MODELING THE PROPERTIES OF SELF-COMPACTING CONCRETE: AN M-5 MODEL TREE BASED APPROACH

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Abstract

This paper explores the potential of M5 model tree based approach in predicting 28-days compressive strength and slump flow of self-compacting concrete. A total of 80 data collected from the exiting literature are used in present study. To compare the performance of the technique, prediction was also done using a back propagation neural network model. A correlation coefficient of 0.908 with a root mean square error of 5.92 for strength prediction was achieved by M5 model tree approach. In comparison, a value of 0.906 as correlation coefficient and 6.01 as root mean square error was obtained by neural network approach. For slump flow prediction, correlation coefficient values of 0.901 and 0.914 (root mean square error of 9.174 and 8.778) were achieved by M5 model tree and neural network modelling approaches respectively. Results from this study suggests a comparable performance by M5 model tree based approach to neural network approach for both strength and slump prediction. It was observed that in comparison to neural network, M5 model tree requires no user-defined parameters to be set and also involves using a small computational cost , as choice of suitable architecture has always been a problem with neural network approach and requires lot of efforts and computational cost.

1. INTRODUCTION

Concrete is one of the most versatile construction material that has been widely used for almost a century now. The mechanical performance and long term durability of concrete structures are greatly affected by compaction work of fresh concrete during placement at construction sites. Further, the compaction has to be compromised due to use of congested and heavily reinforced concrete structural members, the limited access of mechanical vibrators in hard to reach areas, the lack of skilled labor and the noise levels associated with mechanical vibrators. These problems were overcome by developing a new type of flowable concrete called Self-Compacting Concrete (SCC).

SCC was developed initially in Japan in the 1980's (Okamura,H., [1]) and later adopted by countries like UK and other European countries. The successful development of SCC must ensure a good balance between deformability and stability. It requires the manipulation of several mixture variables to ensure acceptable rheological behavior and proper mechanical properties. Some guidelines which have been set for mixture proportioning of SCC are i) reducing the volume ratio of aggregate to cementitious material; increasing the paste volume and water-cement ratio (w/c); ii) controlling the maximum coarse aggregate particle size and total volume; and iii) using various viscosity-enhancing admixtures (VEA) (Nagamoto et al. [2]). Some attempts have been made to describe engineering properties using traditional regression analysis tools and statistical models (Sonebi,M.,[3-4]). Neural Network have also been successfully applied to prediction of compressive strength of concrete mixes[5-12].

The objective of this paper is to predict the slump and compressive strength of SCC mixtures using a tree based regression methodology. M5 Model Tree used in present study was proposed by Quinlan [14]. This approach is being used effectively in different civil engineering problems [15-17] and has been found to work well in comparison to much used neural network approach [13].

Design of a neural network involves in using non-linear optimization problem that provides a local minima. During training process a large number of training iterations may force artificial neural networks to over train, which may affect the predicting capabilities of the model. Several studies suggested using a validation data set to have an idea about the suitable number of iterations for a specific data set. This may be a problem for studies where number of data set is limited, like concrete strength predictions. Choice of a suitable architecture has always been a problem with neural network approach and requires a lot of efforts and computational cost. Presence of local minima due to the use of a non-linear optimization problem with a back propagation neural network approach is another drawback while the advantage of using M5 model tree is its speed and requiring no user-defined parameter.

2. M5 MODEL TREE

The parameter space is split into areas (subspaces) by this technique and it builds in each of them a linear regression model.The M5 model tree approach is based on the principle of information theory that makes it possible to split the multi-dimensional parameter space and generate the models automatically according to the overall quality criterion.

The splitting in M5 Modal Tree approach follows the idea of a decision tree , but instead of the class labels it has linear regression functions at the leaves, which can predict continuous numerical attributes. Model trees generalize the concepts of regression trees, which have constant values at their leaves (Witten & Frank, [19]). The major advantage of model trees over regression trees is that model trees are much smaller than regression trees and regression functions do not normally involve many variables. The working of M5 algorithm is used in the present study for inducing a model tree is described as:

Suppose a set of T training examples is available. Each example is characterized by the values of a fixed set of (input) attributes and has an associated target (output) value. The set T is either associated with a leaf, or some test is chosen that splits T into subsets corresponding to the test outcomes and the same process is applied recursively to the subsets. The splitting criterion for the M5 model tree algorithm is based on treating the standard deviation of the class values that reach a node as a measure of the error at that node, and calculating the expected reduction in this error as a result of testing each attribute at that node.

After examining all the possible splits, M5 chooses the one that maximizes the expected error reduction. Splitting in M5 ceases when the class values of all the instances that reach a node vary just slightly, or only a few instances remain. In smoothing, the adjacent linear equations are updated in such a way that the predicted outputs for the neighbouring input vectors corresponding to the different equations are becoming close in value.

3. DATABASE

The model's success in predicting the behaviour of SCC mixtures depends on comprehensiveness of the training data.The basic parameters considered in this study are cement content, sand, coarse aggregate, PFA (Pulverised Fly Ash), water to powder ratio and dosage of Superplasticizer. The response has been derived for slump flow and compressive strength at 28-days. The data has been identified from the literature having mixture component with comparable physical and chemical properties. The exclusion of one or more of SCC properties in some studies and the ambiguity of mixture proportions and testing methods in others was responsible for setting the criteria for identification of data.

Table 1: Source of training data

S.N.	Source of training data	No. of training data	Comments
1.	Bouzoubaa and Lachemi (2001)	9	Laboratory data
2.	Ghezal and Khayat (2002)	18	Experimental data
3.	Bui et al. (2002)	14	Laboratory data
4.	Patel et al. (2004)	21	Laboratory data
5.	Sonebi(2004)	18	Laboratory data

The M5 model tree was designed using 69 pairs of input and output vectors for slump prediction and 80 data for strength prediction. The data sets are collected from studies(table1)[20-23,3-4]. Input vector consisted of mixture variables and an output vector of one element i.e. slump flow and compressive strength at 28-days. For slump flow and strength prediction, the input parameters are weight of cement, sand, coarse aggregate, water-binder ratio, volume of superplasticizer and PFA. A back propagation neural network was also used to compare its performance with M5 model tree based approach. A neural network based modelling algorithm requires setting up of different learning parameters (like learning rate, momentum), the optimal number of nodes in the hidden layer and the number of hidden layers so as to have a less complex network with a relatively better generalisation capability.

4. RESULTS AND ANALYSIS

The acceptance / rejection of the model developed is determined by its ability to predict the rheological behavior and compressive strength of SCC. Also, a successfully trained model is characterized by its ability to predict slump flow and compressive strength values for the data it was trained on. A 10-fold cross validation was used to predict the slump flow and compressive strength for the data set used in this study. The cross validation is the method of accuracy of a classification or regression model. The input data set is divided into several parts (a number defined by the user), with each part intern used to test a model fitted to the remaining part. The correlation coefficient and root mean square error (RMSE) was used to judge the performance of M5 model tree as well of the neural network approach in predicting the slump and strength.

Table 2 provides the correlation coefficient and RMSE obtained with this data using M5 model to predict the slump flow and 28 days compressive strength. To compare the performance of M5 model tree, graphs between actual and predicted slump flow and strength are plotted. The performance of M5 model tree based approach in predicting the compressive strength for this data set is shown in Figure 1. Results suggest that most of the points are lying within ± 20% of the line of perfect agreement, which suggest that M5 based modelling approach, can effectively be used to predict the compressive strength for self-compacting concrete data. A correlation coefficient of 0.91 (RMSE = 5.9) was achieved with this approach (Table 2).

Figure 2 provide the plots between the actual and predicted values of slump for the used data set. Results suggest a better performance by M5 model tree for this data set in slump prediction also. Most of the points are again lying within ± 20% of the line of perfect agreement (Figure 2) and a correlation coefficient of 0.90 (RMSE = 9.17) was achieved.

To compare the performance of M5 model tree a back propagation neural network based modelling approach is used. An Architecture performing well for both data sets is chosen after a large number of trials.

The back-propagation neural network used for slump and strength prediction uses a learning rate of 0.3-momentum value as 0.2 and one hidden layer with six numbers of nodes; weights and biases were initialized randomly. Correlation coefficient and RMSE achieved by using neural network modelling approach for strength and slump prediction is given in table2. A comparison of results obtained by M5 model tree and neural network approach suggest a comparable performance by both modelling approaches for both strength and slump prediction. Figure 3 and Figure 4 provides the plot between the actual and predicted values of slump flow and compressive strength by neural network approach.

5. CONCLUSIONS

Results from this study suggest that M5 model tree based modelling approach perform well in predicting both strength and slump flow for the data set for SCC used in present study. The SCC mixture can be designed as per specifications, and then presented to the M5 model to predict its properties. The results obtained suggest that M5 model tree based approach can effectively be used to analyse the complex relationship between various parameters used in predicting the compressive strength and flow of self-compacting concrete as an alternative to neural network approach.

Table 2: Summary of coefficients by Neural Network and M5 Modelling Technique

Methodology	Property	Correlation Coefficient	Mean Absolute Error	Root Mean Square Error
NN	Slump	0.914	7.085	8.778
	Strength	0.906	4.819	6.005
M5	Slump	0.901	7.197	9.174
	Strength	0.908	4.514	5.923

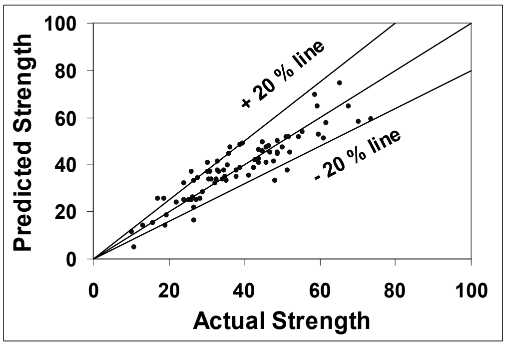

Figure 1: Actual v/s Predicted value for Strength (MPa) by M5 Model Tree.

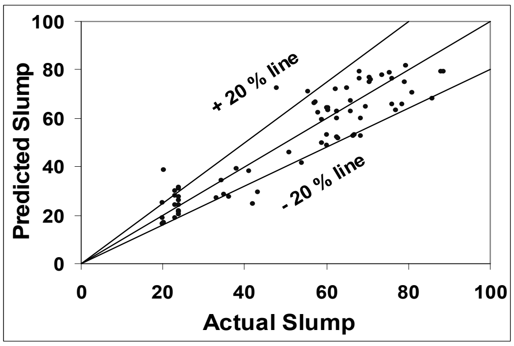

Figure 2: Actual v/s Predicted value for Slump Flow (cm) by M5 Model Tree.

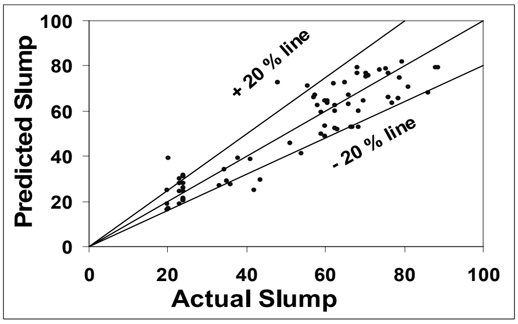

Figure 3: Actual v/s Predicted value for Slump Flow (cm) by Neural Network

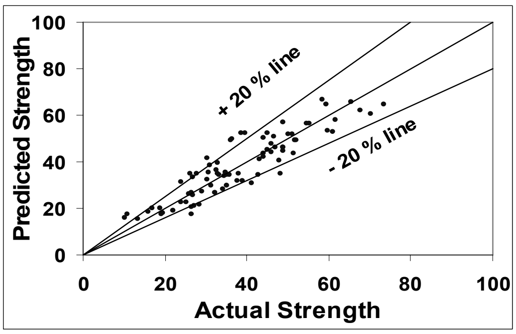

Figure 4: Actual v/s Predicted value for Strength (MPa) by Neural Network.

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