# Prediction of Compressive Strength of Self-Compacting Concrete Using Intelligent Computational Modeling

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**Abstract :** In the present scenario, computational modeling has gained much importance for the prediction of the properties of concrete. This paper depicts that how computational intelligence can be applied for the prediction of compressive strength of Self Compacting Concrete (SCC). Three models, namely, Extreme Learning Machine (ELM), Adaptive Neuro Fuzzy Inference System (ANFIS) and Multi Adaptive Regression Spline (MARS) have been employed in the present study for the prediction of compressive strength of self compacting concrete. The contents of cement (c), sand (s), coarse aggregate (a), fly ash (f), water/powder (w/p) ratio and superplasticizer (sp) dosage have been taken as inputs and 28 days compressive strength ($f_{ck}$) as output for ELM, ANFIS and MARS models. A relatively large set of data including 80 normalized data available in the literature has been taken for the study. A comparison is made between the results obtained from all the above-mentioned models and the model which provides best fit is established. The experimental results demonstrate that proposed models are robust for determination of compressive strength of self-compacting concrete.

**Keywords:** Self Compacting Concrete (SCC), Compressive Strength, Extreme Learning Machine (ELM), Adaptive Neuro Fuzzy Inference System (ANFIS), Multi Adaptive Regression Spline (MARS).

## 1 Introduction

Concrete is composed mainly of cement (commonly Portland cement), fine aggregate, coarse aggregate and water. Concrete is a versatile material that can easily be mixed to meet a variety of special needs and formed to virtually any shape. Concrete solidifies and hardens after mixing with water and placement due to a chemical process known as hydration. The water reacts with the cement, which bonds the other components together, eventually creating a stone-like material. The uniaxial compressive strength of concrete is considered as the most crucial property in case of concrete mix design and quality control

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which is determined by number of factors. Several factors affect the concrete mix design like to derive a concrete as High-Performance Concrete, it should possess, in addition to good strength, several other favorable properties. The water/cement (w/c) ratio in the concrete is lower than normal concrete which requires special additives in the concrete, along with a superplasticizer to obtain good workability.

The nature of aggregate is important to incur high strength. The gradation of the aggregates influences the workability. The order in which the materials are mixed is also important for the workability of the concrete. From engineering point of view, strength is the most important property of structural concrete. The strength of the concrete is determined by the characteristics of the mortar, coarse aggregate, fine aggregate and the interface. Property of concrete is influenced by the properties of each constituent added in it. For example, for the same quality mortar, diverse types of coarse aggregate with different shape, texture, mineralogy, and strength may result in different concrete strengths. The tests for compressive strength are generally carried out at about 7 or 28 days from the day when the concrete is casted. Generally, strength after 28-days is standard and therefore essential and if required strength for other ages can be carried out. Accidentally, if there is some experimental error in designing the mix, the test results will fall short of required strength, the entire process of concrete design must be repeated which may be a costly and time consuming. The same applies to all types of concrete, i.e. normal concrete, self-compacting concrete, ready mixed concrete, etc. It is well acknowledged that prediction of the compressive strength of concrete is most important in modern concrete designing and in taking engineering decisions.

The property of a self-compacting concrete (SCC) [Schutter et al (2008)] is the fresh concrete should flow around reinforcement and consolidate within formwork under its own weight that exhibits no defects due to segregation or bleeding. The guiding principle for this type of concrete is that the sedimentation velocity of a particle is inversely proportional to the viscosity of the floating medium in which the particle exists. The mix design principle is that the flowability and viscosity of the paste is adjusted by proportioning the cement and additives, water to powder ratio and then by adding superplasticizers and Viscosity Modifying Admixtures (VMA). It requires manipulation of several mixture variables to ensure satisfactory flowable behavior and proper mechanical properties. Also, absence of theoretical relationships between mixture proportioning and measured engineering properties of SCC makes it more complex.

This study adopts Extreme Learning Machine (ELM), Adaptive Neuro Fuzzy Inference System (ANFIS), Multivariate Adaptive Regression Spline (MARS) for prediction of 28 days compressive strength of Self Compacting Concrete (SCC). ELM proposed by Huang et al. (2004), is an easy-to use and effective learning algorithm of single-hidden layer feed-forward neural networks (SLFNs). The classical learning algorithm in neural network, e. g. backpropagation, requires setting several user-defined parameters and may get into local minimum. ELM is used in various fields like Renewable Energy [Wang et al. (2015)], Neurocomputing [Fu A-M. et al. (2014)], Mechanical Engineering [Gao et al. (2013)], Bioinformatics [Priya et al. (2012)]. ANFIS [Takagi and Sugeno (1985)] can be trained to provide input/output data mappings and one can get the relationship between model inputs and corresponding outputs. ANFIS is a kind of artificial neural network that is based on Takagi-Sugeno fuzzy inference system. It enables the knowledge that has been learnt in the network training to be translated into a set of fuzzy rules that describe the model input/output relationship in a more transparent fashion. It is employed in many fields such as Powder Technology [Pourtousi et al. (2015)], Applied Energy [Yang and Entchev (2014)], Hydrology [Chang and Wang (2013)], Communications [Lee et al. (2012)]. MARS is a flexible, more accurate, and faster simulation method for both regression and classification problems [Friedman (1991); Salford Systems (2001)]. It is capable of fitting complex, nonlinear relationships between output and input variables. Some examples of its usage are Biological conversations [Kandel et al. (2015)], Ecological Modeling [Pickens and King (2014)], Transportation [Sun et al. (2013)].

The data used in both these techniques is taken from Siddique et al. (2011).

## 2 Dataset employed

The data used (Table 1) in both the techniques are normalized against their maximum values [Siddique et al. (2011)]. In carrying out the formulation, the data has been divided into two sub-sets:

(a) Training dataset: This is required to construct the model. In this study, 64 (80% of total data) out of the 80 values are considered as training dataset.

(b) A testing dataset: This is required to estimate the model performance. In this study, the remaining 16 (20% of total data) values are considered as testing dataset.

**Table 1:** Details of the data for prediction of compressive strength of SCC

| **Sr. No.** | **Cement** | **Fly ash** | **Water/powder** | **SP dosage** | **Sand** | **Coarse Agg** | **Comp. Strength** |
|---|---|---|---|---|---|---|---|
| | **(kg/m3)** | **(kg/m3)** | | **(%)** | **(kg/m3)** | **(kg/m3)** | **(MPa)** |
| 1 | 290 | 100 | 0.45 | 0.8 | 913 | 837 | 42.7 |
| 2 | 250 | 261 | 0.55 | 0.5 | 478 | 837 | 17 |
| 3 | 210 | 100 | 0.65 | 0.8 | 910 | 837 | 19.1 |
| 4 | 250 | 160 | 0.55 | 0.5 | 742 | 837 | 24.1 |
| 5 | 210 | 220 | 0.45 | 0.8 | 768 | 837 | 26.7 |
| 6 | 290 | 100 | 0.65 | 0.2 | 709 | 837 | 26.6 |
| 7 | 290 | 220 | 0.45 | 0.2 | 625 | 837 | 32.9 |
| 8 | 250 | 160 | 0.55 | 0.5 | 742 | 837 | 26 |
| 9 | 250 | 160 | 0.55 | 0.5 | 742 | 837 | 28.5 |
| 10 | 250 | 160 | 0.55 | 0.5 | 742 | 837 | 26.4 |
| 11 | 250 | 160 | 0.55 | 0 | 739 | 837 | 27.3 |
| 12 | 317 | 160 | 0.55 | 0.5 | 594 | 837 | 29.1 |
| 13 | 210 | 220 | 0.65 | 0.2 | 562 | 837 | 10.2 |
| 14 | 250 | 160 | 0.55 | 0.5 | 742 | 837 | 25.3 |
| 15 | 250 | 160 | 0.38 | 0.5 | 919 | 837 | 36.3 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 16 | 250 | 160 | 0.55 | 1 | 746 | 837 | 26.7 |
| 17 | 250 | 160 | 0.72 | 0.5 | 566 | 837 | 11 |
| 18 | 183 | 160 | 0.55 | 0.5 | 891 | 837 | 22.1 |
| 19 | 220 | 180 | 0.39 | 0.35 | 916 | 900 | 49 |
| 20 | 220 | 180 | 0.39 | 0.35 | 916 | 900 | 49 |
| 21 | 160 | 240 | 0.39 | 0.35 | 886 | 900 | 44 |
| 22 | 193 | 158 | 0.39 | 0.35 | 1024 | 900 | 44 |
| 23 | 220 | 180 | 0.45 | 0.35 | 850 | 900 | 38 |
| 24 | 198 | 232 | 0.34 | 0.2 | 874 | 900 | 46 |
| 25 | 248 | 203 | 0.39 | 0.35 | 808 | 900 | 50 |
| 26 | 237 | 133 | 0.36 | 0.2 | 1034 | 900 | 49 |
| 27 | 220 | 180 | 0.39 | 0.35 | 916 | 900 | 49 |
| 28 | 237 | 133 | 0.43 | 0.5 | 960 | 900 | 46 |
| 29 | 275 | 155 | 0.43 | 0.5 | 827 | 900 | 48 |
| 30 | 280 | 120 | 0.39 | 0.35 | 946 | 900 | 45 |
| 31 | 170 | 200 | 0.43 | 0.2 | 930 | 900 | 31 |
| 32 | 220 | 180 | 0.39 | 0.6 | 916 | 900 | 43 |
| 33 | 220 | 180 | 0.39 | 0.35 | 916 | 900 | 47 |
| 34 | 220 | 180 | 0.39 | 0.1 | 916 | 900 | 44 |
| 35 | 198 | 232 | 0.36 | 0.5 | 872 | 900 | 52 |
| 36 | 220 | 180 | 0.39 | 0.35 | 916 | 900 | 45 |
| 37 | 220 | 180 | 0.33 | 0.35 | 982 | 900 | 51 |
| 38 | 170 | 200 | 0.43 | 0.5 | 928 | 900 | 33 |
| 39 | 275 | 155 | 0.43 | 0.2 | 830 | 900 | 36 |
| 40 | 247 | 165 | 0.45 | 0.12 | 845 | 846 | 34.6 |
| 41 | 238 | 159 | 0.4 | 0.29 | 844 | 844 | 37.8 |
| 42 | 232 | 155 | 0.35 | 0.38 | 846 | 847 | 48.3 |
| 43 | 207 | 207 | 0.45 | 0.4 | 845 | 843 | 33.2 |
| 44 | 200 | 200 | 0.4 | 0.17 | 842 | 843 | 34.9 |
| 45 | 197 | 197 | 0.35 | 0.28 | 856 | 856 | 38.9 |
| 46 | 169 | 254 | 0.45 | 0 | 853 | 853 | 30.2 |
| 47 | 163 | 245 | 0.4 | 0.2 | 851 | 851 | 26.2 |
| 48 | 161 | 241 | 0.35 | 0.3 | 866 | 864 | 35.8 |
| 49 | 350 | 162 | 0.59 | 0.09 | 768 | 840 | 51.7 |
| 50 | 349 | 162 | 0.57 | 0.14 | 779 | 852 | 59.9 |
| 51 | 350 | 133 | 0.52 | 0.16 | 815 | 883 | 55.3 |
| 52 | 350 | 111 | 0.51 | 0.15 | 831 | 900 | 61 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 53 | 250 | 257 | 0.77 | 0.11 | 787 | 853 | 51.5 |
| 54 | 427 | 115 | 0.45 | 0.12 | 779 | 844 | 59.4 |
| 55 | 348 | 224 | 0.5 | 0.43 | 783 | 848 | 58.6 |
| 56 | 350 | 90 | 0.48 | 0.14 | 852 | 923 | 46.5 |
| 57 | 327 | 173 | 0.53 | 0.2 | 902 | 803 | 61.6 |
| 58 | 380 | 145 | 0.48 | 0.1 | 788 | 854 | 73.5 |
| 59 | 350 | 186 | 0.51 | 0.11 | 786 | 851 | 70.4 |
| 60 | 380 | 145 | 0.48 | 0.13 | 988 | 659 | 65.5 |
| 61 | 380 | 192 | 0.53 | 0.1 | 931 | 621 | 67.8 |
| 62 | 275 | 250 | 0.67 | 0.09 | 775 | 840 | 54.5 |
| 63 | 325 | 60 | 0.65 | 0.43 | 899 | 850 | 30.8 |
| 64 | 325 | 60 | 0.65 | 0.43 | 899 | 850 | 32.6 |
| 65 | 325 | 120 | 0.75 | 0.43 | 755 | 850 | 32.2 |
| 66 | 249 | 60 | 0.68 | 0.43 | 1079 | 850 | 24 |
| 67 | 325 | 60 | 0.85 | 0.43 | 722 | 850 | 13.3 |
| 68 | 370 | 96 | 0.57 | 0.25 | 833 | 850 | 39.5 |
| 69 | 400 | 60 | 0.63 | 0.43 | 718 | 850 | 30.4 |
| 70 | 325 | 60 | 0.65 | 0.43 | 899 | 850 | 35.3 |
| 71 | 370 | 24 | 0.69 | 0.62 | 770 | 850 | 18.7 |
| 72 | 325 | 0 | 0.55 | 0.43 | 1042 | 850 | 41.2 |
| 73 | 280 | 96 | 0.87 | 0.25 | 820 | 850 | 19.6 |
| 74 | 325 | 60 | 0.65 | 0.75 | 896 | 850 | 27.7 |
| 75 | 325 | 60 | 0.65 | 0.43 | 898 | 850 | 35 |
| 76 | 325 | 60 | 0.65 | 0.12 | 900 | 850 | 31.4 |
| 77 | 370 | 96 | 0.57 | 0.62 | 830 | 850 | 38.8 |
| 78 | 325 | 60 | 0.65 | 0.43 | 898 | 850 | 34.3 |
| 79 | 280 | 96 | 0.87 | 0.62 | 817 | 850 | 15.9 |
| 80 | 370 | 24 | 0.69 | 0.25 | 772 | 850 | 26.4 |

## 3 Extreme learning machine (ELM) model

The ELM algorithm was originally proposed by Huang *et al.* in 2004 and it makes use of the SLFN. The main concept behind the ELM lies in the random initialization of the SLFN weights and biases. Then, using Theorem 1 and under the conditions of the theorem, the input weights and biases do not need to be adjusted and it is possible to calculate implicitly the hidden-layer output matrix and hence the output weights. The network is obtained with very few steps and very low computational cost.

The defects of gradient-based learning in a single hidden-layer feedforward neural network (SLFN) are avoided by using ELM. It determines optimal weights analytically.

Let us consider the following two datasets.

$$D_{training} = \{x_{1i}, y_{1i}\}_{i=1}^{N} \tag{1}$$

$$D_{testing} = \{x_{2i}, y_{2i}\}_{i=1}^{N} \tag{2}$$

Where x is the input, y is the output and N is number of datasets.

In this paper,

$$x = Normalized[c, s, a, f, w/p, sp]$$

$$y = Normalized[f_{ck}].$$

In a single hidden layer feed forward networks (SLFN), the relation between input and output is given below:

$$\sum_{i=1}^{\overline{N}} \beta_i f(w_i . x_j + b_i) = y_{ji} \text{ , j=1,..N.} \tag{3}$$

where $w_i$ is the input weight vector between the i[th] neuron in the hidden layer and the input layer, $b_i$ means the input bias of the i[th] neuron in the hidden layer, $x_j$ is the j[th] input data vector, f() is an activation function of the hidden neuron, $\beta_i$ is the output weight vector between the i[th] hidden neuron and the output layer, $\overline{N}$ is number of hidden nodes, N is number of training samples and $y_j$ means the target vector of the j[th] input data.

Equation (3) can be written in the following way.

$$H\beta = T \tag{4}$$

where

$$H = \begin{bmatrix} g(w_1.x_1 + b) & \cdots & g(w_{\overline{N}}.x_1 + b_{\overline{N}}) \\ \vdots & \cdots & \vdots \\ g(w_1.x_N + b) & \cdots & g(w_{\overline{N}}.x_N + b_{\overline{N}}) \end{bmatrix}_{N \times \overline{N}}, \beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\overline{N}}^T \end{bmatrix}_{\overline{N} \times m} \text{ and } T = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix}_{N \times m}. \tag{5}$$

where H is the hidden layer output matrix of the network (Huang and Babri, 1998; Huang, 2003).

In ELM, the values of $w_i$ and $b_i$ are not tuned during training. Random values are assigned for $w_i$ and $b_i$ according to any continuous sampling distribution (Huang et al., 2004; Huang and Siew, 2004, 2005). The value of β is determined from the following equation.

$$\beta = H^{-1}T \tag{6}$$

Where $H^{-1}$ is the Moore-Penrose generalized inverse [Serre (2002)] of the hidden layer output matrix H.

ELM has been developed by using MATLAB (MathWork Inc R2012a).

## 4 Adaptive neuro fuzzy inference system (ANFIS) model

Fuzzy logic is a form of many-valued logic and it deals with reasoning that is approximate rather than fixed and exact. The nature of uncertainty in a slope design is very important that should be considered. Fuzzy set theory was developed specially to deal with uncertainties that are nonrandom in nature.

There are several FISs that have been employed in various applications. The most commonly used include:

- Mamdani Fuzzy Model;
- Takagi-Sugeno-Kang fuzzy (TSK) model;
- Tsukamoto fuzzy model;
- Singleton fuzzy model.

In fuzzy system, all sets are not crisp, but some are fuzzy. These fuzzy sets can be modeled in linguistic human terms such as large, small and medium [Takagi and Sugeno (1985)]. This is very valuable to model human behavior. A fuzzy set is a set containing elements that have varying degree of membership. The degree of membership gives fuzzy sets flexibility in modeling [Bezdek (1981)]. The membership can be discrete or continuous type. The most commonly used membership functions are triangular, trapezoidal, gaussian and bell function. ANFIS makes inference by fuzzy logic and shapes fuzzy membership function using neural network [Altrock (1995); Brown and Harris (1995)]. In the literature, there are several inference techniques developed for fuzzy rule-based systems, such as Mamdani and Sugeno [Brown and Harris (1995)]. In this study, Sugeno-type systems have been used. In Sugeno, output of the fuzzy rule is differentiated by a crisp function. Typical representation of a fuzzy rule in Sugeno system is given by: if $x_1$ is $A_1$ and $x_2$ is $A_2$…and $x_N$ is $A_N$ then y=f(x), where $A_1$, $A_2$… and $A_N$ are fuzzy sets and y is crisp function. In this system, outcome of each rule is crisp value and weighted average has been used to calculate the result of all the rules. The definition of the nonlinear mapping of Sugeno-type system ($f_{FS}$) can be given as follows:

$$f_{FS}=\frac{\sum_{i=1}^{m} w_i \prod_{j=1}^{n} \mu_{A_j^i}\left(x_j\right)}{\sum_{i=1}^{m} \prod_{j=1}^{n} \mu_{A_j^i}\left(x_j\right)} \tag{7}$$

In which *m* is the number of rules, *n* is the number of data points and $\mu_A$ is the membership function of fuzzy set A. membership function has been determined iteratively to produce correct outputs by ANFIS. There are different types of membership functions such as triangular, trapezoidal, gaussian and bell function. In this analysis, Gaussian membership function has been used. The form of the gaussian function used is as follows:

$$f\left(x,\sigma,c\right)=e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{8}$$

where, $c$ and is the mean and standard deviation of the data respectively. Learning process in ANFIS methodology is commonly performed by two techniques, i.e. back propagation and hybrid learning algorithms.

ANFIS has been developed by using MATLAB (MathWork Inc R2012a).

## 5 Multi adaptive regression spline (MARS) model

MARS is widely accepted by researchers and practitioners for the following reasons.

- MARS is capable of modeling complex non-linear relationship among variables without strong model assumptions.
- MARS can capture the relative importance of independent variables to the dependent variable when many potential independent variables are considered.
- MARS does not need long training process and hence can save lots of model building time, especially when the dataset is huge.

Finally, one strong advantage of MARS over other classification techniques is the resulting model can be easily interpreted. It not only points out which variables are important in classifying objects/observations, but also indicates an object/observation belongs to a specific class when the built rules are satisfied. The final fact has important managerial and interpretative implications and can help to make appropriate decisions.

The MARS model splits the data into several splines on an equivalent interval basis (Friedman 1991). In every spline, MARS splits the data further into many subgroups (Yang *et al*., 2003). Several knots are created by MARS. These knots can be located between different input variables or different intervals in the same input variable, to separate the subgroups. The data of each subgroup are represented by a basis function (BF). The general form of a MARS predictor is as follows:

$$f(x) = \beta_0 + \sum_{j=1}^{P}\sum_{b=1}^{B}\left[\beta_{jb}(+)Max\left(0, x_j - H_{bj}\right) + \beta_{jb}(-)Max\left(0, H_{bj} - x_j\right)\right] \tag{9}$$

where x=input, f(x) =output, P= predictor variables and B=basis function. Max (0, x-H) and Max (0, H-x) are BF and do not have to each be present if their coefficients are 0. The H values are called knots. The spline function consists of two segments, i.e. truncated functions of the left-hand side of Equation (10) and right-hand side Equation (11) separated from each other by a so-called knot location [Veaux *et al*., 1993], as follows:

$$b_q^-(x-t) = \left[-(x-t)\right]_+^q = \begin{cases} (t-x)^q & \text{if } x > t \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$b_q^+(x-t) = \left[+(x-t)\right]_+^q = \begin{cases} (x-t)^q & \text{if } x > t \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where: $t$ is the knot location and $b_q^-(x-t)$ & $b_q^+(x-t)$ are the spline functions. The MARS algorithm consists of (i) a forward stepwise algorithm to select certain spline basis functions, (ii) a backward stepwise algorithm to delete BFs until the "best" set is found, and (iii) a smoothing method which gives the final MARS approximation a certain degree of continuity. BFs are deleted in the order of least contributions using the generalized cross-validation (GCV) criterion (Craven & Wahba 1979). The GCV criterion is defined in the following way

$$GCV = \frac{\frac{1}{N}\sum_{i=1}^{N}\left[y_i - f(x_i)\right]^2}{\left[1-\frac{C(B)}{N}\right]^2} \tag{12}$$

where N is the number of data and C(B) is a complexity penalty that increases with the number of BF in the model and which is defined as:

$$C(B) = (B+1) + \lambda B \tag{13}$$

where is a penalty for each BF included into the model, it can be also regarded as a smoothing parameter. [Friedman 1991] provided more details about the selection of the MARS has been developed by using MATLAB (MathWork Inc R2012a).

**6 Result and discussions**

Error and Correlation Calculations

The validity of each model can be verified using these following formulas:

The mean absolute error (MAE) is a quantity used to measure how close predictions are to the actual value.

$$MAE = \frac{\sum_{i=1}^{n} | w_{ai} - w_{pi} |}{n} \tag{14}$$

Root-mean-square error (RMSE) is used to measure the differences between predicted value by the models and the actual values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} ( w_{ai} - w_{pi} )^2}{n}} \tag{15}$$

Coefficient of correlation($R$) has been used as main criterion to examine the performance of the developed models. The value of R has been determined by using the following equation:

$$R = \frac{\sum_{i=1}^{n}\left(w_{ai} - \overline{w}_a\right)\left(w_{pi} - \overline{w}_p\right)}{\sqrt{\sum_{i=1}^{n}\left(w_{ai} - \overline{w}_a\right)}\sqrt{\sum_{i=1}^{n}\left(w_{pi} - \overline{w}_p\right)}} \tag{16}$$

ρ is known as the Performance Index is used to check the accuracy of the predicted values.

$$\rho = \frac{RMSE}{\overline{w}_a}\frac{1}{R+1} \tag{17}$$

where $w_{ai}$ and $w_{pi}$ are the actual and predicted W values, respectively, $\overline{w}_a$ and $\overline{w}_p$ are mean of actual and predicted W values corresponding to n patterns. For a predictive model of high accuracy, the value of R should be close to one.

For developing ELM, the numbers of hidden nodes have consequences on training performance. The best performance is obtained at 15 hidden nodes. Therefore, the number of hidden nodes is set to 15. The initial training datasets is assigned as 64. The Block Range is provided as 25. Radial basis function has been adopted as activation function. Graphs are plotted between Actual Normalized Strength and Predicted Normalized Strength. Figure 1 shows the performance of training and testing dataset respectively. After the compilation of the model, following results are obtained.

Training and testing performance are illustrated in the table 4.

As shown in figure 1, the value of R is nearly close to one for training as well as testing datasets. Therefore, the developed ELM proves that it is quite capable of predicting of 28 days compressive strength of SCC.

The value of error and correlation functions for ELM is shown in table 4.

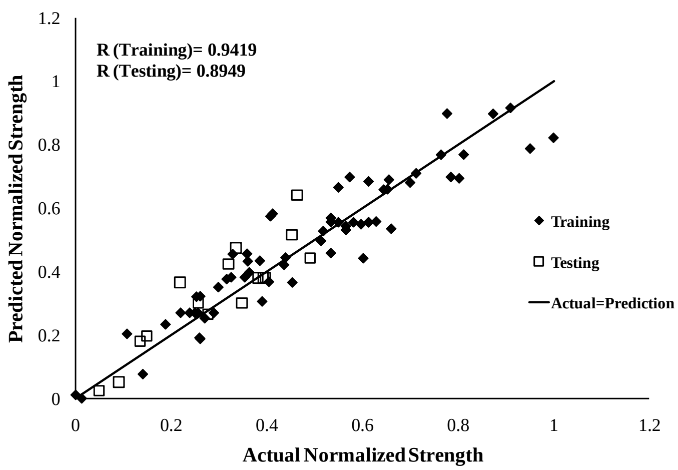


**Figure 1:** Performance of training and testing dataset (ELM)

In ANFIS model, Gaussian membership function has been used in this analysis. The hypothesized initial numbers of membership functions for each input are 55. A suitable pattern has to be chosen for the best performance of the network. Figure 2 shows the architecture of ANFIS model for this study.

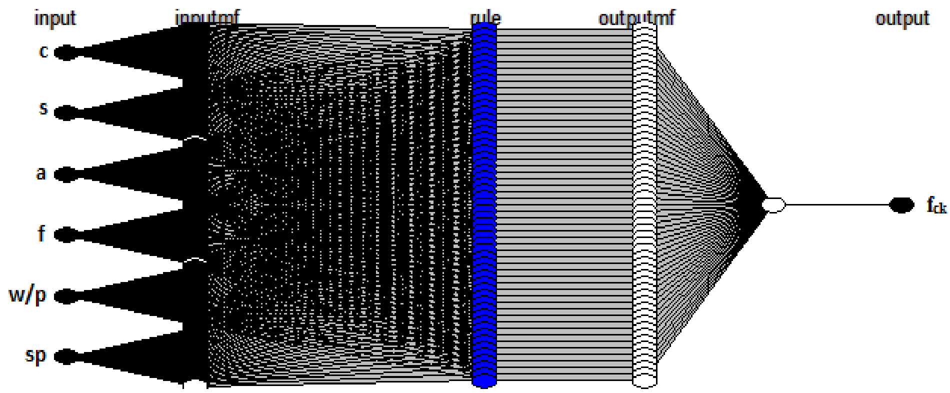


**Figure 2:** Architecture of ANFIS model

After the training (with 50 epochs) was complete, the final configuration for the Fuzzy Inference System (FIS) is:

| | |
|---|---|
| Number of output membership functions | 55 |
| Number of fuzzy rules | 55 |

Neuro-fuzzy adaptive network for Strength:

| | |
|---|---|
| Number of input | 6 (c, s, a, f, w/p and sp) |
| Number of membership function for each input | 55 |
| Type of membership functions for each input | Gaussian |
| Type of membership functions for each output | Linear |
| Number of training epochs | 50 |

Training and testing performance are illustrated in the table 4.

The performance of training and testing dataset has been illustrated in figure 2. It is observed from figure that the value of R is equal to one for training as well as testing dataset. So, this proves that it is the most effective technique/model for the prediction of 28 days compressive strength of SCC.

The value of error and correlation functions for ANFIS is shown in table 4.

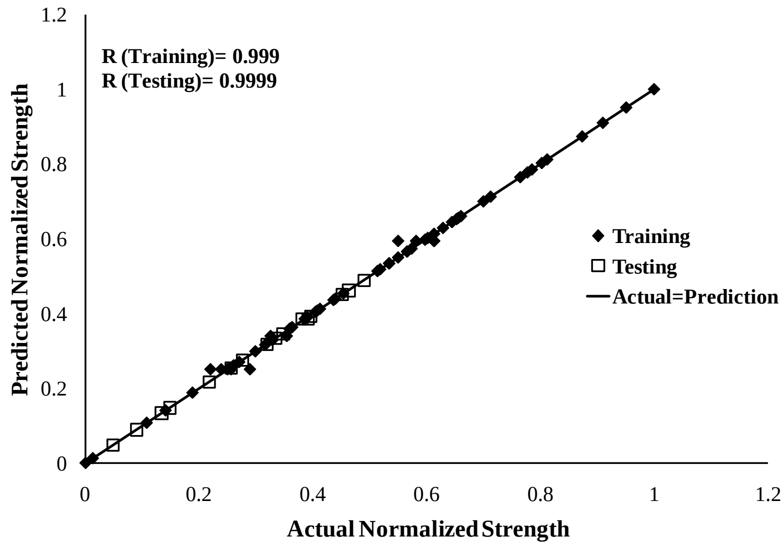


**Figure 3:** Performance of training and testing dataset (ANFIS)

For MARS model, during training, the forward stepwise procedure was carried out to select 42 basis functions (BF) to build the MARS model. This was followed by the backward stepwise procedure to remove redundant basis functions. The final model includes 36 basis functions, which are listed in Table 2 together with their corresponding equations and $a_m$.

**Table 2:** list of basis functions which give the best performance

| Basis Function | Equation | $a_m$ |
|---|---|---|
| BF1 | Max (0, c -0.337078651685393) | 0.4165 |
| BF2 | Max (0, 0.337078651685393 -c) | -0.5637 |
| BF3 | Max (0, a -0.444444444444444) | -0.0704 |
| BF4 | BF3 * max (0, 0.43 -f) | -0.0574 |
| BF5 | BF1 * max (0, 0.333333333333333 -a) | 1.5582 |
| BF6 | Max (0, w/p -0.512479201331115) | 1.1826 |
| BF7 | Max (0, 0.512479201331115 –w/p) | -0.9909 |
| BF8 | Max (0, 0.444444444444444 -a) * max (0, sp -0.923841059602649) | -17.9948 |
| BF9 | Max (0, 0.444444444444444 -a) * max (0, 0.923841059602649 -sp) | 0.0267 |
| BF10 | Max (0, s -0.593869731800766) | 0.8714 |
| BF11 | BF9 * max (0, s -0.555555555555556) | 2.0546 |
| BF12 | BF9 * max (0, 0.555555555555556 -s) | -69.6125 |

| | | |
|---|---|---|
| BF13 | BF1 * max (0, f -0.43) | 23.4321 |
| BF14 | BF1 * max (0, 0.43 -f) | 2.9236 |
| BF15 | BF6 * max (0, f -0.35) | -5.7696 |
| BF16 | BF2 * max (0, s -0.632183908045977) | -1.8302 |
| BF17 | BF2 * max (0, 0.632183908045977 -s) | 101.1253 |
| BF18 | BF17 * max (0, sp -0.748344370860927) | -506.0321 |
| BF19 | BF17 * max (0, 0.748344370860927 -sp) | -2881.9644 |
| BF20 | BF9 * max (0, 0.3 -f) | -1.9861 |
| BF21 | BF6 * max (0, c -0.224719101123596) | -0.8562 |
| BF22 | BF6 * max (0, 0.224719101123596 -c) | -3.9773 |
| BF23 | BF1 * max (0, sp -0.758278145695364) | 1.2984 |
| BF24 | BF1 * max (0, 0.758278145695364 -sp) | -10.7550 |
| BF25 | Max (0, sp -0.735099337748344) | -0.1593 |
| BF26 | Max (0, 0.735099337748344 -sp) | 5.0107 |
| BF27 | BF25 * max (0, f -0.2) | 6.1196 |
| BF28 | BF25 * max (0, 0.2 -f) | 4.4944 |
| BF29 | BF25 * max (0, s -0.689655172413793) | 4.9905 |
| BF30 | BF25 * max (0, 0.689655172413793 -s) | -2.4291 |
| BF31 | BF11 * max (0, f -0.3) | 4.4487 |
| BF32 | BF11 * max (0, 0.3 -f) | -17.1001 |
| BF33 | BF29 * max (0, 0.2 -f) | -3.0855 |
| BF34 | BF27 * max (0, a -0.111111111111111) | -17.1058 |
| BF35 | BF27 * max (0, 0.111111111111111 -a) | -28.8211 |

The final equation for the prediction of strength ($f_{ck}$) based on MARS model is given below:

$$f_{ck} = 0.2947 \; + \sum_{m=1}^{M} a_m B_m(x) \tag{18}$$

where,

$a_0 = 0.2947$ = coefficient of the constant basis function, or the constant term;

$\{a_m\}$ = vector of coefficients of the non-constant basis functions, *m*= 1, 2, …, *M*;

$B_m$ are the basis functions that are selected for inclusion in the model;

The ANOVA decomposition is specified in row wise for each ANOVA function. The columns represent summary quantities for corresponding ones. The first column lists the function number. The second gives the standard deviation (STD) of the function. This gives indication of its (relative) importance to the overall model and can be interpreted in a manner like a standard regression coefficient in a linear model. The third column provides another indication of the importance of the corresponding ANOVA function, by listing the GCV score for a model with the entire basis functions corresponding to that ANOVA function removed. This can be used to judge whether this ANOVA function is making an important contribution to the model, or whether it just slightly helps to improve the global GCV score. The fourth column gives the number of basis functions comprising the ANOVA and the last column of Table 3 gives the predictor variables associated with the ANOVA function. Table 3 shows the ANOVA decomposition for Training dataset.

**Table 3:** ANOVA decomposition for Training dataset

| Function Number | Standard Deviation | GCV | Basis Function | Parameters | Variable(s) |
|---|---|---|---|---|---|
| 1 | 0.112 | 0.059 | 2 | 2 | 1 |
| 2 | 0.108 | 0.1 | 1 | 1 | 2 |
| 3 | 0.005 | 0.003 | 1 | 1 | 3 |
| 4 | 0.197 | 0.225 | 2 | 2 | 5 |
| 5 | 0.596 | 1.645 | 2 | 2 | 6 |
| 6 | 0.508 | 1.174 | 2 | 2 | 1 2 |
| 7 | 0.017 | 0.005 | 1 | 1 | 1 3 |
| 8 | 0.197 | 0.222 | 2 | 2 | 1 4 |
| 9 | 0.048 | 0.058 | 2 | 2 | 1 5 |
| 10 | 0.643 | 1.927 | 2 | 2 | 1 6 |
| 11 | 0.062 | 0.021 | 2 | 2 | 2 6 |
| 12 | 0.001 | 0.003 | 1 | 1 | 3 4 |
| 13 | 0.041 | 0.014 | 2 | 2 | 3 6 |
| 14 | 0.11 | 0.077 | 1 | 1 | 4 5 |
| 15 | 0.116 | 0.08 | 2 | 2 | 4 6 |
| 16 | 0.471 | 1.019 | 2 | 2 | 1 2 6 |
| 17 | 0.081 | 0.033 | 2 | 2 | 2 3 6 |
| 18 | 0.001 | 0.003 | 1 | 1 | 2 4 6 |
| 19 | 0.032 | 0.008 | 3 | 3 | 3 4 6 |
| 20 | 0.013 | 0.004 | 2 | 2 | 2 3 4 6 |

Figure 3 depicts the performance of training and testing dataset. It is observed from figure that the value of R is close to one for training but not close to one for testing datasets. Therefore, the developed MARS proves its feeble ability for prediction of 28 days compressive strength of SCC.

The value of error and correlation functions for MARS is shown in table 3.

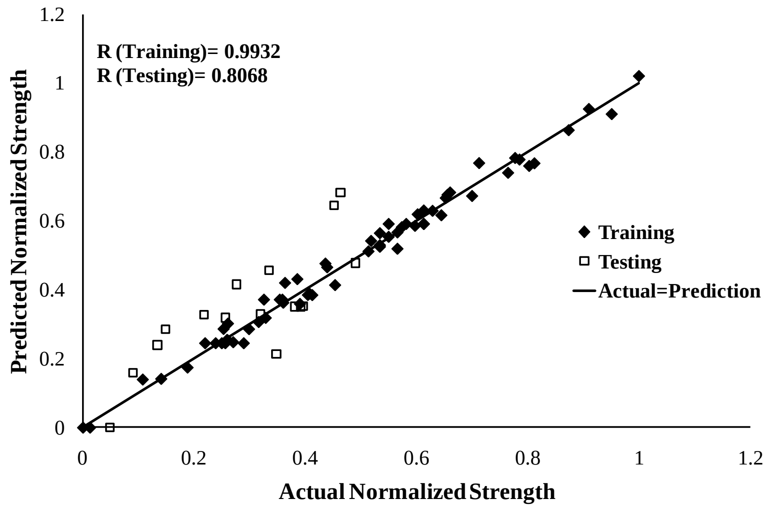


**Figure 4:** Performance of training and testing dataset (MARS)

The approximates of error and correlation functions i.e. mean absolute error (MAE), root-mean-square error (RMSE), coefficient of correlation(R) and performance index (ρ) for all the methods employed are consolidated in table 4.

**Table 4:** Approximates of error and correlation functions

| **Models Employed** | **Mean absolute error (MAE)** | | **Root-mean-square error (RMSE)** | | **Coefficient of correlation(*R*)** | | **Performance Index (ρ)** | |
|---|---|---|---|---|---|---|---|---|
| | **Training** | **Testing** | **Training** | **Testing** | **Training** | **Testing** | **Training** | **Testing** |
| ELM | 0.05842 | 0.06058 | 0.07457 | 0.08010 | 0.9419 | 0.8949 | 0.07918 | 0.14248 |
| ANFIS | 0.00361 | 0.00092 | 0.00985 | 0.00211 | 0.9990 | 0.9999 | 0.01016 | 0.00356 |
| MARS | 0.02106 | 0.09222 | 0.02582 | 0.11046 | 0.9932 | 0.8068 | 0.02671 | 0.20605 |

A comparative study has been carried out between the developed ELM, ANFIS and MARS models. Figure 1, 2 and 3 shows the graph of R value of the training and testing datasets for ELM, ANFIS and MARS models respectively. It can be inferred from figure 2 that the performance of ANFIS is best than the performance of ELM and MARS model. It is also clear from Table 5 that the performance of ANFIS is best.

The performance of training and testing dataset is almost same for the ELM and MARS models but ANFIS shows the best performance among the three models. So, the developed models do not show overtraining. Therefore, the developed models have good generalization capability. Datasets are normalized between for developing the ELM, ANFIS and MARS models. The developed models do not make assumption about the dataset. The developed MARS gives equation for prediction of strength. However, ANFIS and MARS do not use statistical parameters of the dataset for prediction. ELM makes use of single-hidden layer feed-forward neural networks (SLFNs). ANFIS uses membership function for developing the model. MARS adopts basis function for final prediction.

## 7 Summary and conclusions

This study has described the application of ELM, ANFIS and MARS models for the prediction of 28 days compressive strength of Self Compacting Concrete (SCC). The performance of ANFIS is better than ELM and MARS model. User can employ the developed model for prediction of compressive strength. The developed models can be used as a quick tool for prediction of 28 days compressive strength of Self Compacting Concrete (SCC). This paper shows that the developed ANFIS is a robust model for prediction of 28 days compressive strength of Self Compacting Concrete (SCC).

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