Prediction of Compressive Strength of Concrete Using Artificial Intelligence

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PREDICTION OF COMPRESSIVE STRENGTH OF CONCRETE USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Concrete compressive strength is one of the most important mechanical property because it usually indicates the overall quality of the concrete. Compressive strength of concrete is dependent on many factors such as quality of aggregate, strength of cement, water content, water/cement ratio, binder/aggregate ratio and age of concrete. Compressive strength of concrete is mostly depends on the materials of concrete mix design. Although the concrete compressive strength can be measured at different ages, codes usually specify standard 28-day testing. When no specific data are available, compressive strength of 28 days is assumed to be 1.5 times the 7-day strength whereas this ratio was shown to vary generally from 1.3 to 1.7 (Neville, 1986). Artificial Neural Network (ANN) is used in this study in order to predict the compressive strength of concrete. MATLAB software is used to predict the compressive strength of concrete using ANN. Result shows that the predicted values are in good correlation with the experimental values.

KEY WORDS: Artificial Intelligence, Artificial Neural Network, Compressive strength.

1 INTRODUCTION

In civil construction Concrete is one of the most commonly used material. Because of heterogeneous characteristics of concrete, its behavior is highly nonlinear. While designing concrete structures compressive strength is one of the most evaluative parameters. Even in RMC's while proportioning new mixes prediction of compressive strength becomes very important. So as to predict the concrete compressive strength artificial intelligence approach can be adopted.

To predict the concrete mechanical properties several models have been developed, most popular ones are artificial neural networks (ANNs), adaptive neuro fuzzy interference (ANFIS), multiple non-linear regression analysis (MLRA) etc. ANN can be successfully adopted TO predict the concrete compressive strength. The main objective of this project was to develop an ANN model for the prediction of compressive strength of concrete using MATLAB software and to validate the model.

2 LITERATURE REVIEW

There are many research works by earlier investigators on prediction of concrete compressive strength using artificial intelligence.

H N Muliauwan et al, have used three different AI methods to predict the concrete compressive strength such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Linear Regression (LR). Results of the simulation obtained by all these three methods shows that predictive models can be built using these artificial intelligence methods. About 1030 samples were considered to develop the model. Regression value for ANN is 0.909, for SVM 0.779, for LR 0.0.768. By this it can be concluded that ANN is the most accurate method.

Palika Chopra et al, have used Artificial Neural Networks (ANNs) and Genetic Programming (GP) to predict the concrete compressive strength. Total 1442 data sets were used to develop model. R value obtained by ANN model is 1 and by GP is 0.96. It clearly shows that ANN is the best predicting tool.

Overall based on the literature survey to predict the concrete compressive strength, ANN can be the most accurate method

3 MATERIALS AND METHODOLOGY

3.1 Materials used

Cement: Ordinary Portland cement of grade 53 with specific gravity 3.15 was used.
Coarse Aggregate: Coarse Aggregate of size 20mm, 12mm and 10mm with specific gravity 2.67, 2.67 and 2.66 respectively was used.
Fine Aggregate: M sand and Cr sand with specific gravity 2.6 and 2.54 respectively was used as fine aggregate.
Mineral admixture: GGBS (Ground Granulated Blast Furnace Slag) with specific gravity 2.9 was used as Mineral admixture.
Chemical admixture: Endura is a water reducing agent which is a polycarboxylate based and Superflow 35-U which is a sulfonated naphthalene formaldehyde based with specific gravity 1.105 and 1.19 respectively was used.

3.2 Concrete grade used

Five different types of mixes of grade like M10, M20, M25, M30 and M35 have been used to train the model.

3.3 **Methodology**

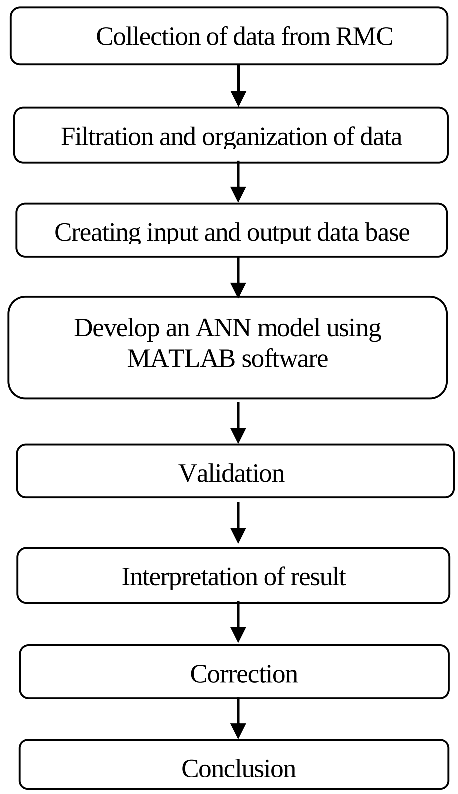

Fig 3.3.1: Flowchart of project Methodology

3.4 Artificial Neural Network (ANN)

An artificial neural network (ANN) is a segment of automatic data processing system designed to imitate the way the human brain analyzes and processes information. It solves problems that would be difficult or impossible by human or statistical standards. ANNs possess self-learning capabilities that helps them to give better results as data availability becomes more.

Artificial neural networks are built like the biological neural network, with interconnected neuron nodes. An ANN has hundreds or thousands of processing units called artificial neurons, which are interconnected by nodes. These processing units consists of input and output units. The input units receives information, neural network tries to learn about information and presents output. ANNs need rules and guidelines to come up with a output just like humans so they use a set of learning rules called backward propagation (backpropagation) to absolute their output results.

An ANN during training phase it learns to recognize patterns in data, whether aurally, visually, or textually. During this phase, the network compares its actual output with desired output. The obtained difference between both the outcomes is adjusted using back propagation. This indicates that the neural network works backward, going from the output unit to the input units to adjust the weight of its connections between the units until the difference between the actual and desired outcome gives the least possible error.

3.5 Inputs and Output

Compressive strength of concrete is dependent on various parameters. By assuming standard condition for batching, mixing, placing and curing following input parameters are considered

Age (days)
Cement (kg/m3)
Ground Granulated Blast Furnace Slag (kg/m3)
W\C ratio
Admixture (kg/m3)
Specific gravity of admixture
Coarse aggregate (20 mm) (kg/m3)
Coarse aggregate (12 mm) (kg/m3)
Coarse aggregate (10 mm) (kg/m3)
Fine aggregate (kg/m3)

Compressive strength is the output of the ANN model. Totally 1195 data sets obtained from the concrete mixes.

3.6 Model construction

Input output fitting problem can be solved by using Neural network fitting app with a two layer feed forward neural network. Neural network maps between numeric inputs and numeric targets. Using mean square error and regression analysis the Neural Fitting app helps in selecting the data, creating and training a network, and evaluating the performance.

The architecture of the network model consists of input layer with 10 nodes, 20 nodes in hidden layer and output layer with one node corresponding to the compressive strength.

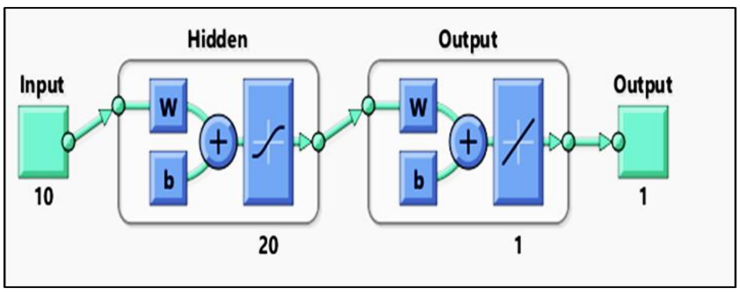

Fig 4.3 ANN architecture

For 1195 mixes, corresponding compressive strength values were obtained for different ages (7 & 28). For each mix influencing factors such as Age (days), Cement (kg/m3), Ground Granulated Blast Furnace Slag (kg/m3),W\C ratio, Admixture (kg/m3), Specific gravity of admixture, Coarse aggregate (20mm,12mm & 10mm) (kg/m3) and Fine aggregate (kg/m3) were collected.

Out of 1195 data approximately 70% was considered for training, 15% for testing and 15% for validation. During training, training data are presented to the network and the network is adjusted based on its error. Network generalization are measured using validation data and training to halt when generalization stops improving. Testing data gives an independent measure of performance of network during and after training because testing data have no effect on training

Levenberg–Marquardt training algorithm is used in this project to train the ANN model. The Levenberg–Marquardt (LM) Algorithm is usually used to solve problems of nonlinear least squares. This method is a combination of the gradient descent and the Gauss-Newton methods. .

4 RESULTS AND DISCUSSION

The neural network with 20 hidden neurons has been selected in one hidden layer to minimize the Mean Squared Error (MSE) and maximized Regression (R). The average squared difference between outputs and targets is nothing but the mean squared error. Lower values of MSE are better. If the value of MSE is zero means no error. Regression values compute the correlation between outputs and targets. An R value of 1 means a close relationship, 0 means a random relationship between the predicted value and target value. The best validation performance was 0.73824 at epoch 12. The non-linear sigmoidal function was taken as the transfer function. Epoch is nothing but the number of iterations required to converge with the neural network model. Epoch is an implication of the number of times the weights have been reset to a satisfactory model with the highest possible correlation. The results of Correlation coefficient (R) obtained during training, validation and testing are given in the table

Table 5.1: Results of training, validation and testing

	Samples	**MSE**	**R**
Training	837	0.70354	0.99077
Validation	179	0.73824	0.98985

Testing	179	0.86217	0.98766

By looking at the results we can say that the developed Artificial Neural Network (ANN) model is successful in learning the relationship between the different input and output parameters. In the developed Neural network model correlation coefficient is almost equal to one. It indicates the accuracy of proposed neural network model.

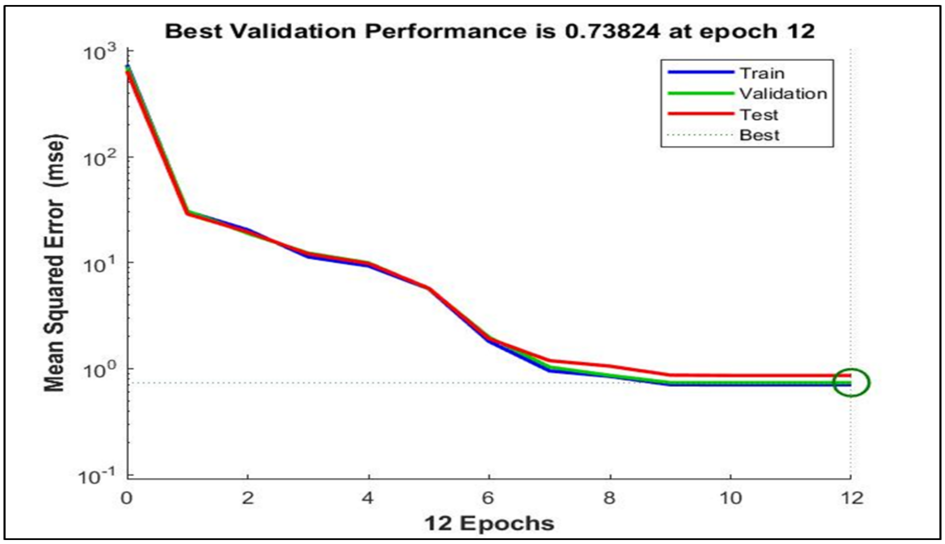

Fig 5.1: The performance of LM network

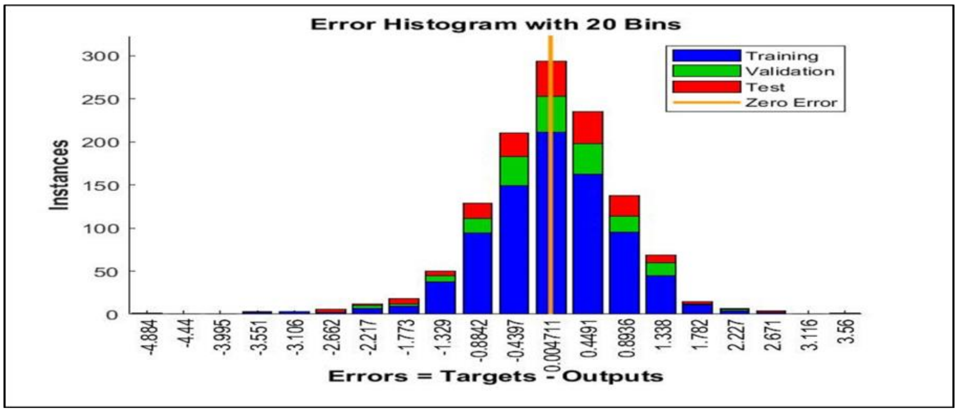

Fig 5.2: Error Histogram of LM Network

Error histogram is a plot of error versus instances. In the error histogram graph number of vertical bars present in the graph are the bins. Each vertical bar represents the number of samples from the dataset, which lies in a particular bin. This shows that most of the data sample has minimum error of 0.004711.

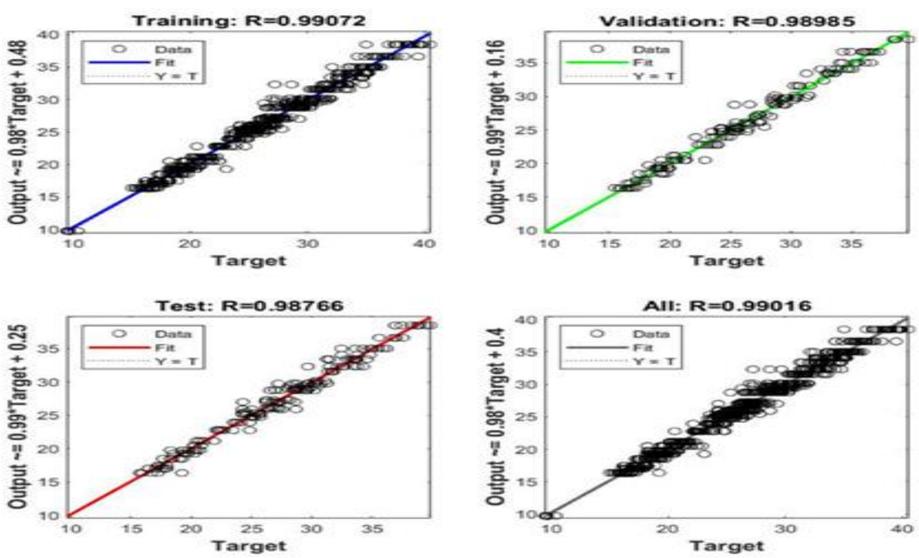

Fig 5.3: The regression of LM network

5 CONCLUSION

- The Artificial Neural Network model (ANN) has been developed using MATLAB which is used to predict the compressive strength of concrete by considering the factors influencing the properties of concrete and the obtained R value is 0.99 which is nearly equal to 1 that shows that there is well-built correlation between predicted and measured values
- Developed ANN model is validated which gave an average error of 0.693N/mm2
- ANN methodology allows a rapid and accurate prediction of compressive strength at site which helps to predict the formwork requirement
- This model helps to control quality and economics (i.e. saving time and expense) in construction and hence necessary changes in mix proportion can be adopted to avoid situation where, required design strength is not reached by concrete or avoiding concrete which is unnecessarily strong
- ANN method can be preferably adopted in the ready-mix concrete plants for mix designing and batching

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