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Artificial Neural Network Modelling Of Fly Ash Concretes – An Overview

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ABSTRACT

Fly ash, a by-product procured from thermal power plants have been used alternatively in varying proportions with cement as a resource material for various civil infrastructure and building constructions. The complexity of delineation of quality of concrete enhances when additives like fly ash other than conventional ingredients are added to cement concrete. However, additives have proved to be exerting their significance in terms of their role in gross cement cost, saving of energy and environmental benefits. Many researchers have attempted with limited success, by application of numerical and empirical modeling work to improve the quality and performance of cement concrete. Alternatively, a new approach known as artificial neural networks (ANNs) can be applied for better prediction of the fly ash concrete strengths. This paper gives an overview of applications of ANN in prediction of the compressive strengths of concretes containing fly ash.

Keywords: Concrete, Fly Ash, Compressive Strength, Artificial Neural Networks

INTRODUCTION

Fly ash (FA), an industrial by-product procured from coal-form thermal power plants obtained in fine powder form possesses pozzolanic property. FA has negligible or no cementitious value but in presence of water at ordinary temperature, it reacts chemically with calcium hydroxide (lime) forming a soluble compound containing cementitious property similar to cement. FA concrete leads to substantial strength development reacting with lime liberated from hydration of cement at later ages, though exhibits very little cementing value at early ages. Availability of quality FA from modern and efficient thermal power station in showing increasing trends for the use of FA as partial replacement of cement and sand in addition to use in Ready Mixed concrete. Addition of mineral additives has not only improved the quality of concrete mix but also has highlighted its significance on overall cost of cement, energy saving and environmental gains.

The compressive strength (CS) of concrete is a critical parameter which is affected by number of parameters. Many researchers have ventured to predict the CS by traditional approach of regression analysis meeting little success. Modeling of nonlinear multivariate interrelationships to understand the complex behaviour of concrete strength by numerical and empirical methods did not favour results to improvise on the quality and performance of concrete strength. To overcome the drawbacks of traditional approach, artificial neural network (ANN) which has scored attention due to its flexibility has been implemented in various engineering applications.

A neural network model is an architecture exhibiting a confound number of human brain's characteristics, such as learning from former experience and customizing from previous examples to new problems. ANN yields significant solutions even when data to be processed is incomplete or with errors and can process information promptly when implemented to solve real world problems.

The present study describes an overview of ANN based model which is trained with a series of experimental data on FA concrete. It is a data driven approach i.e. where the network attunes to the training data to capture the relationship between input and output parameters in terms of weights and biases. Once these parameters are fixed, the trained network with unknown input parameters can be applied to predict the output parameters. The CS at 28 days generally used as a parameter for structural design, concrete proportioning and evaluation of concrete is discussed for different types of concrete, such as control concrete, self-compacting concrete (SCC), high performance concrete (HPC), high strength concrete (HSC), etc.

MATERIALS AND METHODS

ANN is a modern interdisciplinary subject, more versatile in solving various different engineering problems which could not be interpreted by traditional modeling and statistical methods. It is a group of massively parallel architectures applied to interpret complex problems with help of highly interconnected but simple computing elements called artificial neurons. ANNs are capable of collecting, learning, evaluating and processing large number of data procured from experiments or numerical analyses. The trained neural network (NN) aids as analytical tool for qualified estimation of the results, for any given input data which were not incorporated in the learning process of the network. ANN operation is a practically simple, easy and precise in nature.

Interconnected processing elements called as neurons are arranged into two or more layers interacting with each other via weighted connections. For any particular input pattern, a flow of activation forwarded from input to output layer via the hidden layer with the error in output calculated. NNs picks up by modifying weights of the neurons in return to the errors between the actual and target output values.

The neural networks (Fig -1) used for the prediction of the output for the unknown inputs can be mathematically shown in the following steps.

1. Summation of weighted inputs, i.e.

$$N_j = \sum_{i=1}^{N_i} (W_{ij} * n_i) + b_j \qquad .. (1)$$

Where, N_j = sum of the j^{th} hidden node,

N_i = total sum of input nodes,

W_{ij} = connection weight between i^{th} input and j^{th} hidden node,

n_i = normalized input at i^{th} input node,

bj = bias value at jth hidden node.

2. Transforming the weighted inputs,

$$O_j = 1 / [\, 1 + e^{-N_j}\,] \qquad ... (2)$$

Where, O_j = output from the j^{th} hidden node.

3. Summation of hidden node outputs,

$$N_k = \sum_{j=1}^{N_h} (W_{jk} * O_j) + b_k \qquad ... (3)$$

Where, N_k = sum of the k^{th} output node,

N_h = total sum of hidden nodes,

W_{jk} = connection weight between the j^{th} hidden and k^{th} output node,

bk = bias value at kth output node.

4. Transforming the weighted sum,

$$O_k = 1 / [1 + e^{-Nk}] \quad \text{... (4)}$$

Where, O_k = output at the k^{th} output node.

Global Error can be minimised, as given by,

$$E = 1/P \sum_{1}^{P} E_p \quad \text{... (5)}$$

Where P = total number of training patterns.

E_p is given by,

$$E_p = 1/2 \sum_{k=1}^{N} (O_k - t_k) \quad \text{... (6)}$$

Where N = total sum of output nodes,

O_k = network output at the k^{th} - output node,

t_k = target output at k^{th} - output node.

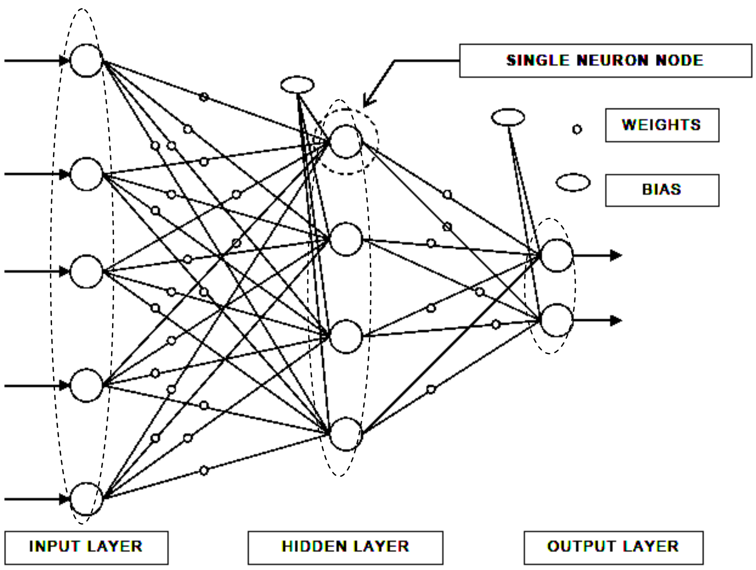

Figure 1 Feed Forward Neural Network

Review of earlier works

This paper is an attempt to highlight the applications of ANN in the area of fly ash concrete. The CS of different types of concrete, i.e., control concrete, HPC, HSC, SCC, etc. has been presented with summarizing each of author's experiences on application of ANN.

Control Concrete

Concrete containing FA influences mainly on water demand and workability as ascribed by the spherical shape of FA particles in comparison with Portland-cement only mix having same cementitious content. Many researchers have demonstrated different replacement levels of FA with cement as optimum to get maximum concrete strengths. FA concretes shows considerable increase in long-term CS and durability aspects with low water to binder ratios. Research carried out on FA concrete using ANN is briefed below.

Yeh [1] used flattened simplex-centroid mixture experiment design to get meaningful data as there were seven components with each five levels and total of 78,125 mixtures. NNs were used to test the varying effect of parameters on the CS of low and high concrete strength exploring effects with interaction of the strength parameters using generalization capabilities. The NN model efficiently predicted concrete strength experimental values from the testing data with large variations. The strength ratio i.e. concrete containing with and without FA was lower at smaller age and further reduced with higher percentage of FA replacement and low water-binder ratios.

NNs are applied to study the effect of FA replacement and silica fume on the CS of concrete cured for a period of 3 - 180 days [2]. The predicted CS values were very near to experimental values concluding that small amount of SF does not influence the CS values, but the FA content does not contribute to the CS values at early ages compared increased values of CS at later ages.

The ANN and fuzzy logic models were used for estimating low and high-lime FA concrete CS at 7, 28 and 90 days [3]. Concrete strengths with varying FA percentages (10, 20 and 40) were used to build ANN model with NN-9-11-1. The predicted values from these models were similar to experimental results concluding that ANN and fuzzy logic models could be applied for estimating the concrete CS without conducting any experiments.

Atici [4] presented the comparative performance of models developed to estimate the CS of admixture concrete using ANN and multiple regression analysis (MRA). Six different models of MRA and ANN with different concrete mixtures with varying percentages of Portland cement (50%), FA (10-20%) and blast furnace slag (BFS 20-50%) were used to predict CS at different curing times and values of non-destructive techniques like rebound hammer and ultrasonic pulse velocity were determined at 3 to 180 days. A two-layer feed forward network using Levenberg-Marquardt back propagation algorithm was used and demonstrated based on performance indices, ANN models outperformed MRA except for one model and can be effectively used for predicting CS if larger and varying training data is available. Also, ANN was used with CS involving nonlinear functional relationships.

Lee [5] used ANN to predict concrete strength development. A single architecture developed from experimental obtained data had a drawback in predicting CS for change in the curing temperature for a specific curing day. A modular ANN with multiple architecture of 5 ANNs were proposed to predict CS which, showed good correlation. ANN-I determined strength at early age i.e. within 24 hours after casting whereas the ANN-II to ANN-V estimated the CSs from 2nd to 28th day after casting. The stimulation study determined the optimum architectures for 5 ANNs.

Yuan et al. [6] demonstrated hybrid models usage with genetic algorithms (GA) based on back-propagation ANN and adaptive network-based fuzzy inference system (ANFIS) to estimate the concrete CS. In genetic based algorithm, the weights and thresholds of ANN was optimized using GA and for ANFIS model, ANN and FL were investigated and observed that the two hybrid models, ANFIS and GA-ANN outperform the ANN model, showing higher performance in terms of accuracy and applicability, establishing them to have higher potential than conventional regression models.

Rebouh et al .[7] applied hybrid NN-GA system to estimate the concrete CS with natural pozzolana. The connection weights for each neuron of an NN built using experimental collected data was optimized by integrating a GA. The hybrid NNGA showed better performance using same architecture when compared with NN model and also with experimentally data, conducted for validation of results.

High Strength Concrete (HSC)

It is distinguished as a concrete having strength at 28 days greater than 40 MPa which meets performance and homogeneity requirements that cannot be met with conventional ingredients and normal mixing, placing and curing conditions. HSC renders huge cost savings in large scale construction projects. Lately, ANN has become popular in predicting the HSC strength to get an economic and workable mix by use of mineral and chemical admixtures.

Oztas et al. [8] proposed the use of NN to model the complex behaviour of HSC to predict its performance. Models considered using NN-7-5-3-1 i.e., (CS and slump values as output parameters) were trained using scaled conjugate gradients algorithms and sigmoid activation function. Satisfactory results were obtained from the models compared to experimental values. The study presented that the model enhanced from the literature studies can be easily continued to experimental data to save time and decrease wastage of material with design cost.

Baykasoglu et al.[9] used multi-objective optimization (MOO) technique with soft computing (gene expression programming, regression analysis and NNs) to predict HSC strength parameters. Two step approaches was used to select values of variables that determines composition, CS, workability, cost, etc. of HSC. NN produced accurate results in the first step and regression analysis being worst in prediction. In second step, MOO models were generated and solved using generic algorithms which was later combined with hierarchical approaches to interpret multiple objectives.

High Performance Concrete (HPC)

HPC is taking place of high strength concrete, a recent terminology in concrete construction industry which includes additional cementitious materials like FA, BFS and chemical admixtures like superplasticizer along with basic ingredients. Many studies have shown that performance of HPC is not only affected by water-cement ratio (w/c) and content of other basic constituents. Modeling the complex behaviour of HPC was simplified by using ANN as discussed below.

Yeh[10] demonstrated the capability of ANN to model the strength of a highly complex material, HPC. Literature covering all major parameters was divided into 4 sets of 2 types to include different references and randomly shuffled and combined data sets. A back propagation neural network with NN-8-8-1 was developed. The network was trained until the weights and bias was randomly initialised to predict the strength with given mix proportion and age. Acceptable values were obtained to conclude that ANN could effectively be used to assess the individual variable effect on the mix proportion compared to regression analysis.

Yeh[11] developed a program - HPC2N (High Performance Concrete design package using NN and nonlinear programming) to obtain optimum concrete mix design of HPC using ANN and non-linear programming. The network was considered using NN-8-8-1. After training the network, significant coefficient of correlation of strength values were obtained which cuts down on the number of trail mixes for the starting trail batch since the strength is influenced by component types and other major properties of concrete like mixing proportions and mixing preparation techniques.

The CS of HPC was determined by comparing performance of neural network models developed based on three approaches namely validation set, maximum marginal likelihood and full Bayesian [12]. The network was considered using NN-8-x-1 (x=varying number of neurons). Comparison between experimental results and models for testing dataset were obtained better in case of Bayesian neural network.

Khan[13] used ANN to predict properties i.e., tensile strength, CS, gas permeability and rapid chloride penetration of high performance composite cementitious systems. ANN models using radial basis function was considered to train the network using experimentally obtained data. The model took care of wide range of silica fume and pulverised FA additions along with w/b ratios and strengths. Good correlation was obtained between predicted values using models and experimentally obtained values.

Chou and Pham [14] applied ensemble method to predict the HPC CS using experimental datasets obtained for several laboratories. The performance of SVM, ANN, CART, chi-squared automatic interaction detector, LR, and generalized linear was applied to construct individual and ensemble models. Analytical results show that the ensemble technique combining two or more models obtained the highest prediction performance.

Self-Compacting Concrete (SCC)

It is a new class of HPC, highly workable which flows under its own weight through congested areas without the need of mechanical vibrators and effectively fill voids without segregation and bleeding. It eliminates the necessity for compaction while placing fresh concrete that saves time, reduces overall cost, better working environment, etc. With addition of superplasticizer to SCC its behaviour becomes more complex to model which is solved using ANN as discussed below.

Nehdi et al. [15] assessed the properties of SCC using ANN technique. A back propagation neural network was developed for each of SCC property (slump flow, filling capacity, segregation and 28 day CS) using same network architecture due to limited literature including all SCC properties. The model was created with NN-10-10-5-1 for each of SCC property. It was concluded that the model did not account for mixing, handling and curing methods which affect the performance of SCC due to lack of information on respective aspects from literature. And also better results could be obtained with large data base.

Prasad et al. [16] used ANN to estimate the CS at 28 days and slump flow of SCC and HPC with high volume FA. ANN models with NN-10-10-5-1 were considered for the SCC, with low volume FA data collected from literature due scarcity of high volume FA SCC data. Same model has been used to predict CS of HPC with NN-9-9-5-1 by intuitively relating with ratios like water and binder (w/b), w/c, etc. which is a major benefaction of this study. Further, the predicted values for SCC and HPC procured from the models were compared with experimental results over a large range of the CSs varying from 30 to 60 MPa.

Uysal and Tanyildizi [17] used ANN to predict the core CS of SCC with mineral additives like FA, marble powder and limestone powder. One conventional concrete (vibrated) and 6 SCC mixtures with 15 to 30% of mineral additives replaced with cement was used to develop an ANN model with NN-10-14-10-1 architecture. Data sets were divided into 50-50 for training and testing purposes. The network was trained using fletcher-powell conjugate gradient and Levenberg-Marquardt back propagation algorithm with nonlinear sigmoid activation function. The study concluded the former learning algorithms to be more efficient in predicting the CS values with high correlation coefficient.

Douma et al. [18] used ANN to determine the rheological and mechanical properties of FA contained SCC. A multilayer feed forward model was developed to determine large number of outputs (slump flow diameter, the L-box ratio, the V-funnel time and 28 days CS) with minimum inputs. The network model was developed with NN-6-17-4. Weights and bias was fixed by use of tangent sigmoid transfer function at all neurons. The model helped to investigate the complex relationship between independent and dependent variables of SCC.

Yaman et al.[19] attempted the use of ANN in proportioning of SCC mixes. Two models were developed, first ANN-I was built using multi input – multi output neural network with six ingredients as outputs to predict the ingredients of SCC mixes and second ANN-II built as multi input – single output neural network with six ingredient outputs predicted separately from six different neural networks of multi input – single output type in each step which is considered more effective compared with obtaining all ingredients in one step.

Other Concretes

The CS of few others concretes like polymer concrete which is obtained using polymers to replace lime-type cements as binder and geopolymers, an artificial synthetic alumino silicate material which are new materials for fire, acid and heat-resistant are also predicted using ANN are discussed below.

Barbuta et al.[20] used NNs for estimation of properties polymer concrete with FA. Multilayer perceptron network models (3-16-1) was built using experimentally obtained data with varying percentages of FA and resin. Trained models gave good agreement between predicted and experimentally procured values of the CS and flexural strength of polymer concrete. Reverse modeling showed that the largest values of the CS and flexural strengths were obtained for resin and FA content of 15-16% and 8-9%.

Nazari and Torgal [21] used ANN to predict the CS of different types of geopolymers. Six different two-layer feed forward-back propagation networks were proposed based on experimental data obtained from literature. Comparison between the estimated values by models and experimentally values in the given range showed good correlation when the training phase was aborted for minimum percentage of absolute error.

Hierarchical classification and regression (HCR) approach was used to predict the HPC CS [22]. For the data gathered from University of California, Irvine data repository, HCR showed improvement in performance of highly nonlinear behaviour of HPC in comparison with single flat regression models like linear regression, ANNs and support vector regression. It was concluded that HCR with 4-class SVM classifier in first level, combined with MLP as regression model for second level showed best results with the lowest mean absolute percentage error.

The artificial intelligence hybrid systems were applied to predict the CS of HPC [23]. The artificial intelligence hybrid systems fuse FL, weighted support vector machines and fast messy algorithms into an evolutionary fuzzy support vector machine (SVM) inference model for time series data (EFSMIT). It was concluded that EFSMIT could be efficiently used to predict highly nonlinear behaviour of HPC, which obtained higher performance than SVM and satisfactory results in comparison with back-propagation NN.

Chou et al. [24] assessed the CS of HPC using advanced machine learning techniques. Individual and combined learning classifiers were built using ANN, SVM, classification and regression tree (CART) and linear regression (LR) constructed using concrete data from various countries. Voting, bagging and stacking approaches were used for ensemble learning based models. It was concluded that ensemble models outperform single learning based models. In spite of SVM and ANN been best learning models, study showed that stacking-based ensemble model of ANN/CART, SVM and LR in first level and SVM in second level showed best results in comparison with experimental data.

CONCLUSIONS

Several past studies on applications of ANN were carried out on different types of concrete i.e., control concrete, HPC, HSC, SCC, etc. to predict the CS. The CS values are influenced by many parameters such as mix proportions, handling, methods of mixing, transporting, curing conditions placing and testing of concretes. With each type of concrete and for selection of appropriate mix required for various civil infrastructures and building constructions becomes difficult to select the type of mix. Traditional approaches cannot be used to select the suitable mix due to the nonlinear correlation between the dependent and independent variables. ANN is a versatile approach, which can be efficiently used to model and predict the behavior of different types of concrete for given unknown inputs. From these studies, it is concluded that ANN models predict values with good correlation. Hence, ANN individually or combined with other machine learning techniques yields satisfactory results.

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