OPTIMIZATION OF COLUMN DESIGN USING MATLAB

[1]Hardik Chaudhari, [2]Satyen Ramani
[1]Post Graduate Student, [2]Professor
Department of Civil Engineering
SAL Institute of Technology and Engineering Research, Ahmedabad, India

Abstract ***— In this paper, the optimization of longitudinal reinforcement for RC column has been carried out. RC Column is loaded with axial load and uniaxial bending moment in this study. Optimization carried out in MATLAB by supervised feed forward back-propagation Neural Network. For training of NN for optimization, Excel spread sheet data use, which consists of Pu-Mu interaction curve for unsymmetrically arranged longitudinal reinforcement in RC column. Result shows that the capacity of unsymmetrical arrangement is more than the symmetrical arrangement of longitudinal reinforcement. By trained NN optimized area of each four layer of longitudinal reinforcement along depth we to get. And it gives lesser area of longitudinal reinforcement as compare to symmetrically arranged reinforcement.***

Index Terms— Area optimization, Longitudinal reinforcement, MATLAB, Neural Network, RC column

[1]hardikchaudhari11@gmail.com, [2]satyen.ramani@sal.edu.in

I. INTRODUCTION

Optimization is the process of finding a minimum or maximum value of function. Optimum design of reinforced concrete elements plays important role in economical design of reinforced concrete structures. An attempt has been made to achieve the optimal design of RC column by optimizing the longitudinal reinforcement. It can be done by using MATLAB software. The optimization problem is resolved by formulating Pu-Mu interaction curves for various sets of data with unsymmetrically distributed longitudinal reinforcement in RC column. In the present study, Optimization process is done for different grades of concrete, grade of steel and diameter of steel.

The result obtained from the analytical study is carried out based on effect of grade of concrete, grade of steel and arrangement of reinforcement, which gives the different Pu-Mu interaction curve's points. Design of RC column has been ensured under the provision of IS: 456-2000. This data is carried out in Excel spread sheet, which used to train the feed forward back-propagation neural network in matlab. So many different Pu-Mu interaction curve data are developed for training data of optimization in neural network. The efficiency of the algorithm was examined and found to be good. It gives optimized area for each layer of longitudinal reinforcement in RC column.

II. DEVELOPMENT OF INTERACTION CURVE

Pu-Mu Interaction curve plotting method for unsymmetrically arranged longitudinal reinforcement is taken from the book of Dr. V.L. Shah and Late Dr. S.R. Karve, "Limit State Theory and Design of Reinforcement concrete" Sixth Edition: 2012. The excel sheet for the plotting of interaction curve prepared. Also Pu-Mu interaction curve for SP-16 plotted and compared.

									mm^2	pt in %
Fck	20	N/mm^2		p_t	2.403	%		As1	1119	0.82903
Fy	415	N/mm^2		p_t/Fck	0.12			As2	716	0.53058
b	300	mm		Ast	3244	mm^2		As3	0	0
D	450	mm		Fs	327.7	N/mm^2		As4	0	0
d'	45	mm		Es	2E+05	N/mm^2		As5	0	0
d	405	mm						As6	515	0.38165
dc'	45	mm						As7	893	0.66148

Fig. 1 Data for unsymmetrically arranged reinforcement

									mm^2	pt in %
Fck	20	N/mm^2		p_t	2.457	%		As1	1030	0.76329
Fy	415	N/mm^2		p_t/Fck	0.123			As2	628	0.46542
b	300	mm		Ast	3318	mm^2		As3	628	0.46542
D	450	mm		Fs	327.7	N/mm^2		As4	1030	0.76329
d'	45	mm		Es	2E+05	N/mm^2		As5	0	0
d	405	mm						As6	0	0
dc'	45	mm						As7	0	0

Fig. 2 Data for symmetrically arranged reinforcement

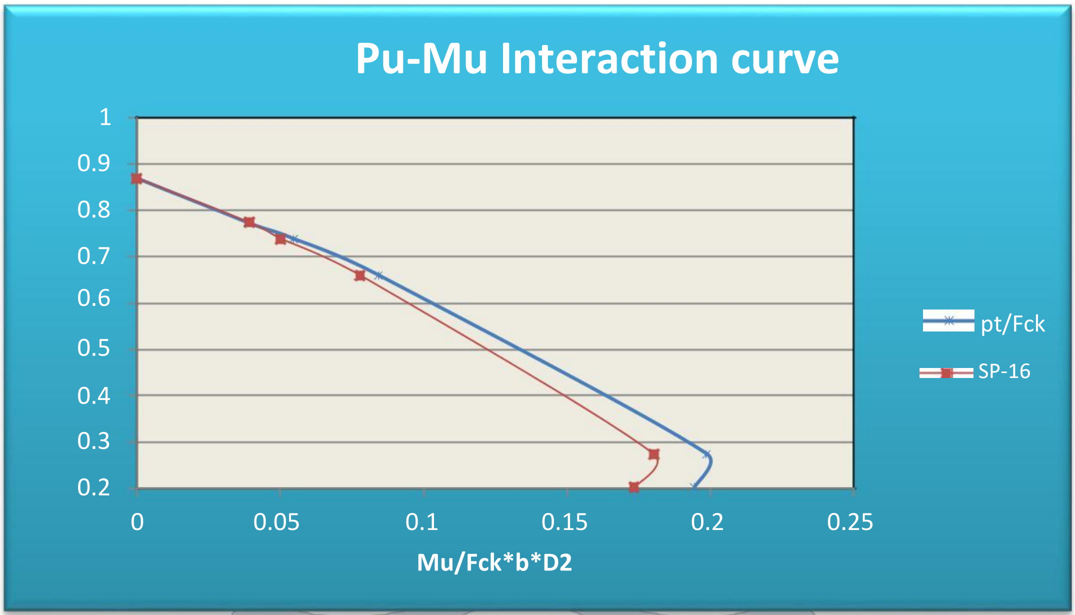


Fig. 3 Comparison between both arrangements

III. OPTIMIZATION

In this paper Pu-Mu curve point is used as data set for the optimization by neural network. Here we used the feed forward back-propagation algorithm for supervised training of neural network. Optimization for each layer of reinforcement is very difficult to calculate, because it gives the four different optimized area of longitudinal reinforcement. Neural network work on noisy data too. So, the neural network for this optimization is considered. It is used the inner weight between neurons in neural network. This weight provide pivotal role for optimization.

Method

From the Excel spread sheet input and target data for training of the neural network is use. Around 720 data is used for the training of the neural network. Input and output data is given below.

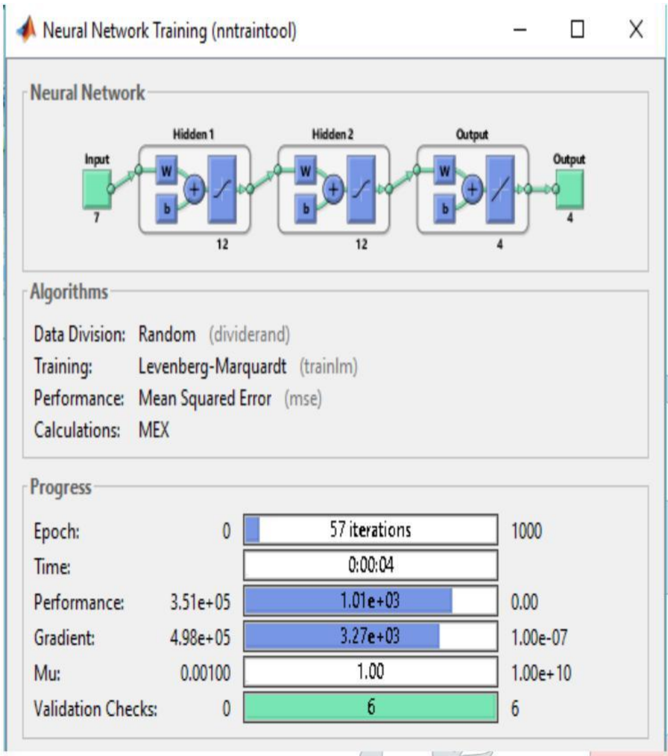
Input: Target:

b(mm)	D(mm)	Fck(N/mm^2)	Fy(N/mm^2)	Pu(N)	Mu(N*mm)	pt %	Area of Steel according to Layers in mm^2			
300	450	20	415	2195952	0	2.086	893	628	402	893
300	450	20	415	1957461	44042877	2.086	893	628	402	893
300	450	20	415	1862786	55213151.7	2.086	893	628	402	893
300	450	20	415	1668889	86261074.6	2.086	893	628	402	893
300	450	20	415	672345.8	189792174	2.086	893	628	402	893
300	450	20	415	343330.5	186119888	2.086	893	628	402	893
300	450	25	415	2490722	0	2.086	893	628	402	893
300	450	25	415	2221828	49991137.3	2.086	893	628	402	893
300	450	25	415	2126899	60101021.5	2.086	893	628	402	893
300	450	25	415	1907363	95144079.1	2.086	893	628	402	893
300	450	25	415	808318.2	205678936	2.086	893	628	402	893
300	450	25	415	445555.3	200747347	2.086	893	628	402	893
300	450	30	415	2785491	0	2.086	893	628	402	893
300	450	30	415	2486195	55939397.6	2.086	893	628	402	893
300	450	30	415	2391011	64989089.5	2.086	893	628	402	893
300	450	30	415	2145837	104028010	2.086	893	628	402	893
300	450	30	415	944290.6	221582194	2.086	893	628	402	893
300	450	30	415	547780.1	215396481	2.086	893	628	402	893
300	450	35	415	3080260	0	2.086	893	628	402	893
300	450	35	415	2750563	61887657.9	2.086	893	628	402	893
300	450	35	415	2655124	69877296.7	2.086	893	628	402	893
300	450	35	415	2384311	112912591	2.086	893	628	402	893
300	450	35	415	1080263	237497031	2.086	893	628	402	893
300	450	35	415	650004.8	230060828	2.086	893	628	402	893
300	450	40	415	3375030	0	2.086	893	628	402	893
300	450	40	415	3014930	67835918.2	2.086	893	628	402	893
300	450	40	415	2919236	74765605.3	2.086	893	628	402	893
300	450	40	415	2622786	121797647	2.086	893	628	402	893
300	450	40	415	1216235	253420308	2.086	893	628	402	893
300	450	40	415	752229.6	244736265	2.086	893	628	402	893
300	450	20	500	2404228	0	2.086	893	628	402	893
300	450	20	500	2141797	48190433.8	2.086	893	628	402	893

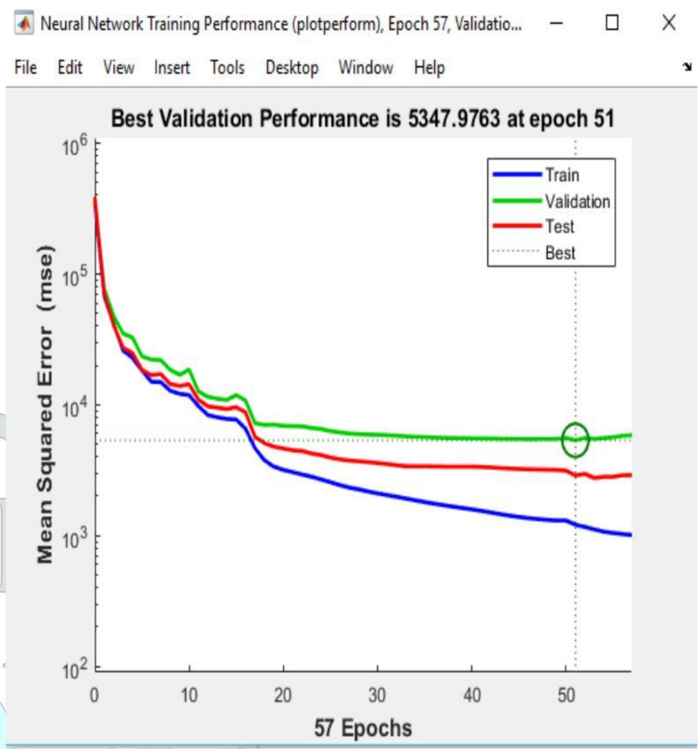
Neural Network

For taining of neural network, hidden layer is used in network. Various numbers of hidden layer used for training of neural network. Here two hiddeen layer is used for better performance of neural network.

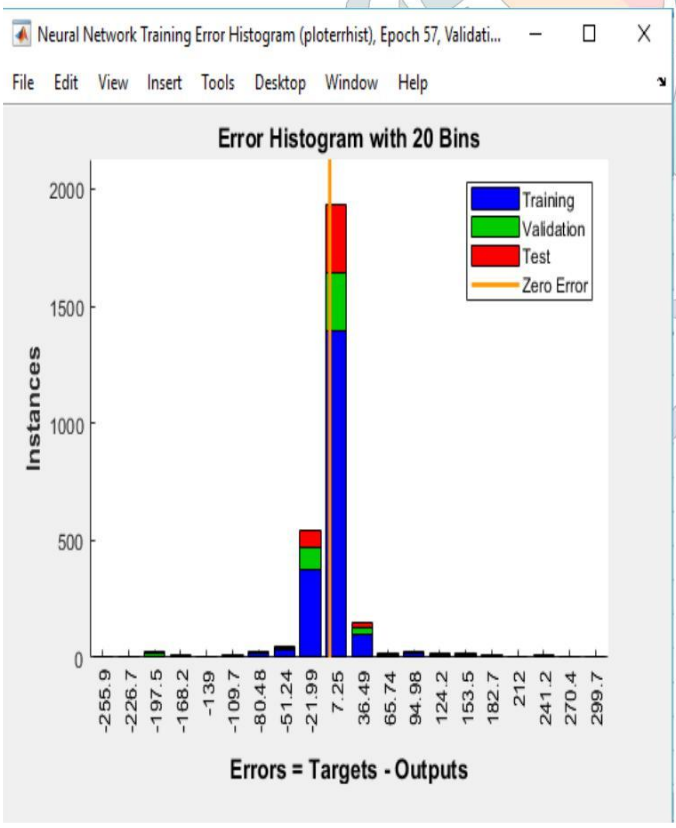
For two hidden layer with 12 neuron each :



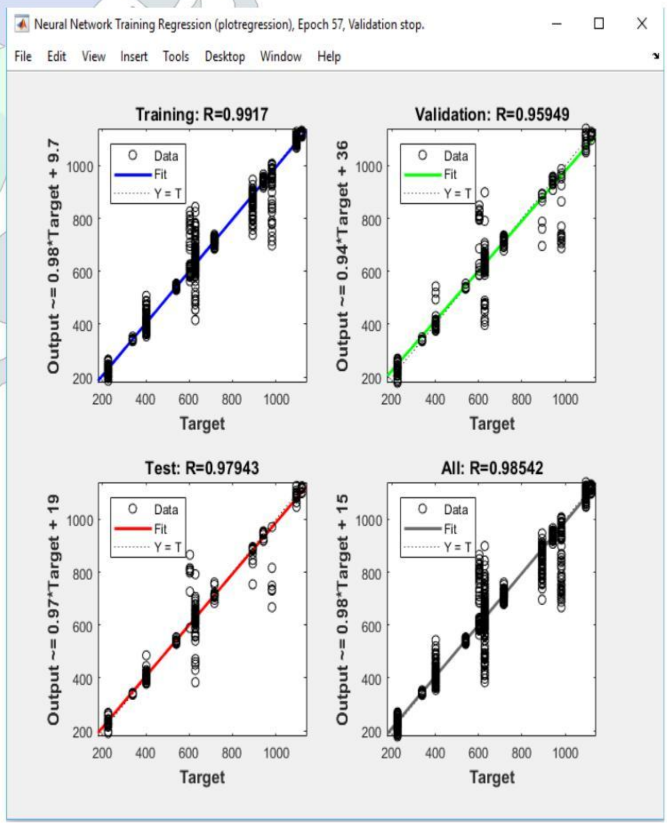
Neural network training



Performance of NN



Error Diagram



Regression analysis

IV. Result discussion

We used different hidden layer to improve the final outcome of the trained neural network. Multi Hidden layers used for training of neural network are (10,10), (11,11), (12,12) and single layers are 10,11,12 and many more to reach the desired outcome for the optimization. Result shows those multilayer hidden layers are more useful in this study of optimization. (12,12) hidden layer gives the best optimization result compare to others.

Comparison between Different neurons in hidden layer of NN

Number of neurons in hidden layer	10,10	11,11	12,12	Exact (original)
Layers		Area of steel Reinforcement(mm^2)		
1	1104.808	1084.032	1094.025	1095
2	636.1197	625.7931	630.6984	628
3	411.4127	427.3678	401.2548	402
4	1104.808	1084.032	1094.025	1095

Table 1 Comparison between Different neurons in hidden layer of NN

V. Conclusion

Optimization of longitudinal reinforcement with respect to each of its layers is a very difficult task to perform. But with use of neural network it can be done very efficiently. This optimization method is little time consuming while training of dataset in neural network, but once it trained after that we easily find the optimization result within fraction of time. In this paper we take Uniaxial loaded RC column for optimization of the each layer along the depth of longitudinal reinforcement. The conclusions achieved from present work are:

1. The efficiency of the Feed Forward Back-Propagation algorithm for training neural network and for optimization was examined and found to be good.
2. The effect of unsymmetrically and symmetrically arranged longitudinal reinforcement were studied and it was found that use of unsymmetrically arranged longitudinal reinforcement in RC column needs lesser reinforcement area than symmetrically arranged longitudinal reinforcement.
3. This seamless procedure reduces the post processing time and gives all the optimized area results for user verification in a single click of the button with well documented format.

In the present work, Optimization of longitudinal reinforcement with respect to each of its layers is to perform. For that we use various variables like characteristic compressive strength of concrete, characteristic strength of reinforcement, load combination and different arrangement of reinforcement. For further study, Spacing between reinforcement as variable also can bee use.

VI. Acknowledgment

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References

[1] L. N. Ramamurthy and T. A. Hafeez Khan, “L-SHAPED COLUMN DESIGN FOR BIAXIAL ECCENTRICITY”, Journal of Structural Engineering, Vol. 109, No. 8, August, 1983. ©ASCE

[2] Cheng-Tzu Thomas Hsu, “BIAXIALLY LOADED L-SHAPED REINFORCED CONCRETE COLUMNS”, *Journal of Structural Engineering*, Vol. 111, No. 12, December, 1985. ©ASCE

[3] Dr T M M Pillai, P I Karthekeyan “Artificial Neural Network Based Approach for Design of RCC Columns”, IE (I) Journal.CV, Vol. 86, November 2005

[4] Dr. V.L. Shah and Late Dr. S.R. Karve, “Limit State Theory and Design of Reinforcement concrete” Sixth Edition: 2012.

[5] IS: 456:2000. .Plain and Reinforced Concrete. Code of Practice. Bureau of Indian Standards, Manak Bhavan, New Delhi.

[6] SP: 16-1980. .Design Aids for Reinforced Concrete to IS: 456. 1978. Bureau of Indian Standards, Manak Bhavan, New Delhi.

[7] S. Rajasekaran, G.A. Vijayalakshmi Pai, “Neural Network, Fuzzy Logic, and Genetic Algorithms” Fifteenth edition: JULY,2011

[8] MATLAB, Mathwork.com

[9] E. Herna´ndez-Montes, M. Aschheim and L. M. Gil-Martı´n “Impact of optimal longitudinal reinforcement on the curvature ductility capacity of reinforced concrete column sections” Magazine of Concrete Research, 2004, 56, No. 9, November, 499–512

[10] Ho Jung Lee, Mark Aschheim, Enrique Hernández-Montes, Luisa María Gil-Martín “Optimum RC column reinforcement considering multiple load combinations” Structural Multidisc Optimization (2009) 39:153–170 DOI 10.1007/s00158-008-0318-4

[11] Luisa Marı´a Gil-Martı´n, Enrique Herna´ndez-Montes, Mark Aschheim "Optimal reinforcement of RC columns for biaxial bending" Materials and Structures (2010) 43:1245–1256, DOI 10.1617/s11527-009-9576-x

NOTATION

Asi	Area of steel for each layer
Ast	Area of steel
b	Width of column
d	Depth of bottom reinforcement from top compression fibre
d'	Concrete cover in tension
dc'	Concrete cover in compression
D	Depth of column
Es	Modulus of elasticity of steel
Fck	Characteristic compressive strength of concrete
Fy	Characteristic yield strength of reinforcement
Pt	Percentage of steel reinforcement in column