PREDICȚIA REZISTENȚEI LA COMPRESIUNE A BETONULUI DE ÎNALTĂ PERFORMANȚĂ UTILIZÂND MODELUL ROIULUI DE ALBINE
COMPRESSIVE STRENGTH PREDICTION OF HIGH PERFORMANCE CONCRETE USING ARTIFICIAL BEE COLONY ALGORITHM

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Because high performance concrete (HPC) is a complex composite material, model of its compressive strength is highly nonlinear. Common mathematical models cannot handle this nonlinearity and recent studies tried to propose predictive models based on advanced machine learning approaches. Support vector regression (SVR) by incorporating different linear and nonlinear kernels has proved its effectiveness to solve such problems. However, the problem of model selection in SVR, provided limitation for effective concrete compressive strength (CCS) prediction. We employed the search ability of evolutionary algorithms and proposed a hybrid SVR-artificial bee colony (SVR-ABC) algorithm for the problem of CCS prediction. The proposed method can estimate CCS of different composition concretes with a high accuracy.

Keywords: *Concrete Compressive strength; Prediction; Support Vector Regression; Artificial Bee Colony*

1. Introduction

High-performance concretes (HPC) are made with carefully selected high-quality ingredients and optimized mixture designs; these are batched, mixed, placed, compacted and cured to the highest industry standards. The use of chemical and mineral admixtures is the main difference between normal strength concrete and high-performance concrete. The use of chemical admixtures reduces the water content, and so the porosity of concrete will be reduced.

Mineral admixtures, and also called Supplementary Cementing Materials, are used for various purposes depending upon their properties. The silica fume, the blast furnace slag and the fly ash has been used widely as supplementary cementitious materials in HPC. These act as pozzolanic materials as well as fine fillers; therefore, the microstructure of cement matrix after hardening becomes denser and stronger. Fly ash used as a partial replacement for cement in concrete provides very good performance. The setting time is increased, also ultimate strengths are usually improved when fly ash is used. Silica fume tends to improve both mechanical properties and durability of concrete. The ultimate strengths with slag are generally improved; the durability is also improved with the replacement of cement by slag. The mineral admixtures are generally industrial by-products and their use can provide a major economic benefit. Thus, the combined use of superplasticizer and cement replacement materials can lead to economical high-performance concrete with enhanced strength, workability, and durability.

Between mechanical properties of concrete, compressive strength is the most important property, which is usually measured at 28 days age. Mathematically modeling HPC is very difficult because the relationships between concrete components and its properties is very complex and highly nonlinear. Therefore, traditional models are inadequate for modeling of HPC compressive strength [1]. In this paper, the main aim is to make a system that memorize from an experimental data set of HPC mixes and can foresee compressive strength according to concrete mixture. This can be realized using new methods of artificial intelligence and machine learning. In recent years, some studies employed machine learning methods to predict concrete compressive strength. Boukhatem et al. surveyed the application of recent progresses in information technology on concrete mix design. They expressed that techniques include simulation models, decision support and artificial intelligence systems are useful tools to solve linear and nonlinear problems in concrete technology [2]. Many of studies have applied methods based on Artificial Neural Networks (ANNs) techniques [3-5]. Chithra et al. used multiple regression analysis and ANN

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models to predict the compressive strength of High Performance Concrete containing nano silica and copper slag as partial cement and fine aggregate replacement, respectively. They found the best fit from ANN with Levenberg–Marquardt learning algorithm [1]. Oh et al. applied the neural network, which trained with some data, to concrete mix proportioning to optimize the proportion of normal strength concrete mixture. They showed that the results can be obtained with maximum error of 5.9% [6]. Zhou et al. estimated compressive strength of hollow concrete masonry prisms using ANN and adaptive neuro-fuzzy inference systems. The two models were trained and tested and then verified by comparison with other empirical calculation methods [7]. Kasperkiewicz et al. also used an ANNs of the fuzzy-ARTMAP type for predicting strength properties of HPC mixes with composition of cement, silica, superplasticizer, water, fine aggregate, and coarse aggregate [8]. Nazari et al. modeled compressive strength of different types of alkali-activated binders, using adaptive neuro-fuzzy interfacial systems [9]. Yeh used ANNs to predict the compressive strength of HPC as a function of cement, fly ash, blast furnace slag, water, superplasticizer, coarse aggregate, fine aggregate, and age of testing. They concluded that the strength model based on the ANN is more accurate than the model based on regression analysis [10]. Ramezanianpour et al. practiced adaptive network-based fuzzy inference systems (ANFIS) to predict 28-days compressive strength of concrete (CSC) [11]. Zarandi et al. designed a new method to predict 28-CSC. They employed a fuzzy polynomial neural network (FPNN) to predict 28-CSC and compared the results of the FPNN with the results of ANFIS. They concluded that FPNN predictions are more accurate in comparison to those obtained from ANFIS [12].

Another machine learning approach which has been used in literature for prediction of concrete compressive strength is support vector regression (SVR) [13]. SVR is an extension of support vector machines (SVMs), for solving nonlinear regression problems. The SVM which was first introduced by Vapnik [14], is a powerful method in the category of statistical learning theory and its main application was in pattern recognition problems. Very promising results of SVM in various classification problems such as detecting construction materials in digital images [15], ECG beat classification [16-18], detection of Alzheimer's disease and mild cognitive impairment [19, 20], and so on, made it a popular methodology. Interestingly, SVR also showed excellent performance in various prediction fields, such as failure prediction and reliability analysis [21], backbreak prediction in blasting operation [22], and the like. Recently, some authors used SVR to predict concrete compressive strength [23-25]. However, despite the great potential of SVR models, they have not received the attention they deserve in the CCS prediction literature as compared to other research fields. In addition, it has been pointed out that the performance of SVR is greatly affected by the values of model parameters and yet there is no general rule to find appropriate SVR parameters [26]. The popular methods of model parameter setting are grid search and gradient descent which have drawbacks such as vulnerability to local optimum. Evolutionary algorithms such as genetic algorithm (GA) and particle swarm intelligence (PSO) have been adopted to find global optimum solution by proper setting of SVR model parameters. A new emergence global optimization algorithm is the artificial bee colony algorithm (ABC) [27, 28]. ABC has been found to be a useful tool in many of the real world optimization problems, due to the simplicity, few number of control parameters, and outstanding performance [28]. Some authors compared the performance of ABC with that of other optimization methods, such as the genetic algorithm, differential evolution, and PSO [27, 29]. They showed that ABC is superior to the other methods in various problems such as signal processing, clustering, and geotechnical stability. Interested readers are referred to [28] for more information on ABC. In this paper, ABC algorithm is adopted to select the optimum parameters for SVR model.

2. Methods

2.1.Dataset description

The experimental dataset that is used in this study was obtained from the University of California, Irvine data repository [10]. A collection of 1030 samples of HPC was obtained from various university laboratories. All tests were performed on standard cylindrical specimens with diameter of 15 centimeters. Table 1 shows the experimental dataset that is used in this study. Figure 1 represents the distribution of compressive strength values in this dataset.

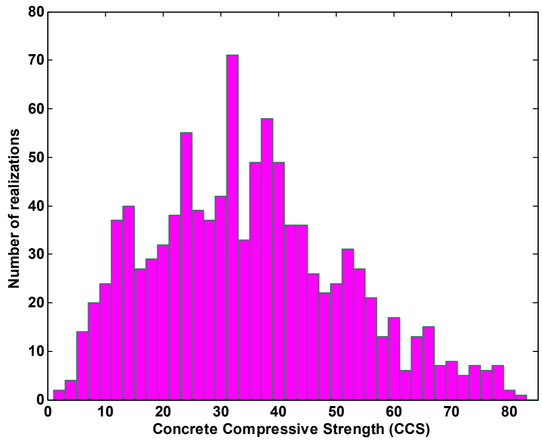


Fig. 1 - Concrete compressive strength values distribution in dataset.

Table 1

Concrete mixture properties

Component	Unit	Minimum	Maximum	Average	Standard deviation
Cement	Kg/m^3	102	540	281.2	104.5
Blast Furnace Slag	Kg/m^3	11	359.4	107.3	61.9
Fly Ash	Kg/m^3	24.5	200.1	83.9	40
Water	Kg/m^3	121.8	247	181.6	24.4
Superplasticizer	Kg/m^3	1.7	32.2	8.5	4
Coarse Aggregate	Kg/m^3	801	1145	973	77.8
Fine Aggregate	Kg/m^3	594	992.6	773.6	80.2
Age of Testing	Day	1	365	45.7	63.2
Concrete Compressive Strength	Mpa	2.3	82.6	35.9	16.7

2.2. Artificial Bee Colony (ABC)

Artificial bee colony (ABC) algorithm is one of the most recently introduced algorithms, inspired by the intelligent behavior of honey bees [28]. It is a simple algorithm like particle swarm optimization (PSO) and does not have many parameters like genetic algorithms (GA). Its parameters are only common parameters like colony size and maximum cycle number. ABC provides a population-based search in which a colony of artificial forager bees search for artificial food sources with high nectar amount. To apply ABC, the considered optimization problem is first converted to the problem of finding the best parameter vector which minimizes an objective function. Three essential components of ABC algorithm includes: employed and unemployed foraging bees, and food sources. The first two components, employed and unemployed foraging bees, search for rich food sources, which is the third component, close to their hive. Employed bees are associated with specific food sources. Unemployed bees include onlooker and scout bees. Onlookers choose a food source by watching the dance of employed bees within the hive. Scouts search for food sources randomly.

In ABC, position of food sources represents possible solution of the problem while the amount of nectar of food source represents quality or fitness of that solution. Employed and onlooker bees fly around in a multidimensional search space and choose food sources depending on the experience of themselves and their nest mates, and adjust their positions. Scout bees fly and choose the food sources randomly without using experience. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. Thus, ABC system combines local search methods, carried out by employed and onlooker bees, with global search methods, managed by onlookers and scouts, attempting to balance exploration and exploitation process. The ABC algorithm can be split in four different phases, namely: initialization phase, employed bees phase, onlooker bees phase and scout bees phase. At the initialization phase a population of NS solutions are initialized randomly and control parameters are set. The value of NS=NP/2, number of food sources, is equal to the number of employed bees and NP is the population size. Each solution u_i (i=1, 2, …, NS) holds n variables u_{ij} (j=1, 2, …, n) which are to be optimized so as to minimize the objective function. The artificial bees (employed bees, onlooker bees and scout bees) thus perform a cyclic search until a maximum cycle number according to some specific rules. At the employed bees phase each employed bees search for new candidate food source position (v_i) on the neighborhood of the previously selected food source (u_i) to update feasible solutions. The quality (fitness) of the candidate solution is compared to the old one. If the fitness of the new solution is equal to or higher than the previous solution, the old one is replace by the candidate one (greedy selection). A neighbor solution can be determined from the old one using the following formula:

$$v_{ij} = u_{ij} + \emptyset_{ij}(u_{ij} - u_{kj}) \quad (1)$$

where k and j are randomly chosen indexes in range [1 NS] and [1 n], respectively (k≠i) and $\emptyset_{ij}$ is a uniformly distributed random number within the range of [−1,1].

In the onlooker bees phase, employed bees share the information on the food sources they have found with the onlooker bees returning to their hive. Then each onlooker bee probabilistically selects one food source depending on this information. The probability value p_i of a food source with which is chosen by an onlooker bee can be calculated as:

$$p_i = \frac{fit_i}{\sum_{j=1}^{NS} fit_j} \quad (2)$$

where fit_i is the fitness value of food source I and is calculated from the objective function of food source as (in minimization problems):

$$fit_i = \begin{cases} \frac{1}{1+f_i} & f_i \geq 0 \\ 1 + |f_i| & f_i < 0 \end{cases} \quad (3)$$

By increasing the fitness value of a food source the probability of selection increases. After a food source u_i is selected by an onlooker bee, a new food source V_i in the neighborhood of selected onlooker bee is determined. The new food source can be calculated by using Equation (1). Then its fitness value is computed and solutions u_i and v_i are compared by a greedy selection. Therefore, more onlooker bees are recruited to richer food sources and consequently positive feedback behavior appears. If the position of an employed bees cannot be improved further through a limited number of cycles, in the scout bees phase, then that solution are abandoned and becomes a scout bee. Scouts are unemployed bees that choose their food sources randomly. The maximum abandonment limit is specified by user. A new food source is determined by the scout bees for abandoned source as follows:

$$u_{ij} = u_{jmin} + rand \times (u_{jmax} - u_{jmin}) \quad (4)$$

where u_{jmin} and u_{jmax} are lower and upper bounds of u_{ij}, respectively, and $rand$ is a random number between 0 and 1 drawn from a uniform distribution. The flowchart of ABC algorithm is shown in Figure 2.

2.3. Support Vector Regression (SVR)

Support vector machine (SVM) is one of the most popular machine learning methods that has been widely applied to solve many learning tasks such as classification and regression [14]. Support vector regression (SVR) is a regression version of SVM which solves regression problems by use of an alternative loss function [13]. In SVR, the original data x is mapped to a high dimensional feature space and then a linear regression problem is solved in this space. SVR formulation follows the principle of structural risk minimization instead of the principle of empirical risk minimization. In other words, SVR tries to minimize an upper bound of the generalization error instead of minimizing the prediction error on the training set. Consider a data set $\left[(x_i, y_i) \mid i = 1, \dots, l\right]$, where $\boldsymbol{x_i}$ is a D-dimensional input vector, y_i is a scalar output or target, and l is the number of points. The nonlinear relationship between the input and the output can be described by a regression function as

$$f(x) = w^T \varphi(x) + b \quad (5)$$

Where f(x) = predicting values; $\varphi(x)$ = nonlinear mapping function; and w and b = coefficients to be adjusted.

The coefficients w and b are estimated by minimizing the regularized risk function

$$R(C) = R_{emp} + \frac{1}{2}\|w\|^2 = C\frac{1}{l}\sum_{i=1}^{l} L_\varepsilon\left[y_i, f(x_i)\right] + \frac{1}{2}\|w\|^2 \quad (6)$$

$$L_\varepsilon\left(y_i, f(x_i)\right) = \begin{cases} |y_i - f(x_i)| - \varepsilon & |y_i - f(x_i)| \geq \varepsilon \\ 0 & |y_i - f(x_i)| < \varepsilon \end{cases} \quad (7)$$

where R(C) and R_{emp} = regression and empirical risks. In Equation (6), the first item is the empirical error, which is estimated by the ε-insensitive loss function in Equation (7). The second item is the regularization. The value C is the trade-off parameter between the first and second terms of the equation. The parameter ε can be viewed as a tube size equivalent to the approximation accuracy in the training data.

Two positive slack variables ξ and ξ* are introduced to represent the distance from the actual values to the corresponding boundary values of the ε-tube. Then minimization of Equation (6) is converted into the following constrained form:

Minimize

$$R(w, \xi, \xi^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \quad (8)$$

Subject to

$$\begin{cases} y_i - w\varphi(x_i) - b \leq \varepsilon + \xi_i \\ w\varphi(x_i) + b - y_i \leq \varepsilon + \xi \\ \xi_i, \xi_i^* \geq 0 \end{cases} \quad (9)$$

This optimization formulation can be transformed into the dual problem by introducing Lagrange multipliers as

Minimize

$$R(\alpha_i, \alpha_i^*) = -\frac{1}{2}\sum_{i,j=1}^{l}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_i - \alpha_j^*\right)K\left(x_i, x_i\right)$$

$$-\varepsilon\sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right) + \sum_{i=1}^{l} y_i(\alpha_i + \alpha_i^*) \quad (10)$$

Subject to

$$\sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right) = 0, \quad 0 \leq \alpha_i, \quad \alpha_i^* \leq C \quad (11)$$

Where α_i, α_i^* = Lagrange multipliers and

$K\left(x_i, x_j\right) = \varphi\left(x_i\right)^T \varphi\left(x_j\right)$ =kernel function.

The most applicable kernel function is the radial basis function (RBF) kernel

$$K\left(x_i, x_j\right) = \exp\left(-\gamma\|x_i - . \quad (12)$$

Where γ = kernel parameter.

The RBF kernel has only one parameter to be determined, and SVR with a RBF kernel exhibits excellent nonlinear predicting performance [30].

The coefficient of Equation (5) can be obtained by the obtained Lagrange multipliers as

$$w = \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right)\varphi\left(x_i\right) \quad (13)$$

The regression function of SVR can be expressed as

$$f(x) = \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right)K\left(x_i\right. \quad (14)$$

Based on Karush-Kuhn-Tucker's conditions for solving quadratic programming problems, only some of $\left(\alpha_i - \alpha_i^*\right)$ in Equation (14) are held as nonzero values. The corresponding data points of $\left(\alpha_i - \alpha_i^*\right) \neq 0$ are support vectors, which are employed in determining the decision function. There are three user-determined parameters, C, γ, and ε, the selection of which plays an important role in SVR performance.

2.4. Performance measures

The MAPE (Mean Absolute Percent Error) measures the size of the error in percentage terms. It is calculated as the average of the unsigned percentage error, as shown in the below

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y-\overline{y}}{y}\right| \times \qquad (15)$$

Where y is the actual value and $\overline{y}$ is the predicted value.

Root mean squared error (RMSE) is a frequently used measure of the differences between values predicted by a model and the values actually observed, and is calculated by the following equation:

$$RMSE = \sqrt{\frac{\sum\left(y-\overline{y}\right)^2}{n}} \qquad (16)$$

R squared, is a number that indicates the proportion of the variance in the dependent variable that is predictable from the independent variable

$$R^2 = 1 - \left(\frac{\sum_j\left(y_j-\overline{y}_j\right)^2}{\sum_j\left(\overline{y}_j\right)^2}\right) \qquad (17)$$

3. Results

3.1. Procedure

Figure 2 shows the flowchart of the proposed SVR-ABC algorithm. Concrete components were inputs of the model and CCS predicted value was the output of the model. The hybrid SVR-ABC algorithm was proposed in this paper to predict CCS from the concrete components. ABC was employed for SVR model selection. The kernel of SVR was selected experimentally. In various applications, radial basis function (RBF) kernel has shown the best performance compared to linear and other nonlinear kernels. We also tested different kernels and the RBF kernel showed the best performance. Thus, we selected the RBF kernel. The RBF kernel has one parameter to be optimized for best performance. In addition, the C penalty parameter of SVR should be optimized. So, there were two parameters in SVR model which should be tuned, i.e. C penalty parameter and Sigma of the RBF kernel.

Table 2

ABC algorithm control parameters

ABC control parameter	value
The number of colony size (employed bees+onlooker bees)	20
The number of food sources	10
Limit	100
Maximum cycle number	100

The SVR-ABC algorithm started with a random population of values of C and Sigma in range [0 106] and [0 1], respectively. Control

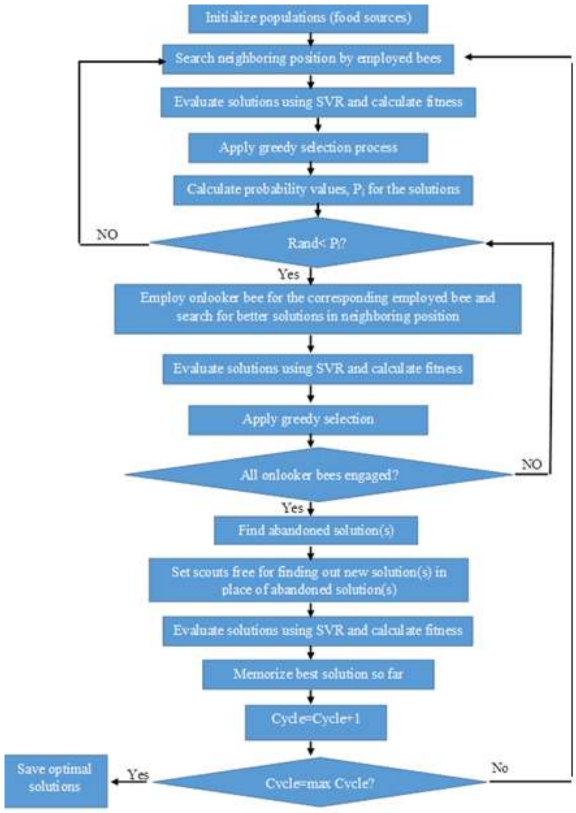


Fig. 2 - The whole procedure of the proposed method

parameters of ABC algorithm are shown in Table 2. The performance of each population member was evaluated by constructing the corresponding SVR model. Ten-fold cross-validation strategy was employed to assess the ability of each model in CCS prediction. Ten-fold cross-validation is a popular method in pattern recognition problems to avoid bias of random sampling in other cross-validations such as holdout method. The data was randomly split in ten subsets and at each fold, nine subset was used for training and another subset was used as testing. At the end of ten-fold cross-validation, each subset has been used once and only once as testing subset. At each fold, RMSE of prediction was calculated and finally the averaged RMSE in ten folds was reported as the final performance measure.

Because the number of samples in dataset was 1030, at each fold, 927 samples were used as training and the other 103 samples were used as testing.

Evaluated population went through iterations in ABC to evolve to an optimum population. The maximum number of cycles to stop SVR-ABC algorithm was set to 100.

3.2. Prediction of CCS using SVR-ABC

The minimum RMSE obtained until each iteration of SVR-ABC was saved as global optimum solution and evolution of global optimum RMSE has been shown in Figure 3. The horizontal axis

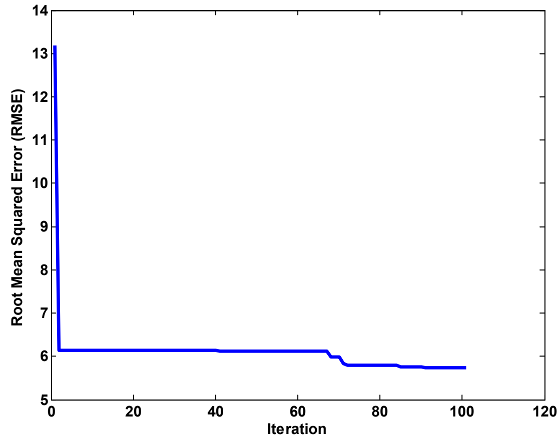


Fig. 3 -: *The value of RMSE in iterations of SVR-ABC algorithm.*

represents iteration number and vertical axis represents root mean squared error (RMSE) value. The algorithm had a rapid convergence to optimum value at first 5 iterations and at the next iterations showed a little improvement in its global optimum RMSE. The final global optimum was 5.73. We plotted a regression view of test samples (over ten folds), in Figure 4a. The horizontal axis represents actual values of CCS and vertical axis represents predicted values of CCS. The blue line represents the fit line to the data while the dotted line represents the diagonal line. The more points forgathered about the diagonal line, the better performance for the model can be concluded. Figure 4b shows the predicted and actual CCS across samples in testing set. It can be seen from figures that the proposed model can properly predict the values of CCS for samples. Figure 5 represents the predicted vs. actual values of CCS in training set in each fold. As it can be seen from figures, correlation coefficients for training set were in range of 0.97, higher than the correlation coefficient 0.94 for testing set. In Figure 5, the model was trained using training set and tested again using training samples in each fold. Thus, it is reasonable to have better prediction compared to situation where testing samples are different from training samples (Figure 4).

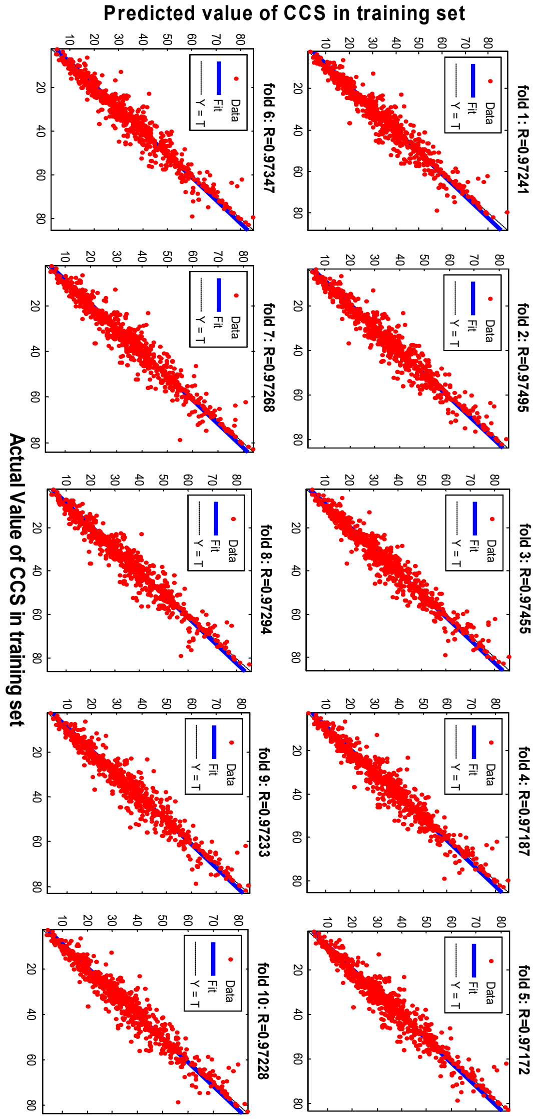
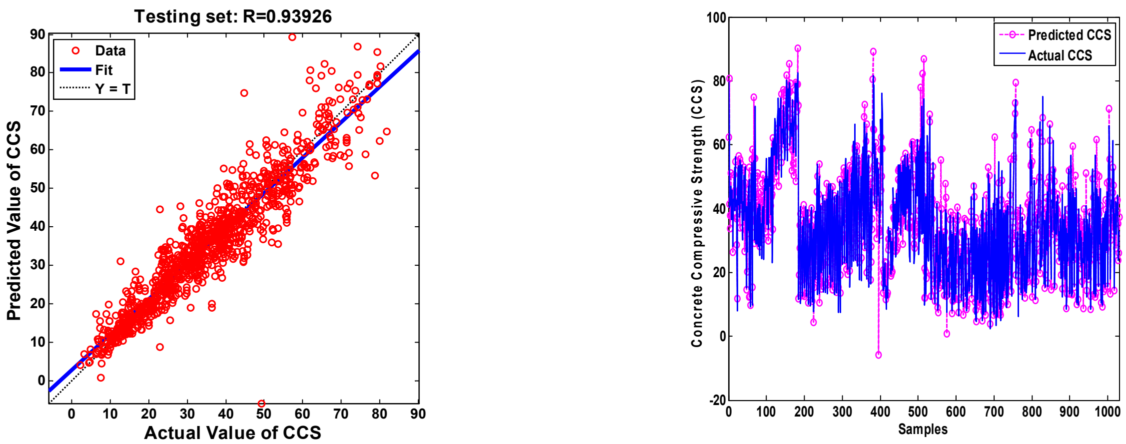


Fig. 5 - Proposed model predictions vs. actual results of CCS in training set.



a b

Fig. 4 - a) Proposed model predictions vs. actual results of CCS in testing set. b) Predictions and actual values of CCS vs. Samples

Table 3

Results of correlation between concrete components and CCS

	Cement	BFS	FA	Water	SP	Cag	FAg	Age
Pearson's correlation coefficient value	0.5	0.13	-0.11	-0.29	0.37	-0.17	-0.17	0.33
Corresponding p-value	1.32e-65	1.41e-05	6.75e-04	2.35e-21	5.13e-34	1.02e-07	6.7041e-08	2.11e-27

3.3. Effect of each concrete component on CCS

Some of concrete components may have more effect on CCS. We examined this effect using a simple Pearson's correlation coefficient between each component's values across all subjects and corresponding CCS values as follow:

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} \tag{18}$$

where σ_X and σ_Y are standard deviation of X and Y, respectively. cov is the covariance and is calculated as follow:

$$\mathrm{cov}(X,Y) = E[(X-\mu_X)(\tag{19}$$

where E is the expectation and μ_X and μ_Y are the mean of X and Y, respectively.

The closer correlation coefficient to one, the more effect of that component in CCS. Figure 6 and Table 3 show the correlation coefficient values obtained for each component of concrete. In addition, the corresponding p-value of each correlation was presented in Table 3. It can be seen from figure and table that some components have positive correlation and some other have negative correlation. The weight of cement in concrete mixture has the most effect on CCS value and its correlation is positive, i.e. increase of its weight will increase the value of CCS and vice versa. The other two strong positive correlations were related to the weight of superplasticizer and the age of concrete. The weight of water has strong negative correlation with the value of CCS, i.e. increasing the value of water will decrease the value of CCS. Although, the correlation of weight of blast furnace slag, weight of fly ash, weight of coarse aggregate, and weight of fine aggregate were lower than the other components, however, their correlation were also significant because their corresponding p-values were lower than the significance threshold ($p<0.05$).

3.4. Prediction of CCS using a subset of concrete components

At the last experiment we compared performance of the proposed model when using the full set of components for CCS prediction with the ones that the model uses only a subset of components for prediction. Two subsets were used: first subset includes the four components with stronger correlation (positive or negative), i.e. cement, water, SP, and Age and the second subset includes the other four components with weaker correlation, i.e. BFS, FA, CAg, and FAg. The same algorithm as the original set of components were implemented on the last two subsets to have a fair comparison on results. The selected kernel for SVR was RBF and the ABC algorithm was used to find the optimum values of SVR model, i.e. C and Sigma.

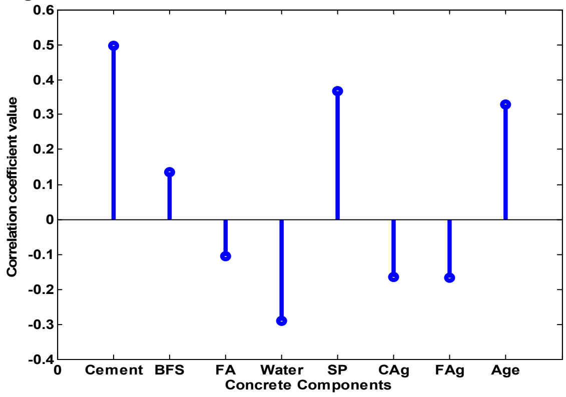


Fig.6 -Correlation of concrete component values across samples and corresponding CCS values. BFS: blast furnace slag, FA: fly ash, SP: superplasticizer, CAg: coarse aggregate, FAg: fine aggregate.

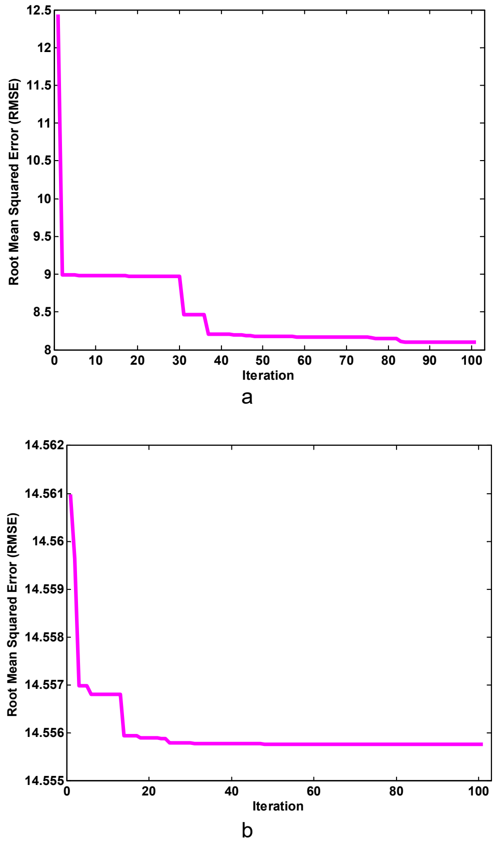


Fig.7- The value of RMSE in iterations of SVR-ABC algorithm on a) subset1 and b) subset2.

Table 4

Comparative results of proposed SVR-ABC algorithm for prediction of CCS on different data sets

method	Input variables	Evaluation measures			SVR model parameters	
		RMSE	R^2	MAPE	C	Sigma
SVR-ABC on original set	All components of Table 1	5.73	0.89	12.79%	953560.66	3.21e-06
SVR-ABC on subset 1	Cement, Water, SP, and Age	8.10	0.77	19.77%	998176.61	1.09e-05
SVR-ABC on subset 2	BFS, FA, CAg, and FAg	14.56	0.32	45.96%	471650.98	0.045

The maximum cycle number of ABC was set at 100 iterations and the other control parameters for ABC were also same as the original set (Table 2). Figure 7 shows the obtained results for each subset. The global optimum value of RMSE for the first subset was 8.1 and for the second subset was 14.56 which both of them were lower than the RMSE of 5.73 of the original set.

Table 4 shows detailed results for original set of components and two subsets of components. In addition to the RMSE, the value of R^2 and MAPE were also calculated for the final optimum solution of each set. The optimum values of SVR model parameters, i.e. C and Sigma were presented in Table 4.

4. Conclusion

Due to the high nonlinearity, it is hard to establish an effective prediction model for estimating CCS for HPC. A novel hybrid approach based on SVR-ABC was proposed. In the proposed approach, an ABC employed to optimize SVR model. Different performance measures were calculated and results proved the efficiency of the proposed method.

The main contribution of this paper is employing an evolutionary algorithm for optimization of regression model. This is the first study that uses ABC for finding the best regression model. ABC is a recently proposed optimization method that has many advantages compared to the other evolutionary algorithms. It has a strong global search optimum ability and, at the same time, is fast, easy to implement and few parameters to tune compared to the other optimization algorithms such as genetic algorithms and ant colony. Thus, the proposed SVR-ABC approach is faster than the other approaches while it is easy to implement. The results in this paper showed that the proposed approach is accurate and can predict CCS with a small RMSE. Another contribution of this study is finding the most important components of concrete for CCS prediction. Some of concrete components have strong correlation with CCS and changing their values in concrete has significant influence on CCS value. The most important component was the weight of cement in mixture. Other important components were the weight of superplasticizer and the age of concrete. The last experiment of this paper showed that the performance of CCS prediction is dropped when the value of these components were eliminated from the model.

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Topics:

-Materials (e.g. cementitious materials, aggregates, chemical admixtures, recycled materials, geopolymers, reinforcing steels etc)
– Structures (e.g. shear design, design of columns and walls, concrete modelling, earthquake and seismic design, prestress etc)
– Innovations in concrete – design and construction (e.g. 3D printing)
– Durability
– Repair and retrofit
– Environmental
– Precast concrete (e.g. design, construction, architectural etc.)
– Case studies and major projects
– Constructability (e.g. construction and infrastructure developments, forensics, formwork, etc,)
– Education
– History and development of concrete
– Any interesting application and use advancing concrete materials and structures

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