Strength Assessment of HVFA Concrete using Soft Computing Techniques

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High volumes of fly ash (HVFA) for cement in concrete, the future material of construction industry is extensively explored for in sustainable developments on a large scale. More ingredients in concrete make its nature complicated, determining whose properties become tedious and uneconomical using traditional prediction methods. From the literature, it is evident that soft computing techniques (SCT) have proven their potentiality in predicting the highly non-linear behavior of concrete. In this study, 119 datasets of HVFA control concrete compressive strength (CS) collected from literature is used to train SCT models such as artificial neural network (ANN), Support vector machine (SVM), particle swarm optimization-based ANN (PSO-ANN), and PSO-SVM models; and a dataset of 12 nos. from an individual experimental study is used for testing the models. Cement, fly ash, water-binder ratio, superplasticizer, fine aggregate, coarse aggregate, specimen type and fly ash type are the models' input parameters for predicting the HVFA concrete CS. PSO is used to optimize the individual ANN and SVM parameters to improve their performance. Statistical parameters i.e., correlation coefficient, root mean square error and scatter index are used to measure the models' efficacy. Both individual and hybrid model results show good predictions of the HVFA control concrete CS for an individual experimental study.

Keywords: Concrete, Fly ash, Compressive strength, ANN, SVM, PSO.

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1 Introduction

Fly ash usage in large volumes has increased globally to minimize the usage of cement for construction purposes. The use of industrial waste i.e., fly ash in large volumes is contributing to the reduction of greenhouse gas emissions. The HVFA concrete is proportioned by replacing cement with fly ash by more than 40% in concrete. Enormous literature is available determining the mechanical and durability properties of HVFA concrete in view of increasing its large-scale usage globally. It is seen that HVFA control concrete has properties similar to conventional concrete at later ages though requires the addition of chemical additives to improve its fresh and early age properties [1].It is known that for the proper usage of the concrete for any of the specific job requirements it is important to perceive its properties beforehand. Available traditional prediction methods have many drawbacks to be used for determining concrete behavior using more ingredients.

Soft computing techniques (SCT) which is developed based on human thinking mechanism has successfully provided solutions to many of the highly complex civil engineering problems. Due to its proficiency to sustain tolerating imprecision, uncertainty, and partial truth in order to obtain tractability and robustness on simulating human decision-making behavior with low cost, it's become more popular across all disciplines. It mainly consists of Expert System, Fuzzy Logic (FL), Artificial Neural Networks (ANN), and Evolutionary Algorithms. Optimization techniques such as PSO, ant colony optimization (ACO), etc. are combined with the individual models in view of improving the model performance [2, 3].

From the literature, it is evident that individual models such as ANN, fuzzy logic, SVM, genetic algorithms, etc. are optimized using PSO. PSO based ANN models have been successfully implemented to evaluate the construction outcomes which helps to decide for litigation and for prediction of early warnings of nearing floods and evacuation measures of ShingMun River water stage; to locate the best position of trench layer arranged about the pipeline to attain least liquefaction potential; to predict the behavior of load-deformation of axially loaded piles; to estimate the safety factor for slope stability analysis to identify the potential sections of landslides; to predict the CS of HVFA concrete, etc. Also, PSO-based SVM models give solutions to real-time problems such as predicting the damage level of non-shaped berm breakwater, predicting wave transmission over the submerged reef of tandem breakwater; predicting the hydraulic performance of stepped spillway, etc.[2, 3, 4, 5].

The objective of this study is to illustrate the use of SCT models such as ANN, SVM, PSO-ANN, and PSO-SVM models in predicting the CS of individual HVFA concrete studies using basic ingredients of the mix proportions.

2 Methodology

2.1 Artificial Neural Network (Ann)

ANN is programmed to simulate real-time problems and provide solutions similar to human thinking mechanisms. Information is passed forward through different layers of the well-connected network through artificial neurons. Fig. 1 shows the structure of an artificial neuron [2].This feed-forward network consists of input, hidden and output layers with neurons grouped and arranged systematically. All the neurons in the network are associated with a weight that has a significant effect on the network output. The input and output layer consists of neurons as applicable to the selected problem while hidden layer neurons are optimized on a trial-and-error basis to get a minimum error. The neurons in each of these layers are summed and activated using relevant functions. The network is trained over a number of epochs by adjusting the parameters until the input is mapped to the output. The error between actual and predicted values is propagated back to the network using the Levenberg-Marquardt technique [6]. The trained network with the least error is used for simulating new input data.

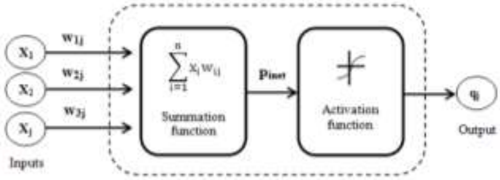

Fig. 1. An artificial neuron

2.2 Support Vector Machine (SVM)

SVM is used as an optimization tool for classification and regression problems [7, 8]. It separates the given data linearly into different classes and increases the margins between them using a hyperplane. For non-linear data, the data is transformed into higher dimensional space using kernel functions for locating the hyperplanes and the solution for the linear regression problem is found in this feature space. In this method, a loss function is used to neglect the error in true values within a certain distance of the maximized hyperplane margins which reasons the obtained solution. The number of support vectors lying on these hyperplanes governs the knowledge of data separation.

Considering a training data sample of$\{(a_k, b_k)\}_{k=1}^{n}$, where n represents the training data size, $a_k \in T^n$represents the input training vectors and $b_k \in \{+1, -1\}$ is the related scalar output. Fig. 2 shows the SVM regression graphical representation [3].

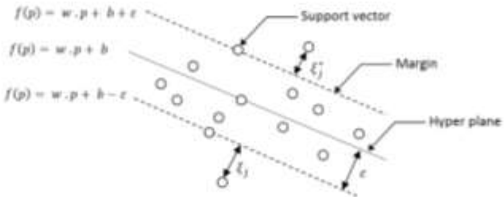

Fig. 2.A typical diagram of SVM regression with slack variables and ε-insensitive zone

In SVM regression, the input space c_k is projected onto m-dimensional feature space by non-linear mapping, for construction of linear model given by Equation (1),

$$\mathrm{b} = f(a, \omega) = w^T \emptyset(a) + \mathrm{p} \tag{1}$$

Where, w is the weight vector, p is the bias, w &p shows the hyperplane location, and $\emptyset(a)$ represents the non-linear data transformed to the higher dimensional feature space.

Vapnik proposed the use of ε -insensitive loss function in SVM regression with assurance of global minima along with minimization of the empirical risk, where the empirical risk is given by Equation (2)

$$R_{em}(\omega) = \frac{1}{m}\sum_{j=1}^{m} L_\varepsilon(b_j, f(a_j, \omega)) \tag{2}$$

With the loss function subjected to constraints as given by Equation (3),

$$L_\varepsilon\big(b, f(a, \omega)\big) = \begin{cases} |b - f(a, \omega)| - \varepsilon, \ \text{if } |b - f(a, \omega)| \le \varepsilon \\ \quad otherwise\ 0 \end{cases} \tag{3}$$

Using ε-insensitive loss function, SVM performs linear regression in the higher dimensional feature space and optimizing the model with minimizing$\|w^2\|$. Slack variables $\xi_j, \xi_j^*, j = 1, 2 \ldots. m$, the non-negative variables are proposed to measure the divergence of the input data far from the ε - insensitive region. Hence, the SVM regression is defined by Equation (4),

$$Minimum of \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_j + \xi_j^*) \quad (4)$$

Subject to constraints given by Equation (5),

$$\begin{Bmatrix} b_i, f(a_i, \omega) \leq \varepsilon + \xi_i^* \\ f(a_i, \omega) - b_j \leq \varepsilon + \xi_i \\ \xi_i, \xi_i^* \geq 0, i = 1,2 \ldots. n \end{Bmatrix} \quad (5)$$

The given problem is optimized into a dual problem with the solution given by Equation (6),

$$f(a) = \sum_{i=1}^{n_{sv}}(\alpha_i - \alpha_i^*) K(b_i, b) \quad (6)$$

subject to $0 \leq \alpha_i^* \leq C, 0 \leq \alpha_i \leq C$, where penalty C gives an understanding between complexity of the model and degree of deviation that is greater than epsilon (ε), $\alpha_{i,}\alpha_i^*$ are the Lagrange multipliers and n_{sv} are the support vector numbers and the kernel function is given by Equation (7),

$$K(a_i, a) = \sum_{j=1}^{m} \emptyset_j(a)\emptyset_j(a_i) \quad (7)$$

It is well known that the performance of the SVM model depends on adjusting the parameters such C, ε, and kernel parameters. In this study, the SVM model is developed for different kernel parameters and the best performing model for the corresponding kernel function is selected for the prediction of the HVFA concrete CS.

2.3 Particle Swarm Optimization (Pso)

PSO algorithm is derived from the behavior of natural inhabitants in a group to compute progressive means of qualitative solutions [9, 10]. In PSO, each solution for the problem under consideration is a particle of the swarm which is randomly distributed over the search space. The swarm moves towards the best solution by the knowledge gained by each particle moving through a path of optimum particles and by the entire swarm. The particle's position and velocity are evaluated and optimized based on the associated fitness function. The search for the local and global best is improved with help of cognitive and social factors along with the inertia factor responsible for the particle's current state. During each run, the particle is updated with its local best (p_{st}) and global best (g_{st}) knowledge of the fitness function [11].

For the given problem, the optimum solution is obtained by assigning randomly positions 'Po' and velocity 'Ve' for each particle in the swarm size 's'. The particles are assumed to be randomly occupying 'D' multidimensional hyperspace which is considered to be without mass and volume, with initial position and velocity represented by Equations (8) and (9).

$$Po_0 = \{Po_{1,0}, Po_{2,0}, \ldots\ldots.., Po_{s,0}\} \quad (8)$$

$$Ve_0 = \{Ve_{1,0}, Ve_{2,0}, \ldots\ldots., Ve_{s,0}\} \quad (9)$$

The particle's velocity and position are modified during each run given by Equations (10) and (11)

$$Ve_{j+1}^i = wt_j Ve_j^i + c_1 rn_1(p_{st} - Po_j^i) + c_2 rn_2 (g_{st} - Po_j^i) \quad (10)$$

$$Po_{j+1}^{i} = Po_{j+1}^{i} + Ve_{j+1}^{i} \qquad (11)$$

Where, Po_j^i is the particle current position i with j number of iterations, Ve_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, rn_1 and rn_2 are the numbers randomly selected from 0 to 1 given to the i^{th} particle, wt_j is the parameter of particle inertia, p_{st} & g_{st} are the local best and global best position attained by the i^{th} number particle among all swarm particles.
The p_{st} and g_{st} of each particle are modified as given in Equations (12) and (13)
At iteration j,

$$\text{If } f(Po_{j+1}^{i} < f\left(p_{st,j}^{i}\right) then p_{st,j+1}^{i} = Po_{j+1}^{i}$$
$$else p_{bt,j+1}^{i} = p_{bt,j}^{i} \qquad (12)$$

$$\text{If } f(Ve_{j+1}^{i} < f\left(g_{st,j}^{i}\right) then g_{st,j+1}^{i} = Ve_{j+1}^{i}$$
$$else\ g_{st,j+1}^{i} = g_{st,j}^{i} \qquad (13)$$

It is noted that the size of the swarm affects the rate convergence which is influenced by the social, cognitive, and inertia parameters associated with each during the search process.

2.4 PSO based ANN and SVM Models

The performance of the individual ANN and SVM models' architecture is optimized by the PSO algorithm as shown in Fig.3 in form of a flow chart. The model optimization by PSO is demonstrated in the steps as given below:

Step 1: The collected data is preprocessed and normalized which is divided into train and test datasets.
Step 2: ANN/ SVM model parameters are assigned with random values to optimize using the PSO algorithm.
Step 3: Position and velocity values for each particle are randomly assigned to a swarm size of 119 particles to train the individual network with PSO.
Step 4: The fitness function is evaluated for the respective particle position in the swarm using ANN/ SVM.
Step 5: The previous particle position with a 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 (12) and (13).
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/ SVM are used to simulate the given test data.

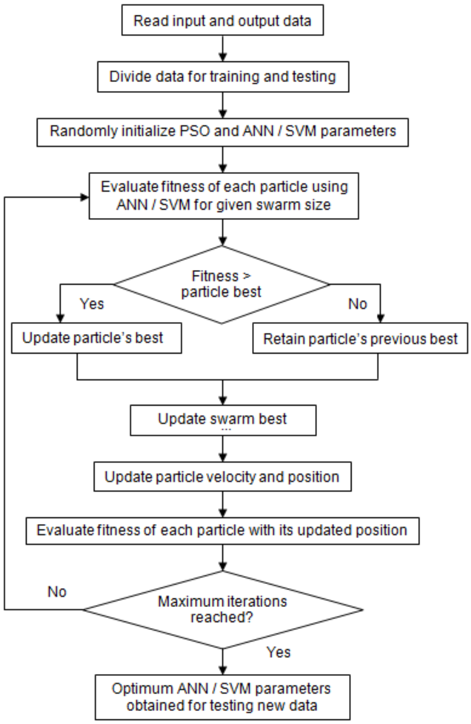

Fig.3.PSO-ANN / PSO-SVM model flow chart

2.5 Experimental Data Collection

This study consists of 131 datasets collected from peer-reviewed journals pertaining to HVFA control concrete CS which are normalized between 0 to 1. The data collected includes concrete ingredients such as cement, fly ash, water-binder ratio, superplasticizer, fine aggregate, coarse aggregate and 28-day compressive strength. Each of the input and output parameters with minimum and maximum values are given in Table 1. 119 datasets are used for training the developed SCT models [12-35] and an individual experimental study with 12 nos. of datasets [36] is selected to test the efficacy of the developed SCT individual and hybrid models. A time series plot is shown to illustrate the distribution of input and output parameters for training and test data in Fig.4.

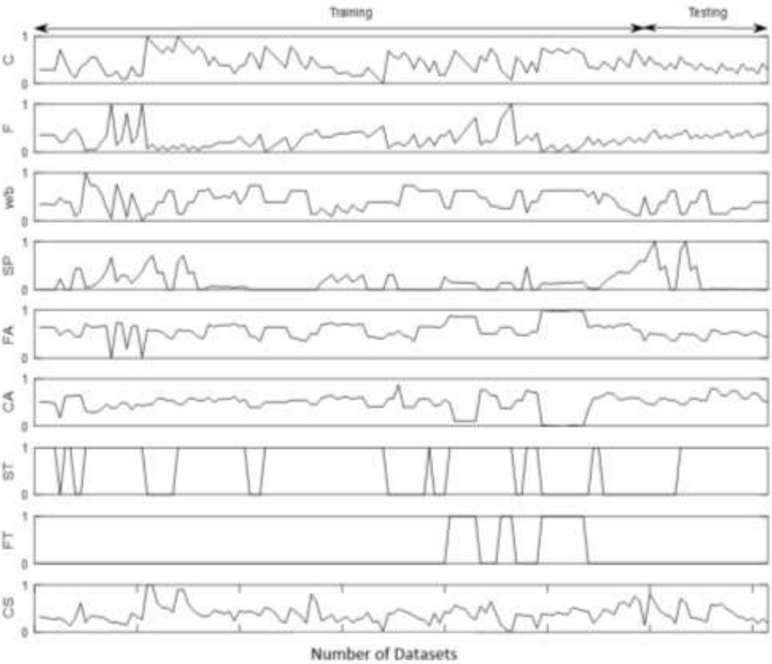

Fig.4. Time series plot of input and output parameters (Training-119, Testing- 12 datasets)

Table 1. Range of Input and Output parameters.

Parameters	Abrv.	Min	Max
Input			
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
Output			
Compressive strength at 28 days (N/mm^2)	CS	9.7	86

2.6 Model Development

A feed-forward neural network is constructed with the Levenberg-Marquardt algorithm with 8 neurons in the input layer and 5 hidden layer neurons optimized by trial and error. The data from input and hidden layer neurons are passed through hyperbolic tangent sigmoid and linear transfer activation functions. The ANN model parameters are optimized by trial and error to obtain the least error between the actual and predicted values. Also, the SVM model is constructed with the same 8 input neurons using polynomial, radial bias function (rbf), erbf, spline, and b-spline as kernel functions. The parameters of the SVM (C, ε) and kernel (d, γ) function are adjusted to obtain the best performing model with the least errors. In the present study, the actual values are obtained by neglecting the error within a definite distance using the quadratic loss function. 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)are used as the 8 input neurons to predict the HVFA concrete 28-dayCS as the output. The models are trained with 119 datasets and tested over a dataset of 12 nos. on the MATLAB platform.

The ANN and SVM model parameters are optimized further by using the PSO algorithm to obtain the best-performing model with the least errors in the predicted HVFA concrete CS. Initially, random values are assigned for ANN, SVM, and PSO parameters such as the size of the swarm, inertia weight; social and cognitive parameters, which are refined over a number of epochs to obtain the best performing hybrid PSO-ANN and PSO-SVM models.

2.7 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 M_i and N_i denotes the actual and predicted HVFA control concrete CS, n the total number of data sets, σ_1 denotes the standard deviation, $\overline{M_i}$ and $\overline{N_i}$ are the values of average actual and predicted HVFA concrete CS respectively, the statistical parameters are given by Equations (14) to (16):

$$CC = [\sum_{i=1}^{n}(M_i - \overline{M_i})(N_i - \overline{N_i})]/[\sqrt{\sum_{i=1}^{n}(M_i - \overline{M_i})^2(N_i - \overline{N_i})^2}] \quad (14)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(M_i - N_i)^2}{n}} X\ 100 \quad (15)$$

$$SI = \frac{RMSE}{\sigma_1} \quad (16)$$

3 Results and Discussion

The hybrid PSO-ANN and PSO-SVM models' efficacy is investigated by comparing with the individual model results constructed using experimental data collected from the literature. The models are trained with 119 datasets and tested over an individual experimental study consisting of 12 datasets.

3.1 Performance of ANN and PSO-ANN Models

Firstly, an ANN model with 8-5-1 architecture is constructed which is trained over 40 epochs to obtain optimum parameters. The performance of the ANN model is measured using CC, RMSE, and SI statistical parameters.Fig.5 shows the optimum trained ANN model with weights and bias.

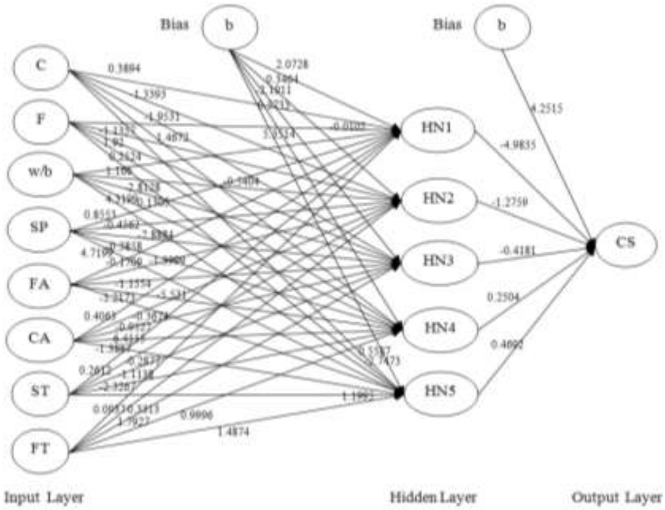

Fig.5. ANN (8-5-1) trained network with weights and bias

The performance of the ANN model is further optimized using the PSO algorithm. The PSO-ANN algorithm is optimized with 100 swarm particles, 7hidden neurons which is trained over 100 epochs with c_1= 0.45, c_2= 2.05, and value of inertia set by trial and error to obtain optimum neuron weights for ANN. The optimum values are obtained for 7 hidden neurons are expressed in terms of statistical parameters. Table 2 shows the comparison of statistical parameters of ANN & PSO-ANN models result for the train and test datasets. The ANN and PSO-ANN model performance for the test dataset obtained are CC values of 0.9607 and 0.9747; RMSE values of 5.7109 and 11.7220; and SI values of 0.1320 and 0.2710 respectively.

Table 2. Comparison of statistical parameters of ANN and PSO-ANN models

Statistical parameters	ANN		PSO-ANN	
	Train	Test	Train	Test
CC	0.9583	0.9607	0.8204	0.9747
RMSE	5.1304	5.7109	10.2781	11.7220
SI	0.1330	0.1320	0.2664	0.2710

Fig.6showsa comparison of CC values of the ANN and PSO-ANN models' performances for the test dataset. The models can predict the HVFA concrete CS values closer to actual values with CC prediction above 0.96.From the result, it can be seen that ANN predicts CS values greater than 50 MPa beyond the actual values compared to PSO-ANN. The CS values lesser than 50 MPa are predicted with good generalization and lower errors by PSO-ANN compared to the ANN model. It is also observed that the hybrid PSO-ANN can converge to global minima faster compared to the ANN model though the negligible difference is found between the models. Thus, both ANN and PSO-ANN models have the potential to be used for predicting HVFA Concrete CS values of an individual experimental study.

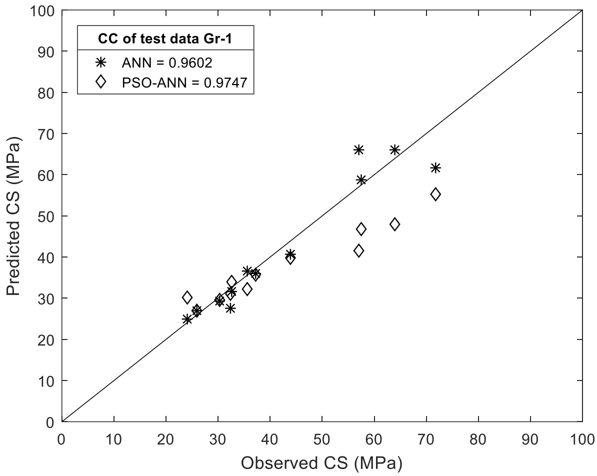

Fig.6. Scatter plot of observed CS with ANN and PSO-ANN models predicted CS

3.2 Performance of SVM and PSO-SVM Models

The SVM model is constructed with optimum kernel functions whose performance depends on the selection of suitable kernel parameters. In this study, the optimum SVM model is obtained using the polynomial kernel function of first order with values C= 100 and n_{sv} = 119. The performance of the SVM model is measured using CC, RMSE, and SI statistical parameters.

The performance of the SVM model is further optimized by the PSO algorithm with a polynomial kernel function of second-order with the size of swarm 20, C_1 = 0.3, and C_2 = 3. Table 3 shows the comparison of statistical parameters of SVM& PSO-SVM models results for the train and test datasets. The SVM and PSO-SVM model performance for the test dataset obtained are CC values of 0.9762 and 0.9783; RMSE values of 5.5503 and 5.2528; and SI values of 0.1353 and 0.1214 respectively.

Table 3. Comparison of statistical parameters of SVM and PSO-SVM models

Statistical parameters	SVM		PSO-SVM	
	Train	Test	Train	Test
CC	0.8500	0.9762	0.8989	0.9783
RMSE	9.4592	5.5503	7.8980	5.2528
SI	0.2452	0.1353	0.2047	0.1214

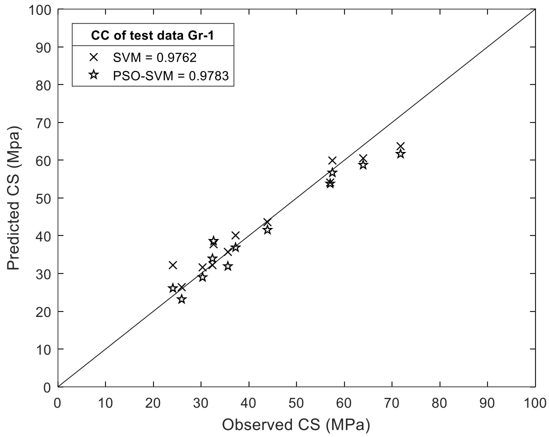

Fig.7. Scatter plot of observed CS with SVM and PSO-SVM models predicted CS

Fig.7 shows a comparison of actual CS with SVM and PSO-SVM models predicted CS for the test dataset. It can be observed that both the individual and hybrid models have predicted HVFA concrete CS values closer to actual CS values with CC higher than 0.97 showing a strong relationship between both the values. Both the SVM and PSO-SVM models have shown good predictions for CS in the range of 25 to 60 MPa for an individual HVFA study. The difference between SVM and PSO-SVM model performance is negligible, thus noting the optimization already obtained by the individual model. For the selected test data, it is observed that both models have shown good predictions with high correlations and lower errors. It is also seen that in comparison to experimental results, SVM and PSO-SVM models are being able to predict the CS of a single study better than ANN and PSO-ANN models.

4 Conclusion

In this study, the CS of HVFA concrete of individual experimental study is selected to check the efficacy of the SCT models such as ANN, SVM, PSO-ANN, and PSO-SVM in comparison to the laboratory procedure. The outcome of this study is summarized below:

- The CS of HVFA control concrete of an individual experimental study is predicted using individual and hybrid SCT models.
- ANN and SVM models have predicted CS values of an individual experimental study with the least errors and higher CC values.
- PSO algorithm has been employed for further improvement of the performance of ANN and SVM models for the HVFA concrete CS prediction.
- The ANN and PSO-ANN models can predict the HVFA concrete CS of an individual experimental study with the compressive strengths 25 to 70 MPa while PSO-ANN has shown good predictions for CS values below 50 MPa.
- The SVM and PSO-SVM models can predict the HVFA concrete CS of an individual experimental study with the compressive strengths in the range of 25 to60 MPa.
- It is observed that the SCT models can be efficiently used for the prediction of the CS of HVFA concrete of an individual experimental study.
- The SCT models aims in reducing the number of trials required to obtain the mix proportions for specific application and also reduce the wastage of non-renewable resources.

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