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Study Of Flat Slab By Ann For Preliminary Design

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Abstract

The aim of this project is to design the flat slab using IS method manually in which Overall Depth and Negative and Positive Reinforcement for Longer and Shorter span are determined. An attempt is made to find the percentage error for overall depth and reinforcement in ANN. For a given unknown Input ANN will predict the output.ANN is trained by Input & output obtained from spreadsheet designed as per IS method to arrive at optimum solution using artificial neural network based on back-propagation network is to be used.
Key Words: - *Flat Slab, ANN, Overall Depth, Negative & Positive Reinforcement*

1. Introduction

Common practice of design and construction is to support the slabs by beams and support the beams by columns. This may be called as beam-slab construction. The beams reduce the available net clear ceiling height. Hence in warehouses, offices and public halls sometimes beams are avoided and slabs are directly supported by columns. Also these types of construction are aesthetically appealing. These slabs which are directly supported by columns are called Flat slabs. The term flat slab means a reinforced concrete slab with drops, supported generally without beams, by columns with or without flared column heads [4]. In the present study flat slab with drop and column head is considered.

For design of flat slabs IS 456-2000 permits use of any one of the Direct Design Method and Equivalent Frame Method. The present study is made by using Direct Design Method [1]. One efficient way of solving complex problems is to decompose system into simpler elements, in order to be able to understand it.

The objectives of the paper are to develop complex relationship among the design parameters of the flat slab based on a Backpropagation neural network algorithm developed in MATLAB software [5, 9].

2. Networks

Networks are one approach for achieving this. There are a large number of different types of networks. All the networks characterized by a set of nodes, and connections between nodes. The nodes can be seen as computational units. They receive inputs, and process them to obtain an output. This processing might be very simple (such as summing the inputs), or quite complex (a node might contain another network...) the connections determine the information flow between nodes. They can be unidirectional, when the information flows only in one sense, and bidirectional, when the information flows in either sense. The interactions of nodes though the connections lead to a global behaviour of the network, which cannot be observed in the elements of the network. This means that the abilities of the network supercede the ones of its elements, making networks a very powerful tool [6, 7].

One type of network sees the nodes as 'artificial neurons'. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might besent to another synapse, and might activate other neurons [5, 6].

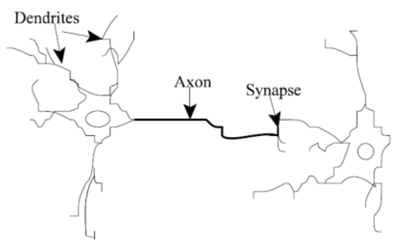

Fig1:- Natural neurons (artist's conception) [6]

The complexity of real neurons is highly abstracted when modelling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependence of a certain threshold). ANNs combine artificial neurons in order to process information. [8]

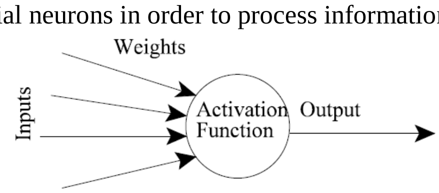

Fig 2:- An artificial neuron [6]

The research intends to explore the full potential of ANN in capturing human knowledge and expertise of the construction process, the design process, and the post-occupancy process [3]. The following figure 3 shows the steps to be taken in training the network.

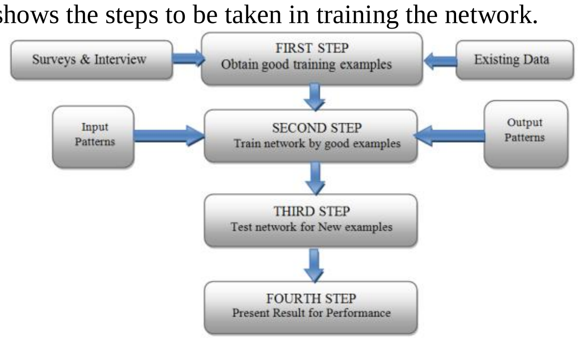

Fig 3:- Developing a Neural Network Model [10]

In the present study following network is used and trained to get the desired results The Input Layer contains processing elements i.e. neurons, each corresponding to a single attribute, like Aspect Ratio, Span in longer direction (L_y), Span in shorter direction (L_x), Load of floor finish and Live Load. That is, each neuron would represent one design constrain in input layer. The output layer on the other hand, contains one or more neurons, these represent the solution to the design problem, and for example, the output of the model could be Negative Reinforcement in longer direction ($A_{st}L$-), Positive Reinforcement in longer direction ($A_{st}L$+), Negative Reinforcement in shorter direction ($A_{st}S$-) and Positive Reinforcement in shorter direction ($A_{st}S$+) as shown in figure 4 below.

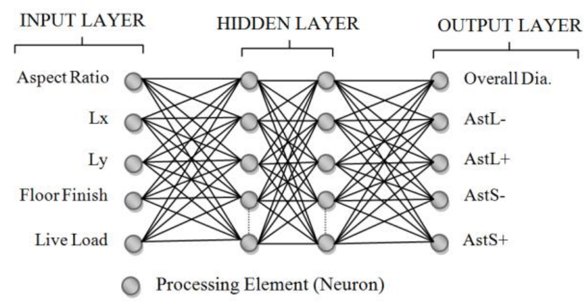

Fig 4:- Architecture of proposed Neural Network

There are mainly three practical aspects related to learning. The first is the choice of the training set and its size. The second is the selection of learning constraint, and the third is when to stop the learning. Unfortunately, there are no "formulas" to select these parameters. Only some general rules apply and a lot of experimentation is necessary. In this regard, the availability of fast simulation environments and extended probing abilities as implemented in MATLAB are a definite asset [6]

The error in backpropagation uses the gradient descent method which searches for the minimum error surface along the steepest negative gradient in order to minimize the error or objective function. The objective function is minimized with respect to independent interconnecting weight variables [13].

3. Result and Discussions

During the preliminary design phase, one of the objectives is to arrive at the member sizes required to start the first cycle of analysis. An equally important goal at this point is to determine fairly accurately the weight of the Flat Slab, because preliminary designs form the basis for competitive bidding and weights are often decisive in winning contracts [4]. In the archives of any large design bureau, a large volume of the data on the weights of similar Flat Slabs designed in the past will normally be available. Also these data can now-a day be generated using high end commercial structural design [12]. These data can be put to good use in predicting the weight of flat slab at the preliminary design phase by using artificial neural networks (ANNs) [11]. Neural networks provide a powerful tool for approximate analysis of structures. Such networks are trained using Back Propagation and radial Basis Function networks [10, 13].

In the present work design data from designers is collected and a spreadsheet is prepared using same design examples. This spreadsheet is then used for generating data (Input and Output) for flat slab which is then used for training of ANN. A program is prepared in MATLAB to train ANN for the inputs and outputs. Then the trained network is tested for few unknown examples and then the output of ANN is compared with the outputs given by spreadsheet for same inputs.

3.1 Training Data:

Following Training data is required to train a neural network.

Input data:

Five input nodes are considered for the training of Back Propagation Network (BPN).

- Live Load =1.5 kN/m^2, 3.5 kN/m^2
- Floor Load =1.5 kN/m2, 2 kN/m2
- L_X (Short Span) =2, 2.5, 3, 3.5, 4, 4.5, 5
- L_y (Longer Span)
- Aspect ratio (AR) = 1, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9 and 2.0

Grade of steel is Fe_{415} and grade of concrete is M_{20} which is kept constant.

Output data:

Five output nodes are considered:

Overall Depth/Thickness of slab (D), Negative Reinforcement in longer direction (A_{st}L-) i.e. at support, Positive Reinforcement in longer direction (A_{st}L+) i.e. at mid span, Negative Reinforcement in shorter direction (A_{st}S-) i.e. at support and Positive Reinforcement in shorter direction (A_{st}S+) i.e. at mid span.

Table 1:- Training data set for flat slab design

INPUT					OUTPUT				
Aspect Ratio	**Lx In**	**Ly in**	**FL In**	**LL In**	**O. D. Out**	**AstL-**	**AstL+**	**AstS-**	**AstS+**
1	2	2	1.5	1.5	125	18214	168	298	41
1.1	2	2.2	1.5	1.5	125	18955	187	384	51
1.2	2	2.4	1.5	1.5	125	19580	206	481	62
1.3	2	2.6	1.5	1.5	125	20121	223	590	74
1.4	2	2.8	1.5	1.5	125	20331	246	729	91
1.5	2	3	1.5	1.5	125	20505	269	887	109
1.6	2	3.2	1.5	1.5	125	20654	292	1066	130
1.7	2	3.4	1.5	1.5	125	20784	314	1266	154
1.8	2	3.6	1.5	1.5	125	21138	329	1455	174
1.9	2	3.8	1.5	1.5	125	21239	351	1697	202
2	2	4	1.5	1.5	125	21335	373	1965	233
1	2	2	2	1.5	125	17710	177	314	45
1.1	2	2.2	2	1.5	125	18438	197	404	55
1.2	2	2.4	2	1.5	125	19054	217	507	67
1.3	2	2.6	2	1.5	125	19587	235	621	80
1.4	2	2.8	2	1.5	125	19814	259	766	98
1.5	2	3	2	1.5	125	20005	282	931	118
1.6	2	3.2	2	1.5	125	20169	305	1116	140
1.7	2	3.4	2	1.5	125	20314	329	1324	165
1.8	2	3.6	2	1.5	125	20664	344	1522	186
1.9	2	3.8	2	1.5	125	20780	367	1773	216
2	2	4	2	1.5	125	20889	389	2050	248
1	2	2	1.5	3	125	16828	193	343	52
1.1	2	2.2	1.5	3	125	17534	216	443	64
1.2	2	2.4	1.5	3	125	18132	237	555	77
1.3	2	2.6	1.5	3	125	18650	258	681	92
1.4	2	2.8	1.5	3	125	18903	283	837	112
1.5	2	3	1.5	3	125	19118	307	1015	134
1.6	2	3.2	1.5	3	125	19306	332	1214	159
1.7	2	3.4	1.5	3	125	19474	356	1436	186
1.8	2	3.6	1.5	3	125	19817	373	1651	211
1.9	2	3.8	1.5	3	125	19955	397	1919	243
2	2	4	1.5	3	125	20085	420	2214	279

Such several problems were used to train the neural network. After training a network is given unknown problems for which ANN gives output. The outputs of ANN and spreadsheet are compared and error is found. The results of which are given below.

Table 2:- Percentage error in Overall Diameter

Aspect Ratio	Lx	Ly	FL	LL	O.D. Out By Program	O.D. Out By ANN	Error in %
1.5	3	4.5	1.5	3	125	129.375	-3.50
2	2.5	5	2	5	125	130.975	-4.78
1.7	5	8.5	2	5	191.741	202.6932	-5.71
1.65	4	6.6	2	5	150.7268	154.4618	-2.48
1.23	3.5	4.305	1.5	5	128.6844	131.8732	-2.48
1.76	2.35	4.136	2	3	125	136.8125	-9.45
1.88	4.35	8.178	1.5	1.5	144.9806	157.2036	-8.43
0.7	5.6	3.92	2	5	218.6987	232.0656	-6.11
2.5	1	2.5	2	3	125	135.1863	-8.15
0.5	5.56	2.78	2	3	206.0682	221.8407	-7.65
0.25	10	2.5	1.5	1.5	396.7016	437.8832	-10.38

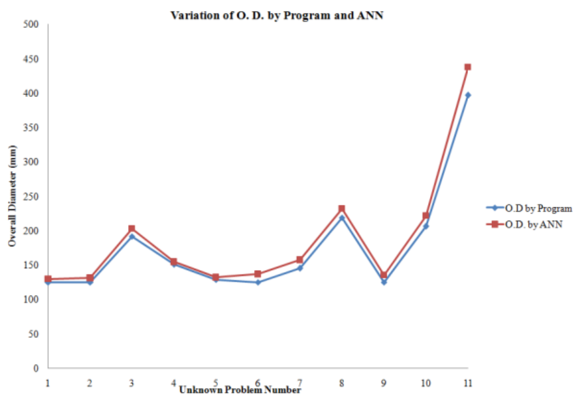

Fig 5:- Variation of O.D.bye Programe & ANN

Table 3:- Percentage error in $A_{st}L-$

Aspect Ratio	Lx	Ly	FL	LL	AstL- By Program	AstL- By ANN	Error in %
1.5	3	4.5	1.5	3	13299.39	13629.33	-2.4809
2	2.5	5	2	5	15231.42	16612.59	-9.0679
1.7	5	8.5	2	5	7406.16	7989.68	-7.879
1.65	4	6.6	2	5	9316.44	10029.52	-7.654
1.23	3.5	4.305	1.5	5	10151.58	10733.44	-5.7317
1.76	2.35	4.136	2	3	16892.47	17586.18	-4.1066
1.88	4.35	8.178	1.5	1.5	9922.35	10691.80	-7.7548
0.7	5.6	3.92	2	5	5531.51	5837.47	-5.5312
2.5	1	2.5	2	3	33022.35	35140.68	-6.4148
0.5	5.56	2.78	2	3	5870.55	6155.16	-4.8481
0.25	10	2.5	1.5	1.5	3058.38	3288.50	-7.5246

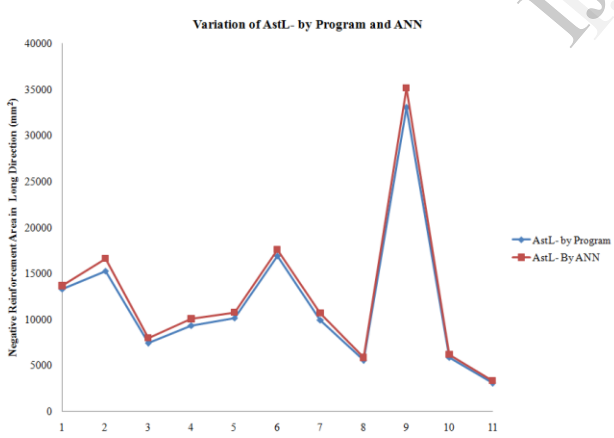

Fig 6:- Variation of $A_{st}L-$ by Program & ANN

Table 4:- Percentage error in $A_{st}L+$

Aspect Ratio	Lx	Ly	FL	LL	AstL+ By Program	AstL+ By ANN	AstL+ % Error
1.5	3	4.5	1.5	3	849.78	931.75	-9.647
2	2.5	5	2	5	856.97	934.96	-9.0997
1.7	5	8.5	2	5	3816.27	4183.98	-9.6353
1.65	4	6.6	2	5	2169.19	2293.09	-5.712
1.23	3.5	4.305	1.5	5	1071.68	1098.23	-2.478
1.76	2.35	4.136	2	3	568.56	614.89	-8.149
1.88	4.35	8.178	1.5	1.5	2598.43	2662.81	-2.478
0.7	5.6	3.92	2	5	1783.31	1968.43	-10.381
2.5	1	2.5	2	3	83.32	89.70	-7.654
0.5	5.56	2.78	2	3	1177.67	1267.81	-7.654
0.25	10	2.5	1.5	1.5	2237.39	2381.32	-6.4328

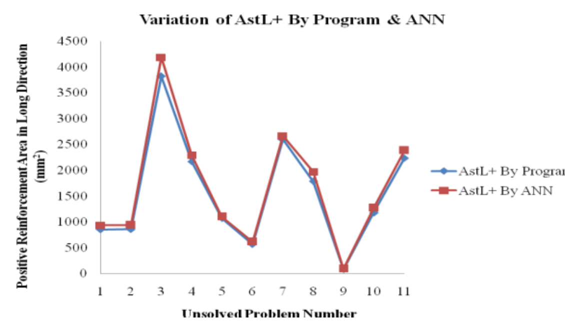

Fig 7:- Variation of $A_{st}L+$ by Program & ANN

Table 5:- Percentage error in $A_{st}S-$

Aspect Ratio	Lx	Ly	FL	LL	AstS- By Program	AstS- By ANN	AstS- % Error
1.5	3	4.5	1.5	3	2821.81	3077.00	-9.0432
2	2.5	5	2	5	4537.35	4884.63	-7.654
1.7	5	8.5	2	5	15703.66	17333.86	-10.381
1.65	4	6.6	2	5	8441.71	9087.83	-7.654
1.23	3.5	4.305	1.5	5	2623.38	2837.15	-8.149
1.76	2.35	4.136	2	3	2428.16	2488.33	-2.478
1.88	4.35	8.178	1.5	1.5	12574.00	13292.23	-5.712
0.7	5.6	3.92	2	5	1871.42	1917.79	-2.478
2.5	1	2.5	2	3	648.07	706.11	-8.957
0.5	5.56	2.78	2	3	718.54	759.58	-5.712
0.25	10	2.5	1.5	1.5	333.98	346.65	-3.7937

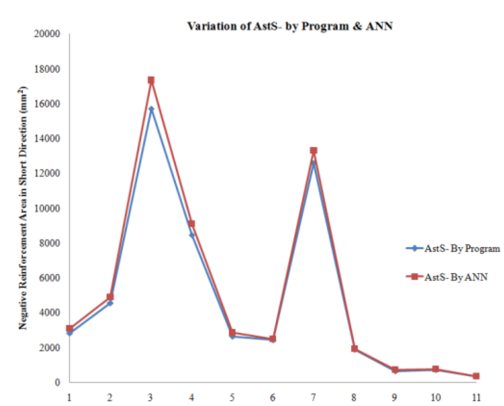

Fig 8:- Variation of $A_{st}S-$ by Program & ANN

Table 6:- Percentage error in $A_{st}S+$

Aspect Ratio	Lx	Ly	FL	LL	AstS+ By Program	AstS+ By ANN	AstS+ % Error
1.5	3	4.5	1.5	3	536.23	571.85	-6.6432
2	2.5	5	2	5	752.84	812.89	-7.9762
1.7	5	8.5	2	5	3138.60	3464.42	-10.381
1.65	4	6.6	2	5	1765.27	1909.13	-8.149
1.23	3.5	4.305	1.5	5	606.51	664.19	-9.5107
1.76	2.35	4.136	2	3	363.26	386.40	-6.3707
1.88	4.35	8.178	1.5	1.5	2583.28	2781.00	-7.654
0.7	5.6	3.92	2	5	432.50	471.91	-9.1127
2.5	1	2.5	2	3	49.59	52.80	-6.4671
0.5	5.56	2.78	2	3	167.15	174.70	-4.5173
0.25	10	2.5	1.5	1.5	73.46	78.17	-6.4161

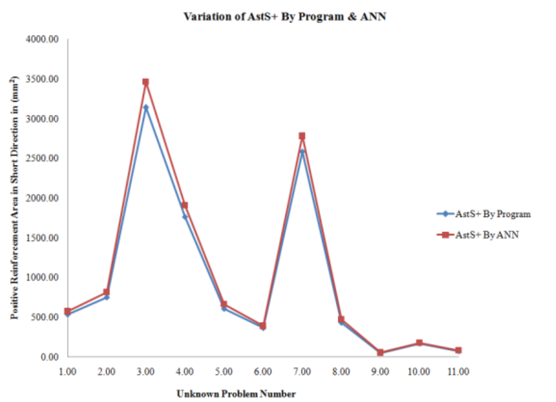

Fig 9:- Variation of $A_{st}S+$ by Program & ANN

4. Conclusion

In present work the Flat slab is analyzed and designed based on Indian Standard (IS: 456-2000). Artificial Neural Network (ANN) is designed in MATLAB. Present work is arrived at the following conclusions.

As ANN is working on neurons it is found that the number of neurons affect the training time. Training time depends on no. of neurons, no. of hidden layers, function used in training; moreover it also depends on data available for the training of neural network. The performance obtained by ANN technology for preliminary design of structures shows the acceptance of the results with not more than 10 % variation of the results.

The only effect on the computation time stems from the fact that each training pass requires the presentation of more points, i.e., the training set becomes larger. This problem can be tackled by considering either parallel implementations, or implementations on a neuroprocessor that can be embedded in a conventional machine and provide considerably better execution times. Such an implementation on neural hardware is one of our near future objectives, since it will permit the treatment of many difficult real-world problems.

5. References

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