Prediction of Compressive Strength of High-Volume Fly Ash Concrete Using Artificial Neural Network

Ramachandra Rajeshwari and Sukomal Mandal

Abstract Sustainable development has led to use of waste materials for replacements in conventional concrete. This study focuses on concretes made by cement replaced with high volumes of fly ash, which exhibits good long-term mechanical and desirable durability properties. Usage of high volumes of fly ash in concrete reduces the energy demand globally also saving the natural resources which are on the verge of depletion. Desirable high-volume fly ash (HVFA) concretes are experimentally achieved by trials, leading to wastage of materials, time and money. An alternate approach, artificial neural network (ANN) can be used, which has lately gained popularity in the civil engineering field. ANN is a soft computing technique impersonating the human brain characteristics, learning from previous situations and adapting to new surroundings without any constraints. In this study, HVFA concrete compressive strength (CS) data collected from past experimental investigations are used for ANN modeling. A total of 270 datasets has been collected from literature, of which 12 nos. from an experimental study is used for testing purpose. An ANN model is developed with eight input parameters (i.e., cement, fly ash, water–binder ratio, superplasticizer, fine aggregate, coarse aggregate, specimen and fly ash type) to predict the CS of HVFA concrete; hidden layer nodes along with weights and biases are fixed by trial and error to achieve the better performing model. Coefficients of correlation for train and test data are obtained as 97 and 97.9% respectively, which shows that ANN could be used for predicting the HVFA concrete strengths.

Keywords Concrete · Fly ash · Compressive strength · Artificial neural network

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1 Introduction

Fly ash, an outcome from coal scorched powerhouse featuring pozzolanic attributes has been adopted for cement replacement in concrete from last few decades. Employment of high volumes of fly ash in concrete has attained popularity in developing countries to meet the rise in metropolitanization and community demands. High-volume fly ash (HVFA) concretes being cost-effective also has advantages of longstanding mechanical properties and good durability properties reducing the greenhouse gas emissions addressing disposal issues of fly ash. A high volume of fly ash along with reduction of the hydration rate in concrete also acts as filler with unreacted silica and aluminum oxides decreasing the concrete porosity. Research has been profoundly carried out to effectively replace cement completely by fly ash for the use in structural applications possessing high-strength properties. Trials on HVFA concrete leads to wastage of materials and requirement of skilled labor for manufacture and testing of the 28 days HVFA CS. These experimental trials are uneconomical since a small manual error will lead to repetition of the whole trial.

From decades researchers are involved in developing various mathematical and computational prediction models to address the shortcomings of experimental investigations. Many mathematical regression models are developed and employed whose prediction accuracy is not satisfactory in comparison with the experimentally predicted values. A unique soft computational approach known as Artificial Neural Network (ANN) has gained attention for applications in the civil engineering domain. ANNs are basically the thumbprints of human brain, where the elements are arranged in the form of layers interconnected with each other through weights. It has the capability to resolve the complex problem with ease, in the process learning from old data and solving for new data without any constraints. Recent findings have presented the applicability of ANN to forecast the CS of concrete with various replacement materials.

From previous studies on HVFA concrete strengths, many researchers have benchmarked their findings with varying percentages of fly ash to be used in various civil engineering applications. Optimized usage of fly ash content could save cost from 10 to 40% compared to control concrete with the use of natural and recycled aggregate (NA and RA) depending on the field requirements [1–3]. From the experimental results, it is evident that Class-F fly ash can be appropriately used up to 50% replacement level for reinforced cement concrete construction, precast elements, and pavement applications with economic benefits and with proper mix proportioning, optimization, and marginal material combinations [2, 4–6]. Suitable use of cement replaced with fly ash up to 80% is proposed for both structural and pavement application with a rational mix proportions for both control concrete and self-compacting concrete(SCC) where 40% of FA content is limited in the latter due to strength loss [7, 8]. Fly ash concretes (0–55%) produce lower tensile strength at later ages in comparison to fracture tests in terms of crack tip opening displacement and final mid-span deflection [9, 10]. At low w/b (water to binder ratio) fly ash concrete mixes contributed higher strength due to improved interfacial bond, also HVFA concretes displayed better resistance to chloride diffusion for longer curing periods and lower degree of hydration [11, 12]. Addition of nano-silica, fiber content, and super plasticizers in HVFA concrete increase strengths of both short and long duration and abrasion resistance [13–18]. The mechanical properties of roller compacted concrete, SCC, high strength concrete (HSC), etc., are studied with high volumes of fly ash content in different curing conditions with NA and RA to be used in pavements and large industrial floor as an alternative to normal Portland concrete [3, 5, 19–39]. The possibility of replacing cement and fine aggregate with fly ash in concrete is also assessed [40].

Literature review work is carried on application of soft computing techniques in prediction of the FA concrete strength. Optimum architectures for artificial neural networks (ANNs) and the prime nodes for coupling between ANNs are determined by simulation study to overcome the drawback of single architecture developed from experimental obtained data in predicting CS [41]. The use of ANN is proposed by many researchers to model the complicated relationship between composition of concrete and the strength [42], over design of experiments to ascertain the effect of replacements of FA on early and late CS [43] along with silica fume content [44]. Also, the CS and slump of HSC with various amounts of additives is predicted using multiple regression analysis (MRA), ANN and fuzzy logic models, hybrid models usage with genetic algorithm (GA) based on ANN and adaptive network-based fuzzy inference system (ANFIS) [45–49]. The feasibility of using ANNs, combined classification and regression techniques and artificial intelligence hybrid system for estimation of the CS of high performance concrete (HPC) are demonstrated over a wide range of mix proportions which is affected by the water content, cement content, w/b, and cement replaced with FA and silica fume [50–55]. Many ensemble methods and machine learning techniques are adapted to predict the CS of HPC [56, 57]. Predictions of the rheological and mechanical properties of SCC are attempted using ANN techniques with low and high volumes of mineral additives [58–63]. The models studies show acceptable performance in expedient accuracy and use in practical production, enhancing their high potentiality to alternate the conventional regression models in real-life scenario.

In this study, a detailed survey on past experimental investigations of high volumes of fly ash usage in concrete has been carried out. The various mix proportions of these HVFA concretes along with their 28 days compressive strength (CS) are collected and the major constituents are used as input parameters for ANN model construction. The ANN architecture consists of input, hidden, and output layers, with each layer connected to other by weights and bias passing through a suitable transfer function and trained over a number of epochs until the error is minimized. The performance of the model is assessed in terms of statistical measures.

2 Artificial Neural Network

ANN is an expert system complementing the metaphor of human neurological system. ANN is a nonlinear type of computational system used for solving complex problems without any fixed formula, the only requisite being a proper data for training the network. The trained ANN models have the capability of logical reasoning and identification of alike patterns of inputs even among the noise data.

ANN is constructed with number of neurons or simple processing units which are interconnected in some arrangement, i.e., layers to allow flow of information within them in a parallel fashion. All the neurons are joined to each other by a link, which is in turn associated with the weights having knowledge about the input signals. The input layer receives facts from exterior surroundings and passes it on to the hidden layer where the information is processed by summing it up and passing through activation function to get the output. The network known as feedforward multi-layer perceptron learns by backpropagation algorithm, where the outputs are compared with the actual values, if the errors are more than the prementioned boundaries then these weights are readjusted until the errors are minimized. Once the network is trained over a number of iterations, then the trained network can be used over new set of inputs.

Figure 1 shows the typical model of an artificial neuron, the calculated output passing through transfer function with Eqs. (1) and (2) is as shown below.

Net of Input,

$$z_{in} = a_1 \cdot w1 + a_2 \cdot 2 + \cdots a_m \cdot w_m + = \sum_{i}^{n} a_i w_i + b \tag{1}$$

Output,

$$Z = F(z_{\text{in}}), \tag{2}$$

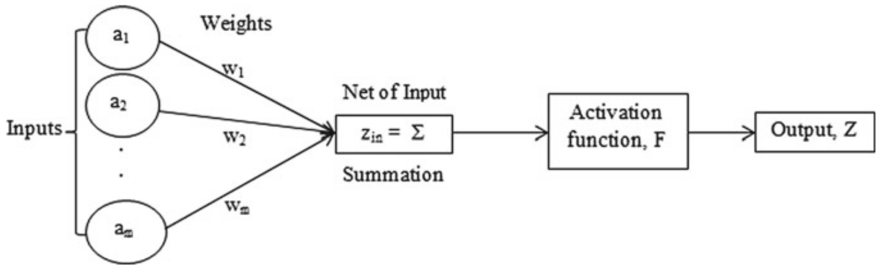

Fig. 1 An artificial neuron

where

m is the number of input neurons
b is the bias
F is the hyperbolic tangent sigmoid activation function = $\frac{2}{1+e^{-(2+n)}} - 1$.

3 ANN Model Parameters and Structure

The ANN model developed in this study consists of eight neurons in the input layer and one neuron in the output layer. The parameters for input layer are cement (C), fly ash (F), water–binder ratio (w/b), superplasticizer (SP), fine aggregate (FA), coarse aggregate (CA), specimen (ST), and fly ash type (FT). The output parameter is the 28 days CS of HVFA concretes. Table 1 shows the limits of each of input and output parameters. A single ANN architecture is developed with the hidden layer neurons fixed by trial and error to attain the best performing model. Figure 2 shows the structure of the proposed ANN model.

A total of 270 datasets from various published literature [1, 2, 3, … 40] is collected and normalized to review the quality of data. The proposed ANN model, which operates in MATLAB, is constructed using 258 datasets for training and a dataset of 12 nos. from an experimental study [9] is used for testing purpose. In the present study, the training algorithm of backpropagation type is used in feedforward with single hidden layer and gradient descent technique is used to minimize the error. The hyperbolic tangent sigmoidal activation function is adopted in the input layer and hidden layer, which is a nonlinear function used to map the inputs with the given outputs.

Table 1 Limits of input and output parameters

	Minimum	Maximum
Input parameters		
Cement (kg/m^3)	78	702
Fly ash (kg/m^3)	0	544
Water-binder ratio	0.19	0.72
Superplasticizer (kg/m^3)	0	35.1
Fine aggregate (kg/m^3)	279	1263
Coarse aggregate (kg/m^3)	712	1405
Specimen type (Cube or Cylinder)	0	1
Fly ash type (Class C or F)	0	1
Output parameter		
Compressive strength at 28 days (N/mm^2)	13.1	122.84

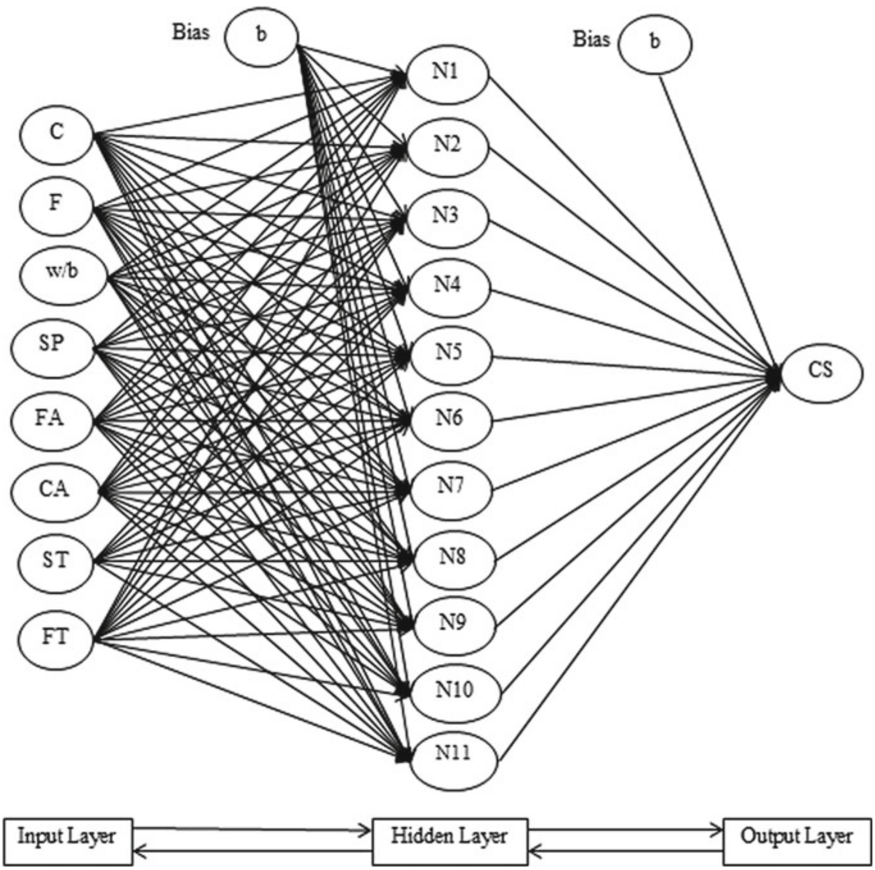

Fig. 2 Structure of ANN model

4 Results and Discussion

The ANN model performance in this study is expressed in terms of statistical measures such as Coefficient of Correlation (CC), Root Mean Square Error (RMSE) and Scatter Index (SI) calculated as shown in Eqs. (3)–(5), respectively.

$$\mathrm{CC} = \left[\sum\nolimits_{i=1}^{n} (O_i - \bar{O}_i)(P_i - \bar{P}_i)\right] \Big/ \left[\sqrt{\sum\nolimits_{i=1}^{n} (O_i - \bar{O}_i)^2 (P_i - \bar{P}_i)^2}\right] \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (O_i - \bar{P}_i)^2}{n}} \times 100 \quad (4)$$

$$\mathrm{SI} = \frac{\mathrm{RMSE}}{\bar{O}_i}, \tag{5}$$

where O_i and P_i are the observed and predicted CSs of HVFA concrete respectively, n is the number of data set used, $\bar{O}_i$ and $\bar{P}_i$ are the average observed CS and predicted CS of HVFA concrete respectively.

The ANN model is developed using eight input parameters as shown in Fig. 2. The ANN model performance with varying number of hidden neurons, .i.e., from 2 neurons to 14 neurons in the hidden layer is evaluated. It is noticed that the ANN model with 11 neurons in the hidden layer with 40 epochs had minimal error showing good correlation between observed and predicted compressive strengths in comparison to other networks. The best ANN architecture for predicting the CS of HVFA concrete is 8-11-1. The ANN trained model parameters values are as shown in Table 2.

Table 2 ANN model parameter values

Model parameters	Values
Number of nodes in Input layer	8
Number of nodes in hidden layer	11
Number of nodes in output layer	1
Learning algorithm	Levenberg–Marquardt
Minimum performance gradient	1e−100
Performance goal	1e−05
Number of epochs	40

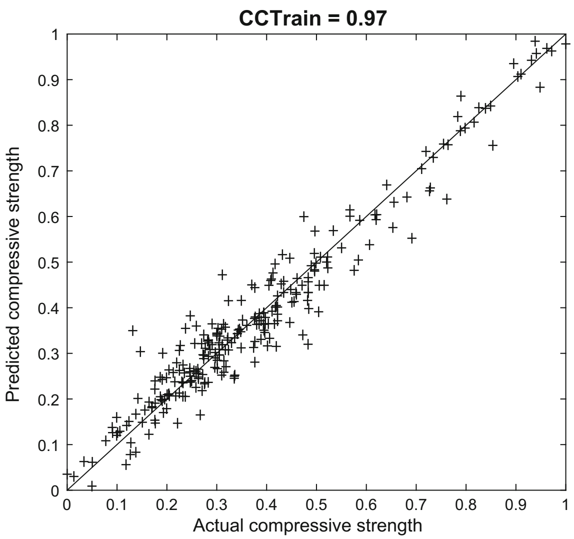

Fig. 3 CC values of ANN train model

Fig. 4 CC values of ANN test model

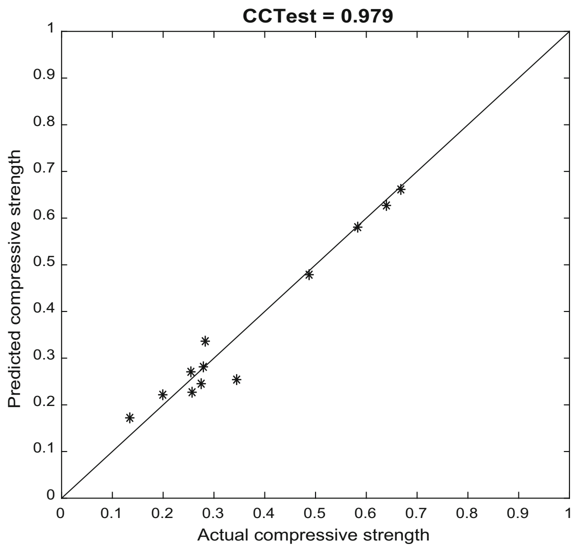

Table 3 Statistical measures of the proposed ANN model

Statistical measures	Training	Testing
CC	0.9700	0.9790
RMSE	5.1113	3.5716
IS	0.1348	0.0973

Comparison between the experimental and predicted CS values for the training and testing data are shown in Figs. 3 and 4 respectively. The performances of the ANN model in terms of statistical measures such as CC, RMSE, and SI are shown in Table 3.

The training values exhibit that the proposed ANN model has successfully mapped the input parameters with the output as 28 days CS of HVFA concrete. The statistical measures for the training data are: CC of 0.97, RMSE of 5.1113 and SI of 0.1348. The performances of the ANN model in terms of all the statistical measures for testing data are— CC of 0.979, RMSE of 3.5716, and SI of 0.0973, which show that it has the capability of predicting the CS values close to the experimental values. It can also be seen that the model has suitably estimated the HVFA CS of a particular dataset from an experimental study, with good correlation. In general the ANN models are not only able predict data, when divided into train and test groups in 70:30, 60:40, etc., ratios as shown in previous studies but are also capable of generalizing the input with the output from a single study with good correlations between the predicted and experimental CS values.

5 Conclusion

The following inferences are drawn from this study:

- The ANN-based model is established to estimate the 28 days CS of HVFA concrete.
- With the increase in the number of input parameters for making of HVFA concrete, the experimental methods led to wastage of materials, time and money.
- ANN has a great potential for estimating the 28 days CS of HVFA concrete.
- In this study, the CSs from a particular experimental study are predicted using ANN model with good correlation (CC = 97.9%).

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