PREDICTION OF COMPRESSIVE STRENGTH OF FIBER REINFORCED CONCRETE USING ARTIFICIAL NEURAL NETWORKS

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Abstract- Fiber reinforced concrete (FRC) is a type of concrete that contains discontinuous fibers distributes randomly among the concrete block. In this paper, the Artificial Neural Networks are utilized to predict the effect of the addition of steel nails as fibers on the compressive strength of concrete. The study involves testing of cubic concrete samples with various mixing proportions and water cement ratios. The results showed that (for mixing proportion 1:1.5:3) the compressive strength has the more increasing when the fibers are added with 12%, while it has the more increasing at 20% fibers adding for mixing proportion (1:2:4). It is also found that the optimum water cement ratio is found to be 46% for the mixing proportion (1:1.5:3) with 12% fibers and 55% for mixing of (1:2:4) with fibers adding 20%. The results showed also that the increasing of the percentage of fibers added with mixing ratio (1:1.5:3) leads the compressive strength to increase more uniformly and effectively than the use of the mixing ratio (1:2:4). Also it is found that using a larger size of nails with low percent of addition will significantly increase the compressive strength with the increasing of percentage of addition the compression strength decreases.

Indexterms- Fiber Reinforced Concrete, Prediction of Compressive Strength, Neural Net Works, Reinforced Concrete

I. INTRODUCTION

Fiber reinforced concrete (FRC) is a type of concrete that contains discontinuous fibers distributes randomly among the concrete block.[1]A fiber is a small discrete reinforcing material produced from various materials like steel, plastic, glass, carbon and natural materials in various shapes and size. The fibers help to transfer load to the internal micro cracks. FRC is cement based composite material that has been developed in recent years. It has been successfully used in construction with its excellent flexural-tensile strength, resistance to spitting, impact resistance and excellent permeability and frost resistance.

It is an effective way to increase toughness, shock resistance and resistance to plastic shrinkage cracking of the mortar. These fibers have many benefits, they can improve the structural strength to reduce the heavy steel reinforcement requirement. Freeze thaw resistance, and durability of the concretecan also be improved which reduces the crack widths. The plain concrete fails suddenly when the deflection corresponding to the ultimate flexural strength is exceeded, on the other hand fiber-reinforced concrete continue to sustain considerable loads even at deflections considerably in excess of the fracture deflection of the plain concrete. Polypropylene and Nylon fibers are used to improve the impact resistance. Many developments have been made in the fiber reinforced concrete.A numerical parameter describing the fiber is its aspect ratio, which is defined as the fiber length, divided by an equivalent fiber diameter [l/d].

An Artificial Neural Network (ANN) is a computational tool that attempts to simulate the architecture and internal features of the human brain and nervous system[2]. A neural network is a non–linear system consisting of a large number of highly interconnected processing units, nodes or artificial neurons (Fig.1). Each input signal is multiplied by the associated weight value (wi) and summed at a neuron. The result is put through an activation function to generate a level of activity for the neuron. This activity is the output of the neuron. When the weight value at each link and the connection pattern are determined, the neural network is trained. This process is accomplished by learning from the training set and by applying for certain learning rule. The trained network can be used to generalize for those inputs that are not including in the training set. Comparing neural network with other digital computing techniques, neural network are advantageous because of their special features such as the possibility of non–linear modeling relationship between input and target especially for problem where the relationship aren't very well known and low sensitivity to error.

Oreta and Kawashima (2003)[3] explored the application of (ANN) to predict the confined compressive strength and corresponding strain of circular concrete columns. Using available data from past experiments, an ANN model with input parameters consisting of the unconfined compressive strength, core diameter, column height, yield strength of lateral reinforcement, volumetric ratio of lateral reinforcement, tie spacing, and longitudinal steel ratio was found to be acceptable in predicting the confined compressive strength and corresponding strain of circular concrete columns subjected to limitations in the training data. The study showed the importance of validating the ANN models in simulating physical processes especially when data were limited. The ANN model was also compared to some analytical models and was found to perform well. Ongpeng (2003) [4] used artificial neural network(ANN) modeling with Levenberg-Marquardt training algorithm to predict the confined ultimate compressive strength produced by wrapping carbon fiber reinforced polymer (CFRP) externally from circular sections reinforced with steel ties and longitudinal bars.

The interaction of both confining materials was investigated. Using collected data from other references, training, testing, and validating different architectures of ANN models from existing models were done to come up with an acceptable model. With the acceptable ANN model, interaction of both confining materials was studied. Kim, et. al (2004)[5] presented the first effort in applying neural network based system identification techniques to predict the compressive strength of concrete based on concrete mix proportions.
Backpropagation neural networks were developed, trained, and tested using actual data sets of concrete mix proportions provided by two ready-mixed concrete companies. The compressive strengths estimated by the neural networks were verified by laboratory testing results.

The results demonstrated that the neural network techniques were effective in estimating the compressive strength of concrete based on the mix proportions. Application of these techniques will contribute significantly to the concrete quality assurance. In thepresent work an attempt is made to use the artificial neural network model for the prediction of compressive strength of fiber reinforced concrete, using nails as fibers. Artificial neural network model is to be developed using MATLAB in order to study the effects of various parameters on the behavior and compressive strength of this type of concrete.

II. EXPERIMENTAL WORK

In the experimental work of this study, 48 cubic samples (150*150*150) mm were tested with 7 days and 28 days ages. The mixing proportion used were (1:1.5:3) and (1:2:4).

The water cement ratio is taken between 40% - 55%. The fibers used are nails with 1" and 1.5"size with adding ratios of 0-20% of the cement weight (Fig. 1). All the processes of the experimental work are performed in the Material Laboratory of the Civil Engineering Department-University of Basrah. The materials used in the tested sample were tested according to the Iraqi Specifications.

Fig. (1) The Nails used as Fibers

III. NEURAL NETWORKS MODELLIN

The computer program “MATLAB Neural Network Toolbox” is employed for the neural network models. The advantage of using this program is that many types of networks are included in the program and many training algorithms with different properties can be used for a specific network model. This technique will be used here to investigate the compressive strength of fiber reinforced concrete. The results of these investigations are presented and discussed to show the performance of the neural network model in solving this problem. In order to find the relationship between input parameters and output parameters a feedforward backpropagation type neural network is used. The configuration and training of neural networks is a trial–and–error process due to such undetermined parameters as the number of nodes in the hidden layer, the learning parameter, and the number of training patterns.

Selection of Training Patterns
The total data (patterns) are divided into two groups; training data, and testing data. The training data are used to train the network to find the relationship between the input and output parameters.
Preparing of training data is a matter of considerable importance in training the neural network. However as mentioned in chapter four, the neural networks interpolate data very well, but the extrapolation of data has not in the same confidence. Therefore, the training data should be selected in such a way that it includes data from all regions of interest.

Selection of Testing Patterns:-
After training network, the weights and biases are fixed and the network can then be run with same or fresh sets of data. In testing the network at first it is necessary to run the network by using the training data to see whether the network produces good approximation to the known output for these data, and then prepare further data which have not been used in training phase and run the network with these data to check the accuracy of this net. This property of network is called generalization. The

generalization depends on the size of the training data set, the architecture of the network, and the complexity of the problem.

The number of testing data are taken randomly approximately (16%) from total database. A more information of the progress of training is given by convergence history (learning curve), which is obtained by evaluating the MSE for the testing data at intervals during the course of training.

Configuration of Artificial Neural Network:-

The successful application (speed of convergence and accuracy of prediction) of a neural network to a problem depends on selecting suitable configuration of the network. Method of trial and error was carried out to define the configuration of the artificial neural network, some aspects were fixed from beginning, including:

1) One node in output layer.
2) Use of feedforward backpropagation algorithm.

Input and Output Layers:-

The nodes in the input layer and output layer are usually determined by the nature of the problem. In this study the parameters which may be introduced as the components of the input vector consist of:-

1)The percentage of added fibers (A).
2) Water cement ratio (w/c).
3)The mixing ratio (C:S:G).
4)The size of single fiber (B).
5)Time of testing (T).

Normalizing Input and Output Data Set:-

Normalization of input and output data sets within a uniform range before they are applied to the neural network are essential to prevent larger numbers from overriding smaller ones, and to prevent premature saturation of hidden nodes, which impedes the learning process. The limitation of input and output values within a specified range are due to the large difference in the values of the data provided to the neural network. In this study equation (4.28) of the previous chapter is used to normalize the input and output parameters. That equation gives the required results with a certain mean square error.

Initialization of Weights:-

The first step in the neural network computation is the initialization of weight factors between the nodes of different layers. Since no prior information about the system being modeled is available, so that in this study two initialization functions are used: Widro-Hoff initialization function which changes the weight after each run and random initialization function with ranges [(-1 to 1), (-0.75 to 0.75), (-0.5 to 0.5), and (-0.25 to 0.25)]. From the comparison between the two initialization functions it is found that the Widro-Hoff gives better performance than other function. Therefore Widro-Hoff initialization function is used in this study. It is preferable to use Widro-Hoff initialization method for differentproblems studied by neural network because this normalization function has no limiting range and can reach good performance for any problem after some attempts.

Number of Hidden Layers and Nodes in Each Hidden Layer:-

The number of hidden layers and the number of nodes in one hidden layer are not straightforward to ascertain. No rules are available to determine the exact number. However, the choice of the number of hidden layer and number of nodes in the hidden layer depends on the network application. Although using a single hidden layer is sufficient in solving many functional approximation problems, some problems may be easier to solve with a two hidden layer configurations. The number of nodes in the hidden layer is selected according to the following rules:

1) The maximum error of the output network parameters should be as small as possible for both training patterns and testing patterns.
2) The training epochs (number of iterations) should be as few as possible. In the present work the network is tested with one and two hidden layer configurations with an increasing number of nodes in each hidden layer(s) (Fig.(2)).

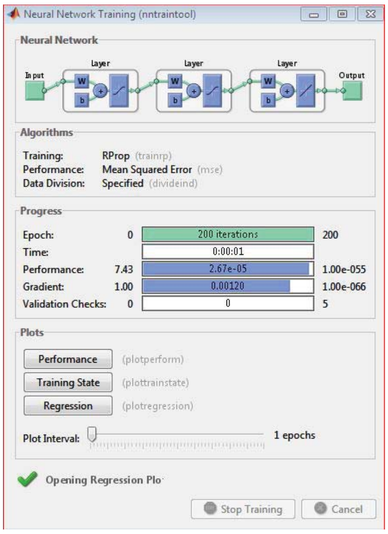

Fig. (2) Neural Network Training

Figure (3) presents the relationship between the target and output data. It can be noted that (R) value is approximately equal to one.

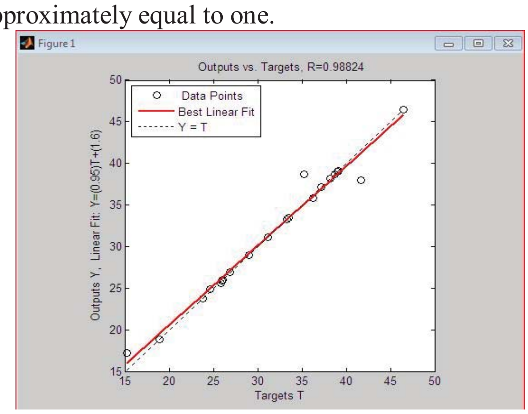

Fig. (3) Output VS. Target

Figure (4) the regressions of the relations between target and output for each of training, testing, and all. It may be noted that the regressions are approximate to one.

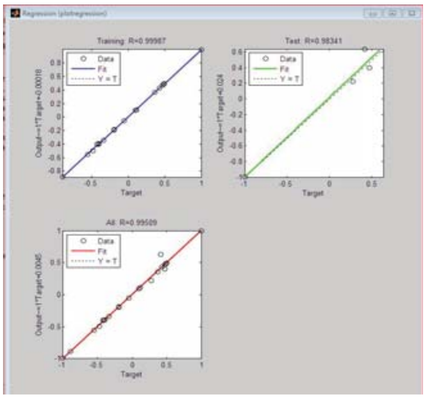

Fig. (4) Regression of Neural Network

Figure (5-4) shows the performance of the trained and tested neural. It may be noted that the performance is approximately equal to zero.

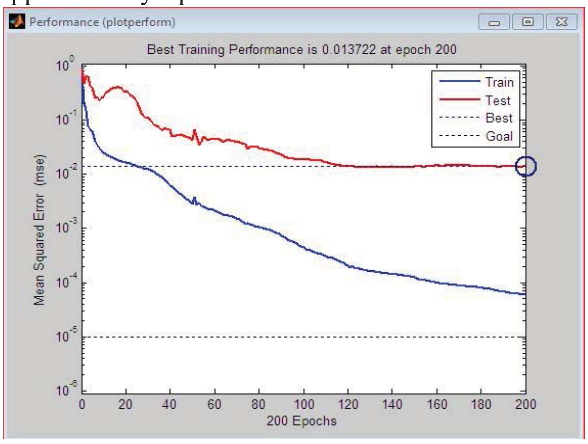

Fig. (5) Performance Of The Network

IV. RESULTS AND DISCUSSION

Table (1) shows the results of the experimental work for 7 days age of concrete

Table (1) Results of Experimental Work for 7 Days Age

Nail	w/c (%)	Mixing Proportion	Fiber	fc
1	55	1:2:4	0	17 2
1	55		6	18 8
1	55		9	24 8
1	55		12	25 6
1	55		15	37 2
1	55		20	37 9
1	46	1:1.5:3	0	26 0
1	46		6	26 8
1	46		9	29 0
1	46		12	33 4
1	55	1:2:4	0	17 2
1	55		6	18 8
1	55		9	24 8
1	55		12	25 6
1	55		15	37 2
1	55		20	37 9
1	46	1:1.5:3	0	26 0
1	46		6	26 8
1	46		9	29 0
1	46		12	33 4

Table (2)presents the results of the experimental works for the mixing of (1:1.5:3 and 1:2:4). The results show that the highest value of the compressive strength is obtained with fiber adding percentage of 12% for mixing of (1:1.5:3) and 20% for (1:2:4) mixing

It may also be noted from this table that the optimum water cement ratio is 46% for mixing of (1:1.5:3) and 55% for (1:2:4) mixing.

Table (2) Results of Experimental Work for 28 Days Age

Nail Size (in.)	w/c (%)	Mixing Proportion	Fiber Addition (%)	fc (MPa)
0	55	1:2:4	0	23.71
1	55		6	25.91
1	55		9	38.71
1	55		12	39.1
1	55		15	48
1	55		20	48.3
1	46	1:1.5:3	0	33.24
1	46		6	38.72
1	46		9	50.2
1	46		12	51.1
1.5	40	1:2:4	20	46.45
1.5	45		20	35.87
1.5	55		20	29.02
1.5	40	1:1.5:3	20	38.96
1.5	45		20	38.14
1.5	55		20	31.08

Table (3) and Fig. (6) present the results of the prediction of the compressive strength with various percentageof fiber addition for 28 days of concrete and (1:2:4) mixing proportion, using 1" nail size and w/c of 40%.

Table(3) Prediction of the Compressive Strength by Changing the Percentage of Fiber Added for 28 Days and (1:2:4) Proportions

Fiber Addition (%)	fc (MPa)
0	22.21
2	21.91
4	22.23
6	23.49
8	25.41
10	27.13
12	28.36
14	29.49
16	31.33
18	34.58
20	38.31
22	40.85
24	42.04
26	42.46
28	42.53

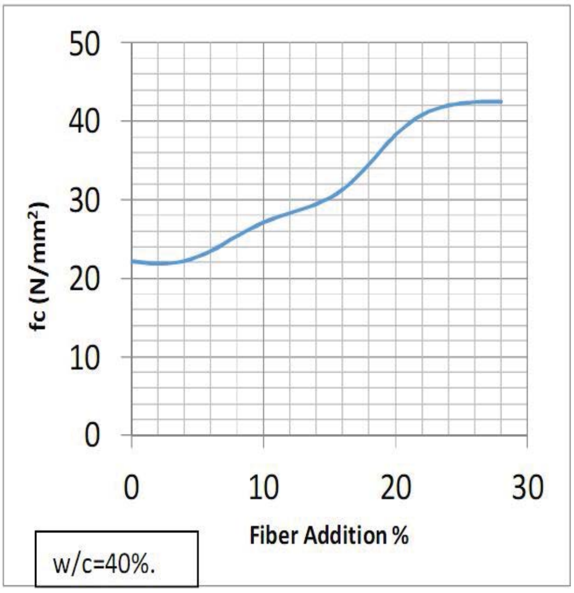

Fig. (6)Compressive Strength vs. Fiber Addition Percentage for 28 Days and (1:2:4) Proportions and Nail Size 1"

It can be noted that the compressive strength increases by about 89% with 28% increasing of fiber addition.

Table (4) and Fig.(7) show the results of the prediction of the compressive strength with various percentage of fiber addition using 1" nail size for 28 days of concrete and (1:1.5:3) mixing proportion with w/c of 40%.

Table(4) Prediction of the Compressive Strength by Changing the Percentage of Fiber Added using 1" nail size for 28 Days and (1:1.5:3) Proportions

Fiber Addition (%)	fc (MPa)
0	31.01
2	32.48
4	34.45
6	36.65
8	38.82
10	40.98
12	43.52
14	47.05
16	51.08
18	53.28
20	53.99
22	54.65
24	55.28
26	55.83
28	56.27

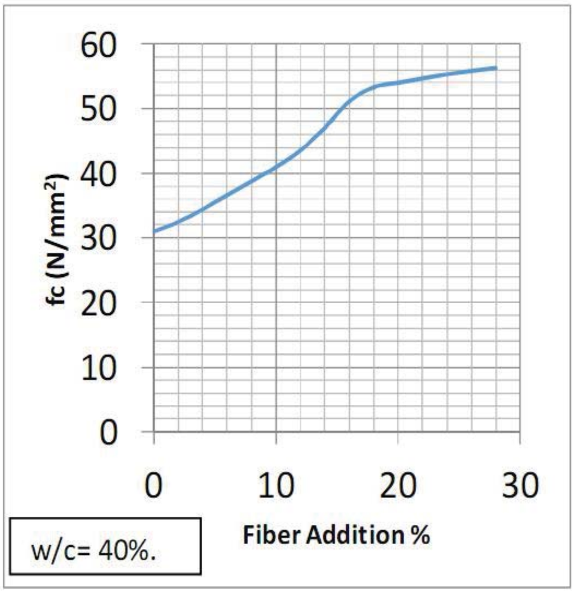

Fig. (7)Compressive Strength vs. Fiber Addition Percentageusing 1" nail size for 28 days of concrete and (1:1.5:3) mixing proportion.

From these results, it may be concluded that the increasing of fiber addition up to 28% leads to increase the compressive strength of concrete about 81%.

Table (5) and Fig.(8) present the results of the prediction of the compressive strength with various percentage of fiber addition using 1.5" nail size for 28 days of concrete and (1:2:4) mixing proportion with w/c of 40%.

Table(5) Prediction of the Compressive Strength with Fiber Size 1.5 in for 28 days of concrete, (1:2:4) mixing proportion with w/c of 40%.

Fiber Addition (%)	fc (MPa)
0	38.21
2	43.39
4	50.78
6	55.58
8	57.62
10	58.14
12	57.85
14	57.05
16	55.91
18	54.5
20	52.9
22	51.22
24	49.53
26	47.92
28	46.45

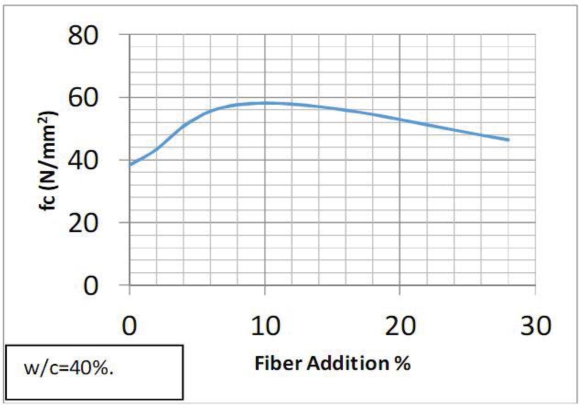

Fig. (8)Compressive Strength vs. Fiber Addition Percentageusing 1.5" nail size for 28 days of concrete and (1:2:4) mixing proportion

The above results showed that the increasing of 1.5' size fiber addition up to 28%, will increase the concrete compressive strength up to 21.5%

Table (6) and Fig. (9) present the result of the prediction of the compressive strength with various percentage of fiber addition using 1" nail size for 28 days of concrete and (1:2:4) mixing proportion with w/c of 50%.

Table(6) Prediction of the Compressive Strength with w/c=50%, mixing proportion of 1:2:4, for 28 days concrete age and 1" nail size.

Fiber Addition (%)	fc (MPa)
0	23.71
2	23.8
4	23.95
6	24.16
8	24.41
10	24.69
12	25.01
14	25.31
16	25.33
18	24.35
20	22.9
22	23.98
24	27.3
26	30.95
28	33.42

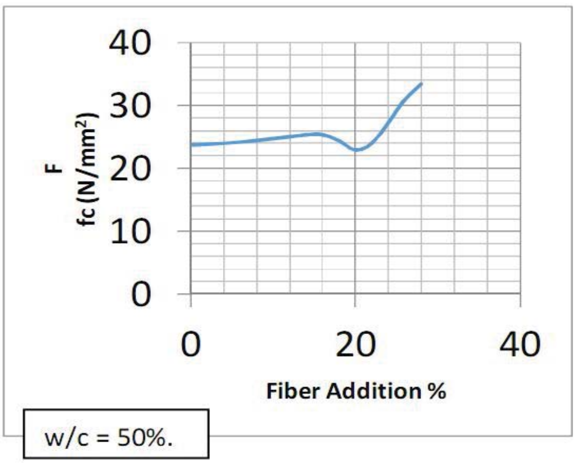

Fig. (9)Compressive Strength vs. Fiber Addition Percentageusing 1" nail size for 28 days of concrete and (1:2:4) mixing proportion

Table (7) and Fig. (10) presents the results of the prediction of the compressive strength with various percentage of fiber addition using 1" nail size for 7 days of concrete and (1:2:4) mixing proportion with w/c of 40%.

Table(7) Prediction of the Compressive Strength with w/c=40%, mixing proportion of 1:2:4, for 7 days concrete age and 1" nail size.

Fiber Addition (%)	fc (MPa)
0	18.63
2	18.05
4	18.00
6	19.04
8	21.8
10	24.72
12	25.27
14	25.07
16	26.00
18	28.99
20	34.31
22	39.43
24	41.58
26	41.42
28	40.43

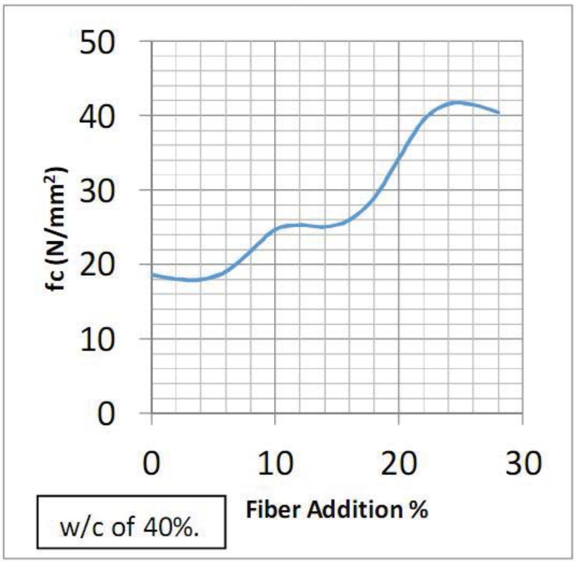

Fig. (10)Compressive Strength vs. Fiber Addition Percentageusing 1" nail size for 7 days of concrete and (1:2:4) mixing proportion

It can be noted from above results that the compressive strength is increased by about 11.7% as the fiber addition increases 28%

CONCLUSIONS

The most important conclusions that can be drawn from the present study are the followings:

1) Neural network model has been proved to be very

effective in the predicting of the compressive strength of FRC. So neural network provides a possible method for handling any complex problem by providing adequate training data and sufficient number of nodes to represent the internal features and relationships that connect input and output parameters.

2) The selected variables (input parameters of neural network) greatly influence the training and generalization performance of network.

3) In the process of training the neural network, the values of input patterns has a large influence on the training time (No. of epoch) of the neural network as a result of the activation function. Normalizing the input and target values of the training patterns seems to greatly reduce the training time.

4) The initial value of weight factors and biases has greatly influenced the performance (mean square error)of the network model.

5) Using two hidden layers in the neural networks, rather than single hidden layer, significantly improves performance of network. The final number of nodes in each hidden layer is determined by the consideration of the training time, the mapping of the neural network for the training pattern, and generalization of the neural network monitored by the test patterns.

6) The neural network trained with the resilient backpropagation (RPROP) algorithm exhibited better behavior than that trained with the gradient descent (GD) algorithm with momentum algorithm. This was found from the reduced training time (No. of epoch) and better mapping of the neural network for the training patterns and generalization for the test patterns. 8) Type and arrangement of activation function affect the response of network. The [tansig, purelin, purelin] and [purelin, tansig, tansig] activation functions are found to give a minimum mean square error for the two cases of columns considered, first and second network respectively.

7) It is found that (for mixing proportion 1:1.5:3) the compressive strength has the more increasing when the fibers are added with 12%, while it has the more increasing at 20% fibers adding for mixing proportion (1:2:4).

8) The optimum water cement ratio is found to be 46% for the mixing proportion (1:1.5:3) with 12% fibers and 55% for mixing of (1:2:4) with fibers adding 20%.

9) By increasing the percentage of fibers added and using mixing proportion (1:1.5:3) the compressive strength increases more uniformly and effectively than the use of the mixing ratio(1:2:4).

10) By using a larger size of nails with low percent of addition will significantly increase the compressive strength but with the increasing of percentage of addition the compression strength decreases.

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