

Compressive Strength Prediction of HVFA Control Concrete Using ANN and PSO-ANN Models

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ABSTRACT

Utilization of high volumes of fly ash (HVFA) in concrete for cement replacement is a major step towards promoting sustainable developments with environmental benefits. Fly ash is abundantly available as secondary product from coal sourced power generation units. HVFA concrete has globally gained researchers' interest in development of cost effective mixes with minimum wastages. Traditionally used prediction methods have been replaced by modern computational methods which have proven its efficacy in solving highly non-linear real-life problems across various disciplines. Lately, design of HVFA concrete mixes with these approaches has become wide area of researches. In this study, 119 datasets of HVFA control concrete compressive strength (CS) collected from literature is used to train the artificial neural network (ANN) and particle swarm optimization based ANN (PSO-ANN) models; a dataset of 12 nos. each from two individual experimental studies along with their combination is used for testing both models. The models input parameters are cement, fly ash, water-binder ratio, superplasticizer, fine aggregate, coarse aggregate, specimen type and fly ash type for prediction of the HVFA concrete CS. A single hidden layer feed forward ANN using Levenberg-Marquardt algorithm is used, which is optimized by PSO. The models' efficiency is measured in terms of statistical parameters such as correlation coefficient, root mean square error and scatter index. From the results, it is observed that both ANN and PSO optimized ANN models have great potential in predicting the HVFA control concrete CS for a single experimental study.

Keywords: Concrete; fly ash; compressive strength; artificial neural network; particle swarm optimization.

Mathematics Subject Classification: 62M45, 68T20

Journal of Economic Literature (JEL) Classification: C45, C61

1. INTRODUCTION

Construction industry is considered as one among the factors aiding for greenhouse gas emissions creating environmental hazards. Use of binders having pozzolanic properties as cement alternatives in concrete in varying percentages has reinstated lately to satisfy the growing cement consumption.

Fly ash, a secondary product considered to be waste in coal used power generation units is abundantly available globally. Discarding of fly ash in landfills has grown to be a major hazard for ecology, as a step towards sustainable constructions it is used as a resourceful material in concrete manufacture. Only 6% of the globally available fly ash quantities are used in concrete production in low percentages (20-30%) (Rashad, 2015). This has attracted many researchers' interest to replace cement with large fly ash volumes. Cement replaced by fly ash above 40% is considered to be HVFA concrete, while few researchers have suggested the replacement to be above 50%. With availability of no standard guidelines to amend the fly ash percentage for cement replacement in concrete, numerous experimental trials are depleting the natural resources. Concrete by itself has established to be an important construction material from decades, and any error during the experimental procedure leads to the repetition of the laborious procedure with wastage of materials, money and time. With the CS been one of the important deciding factors for the structural performance, knowing it beforehand has played a major role in its applications.

From decades the use of traditional prediction methods for determining the concrete CS has achieved limited success, creating greater opportunities for researchers to contribute towards this area. Across various disciplines, modern computational methods have proven its efficacy in providing adequate solutions for highly non-linear real-life problems. Among them, soft computing techniques like ANN, genetic algorithms, simulated annealing, fuzzy optimization, etc. based on the biological and molecular behavior of living things have gained upper hand over traditional optimization methods (Rao, 2009; Tuzun et al., 2007; Garg and Jothiprakash, 2010). ANN consists of neurons or nodes similar to human biological brain arranged in parallel pattern is capable of solving non-linear problems. It simply requires sufficient quantity of input and output information to train the network and produce desired output. There are limitations of these algorithms of having slow learning rate and considered to be cornered in local minima. To overcome these drawbacks, researchers have suggested the use of metaheuristic algorithms namely genetic algorithms, differential evolution, particle swarm optimization, ant colony optimization, etc. (Suribabu, 2006; Kalra et al., 2008). This has led to the development of various hybrid optimization techniques such ANN-GA, PSO-ANN, ACO-ANN, etc. PSO is a metaheuristic optimization approach initiated on colony of various living species showing mutual and collegial behavior. It is a population based algorithm which moves rapidly towards the global optimal positions, resolving and generating better results compared to evolutionary algorithms (Kennedy & Eberhart, 1995; Eberhart & Kennedy, 1995; Shi & Eberhart, 1998). It has also been used to optimize the architecture of ANN for better prediction purposes. With the only drawback of the metaheuristic algorithms is their inability in search of local minima.

From literature survey, it is observed that the application of the PSO-ANN algorithm has been lately employed in civil engineering domain. Chau (2006, 2007) proposed the use of PSO-based neural network to claim the construction outcomes which helps in evaluating whether to put forth the case to litigation; and also for the prediction of ShingMun River water stage to issue early warnings of nearing floods and evacuation measures. Choobbasti et al. (2014) have applied ANN and PSO algorithm to determine the best position of trench layer location arranged about the pipeline to attain least liquefaction potential, which has found that the location beneath the pipeline to be best for trench

location. Ismail et al. (2013) have applied an exceptional PSO- back propagation (BP) hybrid algorithm for training to predict the behavior of load-deformation of piles that are axially loaded, which has yielded better results compared to hyperbolic and t-z developed models. Mashhadban et al. (2016) investigated self-compacting concrete (SCC) performance with fibers using PSO-ANN algorithm, which is proven to be better in predicting the mechanical properties of SCC. Momeni et al. (2014) have proposed the use of PSO hybridized ANN model to predict the uniaxial rock sample CS which have exhibited superior results. Qi et al. (2018) have predicted the unconfined CS of cemented backfill paste using neural network and PSO optimization which has yielded accurate results compared to experimental values. Rukhaiyar et al. (2017) have discussed the application of PSO hybridized ANN model to estimate the safety factor for slope stability analysis to identify the potential sections of landslides and the results are compared with conventional methods. Zaji & Bonakdari (2014) have predicted the capacity of weirs discharge with modified triangular side using individually two neural networks and PSO techniques and assessed their performance resulting in high prediction accuracy. Zubaidi et al. (2018) have proposed the use of hybrid PSO-ANN algorithm coupling with a pretreatment signal technique to quantify water demand through the climatic factors assessment and the results have shown PSO-ANN to be reliable compared to BP-ANN.

The major objective of this research is to efficiently predict the HVFA concrete CS of single experimental investigation using ANN and PSO optimized ANN.

2. METHODOLOGY

2.1 Artificial neural network (ANN)

ANN stimulated by the biological neural system of human brain has been successful in incorporating its characteristics such as identifying, learning and adapting to new environment. It consists of well-connected information transforming units called artificial neurons. These neurons grouped in parallel layers consisting of input, hidden and output, are chosen on basis of the given issue; whereas the sum of neurons in hidden layer is accessed by trial and error to obtain the optimum network. Each of these neurons associated with weights is passed through summation and activation functions to obtain output, used as input for neurons in the next layer. Figure 1 gives the basic components of an artificial neuron. The network learns to associate the given input with output through training. The weights are adjusted during each epoch by back propagating the errors in epochs until the desired output is obtained. This is generally known as multi-layer feed-forward neural network with error back propagation learning technique, where Levenberg-Marquardt (LM) is usually favored for efficient error converging between original and predicted output values. The LM method described by Kumar and Rajasekhar (2017) is used for the present study. ANN known for its irregular manner makes it easy to execute approximation of functions, classification, and pattern recognition (Nehdi et al. 2001).

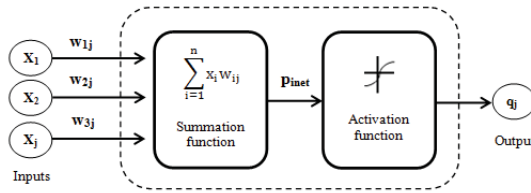


Figure 1 An artificial neuron

The total summation of input neurons for all hidden and output neuron is represented mathematically as given in Equation (1).

$$p_{inet} = \sum_{i=1}^n x_i w_{ij} + b_j \quad \dots (1)$$

Further, the total summation of input neurons is passed through the activation function (.i.e. hyperbolic tangent sigmoid) to obtain the neuron output in the next layer. So that the hidden layer neuron resultant is given by Equation (2)

$$q_j = \frac{2}{1 + e^{-(2+n)}} - 1 \quad \dots (2)$$

Where, p_{inet} = Total sum of inputs, x_i = Input node, w_{ij} = Weighted connection of neurons between i^{th} input and j^{th} hidden layer nodes, b_j = bias of j^{th} hidden layer node, n = input parameters number, q_j = Output layer neuron.

2.2 Particle swarm optimization

Particle swarm optimization (PSO) originally schemed on the primitive behavior of fish, insects, birds, etc. within a group is a gradient-free search approach. It is an evolutionary means of computing found to be better performing compared to other metaheuristic algorithms in terms of achievements and result quality. For the given problem, each solution considered as particle in the swarm is in search of the ideal global solutions which are casually dispersed in the multidimensional hyperspace. The particles' movement in the search space is administered by its individual knowledge known as local best (p_{bt}) and overall swarm knowledge known as global best (g_{bt}). These experiences are intensified further with help of cognitive and social factors along with the inertia factor guiding the current state of the particle. The particles keep record of the best local and global knowledge in terms of positions and velocity and are updated with each epoch.

In PSO algorithm, to determine the optimum solution for the given problem, initially each particle in the swarm of size 's' is randomly positioned at 'P' and the momentum assigned with some velocity 'V'. The particles assumed to be scattered in 'D' multidimensional hyperspace is treated without mass and volume, with initial position and velocity represented by Equations (3) and (4).

$$P_0 = \{P_{1,0}, P_{2,0}, \dots, P_{s,0}\} \quad \dots (3)$$

$$V_0 = \{V_{1,0}, V_{2,0}, \dots, V_{s,0}\} \quad \dots (4)$$

The particle's velocity and position are modified during each run given by Equations (5) and (6)

$$V_{j+1}^i = w_j V_j^i + c_1 \text{rnd}_1 (p_{bt} - P_j^i) + c_2 \text{rnd}_2 (g_{bt} - P_j^i) \quad \dots (5)$$

$$P_{j+1}^i = P_{j+1}^i + V_{j+1}^i \quad \dots (6)$$

Where, P_j^i is the particle current position i with j number of iterations, V_j^i is the velocity of search corresponding to i^{th} particle number, c_1 & c_2 are the parameters corresponding to cognitive and social behavior, rnd_1 and rnd_2 are the numbers randomly selected from 0 to 1 given to the i^{th} particle, w_j is the parameter of particle inertia, p_{bt} & g_{bt} are the local and global best position attained by the i^{th} number particle among all swarm particles.

The p_{bt} and g_{bt} of each particle are modified as given in Equations (7) and (8)

At iteration j ,

$$\begin{aligned} &\text{If } f(P_{j+1}^i) < f(p_{bt,j}) \text{ then } p_{bt,j+1}^i = P_{j+1}^i \\ &\text{else } p_{bt,j+1}^i = p_{bt,j}^i \end{aligned} \quad \dots (7)$$

$$\begin{aligned} &\text{If } f(V_{j+1}^i) < f(g_{bt,j}) \text{ then } g_{bt,j+1}^i = V_{j+1}^i \\ &\text{else } g_{bt,j+1}^i = g_{bt,j}^i \end{aligned} \quad \dots (8)$$

It is seen that the convergence rate is influenced by the swarm size and the cognitive parameter determines the particle learning method during the process of searching the optimal solution. Also, the social parameter determines the learning assistance among the swarm particles during the search event. The algorithm can start with initial swarm size with randomly placed positions and can terminate when maximum epochs are reached.

2.3 PSO based ANN model

An effective global optimum is obtained by the developed PSO-ANN model beyond negotiating the local optimum, thereby increasing the efficiency of the model. The best trained ANN model with faster convergence rate is obtained using PSO for optimizing its structure.

The optimization process of the PSO-ANN model outlined in Figure 2 is expressed in the following steps.

Step 1: The given data is preprocessed and separated into train and test datasets after normalization of values.

Step 2: Assign the ANN structure with random number of hidden layers and neurons to optimize using PSO algorithm.

Step 3: Initially assign random values of position and velocity for each particle of given swarm size. In this, 119 particles are assigned with random values to train the network with PSO.

Step 4: The fitness function is evaluated for respective particle position in the swarm using ANN.

Step 5: The previous particle position with better fitness function is saved as the best and updated as the best swarm position.

Step 6: The particle position and velocity are updated using Equations (5) and (6).

Step 7: The fitness function is re-evaluated using the updated particle positions until the maximum iteration is reached.

Step 8: Repeat steps 2-5 until the optimum values are obtained.

Step 9: The optimum values obtained for the ANN are used to assess the given test data fitness.

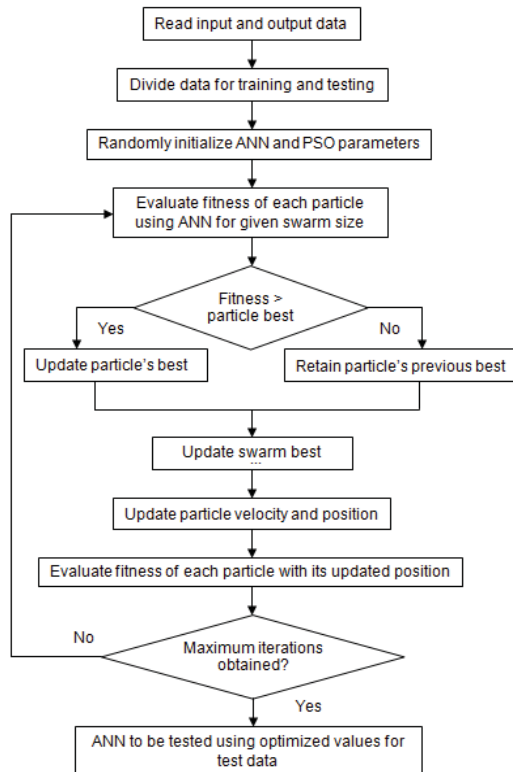


Figure 2 PSO-ANN model flow chart

2.4 Experimental data

In this study, a total of 143 datasets pertaining to control concrete CS with HVFA is collected from literature and normalized in the range 0 to 1. The concrete ingredients include cement, fly ash, water-binder ratio, superplasticizer, fine and coarse aggregate. The minimum and maximum values of each input and output parameters is given in Table 1 along with their abbreviations. 119 datasets are used for training purpose (Alaka and Oyedele, 2016; Atis, 2003; Atis, 2005; Babu and Neeraja, 2017; Bentz et al., 2015; Bouzoubaa and Fournier, 2003; Cao et al., 2000; Demirboga et al., 2004; Hazaree and Ceylan, 2006; Huang et al., 2013; Jiang and Malhotra, 2000; Kein, 2015; Kou and Poon, 2013; Kurad et al., 2017; Malhotra, 1990; Mukherjee et al., 2011; Nehdi et al., 2001; Poon et al., 2001; Poon et al., 1999; Sarker and Mckenzie, 2009; Shaikh and Supit, 2014; Shaikh et al., 2014; Yazici and Arel, 2012; Zhang andIslam, 2012), while two individual experimental datasets of 12 nos. each by Lam et al. (1998) and Yoon et al. (2014) and their combination of 24 datasets are selected to test the capability

of the developed ANN and PSO-ANN models. Time series plot is shown to illustrate the distribution of input and output parameters for training and test data in Figure 3.

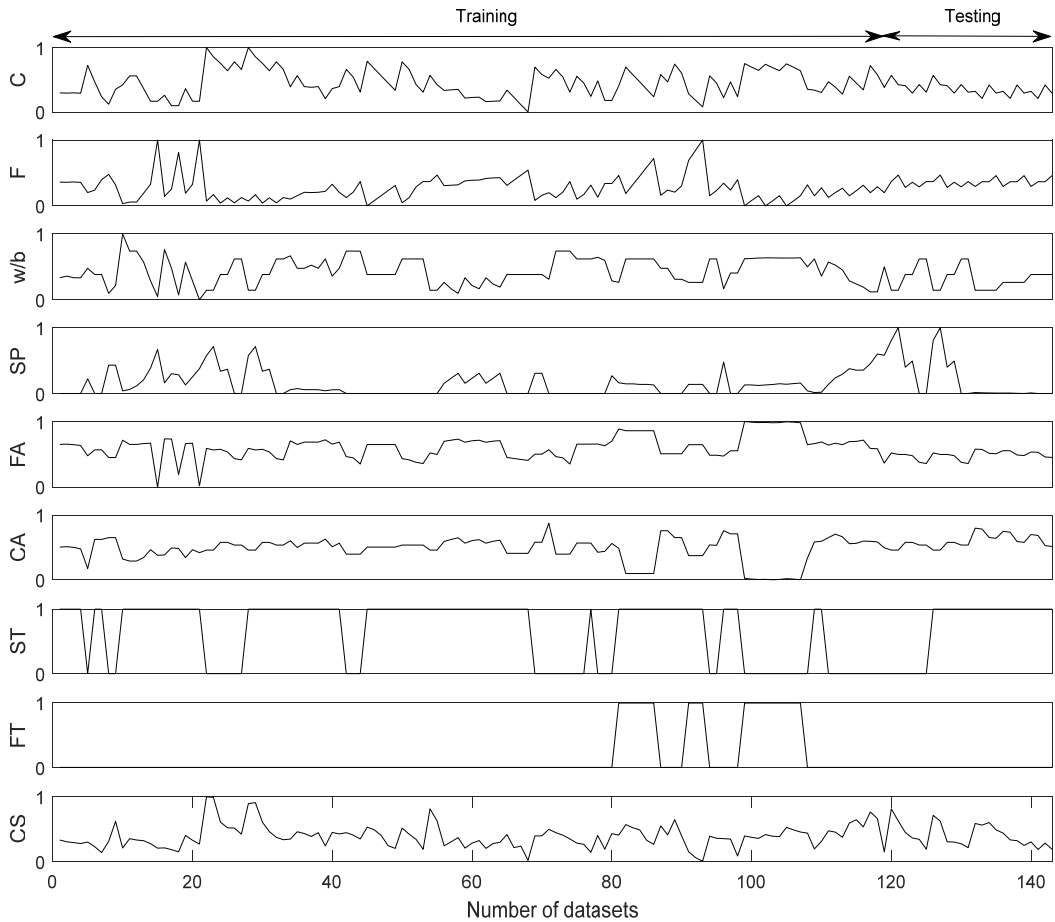


Figure 3 Time series plot of input and output parameters

Table 1 Input and Output parameter limits

Parameters	Abrv.	Min	Max
<i>Input</i>			
Cement (Kg/m ³)	C	78	425
Fly ash (Kg/m ³)	F	18	544
Water-binder ratio	w/b	0.24	0.66
Superplasticizer (Kg/m ³)	SP	0	13
Fine aggregate (Kg/m ³)	FA	279	990
Coarse aggregate (Kg/m ³)	CA	813	1405
Specimen type (Cube or Cylinder)	ST	0	1
Fly ash type (Class C or F)	FT	0	1
<i>Output</i>			
Compressive strength at 28 days (N/mm ²)	CS	9.7	86

2.5 Model development

In this study, a feed forward ANN model is developed using Levenberg-Marquardt algorithm with one hidden layer. Eight neurons are used in the input layer .i.e. cement (C), fly ash (F), water-binder ratio (w/b), superplasticizer (SP), fine aggregate (FA), coarse aggregate (CA), specimen type (ST) and fly ash type (FT). The HVFA concrete CS at 28 days is predicted as the output with neurons of the hidden layer varying from 2 to 8 to obtain the best ANN architecture. The activation functions selected for the hidden and output layers are hyperbolic tangent sigmoid and linear transfer function. Figure 4 shows the proposed ANN architecture with optimum neurons in the hidden layer. The trained model of ANN with 119 datasets is used for testing 3 groups of data set [Gr-1, Gr-2, Gr-3]. Here, Gr-1 and Gr-2 considered are from individual experimental studies from Lam et al., (1998) and Yoon et al., (2014) respectively, each having a dataset of 12 nos. and Gr-3 having 24 dataset is the combination of Gr-1 and Gr-2. The proposed model is constructed, trained and executed in MATLAB platform.

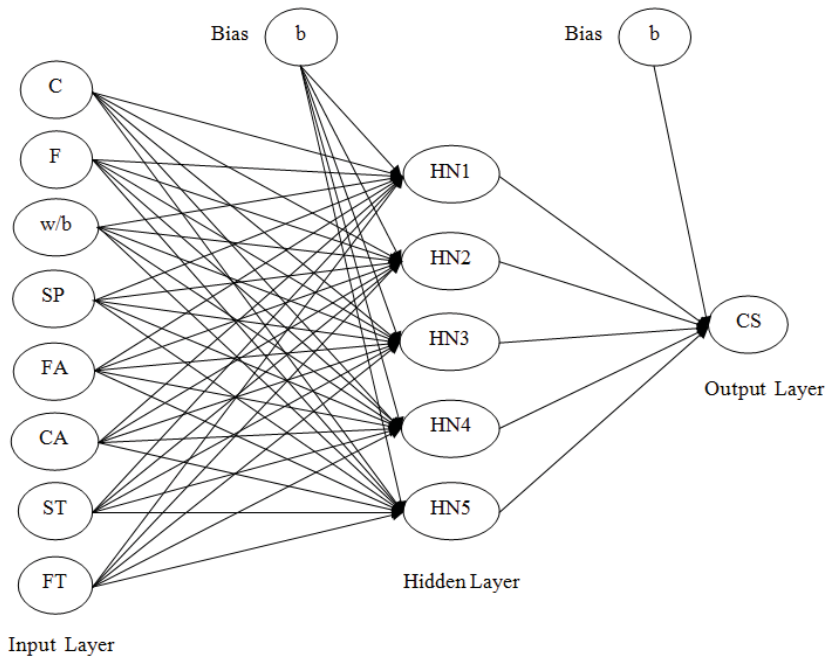


Figure 4 Proposed ANN model structure

The PSO-ANN model developed has parameters associated with both PSO and ANN. Initial values of hidden layer neurons, swarm size, inertia weight; social and cognitive parameters are assigned. The accurate models are obtained by trials to get best prediction of the CS of HVFA concrete.

2.6 Evaluation of models performance

The ANN and PSO-ANN models' performance is computed using statistical dimensions namely Coefficient of Correlation (CC), Root Mean Square Error (RMSE) and Scatter Index (SI). If S_i and R_i denotes the actual and predicted CS of HVFA control concrete, n gives the total sum of data sets, σ_1

denotes the standard deviation, $\bar{S}_i$ and $\bar{R}_i$ are average values of the actual and predicted HVFA concrete CS respectively, the performance parameters are defined by Equations (9) to (11):

$$CC = [\sum_{i=1}^n (S_i - \bar{S}_i)(R_i - \bar{R}_i)] / [\sqrt{\sum_{i=1}^n (S_i - \bar{S}_i)^2} \sqrt{\sum_{i=1}^n (R_i - \bar{R}_i)^2}] \quad \dots (9)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (S_i - R_i)^2}{n}} \times 100 \quad \dots (10)$$

$$SI = \frac{RMSE}{\sigma_1} \quad \dots (11)$$

3. RESULTS AND DISCUSSIONS

The PSO-ANN model efficacy is investigated in this particular study by comparing with ANN model using HVFA concrete CS data gathered from literature of investigations carried out experimentally. In this regard, an ANN model is formed with 8 neurons of input to predict the HVFA concrete CS at 28 days as the output with hidden neurons varying from 2 to 8. The model is trained over 40 epochs to obtain the best architecture. For comparing the efficiency of the models, statistical parameters such as CC, RMSE and SI are used. From literature it is observed that for CC values close to 1, the predicted results by models are closer to those of experimental values. Also, for smaller RMSE values, the model predicted results will be closer to the experimental results and vice-versa. From literature, it can be observed that the dataset is usually grouped into train and test data in the ratios of 50:50, 60:40, 70:30, etc. However, in this study, individual experimental studies along with their combination have been selected for testing the ANN and PSO optimized ANN models performance.

Table 2 Statistical parameters of ANN model

Network (I-H-O)	Test Datasets								
	Gr-1			Gr-2			Gr-3		
	CC	RMSE	SI	CC	RMSE	SI	CC	RMSE	SI
8-2-1	0.8996	13.0547	0.3018	0.8996	8.7107	0.2312	0.8983	11.0973	0.2742
8-3-1	0.9072	11.3851	0.2632	0.9443	6.9796	0.1853	0.9197	9.4429	0.2334
8-4-1	0.9549	6.3694	0.1472	0.9485	7.7830	0.2066	0.9439	7.1114	0.1757
8-5-1	0.9607	5.7109	0.1320	0.9643	6.6751	0.1772	0.9558	6.2117	0.1535
8-6-1	0.9395	13.410	0.3100	0.9498	18.3706	0.4877	0.9207	16.0827	0.3974
8-7-1	0.9394	18.0572	0.4174	0.9160	10.4436	0.2772	0.8937	14.7501	0.3645
8-8-1	0.8874	12.7380	0.2944	0.8871	11.5483	0.3066	0.8575	12.1577	0.3005

The statistical parameters of the test datasets for ANN models with hidden layer neurons varying from 2 to 8 are given in Table 2. From the table, it is evident that NN-8-5-1 (Fig 4) has predicted CS values closer to actual experimental CS compared to other networks. Also, test dataset Gr-2 has obtained CC higher than test dataset Gr-1, which may be due to various stages involved in the concrete manufacture such as quality of materials, mixing, placing, curing, environmental conditions, etc. The test dataset Gr-3 has also shown good prediction. The statistical parameters for NN-8-5-1 are CCs of

0.9607, 0.9643 and 0.9558; RMSEs of 5.7109, 6.6751 and 6.2117; and SI is of 0.1320, 0.1772 and 0.1535 for the corresponding 3 test datasets.

Table 3 Comparison of statistical parameters of ANN and PSO-ANN models

Test dataset	ANN			PSO-ANN		
	CC	RMSE	SI	CC	RMSE	SI
Gr-1	0.9607	5.7109	0.1320	0.9747	11.7220	0.2710
Gr-2	0.9643	6.6751	0.1772	0.9673	8.6553	0.2298
Gr-3	0.9558	6.2117	0.1535	0.9726	10.3034	0.2546

Further, the ANN model performance is maximized using PSO algorithm. The PSO-ANN algorithm is initialized with 100 swarm particles, hidden neurons number varying from 2 to 8 is trained over 100 epochs with $c_1 = 0.45$, $c_2 = 2.05$ and inertia value fixed by trial and error to get optimum weights for ANN. The optimum values are obtained for 7 hidden neurons are expressed in terms of statistical parameters. Table 3 shows the comparison of ANN & PSO-ANN models result for the 3 test datasets. The PSO-ANN model performance obtained are CC values of 0.9747, 0.9673 and 0.9726; RMSE values of 11.7220, 8.6553 and 10.3034; and SI values of 0.2710, 0.2298 and 0.2546 for the corresponding 3 test datasets. It is noted that higher CC values are obtained for Gr-1 by PSO-ANN model in comparison to Gr-2 and Gr-3.

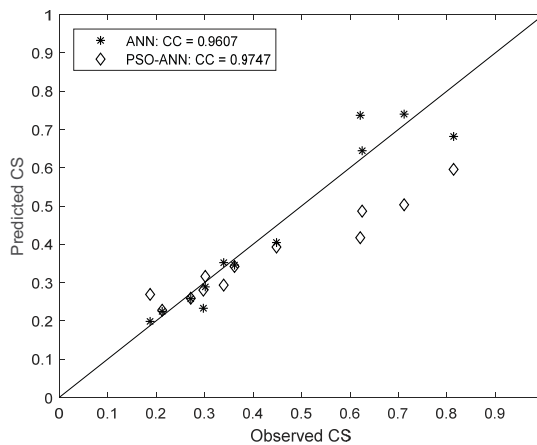


Figure 5 Performance of ANN and PSO-ANN models for test data Gr-1

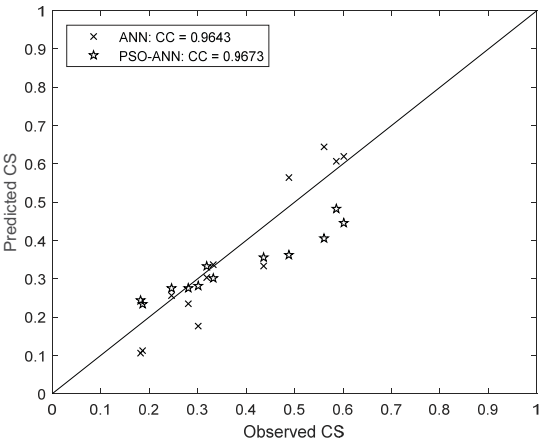


Figure 6 Performance of ANN and PSO-ANN models for test data Gr-2

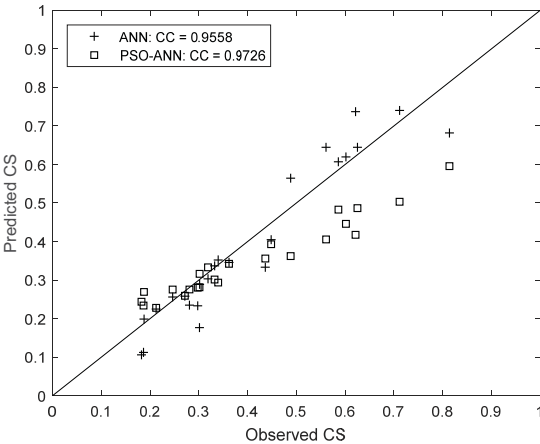


Figure 7 Performance of ANN and PSO-ANN models for test data Gr-3

Figure 5, 6 and 7 shows comparison of CC values of the ANN and PSO optimized ANN models' performances for all 3 test data groups. The models are able to predict the HVFA concrete CS values closer to actual values in all three test datasets with prediction in terms of CC above 95%. Although, the performance differences between the models are negligible, the PSO-ANN model is able to converge to the global minima at faster rate.

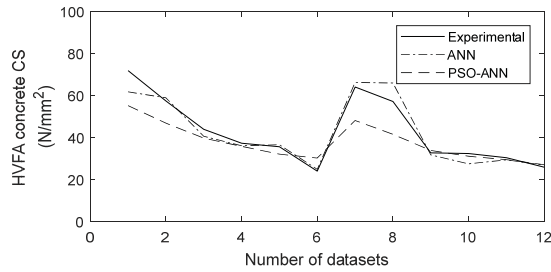


Figure 8 Time series plot of actual and predicted CSs for test dataset Gr-1

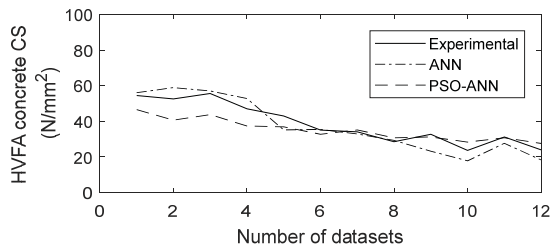


Figure 9 Time series plot of actual and predicted CSs for test dataset Gr-2

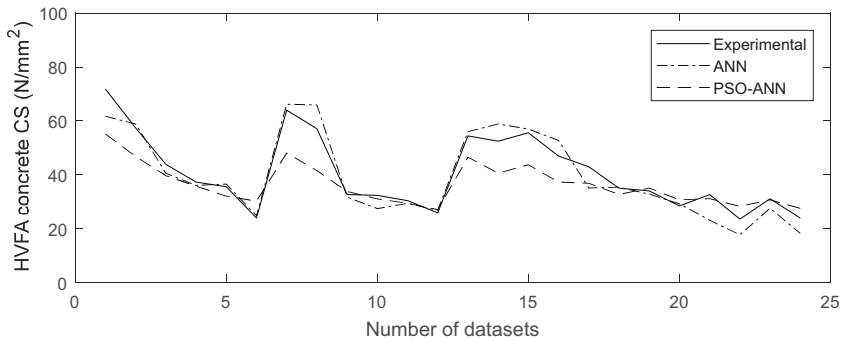


Figure 10 Time series plot of actual and predicted CSs for test dataset Gr-3

The time series plot of CS of HVFA concrete .i.e. actual and those predicted by ANN and PSO-ANN models of all three test datasets are shown in Figs 8, 9 and 10. It is observed that ANN is able to overestimate the CS values compared to PSO-ANN models for higher CS values whereas for lower CS values PSO-ANN predicts very close to actual CS values compared to that of the ANN model for individual studies. Also, it is observed that the same trend follows in the combination test dataset .i.e. Gr-3. The test dataset results illustrate that the PSO-ANN model has lower errors and higher capacity of generalization. Hence, ANN and PSO-ANN have great potential eventually used for the estimation purpose to overcome the laboratory investigation procedure conserving natural resources and producing cost-effective mixtures.

4. CONCLUSIONS

Cement in control concrete is being replaced by mineral admixture such as fly ash which is available abundantly as waste from industries and harmful to environment is paving way to evolution of HVFA concrete. The maximum percentage of cement to be replaced by fly ash in concrete for structural usage is still at research level though higher fly ash volumes are used for non-structural purposes. HVFA concrete has shown remarkable similarity to control concrete with adequate mechanical and durability properties. With research been carried out to use HVFA concrete in larger scale, soft computing techniques considered to be powerful tool for modeling and prediction of complex problems have inspired researchers for the development of cost-effective HVFA concrete mixtures to save on natural resources and time. In this study, the CS of control concrete with high fly ash volumes from various experiments conducted in the past are collected to determine the efficiency of ANN and PSO-ANN models in predicting their compressive strength. Also, an attempt has been made to determine the CS of HVFA concrete of individual experimental investigations to overcome the tedious and laborious laboratory procedure. The outcome of this study is summarized below:

- The CS of HVFA control concrete are predicted using individual ANN and PSO optimized ANN models with network trained with low to high fly ash volumes in control concrete.
- The ANN models for architecture NN-8-5-1 have shown good prediction results for the three test datasets Gr-1, Gr-2, Gr-3 with CC of 0.9607, 0.9643 and 0.9558 respectively.
- PSO algorithm has been employed for further improvement of the performance of ANN for the HVFA concrete CS prediction.
- The developed ANN and PSO hybridized ANN models are able to successfully estimate the CS of individual experimental studies with the compressive strengths ranging from 20 to 90N/mm².
- The PSO-ANN model results in terms of CC is better in predicting the CS of HVFA control concrete in comparison to ANN models for single experimental studies and their combination.
- The results have shown that these models can be efficiently used for the prediction of the CS of HVFA concrete promoting sustainable constructions.
- Selection of the individual experimental studies for testing is to minimize on the number of trials to obtain the required mix proportions for the intended purpose to reduce the wastage of natural resources.

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