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Cascade and Feed Forward Back propagation Artificial Neural Network Models for Prediction of Compressive Strength of Ready Mix Concrete

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ABSTRACT: *In this research work, comparative study for prediction for 28-days compressive strength of Ready Mix Concrete(RMC) have been carried out using Feed forward back propagation and Cascade forward back propagation algorithms. The study was conducted by varying the number of neuron in the hidden layer using tansigmoidal transfer function. Various models have been developed for different input scenarios, non-dimensional ratios were used for modelling and the ratios such that their changes resulted in corresponding changes in the output. The compressive strength was modelled as a function of five variables: water/cement, fine aggregate/course aggregate, fly ash/cement, admixture/water, and water/total density. The effects of each parameter on networks were studied for Feed forward back propagation algorithm and Cascade forward back propagation algorithm of Artificial Neural Network (ANN). The Cascade forward back propagation algorithm of Artificial Neural Network (ANN) models performed better than Feed forward back propagation algorithm models, especially in reducing the scatter of predictions.*

Keywords *- Artificial Neural Network (ANN), Cascade Forward Back propagation (CFB), Compressive Strength, Feed Forward Back propagation (FFB), Ready Mix Concrete*

1. INTRODUCTION

Compressive strength of Ready Mix Concrete is a major and perhaps the most important mechanical property, which is usually measured after a standard curing of 28 days. Concrete strength is influenced by lots of factors like concrete ingredients, age, ratio of water to cementitious materials, etc. Conventional methods of predicting the strength of concrete are usually based on the linear and nonlinear regression methods [1,2]. Nowadays, the artificial intelligence based techniques like the artificial neural networks [3–5] have been successfully applied in this area. In the recent years the prediction of the mechanical properties of construction materials, in particular the 28-days compressive strength of concrete (28-CSC), has been gained a great attention between the researchers of material science [3–9]. This problem is usually used as a key example for verification of the novel soft computing systems [10]. Many research works can be found in the literature that focused on the prediction of the various properties of concrete.

Artificial neural networks (ANNs) are a family of massively parallel architectures that are capable of learning and generalizing from examples and experience to produce meaningful solutions to problems even when input data contain errors and are incomplete. This makes ANNs a powerful tool for solving some of the complicated engineering problems. Basically, the processing elements of a neural network are similar to the neuron in the brain, which consists of many simple computational elements arranged in layers. The basic strategy for developing a neural network-based model for material behavior is to train a neural network on the results of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the trained neural network will contain sufficient information about material's behavior to qualify as a material model (Hakim, Mesri and Selaru) [11, 12, 13]. Such a trained neural network not only would be able to reproduce the experimental results, but also it would be able to approximate the results in other experiments through its generalization capability. A compressive strength of concrete is a major and important mechanical property, which is generally obtained by measuring concrete specimen after a standard curing of 28 days. Concrete strength is influenced by lots of factors. Some of these parameters include quality of aggregate, strength of cement, water content and water-to cement ratio. The traditional approach used in modeling the effects of these parameters on the compressive strength of concrete starts with an assumed form of analytical equation and is followed by a regression analysis using experimental data to determine unknown coefficients in the equation, Dias [14].

Artificial Neural Network (ANN) is a neurobiologically inspired paradigm that emulates the functioning of the brain based on the way that neurons work, because they are recognized as the cellular elements responsible for the brain information processing. ANN models can detect patterns that relate input variables to their corresponding outputs in complex biological systems for prediction. Methods for improving network performance include finding an optimum network architecture and appropriate number of training cycles, using different input combinations [15]. So we compare two types of ANN network for prediction of compressive strength of RMC. First network is Feed forward back propagation and second is Cascade forward back propagation.

So far very few literatures are available in application of soft computing technique RMC modelling and comparison of networks in ANN. Hence an attempt has been made to do comparative study of network and to develop predicting model for compression strength of RMC by soft computing technique and evaluate the performance of each network for selection of best network.

2. OBJECTIVE

The main objective was to compare and to explore the feasibility of Feed forward back propagation and Cascade forward back propagation network in ANN models for predicting the strength and recommend the most suitable network for RMC batch plant.

3. METHODOLOGY

3.1Artificial Neural Network Artificial neural networks (ANNs) are non-linear data driven self-adaptive approach as A neuron is a real function of the input vector (yj.....yk). The output is obtained as $f(x) = fa_i + [\sum_n^k W_{ij} \times Y_j]$ Where f is a function, typically the sigmoid (logistic or tangent hyperbolic) function. Mathematically a Multi- Layer Preceptor network is a function consisting of compositions of weighted sums of the functions corresponding to the neurons. Feed-forward and Cascade-forward networks are especially useful in function approximation when a set of inputs and outputs is all that is known of the system, which is the situation in this study.

3.2Data Collection and Modelling

The data for the ready mixed concretes (RMC) were collected from RMC batching plant. Of these records were used for training and for testing. The input parameters were the weights per unit concrete volume of: i) cement; ii) water; iii) fine aggregate; iv) coarse aggregate; and v) admixture with some water reducing properties. The output parameter standard 28-day cube strength. When the data were transformed into non-dimensional ratios, the input ratios were: i) water/ Cement; ii) water /Total where ‘total’ refers to the weight of all the mix; iii) Coarse aggregate /fine aggregate; and iv)Admixture/cement; v)Fly ash/cement and the outputs remained strength.

3.3Training and Testing of ANN Network

3.3.1Feed Forward Back propagation Network

Feed forward back propagation artificial neural network model shown in Fig.1 consists of input, hidden and output layers. Back propagation learning algorithm was used for learning these networks. During training this network, calculations were carried out from input layer of network toward output layer, and error values were then propagated to prior layers. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The outputs of a network such as between 0 and 1 are produced, then the output layer should use a sigmoid transfer function (tansig) [17].

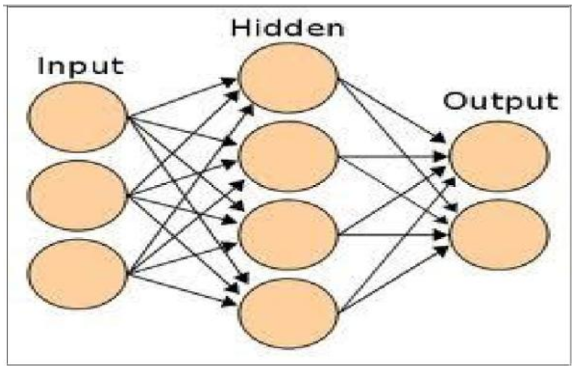

Fig.1 Feed Forward Back propagation Network

3.3.2Cascade Forward Back propagation Network

Cascade forward back propagation model shown in Fig.2 is similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. While two-layer feed forward networks can potentially learn virtually any input output relationship, feed-forward networks with more layers might learn complex relationships more quickly. Cascade forward back propagation

ANN model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, but the main symptom of this network is that each layer of neurons related to all previous layer of neurons [17].

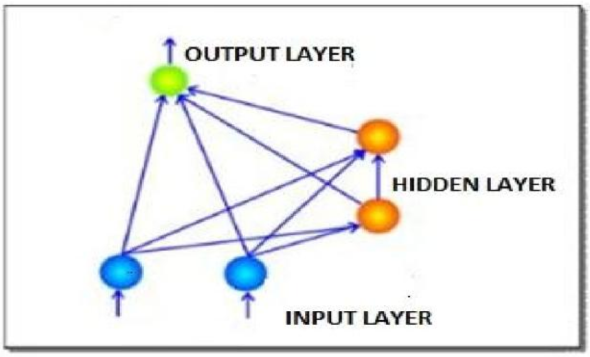

Fig.2 Cascade Forward Back propagation Network

Tan-sigmoid transfer function was used to reach the optimized status. The performance of cascade forward back propagation and feed forward back propagation were evaluated using Mean Square Error (MSE), Mean Absolute Error (MAE), Mean Relative Error (MRE) and Coefficient of Correlation (Cc). The data set having five input and one target is divided as training and testing as 18 mixes used for training and 9 for testing to develop different models in Feed forward back propagation and Cascade forward back propagation.The training of the neural networks was carried out with various numbers of nodes in the one hidden layer and various target accuracies. The data set is trained and tested by using feed forward back prop neural network and cascade forward back propagation neural network having one hidden layers using tan sigmoid transfer function for one to five numbers of neurons.

3.4Modelling Performance Criterions

In order to evaluate the prediction accuracy of ANN models three norms were used for comparative evaluation of the performance of each model. These norms are Mean Absolute Error (MAE), Mean Square Error (MSE), Mean Relative Error (MRE) and Coefficient of Correlation (Cc) was employed.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\text{observed} - \text{predicted})^2 \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\text{observed} - \text{predicted}| \tag{2}$$

$$\mathrm{CC} = \frac{\sum(x-x')(y-y')}{\sqrt{\sum(x-x')^2(y-y')^2}} \tag{3}$$

$$\mathrm{MRE} = \frac{1}{n}\sum_{i=1}^{n}\frac{(\text{observed} - \text{predicted})}{(\text{observed})} \tag{4}$$

Where n is the number of data patterns in the independent data set. Where x and y are the sample means

AVERAGE (observed) and AVERAGE (predicted), X' and y' are average of observed and predicted values.

4. RESULT AND DISCUSSION

ANN network have been developed using three layers. Input consists five neurons representing i) water/ Cement; ii) water /Total where 'total' refers to the weight of all the mix; iii) Coarse aggregate /fineaggregate; and iv)Admixture/cement; v)Fly ash/cement. Out layer contain one neuron represent 28-days compressive strength of Ready Mix Concrete. In hidden layer number of neuron varied from one to five to find the best fitting hidden layer structure. From Table 1 it can be observed that cascade forward back propagation algorithm outperform feed forward back propagation algorithm. In the hidden layer with three neuron for cascade forward back propagation network gives best result.Cascade forward back propagation network shows the excellent performance where the MRE and MAE are showing very less error while Coefficient of correlation shows the very good nearly one. While Feed forward back propagation network shows less performance than Cascade forward back propagation network.

All the testing results are presented From Table 1, it is appeared that the optimal performance of ANN

Cascade forward back propagation network using three neurons in hidden layer was obtained best than other with respect to MRE, MAE and Cc in testing. The Cc is almost close to 1 such as 0.99 which is quite satisfactory during testing. There is deviation of Cc in Feed forward back propagation network during testing. The MAE is also very low in Cascade forward back propagation network testing, which reflects testing was proper than other structures.

Table 1- Performance for 1 to 5 neuron model for cascade forward back propagation algorithm and feed forward back propagation algorithm

No. Neuron	Feed Forward Back propagation				Cascade Forward Back propagation			
	MAE	CC	MRE	MSE	MAE	CC	MRE	MSE
1	1.7280	0.9915	0.0645	3.8881	4.0503	0.9870	0.1307	20.9650
2	16.8812	0.5188	0.4850	391.8108	6.7834	0.9321	0.2261	62.8889
3	15.0973	0.0932	0.3917	389.0840	5.2468	0.9919	0.1824	34.8860
4	8.0834	0.8615	0.2332	108.0995	3.4275	0.9852	0.1217	17.0672
5	6.0679	0.9534	0.2223	56.9898	12.1956	0.8593	0.3719	195.5325

During testing predictions by cascade forward back propagation algorithm shows high correlation with observed compressive strength shown in Fig.3.

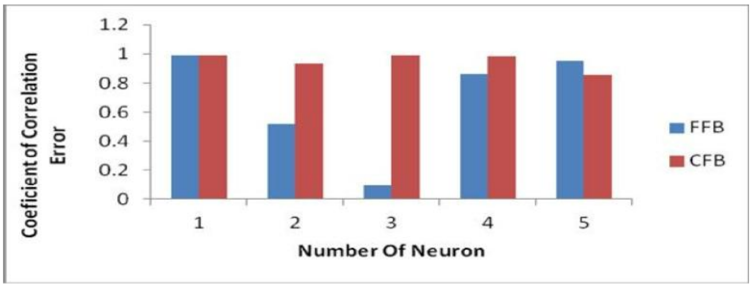

Fig.3 Comparison of FFB and CFB Model w.e.f. Coefficient of Correlation

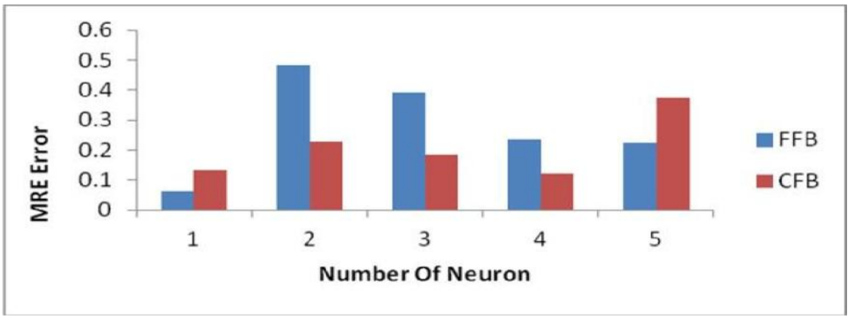

Fig.4 Comparison of FFB and CFB Model w.e.f. MRE

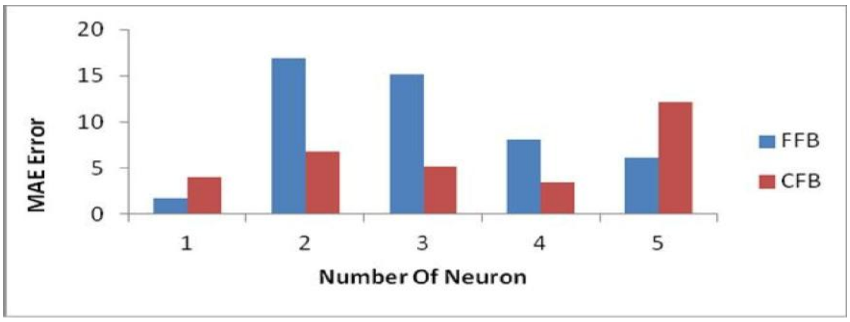

Fig.5 Comparison of FFB and CFB Model w.e.f. MAE

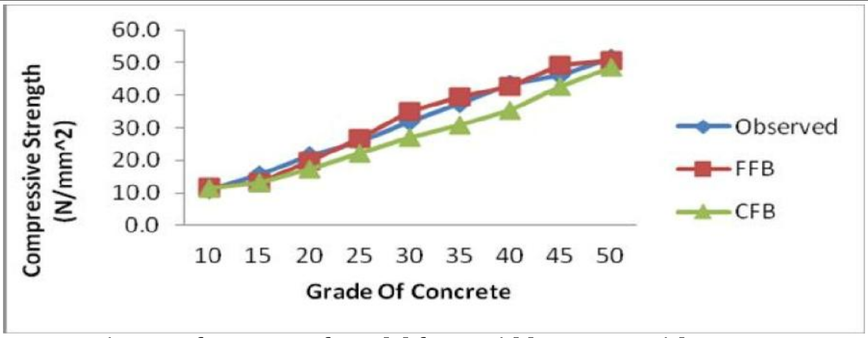

Fig.6 Performance of Model for a Hidden Layer with One Neurons

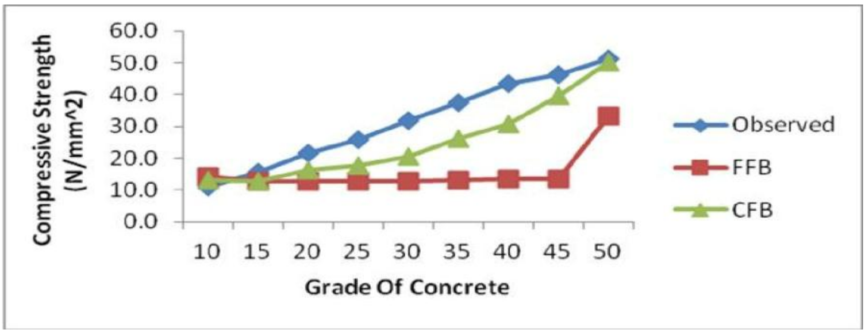

Fig.7 Performance of Model for a Hidden Layer with Two Neurons

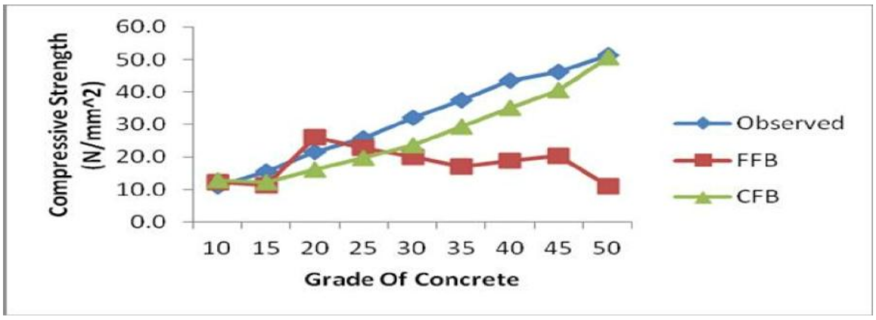

Fig.8 Performance of Model for a Hidden Layer with Three Neurons

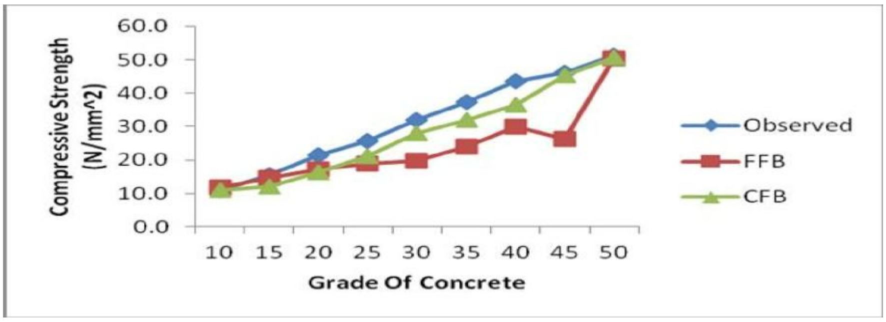

Fig.9 Performance of Model for a Hidden Layer with Four Neurons

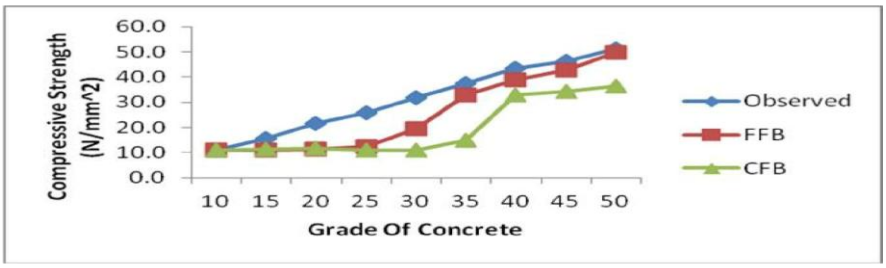

Fig.10 Performance of Model for a Hidden Layer with Five Neurons

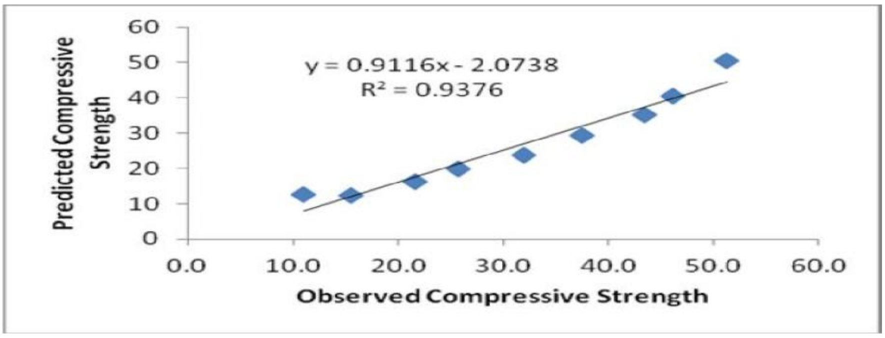

Fig.11 Scattered Graph for Observed and Predicted Values

5. CONCLUSION

The study for prediction for 28-days compressive strength of Ready Mix Concrete have been carried out using Feed forward back propagation and Cascade forward back propagation algorithms. The study reveals that the performance of cascade forward back propagation algorithm is better than feed forward back propagation algorithm for all concrete mixes. The hidden layer structure with three neuron performed better as compared to other hidden layer structures. The scatter for three neuron hidden layer structure is very low. This may enable the decision maker for improvement of the activities of RMC batch plant. A similar study should be conducted by using different transfer function and the different properties of Ready Mix Concrete.

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