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Prediction of concrete strength in presence of furnace slag and fly ash using Hybrid ANN-GA (Artificial Neural Network-Genetic Algorithm)

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Abstract. Mineral admixtures have been widely used to produce concrete. Pozzolans have been utilized as partially replacement for Portland cement or blended cement in concrete based on the materials' properties and the concrete's desired effects. Several environmental problems associated with producing cement have led to partial replacement of cement with other pozzolans. Furnace slag and fly ash are two of the pozzolans which can be appropriately used as partial replacements for cement in concrete. However, replacing cement with these materials results in significant changes in the mechanical properties of concrete, more specifically, compressive strength. This paper aims to intelligently predict the compressive strength of concretes incorporating furnace slag and fly ash as partial replacements for cement. For this purpose, a database containing 1030 data sets with nine inputs (concrete mix design and age of concrete) and one output (the compressive strength) was collected. Instead of absolute values of inputs, their proportions were used. A hybrid artificial neural network-genetic algorithm (ANN-GA) was employed as a novel approach to conducting the study. The performance of the ANN-GA model is evaluated by another artificial neural network (ANN), which was developed and tuned via a conventional backpropagation (BP) algorithm. Results showed that not only an ANN-GA model can be developed and appropriately used for the compressive strength prediction of concrete but also it can lead to superior results in comparison with an ANN-BP model.

Keywords: artificial neural network; genetic algorithm; prtial replacement; furnace slag; fly ash

1. Introduction

Fly ash (pulverized fuel ash) as a residue has been gained from the combustion of pulverized coal in furnaces of thermal power plant. One of the essential components of concrete is cement; however, producing every ton of cement leads to significant emission of CO_2 into the atmosphere (Hewlett and Liska 2019, Li *et al*. 2019). Cement production only accounts for 7% of the total produced CO_2 in the world (Benhelal *et al*. 2013). Hence, partial replacement of cement in concrete with other pozzolans is a very efficient approach to reduce CO_2. On the other hand, pozzolans can be obtained through waste materials remaining from the manufacturing process of different products. Therefore, the use of such pozzolans in concrete can address not only a solution to decrease the amount of CO_2 but also a mean for the disposal of waste materials (Nguyen *et al*. 2018, Nosrati *et al*. 2018).

1.1 Fly ash

Fly ash (FA), as sort of pozzolan powder, can be used for partial replacement of cement (Davis *et al*. 1937). FA not only increases the workability and integrity of concrete but also declines the adverse byproducts of cement production (Li and Zhao 2003). Although FA can improve the rheology of concrete mixture, the compressive strength and slump reduce (Antiohos *et al*. 2007). Generally, FA is obtained as a remnant of the pulverized coal combustion in furnaces of thermal power plants. The features of FA largely depend on the combustion processing through which the FA is obtained. FA gathered through dry processing is generally homogenous in particle size, whereas the FA obtained by wet processing is highly separated due to the lower sedimentation speed and more quantity of water (Ameri *et al*. 2015).

1.2 Furnace slag

Furnace slag is one of the cementitious materials which

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has a noticeable structural resemblance to cement (Gorai and Jana 2003). According to the precursor studies, furnace slag, as a partial replacement for cement, can increase the compressive strength and durability of concrete (Razak and Sajedi 2011, Shariati *et al*. 2020c). On the other hand, using furnace slag at a higher dosage can cause thermo-hygral damages and cracks, which adversely affect the strength and mechanical properties of concrete (Li and Zhao 2003, Naghipour *et al*. 2020). Furnace slag is a by-product of iron and steel production in furnaces. The composition of raw material in the process of iron production affects the chemical composition of furnace slag which leads to significant variations. Slag is decanted in the furnace by floating on top of the iron. Quick cooling of the molten slag converts it to non-crystalline ingredients with hydraulic characteristics (Bınıci *et al*. 2012). In order to raise the cementitious characteristics of slag, it can be crushed to reach the same fineness as an ordinary Portland cement (OPC) (Boukendakdji *et al*. 2012).

1.3 Artificial Neural Networks (*ANNs*) *and Evolutionary Algorithms* (*EAs*)

Artificial neural networks (ANNs) are intelligence tools which have been widely used in different applications such as function-approximation, classification, and time series prediction (Chan *et al*. 2011, Hinton *et al*. 2012, Esmaeili *et al*. 2014, Safa *et al*. 2016, Toghroli *et al*. 2016, Mansouri *et al*. 2017, Nguyen and Bui 2019, Sedghi *et al*. 2018, Shariati *et al*. 2019a, c, 2020a, Zhou *et al*. 2019). The most considerable advantage of the ANNs is their ability to map a set of inputs to outputs in high dimensional space of problem (Kaastra and Boyd 1996). The performance of the ANNs largely depends on the training process, which is involved. Training means that the weights and biases of the network are obtained which can lead to an acceptable estimation of the actual outputs of the problem. In order to train the ANNs, classic algorithms such as backpropagation (BP) algorithms are conventionally used. Although these algorithms show a high-speed and efficient performance in the training process of ANNs, they have the potential to get stuck in local extremums in some cases (Shariati *et al*. 2019c). As another approach for the training of ANNs, evolutionary algorithms (EAs) such as genetic algorithm (GA), particle swarm optimization (PSO), and imperialist competitive algorithm (ICA) can be used. The global search feature of EAs can eliminate the deficiency of classic algorithms. Hence, these algorithms have been widely used to train the ANNs (Sonmez *et al*. 2006, Ho-Huu *et al*. 2016, Sadeghipour Chahnasir *et al*. 2018, Shariati *et al*. 2019c, d, 2020b).

According to the different applications of structural components, the compressive strength is the critical feature of the concrete. Therefore, the composite beams and floor systems that faced the axial and compressive forces should be investigated under several loading patterns. Besides, the compressive, tensile, and flexural strength of concrete can be evaluated while subjected to different experimental analyzes, and hence, different design parameters and loading scenarios can be estimated with respect to the highest risk. Also, the effectiveness of cementitious additives has been proved by precursor studies where the slag and fly ash represented the most significant role (Shariati *et al*. 2010, 2011, 2012a, b, c, d, 2013, 2014a, b, 2015, 2016, 2017, Shariati 2013, Khorramian *et al*. 2015, 2017, Shahabi *et al*. 2016a, b, Tahmasbi *et al*. 2016, Hosseinpour *et al*. 2018, Nasrollahi *et al*. 2018, Wei *et al*. 2018, Davoodnabi *et al*. 2019).

The compressive strength has been widely discussed and investigated in previous papers, and different concrete mixtures represented various structural behavior along with the experimental tests. Therefore, new mix proportions should be assessed under the compressive tests. Besides, using artificial intelligence, which has been proved to be a convenient approach for engineering applications, could be a wise solution to address the future necessities of experimental analyzes. Consequently, analytical algorithms could be performed on prior experimental studies to predict and evaluate the obtained results (Sinaei *et al*. 2012, Toghroli *et al*. 2014, 2018a, Hamdia *et al*. 2015, Mohammadhassani *et al*. 2015, Shao and Vesel 2015, Toghroli 2015, Mansouri *et al*. 2016, Le-Duc *et al*. 2016, Khorami *et al*. 2017a, Sari *et al*. 2018, Shao *et al*. 2018, 2019, Shariat *et al*. 2018, Armaghani *et al*. 2020, Shariati *et al*. 2019b, Shi *et al*. 2019a, b, Trung *et al*. 2019, Xu *et al*. 2019).

The steel-concrete composite components have been proposed to mitigate the lack of mechanical properties, such as compressive strength. On the other hand, the composite systems have several types that should be investigated by the experimental and analytical tests. Generally, the compressive strength of concrete could affect the composite systems performance; hence each new concrete mixture should be investigated experimentally and analytically and then used in the composite constructions (Arabnejad Khanouki *et al*. 2011, Sinaei *et al*. 2011, Mohammadhassani *et al*. 2014a, b, Khanouki *et al*. 2016, Shah *et al*. 2016, Heydari and Shariati 2018, Luo *et al*. 2019, Xie *et al*. 2019).

Since the pavement would tolerate the direct punch forces and static compressions, the compressive strength of pavement materials such as pervious concrete is one of the most fundamental features in pavement designs which should be enhanced by additive powders like slag and fly ash (Toghroli *et al*. 2017, 2018b, Bazzaz 2018, Bazzaz *et al*. 2018).

Concrete additives are applied to improve the mechanical and chemical properties of the concrete. However, the use of cementitious materials and pozzolans such as FA, slag, silica fume, metakaolin, perlite, and other additives have been carried out to develop the performance of concrete. Besides, FA and slag had a significant effect on the quality of concrete, especially the compressive strength (Arabnejad Khanouki *et al*. 2010, Abedini *et al*. 2017, 2019, Nosrati *et al*. 2018, Sajedi and Shariati 2019). In addition, various methods are currently used to evaluate the structural health monitoring; hence, constructions produced from concrete should be appropriately inspected during serviceability (Hamidian *et al*. 2012).

Also, the concrete could be employed in steel-concrete composite systems. Although the dynamic behavior of composite systems has been a concern for researchers, constructions produced from concrete can be investigated under seismic loading, especially after incorporation of the FA and slag with cement as the cement-replacement additive powders (Daie *et al*. 2011, Kazerani *et al*. 2014, Ghassemieh and Bahadori 2015, Bahadori and Ghassemieh 2016, Najarkolaie *et al*. 2017, Zandi *et al*. 2018).

1.4 Scope and objectives

The purpose of this paper is to predict the compressive strength of concrete in which cement has been partially replaced with furnace slag and fly ash. Hence, rich data, including 1030 data sets were collected from literature, and an artificial neural network (ANN) was developed. The main feature of the gathered data is that it includes concrete specimens with a variety of ages (from one-day to one-year). Also, it includes both specimens in which furnace slag and fly ash have been used separately and together. In contrast to most of the conventional developed ANNs which predict the compressive strength of concrete by considering absolute values of inputs, in this study, inputs were normalized, and their proportions were used. The developed ANN was trained by a genetic algorithm (GA) as an evolutionary algorithm (EA). The performance of the ANN-GA model was assessed by another ANN, which was developed and trained via a conventional backpropagation (BP) algorithm. Finally, the results of the developed ANN-GA and ANN-BP models were compared in terms of performance evaluation values.

2. Methodology

2.1 Artificial neural network (*ANN*) *methodology*

ANNs are intelligence tools inspired by biological neural networks of humans and animals, which can conveniently learn patterns and predict results in high dimensional space of the problem (Naderpour *et al*. 2018, Safa *et al*. 2020). They can map a set of inputs to a set of outputs in a noisy and complex dataset. Multilayer perceptron (MLP) is a simple and reliable class of feed-forward ANNs. A typical MLP network contains an input layer, one or several hidden layers, and an output layer (Alizamir and Sobhanardakani 2018). The Input layer takes the value of inputs and sends them to the available neurons in the hidden layer. Inside each neuron, a weighted sum of inputs is calculated, and this value, plus a value of bias is transformed by an activation function, as shown in Fig. 1. Then, the calculated value is transferred to the neurons in the next layer.

This mathematical process can be formulated by

$$y_j = f\left(\sum_{i=1}^{N} w_{ij}x_i + b_j\right) \tag{1}$$

where x_i and y_j are the nodal values in the previous layer i, and current layer j, respectively. w_{ij} and b_j are also weights and biases of the network.

The used activation (transfer) function in this investigation was hyperbolic tangen function. This function varies between -1 and 1 which is defined as follows

$$Out_j = f(net) = \frac{2}{1+e^{-2x}} - 1 \tag{2}$$

where f is the output variable, and x is the input variable.

Neural networks should be trained to show efficient performance. Training means that the weights and biases of the network are determined such that the minimal error between targets (actual values) and outputs (network values) occurs. Hence, the training process of neural networks culminates in a minimization problem. Backpropagation (BP) algorithms are commonly used in order to train neural networks. Levenberg-Marquardt algorithm (LMA) is often the fastest BP algorithm in training; thus, LMA was used in this study as the BP algorithm.

2.2 Genetic Algorithm (*GA*)

One of the most practical techniques that are utilized in solving optimization problems is the Genetic algorithm (Nimtawat and Nanakorn 2009, Perera and Varona 2009, Kaya 2011, Vo-Van *et al*. 2017, Ziaei-Nia *et al*. 2018, Katebi *et al*. 2019, Khorami *et al*. 2017b). This technique has been inspired by the natural selection mechanism and biological species evolution (Holland 1992). In this technique, a cost function (fitness function) that should be minimized or maximized is described, then, in the available space of the problem, a population of solutions is created.

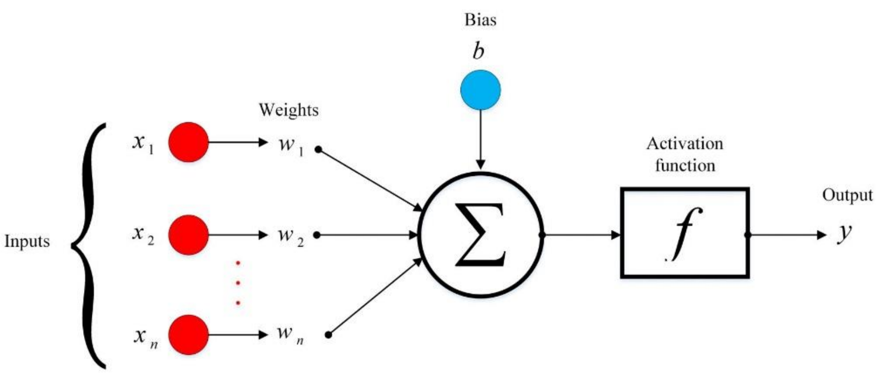

Fig. 1 A typical neuron in ANN

Individuals of this population are represented as strings of chromosomes for each of which the cost function can be calculated. Based on the value of each individual, a percent of the best individuals is selected as parents to reproduce a new generation. Parents are combined through a process which is known as the crossover, and they reproduce offsprings. Some of the offsprings are mutated randomly to represent the actual biological evolution. Finally, in the next generation, the offsprings will play the role of new parents, and this procedure is repeated until the problem is converged, and the best value is obtained for the cost function.

2.3 Artificial neural network-genetic algorithm (ANN-GA)

The appropriate performance of ANN depends on the weights and biases, which are obtained through the training process. In the training process, the difference between actual values (targets) and predicted values (network values) are determined, and an algorithm tries to minimize this error by modifying the weights and biases of the neural network. As mentioned before, GA is an evolutionary algorithm that can solve minimization problems. Therefore, it can be used for determining the weights and biases of the ANN. The cost function (fitness function) of the i^{th} individual can be defined in the term of mean squared error (MSE) as follows

$$f(w_i,b_i)=\frac{1}{S}\sum\nolimits_{k=1}^{S}\left[\sum\nolimits_{l=1}^{O}\{t_{kl}-p_{kl}(w_i,b_i)\}\right]^2 \qquad (3)$$

where f is the cost (fitness) value, t_{kl} is the target output; p_{kl} is the predicted output based on $\boldsymbol{w_i}$ **(weights) and** $\boldsymbol{b_i}$ **(biases)**; S is the number of training set samples; and, O is the number of output neurons. Fig. 2 briefly shows a graphical flowchart of an ANN model which has been combined with GA.

3. Data and preparation

As mentioned before, a big data, including 1030 datasets, was collected from literature for this study (Sarkar and Aitcin 1987, Langley *et al.* 1989, Gjorv *et al.* 1990, Naik and Ramme 1990, Swamy and Bouikni 1990, Hwang 1991, Sivasundaram *et al.* 1991, Giaccio *et al.* 1992, Lessard *et al.* 1993, Lee 1994, Chung 1995, Chang *et al.* 1996, Chang 1997). The details of the input variables are shown in Table 1. As can be seen**,** the prepared data for this study covers a favorable range of each variable with an appropriate frequency.

Although absolute values of inputs have been commonly used in literature for developing ANNs which predict the compressive strength of concrete, it is more practical and reasonable to normalize the input variables. Hence, the new variable of Powder (P), including cement (C), Fly ash, furnace ash, was defined, and the inputs were normalized, as shown in Table 2.

Since the problem of prediction is non-linear, and the presented activation function in Eq. (2) varies between -1 and 1, it is better to normalize the data in the interval of -1 and 1. For this purpose, a preprocessing and postprocessing were conducted on the input data of Table 2 by the following formulas.

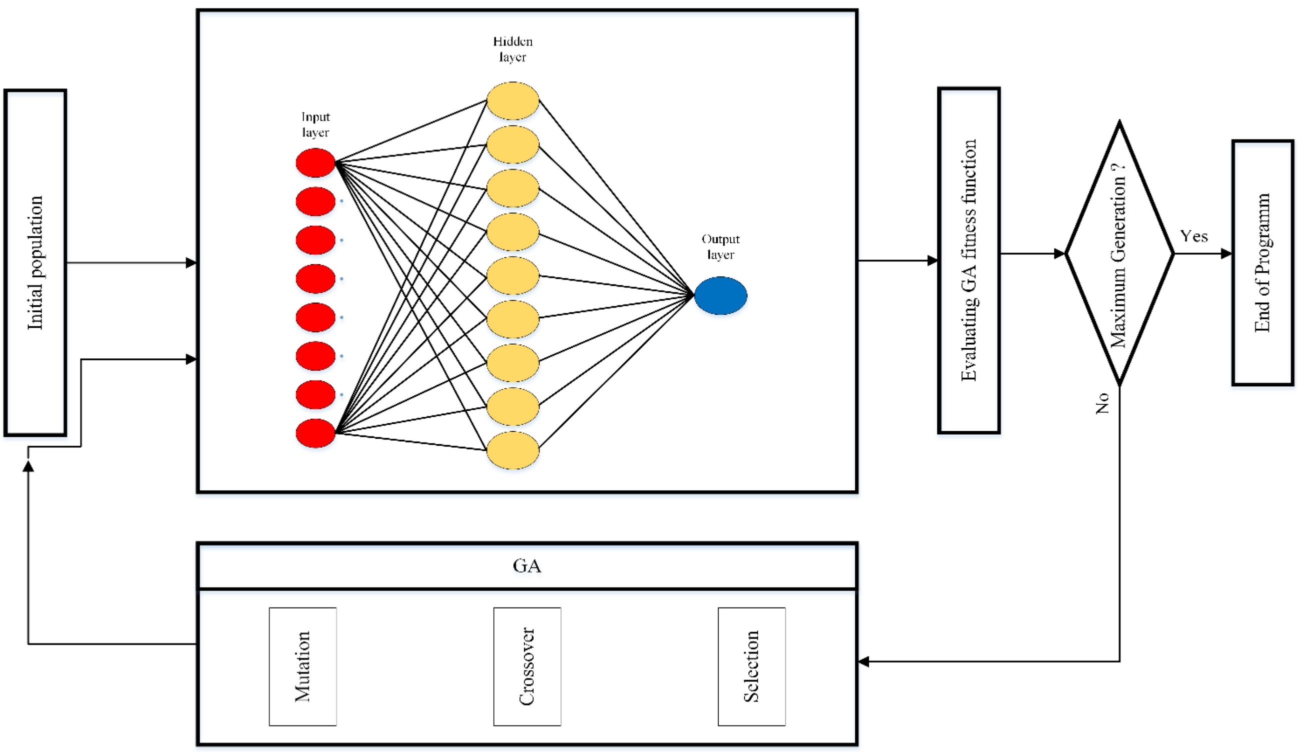

Fig. 2 Flowchart of a typical ANN-GA model

Table 1 Details of hpgthe input variables

Variable	Minimum	Maximum	Mean value	Standard deviation
C (kg/m^3)	102	540	281.17	104.46
FS (kg/m^3)	0	359.4	73.90	86.24
FA (kg/m^3)	0	200.1	54.19	63.97
W (kg/m^3)	121.75	247	181.57	21.35
SP (kg/m^3)	0	32.2	6.20	5.97
CAG (kg/m^3)	801	1145	972.92	77.72
FAG (kg/m^3)	594	992.6	773.58	80.14
Age (day)	1	365	45.66	63.14
f'c (Mpa)	2.33	82.60	35.82	16.70

*C = Cement, FS = Furnace Slag, FA = Fly Ash, W = Water, SP = Superplasticizer, FAG = Fine Aggregate, CAG = Coarse Aggregate, *f'c* = Compressive strength

Table 2 Details of the input variables after normalization

Variable	Minimum	Maximum	Mean value	Standard deviation
W/C	0.27	1.88	0.75	0.31
W/P	0.24	0.90	0.47	0.13
C/P	0.26	1.00	0.69	0.21
Fly Ash/P	0.00	0.55	0.14	0.17
FURNACE SLAG/P	0.00	0.61	0.17	0.20
FAG/P	1.06	4.23	2.01	0.60
CAG/P	1.28	5.63	2.52	0.68
SP/P (%)	0.00	5.66	1.45	1.34
Age/365	0.0027	1.00	0.13	0.17
f'c (Mpa)	2.33	82.60	35.82	16.71

*C = Cement; FS = Furnace Slag; FA = Fly Ash; P = Powder: Cement (C) + Fly Ash (FA) + Furnace Slag (FS); W = Water; SP = Superplasticizer; FAG = Fine Aggregate; CAG = Coarse Aggregate; *f'c* = Compressive strength

$$X_i = \frac{X_{io} - X_{min}}{X_{max} - X_{min}} \times 2 - 1 \quad (4)$$

$$Y_i = \frac{Y_{io} - Y_{min}}{Y_{max} - Y_{min}} \times 2 - 1 \quad (5)$$

Where, X_{io} and X_i are the ith component of each input vector before and after normalization, respectively and Y_{io} and Y_i are the ith component of the output vector before and after normalization, respectively. X_{min}, X_{max}, Y_{min}, and Y_{max} are the minimum and maximum value of each input and output vector, respectively.

4. Performance evaluation

An ANN-BP and an ANN-GA model were developed in this study. In order to evaluate the performance of these models, 70% of the data were randomly selected for the training phase of the neural networks, and the remained 30% were used for the testing phase. The performance of the network in these phases was evaluated by the root mean squared error (RMSE), mean squared error (MSE), determination coefficient (R^2), and Pearson correlation coefficient (r). These parameters are defined as follows

$$MSE = \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (7)$$

$$r = \frac{n(\sum_{i=1}^{n} O_i \cdot P_i) - (\sum_{i=1}^{n} O_i) \cdot (\sum_{i=1}^{n} P_i)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - (\sum_{i=1}^{n} O_i)^2\right) \cdot \left(n\sum_{i=1}^{n} P_i{}^2 - (\sum_{i=1}^{n} P_i)^2\right)}} \quad (8)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right) \cdot \left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right) \cdot \sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \quad (9)$$

Where P_i and O_i are the predicted and observed variables, and n is the total number of considered data.

5. Models development

5.1 ANN architecture

The architecture of an ANN means, how many hidden layers and neurons are considered for developing the neural

Table 3 ANN models and the results of performance evaluation

Model No.	Number of neurons	Training phase				Testing phase			
		r	R^2	MSE	RMSE	r	R^2	MSE	RMSE
1	5	0.924	0.854	40.386	6.342	0.908	0.825	50.071	7.059
2	7	0.926	0.857	40.413	6.357	0.911	0.830	46.179	6.795
3	9	0.933	0.871	35.256	5.931	0.927	0.859	41.933	6.476
4	11	0.926	0.857	40.413	6.357	0.911	0.830	46.179	6.795
5	13	0.928	0.861	38.918	6.216	0.895	0.802	55.193	7.424
6	15	0.931	0.867	37.098	6.086	0.888	0.789	58.530	7.606

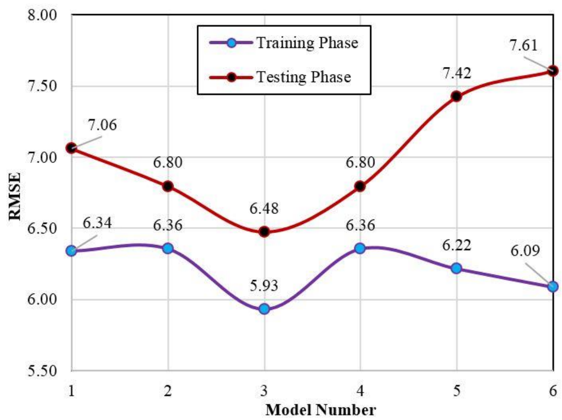

Fig. 3 Determining the architecture of the ANN based on the RMSE values

network so that it leads to the best results. An appropriate approach for finding the architecture of an ANN is that different architectures are developed and for each of which, the performance of the network is evaluated. Finally, the architecture with the best performance is chosen. In this study, a single hidden layer architecture was considered, which generally leads to better results. The number of neurons in the hidden layer is determined by considering six models with different numbers of neurons. Each model was trained by the BP algorithm three times, and the mean values of results were recorded. Table 3 shows the adopted models and corresponding results.

Fig. 3 shows the RMSE value of each mode in the training and testing phase. As can be seen in this figure, in model number 3 (i.e., a single hidden layer with nine neurons), the lowest value of RMSE and difference between the training and testing phases have been obtained. This means that in the number of nine neurons, the developed model is less likely to experience overfitting and it would have the best performance. Therefore, an ANN architecture with a single hidden layer having nine neurons (Fig. 4) was developed to be trained by both of the BP and GA algorithms.

5.2 ANN-GA parameters

ANN-GA parameters, including the percentage of cross-over (P_c), the Percentage of mutation (P_m), and more

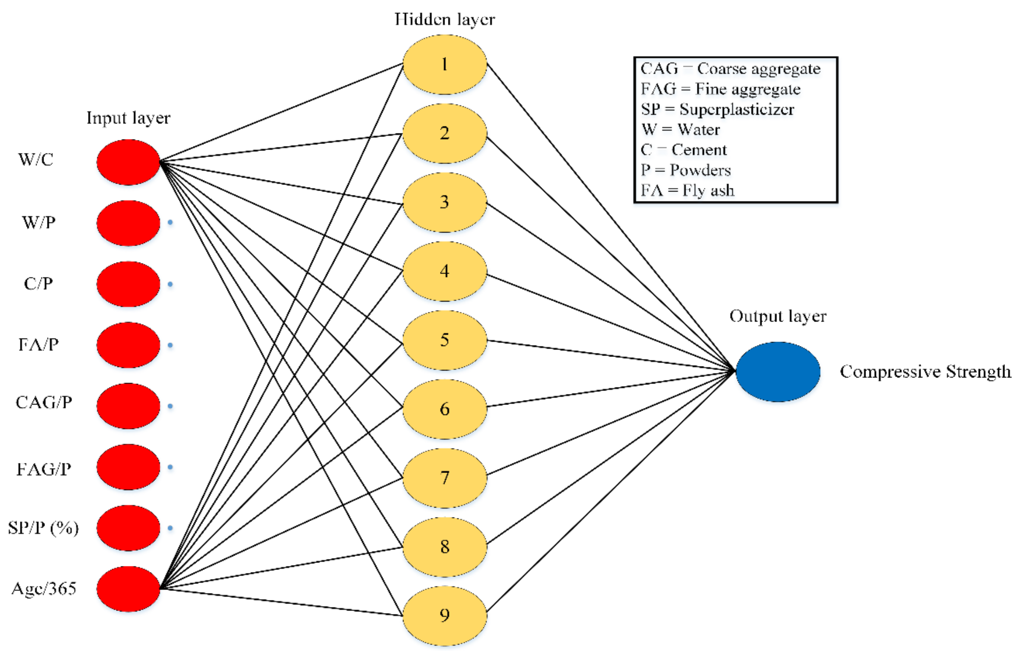

Fig. 4 Considered ANN architecture

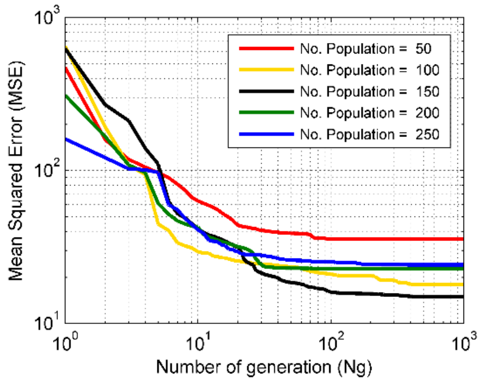

Fig. 5 Convergence rate diagram of ANN-GA

importantly, the population size should be appropriately determined. A trail and error process is usually conducted in order to obtain these parameters. The same process was also accomplished in this study. Several times the ANN-GA model was run for different values of P_c and P_m, and the best performance was observed in P_c = 90% and P_m = 10%. The best population size is determined by different sizes in the range of 50-250, which were tried for the maximum number of generations (N_g) of 1000.

The convergence rate of the ANN-GA model for different population sizes of 50, 100, 150, 200, and 250 in a log-log scale diagram is indicated in Fig. 5. It is clear that the best convergence rate and the lowest value of MSE have occurred in the population size of 150. Consequently, this population size was selected for the ANN-GA model.

6. Results and discussion

Two models, including an ANN-GA and another ANN-BP model, were developed. The same architecture of a single hidden layer containing nine neurons was considered for both of the models. 70% of input data was devoted to the training phase, and 30% were employed in the testing phase.

Fig. 6 shows the results of the ANN-BP model. Fig. 6(a) shows the training phase of this model. In this phase, the values of r, R^2, MSE, and RMSE were obtained equal to 0.945, 0.894, 30.153, 5,49. High values of r, R^2, and low values of MSE, and RMSE demonstrate the appropriate

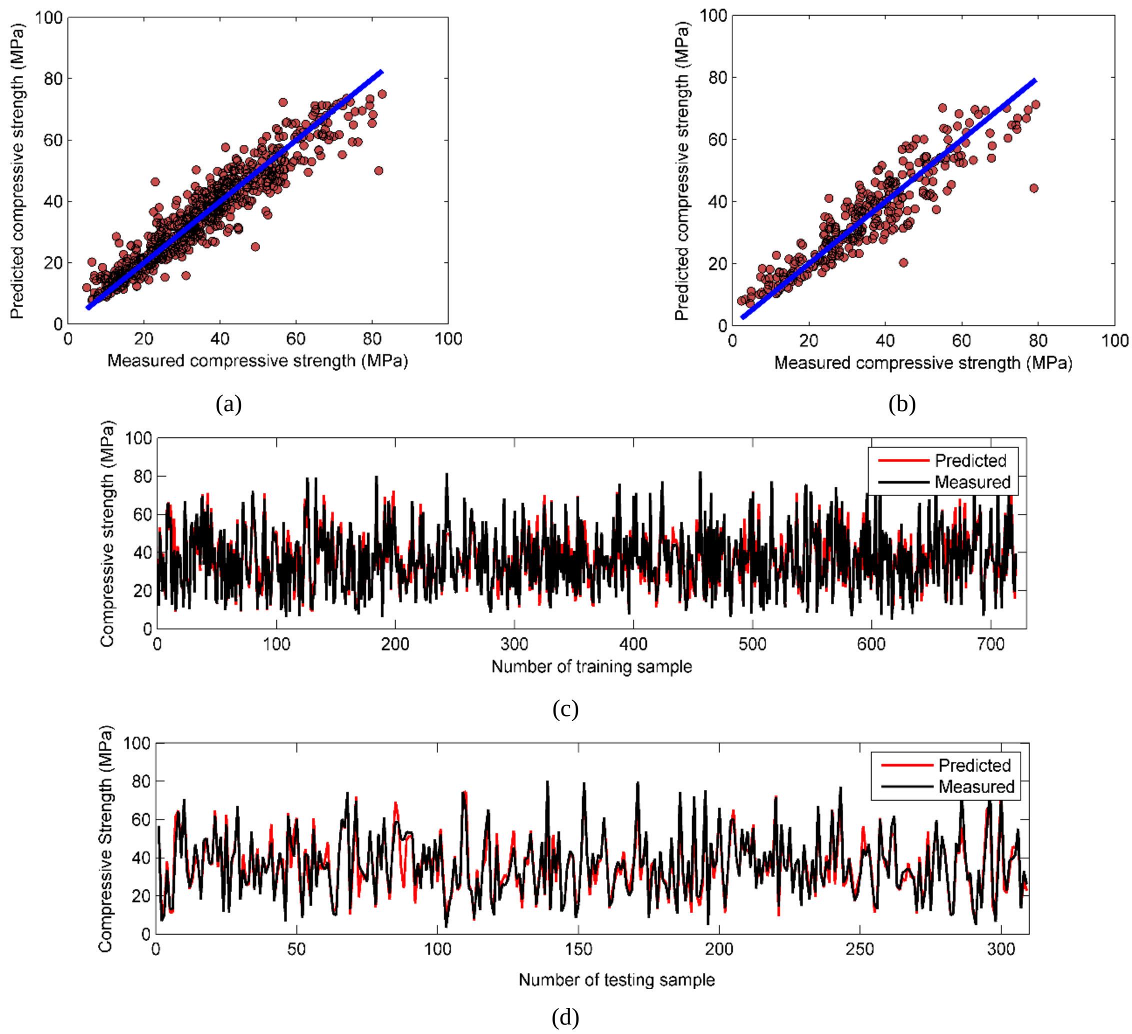

Fig. 6 Results of the ANN-BP model: (a) scatter diagram of the training phase; (b) scatter diagram of the testing phase; (c) target evaluation in the training phase; (d) target evaluation in the testing phase

performance of the ANN-BP model in this phase. The obtained results of the ANN-BP in the testing phase are indicated in Fig. 6(b). In this phase, r, R^2, MSE, and RMSE were determined equal to 0.921, 0.848, 40.564, and 6.369, respectively. The low difference of these parameters with the parameters in the training phase illustrates that no overfitting has occurred, and the developed model has been able to predict the targets accurately. The performance of the ANN-BP model in the testing and training phase is shown clearly in Figs. 6(c) and (d), respectively. As can be seen, the model has predicted targets accurately in most of the samples in both of the phases.

The results of the ANN-GA model is shown in Fig. 7. In the training phase of this model (Fig. 7(a)), the values of r, R^2, MSE, and RMSE were equal to 0.967, 0.936, 17.677, and 4.204, respectively. These values show the perfect performance of the ANN-GA model in the training phase. Fig. 7(b) shows the results of the ANN-GA in the testing phase. In this phase, r, R^2, MSE, and RMSE were obtained equal to 0.951, 0.905, 27.067, and 5.203, respectively. The high values of r, R^2, and the low values of MSE, and RMSE on the one hand, and the low difference between the evaluation parameters in the training and testing phases on the other hand, obviously show the excellent performance of the ANN-GA model. The accuracy of the ANN-GA in the prediction of the targets is shown more clearly in Fig. 7(c) and Fig. 7(d).

Results of the ANN-BP and the ANN-GA models have

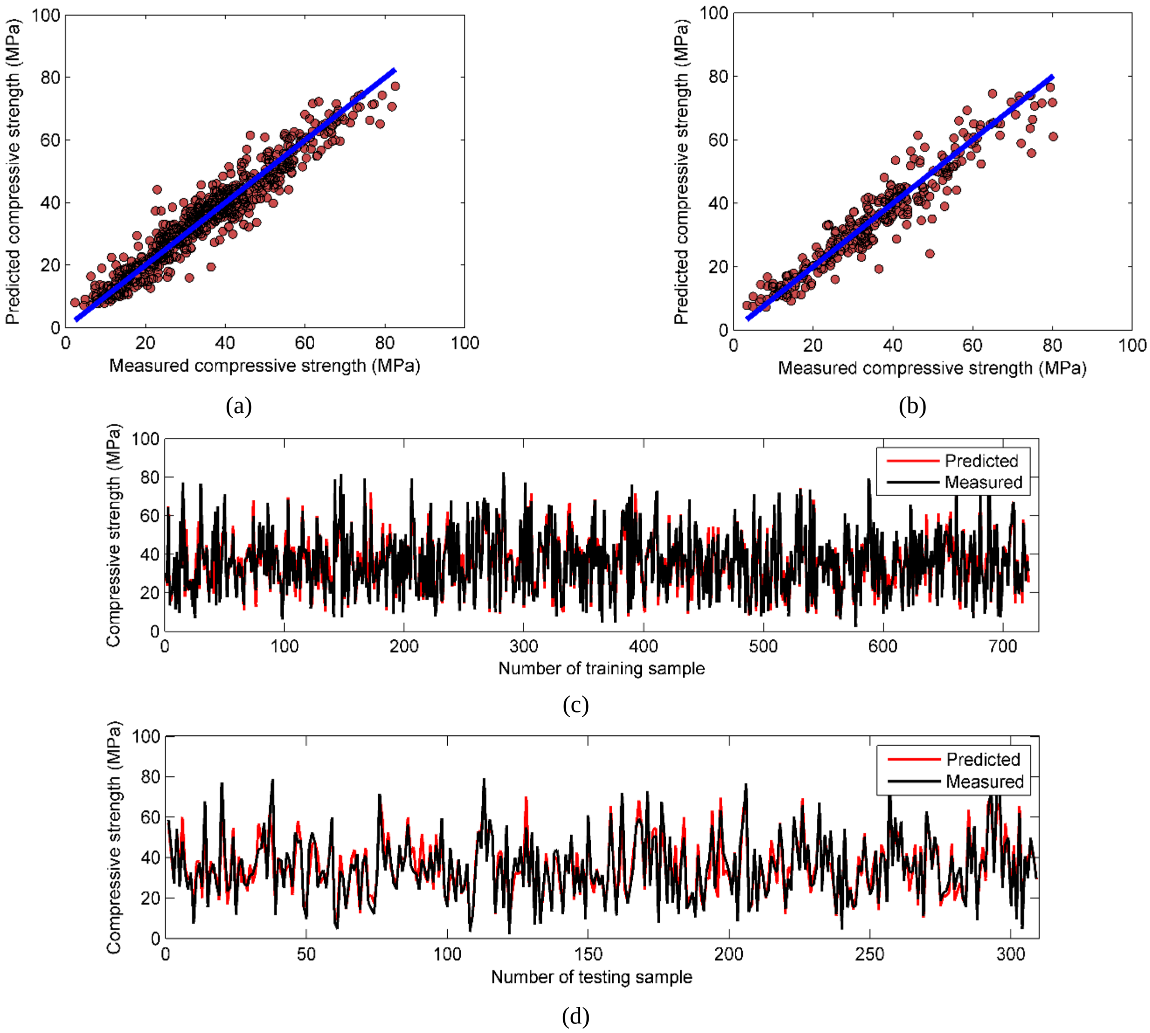

Fig. 7 Results of the ANN-GA model: (a) scatter diagram of the training phase; (b) scatter diagram of the testing phase; (c) target evaluation in the training phase; (d) target evaluation in the testing phase

Table 4 Results of the ANN-BP and the ANN-GA models

Performance	Training				Testing			
	r	R^2	MSE	RMSE	r	R^2	MSE	RMSE
ANN-BP	0.945	0.894	30.153	5.491	0.921	0.848	40.564	6.369
ANN-GA	0.967	0.936	17.677	4.204	0.951	0.905	27.067	5.203

been also summarized in Table 4. As can be realized, using GA has been an efficient approach for training the ANN, and it has led to superior results.

7. Conclusions

Compressive strength prediction of concretes in which cement is partially replaced with other materials can be very challenging. Fly ash and furnace slag are two of the pozzolans which are widely used in concrete as partial replacements for cement. However, compressive strength prediction of concrete after utilization of these materials is a difficult concept. Hence, an artificial neural network (ANN) was developed and trained by both a conventional backpropagation (BP) algorithm and a genetic algorithm (GA). Also, instead of using absolute values of concrete mix design, the proportion of inputs was used. The obtained results can be summarized as follows:

- Both of the ANN-BP and ANN-GA models showed a perfect performance in the compressive strength prediction, and they could reach to acceptable performance values. However, the performance of the ANN could experience some improvement by using GA in the training process.
- The approach of considering proportions of inputs instead of absolute values was efficient so that the developed ANNs could be trained conveniently by both of the algorithms, and no difficulty was observed in the training process.
- The age of concrete specimens was also considered as a variable. Since the developed ANNs showed perfect performances, it can be concluded that age can be appropriately considered as an input in the compressive strength prediction.

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