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Modeling of Deep Beams Using Neural Network

Dr. M. A. Tantary[1] & F. A. Baba[2]
[1]*Associate professor, department of civil engineering, NIT Srinagar*
[2]*PG Student, NIT Srinagar*

Abstract:—The fundamental problem of the reinforced concrete deep beams is that a number of parameters affecting shear behavior have led to a limited understanding of shear failure mechanism and prediction of exact shear capacity. Although, a large number of researchers carried out work, but there is no agreed rational procedure to predict the shear capacity of deep beams. This is mainly due to the non-linear behavior associated with the failure of reinforced concrete deep beams.

Artificial Neural Networks are widely used to approximate complex systems that are difficult to model using conventional modeling techniques such as mathematical modeling. They have been successfully applied by many researchers in several civil engineering problems, structural, geotechnical, management etc. Civil and structural engineers attempt to improve the analysis, design, and control of the behavior of structural systems. The behavior of structural systems, however, is complex and often governed by both known and unknown multiple variables, with their interrelationship generally unknown, nonlinear, and sometimes very complicated. The traditional approach used by most researchers in modeling starts with an assumed form of an empirical or analytical equation and is followed by a regression analysis using experimental data to determine unknown coefficients such that the equation will fit the data. In the last two decades, researchers explored the potential of artificial neural networks (ANNs) as an analytical alternative to conventional techniques, which are often limited by strict assumptions of normality, linearity, homogeneity, variable independence, etc. Researchers found ANNs particularly useful for function approximation and mapping problems, which are tolerant of some imprecision and have a considerable amount of experimental data available. In a strict mathematical sense, ANNs do not provide closed-form solutions for modeling problems but offer a complex and accurate solution based on a representative set of historical examples of the relationship. Advantages of ANNs include the ability to learn and generalize from examples, produce meaningful solutions to problems even when input data contain errors or are incomplete, adapt solutions over time to compensate for changing circumstances, process information rapidly, and transfer readily between computing systems (Flood and Kartam 1994).

While many efforts have been conducted to understand the shear behavior of reinforced concrete deep beams and (or) to derive equations for estimating such shear capacity, some researchers explored the application of ANNs for such predictions. For example, Oreta (2004) applied ANNs to a set of 155 experimental tests to simulate the size effect on the shear strength of reinforced concrete beams without transverse reinforcement.

In this research program, one of the largest, reliable and most confident database of 270 deep beams was utilized to investigate the applicability of the ANN technique to predict the shear capacity of deep beams for a widest range of all affecting parameters. The incorporated variables were width, effective depth, shear span, shear span to depth ratio, compressive strength of concrete, percentage of longitudinal steel, percentage of vertical steel, percentage of horizontal web steel and yield strength of steel. For this important structural criteria, the proposed model predictions were compared with experimental values and five national codes, viz, KBCS, EC-2, CIRIA Guide-2, CSA and ACI-318 and in all the cases, a good confidence level of the proposed model was observed.

I. INTRODUCTION

An artificial neural network is a network of large number of highly connected processing units called neurons. The neurons are connected by unidirectional communication channels (connections). The strength of connections between the neurons is represented by numerical values called weights. Knowledge is stored in the form of a collection of weights. Each neuron has an activation value that is a function of the sum of inputs received from other neurons through the weighted connections. Matlab (2007) was used to develop the neural network model.

Pre-processing of Data:

A comprehensive study was carried out on the collected experimental data to choose the data which can be used in the training of neural network model. A reliable data base of test results of 270 deep beams was obtained for developing the neural network model. The statistics of database is shown in table 1.1

Table: 1.1; Statistics of Experimental Data Base:

	width (mm)	Effective Depth (mm)	Shear Span (mm)	a/d	Cylinder Strength (Mpa)	% Long. Steel	% Vert. Steel	% Hor. Steel	Yield Strength of Steel (N/mm2)	Shear Capacity (kN)
Max	915.00	1750.00	3500.00	3.20	120.00	4.25	2.86	3.17	605.00	8396.00
Min	100.00	125.00	125.01	0.27	14.00	0.01	0.00	0.00	376.00	14.00
Mean	201.70	497.13	672.01	1.30	35.13	1.30	0.33	0.35	430.65	908.67
Stand. Dev	174.76	295.140	553.9	0.37	19.384	1.019	0.404	0.4913	48.220	1209.294

II. SCALING OF DATA

Data scaling is an essential step for neural networks. In a multi-layered NN having a back-propagation algorithm, the combination of nonlinear and linear transform functions can result in well trained process. In the present NNs, tan-sigmoid and linear transform functions were employed in the hidden and output layers, respectively. As upper and lower bounds of tan-sigmoid function output are +1 and -1, respectively, input and output in the database were normalized by dividing each data parameter by the maximum value of the respective parameter in the data base. Also, after training and simulation, outputs having the same units as the original database can be obtained by multiplying the same maximum value of the respective parameters to the simulated output.

III. DIVISION OF DATA

An important factor that can significantly influence the ability of a network to learn and generalize is the number of specimens (beams) in the training set. Although it increases the time required to train a network, increasing the number of training specimens provides more information about the shape of the solution surface and thus increases the potential level of accuracy that can be achieved by the network. Since Back Propagation is most widely used in civil engineering, So it was decided to use feed forward back propagation algorithm for developing the neural network. Back propagation recommends dividing the data set into three sets, training, validation and testing sets. So, it was decided to use 170 specimen of the data for training, 50 for testing and 50 for validation out of the 270 specimens. First of all, training data was selected randomly, and checked to make sure that it satisfies a good distribution within the problem domain.

IV. ARCHITECTURE OF NEURAL NETWORK

The neural network was designed to have an input layer that consists of nine input neurons representing the most important parameters that affect the shear capacity of reinforced concrete beams. Based on careful study of recent approaches for the shear phenomena in concrete members, it was decided to design the input layer to consist of the said nine parameters. The output layer consisted of one neuron representing the ultimate shear capacity of the of the deep beam. There are two hidden layers, the first layer is having nine neurons and second hidden layer has eighteen neurons. The transfer function used is tansig while as it is purelin for output layer. The complete architecture of the network is shown in figure 1.1.

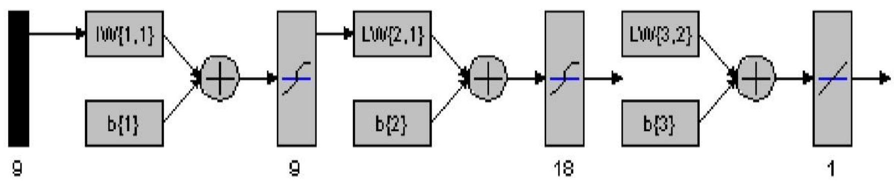


Figure: 1.1; *Architecture of Neural Network*

V. TRAINING OF NEURAL NETWORK:

In a multilayer feed-forward neural network, *training* refers to the iterative process involving the presentation of training data to the network, the invocation of learning rules to modify the connection weights, and, usually, the evolution of the network architecture, such that the knowledge embedded in the training data is appropriately captured by the weight structure of the network. During the training phase, the training data consist of input and associated output pairs representing the problem that we want the network to learn. The training set is used to reduce the ANN error. The error on the validation set is monitored during the training process. The validation set error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation set error increases for a specified number of epochs, the training is stopped. The test set is used as further check for generalization, but has not any effect on the training. Over fittings and predictions in training and outputs of NNs are commonly influenced by the number of hidden layers and neurons in each hidden layer. Therefore, trial and error approach was carried out to choose an adequate number of hidden layers and number of neurons in each hidden layer as shown in figure 1.1 above. In addition, NN performance is significantly dependent on initial conditions, such as initial weights and biases, back-propagation algorithms, and learning rate.

In this study, the training phase of ANN is implemented by using the back-propagation learning algorithm "trainlm". Trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. A backpropagation network typically starts out with a random set of weights. The network adjusts its weights each time it sees an input–output pair. Each pair requires two stages: a forward pass and a backward pass. The forward pass involves presenting a sample input to the network and letting activations flow until they reach the output layer. During the backward pass, the network's actual output (from the forward pass) is compared with the target output and error estimates are computed for the output units. The weights connected to the output units can be adjusted to reduce those errors. We can then use the error estimates of the output units to derive error estimates for the units in the hidden layers. Lastly, errors are propagated back to the connections stemming from the input units.

The back-propagation algorithm updates its weights incrementally, after seeing each input–output pair. After it has seen all the input–output pairs (and adjusted its weights many times), it is said that one *epoch* has been completed. Training a back-propagation network usually requires many thousands of epochs. An error criteria for the network output is usually chosen and the maximum number of iterations is set to provide a condition for terminating the learning process. The performance of ANN can be monitored by monitoring the training error with respect to the number of iterations. If the network "learns," the error will approach a minimum value. After the training phase, the ANN can be tested for the other set of patterns, which the network has never seen, where the final values of the weights obtained in the training phase are used. No weight modification is involved in the testing phase.

During training of the NN, the MSE (mean square error) of the training set was reduced to less than 0.0004 and MSE of validation set was reduced to less than 0.02 as shown in figure 1.2. After 15 epochs, the validation set error started to rise. So, training was stopped after 15 epochs and developed neural network model saved. Then, developed neural network was validated with the new data to check the generalization of network, discussed in the next section.

In this way, the model was developed for predicting the shear capacity of deep beams, and henceforth, the said neural network model is referred as **"PROPOSED MODEL"**.

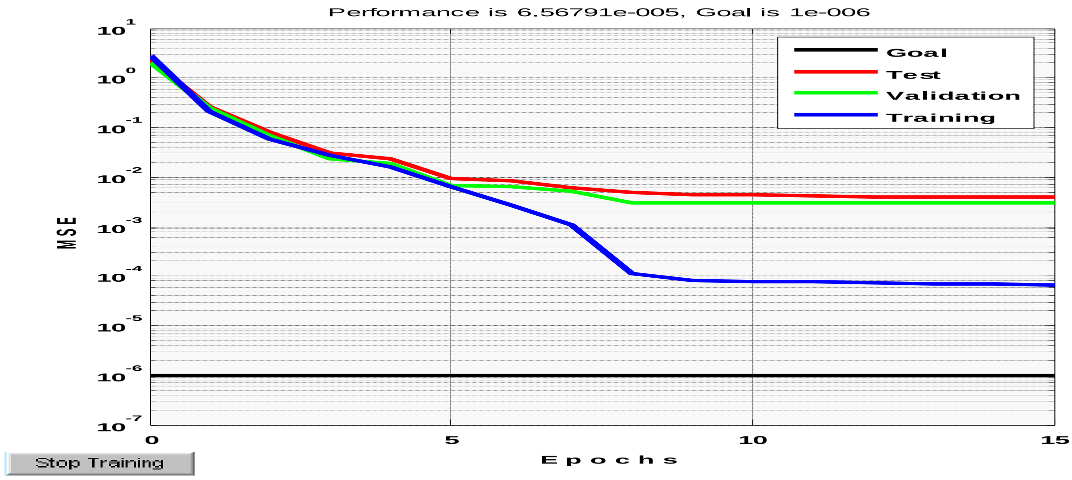


Figure: 1.2; *Training session of Network*

VI. VALIDATION OF PROPOSED MODEL:

Validation of the proposed model is equally important as its development. Without validation, we can't rely on the model. For this purpose, the predictions of shear capacity by the proposed model were compared with the experimental results (from literature) of sixty beams. The model was also compared with the predictions of five national codes, viz ACI-318, CIRIA Guide-2, EC-2, CSA and KBCS. The results of the proposed model are closer to the experimental values than any other national code. The mean error of the proposed model was found equal to 17.41 % which was lowest error, compared to the five national codes. The root mean square deviation of proposed model was 326.21, which was again the lowest. Hence, the confidence level of the said model is best, when compared with the expressions of five national codes. The detailed comparison is presented in Table 1.2.

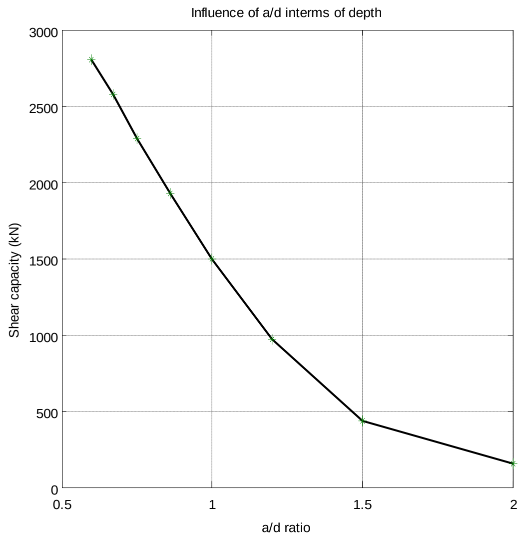
Table: 1.2; Comparison of predictions with experimental results

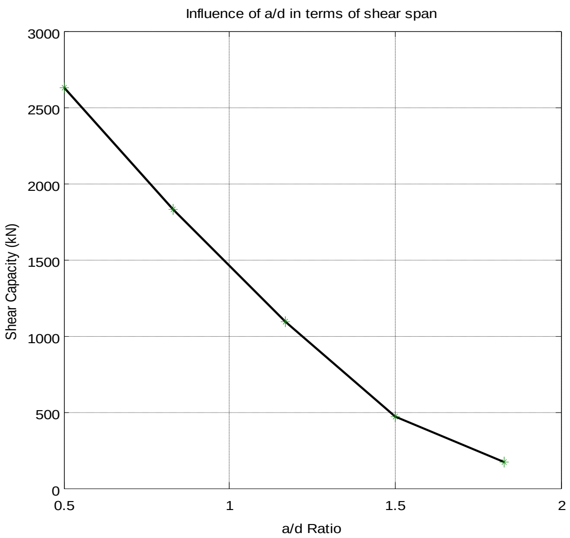
Beam Designation	Experimental	KBCS		EC-2		CIRIA		CSA		ACI		Proposed Model	
	Shear Capa	Shear Capa	% Error	Shear Capa	% Error	Shear Capacity	% Error	Shear Capa	% Error	Shear Capa	% Error	Shear Capa	% Error

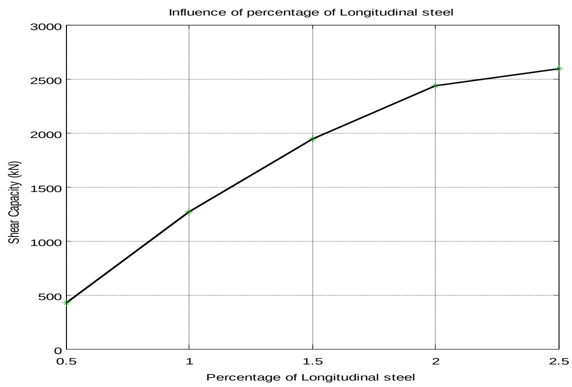
	city (kN)	city (kN)		city (kN)		(kN)		city (kN)		city (kN)		city (kN)	
NNV-1	44	80.18	82.22	169.8	285.9	78.42	78.24	96.21	118.6	80.18	143	46.12	4.82
NNV-2	65	95.86	47.48	122.5	88.48	79.02	21.58	115	76.97	95.86	96.7	32.82	49.5
NNV-3	90	106.4	18.24	231	156.7	110.2	22.48	127.7	41.88	106.4	57.7	72.22	19.7
NNV-4	93.75	110.6	17.98	158.9	69.58	108.8	16.1	132.7	41.58	110.6	57.3	86.87	7.34
NNV-5	105	152	44.82	230.6	119.6	142.7	35.99	127.5	21.48	165.5	56.9	87.15	17
NNV-6	124.1	98.81	20.38	73.38	40.87	79.48	35.96	82.89	33.21	107.5	13.7	119.6	3.62
NNV-7	124.1	101	18.6	76.35	38.48	89.32	28.02	84.74	31.72	109.9	11.8	98.52	20.6
NNV-8	133	45	66.17	150.7	13.36	79.79	40.01	54	59.4	45	54.8	166.6	25.3
NNV-9	134	45	66.42	150.7	12.51	79.79	40.46	54	59.7	45	55.2	166.6	24.3
NNV-10	135	45	66.67	160.2	18.66	83.21	38.37	54	60	45	55.5	128.7	4.64
NNV-11	136.1	70.79	47.99	92.35	32.15	55.21	59.44	84.94	37.59	70.79	30.6	77.68	42.9
NNV-12	137.2	96.55	29.63	70.38	48.7	111.3	18.88	80.99	40.97	105	23.7	102.8	25.0
NNV-13	140.3	101	28	243.6	73.67	109.8	21.72	84.74	39.6	109.9	21.9	134.7	3.95
NNV-14	143.6	99.31	30.84	89.18	37.9	80.27	44.1	83.3	41.99	108	25	121.9	15.0
NNV-15	145.2	98.56	32.12	87.98	39.41	101.5	30.06	82.68	43.06	107.2	26.4	81.42	43.9
NNV-16	149	72.13	51.59	196.3	31.79	73.95	50.37	86.55	41.91	72.13	35.4	105.6	29.0
NNV-17	152.6	95.27	37.57	68.7	54.98	127.8	16.19	79.92	47.63	103.6	32.3	203.4	33.2
NNV-18	155	97.06	37.38	226.7	46.29	147.3	4.94	81.42	47.47	105.6	32.1	174.9	12.8
NNV-19	158.4	96.55	39.05	84.77	46.49	119.3	24.63	80.99	48.87	105	33.9	167.7	5.89
NNV-20	161	95.02	40.98	94.67	41.2	142.4	11.51	79.7	50.5	103.4	36	160.6	0.24
NNV-21	165	45	72.73	160.2	2.91	83.21	49.57	54	67.27	45	63.6	128.7	21.9
NNV-22	178	45	74.72	160.2	10	83.21	53.25	54	69.66	45	66.2	128.7	27.6
NNV-23	242	193.9	19.87	227.3	6.04	157.9	34.74	232.7	3.84	193.9	6.9	290.4	20.0
NNV-24	297	192.9	35.02	136	54.18	186.6	37.15	161.8	45.5	210	29.6	259.8	12.5
NNV-25	298	72.96	75.52	152.5	48.81	113.3	61.97	87.55	70.62	72.96	67.3	269	9.71
NNV-26	310	138.3	55.38	263.5	14.98	175.1	43.51	165.9	46.46	138.3	40.4	462.5	49.2
NNV-27	334	193.9	41.94	299.4	10.35	199.2	40.33	232.7	30.33	193.9	22.5	435	30.2
NNV-28	359	208.5	41.9	333.1	7.21	201.6	43.82	250.2	30.28	208.5	22.5	392.5	9.34
NNV-29	427	256	40.05	198	53.61	231.3	45.82	214.7	49.71	278.6	35	458.7	7.44
NNV-30	448	200.3	55.27	310.7	30.64	220	50.88	240.4	46.32	200.3	40.3	498.2	11.2
NNV-31	534	237.1	55.58	335.9	37.09	455.2	14.74	284.6	46.7	237.1	40.7	542.8	1.65
NNV-32	577	208.5	63.85	333.1	42.27	267.5	53.64	250.2	56.62	208.5	51.7	590.3	2.32
NNV-33	578	201.2	65.18	250.6	56.63	428.5	25.86	241.5	58.22	201.2	53.5	485.8	15.9
NNV-34	582	204.5	64.86	321.9	44.68	265	54.45	245.4	57.83	204.5	53.1	578.9	0.53
NNV-35	600	135.6	77.39	123.1	79.48	213.9	64.34	113.7	81.04	147.6	75.5	421.4	29.7
NNV-36	605	232.3	61.59	324.1	46.42	451.7	25.34	278.8	53.91	232.3	48.7	536.6	11.3
NNV-37	608	204.5	66.36	321.9	47.04	265	56.4	245.4	59.63	204.5	55.1	578.9	4.78
NNV-38	626	208.5	66.68	333.1	46.79	225.5	63.97	250.2	60.02	208.5	55.5	417.9	33.2
NNV-39	655	377.9	42.31	566.5	13.51	261.7	60.04	317	51.6	411.2	37.4	632.9	3.36
NNV-40	681	227.5	66.59	312.2	54.15	448	34.2	273	59.91	227.5	55.4	529.8	22.2
NNV-41	699	498.1	28.74	537.2	23.13	561.4	19.68	597.7	14.49	498.1	4.94	963.4	37.8
NNV-42	735	465	36.73	343.3	53.29	592.7	19.35	558	24.08	465	15.6	808.2	9.97
NNV-43	743	404.7	45.52	317.8	57.22	327.4	55.93	339.5	54.3	440.5	40.9	744.2	0.17
NNV-44	750	558.2	25.56	549.6	26.71	579.2	22.76	605.6	19.24	558.2	3.08	1090	45.4
NNV-45	778	222.5	71.4	300.2	61.41	507.9	34.71	267	65.68	222.5	61.8	848.6	9.08
NNV-46	890	244.8	72.49	187.9	78.88	247.2	72.22	205.3	76.93	266.4	70.2	780.5	12.3
NNV-47	940	386.4	58.89	340.2	63.81	398.3	57.63	463.7	50.67	386.4	45.1	951.5	1.22
NNV-48	988	245	75.2	189.2	80.84	316.8	67.93	205.5	79.19	266.7	73.1	1020	3.3
NNV-49	1050	652.3	37.88	505.5	51.85	430.9	58.96	547.1	47.89	709.9	32.6	1072	2.13
NNV-50	1181	419.3	64.49	436.6	63.03	465.3	60.6	351.7	70.21	456.4	61.5	1081	8.46
NNV-51	1464	2109	44.09	1355	7.39	2138	46.07	1769	20.87	2296	56.1	2000	36.6
NNV-52	1491	1739	16.65	972.3	34.79	2008	34.71	1458	2.15	1893	26.3	1767	18.5
NNV-53	2083	1782	14.41	1015	51.23	2015	3.23	1495	28.2	1940	7.27	1655	20.5
NNV-54	2122	1830	13.74	1064	49.86	2436	14.84	1535	27.65	1992	6.54	2607	22.8
NNV-55	2225	1780	20	1013	54.46	2419	8.73	1493	32.89	1937	13.3	2556	14.8
NNV-56	2296	1987	13.45	1226	46.58	2216	3.48	1666	27.4	2162	6.22	1935	15.6
NNV-57	2657	2061	22.43	1304	50.91	2517	5.24	1728	34.93	2243	15.9	2958	11.3
NNV-58	2923	2260	22.65	1520	47.97	2531	13.39	1896	35.12	2460	16.1	3257	11.4

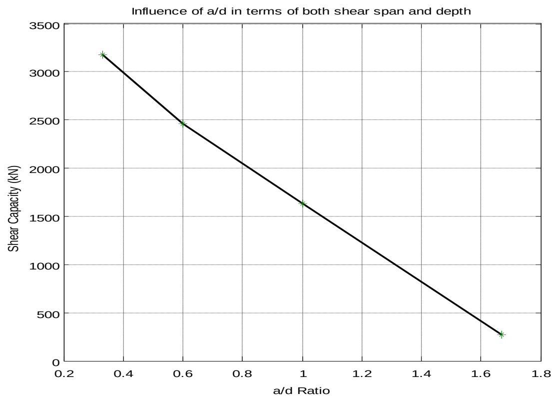
	% Mean Error	**44.6**		**50.16**		**36.2**		**46.47**		**40.1**		**17.4**
	R M S			**872.3**		**718.5**		**797.9**		**511.9**		**326.**

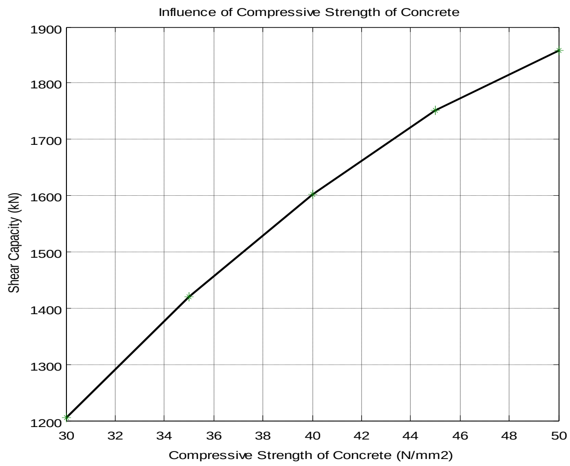
As seen the shear capacity predicted by proposed model was much closer to the experimental results as compared to different codes. The mean error and root mean square deviation of shear capacity predicted by the proposed model was much lesser as compared to different codes. Therefore, proposed model was used for carrying out the parametric study, whereby influence of various parameters on shear capacity was studied.

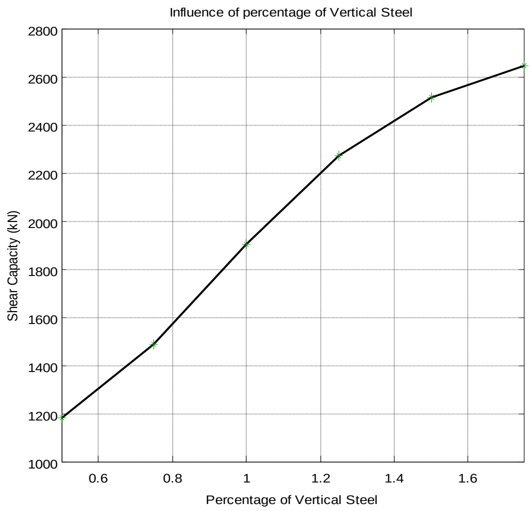


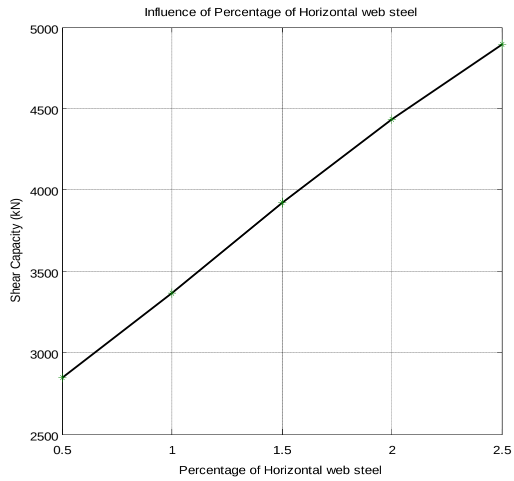





Influence of a/d in terms of both shear span and depth
Shear Capacity (kN)
a/d Ratio
0
500
1000
1500
2000
2500
3000
3500
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8


Influence of Compressive Strength of Concrete
Shear Capacity (kN)
Compressive Strength of Concrete (N/mm2)
1200
1300
1400
1500
1600
1700
1800
1900
30
32
34
36
38
40
42
44
46
48
50


Influence of percentage of Vertical Steel
Shear Capacity (kN)
Percentage of Vertical Steel
1000
1200
1400
1600
1800
2000
2200
2400
2600
2800
0.6
0.8
1
1.2
1.4
1.6



VII. CONCLUSIONS

The proposed model was studied by comparing the shear strength predictions with experimental data (from technical literature) and five national codes viz, KBCS, EC-2, CIRIA Guide -2, CSA and ACI-318 in general. The above comparisons were also made through parametric study. In both the cases proposed model showed good agreements, indicating the consistency of the proposed model. The proposed model adequately predicts the shear capacity of deep beams for different values of influencing parameters like longitudinal steel, shear span to depth ratio etc. Neural Networks have a great capacity of providing the solution to complex problems like deep beams.

REFRENCES

1. Brena & Roy, "Evaluation of Load Transfer and Strut Strength of Deep Beams with short Longitudinal bar anchorage",ACI Structural Journal, title No 106-S63, Oct. 2009,pp 678-689.
2. Christopher,Ahmad & Khaled, "Shear strength of D regions in RC Beams", Can. J. Civ. Eng. Vol.37, 2010, pp.1045-1056.
3. David Barra Birrcher, "Design of RC Deep Beams for Strength and Serviceability", University of Texas, Austin, May 2009.
4. Flood and Kartam, "Neural Networks in Civil Engineering: Principles and Understanding", ASCE Journal of Computing in Civil Engineering, Vol. 8, 1994, pp 131-148.
5. Mohmmad Abdr. Rashid & Ahsanul Kabir," Behavior of Reinforced Concrete Deep Beams Under unform Loading",Journal of Civil Engineering,Institution of Engineers, Bangladesh,Vol.CE 24,No.2,1996, pp 155-169.
6. Mohammad Reza Salamy,Hiroshi & Unjoh,"Experimental and Analytical Study of RC Deep Beams", Asian Journal of Civil Engineering, Vol.6, No. 5,2005,pp.487-499.
7. Oreta, A.C. 2004. Simulating size effect on shear strength of RC beams without stirrups using neural networks. Engineering Structures, **26**(5): 681–691.
8. R.S.Londhe, "Shear Strength Analysis & prediction of Reinforced Concrete Transfer Beams in High rise Buildings", Structural Engineering and Mechanics, Vol. 37,No. 1,Dtd:2011, pp 39-59.
9. R.S.Londhe, "Experimental Study of Shear Strength Concrete Beams Reinforced with Longitudinal Steel", Asian Journal of Civil Engineering (Building & Housing), Vol. 10,No. 3,Dtd:2009, pp 257-264. [13]
10. Rogosky, MacGregor & Ong,"Tests of Reinforced Concrete Deep Beams",Structural Engineering, Report No.109, University of Alberta, Canada,1983.
11. Sagaseta & Vollum," Shear Design of Short Span Beams", Magazine of Concrete Research, 2010, Vol.62, No.4, pp267-282.
12. Seo, Yoon, Lee,"Structural Behavior of RC Deep Beams", 13th World Confrence on Earthquake Engineering, Canada,2004, P.No.58
13. Stephen & Gilbert, "Tests on High Strength Concrete Deep Beams", University of South Wales, Sydney, Australia, 1996.
14. Wen-Yao Lu, Shyh-Jiann Hwang & Ing-Jaung Lin, "Deflection Prediction for reinforced concrete Deep Beams", Computers and Concrete, Vol 7, No. 1, 2010, pp 1-16.