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Predicting the concrete compressive strength through MLP network hybridized with three evolutionary algorithms

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Abstract. In this research, we synthesized an artificial neural network (ANN) with three metaheuristic algorithms, namely particle swarm optimization (PSO) algorithm, imperialist competition algorithm (ICA), and genetic algorithm (GA) to achieve a more accurate prediction of 28-day compressive strength of concrete. Seven input parameters (including cement, water, slag, fly ash, superplasticizer (SP), coarse aggregate (CA), and fine aggregate (FA)) were considered for this work. 80% of data (82 samples) were used to feed ANN, PSO-ANN, ICA-ANN, and GA-ANN models, and their performance was evaluated using the remaining 20% (21 samples). Referring to the executed sensitivity analysis, the best complexities for the PSO and GA were indicated by the population size = 450 and for the ICA by the population size = 400. Also, to assess the accuracy of the used predictors, the accuracy criteria of root mean square error (RMSE), coefficient of determination (R^2), and mean absolute error (MAE) were defined. Based on the results, applying the PSO, ICA, and GA algorithms led to increasing R^2 in the training and testing phase. Also, the MAE and RMSE of the conventional MLP experienced significant decrease after the hybridization process. Overall, the efficiency of metaheuristic science for the mentioned objective was deduced in this research. However, the combination of ANN and ICA enjoys the highest accuracy and could be a robust alternative to destructive and time-consuming tests.

Keywords: ANN; artificial intelligence; concrete compressive strength; evolutionary algorithms

1. Introduction

As a human-made mixture, concrete is one of the most popular materials in the construction industry, which can endure considerable compressive stress (Nehdi *et al*. 2006, Park *et al*. 2016). Generally, reinforced concrete structures show more difficultness in comparison with steel ones due to the mechanical properties of concrete (Mahzan *et al*. 2010, Hakim and Razak 2014). As is known, concrete is a mixture of cement, coarse and fine aggregate, water, etc. It has been proved that by using proper amounts (i.e., dosages) of the mentioned components, improving the long-term properties of the concrete is possible. Compressive strength is one of the most important of these properties, which is generally measured for a 28-days concrete specimen. Considering the compressive strength as an independent variable, it can be influenced by many factors. Due to the crucial role of this property (i.e., compressive strength) in the quality of construction, providing a reliable approach to investigate it is a necessary task. So far, many scientists have implemented different mathematical and statistical-based models to model the mechanical properties of concrete. Abdalhmid *et al*. (2019) performed both experimental and analytical assessments of long-term drying shrinkage strains of self-compacting concrete (SCC). Their results show the compressive strength of the specimen with more than 60% of fly ash (i.e., as cement replacement) reaches 30 MPa. Also, the long-term drying shrinkage of normal concrete specimens from 356 to 1000 days was lower than SCCs. Thirumalai *et al*. (2017) used Pearson and Spearman methods to analyze the compressive strength of concrete. Regression-based methods have also been used based on ultrasonic pulse velocity (UPV) to estimate concrete compressive strength (Galan 1967).

In a general point of view, recent years have witnessed significant advances in various scientific fields toward facilitating difficult analysis (Zhang *et al*. 2020b, Zhao and Li 2020, Sun *et al*. 2021) like construction and waste reduction (Liu *et al*. 2020a, b, Gao *et al*. 2021), environmental modeling (Zhang *et al*. 2020a, c, Hong *et al*. 2021), remote sensing (Han *et al*. 2019), energy-related analysis (Zhao *et al*. 2020b, Zuo *et al*. 2020), optics-related simulations (Zuo *et al*. 2015, 2017), and water treatment (Yang *et al*. 2020, Liu *et al*. 2021). In this sense, different intelligent methods have been designed by scholars to conveniently simulate engineering problems (Seyedashraf

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et al. 2018, Qiao *et al*. 2021). Many studies have focused on concrete parameters (Boğa *et al*. 2013, Zheng *et al*. 2020) like compressive strength modeling. Öztaş *et al*. (2006) developed an artificial neural network (ANN) for forecasting the compressive strength and slump of high strength concrete (HSC). Referring to the mean absolute percentage error of 1,956,208% and also 99.93% accuracy, this study revealed that ANN could act as a promising method for the mentioned purpose. In literature, the ANNs have been found superior to other models like multiple regression analysis (Chithra *et al*. 2016).

As stated, the compressive strength is a function of various parameters of concrete. Considering the industrial aspect of the problem, each ingredient could influence it differently (Oluokun 1994). Fly ash, for example, it increases long-term durability and compressive strength of the structure (Han *et al*. 2003, Topcu and Sarıdemir 2008). Hence, optimizing the concrete mixture is a crucial task that requires enough knowledge about the relationship between the strength and components (Popovics 1990). On the other hand, implementing destructive laboratory tests requires spending a lot of time and money on creating and breaking specimens with complicated equipment. Also, it is an extremely difficult task to practically analyze the impact of the changes of each component on the concrete strength through direct monitoring. It gets even harder when it comes to exploring the changes in more than one component simultaneously. Therefore, the advent of intelligent models could provide easier yet effective methods for evaluating the compressive strength in concrete industry. As well as the measurements in the current time, estimating the proposed parameter for unseen conditions, which might not be executable in the laboratory, is another advantage of the artificial intelligence to the concrete and construction industry (Tien Bui *et al*. 2019).

To achieve more accuracy of prediction, utilizing the evolutionary algorithms is suggested in lots of researches (Chen *et al*. 2016, Wang *et al*. 2017, Xia *et al*. 2017, Xu *et al*. 2019). These algorithms are mostly relying on the colony behavior of different animals (Xu and Chen 2014, Zhao *et al*. 2014, Zhao *et al*. 2020a) (e.g., Harris hawks (Chen *et al*. 2020, Zhang *et al*. 2020e) and grey wolf (Zhao *et al*. 2019, Hu *et al*. 2020)). When they are used for hybridization purposes, these algorithms try to optimize the weights and other hyper-parameters of the base model in order to achieve an optimal configuration (Shan *et al*. 2020, Yu *et al*. 2020, Zhang *et al*. 2020d, Tu *et al*. 2021). An example of the applicability of metaheuristic techniques can be found in studies like Hu *et al*. (2015), Shen *et al*. (2016), Wang and Chen (2020), and Li *et al*. (2018b) for medical diagnosis.

Qi *et al*. (2018) developed a combination of particle swarm optimization (PSO) algorithm and ANN to approximate the unconfined compressive strength of cemented paste backfill. The results of this study showed that PSO could effectively enhance the performance of ANN. Many scholars start to develop and propose hybrid techniques in order to provide a reliable predictive network and solving complex engineering solutions (Akin and Sahin 2017, Chahnasir *et al*. 2018, Fallahian *et al*. 2018, Ghiasi and Ghasemi 2018, Li *et al*. 2018a, Onat and Gul 2018). Nikoo *et al*. (2015a) successfully applied a genetic algorithm (GA) to ANN for accurate prediction of compressive strength of concrete. They compared the proposed model with multiple linear regression (MLR) approaches. Referring to the calculated correlation coefficient of 0.9805 and 0.8873, respectively for evolutionary ANN and MLR, the neural-based model presents a more flexible estimation than the MLR. The GA has also been promisingly applied to self-organization feature map systems (Nikoo *et al*. 2015b). Likewise, in Ref. (Tien Bui *et al*. 2019), the applicability of whale optimization algorithm in algorithm and ant colony optimization was shown.

In this research, three wise evolutionary algorithms, namely the Imperialistic competition algorithm (ICA), GA, and PSO are applied to the artificial neural network to enhance its potency for simulating the compressive strength of concrete. These algorithms replace the conventional training algorithm and makes the network more resistant against issues like local minima (Moayedi *et al*. 2019b, Nguyen *et al*. 2019). To achieve this, a proper dataset containing 103 samples was provided. Note that, seven compressive strength practical factors were considered as the inputs of the ANN and PSO-ANN models. We also defined two broadly-used statistical indices of the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) to evaluate the accuracy of each model. Each model is implemented in its optimal condition, and the results are discussed.

2. Methodology

2.1 Artificial Neural Network

The basic model of the present study is artificial neural network (ANN). The mechanism of the ANN is mimicked from the biological neural system. The idea of using artificial processors (i.e., neurons) was first presented by McCulloch and Pitts (1943). Great abilities of the ANNs (e.g., analyzing non-linear relationships) have made them popular and powerful approximators for a wide variety of engineering high dimensional problems. Assuming a target parameter as a function of several key factors, the back-propagation (BP) learning method (Hecht-Nielsen 1992) is hired to establish a mathematical pattern by means of so-called computational parameters “weights” and “biases”.

Generally, network structure refers to the number of hidden layers and their neurons. For simulating any complex nonlinear function, theoretical works have shown that a single hidden layer can satisfy the MLP; however, it can possess more than one hidden layer (Cybenko 1989, Hornik *et al*. 1989). Fig. 1 depicts the structure of an ANN with one hidden layer. Lastly, the final product is given by applying a transfer function the the neuron response (Anderson 1995). The following equation expresses the mathematical performance of ANN

$$y_k = \sum_{j=1}^{n} w_j \cdot f\left(\sum_{i=1}^{L} w_{ji} \cdot x_i + b_j\right) + b_k \tag{1}$$

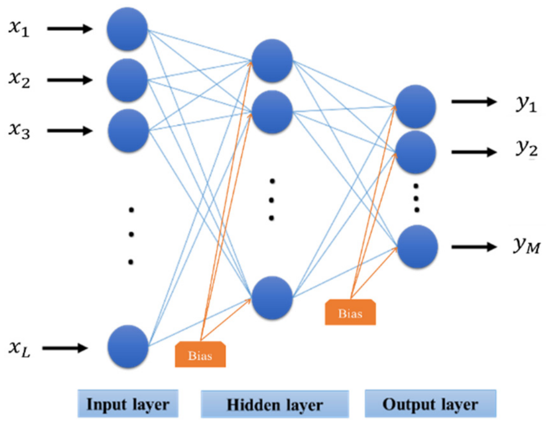


Fig. 1 The general structure of the MLP network

where j = 1, 2, …, n (number of neurons in hidden layer), i = 1, 2, …, L) (number of inputs) and k = 1, 2, …, M (number of outputs), f s the activation function.

Levenberg-Marquardt (LM) algorithm: As stated before, the Levenberg–Marquardt algorithm has been designed to train the ANN, which is an approximation to Newton's method (Marquardt 1963). This technique has a quicker and more accurate performance compared to the conventional gradient descent technique (Cigizoglu and Kişi 2005). Eq. (2) shows Newton's method for minimizing the function $V(x)$ concerning the parameter vector x

$$\Delta \underline{x} = -\left[\nabla^2 V(\underline{x})\right]^{-1} \nabla V(\underline{x}) \tag{2}$$

where $\nabla V(\underline{x})$ and $\nabla^2 V(\underline{x})$ represent the gradient and the Hessian matrix, respectively. According to Eq. (3), the function $V(x)$ can be assumed as a sum of squares function

$$V(\underline{x}) = \sum_{i=1}^{N} e_i^2(x) \tag{3}$$

Then, the following equations can be expressed

$$\begin{aligned} \nabla V(\underline{x}) &= J(\underline{x}) e(\underline{x}) \\ \nabla^2 V(\underline{x}) &= J^T(\underline{x}) J(\underline{x}) + S(\underline{x}), \\ S(\underline{x}) &= \sum_{i=1}^{N} e_i \nabla^2 e_i(\underline{x}) \end{aligned} \tag{4}$$

where $J(x)$ represents the Jacobean matrix. Assuming $S(x) \approx 0$, Eq. (2) is formulated as

$$\Delta \underline{x} = \left[J^T(\underline{x}) J(\underline{x})\right]^{-1} J^T(\underline{x})\, \underline{e}(\underline{x}) \tag{5}$$

Subsequently, based on the Gauss-Newton method, the LM technique is summarized as follows

$$\Delta \underline{x} = \left[J^T(\underline{x}) J(\underline{x}) + \mu I\right]^{-1} J^T(\underline{x})\, \underline{e}(\underline{x}) \tag{6}$$

The algorithm turns to Gauss-Newton and steepest descent (with step $1/\mu$) for small and large values of μ, respectively. Additionally, μ it is multiplied and divided by the factor b for increasing and decreasing $V(x)$, respectively. This is noteworthy that the computation of the Jacobean matrix is the key step in the LM algorithm in which this algorithm can be considered as a trust-region modification to the Gauss-Newton method.

2.2 Particle swarm optimization (PSO)

Particle swarm optimization (PSO) was first introduced by Kennedy (2010). As the name implies, PSO indicates a particle-based approach that presents the possible solution of the problem as the position of so-called units "particle." PSO seeks the optimum solution by changing the position of particles. In other words, they are regularly moved to approach a good area (Poli *et al.* 2007). This technique can be applied to the various artificial intelligent model to improve its performance by finding the optimal values of the parameters of the proposed network. In the case of ANN, PSO updates the weights and biases to achieve better results. This process gets started with a set of randomly-selected ANN parameters. As the results of the particle activities in this technique, two parameters of gbest and pbest (indicating the best global positions and the elite personal) are determined. Eq. (7) and (8) express the position and velocity of the particles, respectively.

$$X2 = X1 + V2 \tag{7}$$

$$\begin{aligned} V2 = \omega \times V1 + C1 \times r1\,(pbest - X1) \\ + C2 \times r2\,(gbest - X1) \end{aligned} \tag{8}$$

In the above equations, ω stands for the inertia weight, C1 and C2 represent acceleration variables, X1 and X2 symbolize the current and new positions of the particles. Likewise, V1 and V2 are the current and new particle velocity values. Additionally, r1 and r2 represent random values varying from 0 to 1.

Normally, the error is expected to be decreased in each iteration, and this continues until a stopping criterion is met (Moayedi *et al.* 2020). Fig. 2 illustrates a graphical description of the PSO performance.

2.3 Imperialist competition algorithm (ICA)

The imperialistic competition algorithm (ICA) was first designed by Atashpaz-Gargari and Lucas (2007). This technique has been satisfactorily used to model many engineering problems (Khabbazi *et al.* 2009). Fig. 3 shows the general procedure of the ICA algorithm. Similar to other optimization techniques, ICA gets started with a so-called initial population, "country." In the next step and regarding an objective function, some of the elite countries are selected as imperialists ruling the remaining countries as colonies. For a minimization issue, the power of imperialists is inversely proportional to the cost function, and the colonies are aimed to be divided among the existing imperialists. When the empires are developed, the colonies (i.e., in each empire) move toward the imperialist to approach them. In the following and by stating the imperialistic competition, the weak empires are projected to

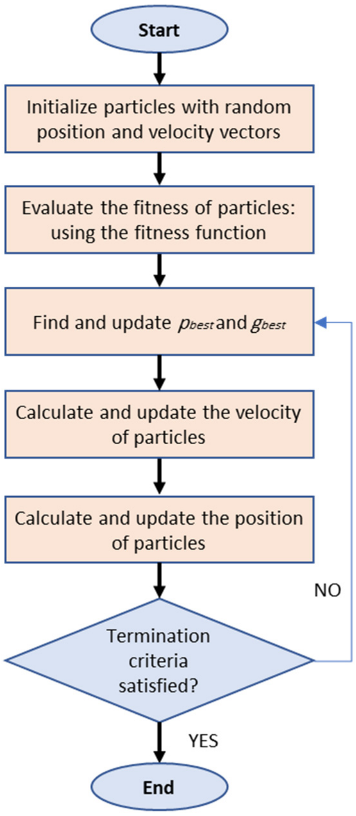


Fig. 2 The flowchart of the PSO algorithm

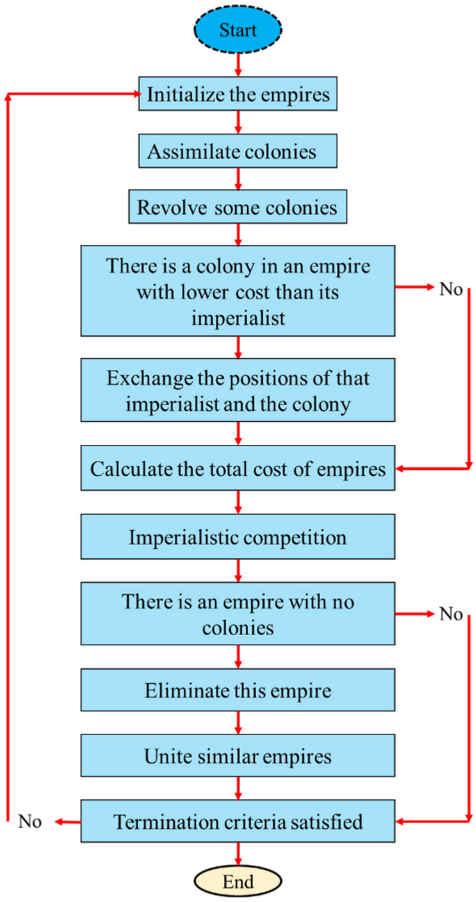


Fig. 3 The flowchart of the ICA algorithm

be eliminated.

As a result of this process, the power of the weaker empires is decreased, and vice versa. Continuing the imperialistic competition, the feeble empires are collapsed due to the lack of capability for enhancing their positions. Eventually, all countries are gathered in a state which is ruled by the elite empire. Notably, the mentioned countries play the role of colonies with the same position and cost (Atashpaz-Gargari and Lucas 2007, Gargari *et al*. 2008).

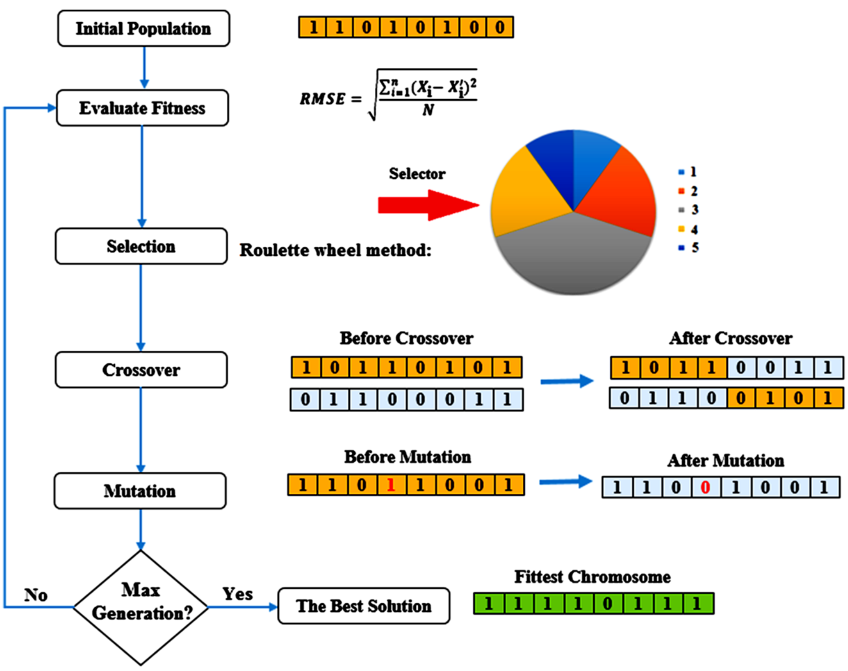


Fig. 4 The general flowchart of genetic algorithm

2.4 Genetic algorithm (GA)

Based on the theory of natural selection, a genetic algorithm (GA) was programmed by Holland (1992). GA is one of the most efficient metaheuristic methods deals with solving and optimizing many engineering problems. Remarkably, this algorithm has been synthesized with various predictive models, ANNs, for example, to enhance their accuracy. As a superiority of this technique, GA can handle highly non-linear problems with changing conditions and variables (Salari *et al*. 2014, Hashemian *et al*. 2019). Geotechnical simulations, for example, are associated with a mutation in loading conditions, linear or nonlinear soil behaviors, and continuous or discontinuous soil media (Ines and Droogers 2002, Moayedi *et al*. 2019c). Regarding the number of parameters that should be optimized for the proper development of GA, it can be classified as a problematic optimization approach. As explained above, the name GA symbolizes a well-known component of evolutionary algorithms (EAs) that follows the natural selection rules to find an efficient solution. GA is drawn on four major stages including crossover, mutation, and selection (Whitley 1994). Fig. 4 depicts a graphical view of GA performance. The crossover operator selects a combination of child chromosomes to be involved. As a result of this work, more fitness is acquired compared to the parents' performance. Thus, the crossover operator determines the ratio and structure of the offspring's chromosome in comparison with parents'. Note that this operator can act based on different methods suchlike uniform, n-point, cycle, tournament, ranking selection, and order (Saeidian *et al*. 2016). The operator of the mutation stage aims to search for new areas in the available dimension. The chromosomes are mutated through changing one or more genes inside them. Note that these genes are selected randomly and their value is changed during this procedure. It is proper to note that that the mutation operator affects either a terminal node (variables and constants) or a function node (arithmetic operations) (Nourani *et al*. 2014). By employing the mentioned

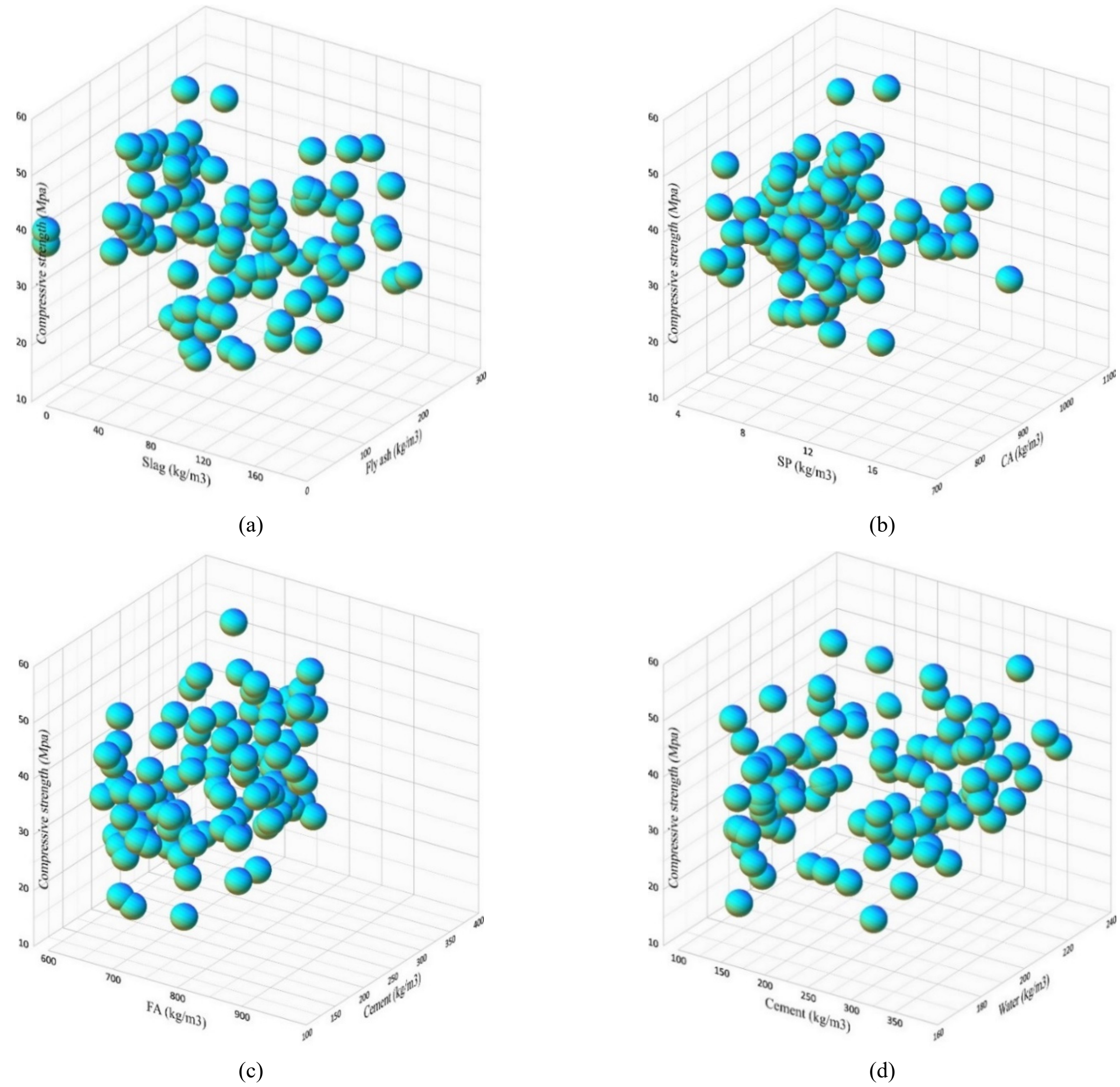


Fig. 5 Spatial distribution of the input variables for compressive strength

Table 1 Descriptive statistics of the used dataset

	Compressive strength (MPa)	Cement (kg/m^3)	Slag (kg/m^3)	Water (kg/m^3)	Fly ash (kg/m^3)	SP (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)
Mean	36.04	229.89	77.97	197.17	149.01	8.54	739.60	883.98
Standard deviation	7.84	78.88	60.46	20.21	85.42	2.81	63.34	88.39
Sample variance	61.44	6221.62	3655.58	408.37	7296.25	7.88	4012.22	7813.04
Skewness	0.19	0.15	-0.19	0.26	-0.68	1.13	0.27	0.12
Minimum	17.19	137.00	0.00	160.00	0.00	4.40	640.60	708.00
Maximum	58.53	374.00	193.00	240.00	260.00	19.00	902.00	1049.90

operators, newly generated child chromosomes will be the next generation parents (Moayedi *et al*. 2019a).

3. Data preparation and statistical description

The required dataset was provided from https://cml.ics.uci.edu/, based on research by Yeh (2007). Seven input parameters were cement, slag, water, fly ash, superplasticizer (SP), fine aggregate (FA), and coarse aggregate (CA), where the compressive strength of cement was taken the output. To better understand the issue, the statistical report of the data used, and the spatial relationship between compressive strength and the influential factors are presented in this part of the study. The 3D scatter charts in Figs. 5(a) to (d) illustrate the distribution of the measured strength versus (a) slug and fly ash, (b) SP and CA, (c) FA and cement, and (d) cement and water. Also, the statistical description of the used dataset is presented in Table 1, based on the minimum, maximum, and average values of the parameters as well as the standard deviation.

4. Results and discussion

4.1 Assumptions and pre-processing

This work evaluates the capability of the particle swarm optimization algorithm for enhancing the efficiency of the artificial neural network in the estimation of the compressive strength of concrete. To do so, the training process was carried out by using 80% of data (82 samples), and the remaining 20% (21 samples) were used to assess the accuracy of the developed predictive methods. Notably, the unnormalized data were used in this study. Moreover, three well-known accuracy criteria of RMSE, R^2, and MAE were defined to calculate the correlation and error of the results, respectively. Eqs. (9) to (11) formulate these indices

$$R^2 = 1 - \frac{\sum_{i=1}^{s}(Y_{i_{predicted}} - Y_{i_{observed}})^2}{\sum_{i=1}^{s}(Y_{i_{observed}} - \overline{Y}_{observed})^2} \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[(Y_{i_{observed}} - Y_{i_{predicted}})]^2} \tag{10}$$

$$MAE = \frac{1}{N}\sum_{I=1}^{s}|Y_{i_{observed}} - Y_{i_{predicted}}| \tag{11}$$

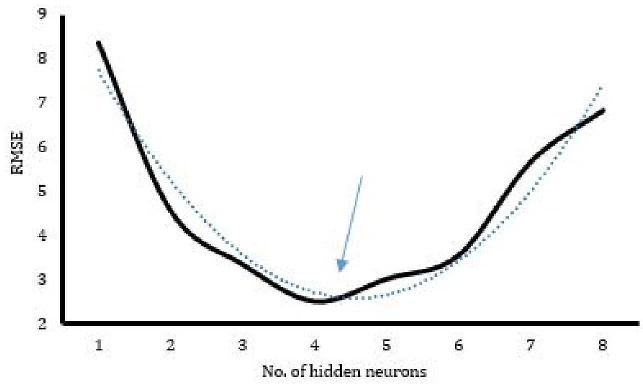
where Yi $_{observed}$, and Yi $_{predicted}$ are the actual and predicted values of a concrete slump, respectively. Also, the term N indicates the number of instances and $\overline{Y}_{observed}$ denotes the average of compressive strength.

4.2 Model implementation

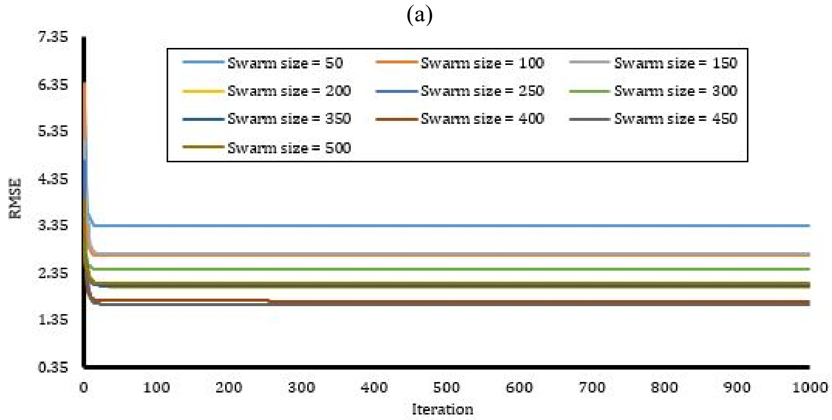
As is known, finding the optimal structure of the proposed networks is a fundamental step in utilizing artificial intelligence models. To achieve this, an extensive trial and error process was performed to find the most efficient network structure for all ANN, ICA-ANN, PSO-ANN, and GA-ANN methods. Note that the error criterion of RMSE is considered for this purpose. For ANN, a multilayer perceptron (MLP) neural network was tested with eight different numbers of neutrons in its unique hidden layer. Remarkably, the activation function of the neurons was selected to be Tansig due to its excellent performance in many similar studies (Salari *et al*. 2012, Salari *et al*. 2014, Moayedi and Armaghani 2018). Considering x as the input parameter, this hyperbolic tangent function is formulated as follows

$$Tansig(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{12}$$

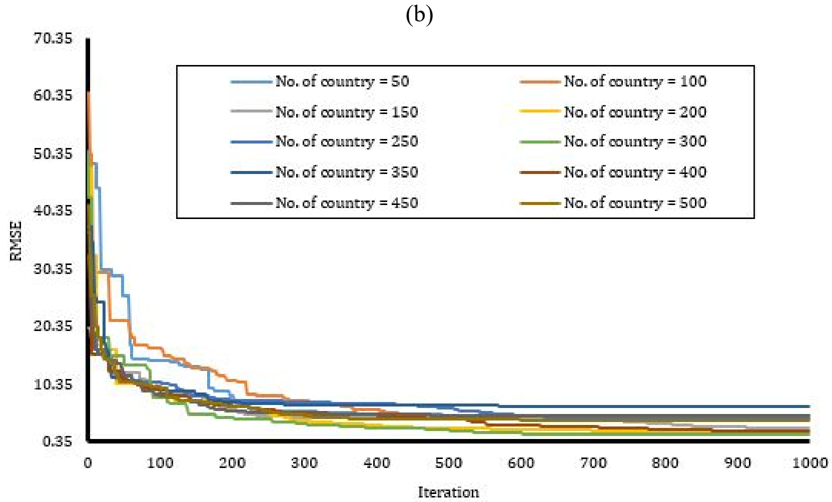
As for the evolutionary techniques, PSO, ICA, and GA algorithms were designed, respectively, based on ten different values of swarm size, a number of countries, and population size (between 50 and 500 with 50 intervals) within 1000 iterations. Figs. 6(a) to (d) shows the results of the sensitivity analysis of the proposed models. According to these figures, ANN containing 3-6 neurons presents a satisfying prediction. However, four hidden neurons yield the lowest RMSE. So, the proposed ANN is structured as 7×4×1, which indicates an MLP neural network with 7, 4, and one neuron in its input, hidden, and output layer, respectively. Moreover, PSO with swarm size = 450, ICA with a number of country = 400, and GA with population size = 450 yielded the most accurate results. Note that other determinant parameters of these algorithms were optimized based on the same trial and error procedure as well as the author's experience in previous works (Clerc and Kennedy 2002). In this sense, 0.25 and two were assigned to the



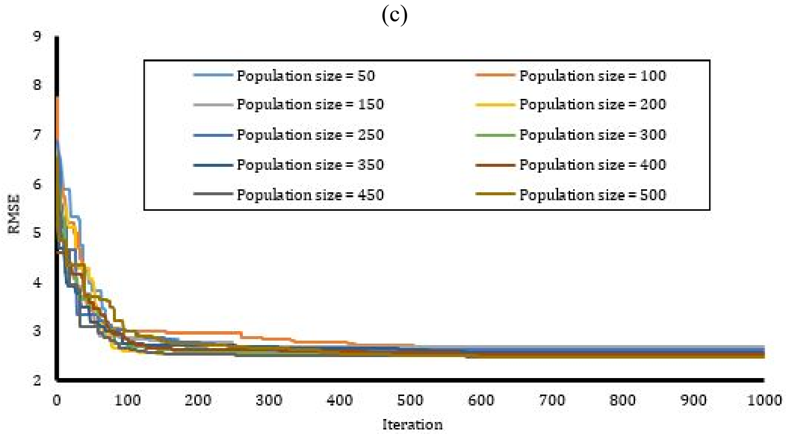
(a)



(b)



(c)



(d)

Fig. 6 Sensitivity analysis for (a) ANN; (b) PSO-ANN; (c) ICA-ANN; and (d) GA-ANN models inertia weight and coefficient of the velocity equation of PSO, respectively. Additionally, the crossover rate and mutation rate of GA were selected as 0.5 and 0.25, respectively. Also, optimal values of revolution rate number of initial imperialists were opted 0.3 and 5 for ICA, respectively. This is noteworthy that no significant change was observed for PSO-ANN and GA-ANN predictive models after the 50th and 600th iteration.

Fig. 6 also says that each algorithm finds the optimum solution by refusing a very large number of candidates. For example, each model is executed for 10 different population sizes each of which works on 1000 solutions. So, all in all, the evolutionary models have dealt with 30000 candidate solutions. Considering the structure of the network and the number of to-be-optimized parameters, it can be deduced that the modeling is of high complexity.

Table 2 Obtained accuracy criteria for ANN and PSO-ANN performance

Model	Dataset					
	Training			Testing		
	RMSE	R^2	MAE	RMSE	R^2	MAE
ANN	1.9080	0.9363	1.5162	2.9032	0.8932	2.2195
PSO-ANN	1.7027	0.9488	1.3626	1.5920	0.9705	1.3494
ICA-ANN	1.1802	0.9753	0.9501	1.3935	0.9744	1.0951
GA-ANN	1.8713	0.9387	1.4992	2.6756	0.9085	2.0025

4.3 Results and accuracy evaluation

Each model was implemented with its optimal structure, and the results are presented in Figs. 7 and 8 in the form of regression charts, respectively, for the training and testing data. Furthermore, Table 2 summarizes the calculated values of RMSE, R^2, and MAE obtained for ANN, PSO-ANN, ICA-ANN, and GA-ANN. The results show that applying the mentioned algorithms improves the performance of ANN to have a more accurate approximation of concrete compressive strength. More clearly, in the training phase, RMSE of ANN decreased from 1.9080 to 1.7027, 1.1802, and 1.8713, and MAE of ANN decreased from 1.5162 to 1.3626, 0.9501, 1.4992, when it was synthesized with PSO, ICA, and GA, respectively. Also, the computed values of R^2 (0.9363, 0.9488, 0.9753, and 0.9387, respectively, for ANN, PSO-ANN, ICA-ANN, and GA-ANN) show higher accommodation between the training results of ensemble models.

In the case of testing data, calculated RMSEs (2.9032, 1.5920, 1.3935, and 2.6756) prove that the error performance of ANN decreased by 45.16%, 52.00%, and 7.83% by employing PSO, ICA, and GA algorithms,

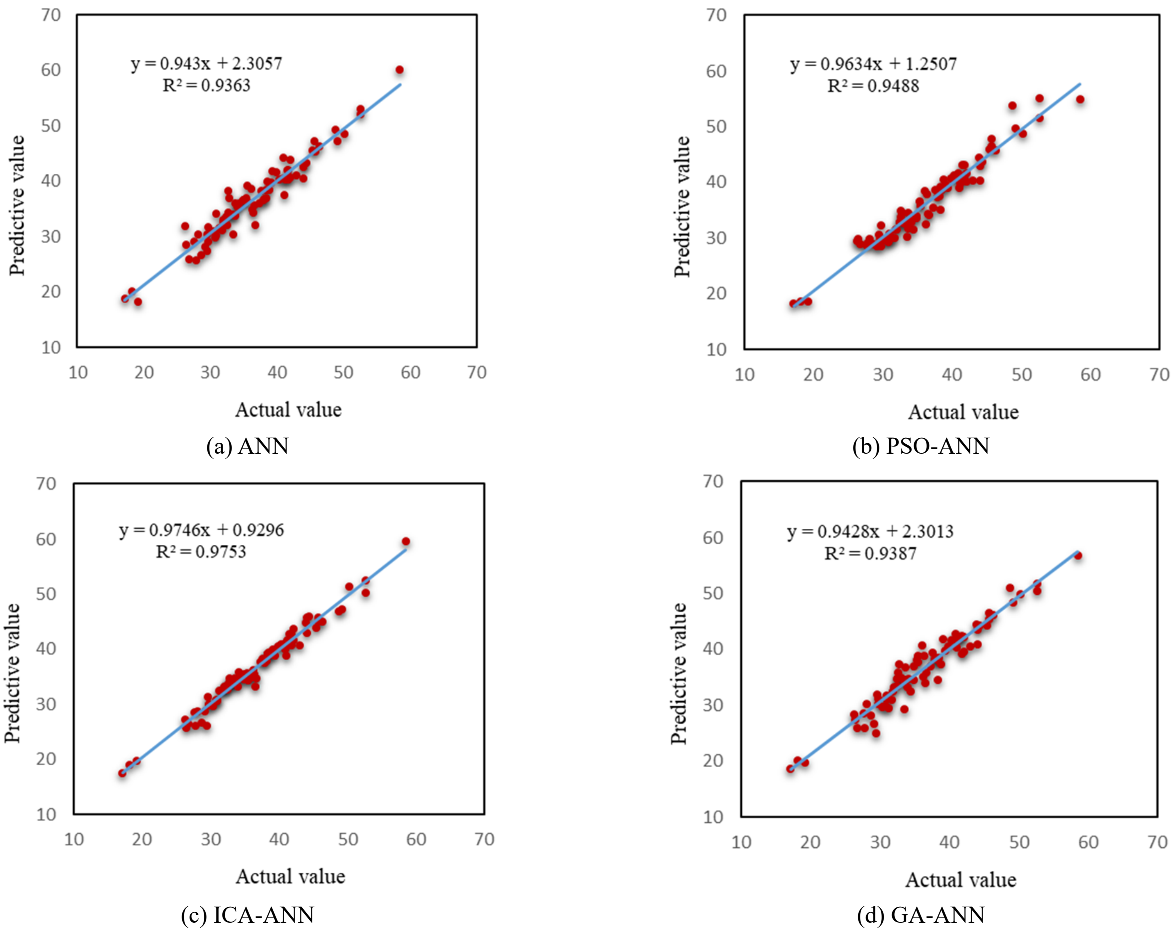
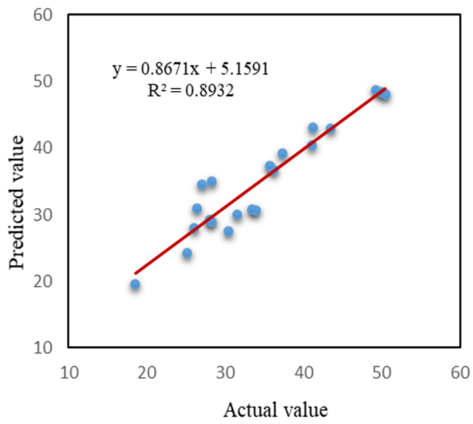
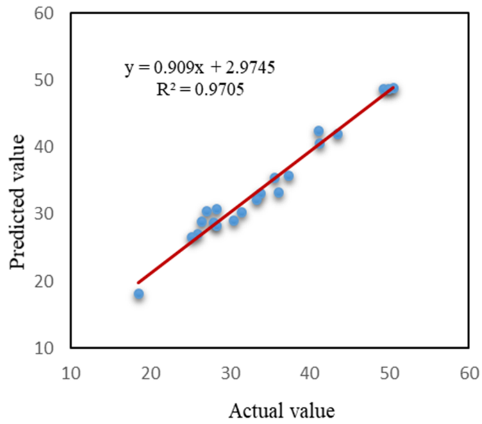


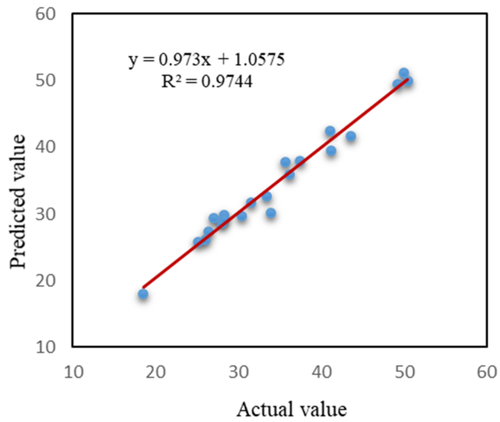
Fig. 7 Correlation between the observed and modelled compressive strength values for training specimens



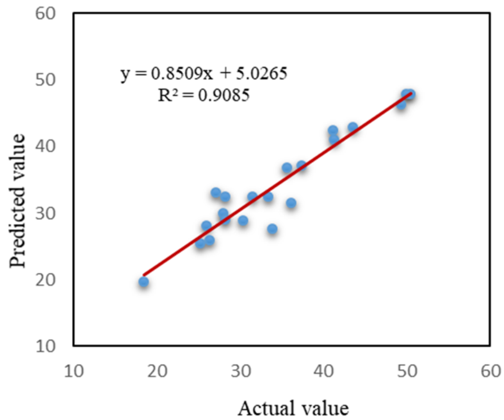
(a) ANN



(b) PSO-ANN



(c) ICA-ANN



(d) GA-ANN

Fig. 8 Correlation between the observed and modelled compressive strength values for testing specimens

respectively. Likewise, we witnessed an appreciable improvement of accuracy, due to the decrease of calculated MAE (2.2195, 1.3494, 1.0951, and 2.0025) as 39.20%, 50.66%, and 9.77%. Similar to the training phase, the correlation between the actual and predicted values of compressive strength increased from 0.8932 to 0.9705, 0.9744, and 0.9085. From a comparison viewpoint, ICA presented the best optimization of ANN parameters due to the highest R^2 (0.9753 and 0.9744), and lowest RMSE (1.1802 and 1.3935) and MAE (0.9501 and 1.0951) in both training and testing phases. After ICA-ANN, PSO-ANN was the most reliable technique, followed by GA-ANN and ANN.

Besides, according to Fig. Seven showing the regression between the actual and estimated values of compressive strength of concrete in the training dataset, more tendency of ICA-ANN outputs to line x = y (i.e., the ideal prediction trend line) demonstrates the higher compatibility of its results compared to PSO-ANN, GA-ANN, and ANN. As for testing data, a significant difference between the computed values of R^2 for ANN (0.8932), PSO-ANN (0.9705), GA-ANN (0.9085), and ICA-ANN (0.9744) indicate the more generalization potential of the latter approach. Referring to Fig. 8, more aggregation of ICA-ANN sample points around the trending line (i.e., with equation 0.909x + 2.9745) is another evidence for this claim.

Fig. 9 demonstrates the graphical error (i.e., the difference between the observed and predicted values of compressive strength). The calculated values of mean absolute percentage error (MAPE) for the prediction of ANN, PSO-ANN, ICA-ANN, and GA-ANN were 5.03%, 3.89%, 2.79%, and 4.74%, respectively. As well as this, the results of the proposed predictive models are also presented in the form of 3D scatter plots based on the predicted compressive strength versus water and cement independent variables (Figs. 10(a) to (d)). Comparing these charts with Fig. 2(d) (which shows the same situation for the actual values of compressive strength), it can be concluded that ICA-ANN has produced more compatible results.

4.4 Formula extraction

In the last part of this work, it was aimed to develop the formula of the best improved ANN. To this end, the weights and biases of the implemented networks were extracted and formulated in the form of Eq. (13) for the ICA-ANN network.

$$\begin{aligned} &Compressive\ strength_{ICA-ANN} \\ &= -0.9836 \times Z1 - 0.4150 \times Z2 + 0.2942 \times Z3 \\ &\quad +0.7156 \times Z4 - 0.7183 \end{aligned} \tag{13}$$

Being more specific, this predictive formula reflects the ruling equation in the output neuron of the neural-based

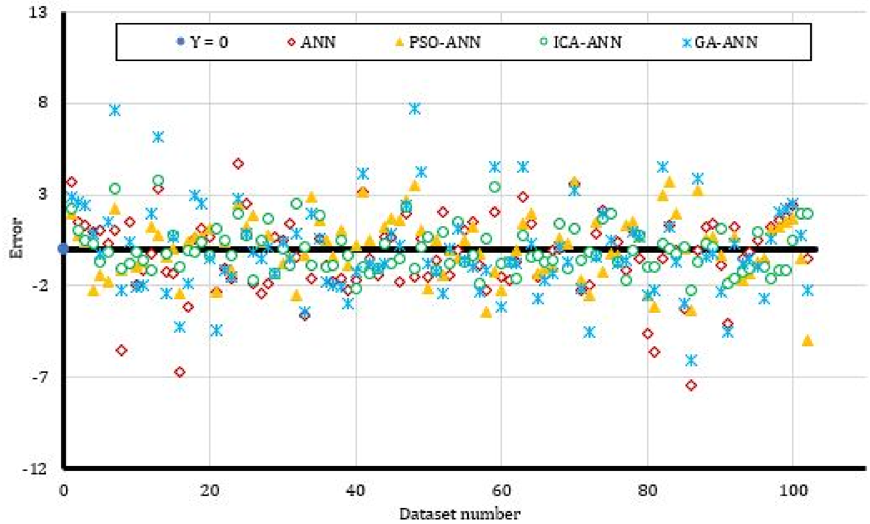
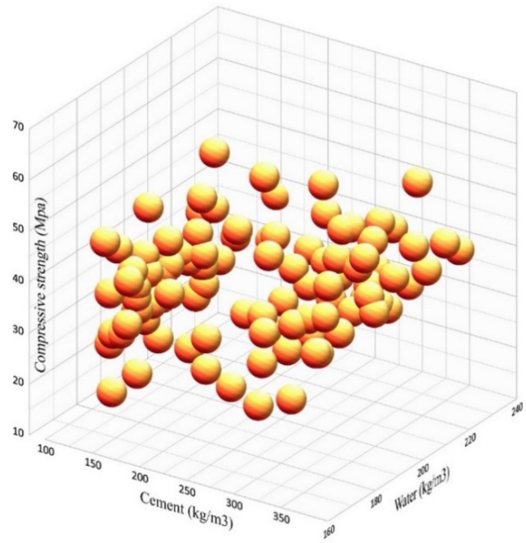
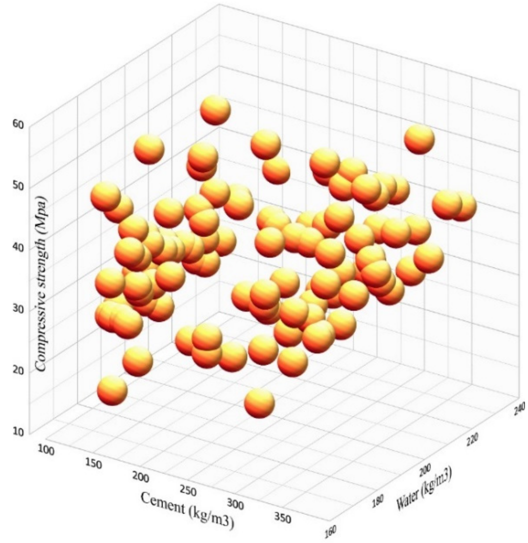


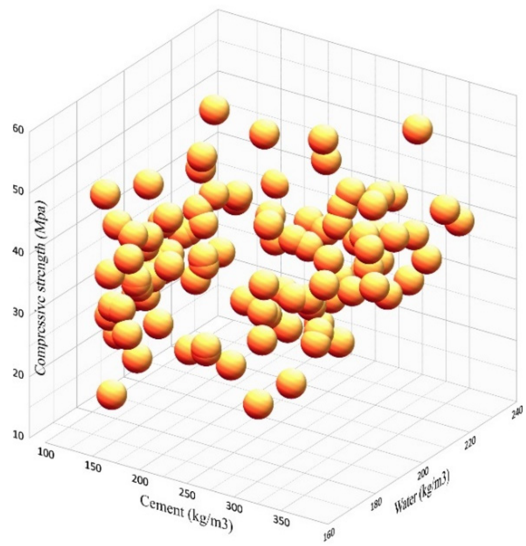
Fig. 9 Graphical difference between the targets and outputs



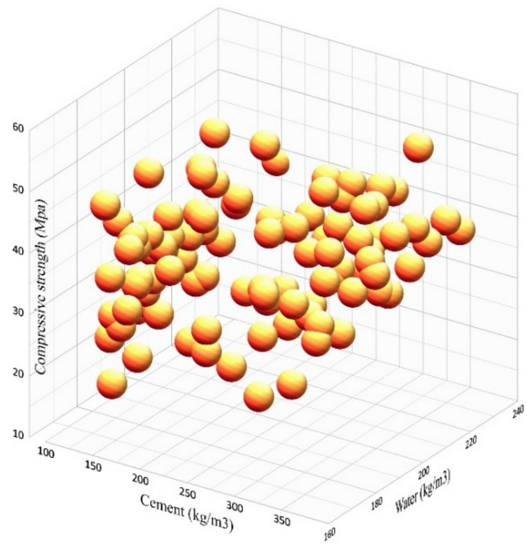
(a) ANN prediction



(b) PSO-ANN prediction



(c) ICA-ANN prediction



(d) GA-ANN prediction

Fig. 10 3D scatter plot of the results of (a) ANN; (b) PSO-ANN; (c) ICA-ANN; and (d) GA-ANN prediction

Table 3 The weight and biases extracted from ICA-ANN

Neuron (i)	W_{i1}	W_{i2}	W_{i3}	W_{i4}	W_{i5}	W_{i6}	W_{i7}	b_i
1	0.3790	0.2485	-0.8373	0.6213	0.6733	-0.6785	-0.8404	-1.7066
2	-0.9658	1.3091	-0.0762	0.3210	0.2028	-0.2235	-0.2571	0.5689
3	0.0681	-0.9043	1.0278	-0.4555	-0.4770	0.5719	0.5211	0.5689
4	-0.0734	-0.9552	1.2262	0.4257	-0.0793	0.5105	0.2076	-1.7066

network (See Fig. 1). Accordingly, utilizing it entails calculating some middle parameters, namely Z1, Z2, …, Z4, which are calculated by Eq. (14), and using Tables 3. The numbers in table represent the weights and biases of the hidden neurons assigned by the training algorithm. In other words, the assignment of these values points out the main contribution of the used ICA algorithm to the problem of compressive strength. This is because the algorithm uses its specific rules to adjust these parameters based on the relationship between the response parameter (i.e., compressive strength) and influential factors.

$$Zi = Tansig(Wi1 \times X_1 + Wi2 \times X_2 + \cdots + Wi7 \times X_7 + bi) \tag{14}$$

This formula is the numerical representation of the ICA-ANN model which, due to reliable performance for the testing data, has good generalizability. The reason for this claim is that the model had to deal with the testing samples and they are considered as unseen concrete mixtures. Hence, it can be used to predict the compressive strength with reliable accuracy. However, it has some restrictions as well. For example, the number (and the type) of the used inputs should be taken into the equation. This formula takes cement, slag, water, fly ash, SP, FA, and CA as inputs and predicts the compressive strength based on these values. For different input combinations, a new ICA-ANN should be executed. Also, the statistical aspect should be regarded, too. This formula works based on weighting for data that is described in Table 1. If the proposed data are in a considerably different extent, it is better to first test it with some given data. However, the used dataset seems effective for regular usages of concrete.

4.5 Complementary discussion

In comparison with earlier researches that pursued the same objective, the results of our research are more promising in Ref. (Nikoo *et al*. 2015a), which improved the ANN using the GA evolutionary algorithm, the correlation pertaining to the proposed model was 0.899 which slightly lower than one our GA-ANN has achieved to. However, the elite ensemble of the present study yielded far better performance (R^2 = 0.9744). Compared to the work by Tien Bui *et al*. (2019), which used the same dataset with more state-of-the-art hybrid techniques, i.e., whale optimization algorithm (WOA), the ICA algorithm of this study could construct a more reliable neural network. More clearly, in both training and testing phases, the ICA-ANN (RMSE = 1.3935 and R^2 = 0.9744) outperformed the WOA-ANN (RMSE = 2.6985 and R^2 = 0.8976). Besides, the correlation between the predicted values with actual 28-day compressive strength in this study was found to be higher than Ref. (Henigal *et al*. 2016) (R^2 = 0.895).

Notably, since simulating the compressive strength is a nonlinear and multidimensional problem, this study has some limitations. The used dataset, for instance, does not contain a number of compressive strength influential factors suchlike air percentage, absorption of the aggregates, temperature, and humidity of the concrete mixture. Besides, the results might be more comprehensive if a wider range of compressive strength is taken into consideration. Moreover, although the implemented models have gained an eye-catching approximation of the problem, the authors believe that optimization of other influential parameters (other than the population size) could be effective in finding a more powerful predictive tool. We also believe that these limitations could be good subjects for future studies to provide the best possible approach for predicting the compressive strength of concrete

5. Conclusions

Having a reliable estimation from the compressive strength of concrete is an important task in the construction industry. This study deals with evaluating the efficiency of three metaheuristic algorithms, namely PSO, ICA, and GA, for remedying the shortcomings of the artificial neural network in the prediction of 28-day compressive strength of concrete. We provided a dataset consisting of cement, slag, water, fly ash, superplasticizer, fine aggregate, and coarse aggregate as the input parameters, and compressive strength was taken the response variable. After a trial and error process, the optimal parameters of the proposed networks were determined. Accordingly, ANN with four hidden neurons, PSO with swarm size of 450, ICA with a number of the country of 400, and GA with a population size of 450 gave the best results. Three statistical indices of root mean square error, coefficient of determination, and mean absolute error were defined to validate the performance of the used models. In this regard, R^2 increased from 0.9363 (for ANN) to 0.9488, 0.9753, and 0.9387 (respectively for PSO-ANN, ICA-ANN, and GA-ANN), and from 0.8932 to 0.9705, 0.9744, and 0.9085, respectively in the training and testing phase. Moreover, RMSE decreased from 1.9080 to 1.7027, 1.1802, and 1.8713, and from 2.9032 to 1.5920, 1.3935, and 2.6756, respectively, in the training and testing phase. Likewise, MAE decreased from 1.5162 to 1.3626, 0.9501, and 1.4992, and from 2.2195 to 1.3494, 1.0951, and 2.0025, respectively, in the training and testing phase. From the comparison viewpoint, ICA outperformed other evolutionary algorithms, and PSO showed more reliability compared to GA. Moreover, the formula of the best implemented ANN was extracted which could be a promising alternative to traditional methods. However, it should be noted that the dataset used in this study has a number of limitations like a limited range of compressive strength, as well as not considering some influential variables of this parameter. Also, comparing the used methodologies to other non-neural conventional methods like least square support vector regression (LS-SVR) could also reflect the most powerful basic theory for such predictions.

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