Smart Structures and Systems, *Vol. 26, No. 6 (2020) 753-763*
DOI: https://doi.org/10.12989/sss.2020.26.6.753

Employing TLBO and SCE for optimal prediction of the compressive strength of concrete

Yinghao Zhao[1,2a], Hossein Moayedi[3,4b], Mehdi Bahiraei[5c] and Loke Kok Foong[*6,7]

[1]*Guangzhou Institute of Building Science Co., Ltd., Guangzhou 510440, China*
[2]*South China University of Technology, Guangzhou 510641, China*
[3]*Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam*
[4]*Faculty of Civil Engineering, Duy Tan University, Da Nang 550000, Vietnam*
[5]*Faculty of Engineering, Razi University, Kermanshah, Iran*
[6]*Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam*
[7]*Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam*

(*Received March 22, 2020, Revised September 5, 2020, Accepted October 18, 2020*)

Abstract. The early prediction of Compressive Strength of Concrete (CSC) is a significant task in the civil engineering construction projects. This study, therefore, is dedicated to introducing two novel hybrids of neural computing, namely Shuffled Complex Evolution (SCE) and Teaching-Learning-Based Optimization (TLBO) for predicting the CSC. The algorithms are applied to a Multi-Layer Perceptron (MLP) network to create the SCE-MLP and TLBO-MLP ensembles. The results revealed that, first, intelligent models can properly handle analyzing and generalizing the non-linear relationship between the CSC and its influential parameters. For example, the smallest and largest values of the CSC were 17.19 and 58.53 MPa, and the outputs of the MLP, SCE-MLP, and TLBO-MLP range in [17.61, 54.36], [17.69, 55.55] and [18.07, 53.83], respectively. Second, applying the SCE and TLBO optimizers resulted in increasing the correlation of the MLP products from 93.58 to 97.32 and 97.22%, respectively. The prediction error was also reduced by around 34 and 31% which indicates the high efficiency of these algorithms. Moreover, regarding the computation time needed to implement the SCE-MLP and TLBO-MLP models, the SCE is a considerably more time-efficient optimizer. Nevertheless, both suggested models can be promising substitutes for laboratory and destructive CSC evaluative models.

Keywords: civil engineering; concrete compressive strength; artificial neural network; metaheuristic optimizers

1. Introduction

Considering several merits of concrete (e.g., durability, construction availability and low cost), it is used as a versatile material all over the globe (Trung *et al*. 2019). The strength of this material is usually defined by its Compressive Strength (CSC) normally measured for 28-days samples. Early assessment of this parameter is an active area of research as it is of high significance in construction projects. Regarding the disadvantages of experimental models (e.g., being costly and time-consuming), utilizing non-destructive evaluative methods has been recommended by scholars (Shariati *et al*. 2020).

Machine learning tools have been effectively used for analyzing different concrete-related parameters like slump (Qiu *et al*. 2019), CSC (Dutta and Barai 2019) and carbonation depth (Felix *et al*. 2019). Dao *et al*. (2020) conducted a sensitivity analysis of Artificial Neural Network (ANN) and Gaussian Process Regression (GPR) using a Monte Carlo simulation for predicting the CSC of high-performance concrete. It was concluded that the testing age and the cement content play the most important roles in this task. Feng *et al*. (2020) suggested the use of adaptive boosting algorithm for accurate prediction of the CSC. Sai and Singh (2019) successfully used Support Vector Regression (SVR) for the same objective. Al-Shamiri *et al*. (2019) proposed the effectiveness of extreme learning machine for simulating the CSC of high-strength concrete. The potential of Support Vector Machine (SVM) along with the K-Fold cross-validation technique was examined by Ling *et al*. (2019) for the CSC modeling in marine environments. In another research, due to the high compatibility of the ANN products with experimental results, Asteris and Mokos (2019) introduced it as a promising non-destructive tool for prediction of the CSC. More researches about the applicability of the ANNs can be found in Refs. (Saldarriaga *et al*. 2009, Yi *et al*. 2013, Shahbazi *et al*. 2014, Shen *et al*. 2014, Onat and Gul 2018).

Application of complex mathematical solutions in solving engineering problems have been always a main concern of scholars in different field (Guan *et al*. 2019, Jiang *et al*. 2019, Xu *et al*. 2019a, 2020, Yang *et al*. 2019, 2020, Dong *et al*. 2020, Lei *et al*. 2020, Liu *et al*. 2020b) and more particularly in the field of engineering (Zhu *et al*.

*Corresponding author, Ph.D.,
E-mail: lokekokfoong@tdtu.edu.vn
[a] Ph.D., E-mail: ctzhaoyinghao@mail.scut.edu.cn
[b] Ph.D., E-mail: hosseinmoayedi@duytan.edu.vn
[c] Ph.D., E-mail: bahira@alumni.iust.ac.ir

http://www.techno-press.org/?journal=sss&subpage=7
ISSN: 1738-1584 (Print), 1738-1991 (Online)

2019, Liu *et al*. 2020a, Song *et al*. 2020, Zuo *et al*. 2020). During the last decade, metaheuristic algorithms and computational intelligence have gained high popularity (Zuo *et al*. 2015, Liu *et al*. 2016, Xu *et al*. 2018, Li *et al*. 2019, Tsai *et al*. 2019, Zhang *et al*. 2019, Lv *et al*. 2020). There have been much examples of optimization in the field engineering (Chao *et al*. 2018, Lu *et al*. 2019a, b, Wu *et al*. 2019, Hu *et al*. 2020, Li *et al*. 2020, Liu *et al*. 2020c, Ni *et al*. 2020). A prominent application for this case is remedying the computational drawbacks of conventional predictors using search techniques (Xu and Chen 2014, Zhao *et al*. 2014, Shen *et al*. 2016, Wang *et al*. 2017, Chen *et al*. 2020). To cover the weakness of conventional computational intelligence-based predictive solutions such as determination of proper network structure, hardware dependence, the difficulty of showing the problem to the network, unexplained behavior of the network, unknown processing duration of the network, a mistake in taking correct local minima, many new extreme machine learning techniques (Wang *et al*. 2014, Hu *et al*. 2015, Chen *et al*. 2016, Xia *et al*. 2017, Wang and Chen 2020), or more particularly hybrid searching optimization algorithms have recently developed. Some of these hybrid techniques such as bacterial foraging optimization, improved ant colony optimization, chaotic moth-flame optimization (Li *et al*. 2018, Xu *et al*. 2019b), grey wolf optimization (Zhao *et al*. 2019), Harris hawks optimization (Zhang *et al*. 2020). Besides, ideas like feature selection (Zhao *et al*. 2015) and adaptive local binary patterns were also largely used by scholars.

Bui *et al*. (2019) examined the efficiency of Whale Optimization Algorithm (WOA) in optimizing the structure of the ANN for approximating the 28-day CSC. Based on the obtained correlation of 0.8976 the suggested ensemble was more accurate in comparison with dragonfly algorithm (0.8209) and ant colony optimization (0.8000). For ground granulated blast furnace slag concrete, particle swarm optimization was used to train an ANN (Han *et al*. 2019). Pham *et al*. (2016) tested firefly algorithm for hybridizing a least-squares SVR in estimating the CSC of high-performance concrete. In a similar study by Cook *et al*. (2019), this algorithm was used to find the optimal values of hyperparameters for a random forest model. Ma *et al*. (2020) used Salp Swarm Algorithm (SSA) for the same subject with ANN. They found it a capable algorithm for analyzing the relationship between the CSC and related factors and water content and coarse aggregate. Likewise, Naseri *et al*. (2019) employed water cycle algorithm and genetic algorithm for modeling the CSC of fly ash concrete in different ages. The results showed the superiority of these techniques over the regression-based approaches (predictions errors of 2.90 and 3.44 vs. 5.47, 9.70 and 5.37). Golafshani *et al*. (2020) found that optimizing the ANN and ANFIS with grey wolf optimizer results in higher accuracy of these predictors. Moreover, they showed the superiority of the ANN-based ensemble.

As the literature denotes, metaheuristic algorithms have shown high robustness in modeling various parameters of concrete (e.g., creep strain (Sadowski *et al*. 2019), slump (Moayedi *et al*. 2019) and punching shear capacity (Vu and Hoang 2016), especially the CSC (Prayogo 2018). It is mostly achieved by coupling these optimizers with regular evaluative models like ANN. Therefore, trying newly-developed algorithms is of high importance toward finding the most proper model. This paper investigates the efficiency of two novel metaheuristic schemes of Shuffled Complex Evolution (SCE) and Teaching-Learning-Based Optimization (TLBO) for optimizing the ANN parameters which reflect the relationship between the CSC and effective factors. The results are also compared to a typically-trained ANN for evaluating the effectiveness of the used algorithms.

Table 1 Descriptive statistics of the compressive strength and key factors

Factor	Minimum	Maximum	Mean	Standard deviation
Compressive strength (MPa)	17.1	58.5	36.0	7.8
Cement (kg/m^3)	137.0	374.0	229.9	78.9
Slag (kg/m^3)	0.0	260.0	149.0	85.4
Water (kg/m^3)	160.0	240.0	197.2	20.2
Fly ash (kg/m^3)	0.0	193.0	78.0	60.5
SP (kg/m^3)	4.4	19.0	8.5	2.8
FA (kg/m^3)	640.6	902.0	739.6	63.3
CA (kg/m^3)	708.0	1049.9	884.0	88.4

2. Methodology and established database

Selecting a proper dataset is an important step in machine learning implementations. For this study, the concrete information collected by Yeh (2007) is used to feed the intelligent models. The dataset contains the results of the slump and 28-day compressive strength tests carried out for 103 concrete specimens. The data can be found on http://archive.ics.uci.edu/ml/datasets/Concrete+Slump+Test. In the present modeling, seven influential parameters of concrete, namely cement, slag, water, fly ash, Superplasticizer (SP), Fine Aggregate (FA) and Coarse Aggregate (CA) play the role of input variables and the CSC is supposed to be predicted (i.e., target variable). Table 1 gives descriptive statistics belonging to each variable. The distribution of the CSC versus each influential factor is also shown in Fig. 1.

For dividing the data into the training and testing phase, the famous ratio of 80:20 is considered. Based on this proportion, the networks first use 82 samples for inferring the relationship between the CSC and input variables. Next, the remaining 21 samples are used as testing data to evaluate the generalization potential of the models under inexperienced conditions.

2.1 Methodology

Shuffled complex evolution: Suggested by Duan *et al*. (1993), the SCE is a well-known search scheme that

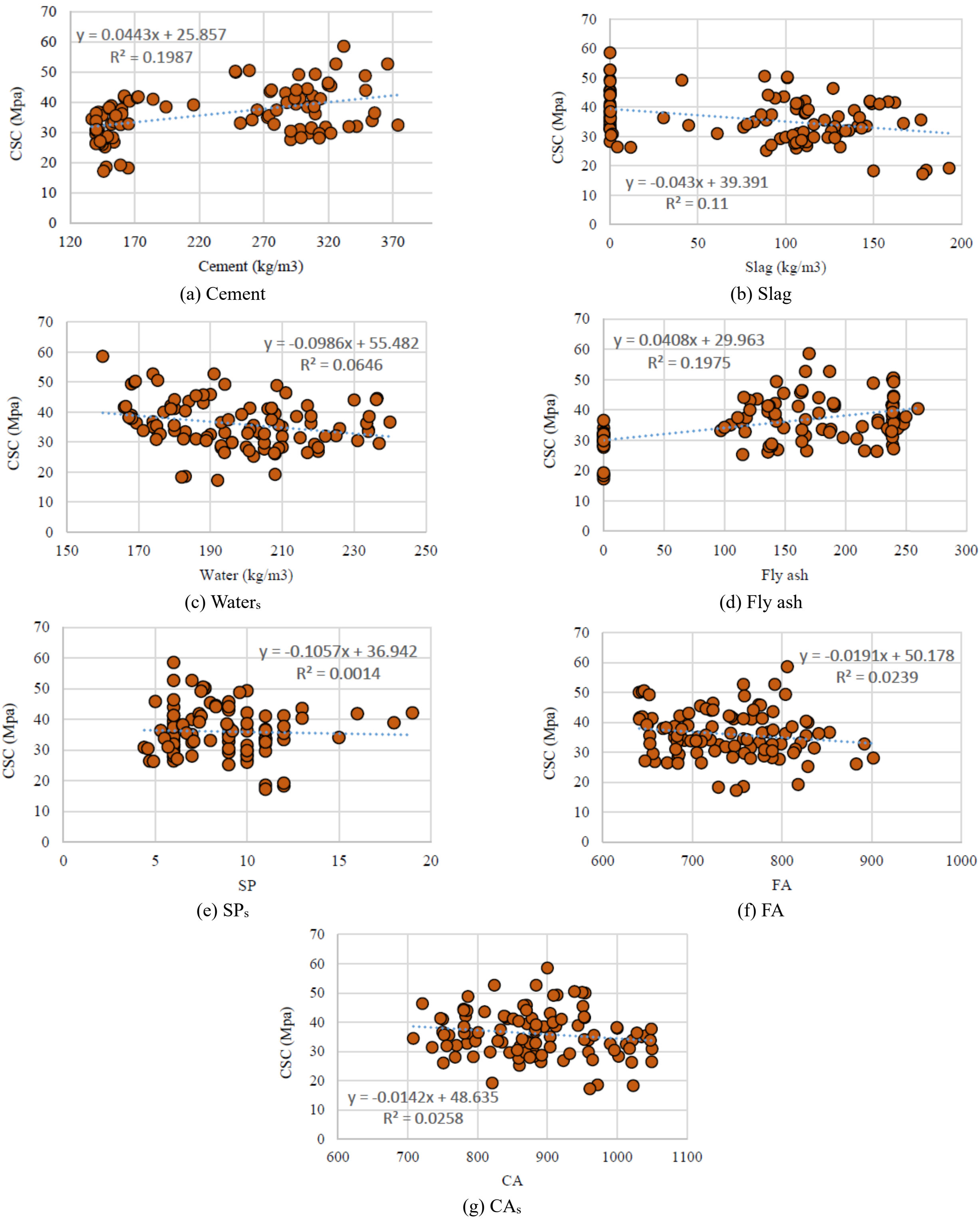

Fig. 1 The graphical description of the CSC influential factors

presents a combination of genetic algorithm, Nelder-Mead simplex technique, complex shuffling and controlled random search (Ira *et al*. 2015). Like other metaheuristic techniques, the SCE serves as population-based methods. The agents move within the problem space to seek a global solution. The population is grouped into units called complex. A so-called strategy “Competitive Complex Evolution (CCE)” is applied to evolve these units. The evolved ones are then combined for creating larger communities which enables the agents to better share the information found so far.

Comprising seven steps, the mechanism of the algorithm can be expressed as below:

a) Initialization: The sample size is calculated by Eq. (1)

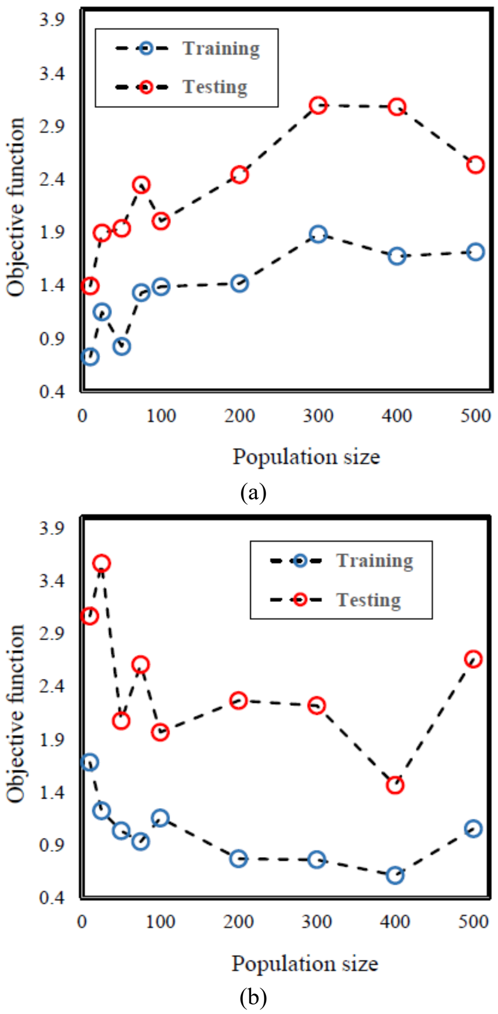

Fig. 2 The sensitivity analysis based on the model complexity of the (a) SCE-MLP; (b) TLBO-MLP

$$s = p \times m \tag{1}$$

where m and p denote the number of points and complexes, respectively. Also, assuming D as the problem dimension, $m \geq D + 1$ and $p \geq 1$.

b) Sample generation: With respect to the lower bound and upper bound, a total of z points (x_1, x_2, …, x_z) are sampled where each one is assigned a Function Value (FV). In other words, z is considered for the Number of Function Evaluations (NFE).

c) Ranking the points: The points are sorted based on the increasing FVs, and eventually, stored in $Q = \{x_i, F_i, i = 1, 2, \ldots, z\}$.

d) Partitioning: The members of this array are then partitioned into n complex units C_1, C_2, …, C_n. Each unit holds p points $C_k = \{x_j^k,\ F_j^k\ |x_j^k = x_{k+n(j-1)},\ F_j^k = F_{k+n(j-1)}, j = 1, 2, \ldots, p\}$.

d) Evolving: This process is carried out based on the CCE method.

e) Shuffling the complexes: C_1, C_2, …, C_n are replaced in Q (i.e., $Q = \{C_k, k = 1, 2, \ldots, n\}$). The sorting procedure is also implemented by taking the increasing FVs into the equation.

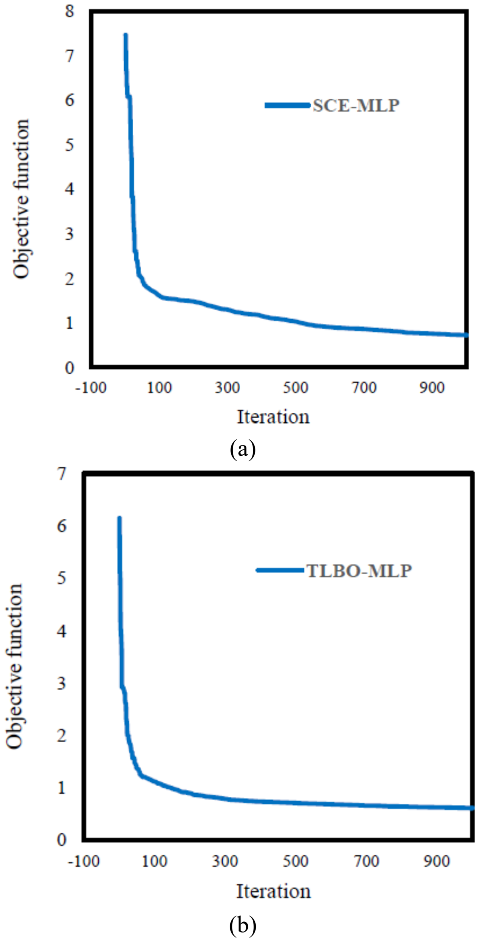

Fig. 3 The convergence curves of the (a) SCE-MLP; (b) TLBO-MLP

f) Checking the convergence: If NFEz > Max_NFEz the algorithm is stopped, otherwise it backs to partitioning.

Teaching-learning-based optimization: By mimicking the educational regulations and the interaction between the teachers and students in a class, the TLBO was presented by Rao *et al.* (2011) in 2011. This algorithm has been effectively used for various optimization tasks (Rao 2016). The students' performance is assessed by artificial exams and it is aimed to maximize the harmony in a class. The optimization potential of the algorithm is influenced by the performance of the teacher in educating the students (Toğan 2012).

Two major stages of the teacher stage and learner stage form the mechanism of the algorithm. In the first one, the teacher tries to improve the average learning efficiency of the pupils. In this regard, the kth student at the kth iteration is defined as follows

$$X_k^t = [X_{k,1}^t,\ X_{k,2}^t, \ldots,\ X_{k,D}^t] \tag{2}$$

where D represents the number of subjects.

The Difference Vector (DV) between the teacher and the average of the population is expressed as follows

$$\mathrm{Diff}-\mathrm{mean}_j^t = (X_{teacher,j}^t - T_F X_{mean,j}^t)\ \mathrm{rand}\ (0, 1) \tag{3}$$

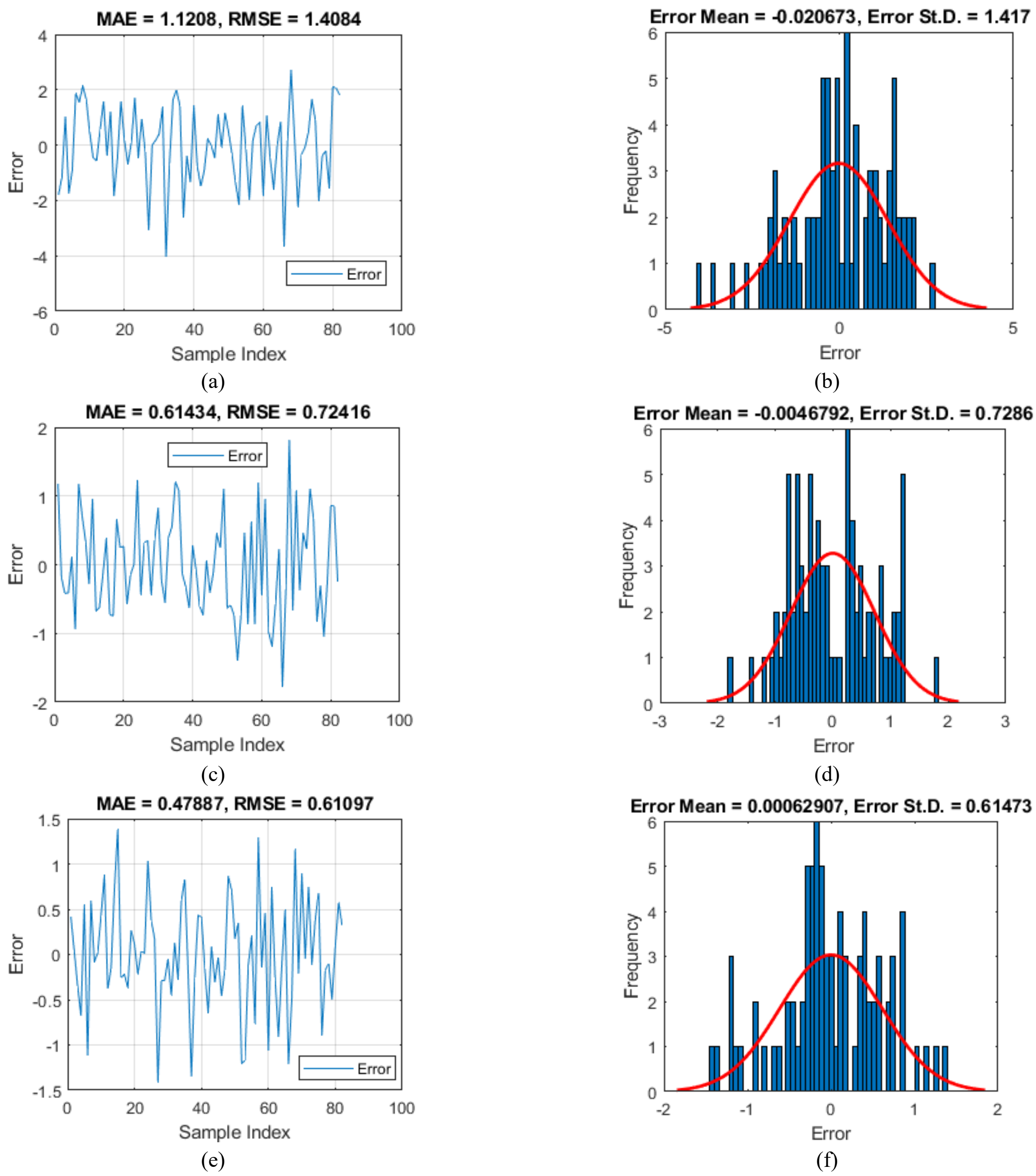

Fig. 4 The results obtained for the training samples by (a), (b) LM-MLP; (c), (d) SCE-MLP; (e), (f) TLBO-MLP

in which 'rand (0, 1)' gives a random value from 0 to 1 and T_F is the teaching factor Also, two terms of $X^t_{teacher,j}$ and $X^t_{mean,j}$ symbolize the j^{th} subject of the teacher and the learners' average, respectively. Next, Eq. (4) is considered for updating the students based on the obtained DV. It is worth noting that for accepting/refusing a new student, his/her fitness needs to be compared to the old ones.

$$\text{new}X^t_{i,j} = X^t_{i,j} + \text{Diff} - \text{mean}^t_j \tag{4}$$

Like reality, students are highly in touch in order to enhance their performance through mutual learning. The partners, however, are randomly assigned. Notably, modifying this relationship is carried out by taking the DV between two individuals into the equation. Assuming X^t_i as the partner of X^t_k member, the learner is updated by the following relationship (Ji *et al*. 2017)

$$\text{new}X^t_{i,j} = \begin{cases} X^t_{i,j} + \left(X^t_{i,j} - X^t_{k,j}\right) rand\ (0,1) & \text{if } f(X^t_i) < f(X^t_k) \\ X^t_{i,j} + \left(X^t_{k,j} - X^t_{i,j}\right) \text{rand}\ (0,1) & \text{otherwise} \end{cases} \tag{5}$$

3. Results and discussion

This paper investigates the capability of two novel optimizers, namely TLBO and SCE for dealing with the CSC prediction problem. These algorithms are applied to an ANN for proper adjustment of computational weights. To achieve this, it is essential to ensure that the best structure

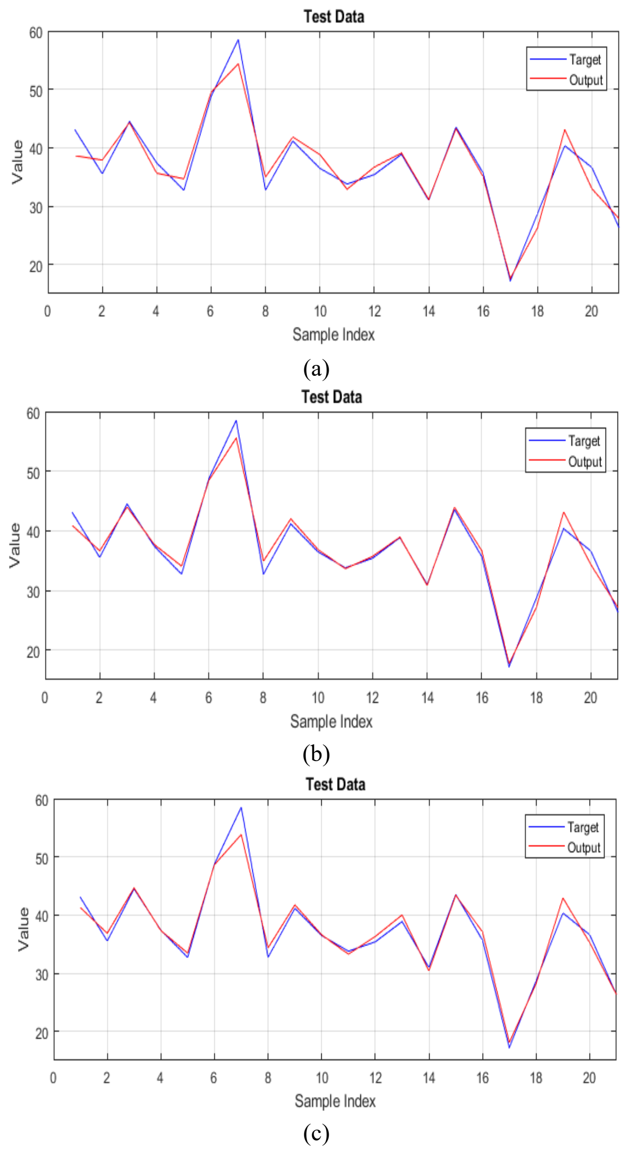

Fig. 5 Comparison between the modeled and expected CSCs for the testing samples of (a) LM-MLP; (b) SCE-MLP; (c) TLBO-MLP

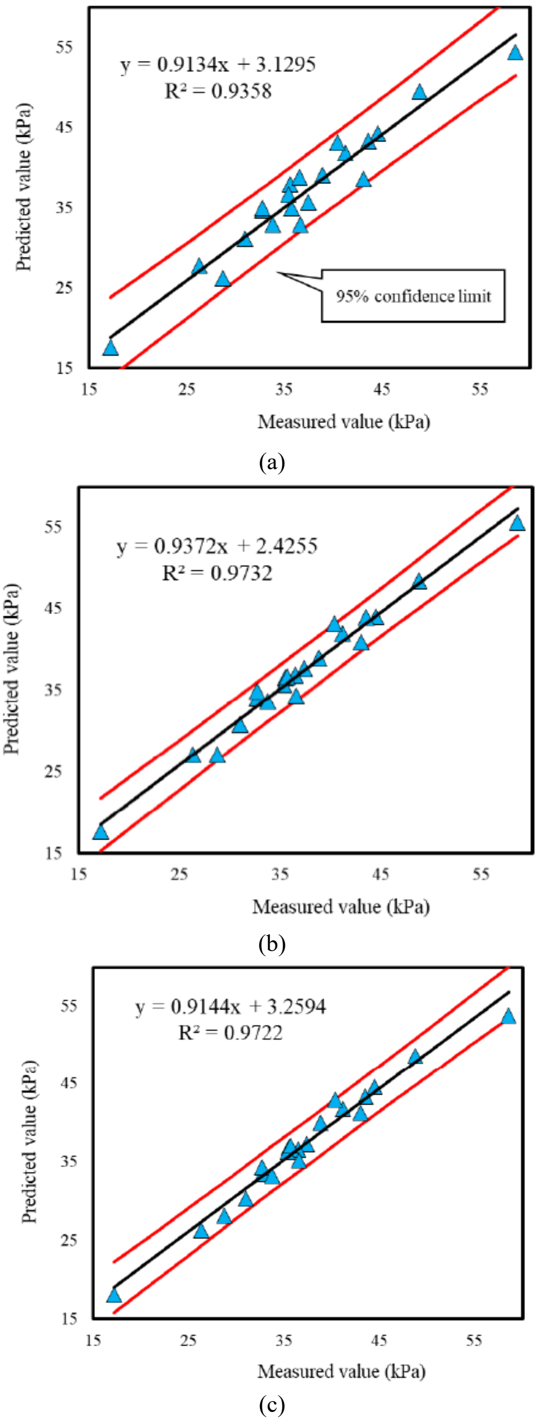

Fig. 6 The correlation of the testing results for the (a) LM-MLP; (b) SCE-MLP; (c) TLBO-MLP

of the ANN is being used. A Multi-Layer Perceptron (MLP) neural network (Hornik *et al*. 1989) represents the ANN in this study. Notably, the MLP is normally trained by the Levenberg-Marquardt (LM) technique (Moré 1978). Considering the number of inputs (7 variables) and output (1 variable), the general structure of the MLP is $7 \times x \times 1$, where x is the number of hidden units that is optimized by a trial and error process. It was shown that $x = 6$ yields the most suitable networks.

3.1 Hybridizing the MLP using metaheuristic techniques

The obtained MLP structure is then given to the CSE and TLBO as the problem function. The variables of this equation were the weights and biases to be adjusted by these optimizers. Based on Eq. (6), Root Mean Square Error (RMSE) is defined to be the objective function.

$$\mathrm{RMSE} = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left[\left(Z_{i_{observed}} - Z_{i_{predicted}}\right)\right]^2} \tag{6}$$

where K is the number of data, $Z_{i\ predicted}$ and $Z_{i\ observed}$ denote the modeled and expected CSCs, respectively.

In implementing the population-based algorithms, determining the appropriate value of population size is an important step. After creating the SCE-MLP and TLBO-

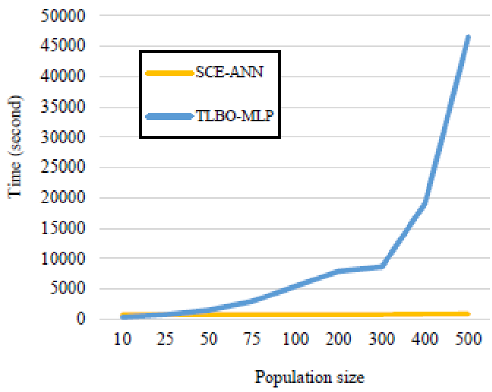

Fig. 7 The computation time required for implementing the proposed ensembles

MLP ensembles, different complexities of these ensembles (nine population sizes of 10, 25, 50, 75, 100, 200, 300, 400 and 500) are tested to achieve the best-optimized models. The results are shown in Figs. 2(a) and (b) for the SCE-MLP and TLBO-MLP, respectively. As is seen, the best-fitted SCE-MLP (RMSE = 0.724158836) is resulted for the population size = 10. Moreover, the number of complexes and offsprings both are selected to be 3. As for the TLBO-MLP, the lowest RMSE is 0.610965805 obtained for the population size = 400. The convergence curves (i.e., the obtained objective functions for 1000 iterations) belonging to these two models are also presented in Fig. 3.

3.2 Accuracy criteria

As was explained in the previous section, the RMSE was used for qualifying the accuracy of different complexities. In addition to that, Mean Absolute Error (MAE) is used as another criterion to measure the performance error of the implemented models. The coefficient of determination (R^2) is also defined for reporting the correlation between the expected and modeled CSCs. Assuming $\bar{Z}_{observed}$ as the average value of the actual CSCs, Eqs. (7) and (8) formulate the MAE and R^2, respectively.

$$MAE = \frac{1}{K}\sum_{I=1}^{K}\left|Z_{i_{observed}} - Z_{i_{predicted}}\right| \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{K}\left(Z_{i_{predicted}} - Z_{i_{observed}}\right)^2}{\sum_{i=1}^{K}\left(Z_{i_{observed}} - \bar{Z}_{i_{observed}}\right)^2} \tag{8}$$

3.3 Accuracy assessment

In this section, the performance of the LM-MLP, SCE-MLP, and TLBO-MLP models is assessed for predicting the CSC from the influential factors. The results are presented for two phases specified to train and test the models.

Fig. 4 depicts the performance of the models training in the training phase. In this figure, the error is defined as the difference between the target and output CSC for each sample. The histogram of the error values is also presented for each model. The RMSE index is obtained 1.4084, 0.7241 and 0.6109, respectively for the LM-MLP, SCE-MLP and TLBO-MLP. The MAEs are also calculated 1.1208, 0.6143 and 0.4788. From evaluating these two indices, it can be derived that the ANNs developed by the SCE and TLBO metaheuristic algorithm can analyze the CSC pattern more accurately than the LM technique. The obtained values of R^2 (i.e., increasing the correlation from 0.9662 to 0.9911 and 0.9936) can support this claim.

As for the testing concrete samples, promising results showed a high level of accuracy for all three tested models. According to the calculated RMSEs (2.1052, 1.3910 and 1.4635), the prediction accuracy of the LM-MLP experienced significant improvements by applying the SCE and TLBO optimizers. The produced CSCs are compared with the expected ones in Fig. 5 As is seen, the hybrid models have performed more successfully in generalizing the CSC pattern.

Moreover, the calculated values of the MAE (1.6716, 1.0576 and 1.0172) indicate that weights and biases suggested by the SCE and TLBO can predict more consistent CSCs for unseen conditions. Also, the correlation values rose from 0.9358 to 0.9732 and 0.9722 by functioning these algorithms. Fig. 6 shows the correlation charts.

3.4 Comparison and neural predictive formula

Apart from the LM-MLP performance, a comparison between the tested hybrid models indicates that the TLBO was more successful in training the ANN (RMSEs of 0.7241 vs. 0.6109). But a discrepancy emerges between the results when the superiority of the SCE-based ensemble is demonstrated in generalizing the CSC pattern. In terms of the RMSE (1.3910 vs. 1.4635) and R^2 (0.9732 vs. 0.9722), the TLBO-MLP presents a slightly more reliable prediction. Regarding the computation time (Fig. 7), there is a considerable distinction between the time required for implementing the hybrid tools. For elite complexities (i.e., the population sizes of 10 and 400 for the SCE-MLP and TLBO, respectively), around 709 and 19123 seconds was needed. It shows that the optimization theory that is based on shuffled complex evolution is more time-effective compared to the that mimics the teaching-learning theory. The faster performance of the SCE versus other metaheuristic algorithms has been observed in earlier studies, too (Zheng *et al.* 2020). Remarkably, the used system operated at 2.5 GHz and 6 Gigs of RAM.

When the results are compared to previous hybrid models, the higher accuracy of the presented models can be clearly deduced. In a study by Ma *et al.* (2020), for example, the combination of ANN and SSA (Mirjalili *et al.* 2017) created a powerful hybrid. The prediction RMSE of this model was 1.6678. In another example, Bui *et al.* (2019) could predict the CSC using a hybrid of WOA (Mirjalili and Lewis 2016) and ANN with the RMSE of 2.6985. Referring to the values of the same index obtained for the SCE-MLP and TLBO-MLP (i.e., 1.3910 and

1.4635), the performance of the proposed models is of greater quality.

Due to the excellent performance of both SCE and TLBO in optimizing the ANN, the neural relationships established by these two algorithms are presented in this section. Eqs. (9) and (10) calculate the CSC for the SCE-MLP and TLBO-MLP predictors. As is seen, utilizing these formulas requires having the value of middle parameters i.e., A, B, …, F and U, V, …, Z. These parameters are calculated from Eqs. (11) and (12). The name Tansig also represents the activation function of the MLP which is expressed by Eq. (13).

$$CSC_{SCE\text{-}MLP} = 0.6469 \times A + 0.3897 \times B - 0.3658 \times C - 0.9004 \times D - 0.9311 \times E - 0.1225 \tag{9}$$

$$CSC_{TLBO\text{-}MLP} = -0.3744 \times U + 0.0645 \times V + 0.0302 \times W - 0.9467 \times X + 0.7433 \times Y - 0.1225 \tag{10}$$

$$\begin{bmatrix} A \\ B \\ C \\ D \\ E \\ F \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} 0.6933 & -0.8866 & -0.7543 & -0.7889 & 0.3431 & 0.5678 & 0.4539 \\ 0.7393 & -0.4036 & 0.8574 & -0.1425 & -0.8459 & 0.4430 & -0.8530 \\ -0.7819 & 0.0983 & 0.9583 & 0.8715 & 0.7319 & -0.2259 & -0.4676 \\ 0.7745 & 0.8572 & -0.0274 & 0.5475 & 0.8131 & 0.2913 & -0.8503 \\ 0.2549 & 0.8951 & 0.5782 & 0.8847 & 0.3442 & -0.6331 & -0.7757 \end{bmatrix} \begin{bmatrix} Cement \\ Slag \\ Water \\ Fly\ ash \\ SP \\ FA \\ CA \end{bmatrix}\right) + \begin{bmatrix} -1.7619 \\ -0.8809 \\ 0.0000 \\ 0.8809 \\ 1.7619 \end{bmatrix}\right) \tag{11}$$

$$\begin{bmatrix} U \\ V \\ W \\ X \\ Y \\ Z \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} -0.7899 & -0.8862 & 0.3601 & 0.7787 & 0.1056 & -0.9594 & 0.1652 \\ -0.3604 & 0.4613 & 0.6753 & -0.5486 & -0.1743 & -0.7016 & -1.2174 \\ 0.5458 & 0.3349 & 0.9382 & -0.7191 & -0.4787 & -0.7514 & 0.7094 \\ 0.9078 & -0.1867 & -0.8181 & 0.4904 & -0.3265 & 0.7351 & -0.8298 \\ -0.4659 & 0.1711 & -0.9686 & 0.8332 & 0.1263 & -0.8768 & -0.6639 \end{bmatrix} \begin{bmatrix} Cement \\ Slag \\ Water \\ Fly\ ash \\ SP \\ FA \\ CA \end{bmatrix}\right) + \begin{bmatrix} -1.7619 \\ -0.8809 \\ 0.0000 \\ 0.8809 \\ 1.7619 \end{bmatrix}\right) \tag{12}$$

$$Tansig\ (x) = \frac{2}{1 + e^{-2x}} - 1 \tag{13}$$

4. Conclusions

This study dealt with two novel optimizations of neural computing, namely shuffled complex evolution and teaching-learning-based optimization used for predicting the concrete compressive strength. The methodologies were applied to real-world data and the results were promising. The complexity of the models was also optimized by conducting a sensitivity analysis. The results first proved that intelligent models, and more particularly, the combination of metaheuristic techniques both metaheuristic algorithms are efficient optimizers for adjusting the ANN parameters. It was derived from increasing the learning accuracy of the ANN from 96.62 to 99.11 and 99.36% by SCE and TLBO, respectively. As for the testing phase, the RMSE experienced 33.93 and 30.48% reduction. Although the TLBO was more successful than SCE in the training phase, the SCE-MLP performed more accurately in the testing phase and also enjoyed far less computation time. Therefore, it can be claimed that both SCE-MLP and TLBO-MLP ensembles are reliable tools for the early prediction of the CSC.

References

Al-Shamiri, A.K., Kim, J.H., Yuan, T.F. and Yoon, Y.S. (2019), "Modeling the compressive strength of high-strength concrete: An extreme learning approach", *Constr. Build. Mater.*, **208**, 204-219. https://doi.org/10.1016/j.conbuildmat.2019.02.165.

Asteris, P.G. and Mokos, V.G. (2019), "Concrete compressive strength using artificial neural networks", *Neural Comput. Appl.*, **2019**, 1-20. https://doi.org/10.1007/s00521-019-04663-2.

Bui, D.T., Ghareh, S., Moayedi, H. and Nguyen, H. (2019), "Fine-tuning of neural computing using whale optimization algorithm for predicting compressive strength of concrete", *Eng. Comput.*, **2019**, 1-12. 10.1007/s00366-019-00850-w.

Chao, L., Zhang, K., Li, Z., Zhu, Y., Wang, J. and Yu, Z. (2018), "Geographically weighted regression based methods for merging satellite and gauge precipitation", *J. Hydrol.*, **558**, 275-289. https://doi.org/10.1016/j.jhydrol.2018.01.042.

Chen, H.L., Wang, G., Ma, C., Cai, Z.N., Liu, W.B. and Wang, S.J. (2016), "An efficient hybrid kernel extreme learning machine approach for early diagnosis of Parkinson's disease", *Neurocomput.*, **184**, 131-144. https://doi.org/10.1016/j.neucom.2015.07.138.

Chen, H., Heidari, A.A., Chen, H., Wang, M., Pan, Z. and Gandomi, A.H. (2020), "Multi-population differential evolution-assisted Harris hawks optimization: Framework and case studies", *Future Gener. Comput. Syst.*, **111**, 175-198. https://doi.org/10.1016/j.future.2020.04.008.

Cook, R., Lapeyre, J., Ma, H. and Kumar, A. (2019), "Prediction of compressive strength of concrete: Critical comparison of performance of a hybrid machine learning model with standalone models", *J. Mater. Civ. Eng.*, **31**(11), 04019255.

https://doi.org/10.1061/(ASCE)MT.1943-5533.0002902.

Dao, D.V., Adeli, H., Ly, H.B., Le, L.M., Le, V.M., Le, T.T. and Pham, B.T. (2020), "A sensitivity and robustness analysis of GPR and ANN for high-performance concrete compressive strength prediction using a Monte Carlo simulation", *Sustainability*, **12**(3), 830. 10.3390/su12030830. https://doi.org/10.3390/su12030830.

Dong, Q., Cui, L. and Si, S. (2020), "Reliability and availability analysis of stochastic degradation systems based on bivariate Wiener processes", *Appl. Math. Model.*, **79**, 414-433. https://doi.org/10.1016/j.apm.2019.10.044.

Duan, Q., Gupta, V.K. and Sorooshian, S. (1993), "Shuffled complex evolution approach for effective and efficient global minimization", *J. Optim. Theory Appl.*, **76**(3), 501-521. https://doi.org/10.1007/BF00939380.

Dutta, D. and Barai, S.V. (2019), *Recent Advances in Structural Engineering*, Springer, USA.

Felix, E.F., Possan, E. and Carrazedo, R. (2019), "Analysis of training parameters in the ANN learning process to mapping the concrete carbonation depth", *J. Build. Pathol. Rehab.*, **4**(1), 16. https://doi.org/10.1007/s41024-019-0054-8.

Feng, D.C., Liu, Z.T., Wang, X.D., Chen, Y., Chang, J.Q., Wei, D.F. and Jiang, Z.M. (2020), "Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach", *Constr. Build. Mater.*, **230**, 117000. https://doi.org/10.1016/j.conbuildmat.2019.117000.

Golafshani, E.M., Behnood, A. and Arashpour, M. (2020), "Predicting the compressive strength of normal and high-performance concretes using ANN and ANFIS hybridized with grey wolf optimizer", *Constr. Build. Mater.*, **232**, 117266. https://doi.org/10.1016/j.conbuildmat.2019.117266.

Guan, Z., Xing, Q., Xu, M., Yang, R., Liu, T. and Wang, Z. (2019), "MFQE 2.0: A new approach for multi-frame quality enhancement on compressed video", *IEEE Trans. Pattern Anal. Mach. Intell.*, **2019**, 1902. https://doi.org/10.1109/TPAMI.2019.2944806.

Han, I.J., Yuan, T.F., Lee, J.Y., Yoon, Y.S. and Kim, J.H. (2019), "Learned prediction of compressive strength of GGBFS concrete using hybrid artificial neural network models", *Materials*, **12**(22), 3708. https://doi.org/10.3390/ma12223708.

Hornik, K., Stinchcombe, M. and White, H. (1989), "Multilayer feedforward networks are universal approximators", *Neural Netw.*, **2**(5), 359-366.

Hu, L., Hong, G., Ma, J., Wang, X. and Chen, H. (2015), "An efficient machine learning approach for diagnosis of paraquat-poisoned patients", *Comput. Biol. Med.*, **59**, 116-124. https://doi.org/10.1016/j.compbiomed.2015.02.003.

Hu, P., Cao, L., Su, J., Li, Q. and Li, Y. (2020), "Distribution characteristics of salt-out particles in steam turbine stage", *Energy*, **192**, 116626. https://doi.org/10.1016/j.energy.2019.116626.

Ira, J., Hasalová, L. and Jahoda, M. (2015), "The use of optimization in fire development modeling, the use of optimization techniques for estimation of pyrolysis model input parameters", *Proceedings of the International Conference*, Prague, Czech, April.

Ji, X., Ye, H., Zhou, J., Yin, Y. and Shen, X. (2017), "An improved teaching-learning-based optimization algorithm and its application to a combinatorial optimization problem in foundry industry", *Appl. Soft Comput.*, **57**, 504-516. https://doi.org/10.1016/j.asoc.2017.04.029.

Jiang, Q., Shao, F., Gao, W., Chen, Z., Jiang, G. and Ho, Y. (2019), "Unified no-reference quality assessment of singly and multiply distorted stereoscopic images", *IEEE Trans. Image Process.*, **28**(4), 1866-1881. https://doi.org/10.1109/TIP.2018.2881828.

Lei, Z., Hao, S., Yang, J. and Dan, X. (2020), "Study on solid waste pyrolysis coke catalyst for catalytic cracking of coal tar", *Int. J. Hydro, Energy.*, **45**(38), 19280-19290. https://doi.org/10.1016/j.ijhydene.2020.05.075.

Li, C., Hou, L., Sharma, B.Y., Li, H., Chen, C., Li, Y., Zhao, X., Huang, H., Cai, Z. and Chen, H. (2018), "Developing a new intelligent system for the diagnosis of tuberculous pleural effusion", *Comput. Methods Programs Biomed.*, **153**, 211-225. https://doi.org/10.1016/j.cmpb.2017.10.022.

Li, T., Xu, M., Zhu, C., Yang, R., Wang, Z. and Guan, Z. (2019), "A deep learning approach for multi-frame in-loop filter of HEVC", *IEEE Trans. Image Process.*, **28**(11), 5663-5678. https://doi.org/10.1109/TIP.2019.2921877.

Li, Z., Zhou, H., Hu, D. and Zhang, C. (2020), "Yield criterion for rocklike geomaterials based on strain energy and CMP model", *Int. J. Geomech.*, **20**(3), 04020013. https://doi.org/10.1061/(ASCE)GM.1943-5622.0001593.

Ling, H., Qian, C., Kang, W., Liang, C. and Chen, H. (2019), "Combination of support vector machine and K-fold cross validation to predict compressive strength of concrete in marine environment", *Constr. Build. Mater.*, **206**, 355-363. https://doi.org/10.1016/j.conbuildmat.2019.02.071.

Liu, S., Chan, F.T. and Ran, W. (2016), "Decision making for the selection of cloud vendor: An improved approach under group decision-making with integrated weights and objective/ subjective attributes", *Exp. Syst. Appl.*, **55**, 37-47. https://doi.org/10.1016/j.eswa.2016.01.059.

Liu, C., Deng, X., Liu, J., Peng, T., Yang, S. and Zheng, Z. (2020a), "Dynamic response of saddle membrane structure under hail impact", *Eng. Struct.*, **214**, 110597. https://doi.org/10.1016/j.engstruct.2020.110597.

Liu, C., Wang, F., Deng, X., Pang, S., Liu, J., Wu, Y. and Xu, Z. (2020b), "Hailstone-induced dynamic responses of pretensioned umbrella membrane structure", *Adv. Struct. Eng.*, 1369433220940149. https://doi.org/10.1177/1369433220940149.

Liu, C., Wang, F., He, L., Deng, X., Liu, J. and Wu, Y. (2020c), "Experimental and numerical investigation on dynamic responses of the umbrella membrane structure excited by heavy rainfall", *J. Vib. Control*, **2020**, 1077546320932691. https://doi.org/10.1177/1077546320932691.

Lu, H., Kang, Y., Liu, L. and Li, J. (2019a), "Comprehensive groundwater safety assessment under potential shale gas contamination based on integrated analysis of reliability-resilience-vulnerability and gas migration index", *J. Hydrol.*, **578**, 124072. https://doi.org/10.1016/j.jhydrol.2019.124072.

Lu, H., Tian, P. and He, L. (2019b), "Evaluating the global potential of aquifer thermal energy storage and determining the potential worldwide hotspots driven by socio-economic, geo-hydrologic and climatic conditions", *Renew. Sustain. Energy Rev.*, **112**, 788-796. https://doi.org/10.1016/j.rser.2019.06.013.

Lv, Z., Li, X., Lv, H. and Xiu, W. (2020), "BIM big data storage in WebVRGIS", *IEEE Trans. Ind. Inf.*, **16**(4), 2566-2573. https://doi.org/10.1109/TII.2019.2916689.

Ma, X., Foong, L.K., Morasaei, A., Ghabussi, A. and Lyu, Z. (2020), "Swarm-based hybridizations of neural network for predicting the concrete strength", *Smart Struct. Syst., Int. J.*, **26**(2), 241-251. https://doi.org/10.12989/sss.2020.26.2.241.

Mirjalili, S. and Lewis, A. (2016), "The whale optimization algorithm", *Adv. Eng. Softw.*, **95**, 51-67.

Mirjalili, S., Gandomi, A.H., Mirjalili, S.Z., Saremi, S., Faris, H. and Mirjalili, S.M. (2017), "Salp swarm algorithm: A bio-inspired optimizer for engineering design problems", *Adv. Eng. Softw.*, **114**, 163-191. https://doi.org/10.1016/j.advengsoft.2017.07.002.

Moayedi, H., Nguyen, H. and Safuan, A.R.A. (2019), "Novel metaheuristic classification approach in developing mathematical model-based solutions predicting failure in shallow footing", *Eng. Comput.*, **36**, 1-8.

https://doi.org/10.1007/s00366-019-00819-9.

Moré, J.J. (1978), *Numerical Analysis*, Springer, USA.

Naseri, H., Jahanbakhsh, H. and Moghadas Nejad, F. (2019), "Developing a novel machine learning method to predict the compressive strength of fly ash concrete in different ages", *AUT J. Civ. Eng.*, **2019**, 16124. https://doi.org/10.22060/AJCE.2019.16124.5569.

Ni, T., Xu, Q., Huang, Z., Liang, H., Yan, A. and Wen, X. (2020), "A cost-effective TSV repair architecture for clustered faults in 3D IC", *IEEE Trans. Comput. Aided Des. Integr. Circuits Syst.*, **1**, 1. https://doi.org/10.1109/TCAD.2020.3025169.

Onat, O. and Gul, M. (2018), "Application of Artificial Neural Networks to the prediction of out-of-plane response of infill walls subjected to shake table". *Smart Struct. Syst., Int. J.*, **21**(4), 521-535. https://doi.org/10.12989/sss.2018.21.4.521.

Pham, A.D., Hoang, N.D. and Nguyen, Q.T. (2016), "Predicting compressive strength of high-performance concrete using metaheuristic-optimized least squares support vector regression", *J. Comput. Civ. Eng.*, **30**(3), 06015002. https://doi.org/10.1061/%28ASCE%29CP.1943-5487.0000506.

Prayogo, D. (2018), "Metaheuristic-based machine learning system for prediction of compressive strength based on concrete mixture properties and early-age strength test results", *Civ. Eng. Dimen.*, **20**(1), 21-29. https://doi.org/10.9744/ced.20.1.21-29.

Qiu, C., Gong, S. and Gao, W. (2019), "Three artificial intelligence-based solutions predicting concrete slump", *UPB Sci. Bull. Series C*, **81**(4), 2019.

Rao, R. (2016), "Review of applications of TLBO algorithm and a tutorial for beginners to solve the unconstrained and constrained optimization problems", *Dec. Sci. Lett.*, **5**(1), 1-30. https://doi.org/10.5267/j.dsl.2015.9.003.

Rao, R.V., Savsani, V.J. and Vakharia, D. (2011), "Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems", *Comput. Aided Des.*, **43**(3), 303-315. https://doi.org/10.1016/j.cad.2010.12.015.

Sadowski, Ł., Nikoo, M., Shariq, M., Joker, E. and Czarnecki, S. (2019), "The nature-inspired metaheuristic method for predicting the creep strain of green concrete containing ground granulated blast furnace slag", *Materials*, **12**(2), 293. https://doi.org/10.3390/ma12020293.

Sai, G.J. and Singh, V.P. (2019), "Prediction of compressive strength using support vector regression", *Mendel*, **2019**, 51-56. https://doi.org/10.13164/mendel.2019.1.051.

Saldarriaga, M.V., Mahfoud, J., Steffen, V. and Hagopian, J.D. (2009), "Adaptive balancing of highly flexible rotors by using artificial neural networks". *Smart Struct. Syst., Int. J.*, **5**(5), 507-515. https://doi.org/10.12989/sss.2009.5.5.507.

Shahbazi, Y., Delavari, E. and Chenaghlou, M.R. (2014), "Predicting the buckling load of smart multilayer columns using soft computing tools", *Smart Struct. Syst., Int. J.*, **13**(1), 81-98. https://doi.org/10.12989/sss.2013.13.1.081.

Shariati, M., Mafipour, M.S., Mehrabi, P., Ahmadi, M., Wakil, K, Trung, N.T. and Toghroli, A. (2020), "Prediction of concrete strength in presence of furnace slag and fly ash using Hybrid ANN-GA (Artificial neural network-genetic algorithm)", *Smart Struct. Syst., Int. J.*, **25**(2), 183-195. https://doi.org/10.12989/sss.2020.25.2.183.

Shen, C.Q., Wang, D., Liu, Y.B., Kong, F.R. and Tse, P.W. (2014), "Recognition of rolling bearing fault patterns and sizes based on two-layer support vector regression machines", *Smart Struct. Syst., Int. J.*, **13**(3), 453-471. https://doi.org/10.12989/sss.2014.13.3.453.

Shen, L., Chen, H., Yu, Z., Kang, W., Zhang, B., Li, H., Yang, B. and Liu, D. (2016), "Evolving support vector machines using fruit fly optimization for medical data classification", *Knowl. Based Syst.*, **96**, 61-75. https://doi.org/10.1016/j.knosys.2016.01.002.

Song, J., Zhong, Q., Wang, W., Su, C., Tan, Z. and Liu, Y. (2020), "FPDP: Flexible privacy-preserving data publishing scheme for smart agriculture", *IEEE Sensors J.*, **1**, 1. https://doi.org/10.1109/JSEN.2020.3017695.

Toğan, V. (2012), "Design of planar steel frames using teaching-learning based optimization", *Eng. Struct.*, **34**, 225-232. https://doi.org/10.1016/j.engstruct.2011.08.035.

Trung, N.T., Alemi, N., Haido, J..H, Shariati, M., Baradaran, S. and Yousif, S.T. (2019), "Reduction of cement consumption by producing smart green concretes with natural zeolites", *Smart Struct. Syst., Int. J.*, **24**(3), 415-425. https://doi.org/10.12989/sss.2019.24.3.415.

Tsai, Y.H., Wang, J., Chien, W.T., Wei, C.Y., Wang, X. and Hsieh, S.H. (2019), "A BIM-based approach for predicting corrosion under insulation", *Auto. Constr.*, **107**, 102923. https://doi.org/10.1016/j.autcon.2019.102923.

Vu, D.T. and Hoang, N.D. (2016), "Punching shear capacity estimation of FRP-reinforced concrete slabs using a hybrid machine learning approach", *Struct. Infrastruct. Eng.*, **12**(9), 1153-1161. https://doi.org/10.1080/15732479.2015.1086386.

Wang, M. and Chen, H. (2020), "Chaotic multi-swarm whale optimizer boosted support vector machine for medical diagnosis", *Appl. Soft Comput. J.*, **88**, 105946. https://doi.org/10.1016/j.asoc.2019.105946.

Wang, S.J., Chen, H.L., Yan, W.J., Chen, Y.H. and Fu, X. (2014), "Face recognition and micro-expression recognition based on discriminant tensor subspace analysis plus extreme learning machine", *Neural Process. Lett.*, **39**(1), 25-43. https://doi.org/10.1007/s11063-013-9288-7.

Wang, M., Chen, H., Yang, B., Zhao, X., Hu, L., Cai, Z., Huang, H. and Tong, C. (2017), "Toward an optimal kernel extreme learning machine using a chaotic moth-flame optimization strategy with applications in medical diagnoses", *Neurocomputing*, **267**, 69-84. https://doi.org/10.1016/j.neucom.2017.04.060.

Wu, C., Wang, X., Chen, M. and Kim, M.J. (2019), "Differential received signal strength based RFID positioning for construction equipment tracking", *Adv. Eng. Inf.*, **42**, 100960. https://doi.org/10.1016/j.aei.2019.100960.

Xia, J., Chen, H., Li, Q., Zhou, M., Chen, L., Cai, Z., Fang, Y. and Zhou, H. (2017), "Ultrasound-based differentiation of malignant and benign thyroid nodules: An extreme learning machine approach", *Comput. Methods Programs Biomed.*, **147**, 37-49. https://doi.org/10.1016/j.cmpb.2017.06.005.

Xu, X. and Chen, H.L. (2014), "Adaptive computational chemotaxis based on field in bacterial foraging optimization", *Soft Comput.*, **18**(4), 797-807. https://doi.org/10.1007/s00500-013-1089-4.

Xu, M., Li, T., Wang, Z., Deng, X., Yang, R. and Guan, Z. (2018), "Reducing complexity of HEVC: A deep learning approach", *IEEE Trans. Image Process.*, **27**(10), 5044-5059. https://doi.org/10.1109/TIP.2018.2847035.

Xu, M., Li, C., Chen, Z., Wang, Z. and Guan, Z. (2019a), "Assessing visual quality of omnidirectional videos", *IEEE Trans. Circuits Syst. Video Technol.*, **29**(12), 3516-3530. https://doi.org/10.1109/TCSVT.2018.2886277.

Xu, Y., Chen, H., Luo, J., Zhang, Q., Jiao, S. and Zhang, X. (2019b), "Enhanced moth-flame optimizer with mutation strategy for global optimization", *Inf. Sci.*, **492**, 181-203. https://doi.org/10.1016/j.ins.2019.04.022.

Xu, M., Li, C., Zhang, S. and Callet, P.L. (2020), "State-of-the-art in 360° video/image processing: Perception, assessment and compression", *IEEE J. Select. Topics Signal Process.*, **14**(1), 5-26. https://doi.org/10.1109/JSTSP.2020.2966864.

Yang, R., Xu, M., Liu, T., Wang, Z. and Guan, Z. (2019), "Enhancing quality for HEVC compressed videos", *IEEE Trans. Circuits Syst. Video Technol.*, **29**(7), 2039-2054.

https://doi.org/10.1109/TCSVT.2018.2867568.
Yang, Y., Liu, J., Yao, J., Kou, J., Li, Z., Wu, T., Zhang, K., Zhang, L. and Sunm, H. (2020), "Adsorption behaviors of shale oil in kerogen slit by molecular simulation", *Chem. Eng. J.*, **387**, 124054. https://doi.org/10.1016/j.cej.2020.124054.
Yeh, I.C. (2007), "Modeling slump flow of concrete using second-order regressions and artificial neural networks", *Cement Concrete Compos.*, **29**(6), 474-480. https://doi.org/10.1016/j.cemconcomp.2007.02.001.
Yi, T.H., Li, H.N. and Sun, H.M. (2013), "Multi-stage structural damage diagnosis method based on energy-damage theory", *Smart Struct. Syst., Int. J.*, **12**(3-4), 345-361. https://doi.org/10.12989/sss.2013.12.3_4.345.
Zhang, K., Wang, Q., Chao, L., Ye, J., Li, Z., Yu, Z., Yang, T. and Ju, Q. (2019), "Ground observation-based analysis of soil moisture spatiotemporal variability across a humid to semi-humid transitional zone in China", *J. Hydrol.*, **574**, 903-914. https://doi.org/10.1016/j.jhydrol.2019.04.087.
Zhang, Y., Liu, R., Wang, X., Chen, H. and Li, C. (2020), "Boosted binary Harris hawks optimizer and feature selection"., *Eng. Comput.*, **2020**, 1-13. https://doi.org/10.1007/s00366-020-01028-5.
Zhao, X., Li, D., Yang, B., Ma, C., Zhu, Y. and Chen, H. (2014), "Feature selection based on improved ant colony optimization for online detection of foreign fiber in cotton", *Appl. Soft Comput.*, **24**, 585-596. https://doi.org/10.1016/j.asoc.2014.07.024.
Zhao, X., Li, D., Yang, B., Chen, H., Yang, X., Yu, C. and Liu, S. (2015), "A two-stage feature selection method with its application", *Comput. Elec. Eng.*, **47**, 114-125. https://doi.org/10.1016/j.compeleceng.2015.08.011.
Zhao, X., Zhang, X., Cai, Z., Tian, X., Wang, X., Huang, Y., Chen, H. and Hu, L. (2019), "Chaos enhanced grey wolf optimization wrapped ELM for diagnosis of paraquat-poisoned patients", *Comput. Biol. Chem.*, **78**, 481-490. https://doi.org/10.1016/j.compbiolchem.2018.11.017.
Zheng, S., Lyu, Z. and Foong, L.K. (2020), "Early prediction of cooling load in energy-efficient buildings through novel optimizer of shuffled complex evolution", *Eng. Comput.*, **2020**, 1-15. https://doi.org/10.1007/s00366-020-01140-6.
Zhu, J., Wang, X., Chen, M., Wu, P. and Kim, M.J. (2019), "Integration of BIM and GIS: IFC geometry transformation to shapefile using enhanced open-source approach", *Auto. Constr.*, **106**, 102859. https://doi.org/10.1016/j.autcon.2019.102859.
Zuo, C., Chen, Q., Tian, L., Waller, L. and Asundi, A. (2015), "Transport of intensity phase retrieval and computational imaging for partially coherent fields: The phase space perspective", *Opt. Lasers Eng.*, **71**, 20-32. https://doi.org/10.1016/j.optlaseng.2015.03.006.
Zuo, C., Sun, J., Li, J., Asundi, A. and Chen, Q. (2020), "Wide-field high-resolution 3d microscopy with fourier ptychographic diffraction tomography", *Opt. Lasers Eng.*, **128**, 106003. https://doi.org/10.1016/j.optlaseng.2020.106003.

CC