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Design of Beam using Artificial Neural Network based Approach

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Abstract
Recent developments in artificial neural network (ANN) have opened up new possibilities in the field of structural engineering. This paper demonstrates the applicability of ANN for the design of beams subjected to moment and shear. An attempt has been made to capture the mapping between the design variables using ANN. There is no direct method for design of beams. A feed forward network and back propagation training algorithm has been used. For training, about 48 data sets were generated. After successful learning, the model predicted the depth of the beam, area of steel, spacing of stirrups required for new problems with accuracy satisfying all design constraints.

Keywords: *Artificial neural network, beams, steel, area, depth, moment, shear*

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INTRODUCTION
Structural engineering involves understanding of material behavior, laws of mechanics, intuition, past experience or expertise and analysis techniques. The neural network exploits the massively local processing and distributed representation properties that are believed to exist in the brain. The main benefit in using a neural network approach is that the network can be trained to learn the relationship between input and output parameters. The neural network architectures can provide improved computational efficiency relative to existing methods when an algorithmic description of functional relationships, is either totally unavailable or is very complex in nature. Such a modeling strategy has important implication for designing highly non- linear complex design problem especially that of RCC beams. Structural engineering involves understanding of material behavior, laws of mechanics, intuition, past experience or expertise and analysis techniques. The modern computer can bring speed, efficiency and accuracy in analysis of structures. But to computerize the areas such as conceptual design, modeling of natural phenomenon and material behavior, damage assessment, etc., is extremely difficult as it requires human expertise. Structural design is an iterative process. The initial design is the first step in design process. Though the various aspects of structural design are controlled by many codes and regulations, the structural engineer has to exercise caution and use his judgment in addition to calculations in the interpretation of the various provisions of the I.S 456–2000 code to obtain an efficient and economic design. After the design process the designer makes an overall guess about the possible optimum solution consistent with designer's experience, knowledge, constraints, and requirements. The analysis of the structure is then carried out using initial design. Based on the results of analysis, a redesign is then carried out if the design is not proper. Hence, a good initial design reduces the number of design analysis cycles [1–4].

ARTIFICIAL NEURAL NETWORK (ANN)
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 a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and 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 a learning algorithm. A Multi-layer perceptron (MLP) consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that is not linearly separable.

The main advantage of ANNs is that one does not have to assume a model form, which is a pre-requisite in the parametric approach. ANN automatically manages the relationships between variables and adapt based on the data used for their training. It is important to collect a large number of experimental data to carry out the modeling of the system. Typically, the neurons in each layer of the network have as their inputs the output signals of the preceding layer only. The set of output signals of the neurons in the output layer of the network constitutes the overall response of the network to the activation pattern supplied by the source nodes in the input layer. The accuracy of the predictions of a network was quantified by the root of the mean squared error difference (RMSE), between the measured and the predicted values, mean absolute error (MAE): the same as root mean square except using absolute differences instead of squared difference and the multiple coefficient of determination which compares the accuracy of the model with the accuracy of a superficial benchmark model wherein the prediction is the mean of all samples.

APPLICATION OF ANN USING SOFTWARE

The multilayer perceptron approach has been used for the modeling purpose. Back propagation approach is used. Back propagation is common method of training artificial neural networks so as to minimize the objective function. It is a supervised learning method and a generalization of the Delta rule. The activation function used is the log-sigmoidal function. A sigmoid curve is produced by a mathematical function having an "S" shape. Often, sigmoid function refers to the special case of the logistic function shown below (Figure 1) and defined by the formula:
$S(t) = 1 / (1+e^{-t})$.

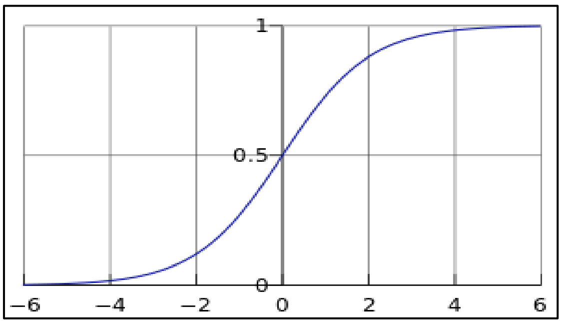

Fig. 1: *Logistic Curve.*

ANN TRAINING ALGORITHM

The ANN training algorithm is as follows:

- Apply input vector.
- Calculate output of the network.
- Compare output with the target/desired output.
- Feedback the error i.e. the difference through the network.
- Weights are changed accordingly to an algorithm that tends to minimize the error.
- All the vectors of the training set are applied sequentially.
- Error is calculated.
- Weights are adjusted for each vector till error for entire training set is at an acceptably low (Figure 2).

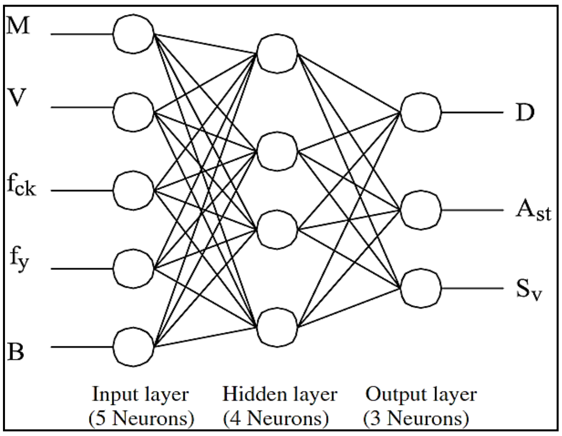

Fig. 2: *Artificial Neural Network.*

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DATABASE

The database consists of the following elements in the design of a beam to carry different loads values, grade of concrete and grade of steels (Table 1) [5–7]:

Grade of concrete used: - 20, 25 (N/mm^2)

- Grade of steel used: - Fe-250, 415,500 (N/mm^2)
- Breadth (mm): - 250,300,350
- Design as per limiting section IS-456:2000.
- Formula for $M_{u,lim}$
  For Fe250 :- $0.148\ f_{ck}\ Bd^2$
  For Fe415 :- $0.136\ f_{ck}\ Bd^2$
  For Fe500 :- $0.134\ f_{ck}\ Bd^2$
- Formula for A_{st}
  For Fe250 :- $0.2193\ f_{ck}\ Bd/f_y$
  For Fe415 :- $0.1986\ f_{ck}\ Bd/f_y$
  For Fe500 :- $0.1903\ f_{ck}\ Bd/f_y$
- Formula for S_v (Using 8 mm 2-legged stirrups with A_{sv} =100.5 mm^2): - $100.5(0.87f_y)\ d/V_s$

Table 1: *Calculate the Depth, Area of Steel, Spacing of Stirrups.*

S.No.	Moment	Shear	Grade of Concrete	Grade of steel	Breadth (B)	Depth of Beam (d)	Area of steel (A_{st})	Spacing of stirrups (S_v)
1	30	70	20	250	250	200	877	60
2	30	70	20	415	250	210	500	105
3	30	70	20	500	250	215	410	130
4	30	70	25	250	250	180	986	95
5	30	70	25	415	250	190	568	50
6	30	70	25	500	250	190	452	115
7	40	80	20	250	300	215	1131	55
8	40	80	20	415	300	220	631	95
9	40	80	20	500	300	225	513	120
10	40	80	25	250	300	190	1250	50
11	40	80	25	415	300	200	717	90
12	40	80	25	500	300	200	570	105
13	50	80	20	250	350	220	1350	60
14	50	80	20	415	350	230	770	100
15	50	80	20	500	350	230	612	120
16	50	80	25	250	350	195	1496	50
17	50	80	25	415	350	205	858	90
18	50	80	25	500	350	210	699	110
19	60	100	20	250	300	260	1368	55
20	60	100	20	415	300	280	803	100
21	60	100	20	500	300	275	627	120
22	60	100	25	250	300	235	1546	50
23	60	100	25	415	300	240	861	85
24	60	100	25	500	300	245	700	105
25	70	90	20	250	300	280	1473	75
26	70	90	20	415	300	300	861	135
27	70	90	20	500	300	295	673	160
28	70	90	25	250	300	250	1644	70
29	70	90	25	415	300	260	933	115
30	70	90	25	500	300	265	756	140
31	80	90	20	250	300	300	1578	70
32	80	90	20	415	300	315	904	125
33	80	90	20	500	300	315	719	150
34	80	90	25	250	300	270	1776	60
35	80	90	25	415	300	280	1004	110
36	80	90	25	500	300	285	813	135
37	90	90	20	250	300	320	1684	75
38	90	90	20	415	300	335	961	130

39	90	90	20	500	300	335	765	160
40	90	90	25	250	300	285	1875	65
41	90	90	25	415	300	300	1076	115
42	90	90	25	500	300	300	856	140
43	100	120	20	250	300	340	1789	60
44	100	120	20	415	300	350	1004	100
45	100	120	20	500	300	355	810	125
46	100	120	20	250	300	300	1973	90
47	100	120	25	415	300	315	1130	50
48	100	120	25	500	300	320	913	110

Table 2: *Actual vs. Predicted Values along with Error for Various Parameters.*

Depth of Beam			**Area of Steel**			**Spacing of Stirrups**		
Actual	Predicted	Error	Actual	Predicted	Error	Actual	Predicted	Error
190	205.544	15.544	568	564.731	–3.269	50	97.154	47.154
280	273.202	–6.798	803	787.217	–15.783	100	90.922	–9.078
180	188.713	8.713	986	1069.226	83.226	95	63.519	–31.481
300	290.513	–9.487	861	859.698	–1.302	135	125.081	–9.919
235	239.756	4.756	1546	1518.948	–27.052	50	53.783	3.783
195	197.082	2.082	1496	1554.886	58.886	50	54.66	4.66
265	268.751	3.751	756	760.379	4.379	140	121.698	–18.302
315	319.03	4.03	904	904.376	0.376	125	128.989	3.989
225	227.902	2.902	513	548.16	35.16	120	127.422	7.422
190	193.482	3.482	452	501.064	49.064	115	74.405	–40.595
275	284.953	9.953	627	675.232	48.232	120	112.153	–7.847
220	217.918	–2.082	1350	1353.115	3.115	60	94.035	34.035
315	315.749	0.749	1130	1129.015	–0.985	50	87.192	37.192
200	202.025	2.025	570	582.394	12.394	105	103.114	–1.886
320	320.772	0.772	1684	1673.341	–10.659	75	78.467	3.467
285	285.016	0.016	1875	1882.952	7.952	65	79.334	14.334
245	236.707	–8.293	700	702.137	2.137	105	109.264	4.264
335	327.448	–7.552	961	981.95	20.95	130	145.3	15.3
335	327.127	–7.873	765	796.77	31.77	160	151.325	–8.675
280	278.678	–1.322	1004	1013.299	9.299	110	120.105	10.105
300	301.121	1.121	856	863.079	7.079	140	144.319	4.319
250	246.442	–3.558	1644	1654.527	10.527	70	66.982	–3.018
315	313.334	–1.666	719	722.888	3.888	150	156.602	6.602
215	208.712	–6.288	410	386.869	–23.131	130	103.736	–26.264
260	260.275	0.275	933	936.487	3.487	115	99.634	–15.366
200	210.111	10.111	877	877.01	0.01	60	114.071	54.071
210	204.341	–5.659	699	702.185	3.185	110	117.333	7.333
205	202.077	–.923	858	861.337	3.337	90	98.734	8.734
280	278.52	–1.48	1473	1489.655	16.655	75	67.351	–7.649
215	216.072	1.072	1131	1115.426	–15.574	55	106.133	51.133
230	225.05	–4.95	770	777.605	7.605	100	98.312	–1.688
300	300.203	0.203	1578	1593.708	15.708	70	74.782	4.782
285	282.788	–2.212	813	783.657	–29.343	135	127.766	–7.234
295	302.719	7.719	673	668.024	–4.976	160	136.826	–23.174
355	354.632	–0.368	810	840.011	30.011	125	136.878	11.878
210	209.094	–0.906	500	520.12	20.12	105	86.93	–18.07
240	242.358	2.358	861	892.856	31.856	85	55.658	–29.342
220	223.297	3.297	631	650.416	19.416	95	101.869	6.869
200	200.366	0.366	717	733.947	16.947	90	84.037	–5.963
260	262.469	2.469	1368	1369.212	1.212	55	55.794	0.794
320	331.519	11.519	913	909.482	–3.518	110	89.375	–20.625
230	234.184	4.184	612	632.862	20.862	120	108.384	–11.616
300	301.876	1.876	1076	1055.62	–20.380	115	109.072	–5.928

340	301.863	–38.137	1789	1882.567	93.567	60	56.022	–3.978
270	266.421	–3.579	1776	1759.86	–16.14	60	69.503	9.503
300	340.387	40.387	1973	1725.414	–247.586	90	80.377	–9.623
350	353.024	3.024	1004	1010.748	6.748	100	57.996	–42.004
190	187.855	–2.145	1250	1244.75	–5.25	50	56.977	6.977

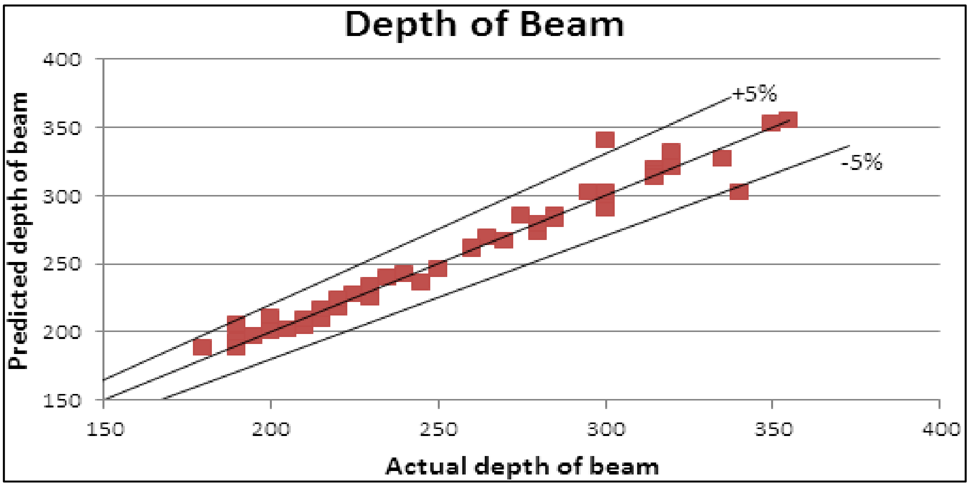

Fig. 3: *Actual vs. Predicted Depth of Beam.*

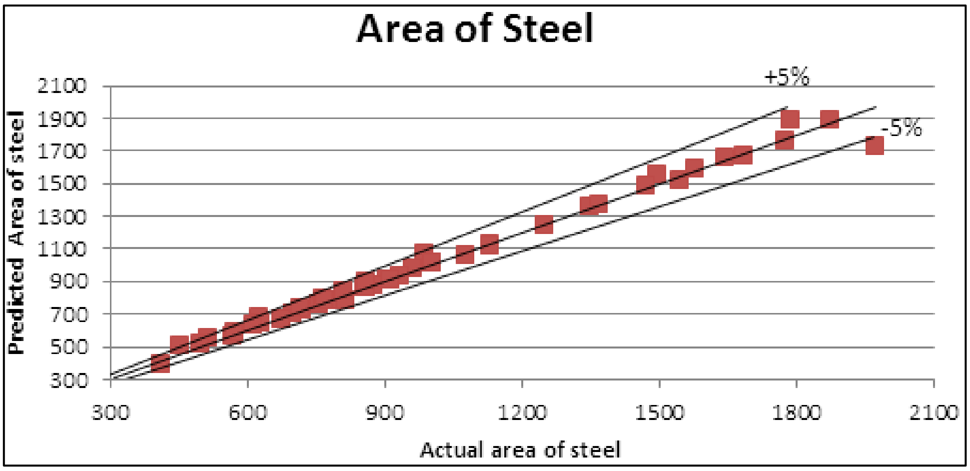

Fig. 4: *Actual vs. Predicted Area of Steel.*

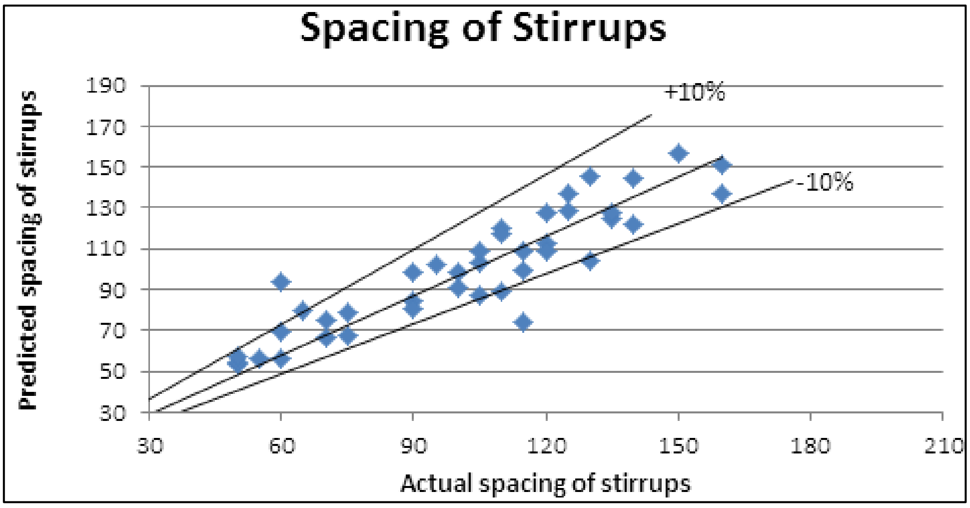

Fig. 5: *Actual vs. Predicted Spacing of Stirrups.*

Table 3: *Result Analysis for Different Parameters.*

Parameters	**Correlation Coefficient (CC)**	**Mean Absolute Error (MAE)**	**Root mean squared error (RMSE)**	**Relative absolute error (RAE) (%)**	**Root relative squared error (RRSE) (%)**
Depth of Beam	0.9814	05.5424	09.5858	12.2472	18.5908
Area of Steel	0.9943	23.0022	44.7092	06.6982	10.7108
Spacing of Stirrups	0.7730	14.9589	20.4621	53.8174	62.5554

CONCLUSIONS

The results suggest that most of the points are lying within ±10% of the line of perfect agreement for spacing of stirrups, ±5% for depth of beam and area of steel, which suggest that neural network, can effectively be used to predicting the various parameters. The predicted results of this study are acceptable as correlation coefficient value lies between 0.8 and 1.0. This report demonstrates the use and adaptability of the artificial neural networks in design of beam problems. Successful prediction of the outputs was done for all parameters, which indicated that ANN could be useful modeling tool for engineers and research scientists in the area of construction.

Artificial neural networks are viable computational models for a wide variety of problems including prediction problems. The neural network can be used for a particular problem when deviation in the available data is expected and accepted and also when a defined methodology is not available as in the case of present study. Actual field data were used for accurate prediction. Hence, the results in the form of correlation coefficient, MAE and RMSE values were found to be better for the data obtained experimentally. The analysis demonstrates the feasibility of using neural networks for capturing non-linear interactions between various parameters in complex civil engineering systems. Thus, it can be concluded that the application of ANN is more user-friendly and more explicit model can be made which help the construction industry to avoid the risk of faulty or deficient structures that often entails durability and safety problems.

REFERENCES

1. Mishra A K, Akhil Upadhyay. Column Design using ANN. *Indian Conc. Inst. J.* 2004; 17–19p.
2. Mukharjee A, Deshpande. Application of Artificial Neural Networks in Structural Design Expert Systems. *Compute & Struct.* 1995; 54(3): 367–375p.
3. Namhee Kim Hong, Sung-Pil Chang, Seung-Chul Lee. Development of Ann-based Preliminary Structural Design Systems for Cable-stayed Bridges. *Adv. Eng. software* 2002; 33: 85–96p.
4. H Sudarsana Rao, B Ramesh Babu. Hybrid Neural Network Model for the Design of Beam Subjected to Bending and Shear. *Sadhana.* October 2007, 32(5): 577–586p.
5. Patodi S C, Purani V S. Modelling Flexural Behaviour of Steel Fibre Reinforced Concrete Beams using Neural Networks. *J. New Build. Mater & Construct. World* 1998; 4(5): 28–35p.
6. Sanad A, Saka M P. Prediction of Ultimate Strength of Reinforced Concrete Deep Beams by Neural Networks. *ASCE J. Struct. Eng.* 2001; 127(7): 818–828p.
7. Ni Hong-Guang, Wang Ji-Zong. Prediction of Compressive Strength of Concrete by Neural Networks. *Cem. Concr. Res.* 2000; 30: 1245–1250p.