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Estimation of 28-day Compressive Strength of Self-compacting Concrete using Multi Expression Programming (MEP): An Artificial Intelligence approach †

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Abstract: Self-compacting concrete (SCC) is an innovative building material having special properties such as increased flowability, good segregation resistance and compaction without vibration etc. Despite the benefits of SCC over conventional concrete, there are very few methods reported in the literature that can predict the 28-day compressive strength of SCC accurately. Thus, to promote the use of SCC in construction industry, an innovative machine learning technique named Multi Expression Programming (MEP) is employed to forecast the 28-day compressive strength of SCC. A database consisting of 216 points is constructed using extensive literature search. The resulting equation obtained by employing MEP algorithm relates compressive strength of SCC with six most influential parameters i.e., water-cement ratio, fly ash and silica fume, quantities of fine and coarse aggregate and superplasticizer dosage. The database is split into training and validation datasets used for training and validation of the algorithm respectively. The accuracy of the algorithm is verified by using three statistical error metrices: mean absolute error (MAE), root mean square error (RMSE), and coefficient of correlation (R). The results revealed that the errors are within the prescribed limits for both training and validation sets and the developed equation have excellent generalization capacity. This is also verified from the scatter plots of the training and validation datasets. Thus, the developed equation can be used practically to forecast the strength of SCC containing fly ash and silica fume.

Keywords: Artificial Intelligence (AI); Multi Expression Programming (MEP); Self-compacting Concrete (SCC)

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1. Introduction

SCC is a unique type of concrete possessing properties such as good segregation resistance, enhanced flowability and it can compact itself without external vibrations [1]. It leads to better quality concrete by eliminating the need for compaction, accelerates the construction of precast concrete products and improves working conditions [2].

The use of SCC results in reduced cost and time needed to compact and place the concrete. The mixture composition of SCC is designed such that it can achieve the required self-compacting and flowing characteristics. One major component of this mixture composition is to use high level of fines to fill the spaces between the coarse aggregates. These fines typically include sand, fly ash, silica fume or other industrial wastes mixed a chemical admixture called superplasticizer that helps to increase the flowing ability of concrete. Several studies [3-6] reported the use of waste materials in the production of SCC. SCC also have high water-to-cement ratio, less quantity of coarse aggregates to achieve the flowing and self-compacting properties [7]. Despite the many advantages of SCC over conventional concrete, there is a lack of work regarding the accurate estimation of its strength. It is mainly due to the highly non-linear behaviour of SCC in relation to its mixture components [8]. This is because any change in cement and sand content, mineral and chemical admixtures can have significant impact on the strength of SCC [9]. Thus, this study aims to develop an accurate prediction model that can predict the strength of SCC based on its mixture composition.

Recently, the prediction of different properties of SCC using Machine Learning (ML) algorithms have attracted the attention of researchers as an effective way to accurately estimate different properties of concrete [10-12]. Although the researchers are using ML algorithms to predict different properties of SCC, there are very few works focusing on estimating the 28-day compressive strength of SCC containing fly ash and silica fume as mineral admixtures particularly using Multi Expression Programming (MEP). Thus, this study is focused on developing an effective model to forecast strength of SCC using MEP.

2. Multi Expression Programming (MEP)

MEP is a variant of evolutionary algorithms developed recently by Oltean [13]. It is a method used to find the solution to a problem by constructing and evolving a population of mathematical expressions. It simply constructs a population of mathematical expressions and uses evolutionary rules to select the best performing expressions [14]. It is different from other variants of genetic programming because it uses linear representation of chromosomes and it can encode multiple computer programs in a single chromosome, whereas other variants like Gene Expression Programming (GEP) can only encode one solution in a chromosome.

The MEP algorithm initializes by creating a population of random chromosomes then two parents are selected from the population by the process of binary tournament. The two parents then undergo the process of recombination and crossover to produce two offspring [13]. The offspring are then mutated and the worst performing individuals are replaced with the best performing ones. This process continues until the solution converges [15]. This iterative procedure of constructing and evaluating expressions makes MEP a useful tool for solving problems. The flow chart of MEP algorithm [16] is shown in Figure 1.

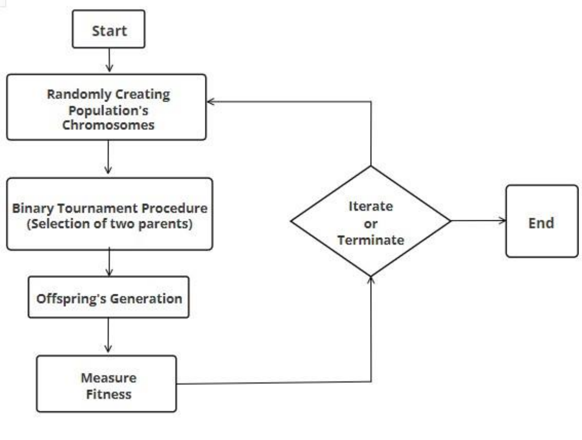

Figure 1. Flow Chart of MEP algorithm.

3. Data Collection and Analysis

The development of a database is essential for a MEP model. Hence, a comprehensive database of 216 instances is created from the internationally published literature [19-26]. For the selection of most influential parameters, several trials were performed, and the following six input parameters were chosen: water-cement ratio, silica fume (kg/m^3), fly ash (kg/m^3), coarse aggregate (kg/m^3), fine aggregate (kg/m^3), and superplasticizer (kg/m^3). The whole dataset is divided into two parts named the training dataset having 70% of the data and the validation dataset having 30% of the data. The training and validation datasets will be used to train and validate the algorithm respectively [25]. The reason for splitting the data is to make sure that the developed model doesn't overfits the training data and performs well on the validation data too. The correlation matirx of the variables is shown in Figure 2. It is used to better understand the variance and covariance between the variables used in the development of the model. It provides information about the relationship between the variables. Note that the correlation matrix has both positive and negative correlations. However, the correlations having values closer to zero are generally of higher importance. The paired correlations of the variables are shown in the form of a scatter matrix in Figure 3. The diagonal of the scatter matrix shows the frequency distribution of the input and output variables.

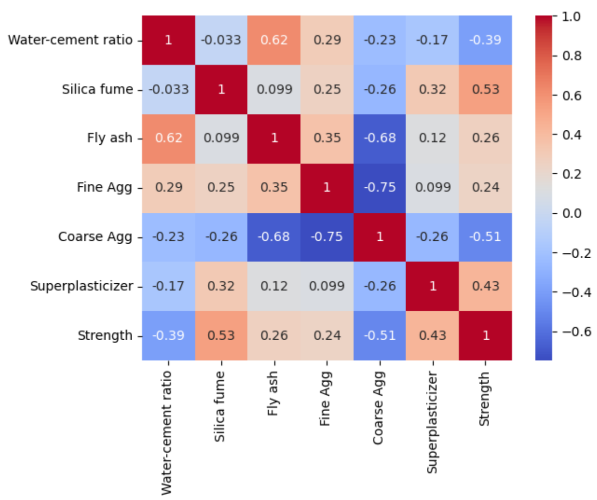

Figure 2. Correlation matrix of the variables used.

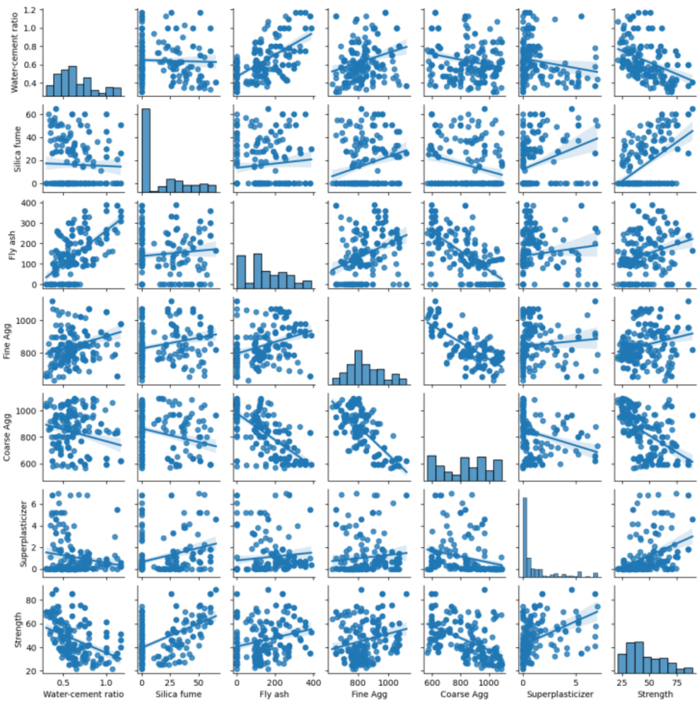

Figure 3. Scatter matrix of the variables used.

4. Model Development and Performance Assessment

4.1. MEP Model Development

The MEP algorithm was implemented using a software MEPX 2021.05.18.0. For the development of an effective and accurate model, numerous MEP tunning parameters need to be selected. These parameters influence the accuracy and complexity of the resulting equation. These parameters are chosen using literature recommendations [26]and trial and error method until the optimal set of parameters presented in Table 1 are obtained. Subpopulation size indicates the number of programs present in the population. Increasing the subpopulation size increases the accuracy and complexity of the model but increasing it beyond a certain point may cause overfitting.

Table 1. Fitting parameters used in MEP model development.

Parameter	Value
No. of Subpopulations	200
Size of Subpopulation	1000
Number of Generations	1000
Functions	+, -, ×, ÷, sqrt, sin, cos, tan

4.2. Performance assessment

The accuracy of the developed equation will be assessed by using the following three error metrices:

$$\text{Mean Absolute Error (MAE)} = \frac{\Sigma\,|x-y|}{n}$$

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{\Sigma(x-y)^2}{n}}$$

$$\text{Coefficient of Correlation (R)} = \frac{(n\sum xy-(\sum x)(\sum y))}{\sqrt{(n\sum x^2-(\sum x)^2)(n\sum y^2-(\sum y)^2)}}$$

For a model to be reliable, its R *value should be* greater than 0.8. The two error metrices MAE and RMSE measure the average magnitude of error between actual and predicted values and thus should be minimized [27].

5. Results

The output of MEP algorithm is given in Equation (1). In equation (1), f_c' represents compressive strength (measured in MPa) and $x_0, x_1, x_2, x_3, x_4, x_5$ represents water-cement ratio, silica fume, fly ash, fine aggregate, coarse aggregate, and superplasticizer respectively.

$$f_c' = \frac{(x_1x_5+x_2)+[(x_1\sqrt{\sqrt{x_3+x_4}})-\sqrt{x_3+x_4}]+(\frac{x_1+x_2+x_3}{x_0})}{(\sqrt{x_3+x_4})+(\tan(\sin(x_4)))^2} - \cos(x_1) \qquad (1)$$

The accuracy of the algorithm can be visualized by plotting scatter plots between the actual and predicted strength values for both training and validation datasets. Figures 4 and 5 represent the scatter plot of training and validation data respectively. The error metrices calculated for both training and validation datasets are shown in Table 2. Notice from table 2 that the value of R for both training and validation datasets is greater than 0.8 which shows that the developed equation is accurate and reliable.

Table 2. Error metrices of training and validation data.

Error Metric	Training	Validation
MAE	3.66	3.15
RMSE	4.68	3.69
R	0.94	0.96

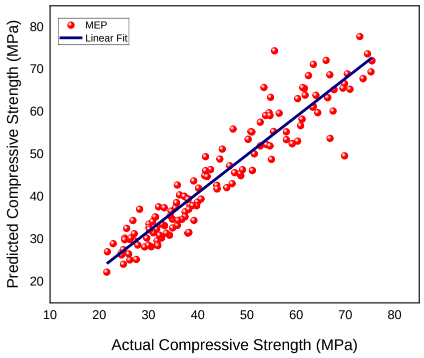

Figure 4. Scatter plot of training data

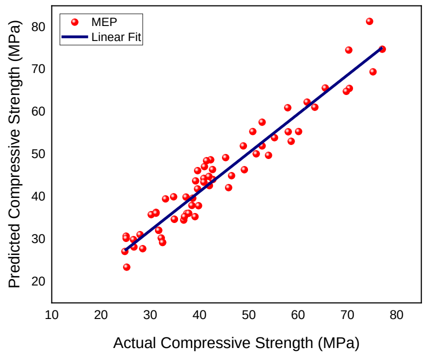

Figure 5. Scatter plot of validation data

6. Conclusions

This study focused at enhancing the use of SCC containing industrial wastes in concrete industry by developing an empirical equation to estimate its 28-day compressive strength using MEP algorithm. The comprehensive database of 216 points was used for this purpose which resulted in an equation relating strength with six most influential input parameters. The accuracy of the algorithm is checked by drawing scatter plots and calculating the commonly used error metrices for both training and validation datasets. The statistical assessment showed that the developed equation is accurate and reliable and can be effectively used to predict the 28-day compressive strength of SCC.

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Data Availability Statement: The data is available with the author and will be furnished upon request.

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