

# **Optimal Design of R.C Beams Using Genetically Optimized Artificial Neural Network**

R.Deepan<sup>1</sup>, S.L.Sivasubramanian<sup>2</sup>, M.Gobinath<sup>3</sup>, S.Kearthi<sup>4</sup>

P.G. Scholar, Department of Civil Engineering, Bannari Amman Institute of technology, Sathyamangalam, India<sup>1</sup>,

P.G. Scholar, Department of Civil Engineering, Bannari Amman Institute of technology, Sathyamangalam, India<sup>2</sup>,

P.G. Scholar, Department of Civil Engineering, Bannari Amman Institute of technology, Sathyamangalam, India<sup>3</sup>

P.G. Scholar, Department of Civil Engineering, Bannari Amman Institute of technology, Sathyamangalam, India<sup>4</sup>

**ABSTRACT:** In this paper optimal design of two types of RC beams with two types of loading conditions that is concentrated load and uniformly distributed load incorporating the self-weight of the beam, equilibrium and serviceability constraints. Manually the beams have been designed using the limit state design from IS456:2000, classical and nontraditional optimization technique are done and the results are tabulated.

**KEYWORDS:** RC beams, optimal design, optimization, loadings, genetic algorithms.

## **I. INTRODUCTION**

Optimum design of structures has been the topic of many studies in the field of structural design. A designer's goal is to develop an "optimal solution" for the structural design under consideration. An optimal solution normally implies the economic structure without impairing the functional purposes the structure is supposed to serve. The total cost of the concrete structure is the sum of the costs of its constituent materials; these constituent materials are at least: concrete, steel and framework. There are some characteristics of RC structures, which make design optimisation of these structures distinctly different from other structures. Several cost items including the cost of concrete and reinforcement, influence the cost of RC structures. Therefore, in case of RC structures, the minimum weight design is not necessarily the same as the minimum cost design. In fact, for RC structures the optimum cost design is a compromise between the consumption of concrete, reinforcement, which minimises the total cost of the structure and satisfies the design requirements. In the design optimisation of RC structures the cross-sectional dimensions of elements and detailing of reinforcement, e.g. size and number of steel bars, need to be determined. Consequently, the number of design parameters that need to be optimised for a RC structure can be larger than that for a steel structure.

In this paper optimal design of reinforced concrete beams are done by using traditional and non-traditional methods by satisfying the limit state of serviceability, deflection and collapse. The stress strain block diagram of singly and double reinforced beam is as shown below. The codal provisions for the design of beam does not give a design satisfying the requirements directly with a optimal solution. The intuition of a design engineer can give a good design solution which can reduce the trial and error process. The techniques of optimization involves the choice of design variables, constraints in a way to find the optimal single solution satisfying the constraints with respect to geometry and behaviour. Doubly reinforced beams are design when the depth of the beam is restricted for architectural purpose or when the beam is to be loaded with more moment than the limiting moment of resistance. The steel provided in a beam increases the ductility of the beams whereas reduces the long term deflection.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 3, March 2016

The choice of constraints and design variables during the design as well as the optimization process requires the execution of various trial and error process. If artificial neural network is used to do the optimization process it can find a solution in a faster way than the process done manually. Researchers have used non-traditional methods satisfying the ultimate load method by satisfying moment capacity behaviour constraint. In this paper Artificial Neural Network in which the user defined parameters where the learning rate and error goal were optimized by genetic algorithm for the problem concerned to learn the optimal design for the following.

1. Simply supported beam with concentrated load at centre (SSBCL)
2. Simply supported beam with UDL (SSBUDL)
3. Simply Supported Doubly reinforced beam with concentrated load at centre (SDBCL)
4. Simply Supported Doubly reinforced beam with UDL (SDBUDL)

The initial case is taken with respect to the limit state design considering the self-weight of the beam with its parabolic stress block diagram. The optimization of the beam is done by satisfying the moment carrying capacity, durability, actual deflection as recommended by the IS code provisions.

## II. OBJECTIVE FUNCTION

The optimization techniques in general enable designers to find the best design for the structure under consideration. In this particular case, the principal design objective is to minimize the total cost of structure, after full filling all the requirements according to IS456: 2000, and additional requirements according to IS13920: 1993 in other case. Design variables for doubly reinforced beam in case of without ductile detailing are:

- Width of beam
- Depth of beam
- Diameter for main reinforcement in tension side
- Number of bars in tension side
- Diameter for main reinforcement in compression side
- Number of bars in compression side
- Diameter for shear reinforcement
- Spacing for shear reinforcement

### a) Objectives

1. Cost optimization of reinforced concrete beams

### b) Optimization of Doubly Reinforced Beam

The general form of an optimization problem is as follows

- Given - Constant Parameters
- Find - Design Variables
- Minimize - Objective function
- Satisfy - Design Constraint

The chief task of the optimization process is to select the values of variables in a way that satisfies the provisions of the code regarding safety and serviceability within the least cost possible, the function below defines the total cost of the RC simple beam model in terms of the cost of the concrete and reinforcement and form work used.

$$TC = C_c + C_s + C_f$$

$$C_c = C_{vc} * V_c$$

$$C_s = C_{ws} * W_s$$

$$C_f = C_{Pf} * P_f$$

Where,

TC= total cost in Rs

$C_c$  = cost of concrete in Rs

$C_s$  = cost of steel in Rs

$C_f$  = cost of formwork in Rs

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 3, March 2016

$C_{vc}$ =cost per unit volume of concrete Rs/m<sup>3</sup>

$C_{ws}$ =cost per unit weight of steel Rs/kg

$C_{pf}$ =cost per unit area of formwork Rs/m<sup>2</sup>

$V_c$ =volume of concrete in m<sup>3</sup>

$W_s$ =weight of steel in kg

$P_f$ =perimeter of formwork in m<sup>2</sup>

$$V_c = L * X_1 * X_2 - [((\pi/4) * X_3^2 * X_4 * L) + ((\pi/4) * X_5^2 * X_6 * L) + ((\pi/4) * X_7^2 * X_8 * L * 2)]$$

$$= L * X_1 * X_2 - [(\pi/4) * L * ((X_3^2 * X_4) + (X_5^2 * X_6) + (2 * X_7^2 * X_8))]$$

$$C_c = C_{vc} * V_c$$

$$= C_{vc} * L * \{X_1 * X_2 - [(\pi/4) * ((X_3^2 * X_4) + (X_5^2 * X_6) + (2 * X_7^2 * X_8))]\}$$

$$C_s = C_{ws} * W_s$$

$$W_s = ((\pi/4) * L * ((X_3^2 * X_4) + (X_5^2 * X_6) + (2 * X_7^2 * X_8))) * 7850$$

Where,

L is the span length in m.

7850=density of steel in kg/m<sup>3</sup>

$$C_s = C_{ws} * (\pi/4) * L * \{(X_3^2 * X_4) + (X_5^2 * X_6) + (2 * X_7^2 * X_8)\} * 7850$$

$$C_f = C_{pf} * P_f$$

$$P_f = (2 * X_1 * X_2) + (2 * L * X_2) + (L * X_1)$$

$$C_f = C_{pf} * [(2 * X_1 * X_2) + (2 * L * X_2) + (L * X_1)]$$

Therefore

$$TC = C_c + C_s + C_f$$

$$= C_{vc} * L * \{X_1 * X_2 - [(\pi/4) * ((X_3^2 * X_4) + (X_5^2 * X_6) + (2 * X_7^2 * X_8))]\} +$$

$$C_{ws} * ((\pi/4) * L * \{(X_3^2 * X_4) + (X_5^2 * X_6) + (2 * X_7^2 * X_8)\} * 7850 +$$

$$C_{pf} * [(2 * X_1 * X_2) + (2 * L * X_2) + (L * X_1)]$$

Where,

$X_1$ =breadth of the beam in m

$X_2$ =overall depth of beam in m

$X_3$ =diameter of reinforcement bar in tension zone in m

$X_4$ =number of reinforcement bar in tension zone

$X_5$ = diameter of reinforcement bar in compression zone in m

$X_6$ = number of reinforcement bar in compression zone

$X_7$ =diameter of stirrup reinforcement in m

$X_8$ =(length of stirrup/spacing of stirrup)= $L_s/S_v$

$X_9$ =effective cover in m

$L_s$ =length of stirrup in m= $[2 * \{(b - (2 * 25) - 6) + (D - (2 * 25) - 6) + 90\}]$

$S_v$ =spacing of stirrup in m.

## CONSTRAINTS:

Reinforcement constraint:

$$(0.85 * X_1 * (X_2 - X_9)) / f_y < A_{st} < 0.04 * X_1 * X_2$$

$$A_{st} = 0.5 * F_{ck} / F_y * [1 - (1 - 4.6 * \mu_{lim} / (F_{ck} * X_1 * (X_2 - X_9)^2))^{0.5}] * X_1 * (X_2 - X_9)$$

Strength constraint:

$$P_u * L^2 / 8 < Q * X_1 * (X_2 - X_9)^2$$

Where,

$$Q = 0.36 * (X_{umax} / (X_2 - X_9)) * (1 - 0.42 * X_{umax} / (X_2 - X_9)) * F_{ck}$$

Q is the bending moment factor

Deflection constraint:

$$\delta_{max} < \delta_{perm}$$

$$\delta_{max} = PL^3 / 48EI = (P * L^3) / (4 * E * X_1 * (X_2 - X_9)^3)$$

$$\delta_{perm} = L / 360$$

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 3, March 2016

$f_y$	$X_{umax}/d$
250	0.53
415	0.48
500	0.46

- $P_u * L^2 / 8 < 0.36 * (X_{umax} / (X_2 - X_9)) * (1 - 0.42 * X_{umax} / (X_2 - X_9)) * F_{ck} * X_1 * (X_2 - X_9)^2$   
 1)  $P_u * L^2 / 8 < 0.36 * (X_{umax} / (X_2 - X_9)) * (1 - 0.42 * X_{umax} / (X_2 - X_9)) * F_{ck} * X_1 * (X_2 - X_9)^2$   
 2)  $(P_u * L^3) / (4 * E * 10^3 * X_1 * (X_2 - X_9)^3) < (L * 1000) / 360$   
 3)  $(0.85 * X_1 * (X_2 - X_9)) / f_y < 0.5 * F_{ck} / F_y * [ 1 - (1 - (4.6 * M_{ulim} / (F_{ck} * X_1 * (X_2 - X_9)^2)))^{0.5} ] * X_1 * (X_2 - X_9) < 0.04 * X_1 * X_2$

### III. PROCEDURE

In this section, the model of the RC beam is described, showing the fixed parameters, the design variables, the design variables' bounds, the design constraints and the objective function. A typical simply supported rectangular RC beam has a span of L m and may be carrying a Moment kN-m. The grades of concrete considered are M<sub>20</sub>, M<sub>30</sub>, M<sub>40</sub>, M<sub>50</sub>. The grades of steel adopted Fe<sub>415</sub>, Fe<sub>500</sub>, Fe<sub>550</sub>. It is intended to optimize the design of the beam according to the provisions of the IS-456:2000 Code.

### IV. NEURAL NETWORK LEARNING TECHNIQUES

The steepest back propagation takes consecutive steps in the direction of negative gradient of the performance surface. The performance function of the feed forward neural network is a squared error function F(x). The surface of this performance function contains long ravines that are characterized by sharp curvature across the ravine and a gently sloping floor. There was considerable research on the methods to accelerate the convergence of the steepest descent back propagation algorithm. The parameter used for computing the performance of learning techniques is the mean absolute percentage error. The quality of the output from ANN is compared with the mean absolute percentage error. Thus, the quality of output of ANN is compared on the basis of MAPE.

$$MAPE = \frac{\sum_{i=1}^N \frac{|X_i - F_i| * 100}{X_i}}{N}$$

### V. NEURAL NETWORK IMPLEMENTATION

For the design of beams four artificial neural networks were created, two for preliminary optimal design of Simply-Supported Singly Reinforced Beams with UDL and Concentrated Load (SRB-NN), respectively, and two for Simply Supported -Doubly Reinforced Beams with UDL and Concentrated Load (DRB-NN), respectively, are synthesized. The number of inputs and outputs for singly reinforced beams was fixed as 5 and 2, respectively. Thus the input of both singly reinforced beams consists of five inputs, viz., load, span, d to b ratio, f<sub>ck</sub> and f<sub>y</sub>, and the output, are optimum tensile reinforcement percentage and optimum depth of beam (d). A set of 2,22768 optimum design examples were used for training and testing. The number of input and output for Doubly Reinforced Beams using -NN network was fixed as 6 and 2, respectively. Thus the input of both DRB-NN consists of six inputs, viz., load, span, d to b ratio, f<sub>ck</sub> and f<sub>y</sub>, and depth of beam. The output of both Doubly Reinforced Beams using -NN network are cover to reinforcement (d') and optimum tensile steel reinforcement (pt). The optimum compression steel reinforcement is derived from input and output variable values of Doubly Reinforced Beams using -NN network. A set of 2, design examples were used for training and testing. Four 4-layered FFNN consisting of two hidden layers were used MATLAB 13.0 for learning of the optimal design examples. To avoid the trapping of algorithm, the number of neurons in first and second hidden layer

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 3, March 2016

and user-defined parameters of ANN, viz., learning rate and error goal, were optimized for minimum learning error using genetic algorithm with optimization technique given by Deb (2000). The population size was taken as 150 and number of generations as 40. The plot of training error vs  $\beta$  is shown in Fig. for 250 epochs of learning for each chromosome of the population. In this, first the weights are initialized according to a uniform random distribution between  $-1$  and  $1$  and then the magnitude of weight vectors is adjusted in a manner such that each hidden node is linear over only a small interval. Each ANN was trained for 10,000 epochs using various neural learning techniques.

## VI. ARTIFICIAL NEURAL NETWORK RESULTS

The human brain provides proof of the existence of massive neural networks that can succeed at those cognitive, perceptual, and control tasks in which humans are successful. The brain is capable of computationally demanding perceptual acts (e.g. recognition of faces, speech) and control activities (e.g. body movements and body functions). The advantage of the brain is its effective use of massive parallelism, the highly parallel computing structure, and the imprecise information-processing capability. The human brain is a collection of more than 10 billion inter-connected neurons. Each neuron is a cell that uses biochemical reactions to receive, process, and transmit information.

Treelike networks of nerve fibers called dendrites are connected to the cell body or soma, where the cell nucleus is located. Extending from the cell body is a single long fiber called the axon, which eventually branches into strands and sub strands, and are connected to other neurons through synaptic terminals or synapses. The transmission of signals from one neuron to another at synapses is a complex chemical process in which specific transmitter substances are released from the sending end of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If the potential reaches a threshold, a pulse is sent down the axon and the cell is 'fired'.

Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. A wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by McCulloch and Pitts (1943).

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

Thousand singly and doubly reinforced beams each were fed as input into matlab using neural network method and another 100 values were set as target values.

The percentage difference between nontraditional optimization, traditional optimization and using excel software is determined.

### RESULTS AND CONCLUSION: SINGLY REINFORCED BEAM

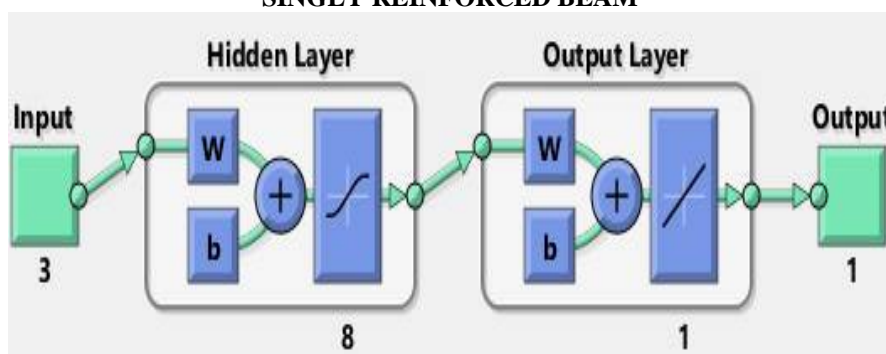
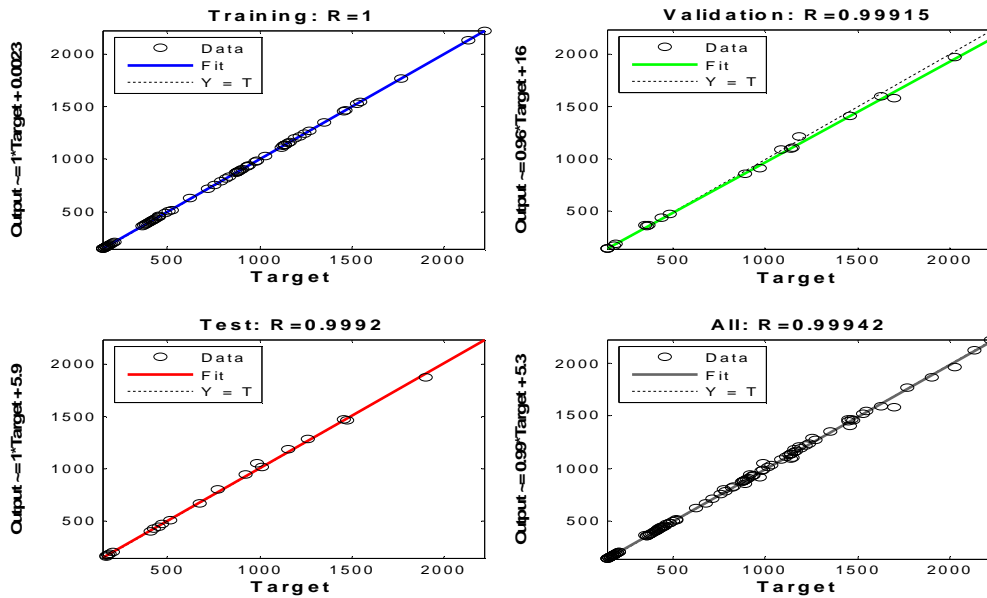


Fig a) Artificial neural network arrangement for singly reinforced beam

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 3, March 2016



**Fig b) Graph showing accuracy of result for singly reinforced beam**

Sl.NO	Fck	Fy	b/D Ratio	Total cost in rs		Accuracy%
	N/mm <sup>2</sup>	N/mm <sup>2</sup>		Classical	Non-traditional	
1	20	415	0.4	4553.497393	4632.369042	98
2	30	415	0.4	4226.747592	4319.631003	98
3	40	415	0.4	3942.964012	4006.893535	98
4	50	415	0.4	3778.937834	3844.904576	98
5	20	500	0.4	3408.734781	3523.295567	98
6	30	500	0.4	3003.887492	3191.94083	98
7	40	500	0.4	2789.458213	2870.331821	98
8	50	500	0.4	5998.230871	6055.008732	99
9	20	550	0.4	5523.458721	5625.345404	98
10	30	550	0.4	4989.926434	5184.069553	98

**Table a) Testing Data of ANN for singly reinforced beam**

Table a) shows the design data chosen for testing purpose using ANN technique in MATLAB. These values are used to the optimum values. Using this input parameter the optimized values of total cost is obtained. Trained experimental minimum error is 0.00001254 and tested experimental minimum error is 0.000012123. by comparing experimental value and ANN 98% of accuracy was obtained. Results from artificial neural network

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 3, March 2016

- The table a) shows the design data chosen for testing purpose using ANN technique in MATLAB. These values are used to the optimum values.
- Using this input parameter the optimized values of total cost is obtained.
- Trained experimental minimum error is 0.000001254
- Tested experimental minimum error is 0.000001212
- By comparing manual valve and ANN 98% of accuracy was obtained.

## DOUBLY REINFORCED BEAM

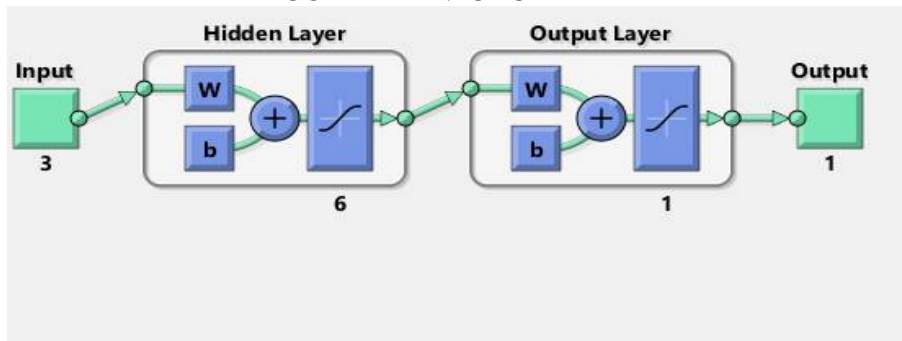


Fig c) Artificial neural network arrangement for doubly reinforced beam

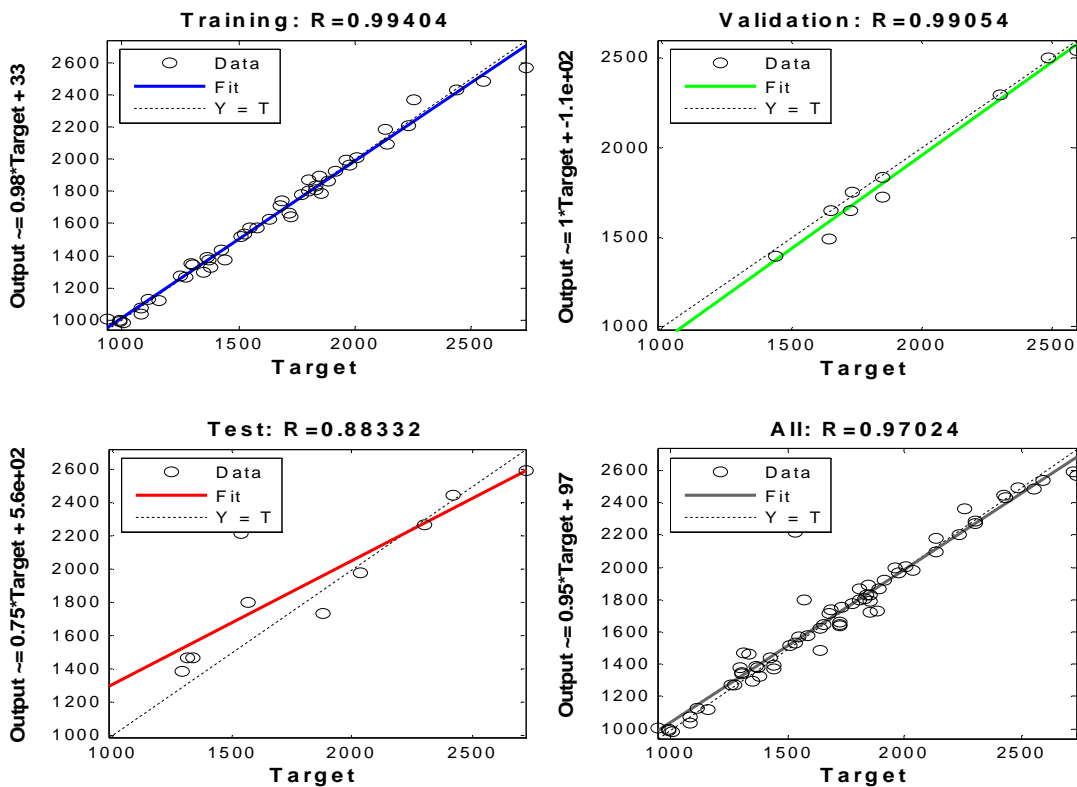


Fig d) Graph showing accuracy of result for doubly reinforced beam

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 3, March 2016

SI.NO	Fck	Fy	b/D Ratio	Total cost in rs		Accuracy %
	N/mm <sup>2</sup>	N/mm <sup>2</sup>		Classical	Non-traditional	
1	20	415	0.4	4553.497393	4632.369042	98
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3	40	415	0.4	3942.964012	4006.893535	98
4	50	415	0.4	3778.937834	3844.904576	98
5	20	500	0.4	3408.734781	3523.295567	98
6	30	500	0.4	3003.887492	3191.94083	98
7	40	500	0.4	2789.458213	2870.331821	98
8	50	500	0.4	5998.230871	6055.008732	99
9	20	550	0.4	5523.458721	5625.345404	98
10	30	550	0.4	4989.926434	5184.069553	97

**Table b) Testing Data of ANN for doubly reinforced beam**

Table b) shows the design data chosen for testing purpose using ANN technique in MATLAB. These values are used to the optimum values. Using this input parameter the optimized values of total cost is obtained. Trained experimental minimum error is 0.0000846354 and tested experimental minimum error is 0.000073563. by comparing experimental valve and ANN 98% of accuracy is obtained.

Results from artificial neural network

- The table b) shows the design data chosen for testing purpose using ANN technique in MATLAB. These valves are used to the optimum values.
- Using this input parameter the optimized valves of total cost is obtained.
- Trained experimental minimum error is 0.00008462
- Tested experimental minimum error is 0.00007356.
- By comparing manual valve and ANN 98% of accuracy was obtained.

## VII. CONCLUSION

### COMPARISON BETWEEN TRADITIONAL AND NON TRADITIONAL METHODS OF OPTMIZATION:

Results from MS-Excel Software:

- The results obtained from MS-Excel software was found to be of around 96% accuracy as compared with the classical method of optimization(Gradient Descent Method)
- The optimal solution for singly reinforced beam design was done using M40 grade of concrete and Fe 550 grade of steel.

Results from Artificial Neural Network:

- The results obtained from Artificial Neural Network was found to be of around 98% accuracy as compared with the classical method of optimization.

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