Comparison of ANN and RKS approaches to model SCC strength

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Abstract:
Self compacting concrete (SCC) is a high performance concrete that has high flowability and can be used in heavily reinforced concrete members with minimal compaction segregation and bleeding. The mix proportioning of SCC is highly complex and large number of trials are required to get the mix with the desired properties resulting in the wastage of materials and time. The research on SCC has been highly empirical and no theoretical relationships have been developed between the mixture proportioning and engineering properties of SCC. In this work effectiveness of artificial neural network (ANN) and random kitchen sink algorithm (RKS) with regularized least square algorithm (RLS) in predicting the split tensile strength of the SCC is analysed. Random kitchen sink algorithm is used for mapping data to higher dimension and classification of this data is done using regularized least square algorithm. The training and testing data for the algorithm was obtained experimentally using standard test procedures and materials available. Total of 40 trials were done which were used as the training and testing data. Trials were performed by varying the amount of fine aggregate, coarse aggregate, dosage and type of super plasticizer and water. Prediction accuracy of the ANN and RKS model is checked by comparing the RMSE value of both ANN and RKS. Analysis shows that eventhough the RKS model is good for large data set, its prediction accuracy is as good as conventional prediction method like ANN so the split tensile strength model developed by RKS can be used in industries for the proportioning of SCC with tailor made property.

1. Introduction
Compaction of concrete is one of the biggest problems in congested and heavily reinforced structural members. Without proper compaction the long term durability and performance of concrete structures are affected significantly. It is very difficult to use mechanical vibrators

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and manual compaction in heavily reinforced sections. Self compacting concrete was developed to provide a solution for these problems. SCC was developed by a Japanese researcher Nagamoto N [1] during the late 1980's. It has high workability and can easily flow through congested heavily reinforced sections under its own weight. It should have high deforming capacity, low yield stress and sufficient viscosity to ensure that the solid particles remain in uniform suspension during transportation, placing and setting of concrete. To achieve all these characteristics the mix proportioning of SCC should be done in such a way that it should satisfy both the rheological and mechanical properties. The mix proportioning of SCC is different from that of ordinary concrete. SCC has finer particles and the sizes of the coarse aggregates are carefully controlled for better workability. It uses superplasticizers in large amounts to reduce the water content and also viscosity modifying agents in small dosages. The compatibility between cement and super plasticizer was studied by Dhanya Sathyan [2] as incompatibility can lead to excessive bleeding, segregation and other undesirable properties.

The mix proportioning of SCC is highly complex and no theoretical relationship has been developed between the mix proportioning and the measured engineering properties of SCC. Due to this large number of trials are required for getting a SCC mix with the desired characteristics leading to wastage of time and materials. The engineering properties of SCC are often described using statistical models, extensive laboratory testing and other optimization methods. All the methods used can be effective only within the experimental domain. This paper shows how regularized least square algorithm along with random kitchen sink algorithm can be used effectively to predict the tensile strength of SCC. It is a non-parametric approach and unlike other parametric models the relationship between the engineering property and mix proportions are generated from the data which was collected by performing experiments in the laboratory.

Gokmen Tayfur [5] used Fuzzy logic and ANN for predicting the strength of high strength concrete and a comparative study between the two models was done. Results show that the errors for Fuzzy logic are comparatively less than ANN for the training data set. I-Cheng Yeh [6] used neural networks and design of experiments (DOE) to analyze the strength of concrete. Anh Duc Pham [7] used Metaheuristic optimized least squares Support Vector regression (LSSVR) to predict the compressive strength of high performance concrete. LSSVR is an advanced artificial intelligence method that can be effectively used for nonlinear modeling. P Yuvraj [8] predicted the fracture characteristics of high strength and ultra high strength concrete beams using Support vector regression(SVR) models. Kezhen Yan [9] predicted the elastic modulus of normal and high strength concrete by SVM.

Effectiveness of tree based modeling approach in predicting compressive strength of highperformance concrete was assessed by Deepa et al [31]. In this work Multilayer Perceptron model, M5P Tree model, Linear Regression model were also used to predict the compressive strength. Tang et al [33] made an investigation on correlation between pulse velocity and compressive strength of concrete. In this study artificial neural network was used to develop a relation between pulse velocity and strength. Tang [32] has modeled the torsional strength of RC beams using radial basis function neural network(RBFN). Testing and training data for the model is taken from previous literatures. Jurmaa [30] predicted the ultimate load capacity of Reinforced Concrete beams using ANN. Data for testing and training of the model is generated using finite element method of a simply supported beam with two point loading. The prediction accuracy of the model is compared with those obtained from limit state theory.
and it is observed that failure load obtained from developed ANN model is more accurate than those from limit state theory. So many other works were also carried out by many researchers in the area of modeling the properties of SCC and concrete [4, 3, 26, 27, 28, 29].

But in all methods space requirement to save the data and the time required for computation are more. Yedu C Nair et al [10] did a spreadsheet implication for classification of data using Random kitchen sink (RKS). Classification has been done in an efficient manner by inheriting concepts from linear algebra and optimization theory. The advantage of this RKS model is the less time requirement for computation. In this work split tensile strength of the SCC is modeled using ANN and RKS and the prediction accuracy of these models are compared.

2. Modeling Methodology

2.1 Artificial neural Network (ANN)

ANN is a computing system that is designed to simulate the way the human brain analyses and process information. ANN are considered nonlinear statistical data modelling tools where the complex relationships between inputs and outputs are modelled or patterns are found. An ANN has several advantages but one of the most recognized of these is the fact that it can actually learn from observing data sets. ANN takes data samples rather than entire data sets to arrive at solutions, which saves both time and money. ANN has multiple layers that are interconnected. The first layer consists of input neurons. Those neurons send data on to the second layer, which in turn sends the output neurons to the third layer. So many studies were carried out to predict the properties of concrete using ANN [4, 5, 6, 29, 30, 32, 33]. In this study to compare the prediction accuracy of RKS, the modeling were also done using ANN and comparison were done using the RMSE value obtained for both the method. Input layer of the proposed ANN model consists of 8 processing unit they are the quantity of cement, Fine aggregate, coarse aggregate, water, Superplasticizers based on their family. Out put layer consist of one processing unit that is split tensile strength of the concrete. The numbers of the parameters used in the proposed model are:

- Number of input layer units = 8, Number of hidden layer = 1, Number of output layer units = 1.
- Learning cycle = 700, Architecture of the ANN used for this study are shown in figure 1 (a).

ANN structure is trained and constructed using Matlab software. In training process of a supervised ANN, weights of the links between the neurons are adjusted to minimize output error.

2.2 Random Kitchen Sink (RKS)

Random kitchen sink algorithm is used for the mapping of the data set which cannot be linearly separated. It is a non linear kernel method which can be used for learning and classifying large data sets. Many methods like SVM, Neural networks, Fuzzy logic and Gaussian mixture model based classifiers are popular out of which SVM is the most popular tool used in machine learning. It is based on finding the hyper plane that gives the maximum margin between the classes of the given data set. It cannot be used in the case of large data sets as the kernel matrix is of higher order resulting in large processing time. This problem was overcome by Ali Rahmi [11] by using random feature mapping. The storage space and processing time is not dependent on the number of data points and only dependent on the feature sizes which is far more than the number of data points. An explicit feature mapping is done $\phi(x)$ corresponding
to radial basis function kernel (RBF). The kernel function is symmetric and a real Gaussian function. The kernel function is taken as the inner product of the mapping functions.

\[ k(m, n) = \langle \phi(m), \phi(n) \rangle \]

Where \( k(m, n) \) is a positive definite function and \( \phi(m), \phi(n) \) are the mapping functions.

The RBF kernel is of the form

\[
k(m, n) = e^{-\frac{1}{\sigma^2}(m-n)^T(z)(m-n)} = e^{-\frac{1}{\sigma^2}z^Tz}
\]

Where \( m-n = z, m \) and \( n \) denotes data points. \( \Sigma = \sigma^{-1} \) represent the covariant matrix and \( I \) is a identity matrix of size \( a \times a \).

The RBF kernel can be conveyed as a Gaussian Probability Density function which is shift invariant

\[ k(m, n) = k(m - b, n - b) = k(0, m - n) \]

\( G(\Omega) \) is the Fourier transform of \( f(z) \) where \( z = m-n \). The inverse of the Fourier transform is given by

\[ G^{-1}(\Omega) = k(m, n) = k(m-n) = \int_{\Omega} e^{i(m-n)^Tz} G(\Omega) d\Omega. \]

This according to Bochners theorem is the expected value of random variable

\[ \mathbb{E}(e^{-i\Omega^Tz}) = \int_{\Omega} e^{i\Omega^Tz} G(\Omega) d\Omega \]

\( G(\Omega) \) follow multivariate normal distribution. The expected value of the random variable \( \Omega \) can be obtained by taking the mean of the samples from the probability density function.

To avoid complex calculations the equations can be converted into their sine and cosine functions. A finite dimensional space \( \varphi(m) \) is created of dimension \( L \).
2.3. Regularized Least Squares (RLS)

Regularized Least Square algorithm is used to train a classifier and obtain accuracies that determine the efficiencies with which different data sets are classified. It is mainly applicable in the case of over determined systems. Regularization is a technique used to capture the real trend of data by function and avoids over fitting. Yedu C Nair et al [10] studied the use of regularized least square algorithm for multi class learning. Let our data set contain \( l \) class of objects. The total number of features is \( x \) and total number of objects is \( y \). The data matrix is of size \( x \times y \) and matrix \( C \) is of size \( x \times l \) which holds the label vectors. Matrix \( v \) of size \( y \times l \) map \( y \) tuple data vectors corresponding to label vector. \( f(v) \) is the objective function.

\[
V^* = \arg \min_{v \in \mathbb{R}^{y \times l}} \| C - XV \|_F^2 + \lambda \| V \|_F^2
\]

\[
f(V) = \| C - XV \|_F^2 + \lambda \| V \|_F^2
\]

\[
t(V) = \text{Tr}(C^T C + V^T X^T XV - C^T XV - \text{Tr}(X^T C) + \lambda V^T V)
\]

\[
\frac{\partial f}{\partial V} = 0 \Rightarrow V^* = (X^T X + \lambda I)^{-1} X^T C
\]

The application of regularized least square and random kitchen sink algorithm comes together in GURLS (Grand unified Regularized Least Square) tool bar which is used in MATLAB. It is a tool bar developed for supervised learning based on regularized least square algorithm. The tool box provides a set of basic functionalities which includes various training strategies and routines to handle computations with very large matrices by means of both memory mapped storage and distributed task execution. It consists of a set of tasks each belonging to a predefined category and a method called GURLS core, implemented through the GURLS routine that is responsible for processing the task pipe line. Workflow in RKS approach is described in figure 1(b).

3. Database preparation

3.1 Experimental Details

The training and testing data was obtained experimentally. SCC was tested for its rheological properties like flowing ability, passing ability and segregation resistance. The mixing process and the materials used were kept the same throughout the preparation of the training and testing data.

The materials used for SCC were Portland Pozzolana cement (PPC), coarse aggregate (CA), fine aggregate (FA), super plasticizer and water. Preliminary test were done on both coarse and fine aggregate according to IS 2386 [18,19]. The aggregate were tested for their specific gravity, water absorption, bulk density and fineness modulus. The values were compared with the specifications given in IS 383 [12] and it satisfies the standard requirement. The results are given in table 1.

| Type | Specific gravity | Water absorption (%) | Bulk density (kg/m³) | Fineness modulus |
|------|------------------|----------------------|----------------------|-----------------|
| CA   | 2.74             | 1.8                  | 1535                 | 7.46            |
| FA   | 2.801            | 5                    | 1320                 | 3.642           |

The cement used was PPC and it was tested for its consistency, specific gravity, fineness and compressive strength according to IS 4031 [13,14,15,16]. The obtained values are 37%, 2.9, 2.95 and 35 N/mm² respectively which were compared with the specifications given in IS
1489 [17] and it satisfies all the standard requirements.

Four families of super plasticizers were used and all of them were tested for their densities and solid content according to IS 9103[20]. The obtained values were compared with the company specifications. The optimum dosage of super plasticizer was found out by doing mini slump and marsh cone test. Based on the solid content and dosage of super plasticizer added the necessary water correction was done in the mix. The test values are given in table 2.

| No | Super plasticizer | Density (g/cc) | Solid content (%) | Optimum dosage (%) |
|----|-------------------|----------------|-------------------|--------------------|
| 1  | PCE (Sp1)         | 1.09           | 36.67             | 0.5                |
| 2  | SMF (Sp2)         | 1.225          | 33.056            | 1                  |
| 3  | SNF (Sp3)         | 1.226          | 37.425            | 0.6                |
| 4  | LS (Sp4)          | 1.17           | 31.61             | 0.6                |

The trials were performed by varying the amount of coarse aggregate, fine aggregate, type of super plasticizer and its dosage. The coarse aggregate to fine aggregate ratio was varied from 3/2 to 2/3. The dosage of super plasticizer was varied with respect to the optimum dosage. The materials were mixed using a tilting drum mixer and the mixing time and mixing sequence was kept as a constant.

Rheological tests were carried out to ensure that the mix satisfies all the properties of SCC. For finding the flowability of the SCC mix Slump flow test was carried out according to UNI 11041 [22]. The spread diameter of the concrete was measured. To find the passing ability of the SCC mix J ring test was carried out according to UNI 11045 [23]. The height of concrete just inside and outside J ring bars was measured and their difference was taken. To find the segregation resistance of the SCC mix V funnel test was carried out according to UNI 11042 [24]. The time required for emptying the funnel after five minutes (T3) was noted. The results obtained from all the three tests were compared with the specifications given in UNI 11040 [25]. A mix which satisfies all the three rheological characteristics was accepted as a SCC mix.

Tensile strength of concrete is very important in construction. Split tensile strength is an indirect test to determine the tensile strength of concrete. It is done in accordance with IS 5816[21]. Cylindrical specimens of diameter 10 cm and height 20 cm are cast with proper tamping in three layers. For each trial three cylinders were cast. The cylinders were cured for 28 days before testing their strength. After 28 days they are taken out and dried for 3 hours before testing. The load is applied uniformly perpendicular to the axis of the specimen. The experimental values obtained for split tensile strength are used for both testing and training of the model.

3.2. Normalisation of data

The accuracy with which the model can predict the tensile strength of SCC mixtures largely depend on how accurate the training data is. Larger the number of training data the model can better understand the correlation between the mixture components and the measured engineering properties. The model was trained using 32 training data sets. The input vector consists of mixture variables like cement, coarse aggregate, fine aggregate, four families of super plasticizers and water as given in table 3. The input parameters are selected based on their effect on the mix. Four families of super plasticizers are given as separate input parameters as
their effect on the mix varies for the same dosage. As the cement, coarse aggregate and fine aggregate used are the same they are all given as single input parameters. More input parameters can be given if we have a large database and more variety of materials is used. The output vector consists of the measured split tensile strength of SCC. To predict the accuracy of the model 8 set of test data is used. All the input and output parameters are normalized using standard norm method. The formula is given by

$$y_m = \frac{y_i}{||y||}$$

$$||y|| = \sqrt{y_1^2 + y_2^2 + y_3^2 + ... + y_n^2}$$

Here $y_m$ is the normalized value and $y_i$ is the original value. The values are normalized to one so they will be in the range from 0 to 1. The normalized value of test data is given in table 3.

| Table 3: Normalised input variables of SCC mixtures used to test predictions |
|--------------------------|-----------------|-----------------|---|---|---|---|---|
| Mixture no | Cement | Coarse aggregate | Fine aggregate | Sp1 | Sp2 | Sp3 | Sp4 | Water |
| 1 | 0.1581 | 0.0456 | 0.0558 | 0.1423 | 0 | 0 | 0 | 0.1558 |
| 2 | 0.1581 | 0.0508 | 0.0508 | 0.0890 | 0 | 0 | 0 | 0.1601 |
| 3 | 0.1581 | 0.0456 | 0.0558 | 0 | 0.1762 | 0 | 0 | 0.1544 |
| 4 | 0.1581 | 0.0508 | 0.0508 | 0 | 0.1982 | 0 | 0 | 0.1565 |
| 5 | 0.1581 | 0.0456 | 0.0558 | 0 | 0 | 0.1766 | 0 | 0.1543 |
| 6 | 0.1581 | 0.0508 | 0.0508 | 0 | 0 | 0.2019 | 0 | 0.1562 |
| 7 | 0.1581 | 0.0456 | 0.0558 | 0 | 0 | 0 | 0.2004 | 0.1537 |
| 8 | 0.1581 | 0.0508 | 0.0508 | 0 | 0 | 0 | 0.2198 | 0.1559 |

4. **Prediction using ANN and RKS models**

The success of the model depends on how well it can predict the split tensile strength of SCC mixtures which are not familiar to the model but similar to the mixes used in the training process. Eight SCC mixtures were given to the model whose tensile strength have been measured experimentally. Tensile strength associated with the eight mixes was predicted using ANN and RKS. The predicted and measured tensile strength values using the RKS and ANN model are given in table 4. The measured values were compared with predicted values of the ANN and RKS model. RMSE values were used to test the prediction accuracy of the model. RMSE values for ANN and RKS are 0.038 and 0.0303 respectively.

The prediction accuracy of the model largely depends on the data available for training. With limited amount of training data available to us the accuracy of the model is limited. It is not able to fully capture the influence of all mixture components on the SCC mix. Also the prediction accuracy largely depends upon the accuracy of the data base available. The predictions are also confined within the experimental domain for the generation of the training data. For unfamiliar mixes the predictions will vary. This can be overcome only by training the model with large database incorporating all the parameters and this can be used in industries in a large scale to develop SCC mixtures with the required properties.
Table 4: Measured and predicted values for split tensile strength of SCC mixtures

| Mix Number | Measured Split tensile strength | Predicted Split tensile strength ANN | Predicted Split tensile strength RKS with RLS |
|------------|--------------------------------|--------------------------------------|---------------------------------------------|
| 1          | 0.0778                         | 0.1461                               | 0.1274                                      |
| 2          | 0.0961                         | 0.1285                               | 0.1262                                      |
| 3          | 0.1738                         | 0.1338                               | 0.1585                                      |
| 4          | 0.1738                         | 0.1389                               | 0.1746                                      |
| 5          | 0.1601                         | 0.1858                               | 0.1874                                      |
| 6          | 0.183                          | 0.1891                               | 0.2056                                      |
| 7          | 0.183                          | 0.1547                               | 0.1487                                      |
| 8          | 0.2013                         | 0.1599                               | 0.1649                                      |

5. Conclusion
This study shows that ANN and RKS with RLS approach can be used effectively to predict the tensile strength of SCC mixtures. These models were also able to predict accurately the tensile strength properties of test mixes which were unfamiliar to the model. The RMSE value of prediction using ANN and RKS are 0.038 and 0.0303 respectively. The comparison between the prediction accuracy of RKS model and ANN model shows that even though RKS model is good for large data set, the model is also successful in capturing the effect of SCC mixture variables on the tensile strength properties for small data set. This model can be used in industries to limit the number of trials thus reducing wastage of materials and labour. The main limitation of the proposed model is the limited amount of data available for training. The model was able to understand all the relationships between the mixtures and their tensile strength properties only on a limited scale. The predictions are also constrained within the experimental domain of the training data. Effect of the change in site conditions, mixing methods, placing methods etc are not included in this model. The model using limited database was able to provide predictions with good accuracy. The accuracy can be improved when a more comprehensive database is available.

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