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Swarm-based hybridizations of neural network for predicting the concrete strength

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Abstract. Due to the undeniable importance of approximating the concrete compressive strength (CSC) in civil engineering, this paper focuses on presenting four novel optimizations of multi-layer perceptron (MLP) neural network, namely artificial bee colony (ABC-MLP), grasshopper optimization algorithm (GOA-MLP), shuffled frog leaping algorithm (SFLA-MLP), and salp swarm algorithm (SSA-MLP) for predicting this crucial parameter. The used dataset consists of 103 rows of information concerning seven influential parameters (cement, slag, water, fly ash, superplasticizer, fine aggregate, and coarse aggregate). In this work, the best-fitted complexity of each ensemble is determined by a population-based sensitivity analysis. The GOA distinguished its self by the least complexity (population size = 50) and emerged as the second time-effective optimizer. Referring to the prediction results, all tested algorithms are able to construct reliable networks. However, the SSA (Correlation = 0.9652 and Error = 1.3939) and GOA (Correlation = 0.9629 and Error = 1.3922) performed more accurately than ABC (Correlation = 0.7060 and Error = 4.0161) and SFLA (Correlation = 0.8890 and Error = 2.5480). Therefore, the SSA-MLP and GOA-MLP can be promising alternatives to laboratorial and traditional CSC evaluative methods.

Keywords: concrete compressive strength; neural computing; metaheuristic optimization algorithms

1. Introduction

Evaluating the compressive strength of the concrete (CSC) is a crucial task in various civil engineering projects. Depending on the project's purpose, the CSC is an important criterion for determining the type of concrete (Moayedi *et al*. 2017, 2019c, Prayogo 2018, Bui *et al*. 2019(a-d)). As the name implies, the CSC indicates the strength of this mixture against compressive stress (Mandal *et al*. 2019), which is generally reported for 28-days specimens. Estimating the final strength of concrete at an early age is a significant and helpful advancement in the construction sector (Kheder *et al*. 2003). Furthermore, due to the fact that the CSC is a function of different elements (and dosages) in the mixture, predicting this characteristic needs many factors to be taken into consideration (Bui *et al*. 2019a). Many scholars have tried to explain the relationship between these constituents with concrete quality using simple methods (e.g., the Abrahams Law for relating the water to cement ratio to the concrete strength (Abrams 1927)). A noticeable difficulty associated with laboratory approaches for evaluating this parameter is being time-consuming as well as susceptible to experimental error (Akande *et al*. 2014). During the last decades, soft computing-based predictive techniques have gained huge popularity for solving complex engineering problems (Moayedi and Rezaei 2017, Moayedi and Hayati 2018a, Alsarraf *et al*. 2019, Bui *et al*. 2019c, d, Liu *et al*. 2019, Moayedi *et al*. 2019a, c, Wang *et al*. 2019, Guo *et al*. 2020, Mehrabi *et al*. 2020, Qiao *et al*. 2020, Zhou *et al*. 2020). Nguyen *et al*. (2019c), for example, proposed the use of artificial neural network (ANN) to evaluate the elastic modulus of the concrete affected by Alkali-silica reaction. Predicting the CSC using these models has received growing attention as well (Behnood *et al*. 2017). Yaseen *et al*. (2018) evaluated the capability of a so-called model extreme learning machine (ELM) in the prediction of the CSC of lightweight foamed concrete. Due to the superiority of the proposed tool to other employed models (like the SVR and M5 tree models (Bui *et al*. 2019d, Nguyen *et al*. 2019b)), they suggested the ELM as a reliable approach for future usages. Also, different studies have successfully used ANNs for estimating the CSC (Altun *et al*. 2008, Alshihri *et al*. 2009, Atici 2011). Nehdi *et al*. (2001), for example, suggested ANN for simulating the CSC of pre-formed foam

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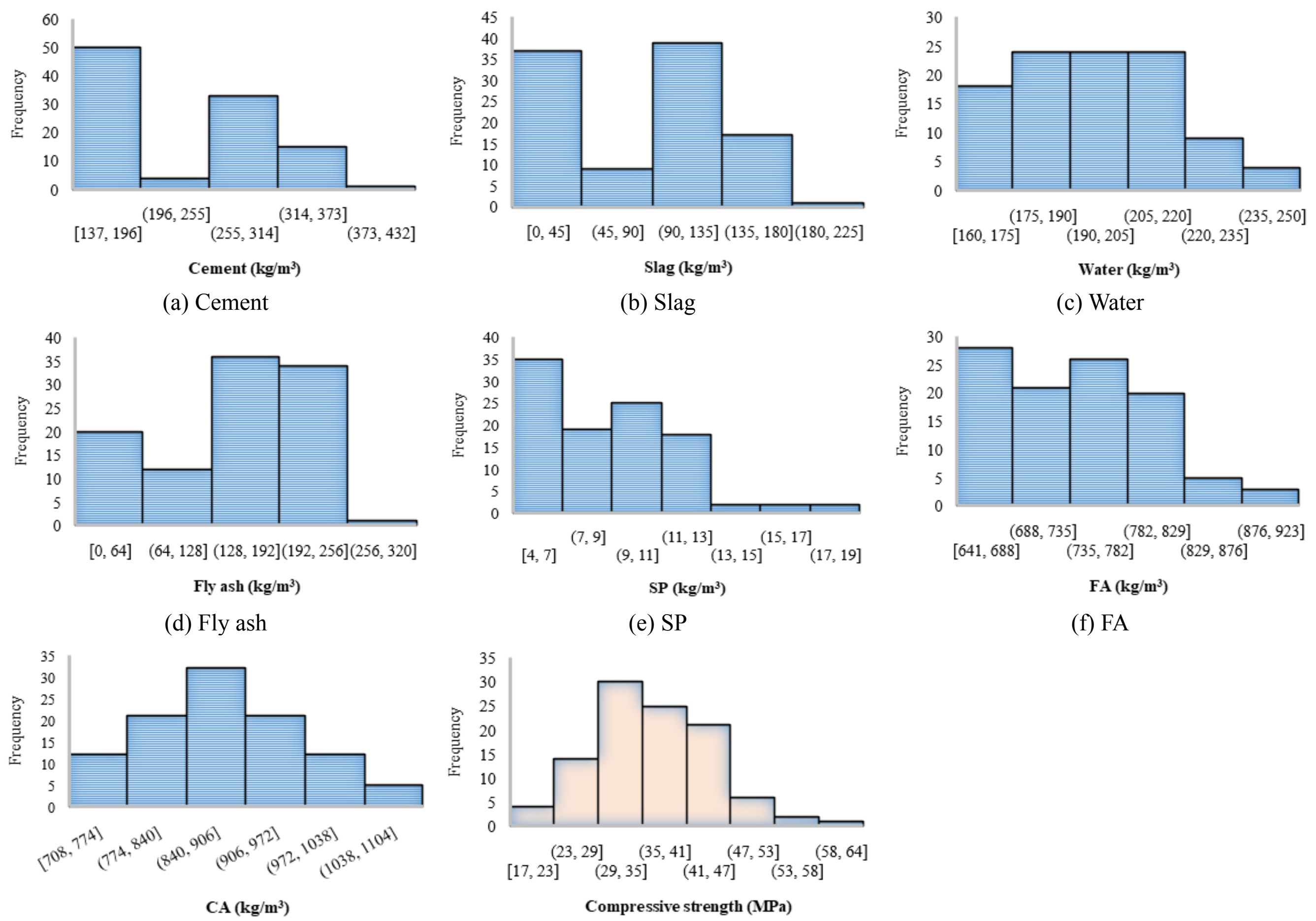
cellular concrete. In their study, four input factors, namely foam-to-cementitious materials ratio, cement content, sand-to-cementitious materials ratio and water-to-cementitious materials ratio were applied. Moreover, Keshavarz and Torkian (2018) reported the superiority of the ANN to adaptive neuro-fuzzy inference system (ANFIS), based on the calculated correlation values (CorrelationANN = 0.942 and CorrelationANFIS = 0.923).

More recently, metaheuristic algorithms have been known as capable techniques for optimizing various engineering problems (Yu *et al*. 2015, Park *et al*. 2016, Akin and Sahin 2017, Chahnasir *et al*. 2018, Fallahian *et al*. 2018, Moayedi and Hayati 2018b, Bui *et al*. 2019b, Moayedi *et al*. 2019b, c, d, e, f, 2020, Xi *et al*. 2019). Another outstanding application of these algorithms is prevailing computational drawbacks of predictive tools like the ANN and ANFIS . In this sense, Yu *et al*. (2019) could optimize the performance of a support vector machine (SVM) model by using particle swarm optimization (PSO) for predicting the concrete expansion caused by alkali aggregate reactivity. Bui *et al*. (2019(a) coupled the whale optimization algorithm (WOA) with an ANN to predict the CSC. They also compared the WOA with dragonfly algorithm (DA) and ant colony optimization (ACO) as benchmark models. Referring to the obtained results (error values were 3.4452, 3.3325, and 2.6985, respectively for the ACO-ANN, DA-ANN, and WOA- ANN), it was shown that the proposed WOA algorithm can be efficiently used to optimize the ANN for the mentioned purpose. In a similar research, de Almeida Neto *et al*. (2018) employed three swarm algorithms of fish school search (FSS), artificial bee colony (ABC), and PSO for fine-tuning support vector regression (SVR). The results indicated that the swarm-based ensembles outperform the typical SVR. However, ABC and FFS surpassed the PSO for this application. Moreover, other scholars like Cheng *et al*. (2013), Rebouh *et al*. (2017), Prayogo (2018). have shown the applicability of metaheuristic algorithms in the field of CSC modeling. More specifically, concerning the use of metaheuristic algorithms (e.g., firefly algorithm (Bui *et al*. 2018) and imperialist competitive algorithm (Sadowski *et al*. 2018)) for optimizing the ANN, many studies have outlined that the incorporation of ANN with these techniques results in powerful predictive models. The wide variety of metaheuristic techniques encouraged the authors to apply four novel types of them, namely artificial bee colony (ABC), grasshopper optimization algorithm (GOA), shuffled frog leaping algorithm (SFLA), and salp swarm algorithm (SSA) to the problem of CSC estimation through optimizing the ANN performance. The algorithms are combined with this model to find the most suitable computational parameters.



(a) Cement (b) Slag (c) Water (d) Fly ash (e) SP (f) FA (g) CA (h) Compressive strength

Fig. 1 The graphical description of the used dataset

2. Methodology and established database

The data we used to train and test the intelligent models of this study are collected and presented by Yeh (2007). The implementation of numerous concrete tests resulted in collocating 103 rows of information about three significant characteristics of concrete, namely slump (*cm*), flow (*cm*), and the 28-day CSC (*Mpa*). Meanwhile, the records of seven concrete elements, namely cement, slag, water, fly ash, superplasticizer (SP), fine aggregate (FA), and coarse aggregate (CA) are considered as the CSC influential parameters. Cement plays the main role in the concrete and its amount is directly proportional to the cohesiveness of the mixture. According to ACI 211.1, for a certain maximum size of coarse aggregate, the water content can directly influence the concrete consistency. This parameter (i.e., the consistency) rises by adding SP when the water does not experience any change. Similarly, the reason for adding pozzolanic admixtures (e.g., fly ash) lies in enhancing consistency. Also, aggregate characteristics need to be properly regarded for having a balance between the water requirement and the desired consistency (Mehta 1986, Yeh 2007).

The histograms of the CSC and seven influential factors are illustrated in Fig. 1. Moreover, Table 1 denotes the descriptive statistics of this dataset in terms of the minimum, maximum, and average values, as well as the standard deviation. As is seen, the content of cement, slag, water, fly ash, SP, FA, and CA varies in [137, 374], [0, 260], [160, 240], [0, 193], [4.4, 19], [640.6, 902], and [708, 1049.9] kg/m^3, respectively. Notably, the slump of these samples ranges from 0 to 29 cm. The correlation between the CSC and these constituents is also measured. According to the results, the largest coefficients are obtained for cement and fly ash (0.199 and 0.198) while the SP and CA have the smallest correlations with the CSC (0.001 and 0.024).

Table 1 Descriptive statistics of the CSC and input factors

	Minimum	Maximum	Mean	Standard deviation
Compressive strength (MPa)	17.1	58.5	36	7.8
Cement (kg/m^3)	137	374	229.9	78.9
Slag (kg/m^3)	0	260	149	85.4
Water (kg/m^3)	160	240	197.2	20.2
Fly ash (kg/m^3)	0	193	78	60.5
SP (kg/m^3)	4.4	19	8.5	2.8
FA (kg/m^3)	640.6	902	739.6	63.3
CA (kg/m^3)	708	1049.9	884	88.4

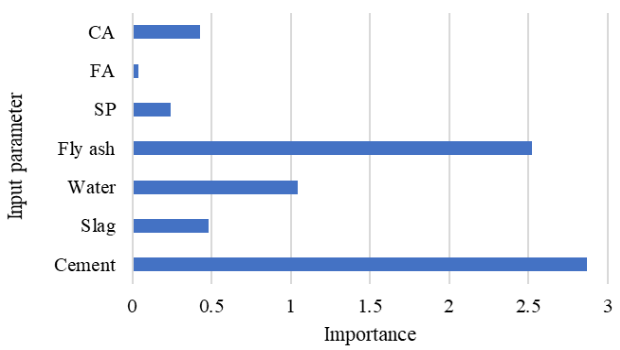


Fig. 2 The results of the sensitivity analysis for determining the importance of the influential factors

Fig. 2 depicts the importance of each influential factor on the CSC. The importance values are calculated by training a bagged ensemble of 200 regression trees and permuting out-of-bag observations among the trees in the Matlab environment (version 2014). According to this chart, the importance of the cement, slag, water, fly ash, SP, FA, and CA are 2.87, 0.48, 1.05, 2.52, 0.24, 0.04, and 0.43, respectively. It confirms the results of the correlation analysis which introduced the cement and fly ash as the most influential parameters.

In this study, 80 % of the whole data (i.e., 82 samples) are specified to the CSC pattern analysis and training the models, and the remaining 20 % (i.e., 21 samples) are used as unseen concrete conditions to evaluate the prediction capability of the models.

2.1 Methodology

Artificial neural network: Artificial neural networks (ANNs) are known as one of the most powerful approximators among diverse artificial intelligence (AI) techniques. This model imitates the relationships and connections of biological neural networks. The first artificial neurons were designed by McCulloch and Pitts (1943). The capability of non-linear analysis of any complex problem is one of the main advantages of this predictive tool. The ANNs have shown high robustness for approximating various engineering parameters by taking into consideration their influential parameters (Kişi 2007, Nguyen *et al*. 2018, Gao *et al*. 2019). Fig. 3 illustrates the structure of the most popular notion of the ANNs, i.e., multi-layer perceptron (MLP) (Hornik 1991), with *J* hidden neurons. This is proper to note that in the MLPs, the number of input and output nodes equals the number of these parameters. Similar to other AI models, two sets of data including training and testing data are required in the development of an ANN. Utilizing the back-propagation

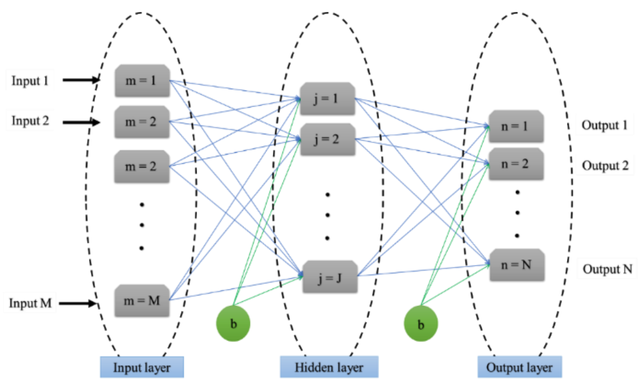


Fig. 3 The general structure of the MLP neural network

(BP) learning method (Hecht-Nielsen 1992), the MLP tries to reduce the learning error (of training samples) within several epochs. After that, it applies the derived pattern to the second dataset (i.e., testing samples) to assess the generalization ability.

Metaheuristic hybrids algorithms: In spite of the high simulation capability of the ANNs, there are appreciable computational drawbacks, like getting trapped in local minima (Moayedi *et al*. 2018), which can lead to reducing the reliability of the model. To deal with this problem, four wise metaheuristic algorithms, namely artificial bee colony, grasshopper optimization algorithm, shuffled frog leaping algorithm, and salp swarm algorithm are used in this study. These algorithms are nature-inspired optimizers which have been widely employed for finding optimal solutions. The ABC algorithm is suggested by Karaboga (2005)based on the foraging behavior of artificial bees. Three kinds of bees (employed bees, onlookers, and scouts) are hired to seek food sources (also known as nectars) which their position indicates a possible solution to the defined problem. The ABC is better detailed in previous literature like (Karaboga *et al*. 2007, Karaboga and Basturk 2007, Nguyen *et al*. 2019a). Mimicking the swarming behavior of grasshoppers, the name GOA represents a recently-developed metaheuristic algorithm which is presented by Saremi *et al*. (2017) in 2017. The position of the insects is updated (based on three parameters of social relationship, gravity force, and wind advection) within exploration and exploitation stages in order to find food. For mathematical relationships of the GOA, the readers may refer to related studies (Aljarah *et al*. 2018, Mirjalili *et al*. 2018, Mafarja *et al*. 2019). The SFLA was proposed by Eusuff and Lansey (2003) as a popular and efficient metaheuristic algorithm. The relationship between randomly produced individuals (frogs), which are defined in so-called containers "memeplexes" is the basis of this algorithm. Like plenty of other swarm-based algorithms, the position of the frogs is repetitively updated to find the optimal solution. More details about this interaction can be found in previous studies (Liping *et al*. 2012, Zhang *et al*. 2012, Chen *et al*. 2019). Mirjalili *et al*. (2017) developed the SSA based on the swarming behavior of salps when navigating and foraging in oceans. In this way, the SSA population is divided into two categories of leader (the chain front positions) and followers. The details of this algorithm are presented in (Ahmed *et al*. 2018, Sayed *et al*. 2018, Abbassi *et al*. 2019).

3. Results and discussion

As explained, to achieve the objective of this paper, the ABC, GOA, SFLA, and SSA hybrid metaheuristic algorithms need to get coupled with the ANN. Different structures of an MLP neural network were tested to ensure the most suitable MLP is used. Among ten values tried for the number of neurons in the hidden layer, 5 neurons gave the best responses. Thus, the used MLP takes the overall form of 7 × 5 × 1 which indicates 7 input neurons, 5 hidden neurons, and 1 output neuron in the corresponding layers. In the following sections, the combination process is explained, and the results are presented and discussed.

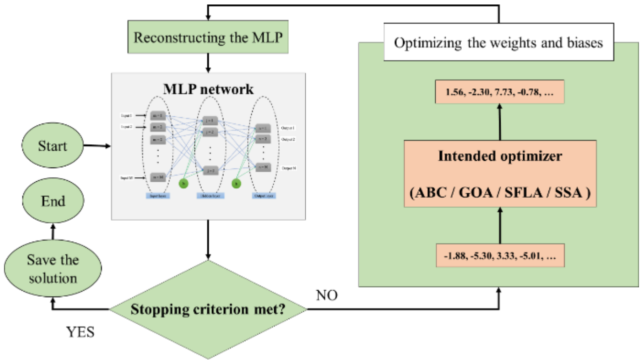


Fig. 4 The procedure of optimizing the ANN using metaheuristic algorithms

3.1 Hybridizing the MLP using metaheuristic techniques

Four hybrid ensembles of ABC-MLP, GOA- MLP, SFLA- MLP, and SSA-MLP were constructed by synthesizing the ANN with the mentioned algorithms. In fact, the general equation of the MLP was given to the ABC, GOA, SFLA, and SSA optimizers. In every iteration, each algorithm suggests a solution matrix, containing the MLP weights and biases, to construct the network. The error between the predicted and actual values of the CSC (for training data) is measured by the objective function (OF) which was root mean square error (RMSE) in this work. This procedure is shown in Fig. 4.

A total of 1000 repetitions were considered for each model to minimize the error. Also, the ensembles were implemented with nine different population sizes (i.e., 10, 25, 50, 75, 100, 200, 300, 400, and 500) in order to optimize the complexity. Fig. 5 shows the obtained RMSEs.

The best populations sizes for the ABC, GOA, SFLA, and SSA are 200, 50, 400, and 300, respectively. Moreover, the convergence curve of these elite networks is shown in this figure. As is seen, the mentioned algorithms achieved the RMSEs of 3.155655672, 1.020918642, 2.134444363, and 0.76517443.

3.2 Accuracy criteria

Two well-known error criteria of RMSE and mean absolute error (MAE) are used to measure the learning and prediction error of the implemented models. Besides, the correlation between the predicted and actual CSCs is reflected by the coefficient of determination (R^2). These indices are formulated by Eqs. (1) to (3).

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

$$MAE = \frac{1}{K}\sum_{I=1}^{K}|Z_{i_{observed}} - Z_{i_{predicted}}| \qquad (2)$$

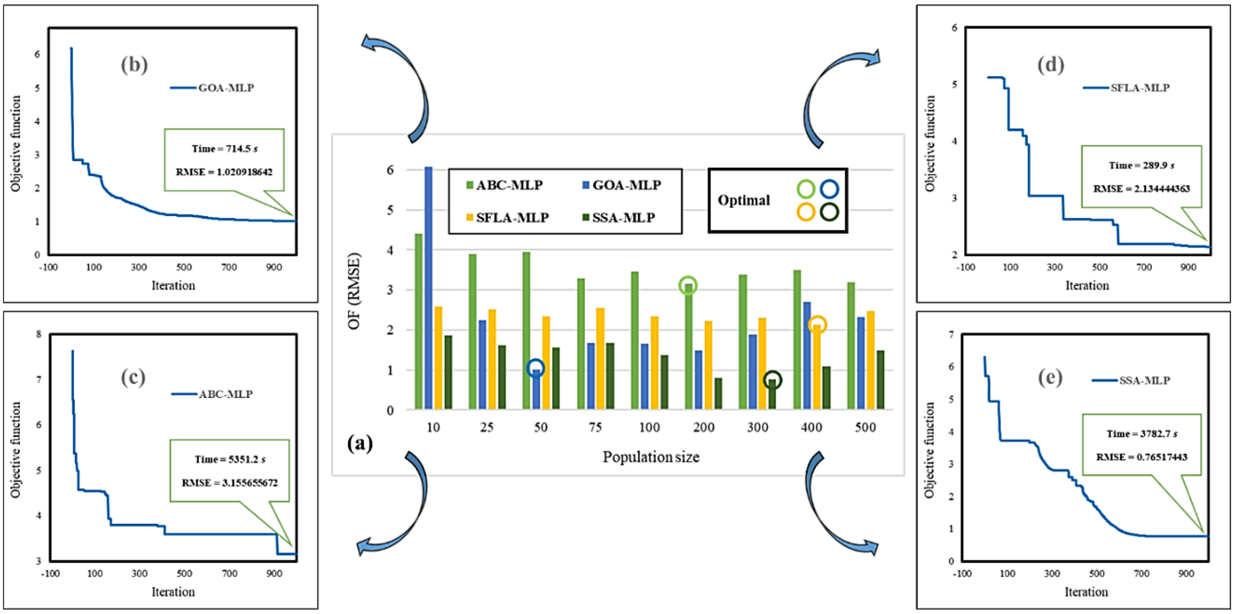


Fig. 5 The sensitivity analysis based on the model complexity

$$R^2 = 1 - \frac{\sum_{i=1}^{K}(Z_{i_{predicted}} - Z_{i_{observed}})^2}{\sum_{i=1}^{K}(Z_{i_{observed}} - \overline{Z}_{observed})^2} \tag{3}$$

where K is the number of data, $Z_{i\,predicted}$ and $Z_{i\,observed}$ denote the predicted and observed CSCs, respectively, and $\overline{Z}_{observed}$ represents the average value of the $Z_{i\,observed}$.

3.3 Accuracy assessment of the implemented predictive models

By applying the mentioned accuracy criteria, the performance of the used models is evaluated in this section. Firstly, the learning quality of the models is assessed by examining the training results. More clearly, it indicates the

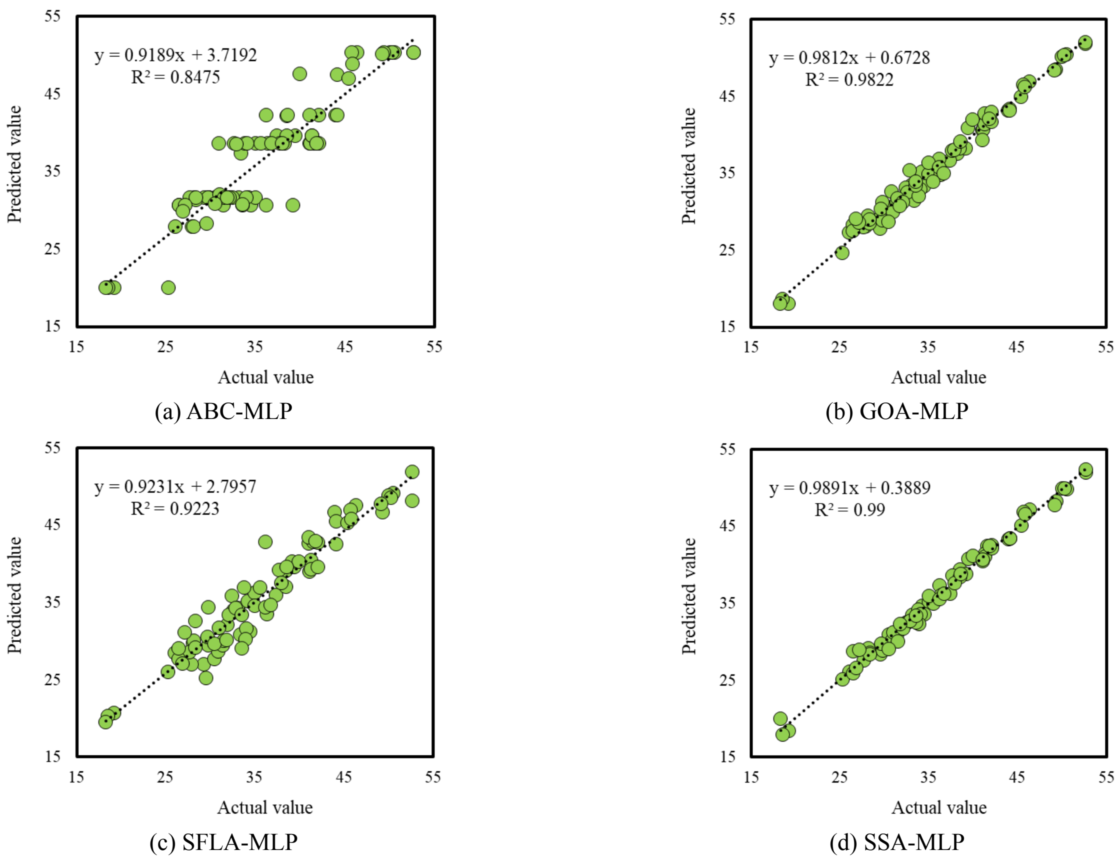


Fig. 6 The correlation of training results for the (a) ABC-MLP; (b) GOA-MLP; (c) SFLA-MLP; and (d) SSA-MLP prediction

capability of them in exploring the relationship between the CSC and concrete element factors. In the other dataset (i.e., the testing data), the quality of the results represents the generalization potential of the models which means predicting the CSC for unseen concrete conditions.

Fig. 6 shows the correlation between the observed and estimated CSCs in the training phase. The observed values vary from 18.2600 to 52.6500, and the estimated values of ABC-MLP, GOA-MLP, FLA-MLP, and SSA-MLP range in [20.0049, 50.3094], [18.0189, 52.0248], [19.5559, 51.8793], and [17.9521, 52.4335], respectively. According to this figure, all four ensembles achieved a consistent prediction of the CSC, due to the obtained R^2 values (0.8475, 0.9822, 0.9223, 0.9900, respectively for the ABC-MLP, GOA-MLP, FLA-MLP, and SSA-MLP) higher than 80 %. However, it can be seen that there is a considerable distinction between the correlation of the ABC-MLP outputs with other models.

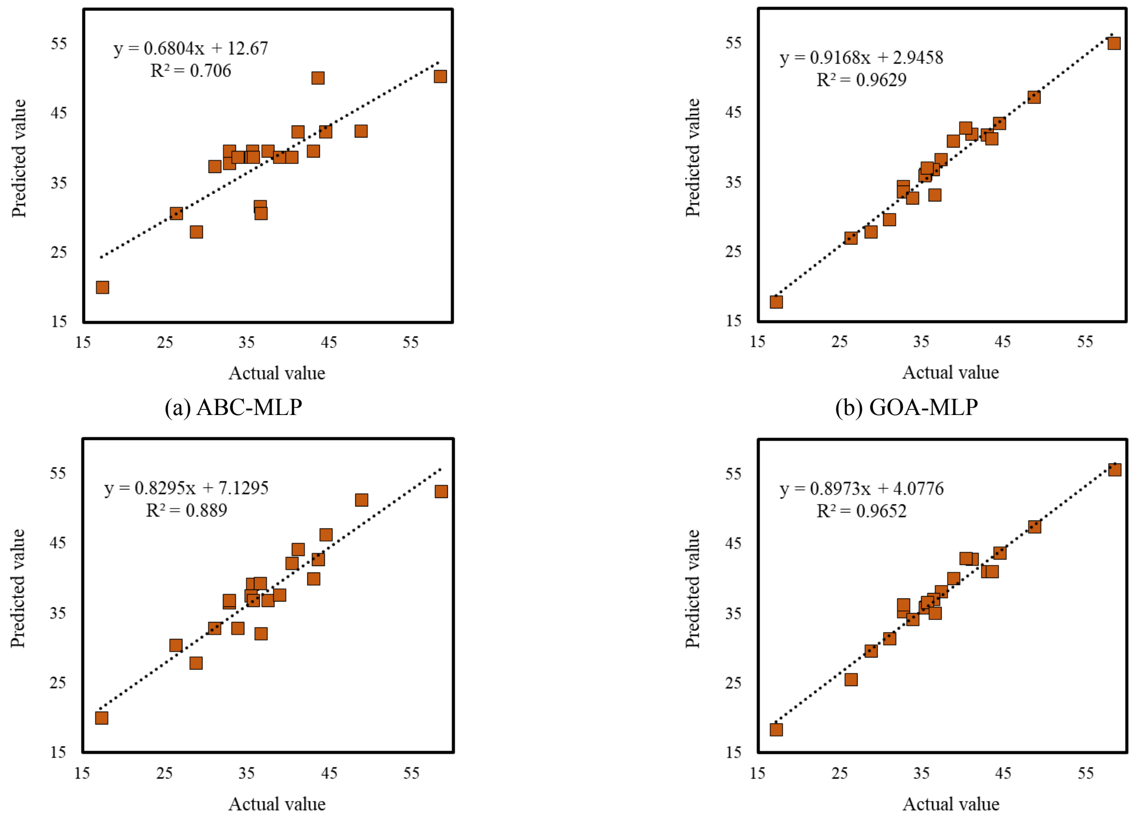
Moreover, regarding the calculated error criteria, it is deduced that the used models have recognized the CSC pattern with an acceptable error. In detail, the largest and smallest calculated mean absolute percentage error (MAPE) is 7.46% and 1.78%, respectively. The RMSEs are 3.1557, 1.0209, 2.1344, 0.7651, which indicate that the SSA-MLP and GOA-MLP performed more accurately than two other colleagues for the mentioned purpose. This claim can also be supported by the obtained MAEs (2.5419, 0.8268, 1.7507, and 0.5935) in this phase.

As for the second phase, the testing results are shown in Fig. 7. The observed CSCs vary from 17.1900 to 58.5300, and the products of the models range in [20.0049, 50.3094], [17.7379, 55.0478], [20.0032, 52.4552], and [18.3108, 55.6466], respectively. similar to the training data, the highest R^2 is obtained for the SSA-MLP (0.9652), followed by GOA-MLP (0.9629), SFLA-MLP (0.8890), and ABC-MLP (0.7060).

Moreover, the error values (the difference between each pair of the observed and estimated CSC) are depicted in Fig. 8, along with the histogram of them. In this phase, the highest and lowest values of MAPE equals 11.16% and 3.80%, respectively. Similar to the training phase, the calculated RMSEs (4.5656, and 1.6446, 2.9191, and 1.6678), as well as the MAEs (4.0161, 1.3922, 2.5480, and 1.3939), indicate that the SSA and GOA are more reliable than the SFLA and ABC for predicting the CSCs under stranger conditions.

According to all three accuracy criteria, all models presented a more accurate estimation of the CSC in the training phase. It means that they were more successful in analyzing the CSC pattern compared to generalizing it. Moreover, it was concluded that in both training and testing phases, the SSA and GOA outperform ABC and SFLA in optimizing the MLP.

Referring to all three indices (i.e., the RMSE, MAE, and R^2 in Table 2), the SFLA, without any discrepancy, performs more efficiently than the ABC algorithm. But establishing a comparison between the SSA and GOA requires more discussions. In this sense, although the SSA grasps a considerably more accurate understanding of the problem, the testing results of the GOA are slightly better in



(a) ABC-MLP (b) GOA-MLP (c) SFLA-MLP (d) SSA-MLP

Fig. 7 The correlation of testing results for the (a) ABC-MLP; (b) GOA-MLP; (c) SFLA-MLP; and (d) SSA-MLP prediction

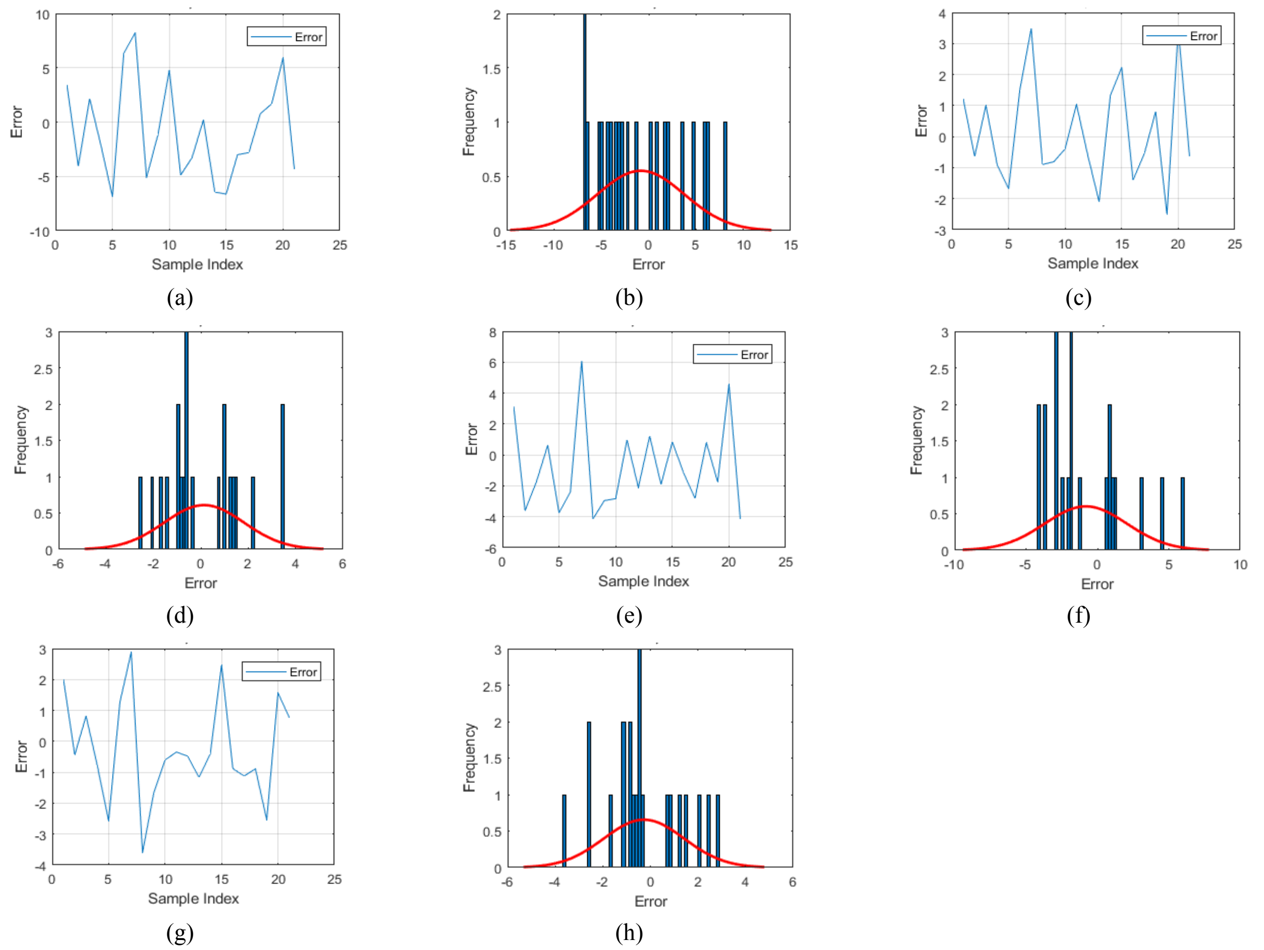


Fig. 8 The results obtained for (a) and (b) ABC-MLP; (c) and (d) GOA-MLP; (e) and (f) SFLA-MLP; and (g) and (h) SSA-MLP predictions for the testing samples

Table 2 The obtained values of RMSE, MAE, and R^2

Models	Network results					
	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ABC-MLP	3.1557	2.5419	0.8475	4.5656	4.0161	0.7060
GOA-MLP	1.0209	0.8268	0.9822	1.6446	1.3922	0.9629
SFLA-MLP	2.1344	1.7507	0.9223	2.9191	2.5480	0.8890
SSA-MLP	0.7651	0.5935	0.9900	1.6678	1.3939	0.9652

terms of the RMSE and MAE. However, the R^2 indicates that the SSA products are 0.23% more correlated. Thus, to acquire an overall comparison between the performance of all four models, a ranking system is developed in Table 3. In this system, based on the calculated values of RMSE, MAE, and R^2, each model receives three scores in each phase. The larger the assigned score is, the higher the accuracy is. According to the obtained overall score (the summation of the scores), the SSA (OS = 12) is the superior optimizer in training the MLP. This is while in the testing phase, the GOA (OS = 11) surpasses the SSA (OS = 10). Therefore, it can be deduced that the GOA enjoys more prediction capability.

As explained, selecting the appropriate training algorithm is a significant step in utilizing ANNs. Each training method benefits its special regulations to properly adjust the computational parameters (i.e., the weights and biases). Due to the large number of the parameters involved, it is a very difficult process that cannot be carried out manually. For example, in the case of the used MLP network, we have 46 parameters (7 × 5 = 35 weights connecting the input and hidden layers, five biases of the hidden neurons, 5 × 1 = 5 weights connecting the hidden and output layers, and 1 bias belonging to the output neuron). In this study, the employed

Table 3 The developed ranking system based on the calculated accuracy criteria

Models	Scores							
	Training				Testing			
	RMSE	MAE	R^2	Overall score (OS)	RMSE	MAE	R^2	Overall score (OS)
ABC-MLP	1	1	1	3	1	1	1	3
GOA-MLP	3	3	3	9	4	4	3	11
SFLA-MLP	2	2	2	6	2	2	2	6
SSA-MLP	4	4	4	12	3	3	4	10

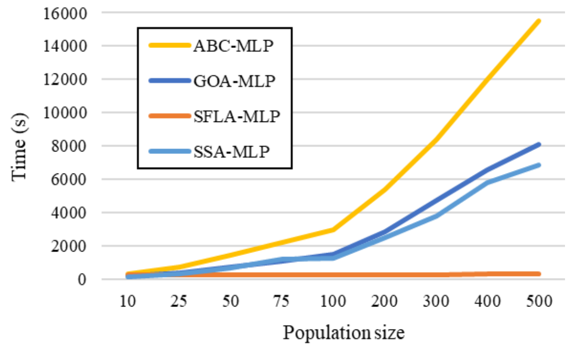


Fig. 9 The computation time elapsed by each optimizer for training the MLP

metaheuristic algorithms could successfully supervise the training process.

The time-effectiveness is of high importance in determining the most suitable predictive model for engineering objectives. Fig. 9 shows the time taken by the ABC, GOA, SFLA, and SSA for optimizing the MLP. As is seen, there are noticeable distinctions between the algorithms. As the disadvantages of the ABC, it not only presented the weakest prediction but also took the longest time for doing the assigned task. On the opposite, the SFLA emerged as the fastest optimizer with good accuracy. The computation times required by the SSA and GOA are very close. Therefore, it can be concluded that selecting the most suitable model depends on the priorities of the task. More clearly, when the time is a more determinant factor (compared to the accuracy), the SFLA-MLP may be used to predict the CSC.

Another significant outcome of this study is the improvement resulted from using capable optimizers. In comparison with the algorithms used by Tien Bui *et al.* (2019) (i.e., WOA, ACO, and DA), our elite models achieved a considerably better understanding of the CSC pattern. In this regard, the training RMSE of their best model (i.e., WOA-MLP) was 1.3576 while this value is obtained 1.0209 and 0.7651 for the GOA-MLP and SSA-MLP modes used in this study. The same goes for the prediction capability of them (RMSE of 2.6985 vs. 1.6446 and 1.6678). Moreover, since the models used in these two studies have been implemented under the same circumstances (i.e., the same operating system), they can be compared in terms of the optimization time. As is shown in Fig. 9, the proposed GOA and SSA needed 714.5 and 3782.7 seconds for optimizing the MLP. These values were 5271 and 7620 seconds for the WOA and DA algorithm used byTien Bui *et al.* (2019). Thus, the ensembles created by the GOA and SSA are more time-efficient predictors, too.

3.4 Presenting the neural predictive formula

Due to the conclusion that both SSA and GOA metaheuristic algorithms constructed the most reliable MLP neural network of the current study, in this part, it was aimed to extract the neural formula of the SSA-MLP and GOA-MLP models to estimate the CSC using its effective factors (i.e., cement, slag, water, fly ash, SP, FA, and CA). The CSC predictive formulas are presented as Equations 4 and 5. This is proper to note that these equations are built by the weights and biases of the unique output neuron of the optimized networks. Hence, the variables of them (i.e., *A* to *E* and *F* to *I*) are the outputs of the hidden neurons which should be calculated by Eqs. (6) and (7), respectively for the SSA-MLP and GOA-MLP formula.

$$CSC_{SSA\text{-}MLP} = -0.6627 \times A - 0.8565 \times B - 0.4422 \times C + 0.3258 \times D - 0.7748 \times E - 0.5664 \tag{4}$$

$$CSC_{GOA\text{-}MLP} = 0.7872 \times F + 0.0508 \times G - 0.3141 \times H - 0.0650 \times I - 0.9800 \times J - 0.2546 \tag{5}$$

$$\begin{bmatrix} A \\ B \\ C \\ D \\ E \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} -0.1142 & 1.0826 & 0.8373 & 0.3316 & -0.1780 & -0.5590 & -0.8741 \\ -0.4213 & -0.7538 & -0.7427 & 0.8302 & 0.2729 & 0.7494 & 0.6940 \\ 0.8414 & -0.3368 & -0.2462 & 0.3406 & -0.3875 & 1.0294 & 0.9468 \\ -0.6837 & -1.0862 & 0.4489 & -0.5146 & -0.3652 & -0.9235 & 0.0686 \\ 0.8386 & -0.0975 & -0.5496 & 0.0282 & 0.8452 & -0.8458 & -0.8116 \end{bmatrix} \begin{bmatrix} Cement \\ Slag \\ Water \\ Fly\ ash \\ SP \\ FA \\ CA \end{bmatrix}\right) + \begin{bmatrix} 1.7619 \\ 0.8809 \\ 0.0000 \\ -0.8809 \\ 1.7619 \end{bmatrix}\right) \tag{6}$$

$$\begin{bmatrix} F \\ G \\ H \\ I \\ J \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} 0.7445 & 0.2724 & -0.5827 & -0.5803 & 1.0659 & 0.2271 & -0.7821 \\ -0.2553 & 0.8266 & -0.8225 & -0.8297 & 0.5067 & -0.0046 & -0.8568 \\ -0.9688 & -0.3549 & 0.4917 & 0.9056 & -0.4452 & 0.8311 & 0.2984 \\ 1.1046 & -0.4176 & -0.9055 & 0.0003 & -0.8882 & 0.3057 & 0.0872 \\ 0.2619 & -1.2706 & 0.4079 & 0.7121 & 0.6021 & 0.4145 & 0.4619 \end{bmatrix} \begin{bmatrix} Cement \\ Slag \\ Water \\ Fly\ ash \\ SP \\ FA \\ CA \end{bmatrix}\right) + \begin{bmatrix} -1.7619 \\ 0.8809 \\ 0.0000 \\ 0.8809 \\ 1.7619 \end{bmatrix}\right) \tag{7}$$

where *Tansig* stands for the activation function of the ANN which for a given input *x*, it is obtained as follows

$$Tansig\ (x) = \frac{2}{1 + e^{-2x}} - 1 \tag{8}$$

4. Conclusions

The optimization capability of four wise metaheuristic techniques namely artificial bee colony, grasshopper optimization algorithm, shuffled frog leaping algorithm, and salp swarm algorithm was assessed in this study. The algorithms were applied to optimize the performance of artificial neural network for predicting the compressive strength of concrete. The carried-out sensitivity analysis revealed that the ABC, GOA, SFLA, and SSA present the best performance by the population sizes 200, 50, 400, and 300, respectively. It was found that all four metaheuristic algorithms can grasp a reliable understanding of the non-linear relationship between the CSC and mixture ingredients. However, due to the eye-catching results of the SSA and GOA-based ensembles, we believe that they can provide non-destructive and accurate approaches for early estimation of the CSC.

Concerning future studies, the authors would suggest conducting comparative studies in which different optimizers (i.e., metaheuristic algorithms) are applied to other basic models (e.g., SVM and ANFIS) to improve the current methodologies available for indirect measurement of the CSC. Moreover, developing a graphical user interface (GUI) from reliable predictive models could be of interest to engineers.

Conflicts of Interest

The authors declare no conflict of interest.

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