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A PATH FOR HORIZING YOUR INNOVATIVE WORK

USE OF ARTIFICIAL NEURAL NETWORK TO IDENTIFYCOMPRESSIVE STRENGTH OF CONCRETE

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Abstract

The strength of concrete determined in situ never be same to cube strength determined in the laboratory. Also the results of non-destructive tests (NDTs), are predicted not an 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 NDT results, data are required. From the number of non-destructive tests Rebound hammer test is generally used to determine compressive strength of existing concrete structures. By Rebound hammer test surface hardness is measured and widely used for predicting compressive strength concrete and it has the advantage of being economical, fast and non destructive. For the prediction of strength, the regression analysis is widely used for determining the correlation curve between rebound number and compressive strength of concrete but it is not suitable in all the situations. In this study Artificial Neural Network is presented for making correlation between DT & NDT to predict the compressive strength of unknown mix. From the study it is clearly observed that artificial neural network predicts the compressive strength very closed to actual compressive strength of cube samples and the suggested model of ANN can be use in general for purpose of predicting the strength of concrete.

INTRODUCTION

Most of the NDT equipments do not measure directly the properties of concrete. In order to determine these properties, the manufacturer of test equipment provides a calibration chart relating the readings to the desired properties. These charts do not appear to be satisfactory because their development is based on the use of certain types and sizes of aggregates, test specimens, and test conditions. The relationship between strength and non-destructive test readings is not unique, and is affected by many factors such as aggregate size, type, and content; cement type and content; water-cement ratio; and moisture conditions. Users must prepare their own calibration charts that are adapted to their situation.

For estimating strength in hardened concrete, a pre-establish calibration chart is done by casting specimens (cylinders or cubes) covering the strength range to be encountered on the job site under laboratory conditions similar as much as possible to the site conditions, submit them to the non-destructive test before doing a core testing. The specimens are made for the particular type of concrete under investigation and the curing period must be the same as the specified control age in the field. The least-squares curve fitting is used to establish the correct form of the relation between the test readings and the concrete strength.

In most of the case, the investigation to assess the strength is done when there is no data of the construction, or when the cylinder strength test result fails, or the quality of concrete is doubtful. In these instances, the common method of determining the strength, when a sufficient number of cores cannot be drilled due to lack of money or other problems, is by establishing a correlation between drilled cores and non-destructive test readings. Non-destructive readings are taken in the location of the cores before their extractions and testing. The correlation curve is then fitted by the least-squares method. The validity of the correlation curve is assessed by the correlation coefficient. The higher is the correlation coefficient the more satisfactory is the correlation curve.

For the determination of strength, the regression analysis for determining the correlation curve 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. In this study Artificial Neural Network is presented for making correlation between DT & NDT to predict the compressive strength of unknown mix.

In previous studies, many approaches were presented by considering the compressive strength and UPV relationship of concrete samples. Hisham Y. Qasrawi presented that ANNs has strong potential as a feasible tool for predicting the compressive strength of concrete. Serkan Tapkın et-al proposed a neural network approach for the evaluation of concrete compressive strength by the use of ultrasonic pulse velocity values and some other factors. The neural network toolbox of MATLAB has been utilized in order to estimate the compressive strength of concrete specimens. MürselErdalcompare regression equations and an artificial neural network (ANN) developed for the estimation of compressive strength of vacuum processed concrete. Manish A. Kewalramani, Rajiv Gupta discuses for prediction of compressive strength of concrete based on weight and UPV for two different concrete mixtures. The prediction is done using multiple regression analysis and artificial neural depicts that artificial neural networks can be used to predict the compressive strength of concrete more effectively. J. Noorzaeifocuses on development of Artificial Neural Networks (ANNs) in prediction of compressive strength of concrete after 28 days. A. Lorenzi[6] focused on the evaluation of the feasibility of developing a specialist ANN tool to find concrete strength using ultra pulse velocity test. Using a neural model, the estimation power of the neural network is better than using traditional modeling techniques, such as regression analysis. Jerzy Hola, Krzysztof Schabowiczpresent

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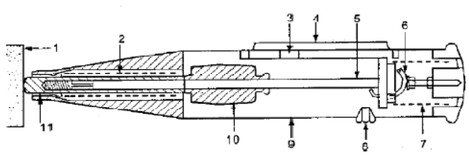
new technique of nondestructively assessing the compression strength of concrete, which employs artificial neural networks. All this study was made either on cylindrical core taken from structure or on a cube of known mix data, therefore it cannot generalize. In this study 216 cube samples have been taken of unknown mix and of different age.

Rebound Hammer (Schmidt Hammer)

This is a simple, handy tool, which can be used to provide a convenient and rapid indication of the compressive strength of concrete. It consists of a spring controlled mass that slides on a plunger within a tubular housing. The schematic diagram showing various parts of a rebound hammer is given as Fig 1



1. Concrete surface

5. Hammer guide

9. Housing

2. Impact spring

6. Release catch

10. Hammer mass

3. Rider on guide rod

7. Compressive spring

11. Plunger

4. Window and scale

8. Locking button

Fig.1 Components of a Rebound Hammer

The rebound hammer method could be used for –

(a) Assessing the likely compressive strength of concrete with the help of suitable co-relations between rebound index and compressive strength.

(b) Assessing the uniformity of concrete

(c) Assessing the quality of concrete in relation to standard requirements.

(d) Assessing the quality of one element of concrete in relation to another.

This method can be used with greater confidence for differentiating between the questionable and acceptable parts of a structure or for relative comparison between two different structures.

The test is classified as a hardness test and is based on the principle that the rebound of an elastic mass depends on the hardness of the surface against which the mass impinges. The energy absorbed by the concrete is related to its strength. Despite its apparent simplicity, the rebound hammer test involves complex problems of impact and the associated stress-wave propagation.

There is no unique relation between hardness and strength of concrete but experimental data relationships can be obtained from a given concrete. However, this relationship is dependent upon factors affecting the concrete surface such as degree of saturation, carbonation, temperature, surface preparation and location, and type of surface finish. The result is also affected by type of aggregate, mix proportions, hammer type, and hammer inclination. Areas exhibiting honeycombing, scaling, rough texture, or high porosity must be avoided. Concrete must be approximately of the same age, moisture conditions and same degree of carbonation (note that carbonated surfaces yield higher rebound values). It is clear then that the rebound number reflects only the surface of concrete. The results obtained are only representative of the outer concrete layer with a thickness of 30–50 mm.

Experimentation:

A total of 216 concrete cube samples of size 150 x 150 x 150 mm of unknown mix and of different age 28 to 365 days are tested for the determination of the Rebound Number (R), before the execution of destructive Compressive strength(fc). The values of the Rebound Number are observed to be lying within 10 to 40 and the concrete cube compressive strengths varied between 2.23 MPa and 39.98 MPa. Data used for analysis normalized before used by applying procedure of MATLAB (R2011a). The following results have been obtained by interpretation of NDT and DT using 'cftool' of MATLAB (R2011a) software.

Correlation between Compressive Strength and Rebound Number by Regression:

For establishing correlation plot has been generated taking Rebound Number(R) on X-axis and Compressive strength (fc) on Y-axis. Results of different linear and nonlinear models are tabulated in Table 3.1 and it is observed that the correlation between Rebound no. and compressive strength is not linear. Comparing their goodness of fit best correlation has been found out. Best fit results are shown in Fig 2. It is observed that 94.9% of readings lies on the regression line and5.1% data remains residual could not be explained by this correlation, MSE observed to be very low.

$$f_c = -1.757 * 10^4 R^4 + 2740 R^3 - 106.8 R^2 + 0.7203 R + 0.02661 \quad \text{Eqn. 3.1}$$

Where,

f_c = Compressive Strength of concrete(MPa)

R = Rebound Number

Regression constants are with 95% confidence bound

Goodness of fit:

R = 0.949 & MSE = 0.00005

Table No. 3.1 Different correlations of RN & Compressive strength

Polynomial	Correlation	R	MSE
Linear	1.616 R-0.04368	0.932	0.000065
Quadratic	$5.675R^2 + 0.964R - 0.02639$	0.934	0.000064
Cubic	$-1090R^3 + 192.1R^2 - 9.084R + 0.1396$	0.947	0.00005
4th Degree	$-17570 R^4 + 2740 R^3 - 106.8 R^2 + 0.7203 R + 0.02661$	0.949	0.00005

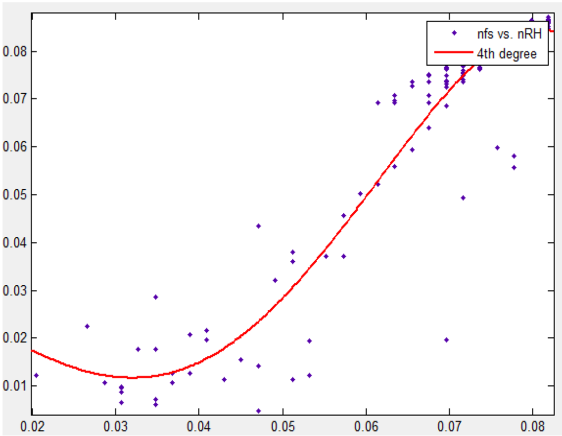


Fig. 2 Plot RH versus f_c generated by 'cftool

Artificial Neural Network Technique:

An Artificial Neural Network is created by preparing Guide User Interface (GUI) in MATLAB (R2011a) to solve a data fitting problem. In this study a two-layer feed-forward LM network is employed to determine compressive strength of concrete using non-destructive test results.

a) Selection of Neural Network:

The problem can be defined as a nonlinear input-output relation among the factors UPV, and compressive strength of concrete values for ANN analyses. The typical multi-layer feed-forward ANNs consist of an input layer, one hidden layer and an output layer. For selecting the network here Ultra-pulse Velocity & the compressive strength of concrete cube samples are considered. This type of ANNs is used in the current application.

On the basis of a review of the literature the following feed forward error back propagation networks are considered for the study-

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

It should be noted that each of the above networks was trained & tested for all the samples to find out the best one for the task. 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. The training phase is stopped when the variation of error became sufficiently small.

The networks are then tested and the results are compared by means of Mean Squared Error (MSE) and coefficient of determination(R). Optimum elements of different network architecture are shown in Table 3.2 and Fig.3

Table 3.2. Optimum elements of different network architecture

Sr.No.	Short Name of Neural Network	Neurons in Hidden Layer	Learn-ing Rate	Number of epochs	Mean Sq. Error	R
1	GDM	20	0.1	134	3.79E -4	0.95
2	GDA	40	0.2	252	4.95E -4	0.999
3	LM	10	0.02	1	5.99E -5	0.968

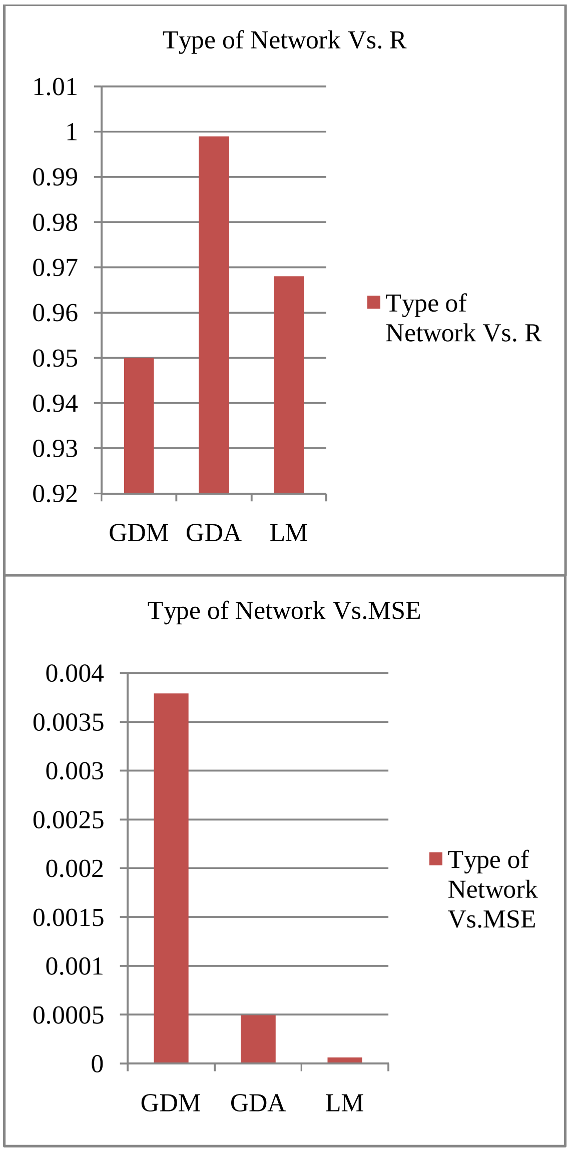


Fig.3 The values of R and MSE for different network architecture

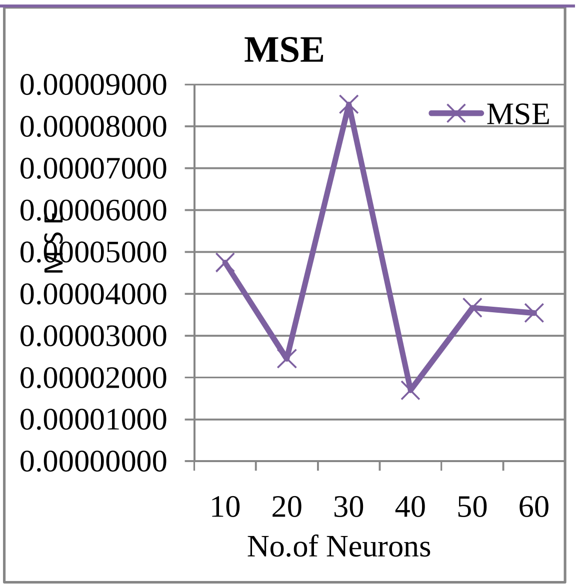
Finally the Levenberg-Marquardt network (LM) is selected on the basis low training and testing MSE value as well as high correlation coefficient R with low learning rate for the detail study. The obtained result is tabulated in the table 3.2.

b) Correlation between Compressive Strength and Rebound Number by LM Neural Network:

After carrying out number of trainings in the neural network simulation, the optimum hidden neuron number and hidden layer number are determined as 20 and 1, respectively and 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 and activation functions as tangent sigmoid. By considering the smallest MSE(2.4526E-5) and the highest R(0.97706) values. The analyst had the optimum flexibility to be able to determine the number of hidden neuron numbers, on a MSE basis. Table 3.3& 3.4 shows the performance of the LM network for different hidden neuron numbers.

Table 3.3: The performance of LM network architecture for different neurons in hidden layer

No. of Neurons	Learning rate	No. of epochs	MSE	R
10	0.04	1000	4.7495E-5	0.97515
20	0.04	1000	2.4526E-5	0.97706
30	0.04	1000	8.52910E-5	0.97538
40	0.04	1000	1.6979E-5	0.97366
50	0.04	1000	3.6715E-5	0.96421
60	0.04	1000	3.5441E-5	0.97185



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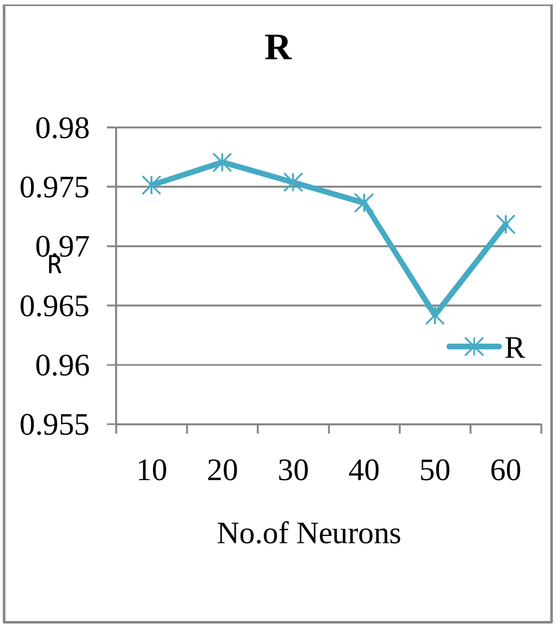
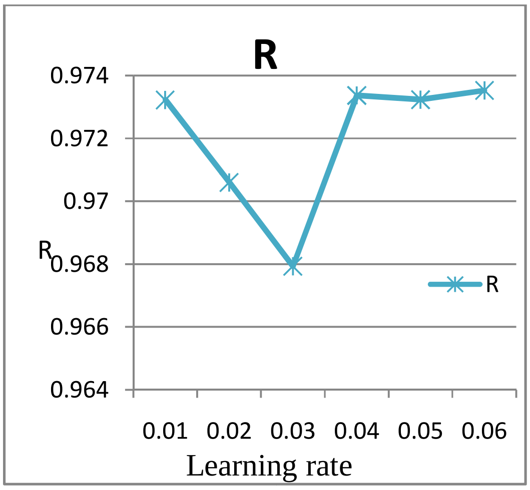


Fig 4: The performance of network architecture for different neurons in hidden layer

After finding number neuron, trials are again taken to found optimistic learning rate. It is founds that at 0.02 learning network shows best performance and is shown in table 3.3. From the Fig. 4 it can be seen that the MSE is smallest (7.89E-5) and the R also highest (0.9706). These values are obtained for 20 neurons in hidden layer.

Table 3.4 : The performance of LM network architecture for different learning rate

No. of Neurons	Learning rate	No. of epochs	MSE	R
20	0.01	1000	8.6897E-5	0.97323
20	0.02	1000	7.890E-5	0.9706
20	0.03	1000	8.2897E-5	0.96793
20	0.04	1000	1.3529E-5	0.97337
20	0.05	1000	2.2215E-5	0.97324
20	0.06	1000	4.1128E-5	0.97353



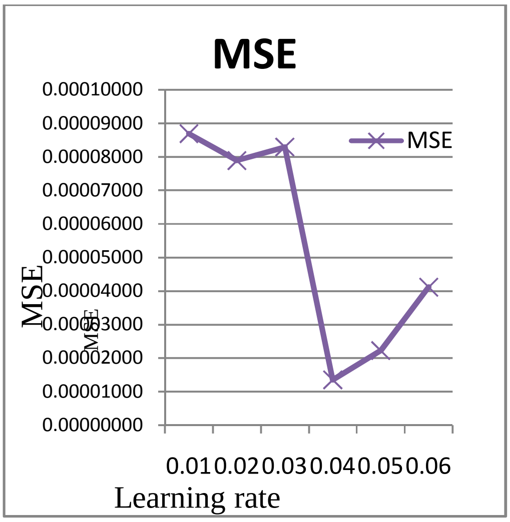


Fig5: The performance of network architecture for different learning rate

The graph of best validation performance is shown in fig 3.5. It is observed that MSE decreases rapidly within 1st epoch and stabilized at 7.89 E-5 after 3 epochs. This trained network gives prediction of compressive strength of concrete samples very close to actual values, it is given in Appendix. Other graph shows regression in target(actual) and output(predicted) values and it is observed that 97.061% of readings lies on the regression line and 2.939% data remains residual could not be explained by this correlation.

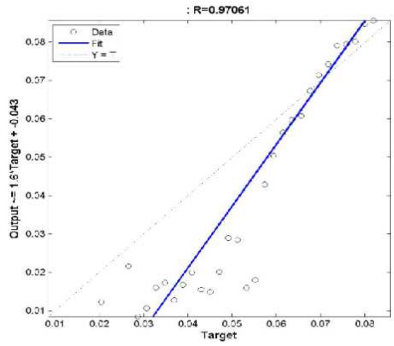
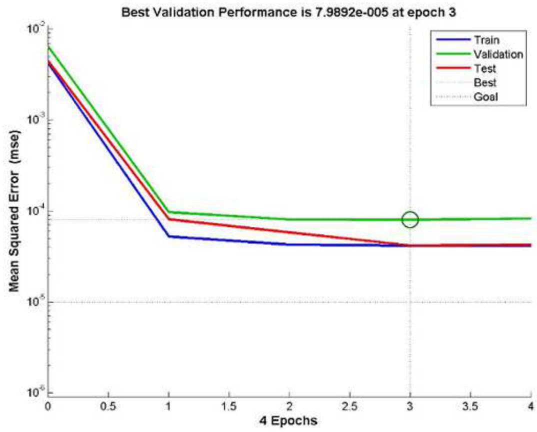


Fig.3.5: The performance of Levenberg-Marquardt (LM) network for Rebound Number & Compressive strength of concrete



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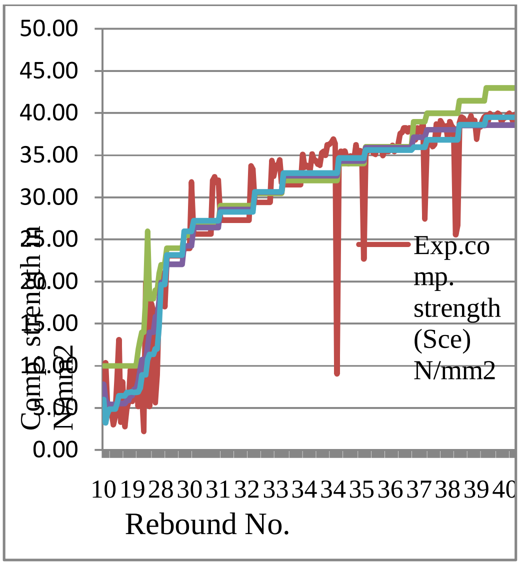

Fig 3.6: Predicted compressive strengths by Manufacturers chart, Regression, ANN for a cube samples

Compressive strengths Predicted by Manufacturers chart, Regression, ANN for a cube samples is shown in Fig 3.6. From the graph it is clearly observed that artificial neural network gives the compressive strength very closed to actual compressive strength of cube samples.

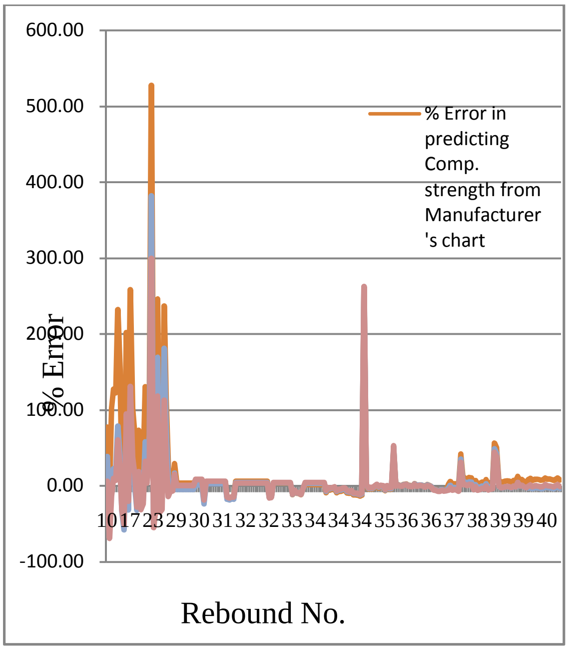

Fig 3.7: % Error in Predicted compressive strengths by Manufacturers chart, Regression, ANN for a cube samples.

Table 6: Average % Error in predicting compressive strengths

Average % Error for		
Manufacturer's chart	Regression Analysis	Artificial Neural Network
17.8	5.62	4.12

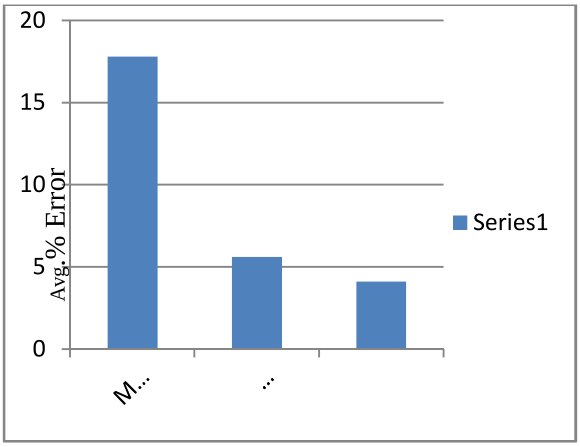

Fig 3.8: Comparative graph of % Error in Predicted compressive strengths by Manufacturers chart, Regression, ANN for a cube samples

Fig 3.8 shows graph of % Error in Predicted compressive strengths by Manufacturers chart, Regression, ANN for a cube samples and values are given in table 6, implies that the accuracy of Manufacturers chart for prediction for compressive strength of cube samples is only 82.2% where as by ANN results shows improvement in prediction up to 95.88%. As the Manufacturers chart was prepared empirical relationships for their own testing system and conditions. Such relationships are not suitable for every kind of concrete. The sudden rise & falls indicates manual or instrumental errors in taking the readings. Up to the Rebound number 25 result quality is very poor for all the techniques.

1. Conclusions:

Simulation is a widely accepted tool in systems design and analysis. Because its basic concepts are easily understood, it has become a powerful decision-making instrument. The estimation power of an ANN is quite significant. The results have shown that an ANN is capable of modeling the relationship strength vs. rebound number. The precision of the estimates will depend on the quality of the information used to train the network. Increasing the number of neurons can also help to improve the model. However, when the size of the net grows or when the error criterion is tightened, the computational time needed to produce a result quickly increases. In short, the simulations carried out, using real data from Rebound Hammertests performed on concrete, demonstrated that ANN can be very useful tools for interpreting the results of NDT. It is possible to create flexible and non-linear models that have better adherence to experimental data than traditional models.

Moreover, it is possible to acquire and store knowledge in a dynamic configuration, creating models that can be constantly updated for different situations.

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