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Prediction of Slump in Concrete using Artificial Neural Networks

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***Abstract*—**High Strength Concrete (HSC) is defined as concrete that meets special combination of performance and uniformity requirements that cannot be achieved routinely using conventional constituents and normal mixing, placing, and curing procedures. It is a highly complex material, which makes modeling its behavior a very difficult task. This paper aimed to show possible applicability of Neural Networks (NN) to predict the slump in High Strength Concrete (HSC). Neural Network models is constructed, trained and tested using the available test data of 349 different concrete mix designs of High Strength Concrete (HSC) gathered from a particular Ready Mix Concrete (RMC) batching plant. The most versatile Neural Network model is selected to predict the slump in concrete. The data used in the Neural Network models are arranged in a format of eight input parameters that cover the Cement, Fly Ash, Sand, Coarse Aggregate (10 mm), Coarse Aggregate (20 mm), Water, Super-Plasticizer and Water/Binder ratio. Furthermore, to test the accuracy for predicting slump in concrete, the final selected model is further used to test the data of 40 different concrete mix designs of High Strength Concrete (HSC) taken from the other batching plant. The results are compared on the basis of error function (or performance function).

***Keywords*—**Artificial Neural Networks, Concrete, prediction of slump, slump in concrete

I. INTRODUCTION

CONCRETE is the major building material being used all over the world. It is known for its high compressive strength, durability, impermeability, fire resistance and abrasion resistance. For contributing to maximum strength of the structure, hundred percent compaction of concrete is necessary. The quality of concrete satisfying the above requirement is termed as Workability, (a parameter, a mix designer requires to specify in the mix design process) which is defined as the property of concrete determining the effort required for placing, compaction and finishing with minimum loss of homogeneity. The effort required to place a concrete mixture is determined largely by the overall work needed to initiate and maintain flow, which depends on the rheological property of the lubricant (the cement paste) and the internal friction between the aggregate particles on one hand, and the friction between concrete and the surface of the framework on the other [1].

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The Workability of concrete is one of the functions of the relative magnitudes of various concrete mix constituents. SLUMP TEST is one of the tests which measure the parameters close to workability and provide useful information about it. It is the most commonly used method of measuring consistency of concrete which can be employed either in lab or at the site. From this test, slump is deduced by measuring the drop from the top of the slumped fresh concrete. Additional information on workability of concrete can be obtained by observing the shape of the slump in concrete [2].

Every type of construction requires testing of the concrete to determine the slump (of the fresh concrete) to ensure, whether the concrete is of desired workability and strength or not [3]. However, researchers have looked into the characteristic parameters that affect slump value of High Strength Concrete. It was understood that proportions of constituents in a concrete mix (i.e. Cement, Water content, Sand, Coarse aggregates, Fly Ash, and Super-Plasticizer) affects workability and are determined on the basis of required properties of concrete. Also, to obtain concrete of desired and suitable workability, technical personnel often tries several mix proportions, which is a time consuming process, resulting in wastage of material and cost of concrete production. Thus, for the sake of saving time and decreasing the design cost, help of Artificial Neural Networks (ANN) is taken to develop models, so that the knowledge extracted from these neural network models, can be utilized to predict slump in concrete.

The basic strategy for developing a neural network based model for predicting slump is to train a neural network on the results of a series of experiments (carried out to determine the slump in concrete), thus minimizing the absolute difference between the target (desired) outputs and the actual outputs, thereby resulting in approximate optimal solutions [4].

Artificial Neural Networks (ANN) have been used as an efficient tools for modeling and predicting complex and dynamic engineering systems such as structural analysis [5]; water demand forecast modeling [6]; prediction of compressive strength of concrete [3, 7, 8]; and shear design of reinforced concrete beams [9].However, the efforts in the area of modeling concrete slump using Artificial Neural Networks has been lacking, but still some researchers have made efforts in this area. Dias and Pooliyadda [10] used back propagation neural networks to predict slump of ready mixed concrete and high strength concrete, in which chemical admixtures and/or mineral additives were used. Bai et al. [11] developed Neural Network models that provide effective predictive capability in respect of the workability of concrete incorporating metakaolin (MK) and fly ash (FA). Bhatti et al. [12] showed possible applicability of Artificial Neural Networks for predicting the slump of High Strength Concrete (HSC). Yeh [13] demonstrated the abilities of Artificial Neural Networks to represent the effects of each material component on concrete slump.

The aim of this paper is to present a methodology for predicting slump in High Strength Concrete (HSC). For this, the slump test data for the Ready Mixed Concrete (RMC) is collected from two batching plants. These slump tests were performed for various grades of concrete (i.e. M10, M15, M20, M25, M30 and M35). The data contained a total of 349 slump tests results, which is used to build the Artificial Neural Network models. Using the data (taken from the first batching plant), Neural Network models are trained for the input (Cement, Fly Ash, Sand, Coarse Aggregate, Water, Super-Plasticizer and Water/Binder ratio) and output (Slump in concrete) parameters. Eight different Neural Network models are created and validation of each network is done to check its effectiveness and flexibility for the unseen input variables. The most versatile Neural Network model is selected to predict the slump in concrete. To test the accuracy in predicting slump in concrete, the final selected model is further used to test the data taken from other batching plant. The results are compared on the basis of error function or performance function (i.e. Mean Square Error and Correlation Coefficient).

II. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are computational systems whose architecture and operation are inspired from our knowledge about biological neural cells (neurons) in the brain. These are not simulations of real neurons in the sense that they do not model the biology, chemistry, or physics of a real neuron. They do however, model several aspects of information like combining and pattern recognition behavior of real neurons in a simple, but still in a meaningful way. Artificial Neural Networks can be used to learn and reproduce rules or operations from the given examples; to analyze and generalize from sample facts and make predictions from these; to memorize characteristics and features of given data; and to match or make associations from new data to old data in a variety of powerful ways [4].

Very important feature of these networks is their adaptive nature, where 'learning by example' replaces 'programming' in solving problems. As long as enough data is available, a neural network will extract any regularity from it and form a solution. Another key feature of ANN is its essential parallel architecture that allows for fast computation of solution when these networks are implemented in customized hardware [14].

Compared to conventional digital computing techniques, Neural Networks are advantageous because of their special features such as the massively parallel processing, distributed storing of information, low sensitivity to error, their very robust operation after training, generalization adaptability to new information [15]. As mentioned earlier, Neural Networks learn by examples. They can therefore be trained with known examples of a problem to 'acquire' knowledge about it. Once appropriately trained, the network can be put to effective use in solving 'unknown' or 'untrained' instances of the problem.

III. Data Sets

The slump test results for the Ready Mixed Concrete (RMC) are collected from the two Ready Mix Concrete batching plants. The data collected from the first batching plant contained total of 349 slump tests results, which are used to build the Neural Network models. The type of Cement used by the Batching plant (for carrying out the Slump tests) was Ordinary Portland Cement (OPC) of 53 Grade. These tests are performed for various grades of concrete (i.e. M10, M15, M20, M25, M30 and M35). Also, the Super-Plasticizer used is ShaliPlast SP-431. Specific weights and range of constituents of concrete of data sets (as collected from the first batching plant) are tabulated in TABLE I and TABLE II respectively.

Similarly, the data collected from the second batching plant contained a total of 40 slump tests results which are used for testing the accuracy of the best Neural Network model developed (using data obtained from the first batching plant). The type of cement used by the second batching plant (for conducting slump tests) is ordinary Portland Cement (OPC) of 43 Grade. These tests are also performed for varying mix design proportions. The Super-Plasticizer that is taken into use is Don-R3. Specific weights and range of constituents of concrete of data sets (as collected from the second batching plant) are tabulated in TABLE I and TABLE III respectively.

IV. Architecture of neural network models

In order to develop a system to predict the slump in concrete, the Neural Network is trained with an input data pattern. In this study, the input data pattern corresponds to following eight parameters: Cement (kg/m^3), Fly Ash (kg/m^3), Sand (kg/m^3), Coarse Aggregate (10 mm) (kg/m^3), Coarse Aggregate (20 mm) (kg/m^3), Water Content (kg/m^3), Water/Binder ratio and Super-Plasticizer (kg/m^3), which are taken as input variables (i.e. neurons in the input layer). The output layer consists of only one neuron, i.e. Slump in concrete (in cm).

Amongst various architectures and paradigms, the Feed-Forward Back-Propagation is one of the simplest and most applicable network being used in performing higher level human task such as classification, decision-making and prediction. It is one of the most popular, effective and easy to learn learning algorithms for complex and multi layered networks. Thus, a multilayered Feed-Forward Back-Propagation Neural Network (created by generalizing the Levenberg-Marquardt's learning rule to multiple layer networks and non-linear differential transfer functions) is used for predicting slump in concrete.

TABLE I
SPECIFIC WEIGHTS OF CONSTITUENTS OF CONCRETE IN DATA SETS
(as collected from both the batching plants)

Concrete Constituents	Specific Weights
Cement	3.15
Fly Ash	2.22
Water	1.00
Super-Plasticizer	1.20
Coarse Aggregate	2.65
Fine Aggregate	2.66

TABLE II
RANGE OF CONSTITUENTS OF CONCRETE IN DATA SETS
(as collected from the first batching plant)

Concrete Constituents	Minimum (kg/m^3)	Maximum (kg/m^3)
Cement	100	450
Fly Ash	0	200
Sand	550	860
Coarse Aggregate (10mm)	350	1114
Coarse Aggregate (20mm)	0	764
Water Content	136	186
Super-Plasticizer	1.00	5.80
Water/Binder ratio	0.37	0.78

A typical Back-Propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but normally there is just one or two. The input layer is connected to the hidden layer and the hidden layer is connected to output layer by interconnection weights, as shown in Fig. 1.

The complex part of this learning mechanism is for the system, to determine that, which input contributed the most to an incorrect output and how does that element get changed to correct the error. To solve this problem, training inputs are provided to the input layer of the network, and desired outputs are compared at the output layer. The difference between the output of the final layer and the desired output is back-propagated to the previous layer (or layers), usually modified by the derivative of the transfer function, and the connection weights are normally adjusted using the Gradient Descent rule

TABLE III
RANGE OF CONSTITUENTS OF CONCRETE IN DATA SETS
(as collected from the first batching plant)

Concrete Constituents	Minimum (kg/m^3)	Maximum (kg/m^3)
Cement	120	400
Fly Ash	0	180
Sand	662	815
Coarse Aggregate (10mm)	365	1067
Coarse Aggregate (20mm)	0	740
Water Content	105	190
Super-Plasticizer	0.00	4.5
Water/Binder ratio	0.32	0.70

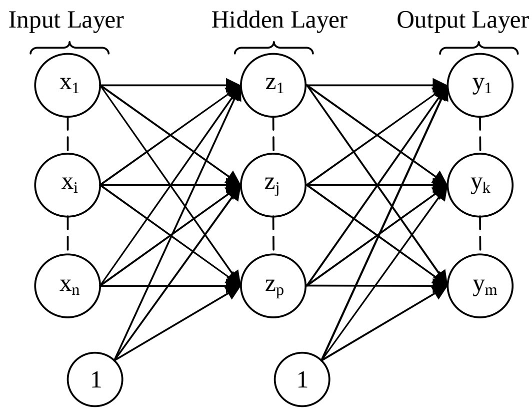

Fig. 1 Typical Feed-Forward Back-Propagation Neural Network

or its variant. This process proceeds for the previous layer, until the input layer is reached [16]. During the training of the network, the same set of data is processed many a times as the weights are refined on a regular basis. The sequence of learning of Neural Networks is shown in Fig. 2.

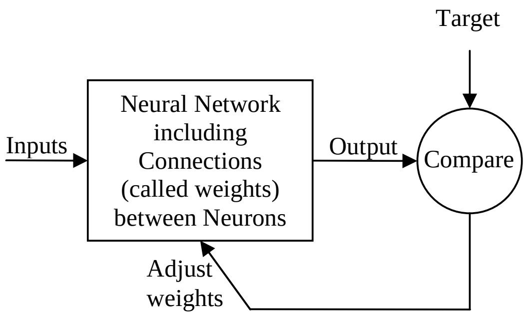

Fig. 2 Sequence of learning of an Artificial Neural Network

To train a network and measure how well it performs, an error function (or performance function) must be defined to provide an unambiguous numerical rating of the system performance. Selection of an error function is very essential for representing the design goals and deciding which algorithms can be chosen. The typical error functions (or parameters that are used to evaluate the performances of neural network models developed) those are commonly used for training Feed-Forward Neural Network and employed in the study are:

1. The Mean Square Error (MSE) of the network errors that is shown in equation:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(t_i - a_i\right)^2 \quad (1)$$

2. Correlation Coefficient (R^2), which is shown in the equation below:

$$R^2 = \frac{\left(\sum_{i=1}^{N}\left(t_i - t_j\right)\times\left(a_i - a_j\right)\right)^2}{\sum_{i=1}^{N}\left(t_i - t_j\right)^2 \times \sum_{i=1}^{N}\left(a_i - a_j\right)^2} \quad (2)$$

Where, N is the number of observations, i, j indexing the output and the average output nodes; t_i, a_i are the target (desired) and actual network output, respectively; and t_j, a_j are the average target (desired) and average actual network output, respectively.

Fig. 3 shows the example of proposed neural network model for the study while TABLE IV shows the architecture of the neural network models developed in the study, having 'One hidden layer' and 'Two hidden layers'.

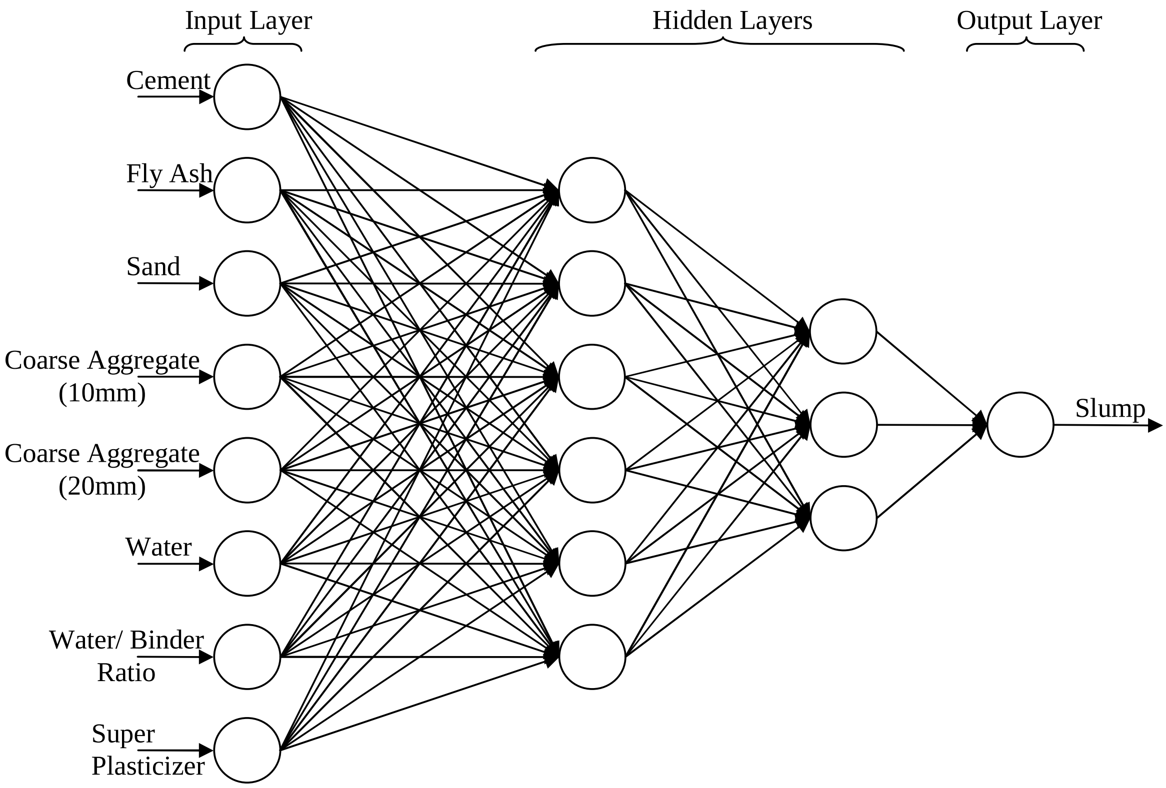

Fig. 3 Proposed Neural Network model

TABLE IV
ARCHITECTURE OF THE NEURAL NETWORK MODELS DEVELOPED HAVING ONE AND TWO HIDDEN LAYERS

MODELS			Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ANN ARCHITECTURE	NUMBER OF NEURONS	Input Layer	8	8	8	8	8	8	8	8
		Hidden Layer 1	11	12	13	14	6	6	7	6
		Hidden Layer 2	-	-	-	-	5	6	6	7
		Output Layer	1	1	1	1	1	1	1	1
	TRANSFER FUNCTION	Hidden Layer 1	Log-sig	Log-sig	Log-sig	Log-sig	Log-sig	Log-sig	Log-sig	Log-sig
		Hidden Layer 2	-	-	-	-	Tan-sig	Tan-sig	Tan-sig	Tan-sig
		Output Layer	Purelin	Purelin	Purelin	Purelin	Purelin	Purelin	Purelin	Purelin

V. SAMPLING OF THE DATA

For creating the Neural Network model (yielding optimal performance) and to minimize the true error between actual and desired output, the data is randomly divided into three disjoint sets namely: Training set, Validation set, and Testing set. Training set is used to train the network and to fit the parameters of the classifier. In multi layer perceptron, this data set is used to find the ‘optimal’ weights with the Back-Propagation algorithm. The Validation set is used to fine tune the parameters of a classifier. This proved to be helpful in deciding the ‘optimal’ number of hidden units or for determining a stop point for the back-propagation algorithm. The Testing set is used to test the performance of a fully trained classifier. This is usually employed to determine the error rate of the final chosen model.

Out of the 349 slump tests results or data sets (as obtained from the first batching plant), 190 data sets (55 %) are used for training, 89 data sets (25 %) are used for validation and remaining 70 data sets (20 %) are used for testing the Neural Network. The easy way of representing the sampling of data is shown in Fig. 4.

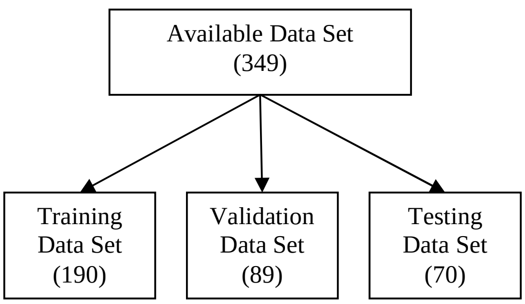

Fig. 4 Sampling of the Data

VI. NEURAL NETWORK MODEL SELECTION AND PERFORMANCE EVALUATION

Following steps are followed for selecting the Neural Network model (yielding the optimal performance):

1) Randomly dividing the available data sets (349) into training (190), validation (89), and testing set (70).
2) Selecting the neural network architecture (Feed-Forward Back-Propagation with Levenberg – Marquardt training algorithm), number of hidden layers and hidden layer neurons), transfer functions (Log-sigmoid and Purelin), training parameters (Learning rate, learning cycles) and training function (TRAINLM) to be employed for modeling slump in concrete.
3) Training the model using the Training Set only, till saturation limit is reached or the error function (Mean Square Error) does not show any appreciable reduction in its value.
4) Evaluating the model using the validation set.
5) Repeating the steps 2 to 4 using different network architecture and training parameters to build different models.
6) Selecting the best model amongst all (i.e. one having optimal performance), on the basis of its error (or performance) function (i.e. Mean Square Error).
7) Assessing the performance of the final model using the testing set.

The results are tabulated in TABLE V.

VII. TESTING THE SELECTED NEURAL NETWORK MODEL WITH UNSEEN DATA

From the results obtained by training the Neural Network (TABLE V), it is evident that Neural Network model 8 is giving least Mean Square Error (MSE) and the maximum Correlation Coefficient (R^2) with the target outputs. Thus, Model 8 is selected as the final Model whose parameters and architecture will be employed to assess the performance of the testing set.

Model 8 had Neural Network architecture of two hidden layers with 6 neurons in first layer and 7 in the second layer. The model (earlier trained with training and validation data sets), is tested with the testing data set so as to compute the final error in the optimized model.

The training parameters included 'Log-sigmoid' as the transfer function in each layer and TRAINLM as the training function. The results obtained are shown in TABLE VI (Also refer Fig. 5 and Fig. 6).The value of Correlation Coefficient (R^2) 0.99848 and the error (MSE) 0.00124 indicates, that the selected Neural Network model has been fully trained to recognize any pattern within the available dataset.

TABLE V
TRAINING AND VALIDATION RESULTS OF ALL NEURAL NETWORK MODELS DEVELOPED

Model	Training Set		Validation Set		
	No. of Data	Mean Square Error (MSE)	No. of data	Correlation Coefficient (R^2)	Mean Square Error (MSE)
Model 1	190	0.000720	89	0.98760	0.08861
Model 2	190	0.000403	89	0.99309	0.00494
Model 3	190	0.000186	89	0.99626	0.00274
Model 4	190	0.000110	89	0.99846	0.00146
Model 5	190	0.000277	89	0.99523	0.00339
Model 6	190	0.000249	89	0.99570	0.00306
Model 7	190	0.000100	89	0.99828	0.00124
Model 8	190	0.000100	89	0.99828	0.00122

TABLE VI
TRAINING AND TESTING OF SELECTED NEURAL NETWORK MODEL

Training of Neural Network		Testing of Neural Network	
Epochs	Mean Square Error (MSE)	Correlation Coefficient (R^2)	Mean Square Error (MSE)
50	0.007649	0.85237	0.10732
100	0.006272	0.92233	0.05645
200	0.004412	0.96887	0.04272
300	0.001477	0.98383	0.02674
400	0.000459	0.99297	0.00886
500	0.000413	0.99792	0.00148
600	0.000353	0.99810	0.00135
800	0.000346	0.99848	0.00124

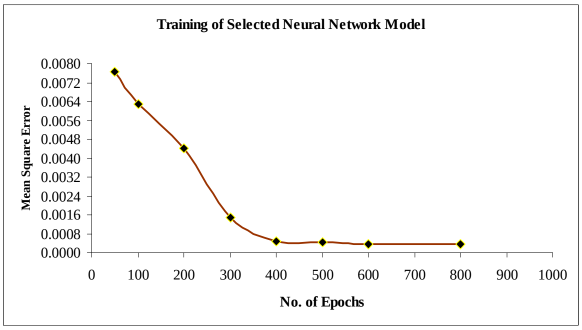

Fig. 5 Training of selected Neural Network Model

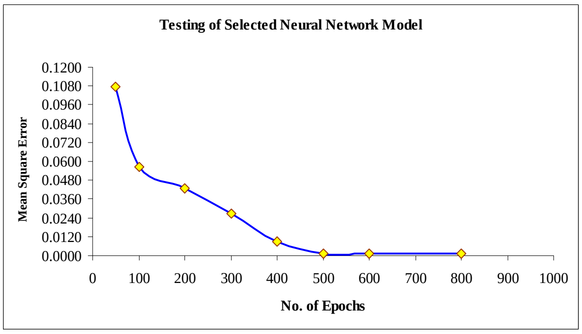

Fig. 6 Testing of selected Neural Network Model

VIII. Testing the Selected Neural Network Model with the Data Obtained from the Second Ready Mix Concrete (RMC) Batching Plant

Since Neural Network model 8 is found out to be most optimal amongst all the models, therefore, it is tested with the data set which is obtained from second batching plant. This testing is done so as to compute the error and compare its performance with the model (that is earlier tested with the testing data set using data obtained from the first batching plant. (Refer TABLE VI). The training parameters includes 'Log-sigmoid' as the transfer function in each layer and TRAINLM as the training function. In TABLE VII**,** the Correlation Coefficient (R^2) 0.91845 and the Mean Square Error (MSE) 0.05795 (Refer Fig. 7 and Fig. 8) indicates, that the chosen Neural Network model has been fully trained to recognized any pattern within the available dataset obtained from the first batching plant, but fails to do so for the dataset which is obtained from the second batching plant. The reason for this is the use of different types of Cement and Super-Plasticizers by both the Ready Mix Concrete batching plants. Adoption of different ranges of constituents of concrete by both the batching plants also affects the results.

TABLE VII
Training and Testing of Selected Neural Network Model with the Data Obtained from the Second Batching Plant

Training of Neural Network		Testing of Neural Network	
Epochs	Mean Square Error (MSE)	Correlation Coefficient (R^2)	Mean Square Error (MSE)
50	0.010134	0.82532	0.12414
100	0.009485	0.83651	0.11619
200	0.006645	0.88546	0.08140
300	0.006286	0.89165	0.07700
400	0.005684	0.90202	0.06963
500	0.005503	0.90514	0.06742
600	0.005369	0.90745	0.06577
800	0.004730	0.91845	0.05795

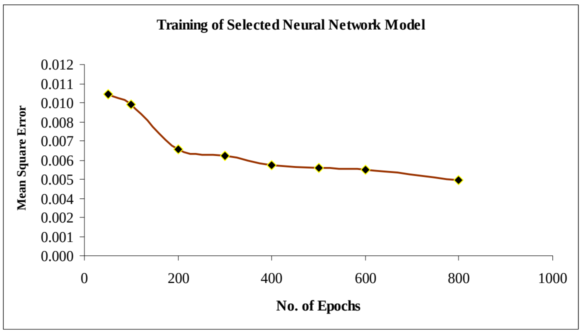

Fig. 7 Training of selected Neural Network Model with the Data obtained from the second batching plant

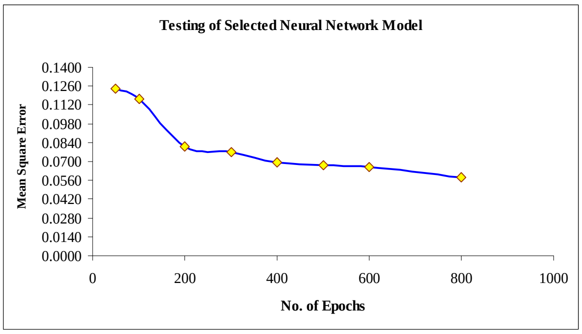

Fig. 8 Testing of selected Neural Network Model with the Data obtained from the second batching plant

IX. Conclusion

The findings of the study presented here are based on the evaluations of the Neural Network models developed on a limited data set. The conclusions made out of the study are as follows:

1) As the final selected and tuned Artificial Neural Network model is tested with the unseen data obtained from the first batching plant, the Mean Square Error (MSE) and the Correlation Coefficient (R^2) is found out to be 0.00124 and 0.99848, respectively. This proves clearly that the Neural Network models developed are reliable and useful, thus proving that splitting the data into three sets (i.e. training dataset, validation dataset and testing dataset) is quite effective for developing and selecting optimal Artificial Neural Network model and its final error estimation.
2) When the final selected and fine tuned Neural Network model is tested with the data obtained from the second batching plant, the Mean Square Error (MSE) and the Correlation Coefficient (R^2) comes out to be 0.05795 and 0.91845, respectively, indicates clearly that the applicability of the selected and fine tuned model for predicting slump in concrete is limited. The model can give optimal performance or can predict any mix proportions (giving suitable or desired slump) as long as their type of Cement, Admixtures (in particular, Super-Plasticizer) and Range of Constituents of Concrete is same.
3) Artificial Neural Networks can be used by engineers to estimate the slump in concrete whose constituents mainly includes cement, fly ash, sand, coarse aggregates, water and super-plasticizer. It becomes convenient and easy to use these

models to predict any mix proportions (giving suitable or desired slump).

X. Further Scope of Study

The present study has been done to predict slump in concrete (of various mix design proportions) considering Cement, Fly Ash, Water, Sand, Coarse Aggregates and Super-Plasticizer as the constituents of concrete. Further research in predicting workability or slump in concrete using Artificial Neural Networks may be:

1) Predicting Slump in concrete using Neural Networks considering many more constituents of Concrete (like Silica, Blast Furnace slag, etc.).
2) Comparing the results or effectiveness of using Artificial Neural Networks for modeling slump in concrete with the linear and non-linear regression models (developed using the same data), for concluding which one is the best.
3) Performance sensitivity analysis (in addition to modeling of Slump in Concrete using Artificial Neural Network), so as to evaluate the impact of various concrete mix constituents on the concrete slump, based on the best Neural Network model developed. In other words, the Neural Networks can be used to explore the cause and affect relationship between networks' input and output.

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