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Concrete compressive strength prediction using the imperialist competitive algorithm

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Abstract. In the following paper, a socio-political heuristic search approach, named the imperialist competitive algorithm (ICA) has been used to improve the efficiency of the multi-layer perceptron artificial neural network (ANN) for predicting the compressive strength of concrete. 173 concrete samples have been investigated. For this purpose the values of slump flow, the weight of aggregate and cement, the maximum size of aggregate and the water-cement ratio have been used as the inputs. The compressive strength of concrete has been used as the output in the hybrid ICA-ANN model. Results have been compared with the multiple-linear regression model (MLR), the genetic algorithm (GA) and particle swarm optimization (PSO). The results indicate the superiority and high accuracy of the hybrid ICA-ANN model in predicting the compressive strength of concrete when compared to the other methods.

Keywords: computer modeling; concrete; concrete structures; construction materials; non-destructive tests (NDT); reinforced concrete (RC)

1. Introduction

Concrete is principally formed by cement paste, aggregates and additives. The compressive strength of concrete is dependent on many factors. These factors include mainly mix proportions, methods of mixing, curing conditions and transporting. The compressive strength of concrete is one of the principal factors affecting the durability of concrete structures (Hoła *et al*. 2015).

Recently, artificial neural networks (ANNs) are one of the most powerful tools used to predict the compressive strength of concrete. The ANNs presents usually high accuracy. However, it also has some disadvantages. For example, due to the high complexity of ANN, the reasonable mathematical relationship between the input and output variables are not produced. To overcome its disadvantages, several techniques have been proposed in the past to reduce its complexity. Therefore, more frequently other techniques such the meta-heuristic algorithms or model trees may be used, e.g., M5P tree model as presented by Behnood *et al*. (2017).

In the author's opinion the imperialist competitive algorithm (ICA) can offer the following advantages: high speed with the least risk of trapping in local minima, the ability to deal with various types of constraints and also a suitable functionality compatible with the GA and PSO. In other words, the ICA is burdening the duty of finding the best weights for the recommended multi-layer perceptron ANN network. According to Kaveh (2017) nowadays ICA is successfully used to solve important civil engineering problems. The recent examples of such applications are:

- the prediction of ground vibration in quarry blasting (Hajihassani *et al*. 2015, Armaghani *et al*. 2018),
- the prediction of the corrosion current density in reinforced concrete (Sadowski and Nikoo 2014),
- the assessment of the adhesion in existing cement composites (Sadowski *et al*. 2017),
- the location of the critical slip surface in 2-dimensional soil slopes (Kashani *et al*. 2016),
- the optimum design of skeletal structures (Maheri and Talezadeh 2018),
- the prediction the surface settlement induced by tunneling (Tashayo *et al*. 2018),
- the optimization of reinforced concrete retaining walls (Sheikholeslami *et al*. 2016),
- the estimation of the bearing capacity of driven pile in cohesionless soil (Moayedi and Armaghani 2018).

In most of these applications ANNs hybridized with ICA resulted of better performance than for conventional multi-layer perceptron ANN. Considering the above, for the purpose of the compressive strength of concrete prediction, the ICA may provide satisfactory performance with enough accuracy. The ICA has been therefore employed to cover the objective of the study.

The remainder of the paper is organized as follows. Section 2 presents the description of related work. Section 3 presents a short description of the ICA. Section 4 presents the experimental setup with background and data acquisition. Section 5 presents experimental results and Section 6 presents the analysis of results, which are summarized by conclusions.

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Table 1 The most commonly used learning algorithms applied by selected authors in ANNs for the prediction of the compressive strength of various types of concretes (data collected on 16.09.2018 from Google Scholar database for the articles published from 2014 to 2018)

Type of the learning algorithm	Average compressive strength of investigated concrete	
	below 60 MPa	over 60 MPa
Levenberg-Marquardt	Kostić and Vasović (2015) Asteris *et al*. (2016) Khademi *et al*. (2016) Chopra *et al*. (2016) Bachir *et al*. (2017) Tanyildizi (2018) Liang *et al*. (2018) Ongpeng *et al*. (2018)	Ghafari *et al*. (2015) Chithra *et al*. (2016) Qu *et al*. (2018)
Broyden-Fletcher-Goldfarb-Shanno	Kao *et al*. (2018)	-
Genetic algorithm	Nikoo *et al*. (2015) Yuan *et al*. (2016) Heidari *et al*. (2017) Rebouh *et al*. (2017)	Cheng *et al*. (2014)
Gene expression programming	Kiani *et al*. (2016) Hadianfard and Jafari (2016)	-
Bayesian	Paul *et al*. (2018)	-
Grey wolves	-	Behnood *et al*. (2017)
Firefly algorithm	-	Bui *et al*. (2018)
Particle swarm optimization	Mashhadban *et al*. (2016) Tsai (2016)	-
Harmony search	-	Ji *et al*. (2017)

2. Related work

Recently the identification of the compressive strength of concrete when relying on mathematical modeling has been the area of interest of many researchers. Bilgehan and Turgut (2010) showed the ability of the backpropagation ANN for the prediction of the compressive strength of concrete using the gradient descent learning algorithm. Nikoo *et al*. (2015) employed ANNs and their combinations with genetic algorithms (GA) for the prediction of the compressive strength of concrete. Khademi *et al*. (2016) predicted the strength of recycled aggregate concrete using the ANN learned using the Levenberg-Marquardt algorithm. However, in recent years, combinatorial formations of the ANN and meta-heuristic algorithms have been found to be more effective for the prediction of the compressive strength of concrete. A combinatory model of the ANN and fuzzy logic presented by Sarıdemir *et al*. (2009) demonstrated the potential for predicting the long-term effects of ground granulated blast furnace slag on the compressive strength of concrete. In order to reduce the cost and save time in the class of the determination problems of compressive strength, a cascade correlation type of ANN was employed by Alshihri *et al*. (2009) with a focus on quick learning. This ANN has a less accurate performance for capturing the intrinsically non-linear nature of patterns in the properties of concrete. For instance, the hybrid multilayer perceptron ANN and center-unified particle swarm optimization (PSO) were used by Tsai (2010). In a similar area, the compressive strength of self-compacting concrete with polypropylene fiber and mineral additives was estimated by Uysal and Tanyildizi (2012). Moreover, the prediction of compressive strength in cement- based materials was accomplished by Alexandridis *et al*. (2012) by analyzing the pressure-stimulated electrical signals. Additionally, Al-Zharani *et al*. (2016) found the ANFIS model effective enough in estimating the corrosion factors for very high core compressive strength. Furthermore, Khademi *et al*. (2016) found the ANN model useful in the prediction of the compressive strength of concrete. Behnood and Golafshani (2018) estimated the compressive strength of silica fume concrete based on ANN hybridized with multi-objective grey wolves algorithm. Table 1 presents the most commonly used learning algorithms applied in ANNs for the prediction of the compressive strength of various types of concretes.

It is visible from Tab. 1 that most of commonly used learning algorithms applied by selected authors in ANNs for the prediction of the compressive strength of various types of concretes is the Levenberg-Marquardt. To the best of our knowledge there is no study related to concrete compressive strength prediction using the ICA.

2. Short description of the imperialist competitive algorithm (ICA)

The ICA is a heuristic optimization method that uses imperialistic competition (IC) as a source of inspiration (Atashpaz-Gargari and Lucas 2007). This algorithm begins with some initial countries as the initial solutions for an investigated problem. Some countries, which are considered as the best solutions, are selected to be imperialist, and other countries form the corresponding colonies. Based on the power of each imperialist, the colonies are partitioned. After partitioning all the colonies among the imperialists

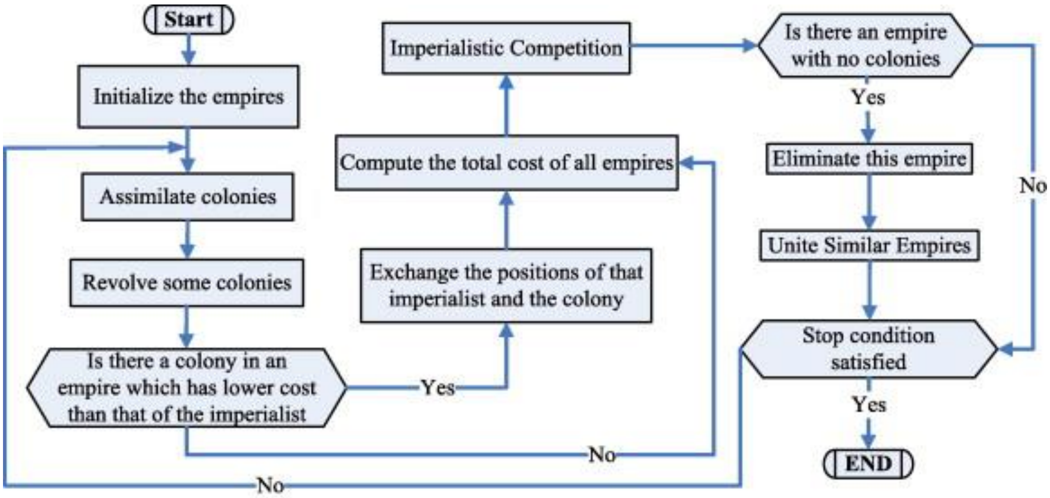


Fig. 1 ICA flowchart (Nazari-Shirkouhi *et al*. 2010)

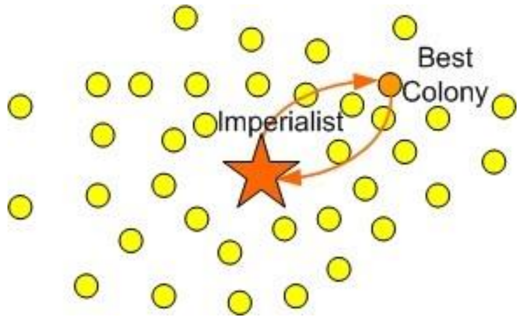
and creating the initial empires, these colonies start moving towards their relevant imperialist. The basis of the ICA, on the other hand, is IC in which the weak empires lose their power and then collapse. In contrast, the powerful ones take the possession of their colonies. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. In IC, all empires try to take possession of the colonies of other empires and control them; consequently, IC converges to a state in which there exists only one empire (Fig. 1).

Assimilation policy establishes the movement of the colonies towards their relevant imperialists. As shown in Fig. 2(a), the colony moves by the x unit towards the imperialist to settle on the new position. Represented in Eq. (1), x and θ are the random variables with a uniform distribution, β and Υ are two parameters determining the area in which the colonies are supposed to search around their imperialist and d is the distance between the colony and imperialist.

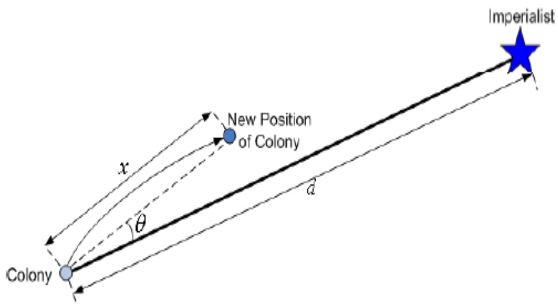
β could be an arbitrary number greater than 1, approximately 2, and in the case that β>1, the colonies become closer to the imperialist state from both sides (Atashpaz-Gargari and Lucas 2007)

$$x \sim (0, \beta \times d) \quad , \quad \theta \sim U(-\gamma, \gamma) \qquad (1)$$

There is a possibility to exchange the position of the colony and imperialist during the movement of the colony towards the imperialist. In this situation, the colony might reach a lower cost than that of the imperialist. Therefore, the former moves to the position of the latter and vice versa. The algorithm then continues with the imperialist in a new position and the colonies start to move towards this position. Fig. 2(b) expresses the proposed concept (Atashpaz-Gargari and Lucas 2007).



(a)



(b)

Fig. 2 Scheme of: (a) movement of colonies towards their relevant imperialist, (b) exchanging the position of the colony and imperialist (Atashpaz-Gargari and Lucas 2007)

4. Experimental setup

173 laboratory concrete samples, including various mix designs, were prepared. The compressive strength of the concrete was measured after 28 days. The data sets, on the other hand, were provided based on the following parameters: the values of slump flow, the weight of aggregate and cement, the water-cement ratio, the maximum size of aggregate and also the compressive strength of concrete. The data was included in (Nikoo *et al*., 2015) while the characteristics of the utilized data are shown in Table 2.

For efficient use of the ANN, however, the pre-process of the aforementioned data sets is necessary. For this, the process of normalization in which all data is arranged in a uniform numerical interval is applied, dependent upon Eq. 2, to provide appropriate inputs for the network

$$X_N = \frac{(X - Min_X)}{(Max_X - Min_X)} \times 2 - 1 \qquad (2)$$

Table 2 Input and output characteristics

No.	Parameters	Type	Unit	Maximum	Minimum	Mean value	Standard deviation
1	slump flow	Input	mm	160	30	67.6	27.0
2	cement weight	Input	kg	549	243	385.55	72.70
3	aggregate weight	Input	kg	1050	559	779.13	95.71
4	maximum size of aggregate	Input	mm	50	5.12	23.89	14.25
5	the water - cement ratio	Input	-	0.63	0.24	0.43	0.19
6	f_c	Output	kg/cm^2	394	173	279.27	54.98

*10 kg/cm^2=1 MPa, 1 Kg=10 N

where X are input data, X_N represents the normalized input data, and Min_x and Max_x the minimum and maximum of all data, respectively.

The multi-layer perceptron (MLP) ANN maps the nonlinear dynamic of the provided information. In its output, the predictive values of the compressive strength of concrete is presented. The ICA, subsequently, is applied on the network so that the optimal weights will be offered. It means that the ANN is trained by the ICA instead of the simple gradient-based approach. To consider a broad comparison, the GA and PSO are applied on the MLP-ANN structure for the purpose of weight optimization. Several performance indices, such as mean square error (MSE) and the coefficient of determination (R^2), were chosen for numerical comparison. Eventually, the performances of ICA-ANN, GA-ANN, PSO-ANN and the MLR model, in predicting the compressive strength of concrete, are compared. The pseudo code for the ICA (Atashpaz-Gargari and Lucas 2007) is as follows:

i. Select some random points on function and initialize the empires.
ii. Move the colonies towards their relevant imperialist (assimilating).
iii. If there is a colony in an empire that has a lower cost than that of the imperialist, exchange the positions of that colony and the imperialist.
iv. Compute the total cost of all the empires (related to the power of both the imperialist and its colonies).
v. Pick the weakest colony (colonies) from the weakest empire and give it (them) to the empire that has the most likelihood to possess it (imperialistic Competition).
vi. Eliminate the powerless empires.
vii. If there is just one empire, stop, and if not go to 2.

5. Experimental results

5.1 Training and testing of the hybrid ICA-ANN model

The well-known MLP is selected for this research and it includes the parameters of the values of slump flow, the weight of aggregate and cement, the water-cement ratio and the maximum size of aggregate in its input layer. 138 patterns (80% of the information) are applied on the ANN for the training phase and 35 patterns (20% of information) are applied for the testing phase. The rule of thumb in equation 1 is used for determining the number of neurons in the hidden layer (Gavin *et al*. 2005)

$$N_H \le 2N_I + 1 \tag{3}$$

where N_H is the maximum number of neurons in the hidden layer and N_I is the number of inputs. With respect to the efficient number of inputs, which is 5 for the proposed network, the maximum number of hidden nodes is equal to 11 ($N_H \le 11$). The compressive strength of concrete was employed in the output layer. The proposed topology has been illustrated in Fig. 3.

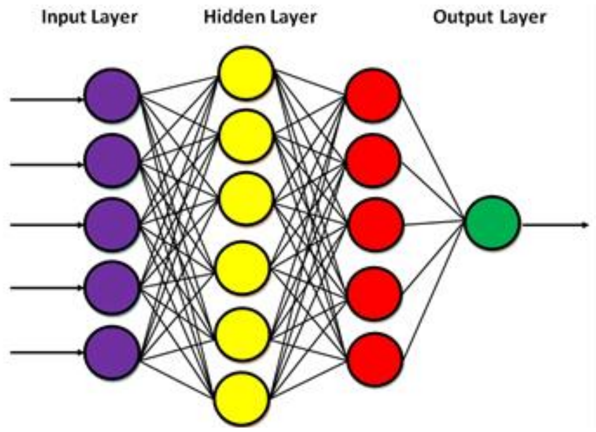


Fig. 3 Proposed MLP-ANN topology

Table 3 The optimal ICA-ANN structure

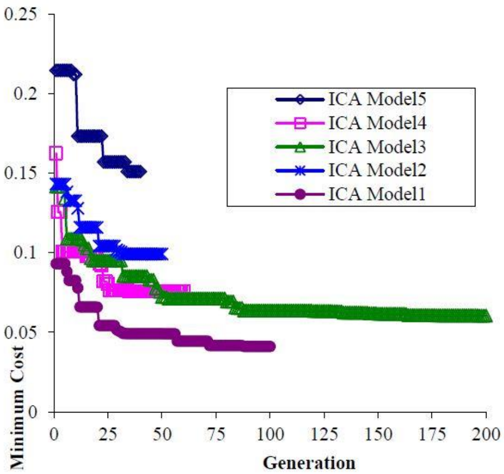
Models' name	ANN features				Utilized initialization parameters in ICA		
	Number of inputs	Number of outputs	Number of hidden layers	Number of nodes in hidden layer	Number of countries	Number of imperialists	Number of decades
ICA-ANN 1	5	1	2	6_4	400	40	100
ICA-ANN 2			1	7	500	50	50
ICA-ANN 3			1	5	500	50	200
ICA-ANN 4			1	4	400	30	60
ICA-ANN 5			1	10	600	60	40

In order to find the optimum weights for the multi-layer perceptron ANN, which results in attaining an appropriate performance, various geometrical structures of the ANN are selected. Afterwards, the proposed ICA with the assorted initialization parameters, such as the number of country, imperialist and iteration, are applied on the mentioned topologies. In Table 3, the recommended models, together with the utilized quantities of ICA parameters, are depicted. The tan-sigmoid transfer function in hidden layer was used according to Dorofki *et al*. (2012) with the mathematical formula as follows:

$$Tansig(n) = \frac{2}{1+e^{-2n}} - 1 \tag{4}$$

Table 4 Results of training and testing of selected ICA-ANN models

Model	R^2		MSE		Best cost
	Testing	Training	Testing	Training	
ICA-ANN 1	0.794	0.841	0.0696	0.0411	0.0411
ICA-ANN 2	0.551	0.721	0.1031	0.0722	0.0722
ICA-ANN 3	0.620	0.763	0.0846	0.0604	0.0604
ICA-ANN 4	0.450	0.707	0.1281	0.0757	0.0757
ICA-ANN 5	0.237	0.509	0.2471	0.1510	0.1510



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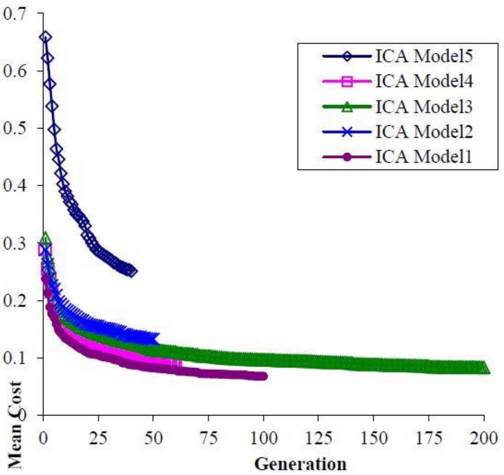
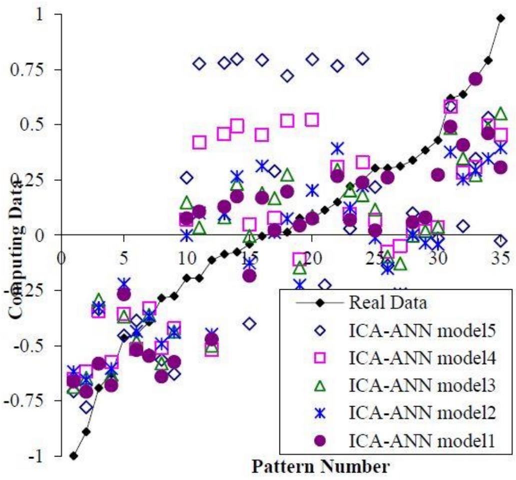


(b)

Fig. 4 Cost diagram for the selected ICA-ANN: (a) minimum cost, (b) mean cost

In addition, Table 4 presents the results of the training and testing phases that correspond to the mentioned structures. For performance evaluation of the models and to determine the best one, the performance has been indicated by using mean average error (*MAE*) and mean squared error (*MSE*). *MAE* and *MSE* are known as reliable indicators to quantify the difference between the values implied by an estimator and the true values of the quantity being estimated. The determination coefficient (R^2) has also been calculated. The R^2 ranges from 0 to 1 and presents an evaluation of how well the observed outcomes are replicated by the model. The best model is the one that



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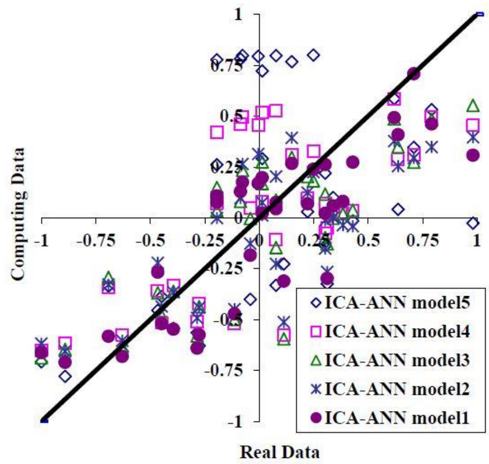


(b)

Fig. 5 Prediction of the compressive strength of concrete for different ICA-ANN models in the: (a) training, (b) testing

Table 5 Statistical results of the optimized ICA-ANN

Error	Training				
	ICA-ANN model5	ICA-ANN model4	ICA-ANN model3	ICA-ANN model2	ICA-ANN model1
MAE	0.979	0.949	0.926	0.918	0.913
MSE	1.221	1.099	1.048	1.001	1.066
RMSE	1.105	1.048	1.024	1.001	1.033
	Testing				
MAE	1.049	1.012	0.950	0.928	0.948
MSE	1.370	1.178	1.027	0.963	1.045
RMSE	1.170	1.085	1.013	0.982	1.022

displays a higher value of R^2.

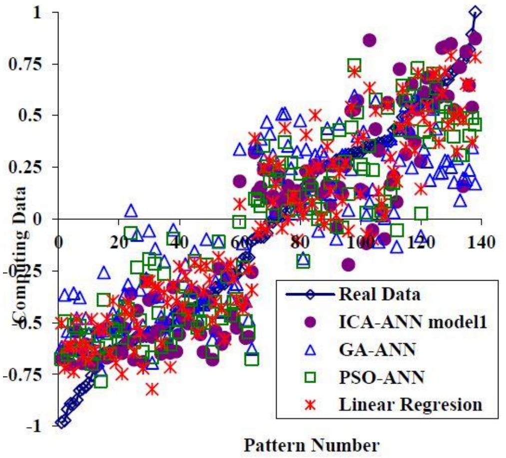
Fig. 4 presents the minimum and mean cost diagrams of the examined models. Fig. 5 shows the prediction of the compressive strength of concrete for different ICA-ANN models in the testing and training phases.

In addition, the statistical results of the optimized ICA-ANN are presented in Table 5.

As can be observed from Table 5 and Figs. 4 and 5, in the first model (ICA-ANN 1) offers the smallest values of MAE errors for training and testing. According to all of

Table 6 Estimation of the compressive strength of concrete with four suggested models

Model	R^2		MSE	
	Testing	Training	Testing	Training
ICA-ANN	0.794	0.841	0.0696	0.0411
GA-ANN	0.388	0.619	0.1326	0.0980
PSO-ANN	0.646	0.789	0.0809	0.0543
Linear Regression	0.707	0.818	-	-



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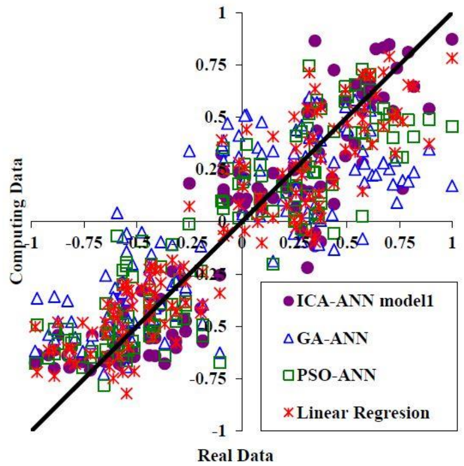
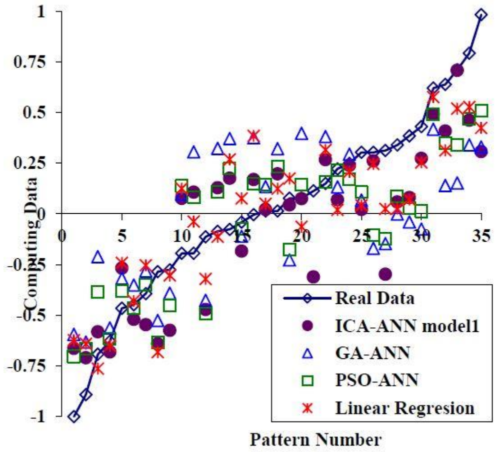


(b)

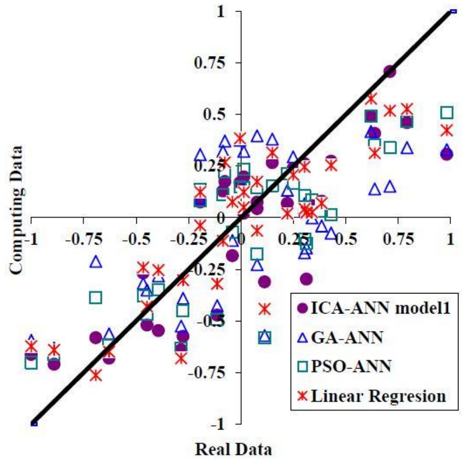
Fig. 6 Comparison of predicted and observed compressive strength with different models in training phase

Table 7 Statistical indicators related to different models of the ANN with the optimization algorithm

Model	Training			
	ICA-ANN	GA-ANN	PSO-ANN	Linear Regresion
MAE	0.913	0.944	0.922	0.933
MSE	1.066	1.028	1.032	1.068
	Testing			
MAE	0.948	0.970	0.941	0.977
MSE	1.045	1.052	1.011	1.089



(a)



(b)

Fig. 7 Comparison of predicted and observed compressive strength with different models in testing phase

these indices, the first model is selected as an optimal network. This model was optimized by means of the assigned number of 400 countries, 40 imperialists and 50 iterations.

5.2 Validation of the selected ICA-ANN model

To validate the selected ICA-ANN model, the GA and PSO are employed. On the basis of the same methodology and the accuracy of the achieved models, they were compared with the ICA-ANN model. The results of the statistical MLR model for the estimation of the compressive strength of concrete are used for a thorough comparison. In this research, different regression models are extracted by using input and output variables.

The best MLR model, which is completely compatible with the data of the compressive strength of concrete, is presented by using Eq. (5)

$$y = -0.119 - 0.257x_1 + 0.373x_2 + 1.14x_3 + 0.199x_4 - 0.269x_5 \quad (5)$$

in which x_1 is aggregate weight, x_2 is maximum size of aggregate, x_3 is cement weight, x_4 is the water-cement ratio and x_5 expresses the slump flow. The output of the equation y is the desired compressive strength of the concrete parameter.

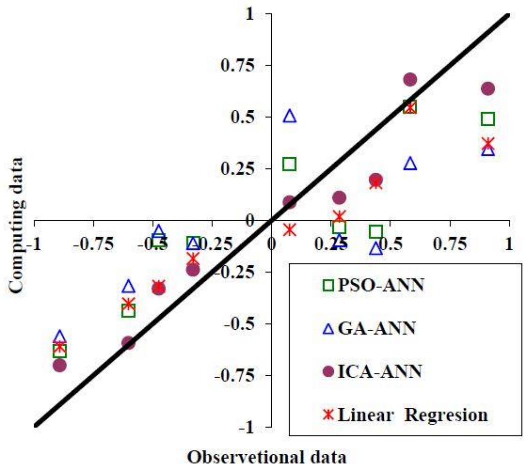


Fig. 8 Accuracy comparison between the suggested models

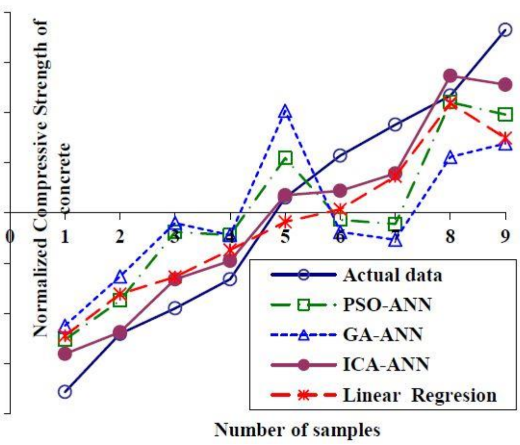


Fig. 9 Prediction of the compressive strength of concrete with different models

The results of the prediction of the compressive strength of concrete with the GA and PSO based MLP models, as well as the MLR model, are presented below. The number of population used in the GA was 150 and the number of the generation was equal to 100. The mutation and cross over rate were 15 and 50, respectively. In PSO, the number of particles was equal to 200 and includes the 35 iterations. Fig. 6 provides a comparison between the obtained quantities of compressive strength in the training phase established upon the four mentioned models.

The recorded values of R^2 and MSE errors reveal the fact that the ICA-ANN model has the highest accuracy in predicting the compressive strength of concrete (Table 6). These observations express that the aforementioned model can offer a suitable adaptation in the learning of the dynamic of data and it can also provide a significant validity in the testing stage.

Fig. 7, moreover, shows that the ICA-ANN model, in comparison with the GA, PSO and MLR models, shows better flexibility and accuracy in testing phase. This may be because of the ability of ICA in solving high complex models. In addition, Table 7 presents the statistical indicators for different models of the ANN with the optimization algorithm.

To appraise the performance of the optimal ICA-ANN model in reality, 9 laboratorial samples are employed to validate the strength of the hybrid ICA-ANN model in predicting the compressive strength of concrete. These samples were not utilized in the training and testing of the proposed models. Figs. 8 and 9 provide an overview of the comparison between the performances of the ICA-ANN model in predicting the compressive strength of concrete. In this model, the obtained values of determination coefficient R^2 for PSO-ANN, GA-ANN, ICA-ANN and Linear Regression were obtained and are equal to 0.762, 0.522, 0.945 and 0.916, respectively.

6. Conclusions

A hybrid ICA-ANN model was proposed for predicting the compressive strength of concrete. 173 samples, including various concrete mix designs, were provided in the laboratory, and the compressive strength of concrete was measured.

Nonlinear mapping in the ICA-ANN model was performed between selected input and output parameters. The prepared input data sets comprise of the values of slump flow, the weight of aggregate and cement, the water-cement ratio and the maximum size of aggregate. The settled output data were the values of the compressive strength of concrete. The utilized optimization algorithm and ICA offered significant superiority for training of the ANN. For validity of the entire model, the performance of the recommended methodology was compared with the GA, PSO and MLR models. The results of simulation clearly indicated that the ICA-ANN model was able to present a more acceptable functionality with satisfactory flexibility in either training, testing or validation.

The recently developed ICA-ANN model can be effectively applied by engineers dealing with the prediction of the compressive strength of concrete. The method offers the reasonable accuracy and low complexity. The presented method is cost- and time-effective. It can also avoid the amount of waste material caused usually by a large number of necessary trials to predict the compressive strength destructively on the concrete samples.

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