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MODELING SLUMP OF READY MIX CONCRETE USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

With rapid growth in the construction industry, Ready Mix Concrete (RMC) is playing a key role in offering high-quality customized concrete to contractors and builders. The workability of concrete involves early stage operations of concrete: placing, compaction, and finishing. Since RMC is manufactured at a plant and transported to the construction site, loss of workability is of prime concern due to the considerable time interval between mixing and placing of concrete. Workability of concrete is measured using a slump test to evaluate the life of the concrete during its transportation phase and the uniformity of the concrete from batch to batch. The proportions of cement, fly ash, coarse aggregates, fine aggregates, water, and admixtures in the concrete govern its workability or slump value. In this study, an Artificial Neural Networks (ANNs) learning from past examples gathered from a RMC plant were used to model the functional relationship between the input parameters and the slump value of concrete. The ANN model provided promising results compared to first-order and second-order regression techniques for modeling the unknown and complex relationships exhibited by the design mix proportions and the slump of concrete. The neural network synaptic weights that control the learning mechanism of ANN were further used to compute the percentage of relative importance of each constituent of RMC on the slump value, providing insight into the composite nature of concrete. The technique presented in the study will enable technical staff to quickly estimate the slump of RMC based on its design mix constituents without having to perform multiple design mix trials in order to achieve a customized slump value.

Keywords: Artificial Neural Network; Concrete slump; Three-way data split technique; Weights Method

1. INTRODUCTION

Ready Mix Concrete (RMC) has emerged as the preferred choice among contractors and builders for reinforced concrete construction, primarily due to its customized combination of constituents resulting in an engineered premium-quality concrete mix. With the adaptability to be transported to congested sites and high conditions of quality control, RMC has stimulated infrastructure growth, providing both reliability and durability of construction. RMC manufactured at a plant is transported to construction sites in a condition ready for placing by the customer. The time span between the production, transportation, and subsequent laying of RMC at the site places a restraint on its shelf life and usefulness since concrete must be laid in position without any reduction in its workability. The workability of concrete—defined as the ease with which fresh concrete can be mixed, transported, and subsequently placed and

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compacted—is therefore of prime concern during the design mix of RMC. The workability of concrete is a function of the rheological properties of the cement paste, internal friction between the aggregate particles, and the external friction between the concrete and the surface of the framework (Yeh, 2007). The complexities of the mentioned associations have made it difficult to quantitatively measure the workability of concrete. The consistency of concrete is most commonly measured using a slump test either in the laboratory or at the construction site. Although the slump test does not measure all factors contributing to workability, it acts as a useful indicator of concrete uniformity from batch to batch.

The factors influencing the slump of concrete—namely cement, fly ash, sand, coarse aggregate, admixture and water-binder ratio—makes the modeling of slump a highly non-linear functional relationship. Over the past two decades, Artificial Neural Networks (ANNs) have gained immense popularity due to their ability to learn from past examples and derive explicit relationships that are difficult to formulate using traditional methods of computing. Inspired by the working of the human brain, ANNs have been widely used for modeling the material behavior governed by a number of parameters whose interactions are either unknown or too complex to represent. ANN has been successfully used in the past to model the slump of ready mix concrete (Dias & Pooliyadda, 2001), the workability of concrete containing metakaolin and fly ash (Bai et al., 2003), and the slump of fly ash and slag concrete (Yeh, 2006), as well as to predict the slump of high-performance concrete (Yeh, 2007; Chine et al., 2010) and high-strength concrete (Oztas et al., 2003).

The research paper presents the application of ANN to a model of complex, non-linear, and unknown functional relationships by modeling the complex nonlinear behavior of concrete for predicting the slump value based on the design mix proportions of RMC. Eleven neural network models of different complexities were prepared using inputs as concrete mix ingredients: cement, fly ash, sand (as fine aggregate), coarse aggregate (20 mm), coarse aggregate (10 mm), admixture and water-binder ratio and output as concrete slump value. The selected neural network model has been compared with first-order and second-order regression models to evaluate its robustness. The synaptic weights in neural networks attribute to the relative importance of the various inputs on the predicted output value. The “weights” method based on neural network weights was used to assess the relative importance of various concrete constituents on the slump value.

2. METHODOLOGY

2.1. Exemplar Patterns for Neural Network Modeling

The modeling of a particular phenomenon using ANN starts with the presentation of input-output pairs. The slump of concrete is a function of the constituents of concrete. Concrete being a composite material, its material properties are difficult to model due to the lack of standard empirical relationships. ANN having the capability to learn from past examples or experimental data, is trained using the design mix data collected from the same 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 a RMC plant. These included the following concrete constituents in kg/m^3: cement, fly ash, sand (as fine aggregate), coarse aggregate (CA) (20 mm), coarse aggregate (CA) (10 mm). The elements analyzed also included admixture, water-binder ratio, and corresponding observed or measured slump value in mm. The available data comprising 565 RMC mix proportions and corresponding slump values were randomly divided into 400 training, 100 validation, and 65 test data sets.

2.2. Artificial Neural Network Architecture

The architecture of an artificial neural network (ANN) is defined by the interconnection of the neurons arranged in layers, a learning algorithm for systematic updating and adjusting of weights and biases, and an activation function. The most commonly used neural network architecture is a "feed-forward neural network," which generally consists of an array of artificial neurons forming an "input layer," an "output layer," and a number of intermediate "hidden layers." In the present problem, RMC mix proportion ingredients—namely, cement, fly ash, sand, coarse aggregate (20 mm), coarse aggregate (10 mm)—admixture, and water-binder ratio form the seven inputs or neurons of the input layer for the neural network. Correspondingly, the value of concrete slump forms the output or neuron of the output layer of the neural network. The intermediate, or "hidden" layers govern the complexity of the neural network and therefore control the learning and generalization ability of the network. A three-layer feed-forward neural network for the present problem is shown in Figure 1.

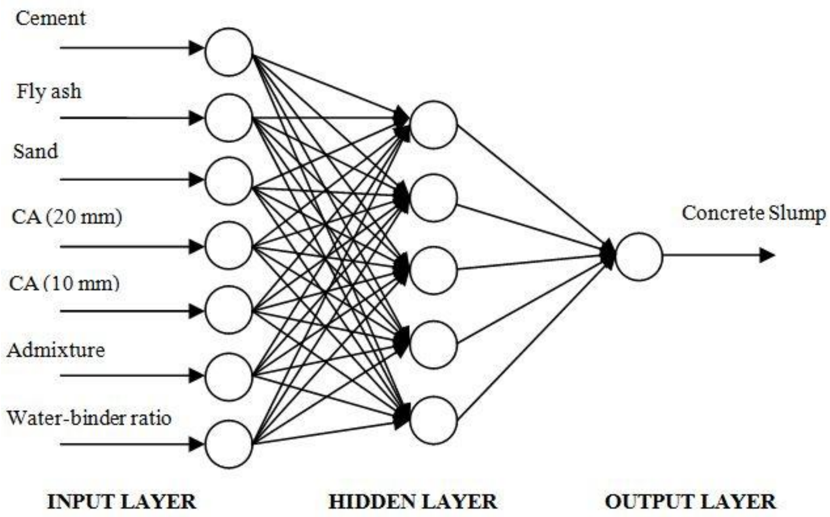

Figure 1 Three layer feed forward neural network

The selection of hidden layers and hidden layer neurons is a trial and error process; it generally begins by choosing a network with a minimum number of hidden layers and hidden layer neurons. The systematic updating of neural network weights is accomplished by a training algorithm. The utility of transfer functions or activation function in neural networks is to introduce non-linearity into the network. Introduction of a transfer function in the neural network enables it to robustly deal with unknown, complex, and nonlinear input-output relationships (Shamseldin et al., 2002). Eleven neural network models of different complexities, shown in Table 1, were developed using MATLAB 2011b software and trained using the Lavenberg-Marquardt training algorithm (*trainlm*). For introducing non-linearity into the network, a hyperbolic tangent sigmoid transfer function (*tansig*) has been used in the hidden layers and to facilitate the comparison of observed slump value with the ANN predicted slump, a linear transfer function (*purelin*) for the output layer has been employed.

2.3. Training, Validation and Testing of Neural Network Models

ANN derives learning capabilities through training using input-output data pairs and subsequent generalization ability when subjected to unseen data. A three-way data split technique is used for training, validation, and testing of neural network models. The procedure adopted for three-way data split includes the following steps:

a) Dividing the available data into training, validation, and test sets
b) Selecting the neural network architecture and training parameters
c) Training the model using the training set
d) Evaluating the model using the validation set

e) Repeating steps (b) through (d) using different architectures and training parameters
f) Selecting the best model and training it using the data from the training and validation set
g) Assessing the performance of this final model using the test set.

Table 1 Neural network architecture and training parameters

Neural Network Architecture						Training Parameters			
		Hidden Layer Neurons				Transfer Function			
Model Name	Hidden Layers	First Layer	Second Layer	Input Neurons	Output Neurons	Hidden First Layer	Hidden Second Layer	Output Layer	Training Function
ANN 1	One	Five	-	Seven	One	tansig	-	purelin	trainlm
ANN 2	One	Six	-	Seven	One	tansig	-	purelin	trainlm
ANN 3	One	Seven	-	Seven	One	tansig	-	purelin	trainlm
ANN 4	One	Eight	-	Seven	One	tansig	-	purelin	trainlm
ANN 5	One	Nine	-	Seven	One	tansig	-	purelin	trainlm
ANN 6	Two	Six	Six	Seven	One	tansig	tansig	purelin	trainlm
ANN 7	Two	Seven	Seven	Seven	One	tansig	tansig	purelin	trainlm
ANN 8	Two	Eight	Eight	Seven	One	tansig	tansig	purelin	trainlm
ANN 9	Two	Nine	Nine	Seven	One	tansig	tansig	purelin	trainlm
ANN 10	Two	Ten	Ten	Seven	One	tansig	tansig	purelin	trainlm
ANN 11	Two	Eleven	Eleven	Seven	One	tansig	tansig	purelin	trainlm

3. RESULTS AND DISCUSSION

3.1. Neural Network Model Selection

For finding the optimal neural network architecture, a trial and error technique was adopted. The neural network architectures ANN 1 to ANN 11 were individually trained using a training data set; their generalization ability was then tested using a validation data set. As the complexity or size of weight and bias matrix of neural network is increased, the root mean square error (*RMSE*) during training continually decreases, with an increase in value of correlation coefficient (*R*) indicating that the neural network is gradually learning. In this case, the *RMSE* value for validation reached a minimum of 6.832 mm for neural network model ANN 8 and again began to rise. This indicates the over-fitting or over-learning of the neural network, leading to poor generalization of the network when presented with unseen data. Since model ANN 8 gave the best generalization among the trained ANN models with a higher value of *R* and a lower *RMSE* (Table 2), ANN 8, which contains two hidden layers, each of which has eight hidden layer neurons, was chosen for modeling RMC slump.

3.2. Testing of Selected Neural Network Model

The selected ANN 8 model was tested by training the model using the combined training and validation datasets, and was subsequently tested using the test dataset. Table 3 shows that the *RMSE* value of test data is computed as 3.359 mm, and the correlation coefficient (*R*) is evaluated as 0.9730. The *RMSE* and *R* values of test data are midway between those obtained during training and validation. This shows that the selected neural network model ANN 8, which has two hidden layers with eight neurons each, achieved a balance of both learning and generalization and therefore can fully recognize any pattern and can predict slump values close to the observed ones.

Table 2 *RMSE* and *R* statistics for training and validation of ANN Models

ANN model	Size of weight and bias matrix	Training		Validation	
		RMSE (mm)	*R*	*RMSE* (mm)	*R*
ANN 1	46	4.386	0.9414	12.422	0.7079
ANN 2	55	3.756	0.9488	10.318	0.8099
ANN 3	64	3.728	0.9512	10.184	0.8215
ANN 4	73	3.474	0.9536	8.906	0.8737
ANN 5	82	3.236	0.9562	8.346	0.8813
ANN 6	97	2.372	0.9797	8.016	0.8980
ANN 7	120	2.346	0.9832	7.953	0.8982
ANN 8	145	1.773	0.9915	6.832	0.9209
ANN 9	172	1.376	0.9935	9.638	0.8537
ANN 10	201	1.058	0.9947	11.700	0.7874
ANN 11	232	0.818	0.9979	14.056	0.6451

Table 3 RMSE and R statistics values for the selected ANN model

Statistics	Training	Validation	Testing
RMSE (mm)	1.7730	6.8320	3.3590
R	0.9915	0.9209	0.9730

3.3. Comparison between Regression and Artificial Neural Network Model

The performance of the trained neural network is compared with that of first-order and second-order regression models. The first-order regression model is adopted as represented by Equation 1:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i \tag{1}$$

The second-order regression model is adopted as

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j}^{k-1} \beta_{ij} x_i x_j \tag{2}$$

where y is a dependent variable or response variable (slump of concrete), $\beta_i, \beta_{ii}, \beta_{ij}$ represent the linear, quadratic, and interaction effects, and β_0 is the intercept term. The terms x_i, x_j, x_k represent the independent variables or influencing variables (mix proportion constituents of RMC).

The available data, comprising 565 data sets, were used for comparing the performance of the neural network model with first-order and second-order regression models. A comparison of statistics—mean, standard deviation, correlation coefficient (*R*), coefficient of determination

(R^2) and root mean square error (*RMSE*)—is exhibited in Table 4. The mean and standard deviation of observed or measured slump was found to be very close to the predicted ANN output. The lowest RMSE value of 2.799 mm was achieved when the ANN model was used. A regression plot between observed slump and ANN predicted values shows a higher R and R^2 value of 0.9807 and 0.961, respectively, in comparison to first order and second order regression models. The results show a strong correlation between the observed slump and the ANN predicted slump.

Table 4 Comparison of observed RMC slump data with ANN, first-order regression, and second-order regression model slump output

Statistics	Observed RMC slump data	ANN output	First-order regression output	Second-order regression output
Mean (mm)	150.133	150.083	149.916	149.949
Standard Deviation (mm)	14.237	14.043	8.548	12.514
Correlation Coefficient (R)		0.9807	0.5898	0.8642
R^2		0.961	0.347	0.746
RMSE (mm)		2.799	11.717	7.300

The observed or measured slump values are compared with ANN, first-order regression, and second-order regression models by plotting a regression plot. Figure 2 shows that all ANN predicted slump outputs fall in the range of +10% and -10 % error lines, showing close agreement with the observed values. The trend line passes midway between the error lines, suggesting a strong concurrence with the observed data. In the case of the first-order regression shown in Figure 3, most of the predicted slump data fall away from the threshold error lines, indicating a poor correlation with the observed data. A significant improvement is achieved with the second-order regression model shown in Figure 4, but the superiority and robustness of ANN prediction are unsurpassed.

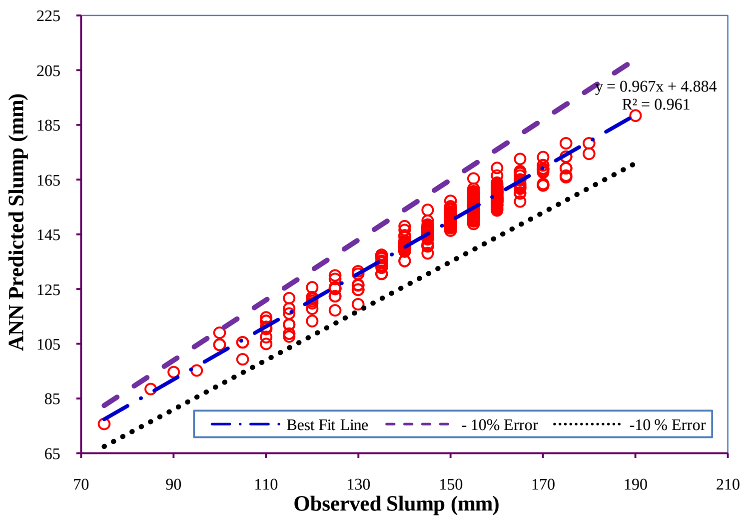

Figure 2 Regression plot between observed concrete slump and ANN predicted concrete slump

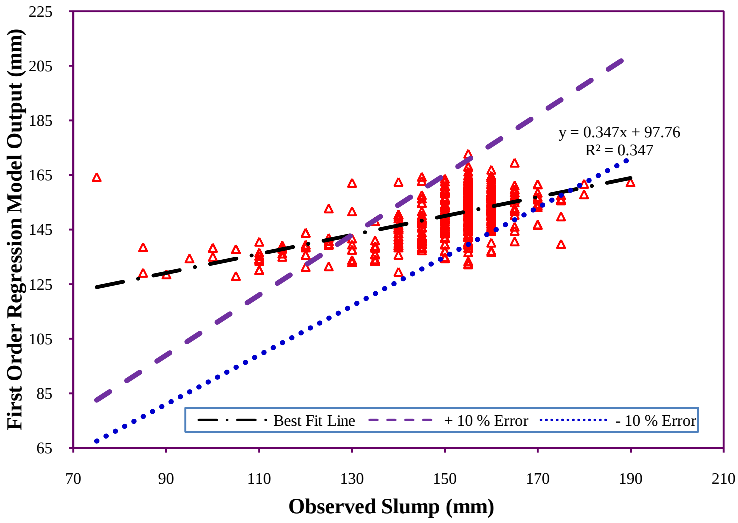

Figure 3 Regression plot between observed concrete slump and first-order regression model output

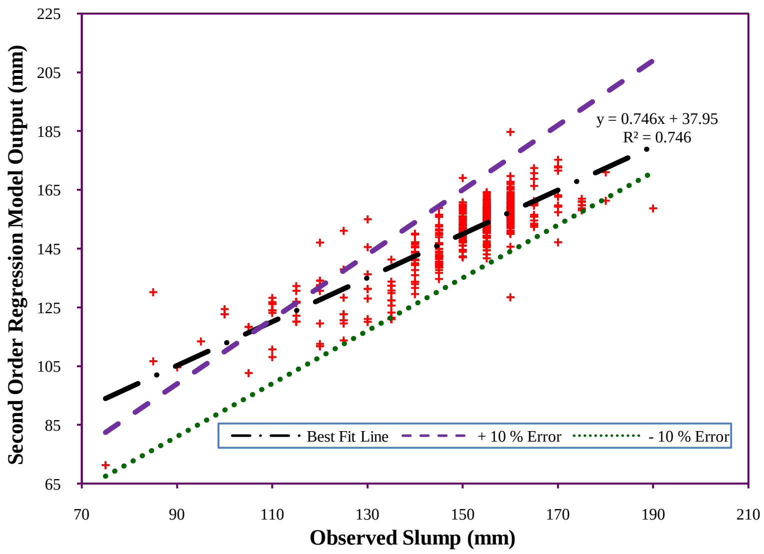

Figure 4 Regression plot between observed concrete slump and second-order regression model output

3.4. Quantifying the Relative Importance of Design Mix Constituents on Slump Value

Concrete is a composite material, and therefore it is not possible to directly evaluate the effect of each design mix constituent on the slump value. In all previous studies, the research has been restricted to the material modeling of concrete. The "weights method" presents a simplified approach by harnessing the knowledge storing parameters of neural networks, known as the synaptic weights, for determining the relative importance of the concrete mix proportions on concrete slump. For a feed forward neural network having N input neurons, L hidden layer neurons, and M output neurons, the product of input-hidden layer neuron weights w_{ij} (i represents the input neuron and j represents the hidden neuron) and hidden-output layer neuron weights v_{jk} (j represents hidden neuron and k represents the output neuron) are summed across all hidden neurons. The relative contributions of the variables are calculated by dividing the absolute value of each variable contribution by the grand sum of all absolute contributions

(Tosh & Ruxton, 2010). Equation 3 gives the percentage impact Q_{ik} of the input variable x_i on the output y_k (Montano & Palmer, 2003).

$$Q_{ik} = \frac{\sum_{j=1}^{L} \left(\frac{w_{ij}}{\sum_{r=1}^{N} w_{rj}} v_{jk} \right)}{\sum_{i=1}^{N} \left(\sum_{j=1}^{L} \frac{w_{ij}}{\sum_{r=1}^{N} w_{rj}} v_{jk} \right)} \times 100 \tag{3}$$

where $\sum_{r=1}^{N} w_{rj}$ denotes the sum of connection weights between the input neurons N and the hidden neuron j. The relative importance of seven neural network inputs on concrete slump is shown in Figure 5.

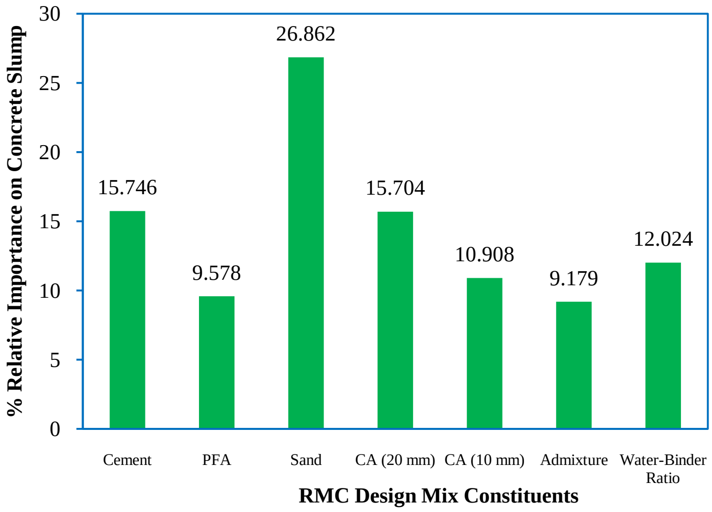

Figure 5 Relative importance of RMC design mix constituent on slump value

Based on the analysis using the "weights method", the following conclusions can be drawn:

i. Natural sand from riverbeds, having smooth and rounded particles, provides better workability. However, the addition of too much fine aggregate can significantly increase the water needed to produce a workable mix. But since water-binder ratio presents a restraint, while designing a mix for a certain compressive strength, fine aggregate is the most important factor in determining concrete slump, with relative importance of 26.862%.

ii. Lower cement content will lower the workability of concrete. On the other hand, higher cement content will lead to higher cohesiveness of concrete, but will make it too sticky to be conveniently finished. Its relative importance in workability was found to be 15.746%.

iii. A rounded aggregate with larger particle size requires more water to produce a workable mix. On the other hand, angular particles with smaller size require less water. A higher percentage of coarse aggregate (approximately 70%) in concrete volume significantly affects concrete workability, which is calculated as 15.704% and 10.908%, respectively.

iv. Water in the concrete performs a dual function, aiding hydration of cement paste and providing lubrication between cement paste and aggregates. Hence the addition of more water aids the workability of concrete, but can also lead to undesirable effects such as bleeding. The present study reveals that there is an approximately 12% effect of water-binder on the workability of concrete.
v. The effect of admixture on concrete slump in the present study is only 9.179%, due to very little use of naptha-based chemical admixture.
vi. Due to higher fineness and higher surface area, the incorporation of PFA (fly ash and metakaolin) into concrete requires less water for workability and therefore contributes 9.578% to the slump of concrete.

4. CONCLUSION

The composite nature of concrete imparts a highly complex functional relationship to the interactions among the concrete mix constituents and concrete slump. This study showed that ANN trained using experimental or observed data presents a promising approach in modeling unstructured problems related to the material behavior of concrete. The study also proved that modeling using ANN methodology is superior to the more conventional use of first-order regression and second-order regression for problems involving a number of independent variables. Based on the concrete mix proportions, the proposed model can be used as concrete design mix support tool for quickly estimating the slump of concrete to a certain degree of accuracy. This will help technical personnel in charge of mix design to make sensible decisions, thereby avoiding multiple trials with different mix proportions.

Studies conducted in the past were restricted to the mathematical modeling of concrete slump using ANN. The present study has also highlighted the use of neural network weights for computing the relative importance of each constituent of concrete on the slump value. The technique also offers the added advantage of drawing inferences regarding the effect of each constituent on the slump value, thus providing insight into the composite nature of concrete.

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