction and requires less manpower reduce the overall cost of production.
2) SCC can be placed easily in complicated formwork and dense reinforcement.
3) It is super workable due to its low water-cement ratio, which gives rapid strength development, more durability, and best quality.
4) As it is self-compacted there are no need to use any vibrator.
5) Bleeding and segregation problems are almost nil.

2. Material Properties

Steel
a) Material: Structural Steel Fe 415 Mpa
b) Young's Modulus E=210000Mpa
c) Poison's ratio =0.3
d) Density =7860kg/m3.

Concrete Properties
a) Grade of Concrete: M30
b) Young's Modulus E=25000Mpa
c) Poison's ratio = 0.16
d) Density=2400kg/m3

Table I: Properties of Materials

Properties steel	Steel	Self- compacting concrete
Density(ρ)	7860 kg/m3	2400 kg/m3
Poison ratio (v)	0.3	0.16
Young's modules (E)	210000MPa	25000 Mpa

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

Feed Forward Back Propagation:
A feed forward neural network is an artificial neural network wherein connections between the units do *not* form a cycle. As such, it is different from networks. The feed forward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. 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.

Basic Models of Artificial Neural Networks:

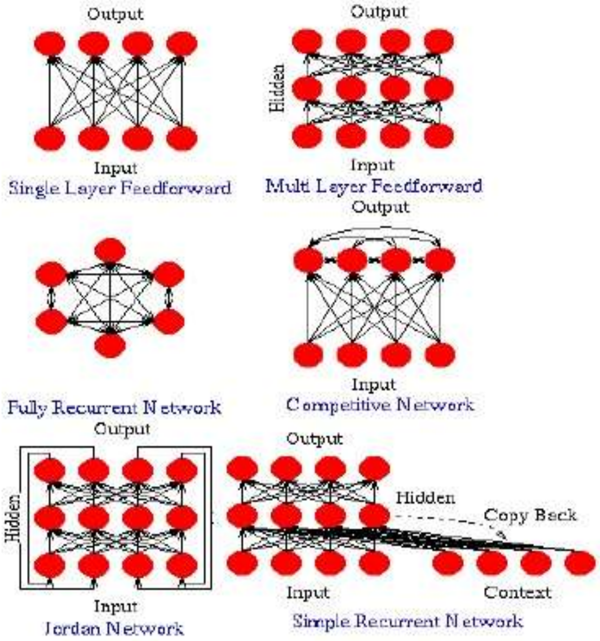


Figure 4: Different types of Models in ANN

Single-Layer Feed-Forward Network:
When a layer of the processing nodes is formed, the inputs can be connected to these nodes with various weights, resulting in a series of outputs, one per node.

Multilayer Feed-Forward Network:
A Multilayer feed-forward network is formed by the interconnection of several layers. The input layer is that which receives the input and this layer has no function except buffering the input signal.

Single Node with its own Feedback:
Single node with its own feedback is simple recurrent neural network having a single neuron with feedback itself.

Single-Layer Recurrent Network:
Single-layer recurrent network with a feedback connection in which a processing element's output can be directed back to the processing element itself or the other processing element or to both.

Multilayer Recurrent Network:
In Multilayer recurrent network, a processing element output can be directed back to the nodes in a preceding layer, forming a Multilayer recurrent network:

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

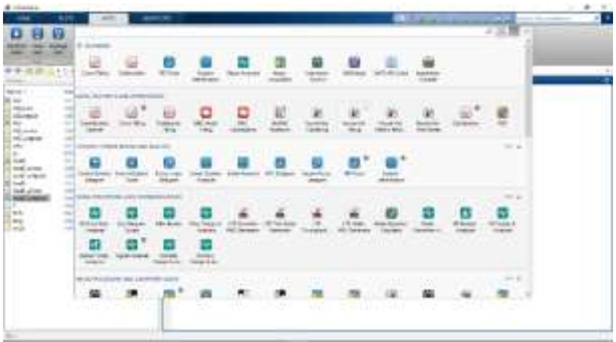
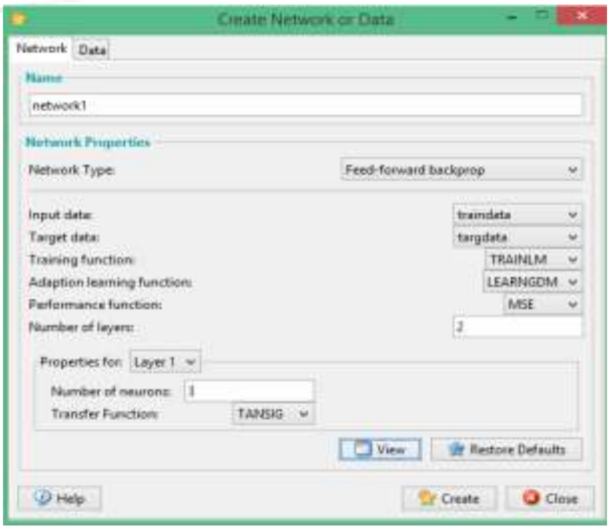


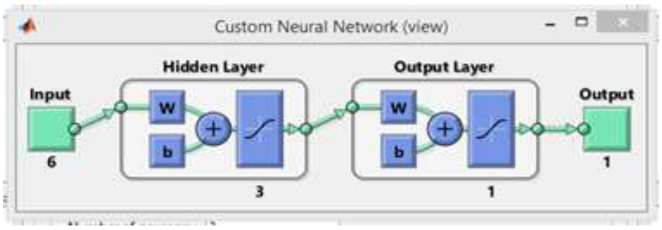
Figure 5: Different Tools in Matlab

Table 2: Collection of data and comparison

Year	Grade	Diameter mm	Length mm	Thickness mm	D/t	L/D	Pu(Exp)KN	Pu(Ec4)kN	Pu(ACI)kN
2007	Hallow	160	750.4	2.5	64	4.69	361.4	367.275	367.275
2007	M20	160	750.4	2.5	64	4.69	491.3	624.468	646.3244
2007	M30	160	750.4	2.5	64	4.69	693.3	713.1	738.0585
2010	Hallow	139.6	800	4	34.9	5.73	453.3	450.63	450.63
2010	M20	139.6	800	4	34.9	5.73	598.6	612.53	633.9686
2010	M30	139.6	800	4	34.9	5.73	712.4	748.5	774.6975
2010	Hallow	139.6	2000	4	34.9	14.32	470.5	460.63	460.63
2010	M20	139.6	2000	4	34.9	14.32	610.3	612.53	633.9686
2010	M30	139.6	2000	4	34.9	14.32	739	748.478	774.6747
2011	Hallow	111.25	750.4	2.5	44.5	6.75	267.3	270.7	270.7
2011	M20	111.25	750.4	2.5	44.5	6.75	331.3	347.9	360.0765
2011	M30	111.25	750.4	2.5	44.5	6.75	427.3	436.6	451.881
2013	Hallow	160	400	2.8	57.14	2.5	261.3	276.42	276.42
2013	M20	160	400	2.8	57.14	2.5	297.5	302.54	313.1289
2013	M30	160	400	2.8	57.14	2.5	371	398	411.93
2013	Hallow	160	1000	2.8	57.142	6.25	283.3	276.42	276.42
2013	M20	160	1000	2.8	57.142	6.25	643	650.7	673.4745
2013	M30	160	1000	2.8	57.142	6.25	687	707.8	732.573
2014	Hallow	60.3	301.5	2.9	20.79	5	99.5	104.53	104.53
2014	M20	60.3	301.5	2.9	20.79	5	153.7	151.1	156.3885
2014	M30	60.3	301.5	2.9	20.79	5	182.1	174.4	180.504
2014	Hallow	60.3	422.1	3.6	16.75	7	112.6	128.2	128.2
2014	M20	60.3	422.1	3.6	16.75	7	168.2	172.8	178.848
2014	M30	60.3	422.1	3.6	16.75	7	195.6	194.6	201.411
2016	Hallow	26.9	215.8	3.2	8.4	8	70	77.7	77.7
2016	M20	26.9	215.8	3.2	8.4	8	80	84.3	87.2505
2016	M30	26.9	215.8	3.2	8.4	8	90	94.3	97.6005
2016	Hallow	26.9	404.8	3.2	8.4	15	75	77.7	77.7
2016	M20	26.9	404.8	3.2	8.4	15	88.3	84.3	87.2505
2016	M30	26.9	404.8	3.2	8.4	15	93.7	94.3	97.6005
2016	Hallow	33.7	215.8	3.2	10.53	6.4	84	81.3	8103
2016	M20	33.7	215.8	3.2	10.53	6.4	101.7	103	106.605
2016	M30	33.7	215.8	3.2	10.53	6.4	112.3	109	112.815
2016	Hallow	33.7	404.8	3.2	10.53	12	90	81.3	81.3
2016	M20	33.7	404.8	3.2	10.53	12	110	103	106.605
2016	M30	33.7	404.8	3.2	10.53	12	120	109	112.815

Create the Network:





4. Predicted and experimental results:

After collecting the data from experimented conducted by previous researches and creating the network using ANN soft-tool to train the the input data to predict the ultimate axial load capacity of the CFST tubes.The below table shows the values obtained from the analysis for different hidden layers like 3-layer, 5-layer, 7-layer, 9-layer, 11-layer and 13-layer.It was observed that 6-11-1 neural architecture provides perfect model to verify the experimental results.

Table 3: Comparision of experimental results with predicted values

Pu(Exp)KN	3 Predicted	5 Predicted	7 Predicted	9 Predicted	11 Predicted	13 Predicte
361.4	314.9966	338.7434	343.6277	360.703	331.4367	351.72
491.3	581.177	568.3525	520.5777	491.5636	526.4367	481.18
693.3	713.4767	645.3646	625.093	574.9953	697.8733	687.14
453.3	466.0467	284.2108	358.0185	451.5268	415.2077	454.52
598.6	596.5283	594.7011	616.1314	583.759	532.7787	640.55
712.4	608.1514	704.112	655.3945	728.3336	624.5909	711.7
470.5	613.5541	731.9961	467.1347	470.9087	485.3388	164.14
610.3	651.03	732.8172	634.0263	610.5987	606.8112	627.01
739	691.656	732.8906	691.352	736.2386	729.3599	737.37
267.3	281.3756	260.8897	269.2642	255.9848	260.9419	266.75
331.3	401.779	318.8291	316.0321	329.817	328.4621	326.59
427.3	582.4718	441.7216	433.777	426.3702	424.3315	419.80
261.3	288.1568	252.7034	120.6895	263.5636	314.6066	269.00
297.5	404.7567	301.5867	290.9152	297.6283	323.7084	297.04
371	597.2144	440.392	380.0147	370.8159	370.5714	369.78
283.3	327.4927	379.471	443.7233	578.9148	313.3582	289.16
643	643.8849	631.2214	649.8856	633.5228	611.5601	646.89
687	719.2798	659.794	694.572	686.9447	701.3057	680.46
99.5	115.2588	117.9167	93.02194	103.7315	108.1961	154.43
153.7	145.1374	164.1498	126.5464	157.2178	145.3197	156.78
182.1	224.7661	186.9307	143.9595	189.6361	188.0083	186.45
112.6	93.16049	129.4297	109.2606	113.8327	115.4762	113.43
168.2	169.3791	180.1009	145.282	166.3428	173.3912	169.10
195.6	212.3985	217.1924	194.2235	227.0744	194.6107	202.23
70	78.61221	81.32536	87.40436	74.30007	75.18073	72.191
80	90.44275	96.82075	113.8902	84.47649	81.05702	86.279
90	115.7763	112.1315	125.0766	92.77435	89.11372	93.658
75	79.68162	92.23153	75.59128	79.30083	100.6867	77.475
88.3	111.2084	126.5488	91.38721	86.30819	93.29501	90.124
93.7	128.3397	194.1824	101.8989	94.47713	113.8685	96.63
84	80.04948	83.97755	93.27025	78.25238	81.43096	74.273
101.7	91.63584	104.9143	120.4207	100.768	87.67586	103.04
112.3	120.0384	124.0497	132.7954	114.2285	103.2849	109.32
90	80.03489	91.31766	80.24103	86.51677	79.98433	93.356
110	108.9763	118.4458	104.3788	101.5939	98.67279	103.47
120	133.9705	146.5784	117.1625	117.7311	100.6967	124.45

Grapical representation of ann and experimental results:

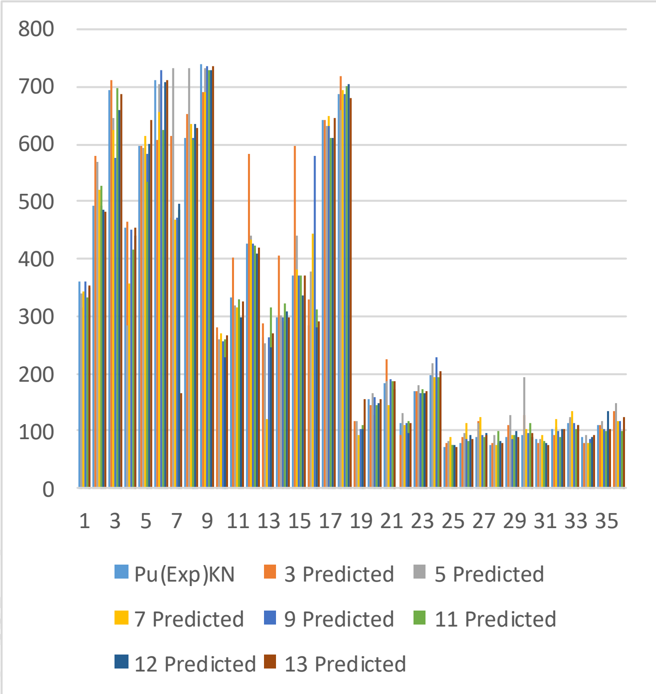


Figure 6: Ultimate axial load for different layers

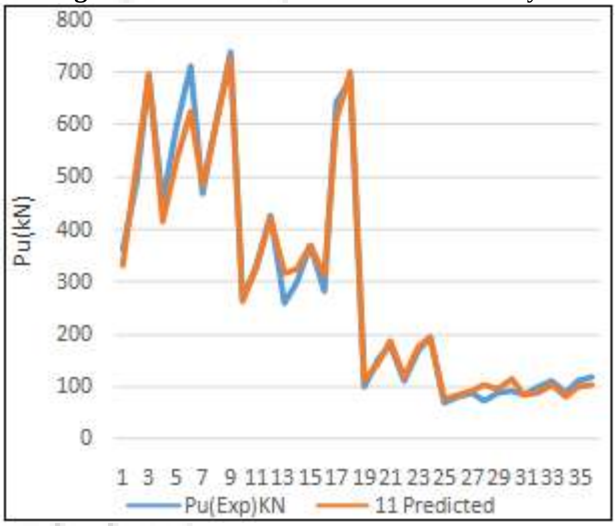


Figure 7: Pu Experimental Vs Pu Predicted(9-layer)

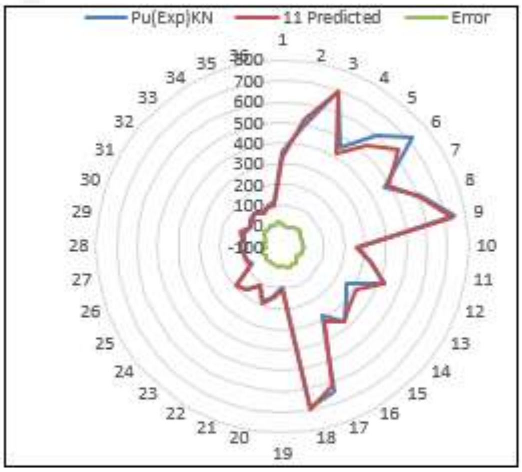


Figure 8: Actual Pu, Predicted Pu, Error on Histogram

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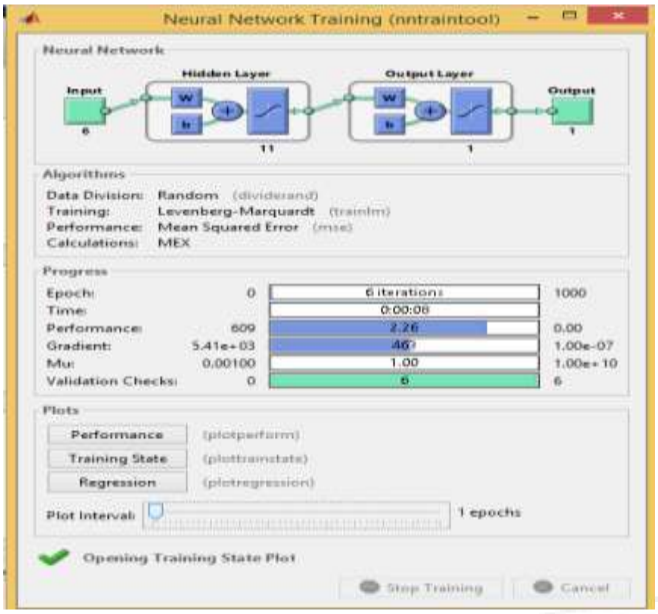

Figure 9: Neural network train tool

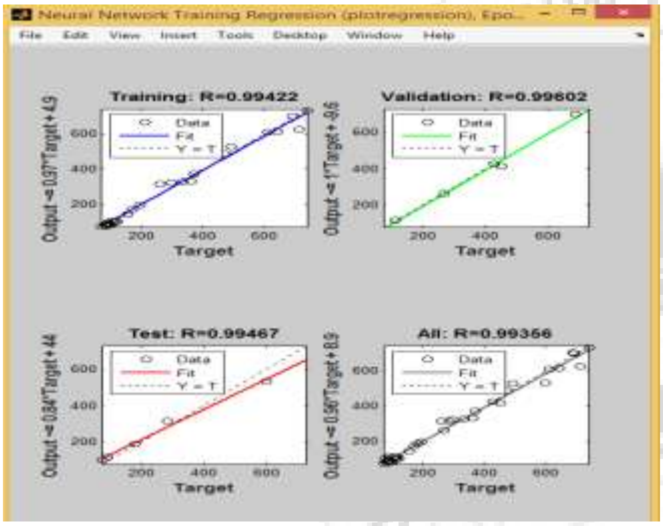

Figure 10: Regression Plot

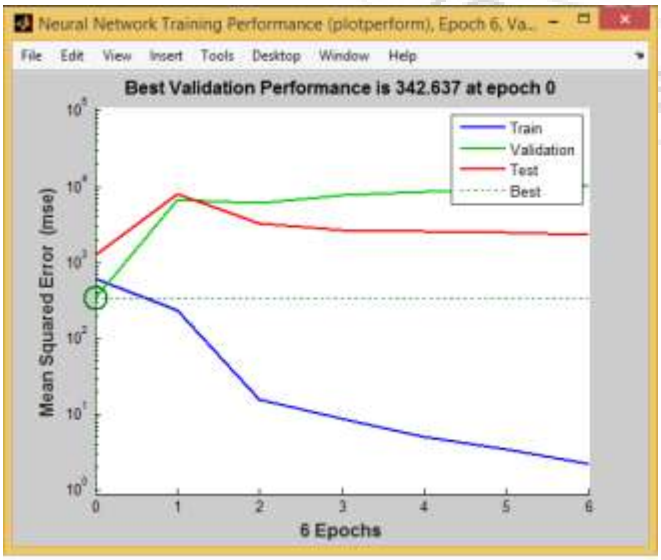

Figure 11: Performance plot

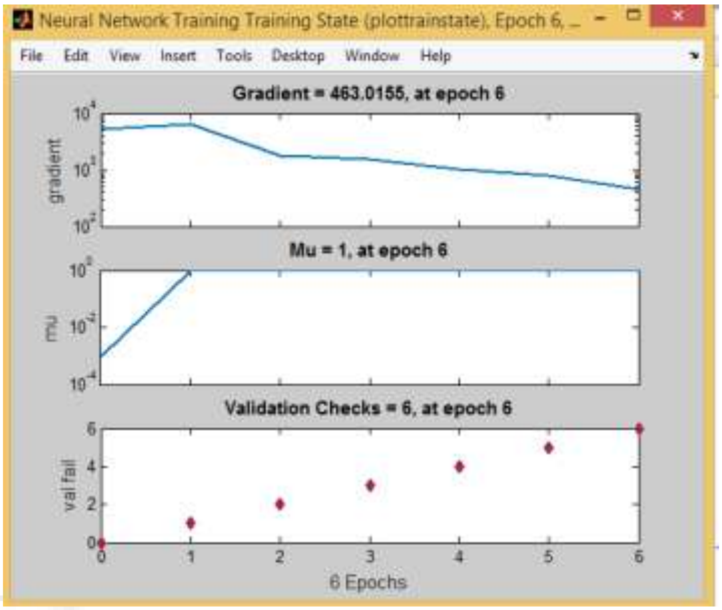

Figure 12: Training state

5. Results and Discussion

The ANN is a soft-tool in MATLAB R2016a Software (matrices laboratory) is one way of including specimen irregularities in the model using the results of the behavior of SCC infilled composite tubes subjected to different loadings.

The neural network has been shown to successfully predict the ultimate load of the composite steel tubes.In which input layer consists of 6 parameters like grade, dia, length, thickness, D/t and L/D and one target value i.e, exp P_u. Feed forward back propagation network shows good results with less error.

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 13 hidden layers and it is verified that the deviations obtained for the 11 hidden layers gives the best results, also with the best regression fit.

6. Conclusion

- ANN model of 6-11-1 neural network architecture satisfies the requirement of determining ultimate load of SCC infilled CFST tubes with different grades of concrete.
- The percentage deviation 0.735356% obtained is best fit results compared with experimental values.
- The performance of feed forward back propagation proves to be better.
- As the increase in the grade of concrete the ultimate capacity of tube to carry load is significantly increases.
- As when the diameter increases and decrease in length the load carrying capacity of CFST columns increases.
- The results are compared with EURO CODE-4, ACI and are proved to be with ANN values.
- ANN network architecture can be used to predict the different values in civil engineering.
- It can be concluded that the application of NNs in concrete field is more user-friendly and more precise model.
- It can also help the concrete industry to prevent some

problems like corrosion, workability loss, strength loss, creep, and shrinkage, which happen regarding durability and safety of concrete.

- This computational intelligent method would be beneficial to ready-mix operators and concrete mix designers in civil engineering.

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