Modelling the minislump spread of superplasticized PPC paste using RLS with the application of Random Kitchen sink

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Abstract. Super plasticizers(SPs) are added to the concrete to improve its workability with out changing the water cement ratio. Property of fresh concrete is mainly governed by the cement paste which depends on the dispersion of cement particle. Cement dispersive properties of the SP depends up on its dosage and the family. Mini slump spread diameter with different dosages and families of SP is taken as the measure of workability characteristic of cement paste chosen for measuring the rheological properties of cement paste. The main purpose of this study includes measure the dispersive ability of different families of SP by conducting minislump test and model the minislump spread diameter of the super plasticized Portland Pozzolona Cement (PPC)paste using regularized least square (RLS) approach along with the application of Random kitchen sink (RKS) algorithm. For preparing test and training data for the model 287 different mixes were prepared in the laboratory at a water cement ratio of 0.37 using four locally available brand of Portland Pozzolona cement (PPC) and SP belonging to four different families. Water content, cement weight and amount of SP (by considering it as seven separate input based on their family and brand) were the input parameters and mini slump spread diameter was the output parameter for the model. The variation of predicted and measured values of spread diameters were compared and validated. From this study it was observed that, the model could effectively predict the minislump spread of cement paste

1. Introduction

Workability is one of the physical parameters of concrete which affects the strength and durability. The development of commercial chemical admixtures made it possible to increase concrete workability at lower W/C ratio. These SPs are classified in to four groups based on their chemical contents as sulphonate melamine formaldehyde, sulphonate naphthalene formaldehyde, modified lignosulphonates, and copolymers containing sulphonyl and carboxyl groups [4,15,16,17]. Murthy [10] briefly explains the use of blended cement in civil engineering constructions. Portland Pozzolona cement (PPC) is the commonly used blended cement for civil engineering construction. It is manufactured by replacing the cement with pozzolonic material like fly ash. It is the most preferred cement for mass concreting because the reduced heat of hydration. Increased durability is observed by the use of this cement because of the microfiller effect and pozzolanic reaction of the flyash present in PPC [9,12]. Usage of PPC reduces the environmental pollution by reducing the emission of CO2 to the atmosphere from the cement during the production of cement. Because of the difference in the
synthesis process of the SP, the performance of the SPs from the same family also differs [4]. It is required to check the cement SP compatibility before using specific combination of cement and SP. Agarwal et al. [1] investigated the cement superplasticizer compatibility with respect to the setting behavior and compressive strength and concluded that the compatibility between cement and superplasticizer has to be checked before it is used for practical application because incompatibility between cement and SP leads to bleeding, segregation and excessive air entrainment. Augullo et al. [2] concluded that in all cases there is a super plasticizer saturation dosage beyond which there is no increase in the relative fluidity and this particular dosage can be used for selecting the type of SP. Methodology for selecting the compatible combination of cement and SP is introduced by previous researchers [5,8] based on the saturation dosage of SP obtained from mini slump and marsh cone test. Governing the workability properties by testing concrete is not always practical. Large amount of materials, labors and time is required for extensive concrete testing so cement paste can be used for studying the workability of concrete. It is the cement paste which has greater influence on the flow behavior of concrete[13].

In order to determine the optimum dosage of SP in cement paste lots of trials has to be done which will lead to wastage of material time and money. So it essential to have some soft computing methods to get an optimal solution for this problem. In conventional material modelling many statistical tools are available like Artificial neural networking (ANN), support vector machine (SVM), regression methods etc. Mohebbi et al. [3] modelled the effect of additives on rheological properties of fresh self-consolidating cement paste and determined the best structure for ANN model. The model could easily predict the rheological parameters. Modeling of the fresh stage properties of concrete using ANN and other soft computing methods are also reported in other studies [25,26].

The problem with these conventional soft computing method is that they consume more time and space for the classification process. In this context Random kitchen sink is a suitable alternative which was introduced by Ali Rahmi [14]. RKS is a new soft computing method which explicitly maps the data points to a higher dimension using Radial basis function and can handle a large non-linear data. Yedu et al. [19] demonstrates the mathematical ideas behind mapping using RKS and implementation of classification algorithm using Regularized least square approach. Any kind of modelling can be achieved by this mighty tool and is available to all common computer users. Traditional linear models are simply inadequate when it comes to modelling data containing non-linear characteristics. The main objective of this work is to obtain a methodology for predicting the workability parameters effectively using the RLS with the application of RKS and to investigate the effect of superplasticizer belonging to four different families on four locally available brand of PPC. In the first part of the work laboratory tests have been performed to evaluate the effect of SP on cement paste and in the second part these data are used to train and test the mini slump model.

2. Approach to modeling and prediction

2.1 Random Kitchen Sink Algorithm (RKS)
Random Kitchen Sink algorithm is a newly developed machine learning algorithm which explicitly maps the data sets which are non-linearly separated using a radial basis function. The advantage of using RKS algorithm over other conventional non-linear kernel method like Neural Network, Fuzzy logic, Gaussian mixture model classifiers is that the method is suitable for learning and classifying large data sets and also that conventional methods not only occupies more space but also consumes more time for classification process. In this context, Random feature mapping [14] using Random kitchen sink algorithm saves as a suitable alternative. Being an explicit data mapping the space and time requirement is not being influenced by number of data points. This in combination with regularized least square algorithm (RLS) for classification help us to obtain a simple classifier that can be used for real time applications. The advantage of regularized least square is that, it can find the
trend of data points. RBF kernel is considered real Gaussian function and it is symmetric in nature. This is the concept of Random Kitchen Sink algorithm. So it can be taken as a multivariate Gaussian probability density function since the Fourier transform of real Gaussian function is also a real Gaussian. The mathematical derivation is as follows [18]. Let kernel function \( k(a_1, a_2) \) can be written as the product of mapping function \( \phi(a) \)

\[
k(a_1, a_2) = <\phi(a_1), \phi(a_2)> = e^{\sigma \|a_1 - a_2\|}
\]

Where \( a_1 \) and \( a_2 \) denotes data pair and

\[
z = a_1 - a_2.
\]

\( z \) is a single vector variable function. \( I \) is a \( d \times d \) identity matrix and \( \Sigma = \sigma^2 I \) represents a covariance matrix

Now the kernel function can be denoted as

\[
f(z) = k(a_1, a_2).
\]

Let \( F(\Omega) \) represent Fourier Transform of \( f(z) \). That is

\[
F(\Omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} f(z) e^{-j\Omega^T z} dz
\]

Now the inverse of \( F(\Omega) \) can be written as

\[
F^{-1}(\Omega) = \int_{-\infty}^{\infty} F(\Omega) e^{j\Omega^T z} d\Omega
\]

Using Bochner’s theorem expected value of \( e^{i\Omega^T z} \) can be written as

\[
E\{e^{i\Omega^T z}\} = \int_{-\infty}^{\infty} F(\Omega) e^{i\Omega^T z} d\Omega
\]

Expected value of this function (here \( \Omega \)) can be obtained by taking the average of different samples from the related probability density function.

\[
k(a_1, a_2) = \phi(a)
\]

\[
\frac{1}{d} \begin{bmatrix} e^{i\Omega^T (a_1 - a_2)} \\ \vdots \\ e^{i\Omega^T (a_1 - a_2)} \end{bmatrix}
\]

To neglect complex number computation here finite \( k \) dimensional \( \phi(a) \) are created by considering cosines and sines of the higher dimensional mapped data thereby obviating complex numbers. This will not change the value of \( k(a_1, a_2) \).

2.2 Regularised Least Square Algorithm (RLS)

After the training and test features are generated, the next step is to train a classifier and obtain accuracies that determine the efficiencies with which different classes were divided. When the number of equations are more than number of unknowns over fitting of data take place. For getting an optimum solution of over determined systems Regularized least square approach is used. The method follows the idea of linear algebra and optimization techniques. The data vectors for training instances are

\[
\{X = x_1, x_2, x_3, \ldots, x_d\}
\]

and the label instances are

\[
\{Y = y_1, y_2, y_3, \ldots, y_d\}
\]

It finds the real trend of data using a weight matrix and control parameter and avoids overfitting of data. The method of regularized least square gives an output label value by developing a weight matrix. The sum of square differences of the predicted output vector and the original vector is minimized. In finding the weight matrix, there is a control parameter. The control parameter should be properly chosen to get more accurate results. Yedu et al.[18] explained the use of RLS for multiclass learning. Let us consider the data set contain \( d \) class of objects. Among this there are \( n \) number of features and \( m \) number of objects. Let \( d \) indicates the class value. The size of the data matrix is \( m \times n \).
matrix $U$ holds corresponding label vectors of size $m \times d$. A matrix $V$ of size $n \times d$ maps $n$ tuple data vectors corresponding to $\text{label \ vector}$.

3 Experimental program

An extensive experimental study was conducted to measure the flow characteristics of super plasticized cement paste. The locally available four brands of PPC is used in this study. Physical properties of cement such as standard consistency, initial and final setting times, fineness and specific gravity tests were performed according to the codal provisions of IS 4031 - part 4, part 5, part 1, part 11 respectively [21-24] and the results were compared with the specification of IS 1489[20]. The obtained test results are tabulated in Table 1.

Table 1: Physical properties of the cement

| Cement | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|--------|-------|-------|-------|-------|
| Fineness (%) | 3.50 | 5.40 | 6 | 6.4 |
| Specific Gravity | 2.85 | 2.80 | 2.80 | 2.72 |
| Standard Consistency (%) | 35.5 | 36 | 37 | 37 |
| Initial Setting Time (minutes) | 160 | 110 | 142 | 75 |
| Final Setting Time (minutes) | 220 | 185 | 194 | 155 |

SP from four different families are used in this study. The solid content and density of the SP were determined as per IS 9103 Annex E [19] and the obtained results were compared with the manufacturer’s data sheet. The obtained test results are tabulated in Table 2.

Table 2: Properties of superplasticizers

| SP | Density (g/cc) | Solid Content (%) | pH |
|----|---------------|------------------|----|
| PCE$_1$ | 1.11 | 36.67 | 6 |
| PCE$_2$ | 1.07 | 29.85 | $\geq 6$ |
| SNF$_1$ | 1.21 | 37.43 | 7-8 |
| SNF$_2$ | 1.21 | 37.83 | 7-8 |
| LS$_1$ | 1.15 | 30.05 | $\geq 6$ |
| LS$_2$ | 1.17 | 31.61 | $\geq 6$ |
| SMF | 1.23 | 33.06 | 7 |
3.1 Mini slump test

Mini slump is a small version of slump cone. This test setup was developed by Kantro [11]. In this test mini slump cone of standard dimension is placed on a flat surface and was lifted after filling it with cement paste (figure 1). Uniform mixing sequence was followed for the preparation of cement paste. The horizontal spread diameter of the paste is measured in all the four directions and average of the spread diameter is calculated. Spread diameter Vs superplasticizer dosage graph is drawn to get an idea about variation of spread diameter with superplasticizer dosage. These studies were conducted on 287 mixes prepared in the lab by varying water content, cement weight, and quantity of seven different super plasticizers.

4. Database preparation and Modeling

The trials were done by varying the SP to cement ratio. Using the results obtained from the experiments (287 trials for mini slump spread diameter), training and testing of the algorithm was carried out. To carry out modelling, 273 data for mini slump were taken as training data and 14 data for testing. Prediction was done for mini slump spread diameter. Water content, cement weight and amount of SP (by considering it as seven separate input depending upon their family and brand) were the input parameter and mini slump spread diameter was taken as the output parameter for the model.

4.1 Normalisation of Data

Normalization process is a technique of mapping original data range into another scale. In order to minimize the data redundancy, data normalization is done. Data normalization can be done in two ways [7]. One is standard deviation method and the other method is by using norm method. In this work norm method is used for normalization. In this modelling, normalization of data is done using norm method. A set of N data, each denoted \(X_1, X_2, \ldots, X_n\), and norm \(Y\) as

\[||Y|| = \sqrt{X_1^2 + X_2^2 + \ldots + X_n^2}\]

Dividing each value by its norm \(||Y||\) will give the normalized value. The values are between 0 to 1. The normalized value given to the model is tabulated in Table 3. The application of regularized least square algorithm and random kitchen sink algorithm comes together in a tool bar in MATLAB called GURLS (Grand unified Regularized Least Square). 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 pipeline. Flow chart of the workflow consisting of 6 stages is shown in Figure 2.

![Flow chart of the workflow](chart.png)

**Figure 2:** Flow chart of the workflow

**Table 3:** Normalized input variables for testing the model

| Mix no | Water  | Cement | PCE₁  | PCE₂  | SNF₁  | SNF₂  | SMF₁  | LS₁   | LS₂  |
|--------|--------|--------|-------|-------|-------|-------|-------|-------|------|
| 1      | 0.161  | 0.059  | 0.066 | 0     | 0     | 0     | 0     | 0     | 0    |
| 2      | 0.157  | 0.059  | 0.135 | 0     | 0     | 0     | 0     | 0     | 0    |
| 3      | 0.161  | 0.059  | 0     | 0.133 | 0     | 0     | 0     | 0     | 0    |
| 4      | 0.154  | 0.059  | 0     | 0.066 | 0     | 0     | 0     | 0     | 0    |
| 5      | 0.159  | 0.059  | 0     | 0     | 0.155 | 0     | 0     | 0     | 0    |
| 6      | 0.160  | 0.059  | 0     | 0     | 0.133 | 0     | 0     | 0     | 0    |
| 7      | 0.157  | 0.0589 | 0     | 0     | 0     | 0.114 | 0     | 0     | 0    |
| 8      | 0.154  | 0.059  | 0     | 0     | 0     | 0.114 | 0     | 0     | 0    |
| 9      | 0.156  | 0.0589 | 0     | 0     | 0     | 0     | 0.177 | 0     | 0    |
| 10     | 0.151  | 0.059  | 0     | 0     | 0     | 0     | 0.111 | 0     | 0    |
| 11     | 0.164  | 0.059  | 0     | 0     | 0     | 0     | 0     | 0.137 | 0    |
| 12     | 0.160  | 0.059  | 0     | 0     | 0     | 0     | 0     | 0     | 0.183|
| 13     | 0.157  | 0.059  | 0     | 0     | 0     | 0     | 0     | 0     | 0.183|
| 14     | 0.157  | 0.059  | 0     | 0     | 0     | 0     | 0     | 0     | 0.206|

**5. Results and discussions**

Predicted and measured value of mini slump spread diameter is tabulated in Table 4. A comparison of both the readings are done in Figure 3.
Table 4: Measured and Predicted Mini slump spread diameter

| Mix no | SP       | Measured spread diameter | Predicted spread diameter |
|--------|----------|--------------------------|---------------------------|
| 1      | PCE₁     | 0.149                    | 0.135                     |
| 2      | PCE₁     | 0.152                    | 0.146                     |
| 3      | PCE₂     | 0.149                    | 0.146                     |
| 4      | PCE₂     | 0.157                    | 0.135                     |
| 5      | SNF₁     | 0.193                    | 0.157                     |
| 6      | SNF₁     | 0.204                    | 0.153                     |
| 7      | SNF₂     | 0.149                    | 0.151                     |
| 8      | SNF₂     | 0.159                    | 0.151                     |
| 9      | SMF₁     | 0.182                    | 0.161                     |
| 10     | SMF₁     | 0.163                    | 0.150                     |
| 11     | LS₁      | 0.175                    | 0.155                     |
| 12     | LS₁      | 0.174                    | 0.162                     |
| 13     | LS₂      | 0.187                    | 0.167                     |
| 14     | LS₂      | 0.184                    | 0.172                     |

Figure 3: Comparison of predicted and measured spread diameter
The model could predict the data accurately. The root mean square error (RMSE) obtained for mini slump spread diameter is 4.04 %. The mean absolute percentage error (MAPE) is 27%. The success of this model depends on how accurately it can predict the workability parameter which is unknown to the model but similar to the mixes used in the training data. In this case the accuracy of the model is limited because it depends up on the number of training data available. The prediction will vary for unfamiliar mixes since predictions are effective only to the experimental domain and this problem can be solved by training the model with more number of datas.

6. Conclusions

This study was aimed at demonstrating possibilities of adopting the features of RKS and RLS algorithm to predict the workability parameters of PPC paste with a water cement ratio of 0.37. The model could predict the mini slump spread with the root mean square error (RMSE) of 4.04 % and the mean absolute percentage error (MAPE) of 27%. From this study it was observed that, RLS approach along with RKS can be used effectively for the prediction of Mini slump spread diameter. The predictions are valid within the experimental domain. The accuracy of the model can be improved by using a wider data base for training. Such an improved model will be useful for industries to limit the number of trials thus reducing wastage of materials and labour.

Nomenclature

PPC  Portland pozzolana cement  
SP   Superplasticizer  
SNF  Sulphonated Naphthalene Formaldehyde 
SMF  Sulphonated Melamine Formaldehyde 
PCE  Polycarboxylic Ether 
LS   Lignosulphates 
RKS  Random Kitchen Sink 
RLS  Regularised Least Square 
ANN  Artificial Neural Networks 
SVM  Support Vector Machine 
RBF  Radial Basis Function 
RMSE Root Mean Square Error 
MAPE Mean Absolute Percentage Error 
GURLS Grand unified Regularized Least Square

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