Research Article Impact Factor: 0.621 ISSN: 2319-507X
AS Gadewar, IJPRET, 2014; Volume 2 (8): 83-99 IJPRET

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

A PATH FOR HORIZING YOUR INNOVATIVE WORK

PREDICTING CONCRETE STRENGTH USING ARTIFICIAL INTILIGENCE

MR. A.S.GADEWAR[1], MR.P.S.LANDE[2], MR.T.N.BOOB[3]

1. Lecturer in Civil Engg; Dr. N. P. Hirani Instt. of Polytechnic, Pusad.
2. Associate Professor, App. Mech. Dept, Govt. College of Engineering, Amravati.
3. Principal, Dr. N. P. Hirani Instt. of Polytechnic, Pusad.

Accepted Date: 15/02/2014 ; Published Date: 01/04/2014

Abstract: The strength of concrete determined in situ never is same to cube strength determined in the laboratory. Also the results of non-destructive tests (NDTs), are predicted not a actual results. So to get more accuracy there is a need to develop a technique which gives more accuracy in prediction. It is not possible to take core from the structure as it may damage the structure. Therefore to find correlation between compressive strength and NDTs data are required. From the number of non-destructive tests Rebound hammer test and Ultra-pulse velocity test are generally used to determine compressive strength of existing concrete structures. For the determination of strength, the use of regression analysis is not sufficient. This is due to the fact that a number of other properties of concrete such as its elastic behavior and in some extent its service performance can be approximated, directly or indirectly, from its strength characteristics. In addition to the correlation curve, a procedure is needed for analyzing the results so that one can estimate the in-place compression strength with a high degree of accuracy. The new approach Artificial Intelligence (Artificial Neural Network) is presented for making correlation between DT & NDT to predict the compressive strength of unknown mix. Three feed forward error back propagation networks are selected for the task. Out of this Levenberg-Marquardt network (LM) is found best on the basis low training and testing MSE value as well as high correlation coefficient R with low learning rate. From the study it is clearly observed that artificial neural network (2-45-1) gives the compressive strength very closed to actual compressive strength of cube samples and can be effectively used for interpreting the NDTs data.

Keywords: Concrete, Compressive strength, Rebound hammer, Ultra pulse velocity, Artificial neural network

Corresponding Author: MR. A.S.GADEWAR

Access Online On:

www.ijpret.com

How to Cite This Article:

AS Gadewar, IJPRET, 2014; Volume 2 (8): 83-99

PAPER-QR CODE

INTRODUCTION

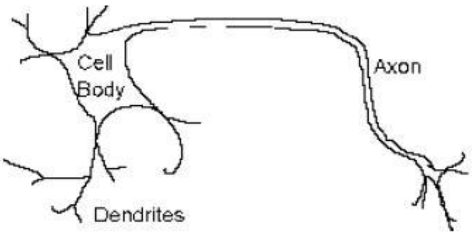
As widely known, concrete is an essential material in civil engineering. However, its properties can vary considerably, depending on the nature and proportions of its constituents, the construction methods applied to create it, and the loading and environmental conditions to which it will be subjected over time. Therefore, the development of control methods to determine the condition and ascertain the quality of concrete is critical. Non-destructive tests can play an important role in this area, since they allow us to monitor the structural health of concrete in terms of its density, homogeneity and providing information about the strength development. For structural health monitoring the Rebound Hammer is being widely used by many consultants. But the rebound hammer should not be used alone for any old structures for predicting the service life or damage assessment. However Ultrasonic pulse velocity is more reliable for such purposes and can be used together with Rebound hammer tests. To ensure that the information provided is reliable, expert knowledge is needed for interpreting the Non-destructive tests (NDT) data. Manufacturers of devices usually give empirical relationships for their own testing system. Such relationships are not suitable for every kind of concrete. Therefore, they need to be calibrated for different mixtures. The conventional approach to derive a mathematical relation relationship using NDTs and compressive strength of concrete by means of regression analysis has not been very successful. Numerous data and the correlation relationships between strength and different NDTs results of concrete have been proposed and presented. In this context, the use of Artificial Neural Networks (ANN) techniques is seen as a viable and adequate strategy. This study is focused on the evaluation of the feasibility of developing a specialist ANN tool. This kind of technique allows provides the processes of specialists when dealing with uncertainty. Using a neural model, it is possible to establish a non-linear correlation between known input data, such as NDT data and a certain output in this case, compressive strength, since it is the most used parameter to determine concrete quality. The net has been trained using a back propagation algorithm to minimize the mean squared error. The results obtained indicate that, the estimation power of the neural network is better than using traditional modeling techniques, such as regression analysis.

To examine this possibility a proper data set for training and testing the neural networks has been created in the laboratory by carrying out DT & NDT tests on concrete cubes representing wide range of strength and of different age. Most suitable type of neural network is worked out by its performance on the basis of mean squared error.

II. ARTIFICIAL NEURAL NETWORK

Artificial neural networks are non-linear data driven self adaptive approach. They are powerful tool for modeling, especially when the underlying data relationship is unknown. Therefore Artificial Neural Network, classed as Artificial Intelligence can use as computational tool for this purpose. Suitable neural network for the analysis of experimental results can be selected on the basis of literature on this subject.

An artificial neural network can be represented as a simplified model of the nervous system consisting of a large number of information processing elements. The elements are called artificial neurons. The prototype of the artificial neuron is the biological neuron. In its cybernetic counterpart the neuron's body is referred to as a processor. From the nerve cell originate thin, branching dendrites, constituting its "input" and a long thicker axon. In the artificial neuron this corresponds to input and output signal. The junction between two nerve cells called a synapse. Through the later signals are transmitted to other nerve cells. Information is transferred in the form of electric impulses called potentials. The structure of the nerve cell and that of its cybernetic counterpart are as shown in fig. 1



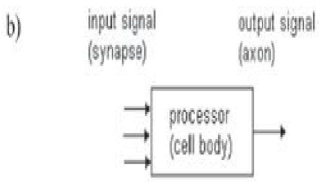


Fig.1 General Structure of nerve cell (a) and its cybernetic counterpart (b)

Artificial neurons connected together form a network. The structure of artificial neural networks is, as a rule, layered. Three functional groups can be distinguished in the artificial neural network, i.e. the inputs receiving signals from the networks outside and introducing them into its inside, the neurons which process information and the neurons which generate results.

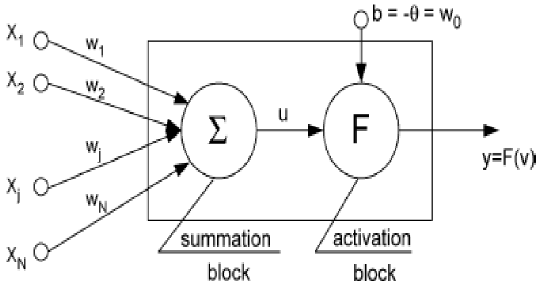


Fig. 2 Model of artificial neuron

A model of the artificial neuron is shown in Fig.2 The model includes N inputs, one output, a summation block and an activation block. The following variables and parameters were used to describe the model shown in the figure above are

$X_I = (X_1, X_2, \ldots \ldots, X_N)$ an input vector,

$w_I = (w_1, w_2, \ldots \ldots, w_N)$ a weight vector,

b = ▯▯▯▯▯▯▯ = w_0 a bias

$$v = u + b = \sum_{j=1}^{N} w_j x_j - ▯$$

Where $\sum_{j=1}^{N} w_j x_j$ a network potential

F(v) an activation function

2.1 Characteristics of neural network:

1) The Neural networks can map input pattern to their associated output pattern.

2) The Neural network architectures can be ‘trained’ with known examples before they are tested for the ‘inference’.

3) The Neural networks are robust system and are fault tolerant. Therefore it recall full pattern from incomplete, partial or noisy pattern.

4) The Neural networks can process information in parallel at high speed and in a distributed manner.

Depending on the way in which the neurons are connected, three types of artificial neural networks are distinguished: unidirectional networks, cellular networks and recursive networks

2.2 Development of an ANN Model:

The various steps in developing a neural network model are-

1) Variable selection: - The input variables important for modeling. Variables under study are selected by suitable variable selection procedures.

2) Formation of training, testing and validation sets:- The data set is divided into three distinct sets called training, testing and validation sets. The training set is the largest set and is used by neural network to learn patterns present in the data. The testing set is used to evaluate the generalization ability of supposly trained network and final check on the performance of trained network is made using validation set.

3) Neural network architecture: - Neural network architecture defines its structure including number of hidden layers, number of hidden nodes and number of output nodes and activation function.

4) Evaluation criteria:-The most common error function minimized in neural networks is the mean squared errors.

5) Neural network training:-The objective of training is to find the set of weights between the neurons that determine the global minimum of error function. This involves decision regarding the number of iteration, selection of learning rate (a constant of proportionality which determines the size of the weight adjustments made at each iteration) and momentum values (how past weight changes affect current weight changes.

III. METHODOLOGY

Methodology to be adopted for strength identification by means of Artificial Intelligence neural network on the basis of NDT are given below

1) Prepare data set for neural network from destructive and nondestructive tests.

2) Develop neural network which includes normalization and denormalization of data using MATLAB- N N Toolbox, Selection of neural network, training and testing of selected network.

3) Validation of neural network.

IV. EXPERIMENTAL STUDY

A total of 216 concrete cube of size 15x15x15 cm samples of unknown mix are tested using Ultrasonic Pulse Velocity tester for the determination of the direct ultra-pulse velocity (V_d) and Rebound Hammer Test for the determination of Rebound number (R) before the execution of destructive compressive test. The values of the V_d are observed to be lying within 2.16 km/s and 5.37 km/s; Rebound number varied from 10 to 40 and the concrete cube compressive strengths varied between 2.23 MPa and 40 MPa.

On the basis of a review of the literature the following feed forward error back propagation networks are selected for the task

- The network descent gradient with adaptive learning rate (GDA)
- The network with momentum and the descent gradient (GDM)
- The Levenberg-Marquardt network (LM)

Gradient descent with adaptive learning rate backpropagation (Traingda) can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance (dperf) with respect to the weight and bias variables X. Each variable is adjusted according to gradient descent:

dX = lr*dperf/dX

At each epoch, if performance decreases toward the goal, then the learning rate is increased by the factor lr_inc. If performance increases by more than the factor max_perf_inc, the learning rate is adjusted by the factor lr_dec and the change that increased the performance is not made.

Gradient descent with momentum backpropagation (Traingdm) can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance (perf) with respect to the weight and bias variables X. Each variable is adjusted according to gradient descent with momentum,

dX = mc*dXprev + lr*(1-mc)*dperf/dX

where dXprev is the previous change to the weight or bias.

Levenberg-Marquardt backpropagation (Trainlm) supports training with validation and test vectors if the network's NET.divideFcn property is set to a data division function. Validation vectors are used to stop training early if the network performance on the validation vectors fails to improve or remains the same for max_fail epochs in a row. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training. 'trainlm' can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate the Jacobian jX of performance perf with respect to the weight and bias variables X. Each variable is adjusted according to Levenberg-Marquardt,

jj = jX * jX

je = jX * E

dX = -(jj+I*mu) \ je   where E is all errors and I is the identity matrix.

It should be noted that each of the above networks has been trained & tested for all the samples to find out the best one for the task.

The experimental data is saved in a mat file which is then used as input data for the network. The data was randomly divided into training (80%), testing (10%) and validation (10%). All the data has been normalizing by applying the procedure of the MATLAB-Neural Network Toolbox simulator to get MSE value nearer to zero and correlation coefficient R nearer to one. While training the network optimum numbers of neurons in the hidden layer and learning rate have been calculated. The neural network learnt to identify the compressive strength of concrete cube samples. The training phase is stopped when the variation of error became sufficiently small. The ANN model is then tested and the results are compared by means of root mean squared error and coefficient of determination.

Table 4.1. Optimum elements and Performance of different network architecture

Sr.No.	NDT	Short Name of Neural Network	Elements of Neural Network						Performance of Different Neural Network	
			Input Data	Hidden Layer	Neurons in Hidden Layer	Output	Learning Rate	No. of Epochs	Correlation Coefficient R	Mean Square Error MSE
1	Rebound Hammer Test	GDM	1	1	10	1	0.02	6	0.997	0.00310
2		GDA	1	1	40	1	0.4	639	0.9993	0.000493
3		LM	1	1	20	1	0.04	3	0.9737	0.000013
1	Ultrasonic Pulse Velocity	GDM	1	1	20	1	0.1	134	0.95	0.003790
2		GDA	1	1	40	1	0.2	252	0.999	0.000495
3		LM	1	1	10	1	0.02	1	0.968	0.000059

Finally the Levenberg-Marquardt network (LM) was selected on the basis low training and testing MSE value as well as high correlation coefficient R with low learning rate, the obtained result was give in the table 4.1 & 4.2.

V. RESULT AND DISCUSSION

The Levenberg-Marquardt network (LM) was selected on the basis low training and testing MSE value and high correlation coefficient R with low learning rate, to obtained result for combination of both NDTs result as an input for output as compressive strength. Ultra pulse velocity and Rebound No. are taken as input and Compressive strength of cube kept as output (target).The data was randomly divided into training (80%), testing (10%) and validation (10%). They were normalizing before testing and denormalize after by applying the procedure of the MATLAB-Neural Network Toolbox simulator. While training the network optimum numbers of neurons in the hidden layer and learning rate were calculated. The neural network learnt to identify the compressive strength of concrete cube samples.

After taking number of trainings in the neural network simulation, the optimum hidden neuron number and hidden layer number are determined as 45 (2-45-1) and other parameters for Levenberg-Marquardt network (LM) found as Learning rate 0.04 with training performance goal 10^{-5}, momentum constant 1.0 and maximum number of epochs 1000 with activation functions as tangent sigmoid. It can be seen that the smallest MSE and the highest R values are obtained by 45 hidden neurons in hidden layer. The analyst had the optimum flexibility to be able to determine the number of hidden neuron numbers, on a MSE basis. Table 4.2 & Table 4.3 show the performance of the LM network for different hidden neuron numbers. Bar chart has been prepared for comparing different type of network tested for the task is as shown in Fig.

Table 4.2 Selection of No. of Neurons in hidden layer of LM-Network for RN, Vd & Fs

No. of Neurons	Learning Rate	MSE	R	No. of Ephocs
10	0.04	0.0000231	0.9817	5
20	0.04	0.0000523	0.9824	8
25	0.04	0.0000424	0.9799	2
30	0.04	0.0000676	0.9704	1
35	0.04	0.0000355	0.9653	1
40	0.04	0.000112	0.9204	1
45	0.04	0.00000704	0.9892	4
50	0.04	0.0000952	0.9584	1
55	0.04	0.00000823	0.9863	4
60	0.04	0.0000582	0.9629	1
65	0.04	0.000107	0.9576	1
70	0.04	0.0000306	0.97	1
75	0.04	0.0000550	0.9896	3
80	0.04	0.0000382	0.9848	3
85	0.04	0.00000736	0.9672	1
90	0.04	0.0000820	0.9534	1
95	0.04	0.000141	0.9806	2

It can be seen that the model of hidden layer with 45 neurons has the smallest MSE (7.04E-06), and it has the highest R (0.98919). The best validation performance is obtain at 4 epoch and MSE value is 7.04E-06 MPa shown in Fig.8.It is not surprising to observe some fluctuations in the mean squared errors due to the nature of the back propagation algorithm. However, it is observed that the modeling results are exceptionally close to the real compressive strength test results; therefore there is no doubt regarding the accuracy of the MSE values.

Table 4.3 Selection of learning Rate of LM-Network for RN, Vd & Fs

No. of Neurons	Learning Rate	MSE	R	No. of Ephocs
45	0.01	3.45E-05	0.9875	2
45	0.02	1.11E-04	0.97681	3
45	0.03	1.06E-05	0.9862	9
45	0.04	7.04E-06	0.98919	4
45	0.05	7.69E-06	0.96561	4
45	0.06	4.44E-05	0.97989	1
45	**0.07**	**1.30E-04**	**0.95805**	**1**
45	0.08	1.52E-04	0.93696	1
45	0.09	1.05E-06	0.98839	7
45	0.1	9.73E-06	0.97552	3

able 4.4 clearly depicts the comparison of results using ANN in terms of average, maximum and minimum percentage of error involved in prediction of concrete compressive strength basis of UPV and Rebound No. of concrete specimen. As seen the maximum percentage error through ANN is 24.47 whereas average %error for all 216 tested sample is only 0.25%. A better inference can be drawn from values of average percentage error, that ANN prediction is observed to perform better for prediction of compressive strength.

The results are plotted in the form of a graph showing comparison of prediction through ANN. Fig.10 shows predicted compressive strengths through ANN and experimental compressive strength for cubes. The figure clearly depicts that experimentally evaluated values of compressive strength are in strong coherence with the values predicted through ANN for most of the samples.

% Error	ANN(LM)

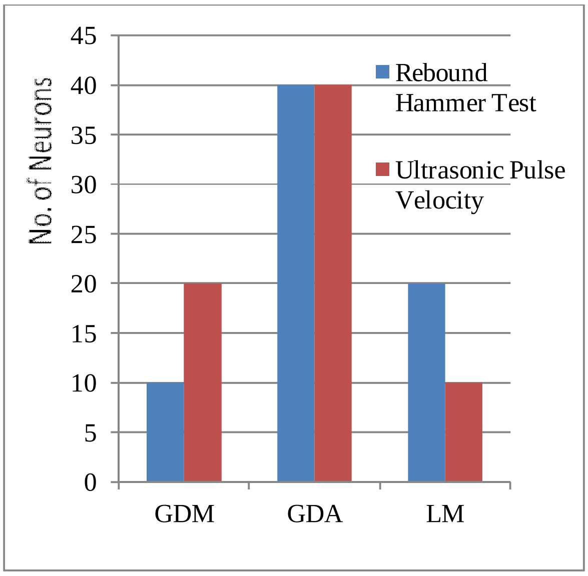
AVERAGE	-0.25
MAXIMUM	24.47
MINIMUM	-96.48

VI. CONCLUSIONS

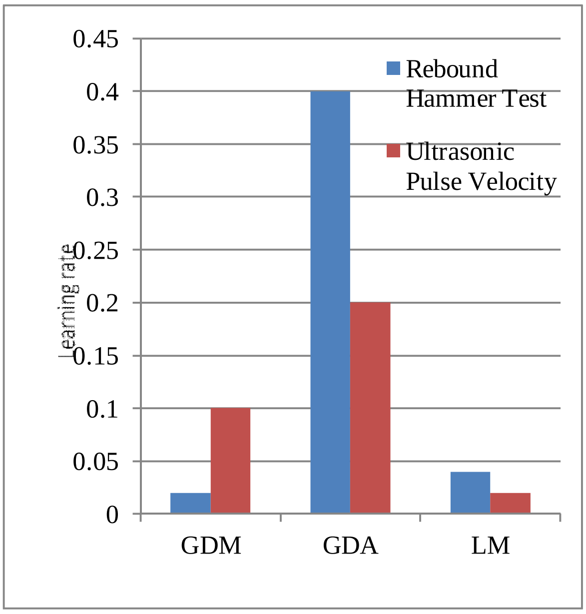
This study indicates the ability of the multilayer feed forward back propagation neural network as a good technique for model the concrete compressive strength with UPV and RN relationship. The ANN model performs sufficiently in the estimation of concrete compressive strength. Gradient descent algorithm and one hidden layer are employed in the analysis. The MSE values are reasonably small indicating that the estimates are most accurate and the trained network yield superior results.

The neural network model to predict compressive strength based on UPV and RN of concrete specimens is utilized in this study. The prediction from values of average percentage error ANN shows a high degree of consistency with experimentally evaluated compressive strength of concrete specimens used. Thus, the present study suggests an alternative approach of compressive strength assessment against destructive testing methods.

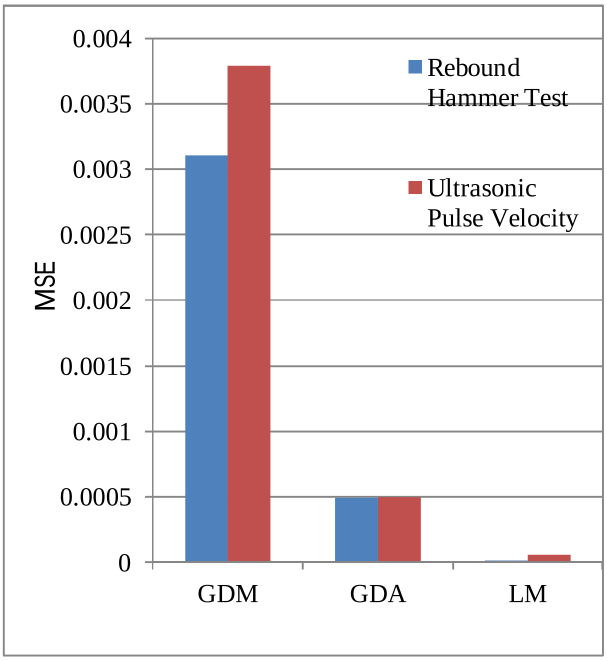
This current study employed data set which is composed of limited input and output vectors. Therefore, it would be reasonable to propose a further works using more data sets from various areas could be needed to generalize the conclusions in this study.


No. of Neurons
45
40
35
30
25
20
15
10
5
0
GDM
GDA
LM
Rebound Hammer Test
Ultrasonic Pulse Velocity

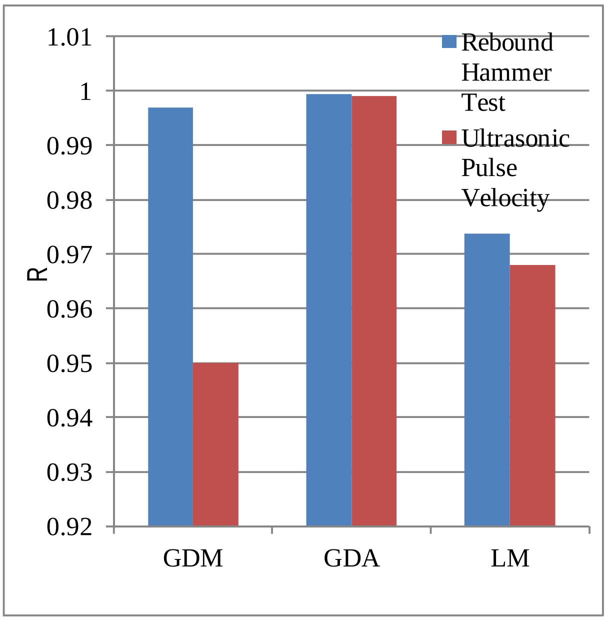
(A)


Learning rate
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
GDM
GDA
LM
Rebound Hammer Test
Ultrasonic Pulse Velocity

(B)



(C)



(D)

Fig. 4.1 Optimum elements (A & B) and Performance (C & D) of different network architecture

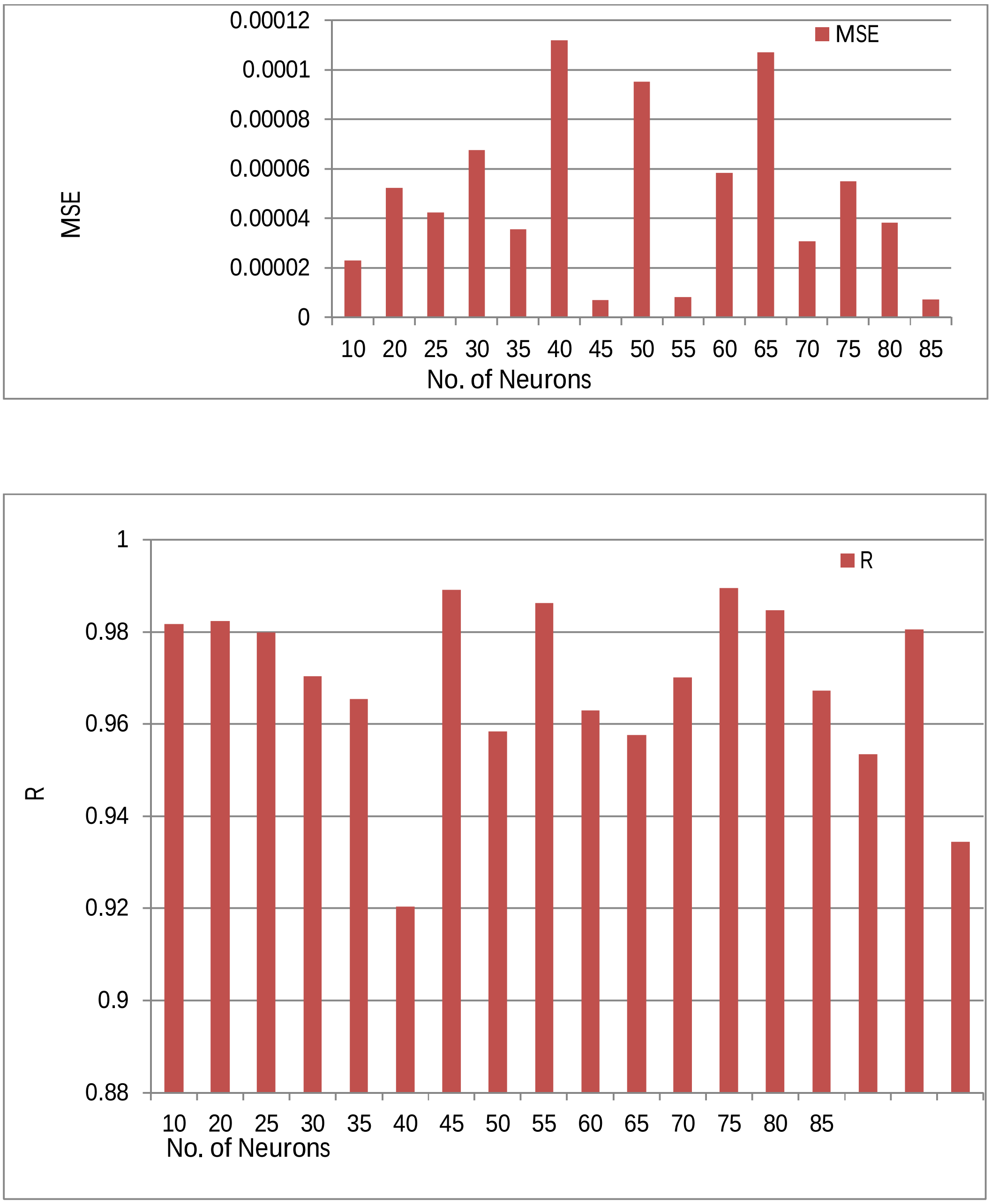


Fig.4.2 The MSE and R plot of Levenberg-Marquardt network (LM) for different no. of neurons

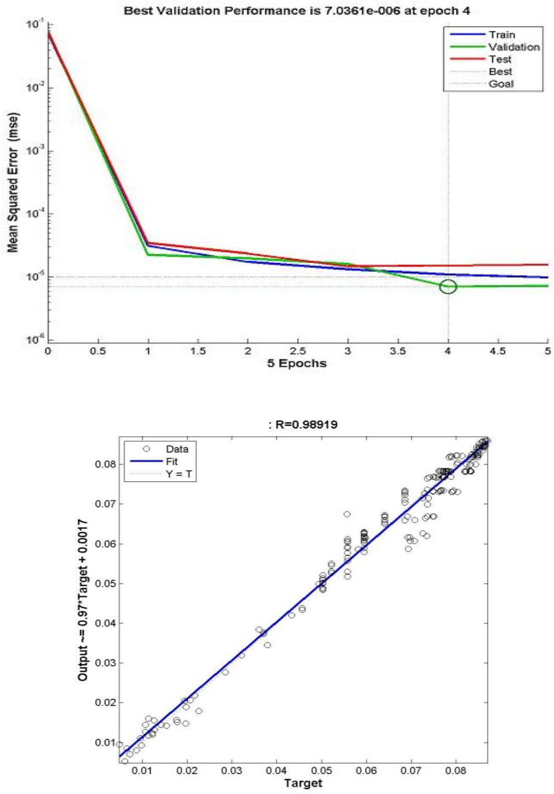


Fig.4.3 The performance and regression plot of Levenberg-Marquardt network (LM)

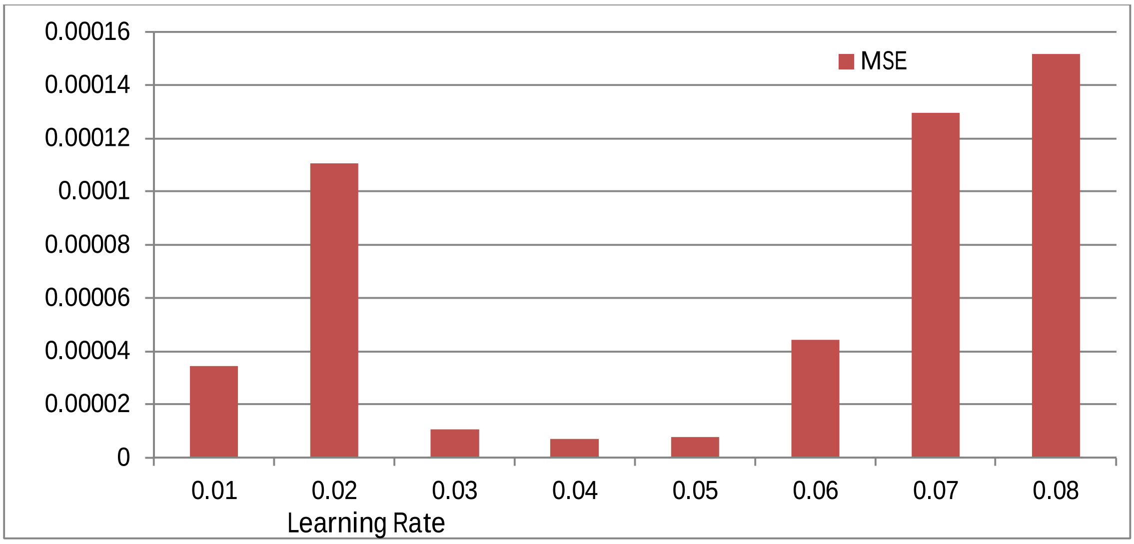


Fig.4.4 The MSE plot of Levenberg-Marquardt network (LM) for different learning rate

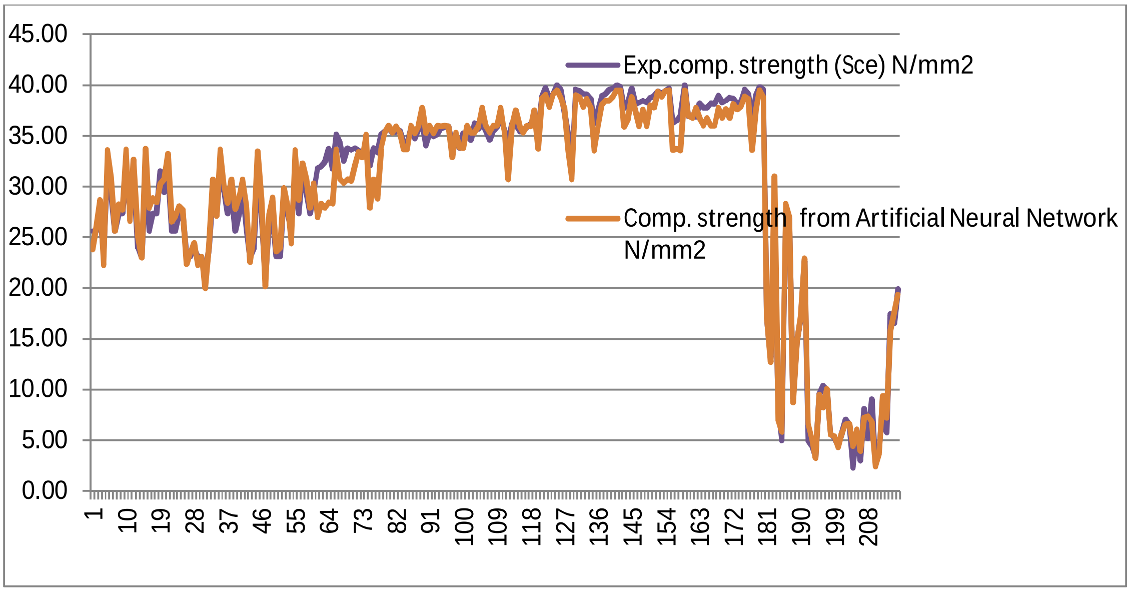


Fig. 4.6 Actual and Predicted compressive strengths through Experimentation and ANN for a cubes

REFERANCES

1. Bureau of Indian Standard (BIS), 'Indian Standard Code of Practice for Nondestructive Testing of concrete- Method of Test (ultrasonic pulse velocity)',IS 13322 (Part-I):1992.

2. Bureau of Indian Standard (BIS), 'Indian Standard Code of Practice for Nondestructive Testing of concrete- Method of Test (rebound hammer)',IS 13322 (Part-II):1992

3. Mahdi Shariati et-al, **"**Assessing the strength of reinforced concrete structures through Ultrasonic Pulse Velocity and Schmidt Rebound Hammer tests**",** *Scientific Research and Essays,* **6(1)**, 213-220, 4 January 2011.

4. Suresh Chandra Pattanaik, **"**Ultrasonic Pulse and Rebound Hammer As NDT Tools For Structural Health Monitoring**",** *International Conference NUiCONE 2010* at Institute of Technology, Nirma University, Ahmedabad from December 09-11, 2010.

5. Lorenzi and et-al, "Using a Back-Propagation Algorithm to Create a Neural Network for Interpreting Ultrasonic Readings of Concrete".

6. Jerzy Hoła & Krzysztof Schabowicz, "Application of artificial neural networks to determine concrete compressive strength based on non-destructive tests", *Journal of Civil Engineering and Management* , **11(1)**,23-32,2005.

7. M. Bilgehan and P. Turgut**,**"The use of neural networks in concrete compressive strength estimation", *Computers and Concrete*,**7(3)**,271-283,2010.

8. Seung-Chang Lee, "Prediction of concrete strength using artificial neural networks", *Engineering Structures*, **25**,849–857,2003.

9. Serkan Tapkın et-al,"Estimation of concrete compressive strength by using Ultrasonic Pulse Velocities and Artificial Neural Networks".

10. S. J. S. Hakim and et-al, **"**Application of artificial neural networks to predict compressive strength of high strength concrete", *International Journal of the Physical Sciences*, **6(5)**,975-981, 4 March, 2011.