Modeling Ready Mix Concrete Slump using Artificial Neural Network

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***Abstract*:-Artificial Neural Networks (ANN) has recently recognised as a powerful tool in modeling highly complex engineering problems those are difficult to solve by traditional computing methods. In this paper eleven Multi – layer Feed – forward Neural Network (MFNN) models are developed and trained to model the complex functionality between Ready Mix Concrete (RMC) constituents and slump. The exemplar data used in training, validation and testing were taken from Ready Mix Concrete batching plant RMC INDIA Pvt. Ltd., Jaipur. Three randomised disjoint sets namely training set (400), validation set (100) and testing set (65) of total 500 unique combinations of mix constituents and their respective slump were used in subsequent training, validation and testing of models created. The learning rate and momentum factor during training and validation were kept 1.0 and 0.5 respectively. The final selected model (on the basis of error function comparison) was fine tuned using a combination of training and validation set comprising 500 data and tested on unseen data using testing dataset (65). The result shown that Artificial Neural Networks have a strong potential for predicting slump value of RMC slump on the basis of quantity of constituents used.**

Keywords: Artificial Neural Networks (ANN), Multi – layer Feed – forward Neural Network (MFNN), Ready Mix Concrete (RMC), Training, Validation, Testing, Slump, Error function.

I. INTRODUCTION

Concrete in past few years has emerged as a prime construction material governing the construction rate and subsequent development of country due to its wide use. High compressive strength, impermeability, fire resistance, ability to be cast in to any shape, high durability and low maintenance cost are the key properties that makes concrete a prime construction material used worldwide [1]. High demand of concrete and increasing congestion at construction sites causes a problem for quality construction and its rate. Ready Mix Concrete (RMC) has emerged as an optimum solution to this problem by providing customized quality and quality of ready to pour concrete at sites. RMC has given impetus to the infrastructure growth providing reliability and durability of construction The time interval between production, transportation and subsequent lying of RMC at sites poses a restrain on its shelf life and usefulness since it is desired to place concrete in position without any loss of workability. It is defined as the property of concrete determining the effort required to place, compact and finish with minimum loss of homogenity [2]. The effort required to place a concrete mixture is determined largely by the overall work needed to initiate and maintain flow [3]. The slump test is preferred in IS: 456 – 2000 [4] and IS: 4926 – 2003 [5] to measure workability of RMC before pour. Slump value in wet state and compressive strength in hard state of concrete are kept as target values in mix design procedure [6]. Regardless to the sophistications and other considerations such as cost, a concrete mix that cannot be placed easily and compact fully is not likely to yield the targeted strength and durability characteristics [2]. Artificial Neural Network (ANN) is an artificial intelligence method that mimics the biological brain's operation and computation performance and has the ability to reflect the underlying linear or non – linear relationships amongst input and target data [7]. In recent years ANN has emerged as a powerful tool, successful in solving many civil engineering problems [8]. As compared to conventional digital computing techniques, procedural and symbolic processing Neural Networks are advantageous because they can learn from examples and can generalise solutions to new rendering of a problem. ANN can adapt to fine changes in the nature of a problem, they are tolerant to errors in the input data, they can process information rapidly, and they are readily transportable between computing systems [9]. This paper presents the attempts to model the complex relationship between RMC constituents and slump, in order to produce a decision support tool for quick identification of mix proportions required to produce concrete mix with some specific workability. The tool will help in reducing the time involved in trials procedure along with wastage and design cost of RMC.

II. BASIC DESCRIPTION OF ANN

ANNs comprising of multiple arrays or layers of simple processing units 'neurons' connected in forward direction only are called 'feed forward neural networks' with information flowing in forward direction only, the 'Feed Forward Neural Networks' generally consists of an 'Input layer' an 'Output layer' and a number of intermediate 'Hidden layers'. Each neuron is connected at least with one neuron, and each connection is evaluated by a real number, called weight coefficient, that reflects the degree of importance of the given connection in the in neural network [10]. The modeling of a particular phenomenon using ANN starts with the presentation of input – output pairs. The ANN through its learning mechanism is able to draw a functional relationship between the input and output data, by minimization of error between the actual output and predicted output. The learning process is undertaken by a learning algorithm which tries to update the neural network weights in such a fashion that the neural error is rendered minimum. The most popularly used learning algorithms are the ‘Back – Propagation Algorithm’. It is, in essence a means of updating neural network synaptic weights by back propagating a gradient vector in which each element is defined as the derivative of an error measure with respect to a parameter [11].

III. MODEL DEVELOPMENT

Selection of the network parameters is dependent upon complexicity of inter – relation to be approximated and the amount with quality of datasets [12]. Slump value of concrete depends upon the quantities (kg/m^3) of mix constituents, hence slump value (mm) can be regarded as a function of quantities of nix constituents viz. Cement content (Kg/m^3), Fly ash (Kg/m^3), Sand (Kg/m^3), Coarse Aggregate 10mm (Kg/m^3), Coarse Aggregate 20mm (Kg/m^3), Admixture (Kg/m^3), Water - binder ratio. In order to model this complex function and develop a decision support tool the Network Architecture used is shown in figure: - 1.

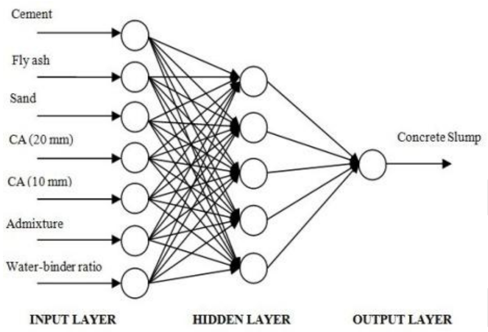

Figure: - 1: Network Architecture

Choosing the number of hidden layers and the number of hidden layer neurons is difficult, because there are no generally acceptable theories. Usually it is recommended to start with only one hidden layer, and if the results are not good, the number of hidden layers can be increased. In present study total eleven MFNN models having varying complexicity in terms of hidden layer and hidden layer neurons were used. Table: - 1 shows the models with their hidden layers and hidden layer neurons along with transfer functions and training functions.

Table: - 1
DESCRIPTION OF NETWORK ARCHITECTURE USED IN MODELS

Neural Network Architecture						Training Parameters			
Model Name	Hidden Layers	Hidden Layer Neurons		Input Neurons	Output Neurons	Transfer Function			Training Function
		Ist Layer	IInd Layer			First Hidden Layer	Second Hidden Layer	Output Layer	
ANN 1	1	5	-	7	1	Tan-sigmoid	-	Linear	Lavenberg-Marquardt
ANN 2	1	6	-	7	1	Tan-sigmoid	-	Linear	Lavenberg-Marquardt
ANN 3	1	7	-	7	1	Tan-sigmoid	-	Linear	Lavenberg-Marquardt
ANN 4	1	8	-	7	1	Tan-sigmoid	-	Linear	Lavenberg-Marquardt
ANN 5	1	9	-	7	1	Tan-sigmoid	-	Linear	Lavenberg-Marquardt
ANN 6	2	6	8	7	1	Tan-sigmoid	Tan-sigmoid	Linear	Lavenberg-Marquardt
ANN 7	2	7	8	7	1	Tan-sigmoid	Tan-sigmoid	Linear	Lavenberg-Marquardt
ANN 8	2	8	8	7	1	Tan-sigmoid	Tan-sigmoid	Linear	Lavenberg-Marquardt
ANN 9	2	9	9	7	1	Tan-sigmoid	Tan-sigmoid	Linear	Lavenberg-Marquardt
ANN 10	2	10	10	7	1	Tan-sigmoid	Tan-sigmoid	Linear	Lavenberg-Marquardt
ANN 11	2	11	11	7	1	Tan-sigmoid	Tan-sigmoid	Linear	Lavenberg-Marquardt

A. Data Collection

In present study the data used were collected from Ready Mix Concrete plant RMC INDIA Pvt. Ltd., situated at SITAPURA INDUSTRIAL AREA, JAIPUR. The data collected from the batching plant (RMC INDIA Pvt. Ltd.) contained various mix constituents and slump, which were used to build the neural network models. The type of Cement used by the Batching plant was Ordinary Portland Cement (OPC) of 53 Grade. The slump tests were performed for varying mix design proportions (i.e. M10, M15, M20, M25, M30, M35 and M40). Also, small dosage of naphtha based Admixture were used. Specific weights and range of constituents of concrete of data sets are tabulated as in Table: - 2 and Table: - 3 respectively.

Table: - 2
SPECIFIC WEIGHTS OF CONSTITUENTS OF CONCRETE

CONCRETE CONSTITUENTS	SPECIFIC WEIGHTS
Cement	3.15
Fly Ash	2.22
Water	1.00
Admixture	1.20
Coarse Aggregate	2.65
Fine Aggregate	2.66

Table: - 3
RANGE OF CONSTITUENTS OF CONCRETE

Constituents of RMC Data	Maximum	Minimum
Cement (kg/m^3)	425	100
Fly Ash (kg/m^3)	220	0
Sand (kg/m^3)	900	550
Coarse Aggregate 20mm (kg/m^3)	788	0
Coarse Aggregate 10 mm (kg/m^3)	1115	343
Admixture (kg/m^3)	5.5	1.0
Water-binder ratio	0.76	0.36
Concrete Slump (mm)	190	75

IV. METHODOLOGY ADOPTED

The modeling of a particular phenomenon using ANN starts with the presentation of input-output pairs [13]. The choice of the input variables was the key to insure complete description of the systems, whereas the qualities as well as the number of the training observations have a tremendous impact on both the reliability and the performance of the neural network [14]. The slump of concrete is a function of the concrete constituents. MFNN models created were trained using the data collected from RMC plant, to mitigate any chances of change caused in the slump value due to change in composition of concrete ingredients. A total number of 565 mix proportions were collected from RMC plant, containing concrete constituents, namely, cement, fly ash, sand (as fine aggregate), coarse aggregate (20 mm), coarse aggregate

(10 mm), admixture, water-binder ratio and corresponding slump value.

A. Steps involved

- Collecting data from RMC plant.
- Randomising data and dividing it in to three disjoint datasets namely training, validation and test datasets (as in Figure: - 2).

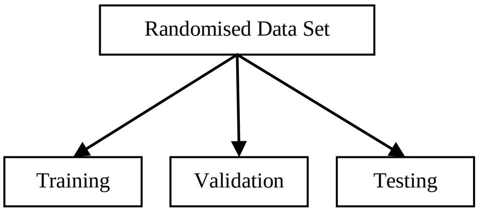

Figure: - 2: Three - way splitting of datasets

- Creating MFNN's models of different complexicities with inputs as Cement content (Kg/m^3), Fly ash (Kg/m^3), Sand (Kg/m^3), Coarse Aggregate 10mm (Kg/m^3), Coarse Aggregate 20mm (Kg/m^3), Admixture (Kg/m^3), Water - binder ratio and outputs as slump value (mm).
- Training MFNN's models using Levenberg – Marquardt's Backpropagation learning Algorithm and validating using validation dataset keeping learning rate and momentum factor 1.0 and 0.5 respectively, till the error function reaches a threshold value.
- Selecting the best fit model on the basis of error function.
- Testing the selected ANN model by training it with combined training validation dataset and computing final network error using test datasets.

B. Error Functions Used

Error = actual slump – predicted slump ..(I)

% Error = {Error/actual slump}X100 ...(II)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2} \quad \text{..........(III)}$$

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

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.

C. Three – Way Data Split Technique

In present study total 565 data sets generated were randomized and out of those, 400 data sets are used for training, 100 data sets are used for validation and the remaining 65 data sets are used for testing the neural network. The breakup of the available data is shown in Figure: - 3. The procedure for three-way data split includes the following steps:

1. Dividing the available data into training, validation and test set,
2. Selecting the neural network architecture and training parameters,
3. Training the model using the training set,
4. Evaluating the model using the validation set,
5. Repeating steps 2 through 4 using different architectures and training parameters,
6. Selecting the best model and train it using the data from the training and validation set.

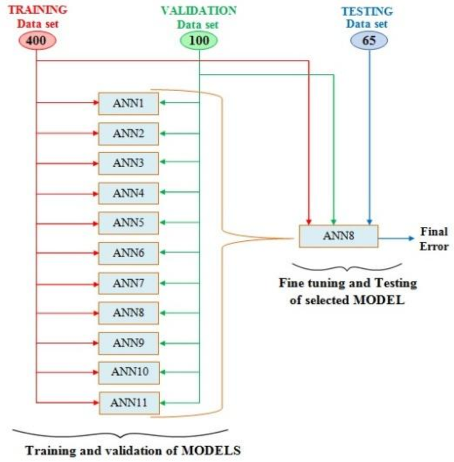

Figure: - 3: Three - way data split technique in network training, validation and testing

V. TRAINING AND VALIDATION OF MODELS CREATED

Detailed description of the training and validation threshold value of RMSE in training and validation for each neural network model are shown in table: - 4.

TABLE: - 4
TRAINING AND VALIDATION RMSE

S.no.	MODEL	Training RMSE	Validation RMSE
1	ANN1	4.461	12.755
2	ANN2	3.706	12.524
3	ANN3	3.689	10.9713
4	ANN4	3.383	10.246
5	ANN5	3.158	9.617
6	ANN6	2.721	9.397
7	ANN7	2.001	7.953
8	**ANN8**	**1.613**	**6.832**
9	ANN9	1.401	11.724
10	ANN10	1.006	11.701
11	ANN11	0.944	13.122

VI. MODEL SELECTION

In present study best fit model was selected by comparing the performance functions of each model, at different comparison backgrounds as:

1) Error range of models in training and validation (Table: - 5 and 6).
2) Minimum RMSE plot (both in training and validation)(Figure: - 4).

3) Minimum RMSE and maximum coefficient of correlation plot (Figure: - 5).

TABLE: - 5
DETAILS OF ERROR (MM) AND %ERROR IN TRAINING

S.NO.	MODELS	ERROR (mm)		% ERROR	
		Minimum	Maximum	Minimum	Maximum
1	ANN1	-25.405	25.831	-29.889	17.814
2	ANN2	-24.448	14.949	-22.300	10.151
3	ANN3	-21.980	13.073	-22.602	9.371
4	ANN4	-21.374	13.815	-17.559	10.448
5	ANN5	-12.717	12.891	-11.561	7.162
6	ANN6	-23.578	11.517	-18.137	7.475
7	ANN7	-9.991	10.752	-6.890	6.325
8	**ANN8**	**-6.016**	**5.299**	**-5.152**	**3.312**
9	ANN9	-6.018	4.106	-5.233	2.832
10	ANN10	-6.123	3.988	-5.324	2.751
11	ANN11	-3.818	3.176	-3.320	2.183

TABLE: - 6
DETAILS OF ERROR (MM) AND %ERROR IN VALIDATION

S.NO.	MODELS	ERROR		%ERROR	
		Min.	Max.	Min.	Max.
1	ANN1	-79.342	37.415	-105.789	23.384
2	ANN2	-79.528	35.529	-106.038	18.700
3	ANN3	-61.152	28.229	-82.537	15.683
4	ANN4	-36.561	30.553	-41.873	19.095
5	ANN5	-36.907	27.677	-40.127	19.088
6	ANN6	-34.999	33.634	-41.175	20.015
7	ANN7	-31.104	36.190	-25.920	42.576
8	**ANN8**	**-19.971**	**22.838**	**-23.495**	**12.818**
9	ANN9	-73.324	30.962	-97.765	16.296
10	ANN10	-81.429	38.125	-65.143	31.771
11	ANN11	-86.148	31.221	-114.864	16.320

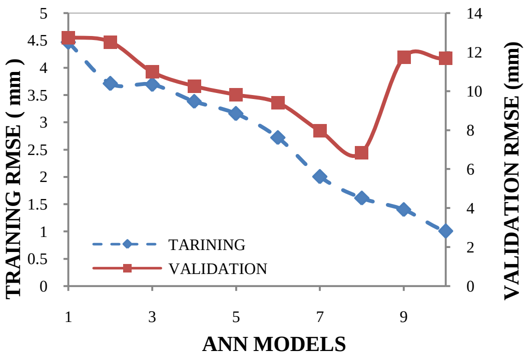

Figure: - 4: Training and validation RMSE plot

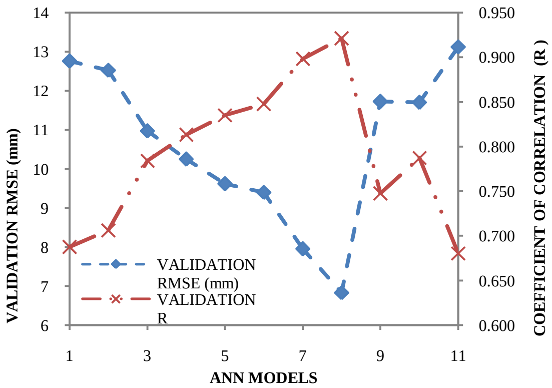

Figure: - 5: Validation RMSE and coeff. of Correlation plot

On the basis of comparison of error functions at backgrounds as stated above Table: - 5 and 6, Figure: - 4 and 5, demonstrates that model ANN8 is the best fit model, as it was found to be optimal (from performance point of view) amongst all models created.

VII. FINE TUNING OF SELECTED MODEL

The selected neural network model i.e. Model 8, which was found to be most optimal (from performance point of view) amongst all the models created, was fine tuned by training with a combination of training set and validation set of data and tested using the test dataset. Figure: - 6 and Figure: - 7, represents the training and testing RMSE of selected model ANN8. The fine tuned model has acquired a balance of both learning and generalization as it was showing final error 3.359 and a coefficient of correlation 0.973.

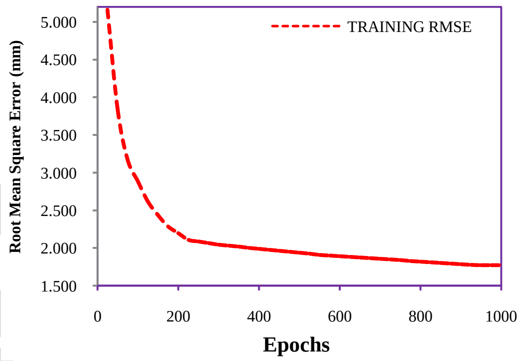

Figure: - 6: Training of selected Model ANN8

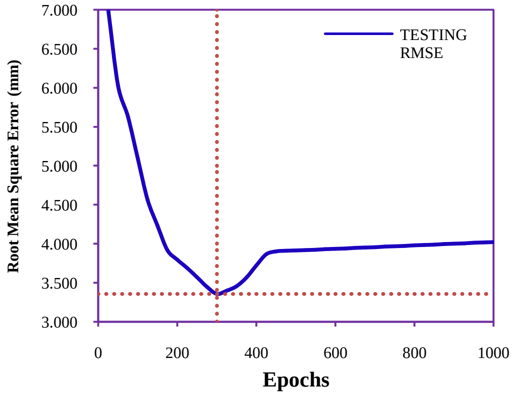

Figure: - 7: Testing of selected Model ANN8

VIII. RESULTS AD DISCUSSIONS

a) The created models were trained and validated using the three – way split technique led the models to approximate the slump value (mm) of RMC depending upon the quantities of mix constituents with some relative error. The minimum RMSE for each model in training and validation along with coefficient of correlation are shown in Table: - 7.

TABLE: - 7
RMSE AND COEFFICIENT OF CORRELATION (R) OF MODELS

MODEL	Training		Validation	
	RMSE	Coefficient of Correlation	RMSE	Coefficient of Correlation

		(R)		(R)
ANNI	4.461	0.940	12.755	0.688
ANN2	3.706	0.962	12.524	0.706
ANN3	3.689	0.963	10.9713	0.784
ANN4	3.383	0.969	10.246	0.813
ANN5	3.158	0.973	9.617	0.835
ANN6	2.721	0.980	9.397	0.847
ANN7	2.001	0.989	7.953	0.898
ANN8	**1.613**	**0.993**	**6.832**	**0.921**
ANN9	1.401	0.996	11.724	0.747
ANN10	1.006	0.997	11.701	0.787
ANN11	0.944	0.998	13.122	0.680

b) Table: - 7 show that Model ANN8 has acquired best fitting in training and validation, giving closest predictions.

c) ANN8 was selected as best fit model amongst all on the basis comparison of error functions at different backgrounds. The selected model was further fine tuned by training on a combined dataset comprising training and validation datasets (total 500 data) then tested using testing dataset comprising 65 data. ANN8 had shown minimum RMSE in training and testing as 1.773 and 3.359 respectively which indicate that the chosen neural network model has been fully trained to recognize any pattern within the available dataset. The RMSE and R (3.359 and 0.9708 respectively) values of test data are midway between those obtained during training and validation.

d) Predicted slump and actual slump along with percentage error plots for each model in validation are shown in Figure: - 8.

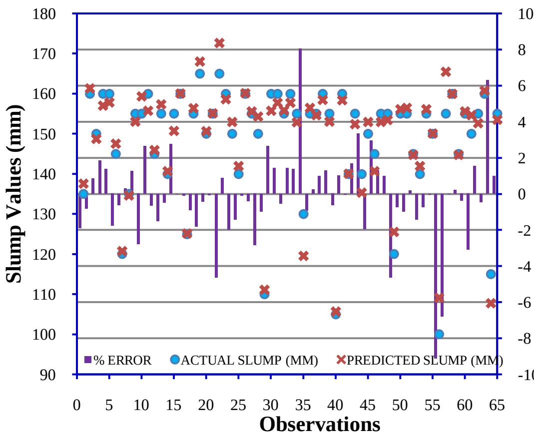

Figure: - 8: Testing result plot for fine tuned model ANN8

IX. CONCLUSION

1) As the final selected and tuned Artificial Neural Network model (ANN8) was tested with the unseen testing dataset (separated during data splitting), the Root Mean Square Error (RMSE) and the Correlation Coefficient (R) was found out to be 3.359 and 0.9708, respectively. This proved clearly that the neural network models developed are reliable and useful, thus proving that splitting the data into three (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) 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 and Ranges of Constituents of Concrete within the range of data used for training.

3) Artificial Neural Networks can be used by engineers to estimate the slump of concrete in quick time, based on concrete constituents.

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