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Metaheuristic-reinforced neural network for predicting the compressive strength of concrete

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Abstract. Computational drawbacks associated with regular predictive models have motivated engineers to use hybrid techniques in dealing with complex engineering tasks like simulating the compressive strength of concrete (CSC). This study evaluates the efficiency of tree potential metaheuristic schemes, namely shuffled complex evolution (SCE), multi-verse optimizer (MVO), and beetle antennae search (BAS) for optimizing the performance of a multi-layer perceptron (MLP) system. The models are fed by the information of 1030 concrete specimens (where the amount of cement, blast furnace slag (BFS), fly ash (FA1), water, superplasticizer (SP), coarse aggregate (CA), and fine aggregate (FA2) are taken as independent factors). The results of the ensembles are compared to unreinforced MLP to examine improvements resulted from the incorporation of the SCE, MVO, and BAS. It was shown that these algorithms can considerably enhance the training and prediction accuracy of the MLP. Overall, the proposed models are capable of presenting an early, inexpensive, and reliable prediction of the CSC. Due to the higher accuracy of the BAS-based model, a predictive formula is extracted from this algorithm.

Keywords: artificial neural network; concrete compressive strength; hybrid metaheuristic algorithms

1. Introduction

Safety management and material strength analysis are inseparable parts of civil engineering jobs (Chen *et al.* 2021, Xie *et al.* 2021, Xu *et al.* 2021). Concrete, due to its wide use in structural sector, receives a growing attention in relevant studies (Yuan *et al.* 2009, Feng *et al.* 2021, Zhang and Abedini 2022). In this sense, many experts have focused on investigating the mechanical parameters of concrete such as its response against fatigue (Luo *et al.* 2021), tension (Shi *et al.* 2022), combined loads (Huang *et al.* 2021), etc. Selecting the appropriate approach is of great importance for these purposes. Earlier, these parameters have been satisfactorily modeled using conventional methods like (Lu *et al.* 2021, Zhang and Tang 2021), but the emerge of more sophisticated tools like regression models and machine learning has opened new doors to such complex calculations.

In a more general perspective, application of artificial intelligence is not limited to structural and concrete-based works (Cao *et al.* 2022). Many environmental phenomena like landslide (Mehrabi *et al.* 2020, Mehrabi 2021), flood (Linh *et al.* 2022), forest fire (Moayedi *et al.* 2020), dam break (Seyedashraf *et al.* 2018), etc. have been promisingly modeled using different notions of soft computing.

As is known, analyzing the compressive strength of concrete (CSC) is a complicated task, due to the non-linear effect of various mixture components on this parameter (Henigal *et al.* 2016, Tien Bui *et al.* 2019). Therefore, many scholars have suggested the use of machine learning for analyzing the relationship between CSC and related factors (Chou *et al.* 2014, Young *et al.* 2019). Different kinds of predictors such as artificial neural network (ANN) and neuro-fuzzy system (ANFIS) have shown high competency in dealing with the mentioned problem (Yeh 2006, Sadrmomtazi *et al.* 2013, Onat and Celik 2017), as well as other parameters like the shear strength of concrete beams (Nehdi *et al.* 2006, Mohammadhassani *et al.* 2014, 2015).

Han *et al.* (2020) suggested using an ensemble of random forests and support vector machine (SVM) for predicting modulus of elasticity of recycled aggregate concrete. Chou *et al.* (2011) presented an optimized prediction of the CSC for high performance concrete by comparing popular data mining tools. The study outlined multiple additive regression tree (MART) superior to other tested models including the SVM and ANN, due to its

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higher efficiency in terms of training time, accuracy, and dealing with overfitting. Likewise, Chopra *et al.* (2018) conducted a comparison amongst well-known predictive models of decision tree, RF, and ANN. They concluded that the ANN is the best possible predictor of the CSC for all considered curing ages (i.e., 28, 56, and 91 days). Dutta *et al.* (2018) proved the competency of three regression-based approaches namely multi adaptive regression spline (MARS), Gaussian process for regression (GPR), and minimax probability machine regression (MPMR) for the same objective. More studies about the applicability of machine learning tools in this field can be reached in the earlier literature (DeRousseau *et al.* 2019, Mirzahosseini *et al.* 2019, Nguyen *et al.* 2020a).

Metaheuristic optimization methods have recently gained large popularity in dealing with complex engineering problems (Nehdi and Greenough 2007, Moayedi *et al.* 2019b, Shariati *et al.* 2020). Various attempts have also been dedicated to the use of these algorithms in modeling concrete characteristics (Prayogo *et al.* 2017, Sadowski *et al.* 2019). Pham *et al.* (2016) suggested the combination of the least squares support vector regression (LS-SVR) and firefly algorithm (FA) for estimating the CSC of high-performance concrete. The main role of the FA was to adjust the parameters of the LS-SVR. Prayogo (2018) applied symbiotic organisms search to the same predictive model. Based on the correlation values (R) of 0.9692 and 0.9117, the hybrid model outperformed the typical LSSVR. Bui *et al.* (2018) could successfully couple a modified version of the FA algorithm with an ANN for setting the weights and biases. Tien Bui *et al.* (2019) compared the optimization efficiency of three potent metaheuristic techniques that are based on the foraging behavior of whale (WOA), dragonfly (DA) and ant (ACO) for predicting the 28-day CSC. These algorithms were coupled with a multi-layer perceptron (MLP) neural system to optimize the weights and biases. Their findings showed that the WOA creates the most powerful predictive model. Also, the DA-based ensemble could predict the CSC more accurately than ACO (error values of 2.5138 vs. 2.8843). another popular search scheme called artificial bee colony was used by Sun *et al.* (2019a) for investigating the relationship between the compressive strength and components like water and silica fume. In a similar effort by Gandomi *et al.* (2010), they applied genetic programming to an orthogonal least squares algorithm to predict the CSC of carbon fiber-reinforced plastic confined concrete cylinders. Duan *et al.* (2020) tested combinations of various machine learning tools (including ANN, XGBoost, SVR, and ANFIS) with a sociopolitical optimizer called ICA for predicting the CSC of recycled aggregate concrete. A comparison between the used models (e.g., respective RMSEs of 2.22, 1.47, 2.14, and 2.76) revealed the superiority of the ICA-XGBoost. Moreover, these algorithms have shown high efficiency in simulating other parameters of the concrete as well (Mashhadban *et al.* 2016). Moayedi *et al.* (2019a) employed and compared ant lion optimization (ALO), biogeography-based optimization (BBO), and grasshopper optimization algorithm (GOA) associated with an ANN for predicting the concrete slump. It was deduced that the ALO scheme enjoys higher capability, due to the obtained root mean square errors (RMSEs) of 3.7788, 4.1859, and 4.9553.

The pivotal focus of this study is on testing two novel hybrids of neural processing for a reliable prediction of the CSC. To this end, shuffled complex evolution (SCE), multi-verse optimizer (MVO), and beetle antennae search (BAS) are considered for adjusting the weights and biases of an ANN. In other words, the main role of these algorithms is to establish the relationship between the CSC and influential factors through a neural network. This idea helps the ANN to surmount its computational drawbacks like local minima (Moayedi *et al.* 2019c). The results of the hybrid models are compared with a standalone ANN to examine the effectiveness of the SCE, MVO, and BAS.

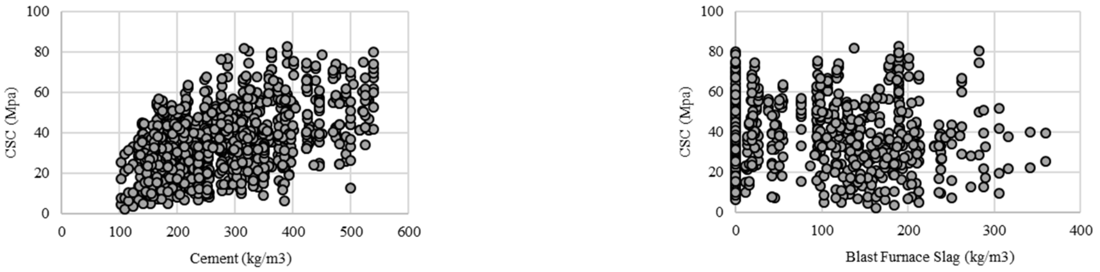
2. Methodology and data

2.1 Established database

The concrete data used to train the proposed intelligent models was provided by Yeh (1998). The dataset consists of the information of 1030 concrete tests. The compressive strength is recorded where the amount of seven components including cement, blast furnace slag (BFS), fly ash (FA1), water, superplasticizer (SP), coarse aggregate (CA), and fine aggregate (FA2), as well as the age of the specimen, is

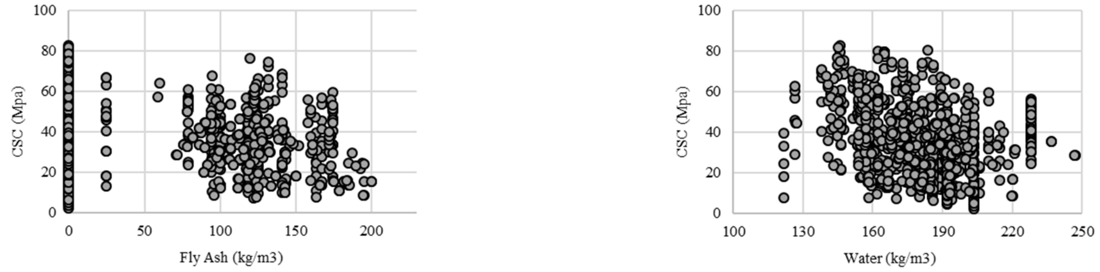
Table 1 Descriptive statistics of the compressive strength and key factors

Parameter	Descriptive index					
	Mean	Standard error	Sample variance	Skewness	Minimum	Maximum
Cement (kg/m^3)	281.17	3.26	10921.74	0.51	102.00	540.00
Blast furnace slag (kg/m^3)	73.90	2.69	7444.08	0.80	0.00	359.40
Fly ash (kg/m^3)	54.19	1.99	4095.55	0.54	0.00	200.10
Water (kg/m^3)	181.57	0.67	456.06	0.07	121.75	247.00
Superplasticizer (kg/m^3)	6.20	0.19	35.68	0.91	0.00	32.20
Coarse aggregate (kg/m^3)	972.92	2.42	6045.66	-0.04	801.00	1145.00
Fine aggregate (kg/m^3)	773.58	2.50	6428.10	-0.25	594.00	992.60
Age (day)	45.66	1.97	3990.44	3.27	1.00	365.00
CSC (MPa)	35.82	0.52	279.08	0.42	2.33	82.60



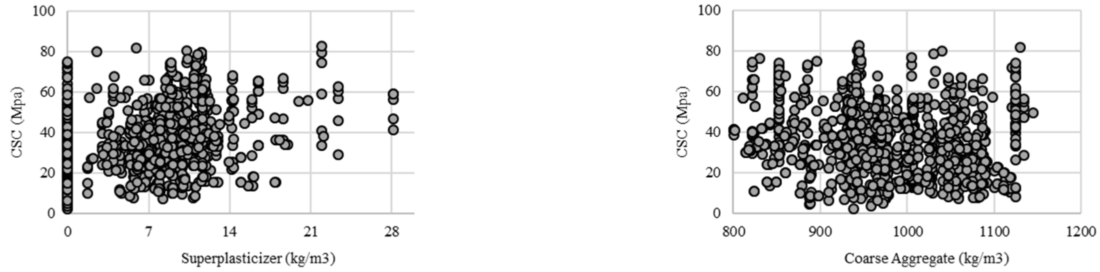
(a) Cement

(B) BFS



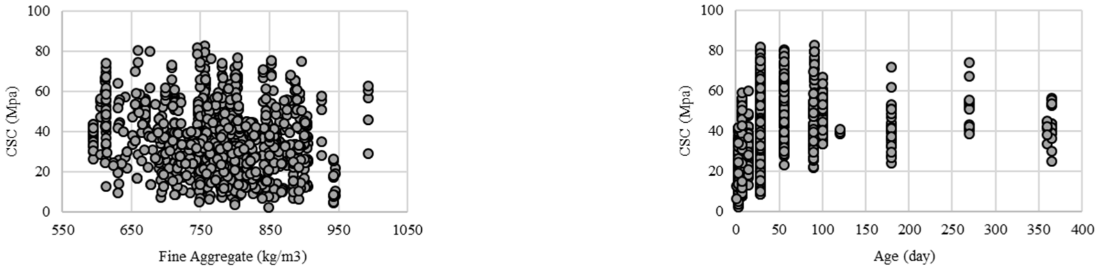
(c) FA1

(d) Water



(e) SP

(f) CA



(g) FA2

(h) Age

Fig. 1 The graphical description of the CSC and the amount of mixture components

considered as the CSC influential parameters.

Amongst these 1030 rows of information, 824 samples (i.e., 80% of the whole) are randomly selected for inferring the relationship between the CSC and independent factors. Next, the remaining 206 samples are given to the developed models to measure their accuracy for unexperienced conditions.

Table 1 gives the descriptive statistics of the used dataset. The curing age receives different values including 1, 3, 7, 14, 28, 56, 90, 91, 100, 120, 180, 270, 360, 365. Also, the values of CSC are illustrated versus each influential factor in Fig. 1. Notably, the mentioned dataset can be reached on http://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength.

2.2.1 SCE

It is well-established that utilizing heuristic search schemes finds a good response to the problems with discontinuous objective functions (Seong *et al.* 2015). The solutions that are suggested by these methods are close to the global optimum. Scholars have been inspired by natural phenomena to design various optimization techniques. Duan *et al.* (1993) suggested the SCE algorithm in 1993. The start point of the SCE is using the controlled random search (CRS) method of Price (Price 1983). The CRS is associated with competitive evolution strategy (Holland 1992), as well as complex shuffling technique (Duan 1991). The principal procedure of the SCE is called competitive complex evolution (CCE) in which the Nelder-Mead algorithm is used to guide the population toward a local optimum. In this process, weak offspring are supposed to be

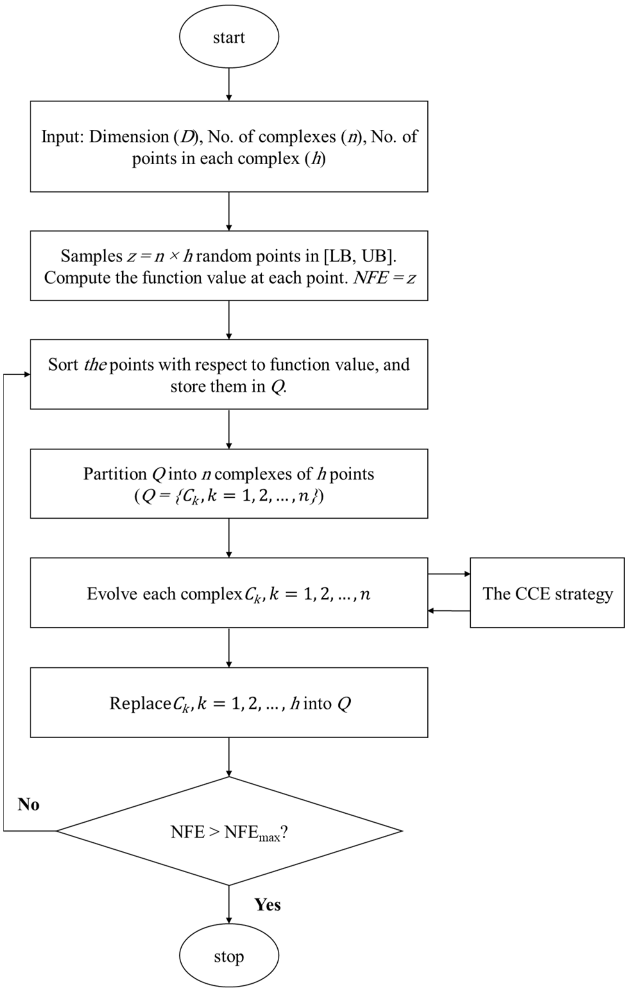


Fig. 2 The flowchart of the SCE algorithm

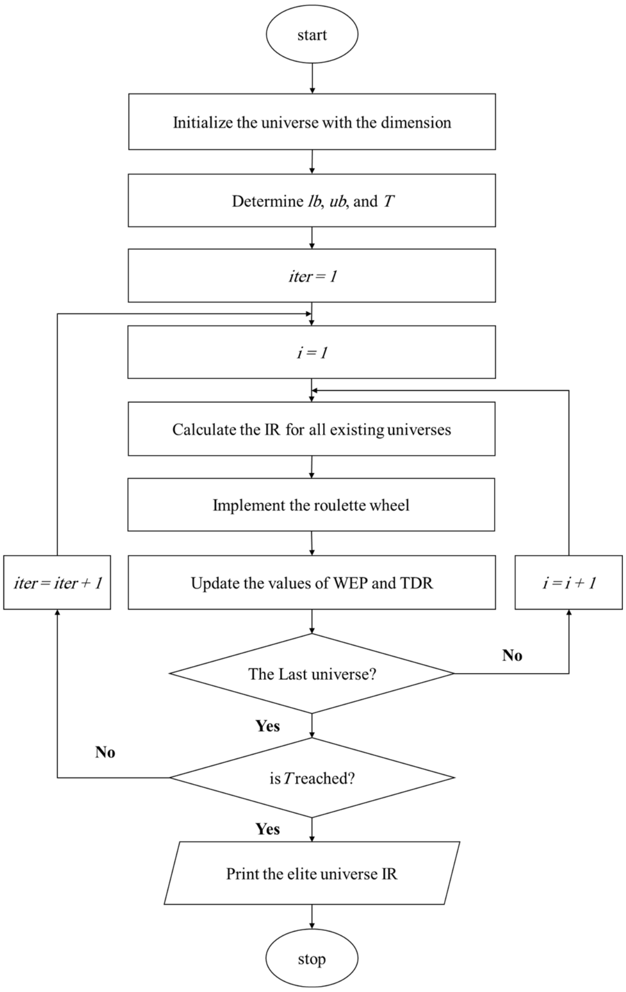


Fig. 3 The flowchart of the MVO algorithm

replaced with new ones (Duan *et al*. 1993).

The flowchart of this algorithm is presented in Fig. 2. In the first step, assuming h and n as the number of points and complexes, respectively, Eq. (1) is used to give the sample size

$$z = n \times h \tag{1}$$

Also, let D denote the dimension of the existing problem, then h ≥ D + 1 and n ≥ 1. Here, z points are sampled by taking into equation the lower bound (LB) and upper bound (UB). A function value (FV) is calculated for each point and the number of evaluations for carried out for them is represented by NFE. The FVs are next evaluated to sort the points in increasing order. The array Q is then considered for string the points

$$Q = \{xi, Fi, i\ =\ 1, 2, \ldots, z\} \tag{2}$$

The members are divided in so called units C_1, C_2, …, C_n so that each one contains h members

$$C_k = \{x_j^k, F_j^k\ | x_j^k = x_{k + n(j-1)},\ F_j^k = F_{k + n(j-1)},\ j = 1, 2, \ldots, h\} \tag{3}$$

The CCE strategy is applied to evolve the system. In the following, the shuffling is fulfilled and the units are replaced in Q as follows

$$Q\ =\ \{Ck,\ \ k\ =\ 1, 2, \ldots, n\} \tag{4}$$

Lastly, the convergence parameter is checked. The algorithm stops once the NFE > $\mathrm{NFE}_{\max}$. If not, it returns to the partitioning stage.

2.2.2 MVO

The MVO is a recent metaheuristic technique that was first presented by Mirjalili *et al*. (2016). As the name connotes, the basis of the MVO algorithm is the multi-verse theory (Tegmark 2003). According to this theory, there are different universes each of those belongs to one bang. White holes, wormholes, and black holes are three major concepts of this algorithm. As is known in cosmology, white holes play the main role of the birth of a universe, wormholes play the role of the connecting channels between different parts of the universe, and the black holes possess a huge gravity that attract everything close to them. Similar to many other algorithms, the search process of the MVO can be defined by two categorize of exploration and exploitation. The first phase is based on the black holes as well as the white holes, while the second phase uses the wormholes.

Fig. 3 illustrates the flowchart of the MVO. A principal assumption of this technique is that an inflation rate (IR) is considered for each universe. The masses flow from universes with lower IRs to those with larger values. It helps in improving the average rates of universes. The larger the IR is, the higher the number of white holes is. A wormhole existence probability (WEP) and a traveling distance rate (TDR) are defined based on Eqs. (5) and (6), respectively. The TDR represents the movement of a mass via the wormhole around the elite cosmos.

$$WEP = a + iter \times \left(\frac{b-a}{T}\right) \tag{5}$$

$$TDR = 1 - \frac{iter^{1/q}}{T^{1/q}} \tag{6}$$

In the above relationships, a and b represent the minimum and maximum in the current iteration iter, respectively. Moreover, the exploitation accuracy and the maximum number of iterations are shown by T and q, respectively.

As is known, the principal rule of metaheuristic techniques for minimizing the error lies in updating the position of the individuals. In the MVO, assuming x_j as the jth element of the elite cosmos, this process is formulated as follows

$$x_i^j = \begin{cases} \begin{cases} x_j + TDR + \left(\left(ub_j - lb_j\right) \times e_4 + lb_j\right) & if\ e_3 < 0.5 \\ x_j - TDR + \left(\left(ub_j - lb_j\right) \times e_4 + lb_j\right) & if\ e_3 \geq 0.5 \end{cases} & if\ e_2 < WEP \\ x^j_{Roulette\ Wheel} & if\ e_2 \geq WEP \end{cases} \tag{7}$$

in which, the upper and lower bounds of the proposed cosmos are represented by ub_j and lb_j, respectively. Also, e_2, e_3, and e_4 represent random numbers varying from 0 and 1. Also, $x^j_{Roulette\ Wheel}$ is the solution element that is obtained from the roulette wheel selection approach (Faris *et al.* 2018, Fathy and Rezk 2018).

2.2.3 BAS

The BAS is another popular metaheuristic scheme for optimization purposes and works based on the foraging behavior of beetle (Jiang and Li 2017). In the optimization task, following the pheromone existing in the air, the beetle uses odor sensors on the antenna to approach the prey. The concentration of the pheromone changes when the distance between the beetle and prey changes. This is how the beetle tracks and moves toward the prey in a continuous way.

Mathematically, the BAS algorithm can be described as follows:

a) A fitness function is established as $f(x^t)$, $x^t = [x^1, x^2, \ldots, x^t]$ and t is the number of iterations.
b) Orientation of the beetle is randomized through the below equation:

$$\vec{b} = \frac{rand\ (j,1)}{||\ rand\ (j,1)\ ||} \tag{8}$$

in which rand () is a $j \times 1$ matrix, giving random orientation of the beetle.

c) In each iteration, the coordinates of the beetle's antenna (x_l and x_r for left and right) are calculated by:

$$x_r = x^{t-1} + d^{t-1}\,\vec{b} \tag{9}$$

$$x_l = x^{t-1} - d^{t-1}\,\vec{b} \tag{10}$$

where d denotes the sensing length which is decided by step τ as follows

$$\tau^t = \lambda_l\ \ \tau^{t-1} \tag{11}$$

where d denotes the sensing length which is decided by step τ as follows

$$d_0^t = \tau^t/n \tag{12}$$

where n stands for a constant value affecting the changes of x_l and x_r.

d) An iterative formula is obtained as follows:

$$x^t = x^{t-1} - \tau\,\vec{b}\ sign\ (f(x_l) - f(x_r)) \tag{13}$$

In the above equation, $sign$ () is a sign function used for comparing the fitness on both sides ($f(x_l)$ and $f(x_r)$) (Jiang *et al.* 2020).

For more details of the BAS algorithm, previous studies like (Sun *et al.* 2019b, Wu *et al.* 2019, Zhang *et al.* 2021) can be regarded.

3. Results and discussion

This study, as explained, pursues a reliable prediction of the CSC using three hybrid models based on the metaheuristic algorithms of SCE, MVO, and BAS. To fulfill this objective, the mentioned algorithms are coupled with an MLP neural network. The results are presented in this part. The accuracy of the hybrid models is compared with the regular MLP for examining the efficiency of the proposed optimizers.

3.1 Accuracy criteria

Three well-accepted accuracy criteria, namely root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2) are used to evaluate the performance of the improved and regular ANNs. As is known, the RMSE and MAE report the error of prediction

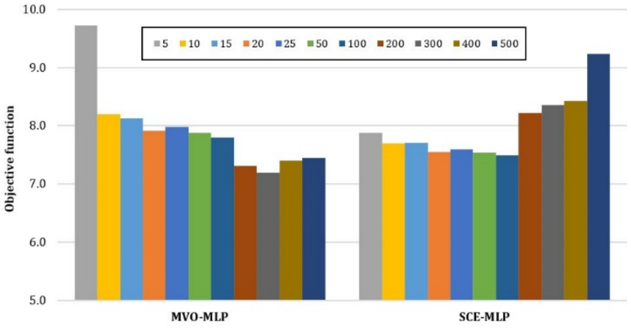


Fig. 4 The sensitivity analysis based on the complexity of the SCE-MLP and MVO-MLP

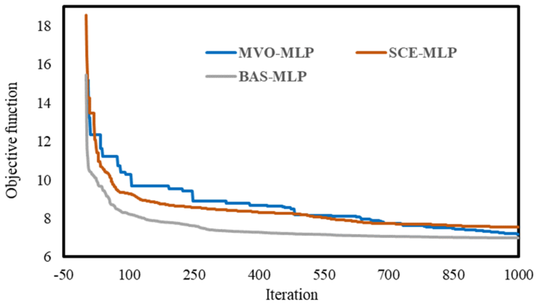


Fig. 5 The convergence curves of the elite SCE-MLP, MVO-MLP and BAS-MLP

(a) BP-MLP (b) BP-MLP

(c) SCE-MLP (d) SCE-MLP

(e) MVO-MLP (f) MVO-MLP

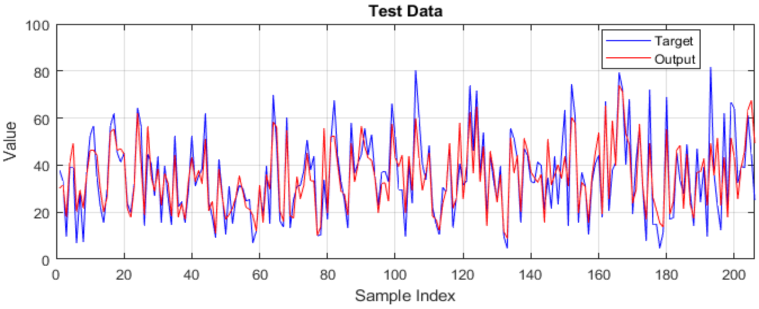
(g) BAS-MLP (h) BAS-MLP

Fig. 6 The results obtained for the training samples while the R^2 indicates the correlation between the produced and expected CSC values. Given K as the number of samples, as well as $Z_{i\ predicted}$ and $Z_{i\ observed}$ as the produced and expected values of CSC, respectively, these indices are expressed by Eqs. (14) to (16).

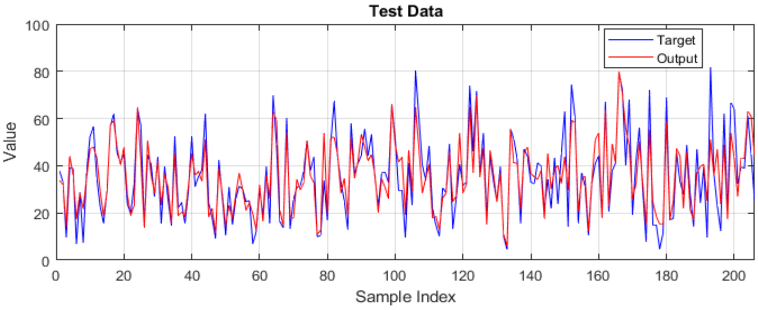
$$RMSE = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left[\left(Z_{i_{observed}} - Z_{i_{predicted}}\right)\right]^2} \tag{14}$$

$$MAE = \frac{1}{K}\sum_{I=1}^{K}\left|Z_{i_{observed}} - Z_{i_{predicted}}\right| \tag{15}$$

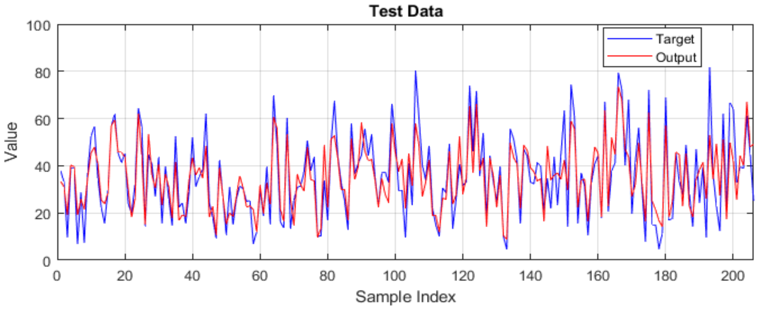
$$R^2 = 1 - \frac{\sum_{i=1}^{K}\left(Z_{i_{predicted}} - Z_{i_{observed}}\right)^2}{\sum_{i=1}^{K}\left(Z_{i_{observed}} - \overline{Z}_{observed}\right)^2} \tag{16}$$



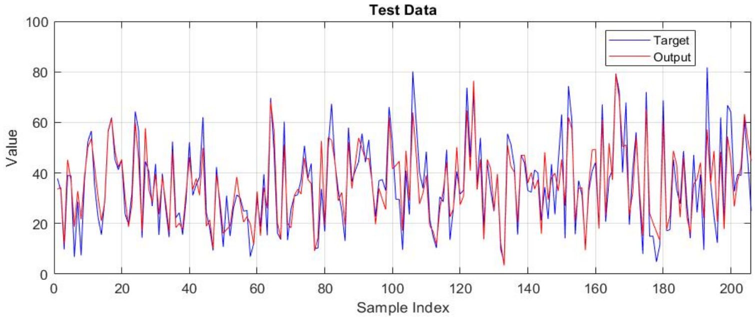
(a) BP-MLP



(b) SCE-MLP



(c) MVO-MLP



(d) BAS-MLP

Fig. 7 Comparison between the modeled and expected CSCs for the testing samples

3.2 Hybridizing the MLP using metaheuristic techniques

As the skeleton of the hybrid models, determining the most appropriate structure of the ANN is of high importance. In this work, ten different values (1,2, …, 10) are tested for this parameter. The results showed that 7 neurons in one hidden layer yield the largest accuracy. The weights and biases are the variables of the network which can be adjusted by different strategies.

In the next step, the SCE, MVO, and BAS optimizers are applied to the designed MLP to find the most proper values for the weights and biases. This process is fulfilled over 1000 iterations where the RMSE represents the objective function. In other words, the changes in the training error are monitored by calculating the RMSE at each iteration. The results are shown in Fig. 4. In this chart, the final RMSEs obtained for eleven different population sizes (including 5, 10, 15, 20, 25, 50, 100, 200, 300, 400, and 500) of the SCE and MVO are compared. It can be seen

(a) Training - BP-MLP

(b) Testing - BP-MLP

(c) Training - SCE-MLP

(d) Testing - SCE-MLP

(e) Training - MVO-MLP

(f) Testing - MVO-MLP

(g) Training - BAS-MLP

(h) Testing - BAS-MLP

Fig. 8 The correlation of the results

that the lowest RMSE (i.e., the highest accuracy) resulted for the SCE-MLP and MVO-MLP is 7.49866315 and 7.19635614 obtained for the population sizes of 100 and 300, respectively.

As for the BAS, it is not a population-dependent model. The best configuration was similarly obtained by trail and error efforts on its parameters. The most important parameters of this algorithm were number of iterations, step length, and d_1, which were 1000, 0.8, and 3, respectively.

Fig. 5 depicts the convergence behavior of the used models.

3.3 Accuracy assessment

In the previous section, the best-fitted structures of the BP-MLP, SCE-MLP, MVO-MLP, and BAS-MLP were determined. The indices of RMSE, MAE, and R^2 are used in this section to evaluate the accuracy of each model. For each sample, the difference between the expected and produced CSCs is obtained as error. Fig. 6 shows these error values along with the corresponding histogram. The learning errors of the BP-MLP, SCE-MLP, MVO-MLP, and BAS-MLP range in [-27.4988, 26.1707], [-30.6562, 25.7315], [-25.6754, 23.6268], and [-21.6389, 20.5103], respectively.

The calculated RMSEs indicate that the training error of the BP-MLP (= 7.8470) is larger than those obtained for the hybrid models (7.5378, 7.1964, and 6.9942 for the SCE-MLP, MVO-MLP, and BAS-MLP, respectively). It shows that metaheuristic algorithms have performed more successfully than the BP method. It is confirmed by the obtained MAEs too. More clearly, the MAE of the BP-MLP fell from 6.1854 to 5.9487, 5.5617, and 5.4683.

A similar process goes for the testing data. As explained earlier, the quality of the testing performance reflects the generalization capability of the models. This is because the testing data are not given to the networks during the training phase. Fig. 7 illustrates the CSC patterns obtained for the real and modeled data. As is seen, all three models acquired a good prediction of the CSC. A comparison between the results, especially for the peak values, shows that the CSCs predicted by the BP-MLP, SCE-MLP, MVO-MLP, and BAS-MLP are more compatible with real values. In this phase, the RMSE experienced a reduction from 8.9753 to 8.3540, 7.8965, and 7.5401. The smaller MAEs of the networks trained by the SCE, MVO, and BAS (6.4657, 5.8917, and 5.8320 vs. 6.8112) demonstrates the effectiveness of these algorithms in comparison with the BP.

$$\begin{bmatrix}\alpha\\ \beta\\ \gamma\\ \delta\\ \varepsilon\\ \zeta\\ \eta\end{bmatrix} = Tansig\left(\left(\begin{bmatrix} 0.0157 & 0.7792 & 0.1151 & 1.0590 & 0.1404 & -0.4573 & 0.5877 & -0.9336\\ -0.6563 & 0.8609 & 0.7220 & -0.2457 & -0.5198 & -0.4464 & -0.2549 & -0.9488\\ -0.3159 & 0.5080 & -0.1876 & -1.0440 & 0.9217 & 0.2836 & -0.6317 & -0.6133\\ -0.9955 & -0.8283 & -0.2081 & -0.9163 & 0.4844 & -0.1021 & 0.5824 & 0.2093\\ 0.3713 & 0.7562 & 0.2550 & -0.3001 & 0.3069 & -0.8887 & -0.2012 & 1.1827\\ -0.8547 & 0.3804 & 0.2639 & -0.7994 & -0.8864 & -0.8513 & 0.2606 & 0.1610\\ 0.3341 & 0.6478 & 0.3851 & -0.6333 & 0.7385 & -0.3241 & 0.9617 & -0.7295 \end{bmatrix}\begin{bmatrix}Cement\\ BFS\\ FA1\\ Water\\ SP\\ CA\\ FA2\\ Age\end{bmatrix}\right) + \begin{bmatrix}-1.7855\\ 1.1903\\ 0.5952\\ 0.0000\\ 0.5952\\ -1.1903\\ 1.7855\end{bmatrix}\right) \tag{18}$$

Moreover, the consistency of the training and testing results are portrayed in Fig. 8. According to these charts, the training correlation of the BP-MLP rose from 0.7734 to 0.7914, 0.8090, and 0.8195 by applying the SCE, MVO, and BAS algorithms. Also, the increase of testing R^2 from 0.7442 to 0.7876, 0.8046, and 0.8211 reveals that the CSCs estimated by the hybrid models are more correlated with the expected values.

From the obtained accuracy indices, it was deduced that both hybrid models outperform the regular MLP. It indicates that the weights and biases found by the SCE, MVO, and BAS can construct a more powerful network, compared to the MLP that is based on the BP scheme. In addition, a larger correlation of the results, as well as smaller errors calculated for the BAS-MLP in the training phases revealed that this algorithm performs more efficiently in training the ANN. Due to the same evidence, this model surpassed the other two ensembles in predicting the CSC as well.

Moreover, considering the computation time taken by each algorithm, the elite complexities, i.e., the SCE and MVO with population sizes of 100 and 300, around 800 and 3926 seconds were required, respectively, while the BAS could optimize the MLP in 212 seconds. Hence, the BAS is the most efficient algorithm in this work.

3.4 Neural predictive formula

In this section, the predictive relationship of the CSC is extracted from the core of the BAS-MLP ensemble. This formula is presented in the form of a linear relationship. For better illustrating the formula, Fig. 9 is drawn regarding the basic structure of the MLP.

Eq. (17) represents the mechanism implemented by the output neuron of the MLP. This neuron is fed by middle parameters that are released by the hidden colleagues (Eq. (18)). Also, Tansig (Eq. (19)) plays the role of the activation function of the hidden layer.

$$\begin{aligned} CSC_{BAS-MLP} = &-0.2105 \times \alpha + 0.7888 \times \beta \\ &+ 0.1578 \times \gamma - 0.2448 \times \delta \\ &+ 0.3008 \times \varepsilon + 0.0205 \times \zeta \\ &- 0.1469 \times \eta - 0.6247 \end{aligned} \tag{17}$$

$$Tansig\ (x) = \frac{2}{1 + e^{-2x}} - 1 \tag{19}$$

3.5 Problem and solution

The feasibility of three integrative methodologies was investigated and approved for the simulation of concrete compressive strength. Needless to say, this parameter is among the most important parameters of concrete which controls the optimal design of concrete mixture for various

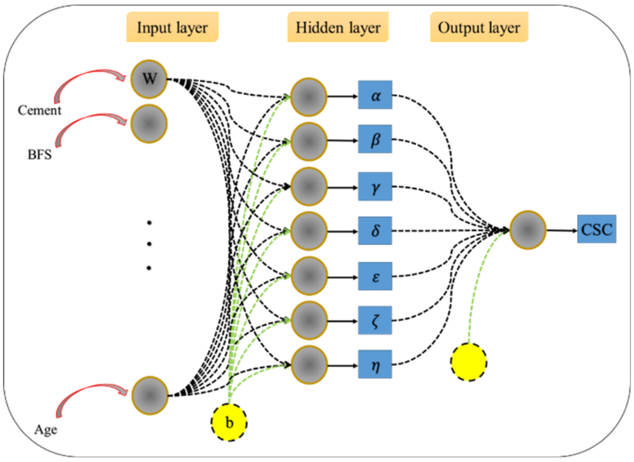


Fig. 9 An illustration of the MLP structure and its parameters

structural purposes (Nguyen *et al*. 2020b).

In many earlier efforts, engineers have used regression and mathematical approaches for obtaining an early assessment of this parameter. But due to the non-linearity and complexity of the problem, more sophisticated models like ANNs could handle this problem more effectively. Even further, the advent of optimization techniques could suggest a more reliable methodologies for this purpose. In many works, it has been shown that predictive models like ANN can take advantage of optimization algorithms to find more effective solutions. In this sense, when an ANN is applied to high dimensional problems (e.g., the contribution of several ingredients here) the solution encounters local minima (Mehrabi and Moayedi 2021). This is while this problem is managed by metaheuristic algorithms which go through an accuracy-growing way (Fig. 5). More clearly, a normal ANN may stops training owing to the misleading of the network after some iterations, while a metaheuristic-integrated ANN seeks a more promising solution for subsequent iterations.

3.6 Practical applications

It is well known that different structures, depending on their application and environmental conditions, require different types of concrete. This difference can be potentially described in terms of concrete strength. Hence, having a reliable pre-evaluation of this parameters can greatly assist engineers and designers.

Normally, reaching a desirable understanding of strength can be achieved with great previous knowledge and heavy laboratory efforts. These efforts which mostly rely on trial and error method, are quite laborious and costly in terms of both time and financial issues. For instance, these tests are been mostly bounded into a period of 90-180 days (Mak and Torii 1995). They also need the presence of experts for managing and controlling the test condition, mixture creation, sampling, etc. Besides, a large number of specimens should be tested in suitable tests conditions and be analyzed in order to obtain a proper CSC trend (Ly *et al*. 2019). This assignment can be easily handled by a trained intelligent model like the ones used in this work. It can help engineers to foresee the CSC trend of the mixture in various conditions (e.g., with diverse configurations and proportions of ingredients). This is how they can optimize the concrete mixture in a fast, convenient, and low-cost way.

For instance, Fig. 10 shows compares the laboratory and predicted CSC trends with respect to the curing age. It can be seen that the sensitivity of the CSC to this parameter is nicely understood by the model. By having such design charts, engineers can acquire a reliable expectation of the CSC before creating and testing any specimens. Likewise, the same assessment can be done for other parameters.

Another appreciable application can be examining the effect of each ingredient on the final CSC. To achieve this, traditionally, many compressive strength tests should be executed, and limited results are obtained that may be associated with uncertainties and inaccuracies. This objective can be fulfilled in different ways using machine learning. First, after evaluating mixture conditions, statistical analysis (e.g., variation of CSC results after regular changes of a specific input) can point out the most influencing inputs. The second way is using a machine learning method which specifically gives an importance assessment (e.g., the RF used by Ma *et al*. (2020)). Recognizing the most influential parameters enables us to design the concrete mixture with respect to specific parameters, instead of dealing with various ingredients.

All in all, the methodologies used in this study are reliable enough to substitute traditional CSC evaluative models. Based on the findings, the obtained accuracy is enough (for compatible data and test condition) to capture the behavior of the CSC and its sensitivity to mixture ingredients.

(a) cement = 181.38, BFS = 0, FA1 = 167.01, water = 169.59, SP = 7.56, CA = 1055.6, and FA2 = 777.8

(b) cement = 427.5, BFS = 47.5, FA1 = 0, water = 228, SP = 0, CA = 932, and FA2 = 594

Fig. 10 Examples of the CSC trends with respect to the curing age for specimens (All units are kg/m^3)

4. Conclusions

This study focused on evaluating three capable hybrid models for predicting the compressive strength of concrete. To do so, a predictive neural network is given to three metaheuristic algorithms, namely shuffled complex evolution, multi-verse optimizer, and beetle antennae search in order to acquire more promising values for the weights and biases. The developed ensembles were applied to a large dataset containing 1030 concrete information. The complexity of the networks was optimized by a trial and error effort. Using three accuracy criteria, it was revealed that all three ensembles outperform the unreinforced ANN in both training and testing phases. The accuracy rose after incorporating the SCE, MVO, and BAS. By comparison, the BAS was found to be the superior optimizer. Last but not least, the suggested hybrid models can be promising substitutes for traditional evaluative approaches for predicting the CSC.

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