**Smart Structures and Systems**, *Vol. 27, No. 5 (2021) 745-759*
DOI: https://doi.org/10.12989/sss.2021.27.5.745

# Efficient metaheuristic-retrofitted techniques for concrete slump simulation

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(*Received August 28, 2020, Revised October 28, 2020, Accepted January 2, 2021*)

**Abstract.** Due to the benefits of the early prediction of concrete slump, introducing an efficient model for this purpose is of great importance. Considering this motivation, four strong metaheuristic algorithms, namely electromagnetic field optimization (EFO), water cycle algorithm (WCA), teaching-learning-based optimization (TLBO), and multi-tracker optimization algorithm (MTOA) are used to supervise a neural predictive system in analyzing the slump pattern. This supervision protects the network against computational issues like pre-mature convergence. The overall results (e.g., Pearson correlation indicator larger than 0.839 and 0.807 for the training and testing data, respectively) revealed the competency of the proposed models. However, investigating the rankings of the models pointed out the superiority of the WCA ($MAE_{train}$ = 3.3080 vs. 3.7821, 3.5782, and 3.6851; and $MAE_{test}$ = 3.8443 vs. 4.0326, 4.1417, and 4.0871 obtained for the EFO, TLBO, and MTOA, respectively). Moreover, the high efficiency of the EFO in terms of model complexity and convergence rate, as well as the adequate accuracy of prediction, demonstrated the suitability of the corresponding ensemble. Therefore, the neural systems trained by these two algorithms (i.e., the WCA and EFO) are efficient slump evaluative models and can give an optimal design of the concrete mixture for any desirable slump.

**Keywords:** concrete; slump modeling; neural system; optimization strategies

## 1. Introduction

Accurate estimation of the concrete parameters like compressive strength (CS) results in a more effective design of this material through reducing the time and cost (Mou *et al.* 2019c, Bao *et al.* 2020). Requiring a low level of energy consumption and being environmentally-friendly (i.e., having the lowest possible pollution) are two important factors that should be considered for designing a mixture for constructing concrete elements (Saha and Rajasekaran 2016). During recent years, machine learning theory has experienced huge success in predicting the parameters of various concrete types. Meesaraganda *et al.* (2020) attained a reliable prediction of the CS of HPC using a hybrid of ANN and fuzzy logic called ANFIS. Their used dataset comprised fine and coarse aggregate, age, water binder ratio, silica fumes, and superplasticizer. Similarly, Vakhshouri and Nejadi (2018) used ANFIS for estimating the CS of self-compacting concrete by considering the effect of slump flow and mixture proportions. Azimi-Pour *et al.* (2020) employed linear and non-linear support vector machines (SVMs) for modeling the CS and fresh properties of high-volume fly ash self-compacting concrete. After testing different kernel functions, they found radial basis performs more accurately in comparison with linear, sigmoid, and polynomial. For slump results, for instance, the coefficient of determination ($R^2$) was 0.5762, 0.8099, 0.9104, and 0.8847 for linear, polynomial, radial bases, and sigmoid, respectively. Continuing with the application of the artificial intelligence-based techniques have shown a high accuracy for undertaking non-linear and complex calculations (Liu *et al.* 2014, 2015, Piotrowski *et al.* 2014). For example, different studies are conducted in the field of environmental concerns (He *et al.* 2018b, c, Liu *et al.* 2018, 2020b, c, Feng *et al.* 2020a, Fu *et al.* 2020a, Han *et al.* 2020, Yang *et al.* 2020d), sustainability (Hu *et al.* 2019), pan evaporation and soil precipitation prediction (Zhang *et al.* 2016, Chao *et al.* 2018, Ghaemi *et al.* 2019, Keshtegar *et al.* 2019, Kisi and Heddam 2019, Roy *et al.* 2020), optimizing energy systems (Chen *et al.* 2017, He *et al.* 2018a, Deng *et al.* 2019, Lu *et al.* 2019, Zhang *et al.* 2019, Wang *et al.* 2020b, Yang *et al.* 2020c, Zhang 2020, Zhu *et al.* 2020b), natural gas consumption (Liu *et al.* 2019, Lu *et al.* 2019, Su *et al.* 2019), water and groundwater supply chains (Yang and Sowmya 2015, Cheng *et al.* 2016, Chen *et al.* 2018, Lyu *et al.* 2019, Feng *et al.* 2020b, He *et al.* 2020, Jia *et al.* 2020, Li *et al.* 2020a, Quan *et al.* 2020, Yang *et al.* 2020c, Chen *et al.* 2021), quantifying climatic contributions (Zhang *et al.* 2020b), measurement techniques (Zhang *et al.* 2006, Qian *et al.* 2020a, b, Yang *et al.* 2020b), signal processing as well as feature selection and extraction

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http://www.techno-press.org/?journal=sss&subpage=7

ISSN: 1738-1584 (Print), 1738-1991 (Online)

problems (Zhao *et al*. 2015, Zhang and Liu 2019, Abedini and Zhang 2020, Xiong *et al*. 2020b, Yue *et al*. 2020, Zhang *et al*. 2020a, Zhu *et al*. 2020a) building and structural design analysis (Mou *et al*. 2019a, Abedini *et al*. 2020, Sun *et al*. 2020, Yu *et al*. 2020, Zhang and Wang 2020), structural material (e.g., steel and concrete) behaviors (Mou *et al*. 2019c, Abedini and Zhang 2020, Gholipour *et al*. 2020, Zhang *et al*. 2020a), or even some complex concerns such as image classification and processing, target tracking and computer vision (Liu *et al*. 2016a, Zenggang *et al*. 2019, Chao *et al*. 2020, Lei *et al*. 2020, Xu *et al*. 2020b, Yan *et al*. 2020, Zhang *et al*. 2020c, Zhu 2020). There have been many decision-making applications works related to engineering complex problems as well (Liu *et al*. 2016b, 2020a, Tian *et al*. 2020). A neural network is known as a series of complex algorithms that helps to recognize underlying connections in a set of data input and outputs through a process that mimics the way the human brain operates (Yang and Chen 2019, Cao *et al*. 2020a, Shi *et al*. 2020a, b, Yang *et al*. 2020a). In another sense, the technique of artificial neural network (ANN) is a sophisticated nonlinear processor that has attracted massive attention for sensitive engineering modeling (Adeli 2001). This model is represented by different notions. Most importantly, a multi-layer perceptron (MLP) (Hornik *et al*. 1989, Lv and Qiao 2020) is composed of a minimum of three layers, each of which contains some neurons for handling the computations—noting that a more complicated ANN-based solution is known as deep learning where it refers as part of a broader family of machine learning methods based on ANN with representation learning (Xu *et al*. 2018, Mou *et al*. 2019c, Qiu *et al*. 2019, Chen *et al*. 2020a, Zhang *et al*. 2020d). For instance, Chen *et al*. (2016), Zhao *et al*. (2015), Wang *et al*. (2014), and Xia *et al*. (2017) employed the use of extreme machine learning techniques on the field of medical sciences.

Moreover, artificial neural network (ANN) has efficiently served in dealing with simulations of complex engineering problems (Liu *et al*. 2015, Xu *et al*. 2018, Li *et al*. 2019), such as concrete parameters, specially slump (Yeh 2008). Abellán García *et al*. (2020) used the ANN as an efficient approach for estimating the CS and slump flow of ultra HPC in different curing ages (i.e., 1, 7, and 28 days). This network was also used by Shahmansouri *et al*. (2020) for approximating the CS of eco-friendly geopolymer concrete incorporated with silica fume and natural zeolite. Unlu (2020) examined the feasibility of four popular machine learning models, namely support vector regression, random forest, M5P trees, and MLPReg for slump flow simulation of HPC. It was shown that the optimum configuration of the latest model yields the best results. Behforouz *et al*. (2020) compared regression and ANN techniques for simulating durability and mechanical characteristics of HPC containing waste ceramic powder. In addition to the suitability of the ANN, they found that the performance of the ANN in durability analysis is not highly dependent on the number of hidden nodes. The superiority of the ANN over response surface methodology for the CS prediction of recycled concrete aggregates was proved by Hammoudi *et al*. (2019). Other applications of ANN in related fields can be found in studies like (Douma *et al*. 2017, Yaman *et al*. 2017, Amlashi *et al*. 2019, Nguyen *et al*. 2020). Application of complex mathematical solutions in solving engineering problems have been always a main concern of scholars in different field (Singh *et al*. 2011, Long *et al*. 2015, Pang *et al*. 2018, Zhu *et al*. 2018, Mou *et al*. 2019a, b, Xu *et al*. 2020a, Zhang *et al*. 2020a, d) and more particularly in the field of engineering (Wu *et al*. 2019, Li *et al*. 2020b, Pang *et al*. 2020, Wang *et al*. 2020a). During the last decade, metaheuristic algorithms and computational intelligence have gained high popularity. There have been much examples of optimization algorithms in the field engineering (Zenggang *et al*. 2019, Chen *et al*. 2020c, Xiong *et al*. 2020a). For instance, the technique of particle swarm optimization is shown a promising method in mechanical fault diagnosis (Chen *et al*. 2020b) or the technique of whale optimization algorithm (WOA) that proved to be reliable in voltage control (Cao *et al*. 2020b). 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). 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 behaviour 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), or more particularly hybrid searching optimization algorithms have recently developed (Fu *et al*. 2020b). 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*. 2019), grey wolf optimization (Zhao *et al*. 2019), Harris hawks optimization (Zhang *et al*. 2020e). Besides, ideas like feature selection (Zhao *et al*. 2015) and adaptive local binary patterns were also largely used by scholars (Liu *et al*. 2016a, Chen *et al*. 2020c, Wang and Chen 2020a).

Firefly algorithm (FA) (Yang 2008) is a well-known optimizer. Sadowski *et al*. (2019) combined this algorithm with ANN for creep strain simulation of green concrete. Moreover, a modified version of the FA was used by Bui *et al*. (2018) to tune an ANN applied to predict both tensile and compressive strength of HPC. They introduced this ensemble as a fast and efficient designing approach for the HPC. An FA-optimized support vector regression was used by Pham *et al*. (2016) to predict the CS of HPC. The prediction (mean absolute percentage) error of the proposed model was 9.81% which was lower than benchmark tools of ANN (13.41%) and SVM (12.02%).

In similar efforts, scholars like Bui *et al*. (2019a) and Bui *et al*. (2019b) tested the optimization competency of various metaheuristic algorithms including whale optimization algorithm ant lion optimization coupled with the ANN for the CS and slump estimation, respectively. Sadowski *et al*. (2018) the applicability of imperialist competitive algorithm for improving the ANN in the CS modeling. Conducted by Dao *et al*. (2019), genetic algorithm and particle swarm optimization (PSO) optimized an ANFIS to predict the CS of geopolymer concrete. With reference to correlation values above 0.92, the suggested models exhibited strong performances. In another research, the PSO could tune the least squares SVM in estimating plastic viscosity and interface yield stress of fresh concrete (Sadowski *et al*. 2019). The $R^2$ values of 0.77 and 0.71 were obtained for the prediction of the mentioned parameters, respectively. Moreover, in efforts by Ma *et al*. (2020) and Moayedi *et al*. (2019a), various metaheuristic algorithms (e.g., shuffled frog leaping algorithm, salp swarm algorithm, ant lion optimization (ALO), biogeography-based optimization (BBO), and grasshopper optimization algorithm (GOA)) are assessed and compared together for approximating the CS and slump of concrete. All algorithms were coupled with an ANN to optimally train it.

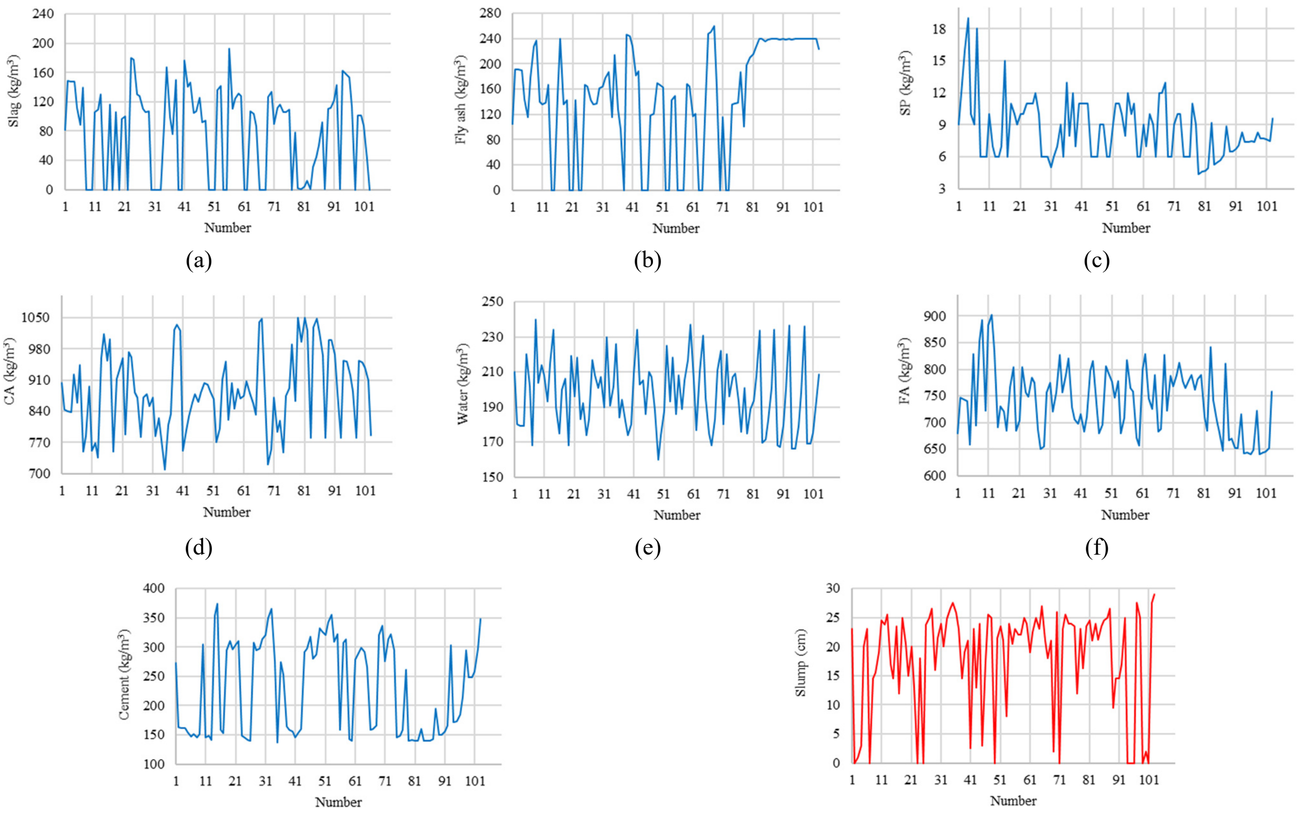
The literature review shows the promising performance of metaheuristic techniques in concrete-related simulations. More specifically, they have derived optimum configurations for standard predictors like ANN and ANFIS (Shi *et al*. 2020a, b) in confronting the barriers of efficient learning (e.g., local minima trap (Moayedi *et al*. 2019b)). Since many scholars have sufficiently regarded illustrious metaheuristic techniques (e.g., the PSO and FA), this study focuses on more recent algorithms including electromagnetic field optimization (EFO), water cycle algorithm (WCA), teaching-learning-based optimization (TLBO), and multi-tracker optimization algorithm (MTOA) for tuning an ANN in predicting the concrete slump. It is noteworthy that few scholars have used these techniques for the same purpose in predicting solar cell parameter (Yurtkuran and Kucukoglu 2018), soil shear strength (Foong *et al*. 2020), building energy performance (Zhou *et al*. 2020), and pile friction capacity (Wu *et al*. 2020). The EFO has so far emerged as a fast optimizer, while the WCA, TLBO, and MTOA are popular for their optimization robustness. Hence, a comparative evaluation of these algorithms returns a highly efficient model.

## 2. Methodology and established database

In this work, the networks aim to investigate how the CSC is affected by the amount of ingredients in the mixtures. To this end, a well-known dataset provided by Yeh (2007) is used (http://archive.ics.uci.edu/ml/datasets/Concrete+Slump+Test). The slump (*cm*) of 103 concrete specimens are recorded in front of the amount of slag, fly ash, superplasticizer (SP), coarse aggregate (CA), water, fine aggregate (FA), and cement all in $kg/m^3$. Fig. 1 shows the variation of the mentioned parameters. Moreover, the correlation of each independent factor with the slump is calculated and presented in Table 1. As is seen, the only factor which gained the $R^2$ larger than 0.1 is the water content ($R^2 = 0.2177$).

### *2.1 Methodology*

**The ANN:** As one of the most popular artificial intelligence techniques, the principal rule of the ANN was



(a) (b) (c)

(d) (e) (f)

(g) (h)

Fig. 1 The variation in the input-target variable(s)

Table 1 The correlation of the independent parameters with the slump

| Parameter | Slag | Fly ash | SP | CA | Water | FA | Cement |
|---|---|---|---|---|---|---|---|
| $R^2$ | 0.0807 | 0.0141 | 0.0453 | 0.0354 | 0.2177 | 0.0409 | 0.0213 |

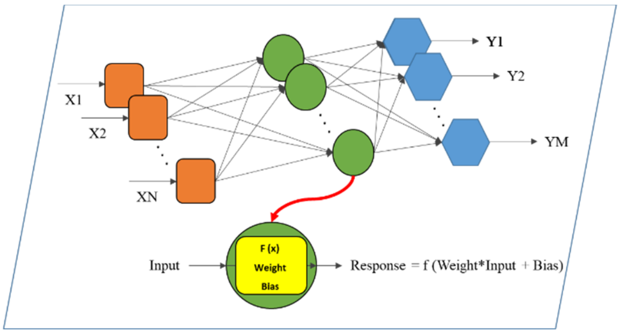


Fig. 2 The MLPNN mechanism

inferred by McCulloch and Pitts (1943). The theories and mechanisms of the ANNs are described in Anderson and McNeill (1992). Utilizing its common strategy, namely back-propagation method (Hecht-Nielsen 1992), an ANN establishes vast connections between its units (called neurons) in order to non-linearly map the relationship between various parameters. Fig. 2 shows a multi-layer perceptron neural network (MLPNN) (Hornik *et al.* 1989) and the computations handled by a neuron. Such networks have three types of neurons where their names are designated according to their home layer. For example, the neurons in the input layer are called input neurons. The same goes for the hidden and output neuron(s).

ANNs are flexible tools that can be trained by various techniques. Levenberg–Marquardt (LM) (Moré 1978) is a standard algorithm for this purpose. Regardless of the trainer type, it tunes the weights and biases for the MLPNN. In this study, the EFO, WCA, TLBO, and MTOA algorithms replace the LM. An MLPNN possesses further parameters such as the number of hidden layers and type of activation function that should be appropriately determined. A pattern comprising all these parameters is finally developed. Notably, the major part of data is analyzed to create this pattern. It is then examined by the rest of the data to see how accurately it can predict for unseen conditions.

**Optimization theories:** As a recently-developed metaheuristic scheme that draws on an electromagnetic rule called "attraction-repulsion", the EFO was proposed by Abedinpourshotorban *et al.* (2016). The agents of the EFO are electromagnetic particles (EMPs). During the optimization, a set of EMPs are produced and sorted according to their fitness. Later, they are classified into three groups each of which is referred to as a magnetic field. The first one contains the EMPs with a positive pole. The next group is dedicated to negative EMPs. The third is formed by the remaining (i.e., neutral) particles. Once a new EMP is produced, it enters the population if it presents a higher fitness than the worst existing EMP. A pole is assigned to the new individual based on its position. The position is selected based on the following steps: one particle is randomly selected in each field. The produced EMP first takes the position (and the pole) of the neutral particle. Next, the positive and negative EMPs affect it with a random force. This reproduction process continues until the desired accuracy/maximum number of tries is met. The EFO is mathematically explained in other studies (Talebi and Dehkordi 2018).

The water cycle (melting of snows, stream flowing, evaporation, and precipitation (David 1993)) is the essential idea of the WCA algorithm proposed by Eskandar *et al.* (2012). After designating the algorithm parameters and initializing the population, the individuals are labeled as streams, rivers, and (one) sea distinguished by typical, good, and best-fitted raindrops, respectively. In order to improve the solution in each iteration, the position of the river is replaced by that of the best (and better) streams, and the position of the sea is replaced by that of a river with a more promising solution. It is worth noting that the WCA keeps the response from local minima by performing raining and generating new streams. Further details of the WCA mechanism can be found in (Luo *et al.* 2016, Heidari *et al.* 2017).

Rao *et al.* (2011) developed a search algorithm based on the teacher-student relationship in an artificial class. An advantage of the TLBO is that this algorithm does not need tuning specific parameters (Rao *et al.* 2013). The teacher aims to establish the best harmony among the learners. The optimization process of the TLBO is carried out in two phases. In the teaching phase, a number of students are randomly generated in the class and the best one is considered as the teacher. The shares his/her knowledge with the students to enhance the quality of their solutions. Next, the students share information with each other in the learning phase. The same process is executed for newly generated individuals to achieve the most optimum solution. Mathematical details of the TLBO are presented in (Shukla *et al.* 2020).

Zakeri *et al.* (2017) introduced the MTOA as a capable search method. There are two kinds of search agents in this algorithm, namely global trackers and local trackers. Compared to the common optimizers, it is an advantage for the MTOA that increases its resistance against challenges like local minima. In the search space, global trackers are scattered. A certain number of local trackers are then placed in a specified radius of each one. A point for scattering these local agents is to sense the changes in the area which leads to a quick convergence as well as online tracking of optimal time-varying points. The search radius around the global trackers is determined based on their rankings addressed by a cost function. In this regard, the first rank is given to the tracker with the lowest cost and vice versa. Previous studies present a detailed description of the MTOA mechanism (Zakeri *et al.* 2019, Wang and Chen 2020).

## 3. Results and discussion

### 3.1 Assumptions and implementation

In order to implement the models, 82 samples were randomly selected as the training data. These records form 80% of the dataset. The EFO, WCA, TLBO, and MTOA algorithms trained a 7 × 6 × 1 MLPNN so as to capture the slump pattern from these records. Notably, this structure represents an ANN with 7 nodes in the input layer, 6 nodes in the hidden layer, and 1 node in the output layer. For the first and third layer, the number of nodes is fixed with the number of input and output parameters, while the value of 6 was derived after a trial and error practice on the number of hidden neurons.

The accuracy of this process is measured by three indicators, namely mean absolute error (MAE), Pearson correlation coefficient (R), and root mean square error (RMSE). Given $G$ as the number of samples (82 for the training phase) and $S_{i_{predicted}}$ and $S_{i_{expected}}$ as the predicted and expected slumps, these indicators are expressed as follows

$$MAE = \frac{1}{G}\sum_{i=1}^{G} |S_{i_{expected}} - S_{i_{predicted}}| \tag{1}$$

$$R = \frac{\sum_{i=1}^{G}(S_{i_{predicted}} - \overline{S}_{predicted})(S_{i_{expected}} - \overline{S}_{expected})}{\sqrt{\sum_{i=1}^{G}(S_{i_{predicted}} - \overline{S}_{predicted})^2}\sqrt{\sum_{i=1}^{G}(S_{i_{expected}} - \overline{S}_{expected})^2}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{G}\sum_{i=1}^{G}[(S_{i_{expected}} - S_{i_{predicted}})]^2} \tag{3}$$

Considering the behavior of the algorithms, the WCA, TLBO, and MTOA were implemented with 1000 iterations, while the EFO needed 30000 iterations to reach a steady optimization situation. Table 2 denotes other parameters of the implemented algorithms.

### 3.2 Training and testing results

The training outputs calculated by the developed models were compared with the corresponding targets to evaluate the searching competency of the used algorithms. This comparison is shown in Fig. 3 along with the regression charts. According to these charts, although the slump pattern experiences sharp fluctuations, the MLPNNs trained by all four optimizers have properly captured it. In this phase, the error indicator of RMSE was obtained 4.8491, 4.1531, 4.6184, and 4.7630 for the EFO-MLPNN, WCA-MLPNN, TLBO-MLPNN, and MTOA-MLPNN, respectively. Moreover, the MAE and R were 3.7821 and 0.8397, 3.3080 and 0.8892, 3.5782 and 0.8519, and 3.6851 and 0.8430 that demonstrate a high agreement between the compared parameters.

The goodness of the training results reflects the suitability of the MLPNN parameters (i.e., the weights and biases) that are tuned by the EFO, WCA, TLBO, and MTOA. As explained, the algorithms could attain their optimal response with different strategies that work based on electromagnetic rules, water cycle, teaching and learning in artificial classes, and global-local tracking.

Each model predicted the slump for the remaining 21 samples to evaluate the relationship acquired from the first group of data. It addresses the accuracy of the models in confronting with cement specimens that do not have any prior knowledge about them.

For each sample, an error value was calculated as $S_{i_{expected}} - S_{i_{predicted}}$. Figs. 4(a), (c), (e), and (g) depicts the values of the obtained errors. The resulted values range in [-9.2493, 8.7079], [-8.3736, 10.1164], [-7.2185, 10.8370], and [-8.9418, 9.7660]. Along with an error chart, a histogram diagram is also presented to give a statistical view of the error values. More clearly, the frequency of the errors shown where $\mu$ and $\sigma$ stand for the mean error and standard error, respectively.

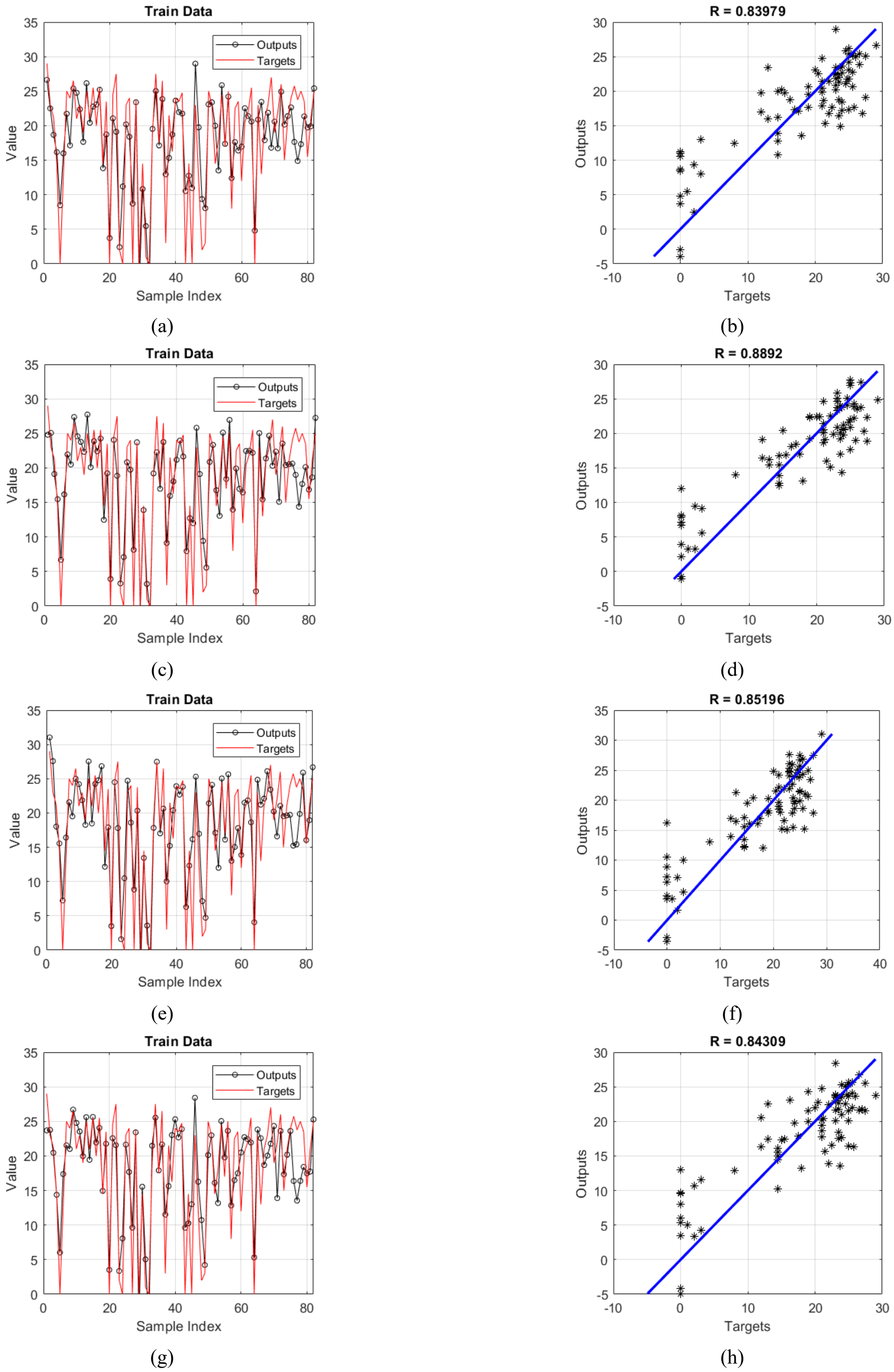
The RMSEs of 4.7479, 4.6325, 4.9074, and 4.8873, as well as the MAEs of 4.0326, 3.8443, 4.1417, and 4.0871, showed the capability of all four models in reproducing the

Table 2 The parameters of the used optimizers

| **Algorithm** | **EFO** | **WCA** | **TLBO** | **MTOA** |
|---|---|---|---|---|
| **Parameter** | $N_P$ = 25<br>Iterations = 30000<br>R_rate = 0.01<br>Ps_rate = 0.01<br>P_field = 0.02<br>N_field = 0.45 | $N_P$ = 200<br>Iterations = 1000<br>$d_{max}$ = 1e-16<br>$N_{sr}$ = 4 | $N_P$ = 500<br>Iterations = 1000 | $N_{GT}$ = 5<br>$N_{LT}$ = 80<br>Iterations = 1000<br>$Rs_{max}$ = $\sqrt{2}$<br>$Rs_{min}$ = 1e-4<br>Beta = 0.95<br>Lambda = 2<br>Theta = pi/8 |

$N_P$ = Population size
$Rs_{max}$ = Maximum search radius
$Rs_{min}$ = Minimum search radius
$d_{max}$ = Intensification controller
$N_{sr}$ = No. of rivers plus one sea

R_rate = Probability of changing one electromagnet of the produced particle with a random one
Ps_rate = Probability of selecting electromagnets of the produced particle from the positive field
P_field = Portion of the population belonging to the positive field
N_field = Portion of the population belonging to negative field
$N_{LT}$ = No. of local trackers
$N_{GT}$ = No. of global trackers

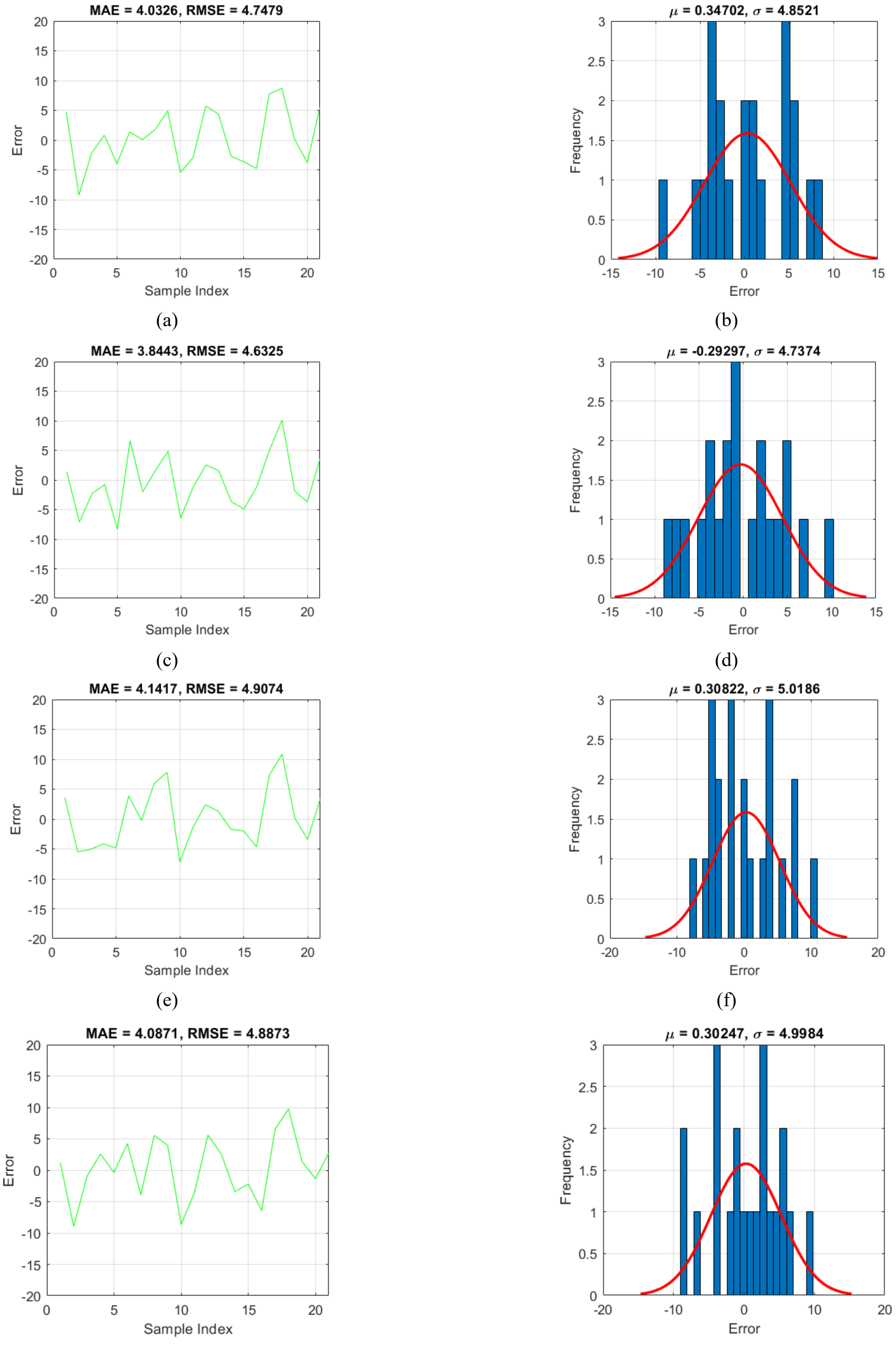


(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 3 Pattern comparison and regression chart of the training results by (a and b) EFO-MLPNN; (c and d) WCA-MLPNN; (e and f) TLBO-MLPNN; and (g and h) MTOA-MLPNN

slump pattern for unseen specimens. In other words, the trained models can present a reliable prediction of the slump by knowing the amount of slag, fly ash, SP, CA, water, FA, and cement used in the proposed mixture.

Moreover, the successful performance of the models can be derived from high correlations obtained between the testing $S_{i_{expected}}$ and $S_{i_{predicted}}$ values. According to Fig. 5, the mentioned agreement is represented by the Rs larger



(a) (b)

(c) (d)

(e) (f)

(g) (h)

Fig. 4 Analyzing the error values in the prediction phase of the (a and b) EFO-MLPNN; (c and d) WCA-MLPNN; (e and f) TLBO-MLPNN; and (g and h) MTOA-MLPNN than 0.80 for all models (i.e., 0.8344, 0.8392, 0.8078, and 0.8195).

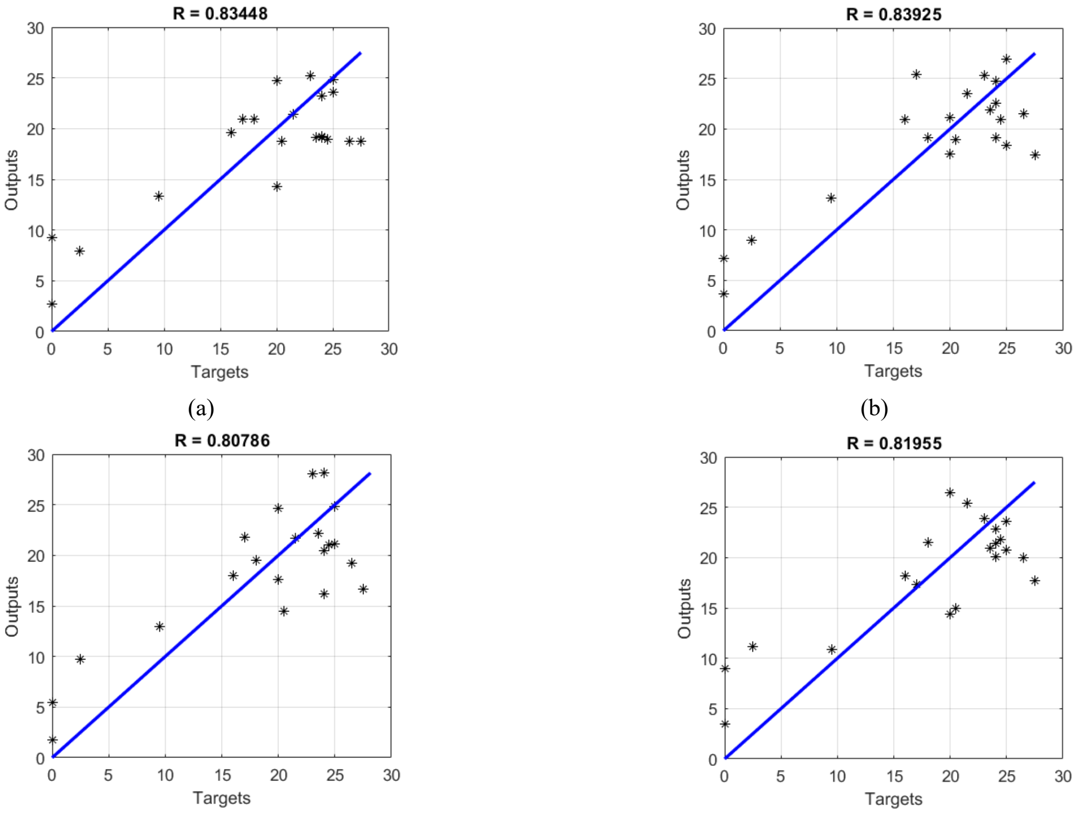
### *3.3 Comparison*

MLPNNs are leading approximators that have shown high adaptability with optimization techniques like bagging approach (Aydogmus *et al*. 2015) and genetic algorithm (Chandwani *et al*. 2015) in dealing with the slump issue. In this study, the MLPNN was supervised by four metaheuristic strategies for exploring the relationship between slump and parameters like slag, fly ash, SP, CA, water, FA and cement. According to earlier studies (Yeh 2009), these parameters are proper influencing factors.

In spite of the good performance observed for the EFO-MLPNN, WCA-MLPNN, TLBO-MLPNN, and MTOA-MLPNN ensemble models, they are compared in terms of prediction accuracy, optimization complexity, and time-effectiveness to recognize the most efficient model.

Table 3 gives the ranking of each model obtained with respect to the used accuracy indicators in both learning and prediction phases. In this sense, a score between 1 and 4 is designated to each indicator so that the higher the accuracy is, the larger the score is. For instance, the WCA-MLPNN takes the score 4 for both R and RMSE because it achieved the largest R and the smallest RMSE. An overall score is defined as the summation of these three scores. Finally, the models are ranked based on their overall scores. The larger this score is, the better the rank is.

Based on the calculated rankings, the WCA-MLPNN achieved the most accurate performance in analyzing the dependence of slump on the input parameters, followed by



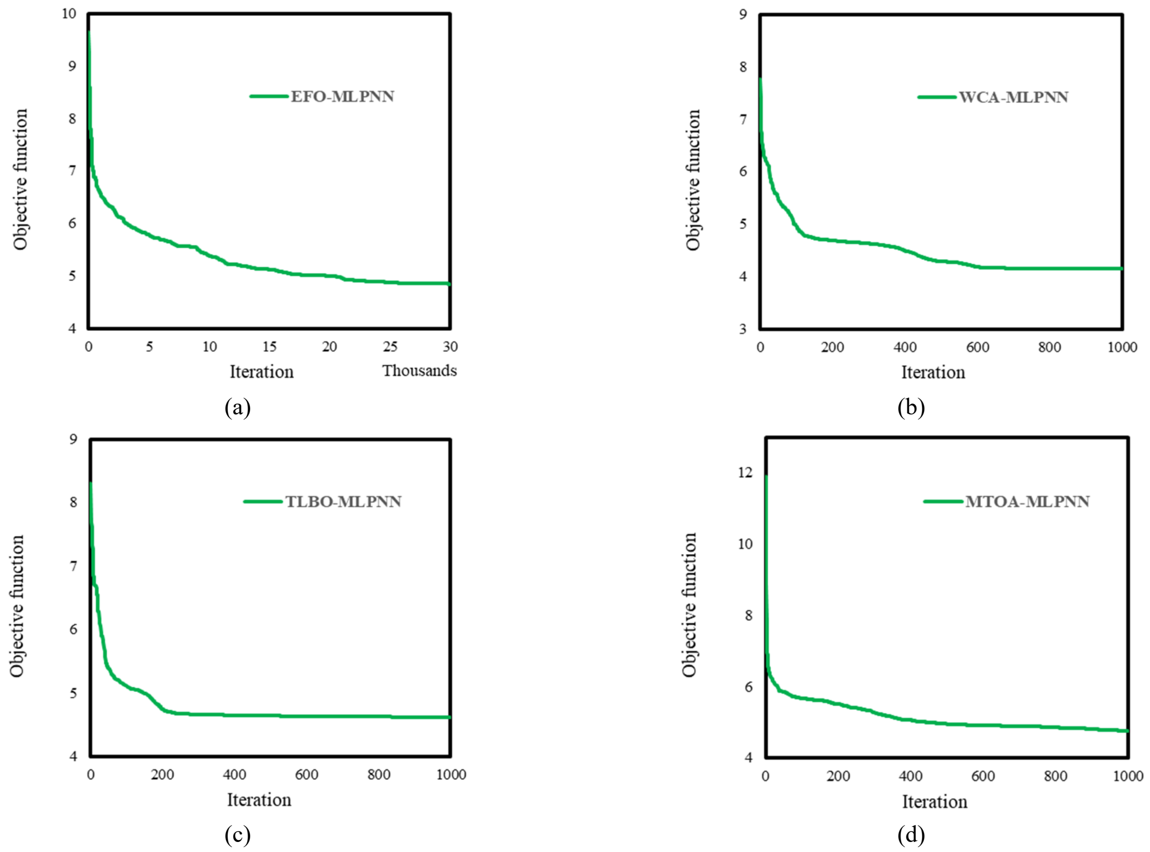
(a) (b)

(c) (d)

Fig. 5 The correlation of the training samples by (a) EFO-MLPNN; (b) WCA-MLPNN; (c) TLBO-MLPNN; and (d) MTOA-MLPNN

Table 3 Ranking of the used models

| Models | Scores | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Training | | | | | Testing | | | | |
| | RMSE | MAE | R | Overall score | Rank | RMSE | MAE | R | Overall score | Rank |
| **EFO-MLPNN** | 1 | 1 | 1 | 3 | 4 | 3 | 3 | 3 | 9 | 2 |
| **WCA-MLPNN** | 4 | 4 | 4 | 12 | 1 | 4 | 4 | 4 | 12 | 1 |
| **TLBO-MLPNN** | 3 | 3 | 3 | 9 | 2 | 1 | 1 | 1 | 3 | 4 |
| **MTOA-MLPNN** | 2 | 2 | 2 | 6 | 3 | 2 | 2 | 2 | 6 | 3 |



(a) (b) (c) (d)

Fig. 6 The convergence curve of the implemented optimizations

the TLBO-MLPNN, MTOA-MLPNN, and EFO-MLPNN. As for generalizing the slump behavior, the WCA, again, emerged as the most successful trainer since the corresponding MLPNN could perform more accurately than others. The EFO-MLPNN and MTOA-MLP gained the second and third rank in this phase, respectively. Surprisingly, the TLBO-based model gave the poorest prediction of the slump.

Fig. 6 shows the convergence behavior of each model. As explained, the most notable distinction between these charts is the number of iterations required for finding the optimum solutions. While the WCA, TLBO, and MTOA minimized the objective function (the RMSE in this study) after 1000 tries, the behavior of the EFO dictated considering 30 times this value. In this work, tuning the parameters of the MLPNN using EFO, WCA, TLBO, and MTOA was executed in 285.4, 1671.1, 11326.7, and 3422.6 seconds, respectively (Intel Core i7 processor at 1.8 GHz and 16 GB of RAM). It is concluded that the EFO, despite the huge number of iterations, takes the shortest time. This algorithm also used a considerably smaller population (25 vs. 200, 500, and 400). After that, the WCA was the second fast optimizer.

Once again, each iteration represents a solution to the problem of optimal ANN. The EFO has spent averagely ($\frac{285.4}{30000}$ =) 0.0095 seconds for each response, while this value is ($\frac{1671.1}{1000}$ =) 1.6711 seconds for the WCA, ($\frac{11326.7}{1000}$ =) 11.3267 seconds for the TLBO, and ($\frac{3422.6}{1000}$ =) 3.4226 seconds for the MTOA.

From the above comparisons, utilizing the WCA-MLPNN is recommended for sensitive works wherein the accuracy is the most regarded factor. But when it comes to a time-effective simulation, the EFO-MLPNN can be the best alternative. Besides, the products of this model, according to Table 3, will be more accurate than the TLBO and MTOA.

Moreover, this study has some improvements relative to earlier similar methods. Moayedi *et al*. (2019a), for example, used the BBO (Simon 2008), GOA (Saremi *et al*. 2017), and ALO (Mirjalili 2015) for training ANNs applied to the same problem. Their best trainer was the BBO with respective RMSE and MAE of 4.4509 and 3.5513. These values show a larger error in comparison with those of the WCA in this study (4.1531 and 3.3080).

## 4. Conclusions

The findings of the present work pointed out important items about the use of four state-of-the-art metaheuristic algorithms in the concrete slump prediction. Electromagnetic field optimization, water cycle algorithm, teaching-learning-based optimization, and multi-tracker optimization algorithm were used for fine-tuning neural computing to predict the slump by having the amount of ingredients in a concrete mixture. Due to the high accuracy of the models, the combination of the ANN with the mentioned metaheuristic algorithms provides reliable slump predictors. The WCA was the most successful algorithm because it outperformed three other optimizers in both training and testing phases. The use of EFO, however, resulted in a more time-effective tuning of the ANN. Although this algorithm, trained the ANN with a larger error accuracy than TLBO and MTOA, its ensemble (i.e., the EFO-MLPNN) was the second accurate model in the prediction phase. As well as the accuracy, the models were compared in terms of time-effectiveness and convergence rate. All in all, regarding the use of simple configurations (i.e., $N_{PS}$ of 25 and 200) and quick convergences (in 285.4 and 1671.1 seconds), two combinations of the ANN with WCA and EFO were denoted as efficient slump evaluative models.

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