International Journal of Engineering and Technical Research (IJETR)
ISSN: 2321-0869, Volume-3, Issue-5, May 2015

Analytical Study on Flexural Strength of Reactive Powder Concrete

Jagannathasn Saravanan, S.Sathiyapriya

Abstract— **The Flexural strength of Reactive powder concrete specimens is done routinely; it is performed on the 28th day after concrete placement. Therefore, strength estimation of concrete at early time is highly desirable. This study presents the effort in applying neural network-based system identification techniques to predict the flexural strength of Reactive Powder Concrete based on concrete mix proportions. Back-propagation neural networks model is successively developed, trained and tested using actual data sets of concrete mix proportions gathered from literature. The test of the model by un-used data within the range of input parameters shows that the maximum absolute error for model is about 20% and 88% of the output results has absolute errors less than 10%. The parametric study shows that water/cement ratio (w/c) is the most significant factor affecting the output of the model. The results showed that neural networks have strong potential as a feasible tool for predicting flexural strength of RPC concrete.**

Index Terms— **Artificial Neural Network, Flexural strength, Reactive Powder Concrete, predicts.**

I. INTRODUCTION

Reactive Powder concrete is a new generation concrete with Ultra-high performance**"**. RPC is a relatively new cementinious material. It is main features include a high percentage ingredient of Portland cement, very low water-to-binder (cement + silica fume) ratio which ranges from 0.15 to 0.25, a high dosage of super plasticizer, and the presence of very fine crushed quartz, GGBS, Fly ash and silica fume. **RPC**, represents one of the most recent technological leaps witnessed by the construction industry. Among already built outstanding structures, **RPC** structures lie at the forefront in terms of innovation, aesthetics and structural efficiency. The unique properties for **RPC**, make it extremely attractive for structural application. **RPC** is an ultra-high-strength, low porosity cement-based composite with high ductility. Unlike conventional concrete, **RPC** containing a significant quantity of steel fibers exhibits high ductility and energy absorption characteristics.

RPC is composed of particles with similar elastic module and is graded for dense compaction, thereby reducing the differential tensile strain and enormously increasing the ultimate load carrying capacity of the material. Interest in ultra-high-strength cement-based materials is not solely because of their increased strength. They possess other high-performance properties, such as low permeability, limited shrinkage, increased corrosion and abrasion resistance, and increased durability**.**

Jagannathasn Saravanan, Assistana Professor, Annamalai university, Annamalainagar, India.608002.

S.Sathiyapriya, Thesis student, Annamalai University, Annamalainagar, India.608002**.**

Many researchers have been carried out studies on RPC in the past years to assess the properties and its behavior. Some of the reports have been presented in this chapter, which are used as guidance for this thesis. Review of papers has been conducted on the mix proportion, mechanical and durability properties of Reactive Powder Concrete (RPC).

J.Dugat,G.Bernier (1996) comparative study of obtain the flexural strength for ordinary concrete, high strength concrete, Reactive powder concrete. In RPC use different ratios of material composition as two mix proportions RPC200 and RPC800. In RPC200 without quartz sand and steel fiber mix, RPC800 without steel fiber . The ratio results compare the ordinary concrete and high strength concrete.

Y.Konishi & M.Numata(2002) Developed on the serviceability limit state of under without cracking on the reinforced concrete beam. A part of the tension zone in the reinforced concrete beam was fortified with Reactive Powder Composite (RPC). Flexural load tests on the beam were carried out in this study. The cracking moment of the beam reinforced with RPC could be estimated by the elastic theory, provided that the stress due to the restraint of reinforcing bar against the autogenously shrinkage of RPC must be taken into consideration. After the generation of cracking, RPC has little effect on the deformation of beam reinforced with RPC due to the Increase of bending moment. However, the flexural capacity of beam fortified with RPC is larger than that of the reinforced concrete beam without RPC and increases with the increase in the reinforced area of RPC.

Mahesh K Maroliya, Chetan D Modhera(2010) investigated on compressive strength and flexural strength of plain Reactive Powder Concrete (RPC) and RPC reinforced with corrugated steel fiber and recron 3s Fibers are compared. Composition of RPC using different ingredient with a water cement ratio of 0.22. Corrugated steel fiber are used 0.4 mm dia. And 13mm long and recron 3s fiber of triangular shape and 12 mm length are incorporated in the concrete.

M K Maroliya(2012) studied the economic cost of loss of durability in major concrete structure including the cost over the service life of maintenance and repair. It introduces the concept that the direct and indirect cost of impeded access for repair and of interruptions to services must also be recognized. (UHPRPC) can be examined in regards to its cost Effectiveness and sustainability. The intention to provide a qualitative statement on the behavior of normal and high strength concrete serves as a comparison The relevant Economic advantages of the (UHPRPC) is obvious regarding the life cycle which exceeds the construction process of a building.

Mohamed A. Arabb, **Nageh N. Melekaa**(**2013**)

Investigated an ultra high strength concrete (UHSC) cast using economical materials. Its mechanical properties were investigated and evaluated by studying the effects of using different cement and silica fume contents and new steel fibers' aspect ratios as reinforcement for this concrete. A flexural strength of 30MPa have been achieved for reinforced RPC contains 800 kg/m3 cement content and silica fume content 30% of cement weight. The test results showed adequate improvements by increasing cement and silica fume contents as well as adding steel fibers on the compressive strength, modulus of elasticity and indirect tensile strength. It showed also a great positive effect on the flexural strength.

Alaa A.Bashandy(2013)

Investigated on the effects of elevated temperatures of 200, 300, 500°C for 2 and 4 hours on the main mechanical properties of economical type of reactive powder concrete (RPC). The main variables in this study are cement content and steel fibers content in reactive powder concrete samples as well as elevated temperature and heating time. Compressive strength and Flexural strength of RPC are obtained after exposure to elevated temperatures. It is found that, RPC can be use at elevated temperature up to 300°C for heating times up to 4 hours taking into consideration the loss of strength. Also, using steel fibers enhance the residual strength of high cement content RPC samples.

Mohamed A.Arab, Nageh N. Melekaa, Alaa A. Bashandy, (2013)

studied the effects of using different cement and silica fume contents and new steel fibers aspect ratios as reinforcement for RPC. The flexural strength of 30.26MPa have been achieved for reinforced RPC contains 800 kg/m3 cement content and silica fume content 30% of cement weight. The test results showed some improvements by increasing cement and silica fume contents as well as adding steel fibers on the compressive strength, modulus of elasticity and indirect tensile strength.

Ali Haghighi, Mohammad Reza Koohkan, Mohammad Shekarchizadeh,(2007)

Studied the effect of super plasticizer amount, water/cement ratio, the cement, silica fume and steel micro fiber content is studied on the ultimate strength of new generation of Ultra High Strength Concrete (UHSC).Known as Reactive Powder Concrete (RPC) and also have used two non-linear functions; Genetic Programming (GP) and Group Method of Data Handling (GMDH), which are two methods in soft computing family. Testing more than 28 different mix propotions and the result shows that GMDH is much exacter than the other methods. Finally sensitivity analysis has been showed the shares of each used parameters in the best model.

A .Serkan Suba(2009) investigate the estimation ability of the effects of utilizing different amount of the class C fly ash on the mechanical properties of cement using artificial neural network and regression methods. Experimental results were used in the estimation methods. Fly ash content (%), age of specimen (day) and unit weight (g/cm³) was used as input parameters and flexural tensile and compressive strengths (N/mm²) were used as output parameters.

The present study developed models and the experimental results were compared in the testing data set.

N. Pannirselvam et al, V. Nagaradjane, K. Chandramouli (2010)

Investigation included yield load, ultimate load, yield deflection, ultimate deflection, maximum crack width, deflection ductility and energy ductility. Artificial Neural Network model was generated to predict the performance characteristics taking percentage of steel reinforcement, thickness of glass fiber reinforced polymer and the type of fiber used in glass fiber reinforced polymer as parameters.

II. DESGN ON ANN MODEL

2.1 Data Collection

Using this program, a neural network model with one hidden layers is constructed, trained, and tested using the available test data of 30 different sets gathered from the technical literature**.** The data used in ANN model are arranged in a format of nine input parameters that cover the cement content, fine aggregate content, silica fume content, water cement ratio, Quartz sand, GGBS, Fly Ash, super plasticizer and steel fiber . The proposed ANN model predicts the 28th day Flexural strength of concrete.

2.2 Neural network modeling background

A number of papers on the application of neural networks in civil and structural engineering revealed that a multilayer feed-forward neural network model is the most widely used network for its efficient generalization capabilities**.** Fig 3.2 presents typical multi-layer feed-forward neural networks used in the current application. This type of Neural Network consists of an input layer, one or more hidden layer(s) and an output layer. Layers are fully connected, as shown on Fig 3.2 by arrows, and comprises number of processing units, the so-called nodes or neurons. The strength of connections between neurons is represented by numerical values called weights. Each neuron has an activation value that is a function of the sum of inputs received from other neurons through the weighted connection. The hidden layers link the input layer to the output layer, extract and remember useful features from the input data to predict the output of the network. The optimum number of hidden layers and the number of neurons in each hidden layer is specific problem. Therefore, trial and error procedure should be carried out to choose an adequate number of hidden layers and the number of neurons in each hidden layer**.**

The Fig. 1 present this chapter an step procedure on ANN model is expressed as,

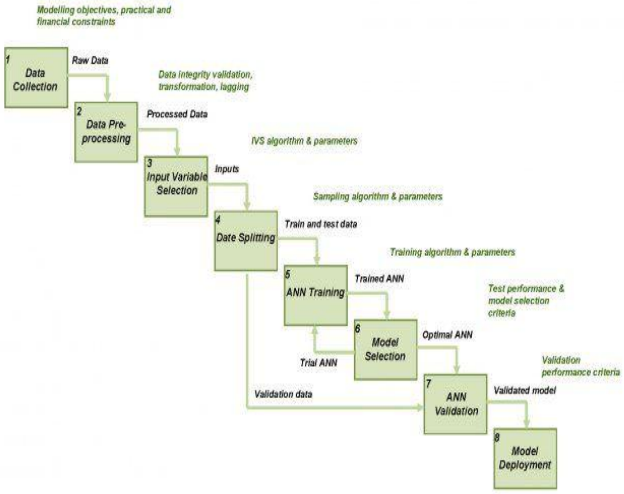

Fig .1 Schematic Representation of Step Procedure on ANN

2.3 Train and Test Data

Training consists of exposing the neural network to a set of known input–output patterns. The data are passed through the multi-layered feed forward neural network in a forward direction only. As the data moves forward, it is subjected to simple processing within the neuron and along the links connecting neurons. The network performs successive iterations to adjust the weights of each neuron in order to obtain the target outputs according to a specific level of accuracy. The adjusting process of neuron weights is carried out to minimize, to a certain level the network error which is defined as a measure of the differences between the computed and target output patterns. After the NN is satisfactorily trained and tested, it is able to generalize rules and will be able to deal with unseen input data to predict output within the domain covered by the training patterns.

2.4 ANN Training:

In this work 30 sets of 28th day concrete strength data are extracted from Experimental tests gathered from literature. The range of Flexural strength of samples is 24.6 to 23.22 MPa, while those of input data are shown in Table (1). To train the ANN models, first, the entire training data file is randomly divided into training and testing data sets. 30 sets, are used to train the different network architectures and they are used for testing to verify the prediction ability of each trained ANN model. Different training functions available in MATLAB are experimented for the current application. The scaled conjugate gradient (SCG) techniques built in MATLAB proved to be efficient training function, and therefore, is used to construct the NN model. This training function is one of the conjugate gradient algorithms that start training by searching in the steepest descent direction (negative of the gradient) on the first iteration. The network architecture or topology is obtained by identifying the number of hidden layers and the number of neurons in each hidden layer. There is no specific rule to determine the number of hidden layers or the number of neurons in each hidden layer. The network learns by comparing its output for each pattern with a target output for that pattern, then calculating the error and propagating an error function backward through the neural network. To use the trained neural network, new values for the input parameters are presented to the network. The network then calculates the neuron outputs using the existing weight values developed in the training process.

2.5 Validation Performance:

After testing and training level give the validation performance for input and output parameters. The multi-layer feed forward back propagation technique is implemented to develop and train the neural network of the current study where the sigmoid transform functions are adopted. The validation performance should be show on given graph plotation. The term "ANN prediction" is reserved for ANN response for cases that are not used in the pre-training stages. This is used in order to examine the ANN's ability to associate and generalize a true physical response that has not been previously "seen". A good prediction for these cases is the ultimate verification test for the ANN models. These tests have to be applied for input and output response within the domain of training. It should be expected that ANN would produce poor results for data that are outside the training domain. Preprocessing of data by scaling is carried out to improve the training of the neural network.

2.6 Correlation Coefficient (r):

The correlation coefficient, R, measures the degree of linear association between the target and the realized outcome and it is a measure to know how far the trends in forecasted values follow those in actual observed values and it is a number between 0 to 1. Higher the correlation coefficient better is the model fit.

The following formula was used to find the correlation coefficient (r):

$$r = \frac{\sum_{i=1}^{n}(x_i)(y_i)}{\sqrt{\sum_{i=1}^{n}(x_i^2)\sum_{i=1}^{n}(y_i^2)}} \qquad \text{(i)}$$

Where,

$x_i = (X_i - \overline{X})$; $y_i = (Y_i - \overline{Y})$;

Xi = i^{th} observed value, Yi = i^{th} predicted value

$\overline{X}$= mean of X, $\overline{Y}$= mean of Y,

n = number of observation of X_i and Y_i

2.7 Root Mean Square Error (RMSE)

The root mean square error is applicable to iterative algorithms and is a better measure for higher values. It offers a general representation of the errors involved in the prediction. The lower the value of RMSE, the better the fit is. The following formula is used to compute RMSE:

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}}{n} \qquad \text{(ii)}$$

2.8 Mean Absolute Error (MAE)

The mean absolute error has the advantage that it does not distinguish between the over and underestimation and does not get too much influenced by higher values. It is generally engaged in addition to RMSE to get the average error without worrying about the positive or negative sign of the difference. Lower the value of MAE the better is the forecasting performance. The following formula is used to compute MAE:

$$MAE = \sum_{i=1}^{n} \frac{|x_i - y_i|}{n} \qquad \text{(iii)}$$

III. INPUT AND OUTPUT PARAMETERS

The input data were collected from several researchers and the values are presented in Table 1.

Table.1. Input Data

S.No	Cement	Silica Fume	GGBS	Fly Ash	Quartz Sand	Fine Aggregat e	Steel Fiber	Super plasticizer	W/C
1	1	0.32	0	0	0.36	1.5	0.02	0.03	0.22
2	1	0	0	0	0	1.76	0.06	0.1	0.18
3	1	0.15	0	0	0	1.76	0.06	0.1	0.18
4	1	0.3	0	0	0	1.76	0.06	0.1	0.18
5	1	0	0	0	0	1.64	0.05	0.1	0.18
6	1	0.15	0	0	0	1.64	0.05	0.1	0.18
7	1	0.3	0	0	0	1.64	0.05	0.1	0.18
8	1	0	0	0	0	1.54	0.05	0.1	0.18
9	1	0.15	0	0	0	1.54	0.05	0.1	0.18
10	1	0.3	0	0	0	1.54	0.05	0.1	0.18
11	1	0	0	0	0	1.76	0.06	0.1	0.18
12	1	0.15	0	0	0	1.76	0	0.1	0.18
13	1	0.3	0	0	0	1.76	0	0.1	0.18
14	1	0	0	0	0	1.64	0	0.1	0.18
15	1	0.15	0	0	0	1.64	0	0.1	0.18
16	1	0.3	0	0	0	1.64	0	0.1	0.18
17	1	0	0	0	0	1.54	0	0.1	0.18
18	1	0.15	0	0	0	1.54	0	0.1	0.18
19	1	0.3	0	0	0	1.54	0	0.1	0.18
20	1	0.3	0	0	0.35	1.5	0	0.03	0.2
21	1	0.3	0	0	0.35	1.5	0	0.03	0.22
22	1	0.3	0	0	0.35	1.5	0	0.03	0.23
23	1	0.18	0.29	0	0	1.47	0	0.03	0.22
24	1	0.18	0.29	0	0	1.47	0.05	0.03	0.22
25	1	0.25	0	0	0	1.25	0	0.03	0.16
26	1	0.25	0	0.25	0	1.5	0.1	0.05	0.18
27	1	0.25	0	0	0	1.25	0.17	0.03	0.16
28	1	0.33	0	0.67	0	2	0.27	0.05	0.25
29	1	0.32	0	0	0	1.5	0	0.032	0.2
30	1	0.32	0	0	0.36	1.5	0.2	0.035	0.22

IV. RESULTS AND DISCUSSION

The experimental results i.e. Flexural strength of Reactive powder concrete Table1 And the results predicted by the neural network, are given in Table 2. A comparison of the experimental results and the neural network results show that the maximum error percentage difference is 7.329, which is negligible. From Figs.2 – 7, it will also be seen that there is a close agreement between the experimental results and the neural network result.

Table 2 Comparison of Experimental and Predicted Results

S.No	Experimental Flexural strength (MPa)	Predicted Flexural strength (MPa)	Error %
1	24.6	24.82	-0.223
2	13.89	13.45	0.44
3	17.99	19.16	-1.169
4	24.51	22.93	1.575
5	17.64	15.59	2.053
6	21.05	21.61	-0.562
7	27.61	24.3	3.314

8	19.98	19.44	0.537
9	23.22	24.66	-1.438
10	30.26	26.23	4.034
11	6.12	13.45	-7.329
12	7.5	7.91	-0.41
13	9.49	10.08	-0.593
14	7.48	8.18	-0.698
15	9.85	10.11	-0.264
16	13.31	13.46	-0.145
17	8.95	9.75	-0.8
18	10.88	13.4	-2.524
19	14.73	16.93	-2.201
20	18	22.56	-4.56
21	27.5	23.78	3.719
22	22	24.24	-2.243
23	27.5	19.88	2.821
24	23.3	24.45	-1.148
25	26.9	27.29	-0.396
26	27.6	29.18	-1.579
27	29.2	30.19	-0.986
28	28.5	28.52	-0.015
29	13.5	11.84	1.66
30	29	26.86	2.138

Figs.2 - .5 shows comparison of Experimental and predicted Flexural strength for using with steel fiber and silica fume & using without silica fume and steel fiber ratios. The results are for Reactive Powder concrete and related to the relative input method. Better predictions (less error and higher correlation between the predicted and actual results).

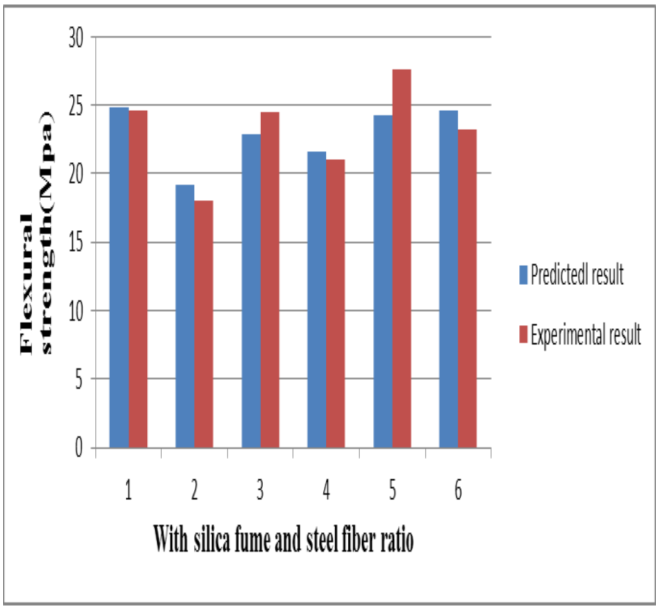

Fig.2 Comparison of Experimental and Predicted Flexural Strength for using with Silica Fume and Steel Fiber

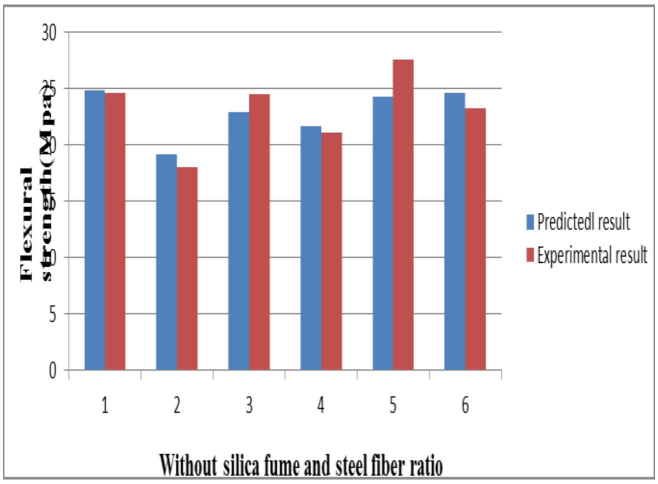

Fig.3 Comparison of Experimental and Predicted Flexural Strength for using without Silica Fume and Steel Fiber

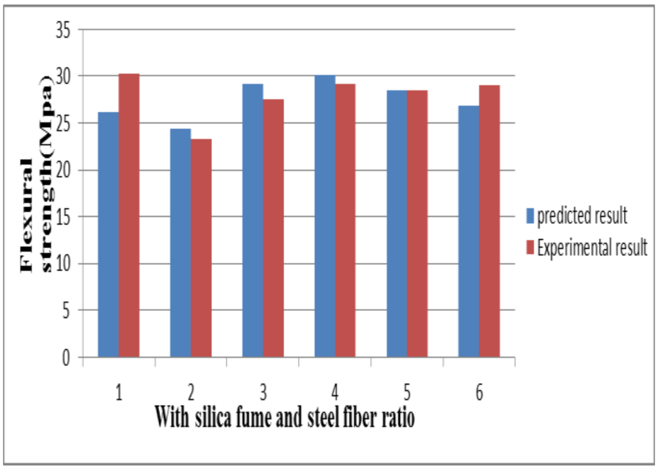

Fig.4 Comparison of Experimental and Predicted flexural strength for using with silica fume and Steel fiber

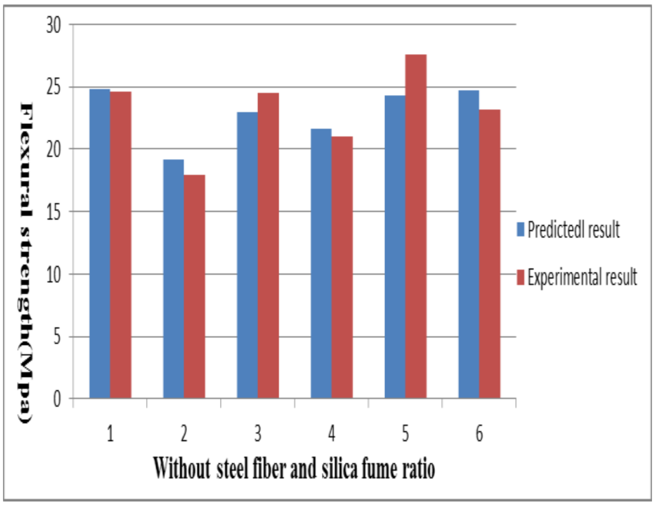

Fig.5 Comparison of Experimental and Predicted Flexural strength using without Silica Fume and Steel Fiber Ratio

Fig.6 shows Comparison of Experimental and predicted Flexural strength using with steel fiber and without silica fume maximum error percentage is 7.329 is negligible. Fig. 7 shows the Comparison of Experimental and predicted result using with silica fume without steel fiber maximum error percentage is 0.8.

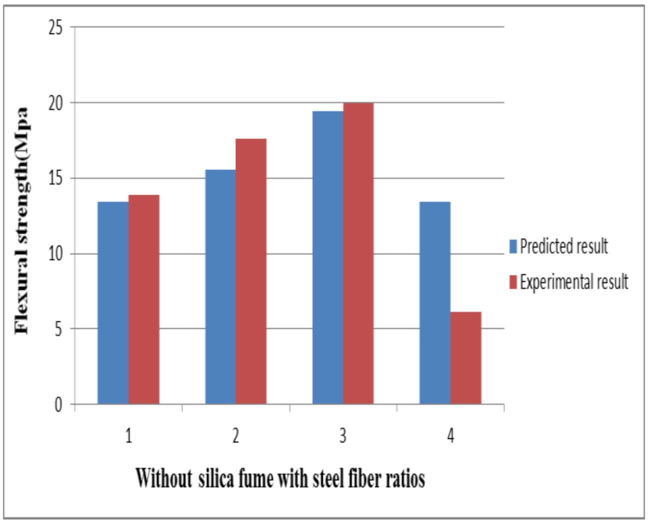

Fig.6 Comparison of Experimental and Predicted Flexural Strength using without Silica Fume And with Steel Fiber Ratio

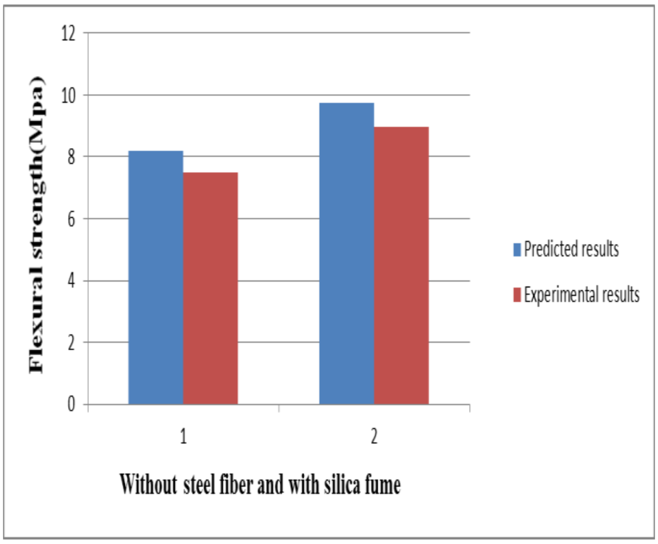

Fig. 7 Comparison of Experimental and Predicted Flexural Strength using without Steel Fiber And without Silica Fume Ratio

Table 3 presents a summary of the performance measurements achieved by the suggested ANN models for Flexural strength of Reactive Powder concrete. All results are based on cross-validation analysis. The validation set was also used in line with the training and test sets to decrease the probability of the over-fitting problem.

Table. 3 Performance results for the generated ANN model.

Data base	Input variables	No. of optimum neurons in the Hidden layer	R	RMSE
Flexural strength	C, Sand, SF, GGBS, FA, QS, Steel fiber, W/C, SP	9-3-1	0.952	0.23

Fig.8, testing strength data were plotted against predicted strength data; show that ANN model predicts the flexural strength of Reactive Powder concrete with R2 of 0.907. Fig. 9 shows that comparison of measured and predicted flexural strength. The modeling of training and testing sheets is shown in Figs.10- 13.

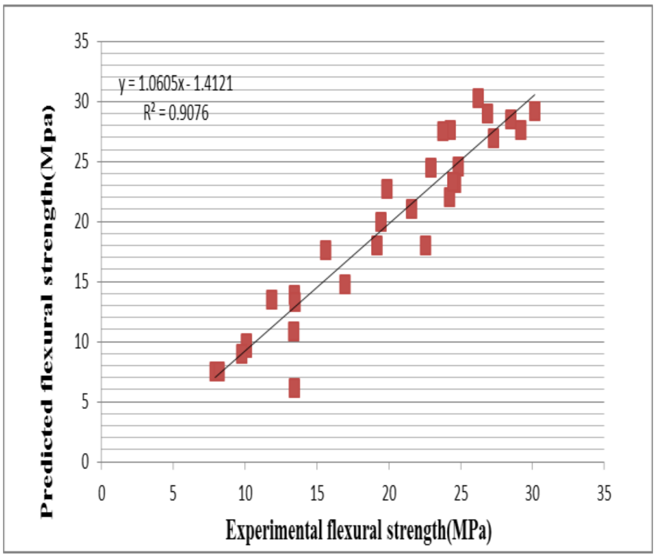

Fig.8 Correlation of the Measured and Predicted Flexural Strength in for ANN Modeling.

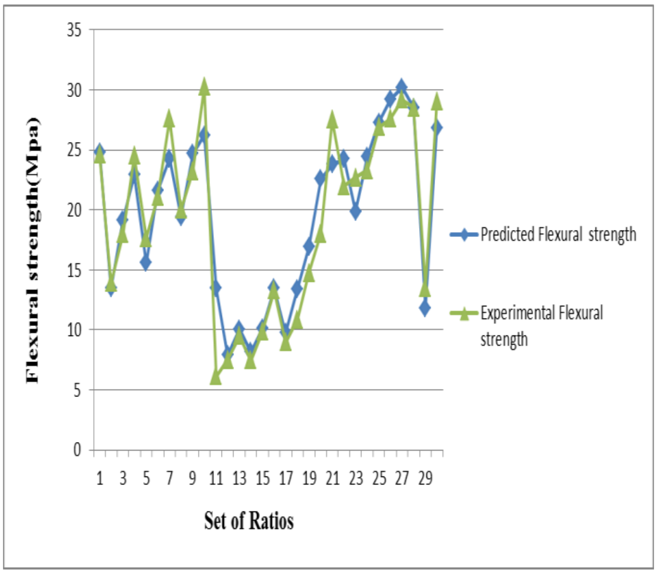

Fig. 9 Comparison of Measured and Predicted Flexural Strength

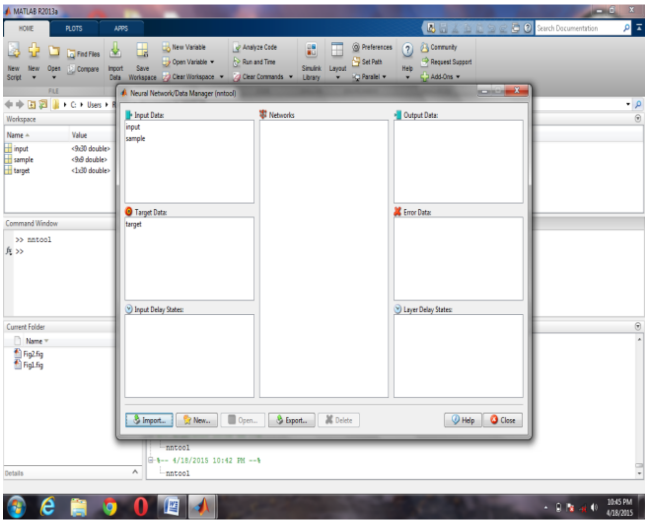

Fig. 10 Data Import from NN tool

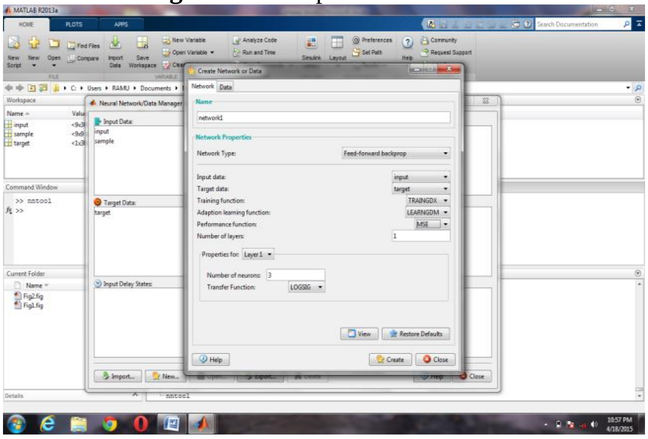

Fig. 11 Network Creation

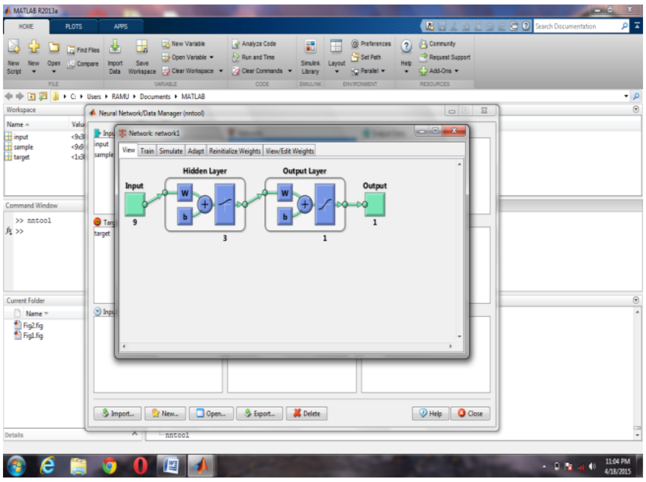

Fig 11 Neural Network Formation

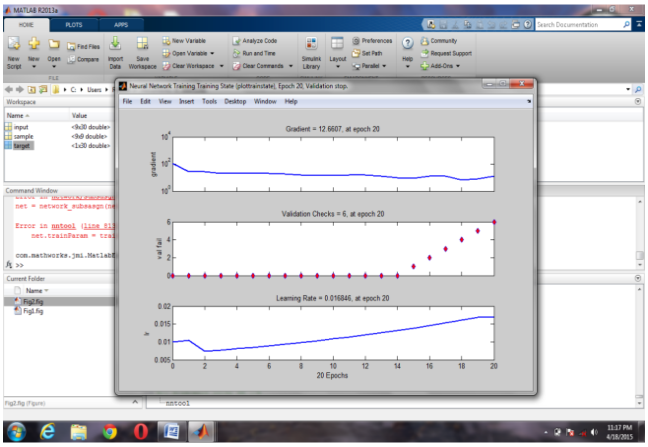

Fig 12 Neural Network Training State Performance

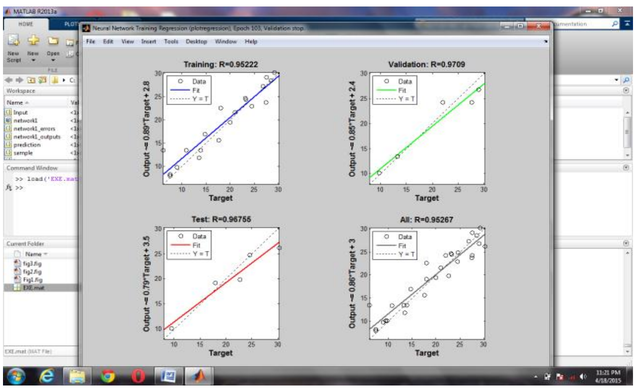

Fig. 13 Validation of network performance

V. CONCLUSIONS

In this study, the historical results of 30 samples were applied to generate an artificial neural network (ANN) to predict the Flexural strength of Reactive powder concrete. The concrete was made of different mix proportions of Cement, Silica fume, Quartz sand, GGBS, Fly ash, Steel fiber, Sand, Super plasticizer and water. The outcome of the created ANN was compared with the results of the experimental work. The selected network and its parameters were;

- ➢ The ultimate network to predict the Flexural strength of RPC concrete was the feed-forward back-propagation neural network, in which the training and transmission function were TRAINGDX and LOGSIG respectively.
- ➢ The results of the created network were close to the results of the experimental effort.
- ➢ The selected ANN can be used to predict the Modulus of Rupture of Concrete with minimum error below 8% and the maximum correlation coefficient close to 1.

REFERENCES

[1] Mahesh K Maroliya1, Chetan D Modhera **Comparative study on Reactive Powder Cocrete containing steel fibers and recron 3s fibers** *Journal of engineering research and studies.*

[2] Dr. Hisham M. Al-Hassani Asst. Prof.Dr. Jasim M. Al-Kafaji (2014)**Flexural behavior of Reactive Powder Concrete** *Journal of engineering and development*, vol 18 (2) , ISSN 1813-7822.

[3] Nageh N. Melekaa, Alaa A. Bashandya, Mohamed A. Arabb(2013) **Ultra High Strength Concrete Using Economical Materials** *International Journal of Current Engineering and Technology*, vol-3(2),ISSN 2277 - 4106 .

[4] LIU Shu-hua , LI Li-hua and FENG Jian-wen (2013) **Study on Mechanical Properties of Reactive Powder Concrete** *Journal of Civil Engineering and Construction*

[5] Nageh N. Meleka, Alaa A. Bashandy, Mohamed A. Arab(2013) **Economical Reactive Powder Concrete Cast Using Available Materials In North Sinai, Egypt ,**Archives Of Civil Engineering, Lix, 2.

[6] Dr. Maha M.S. RidhaDr.Taghreed K. Mohammad Ali Dr. Zeena W. Abbawi(2013) **Behavior of Axially Loaded Reactive Powder Concrete** *Journal of Engineering and development* , Vol. 17(2), ISSN 1813- 7822

[7] Mr. M K Maroliya (2012) **Sustainability of Ultra High strength Reactive Powder Concrete** *International Journal of Engineering Research and Development* Volume 4, Issue 4 .

[8] AamerNajimAbbas(2014) **Experimental Study On Reactive Powder And Normal Concrete Rectangular Beams Under Different Loading Rate** *International Journal of Engineering and Advance Technology Studies* Vol.2(2).