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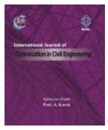

A COMPARATIVE STUDY OF TRADITIONAL AND INTELLIGENCE SOFT COMPUTING METHODS FOR PREDICTING COMPRESSIVE STRENGTH OF SELF – COMPACTING CONCRETES

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ABSTRACT

This study investigates the prediction model of compressive strength of self–compacting concrete (SCC) by utilizing soft computing techniques. The techniques consist of adaptive neuro–based fuzzy inference system (ANFIS), artificial neural network (ANN) and the hybrid of particle swarm optimization with passive congregation (PSOPC) and ANFIS called PSOPC–ANFIS. Their performances are comparatively evaluated in order to find the best prediction model. In this study, SCC mixtures containing different percentage of nano SiO_2 (NS), nano–TiO_2 (NT), nano–Al_2O_3 (NA), also binary and ternary combining of these nanoparticles are selected. The results indicate that the PSOPC–ANFIS approach in comparison with the ANFIS and ANN techniques obtains an improvement in term of generalization and predictive accuracy. Although, the ANFIS and ANN techniques are a suitable model for this purpose, PSO integrated with the ANFIS is a flexible and accurate method due tothe stronger global search ability of the PSOPC algorithm.

Keywords: prediction model; adaptive neuro – based fuzzy inference system; artificial neural network; particle swarm optimization; self – compacting concrete.

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1. INTRODUCTION

Concrete is one of the most extensively used materials in the world. Portland cement–based binders are the primary active components of cementitious composites used in most modern construction. The other components are water, and both fine and coarse aggregates. Other powders are referred to as supplementary cementitious materials (SCMs) since they are used

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to replace some of the more expensive cement. Moreover, chemical admixtures like superplasticizers can be added in small amounts to modify the properties of a cementitious composite for specific applications.

Self–compacting concrete (SCC) is a special concrete which has great flowing ability in fresh state so that it can be placed and compacted under its own weight without vibration [1, 2]. There are many advantages of using SCC such as shorter construction periods, reduction in the labor cost, and better compaction in the structure especially in confined zones where compaction is difficult. In order to obtain the ability of self–compacting in SCC, the common practice is to use new generation high range water reducers, to limit the maximum aggregate size, and to use low water–powder ratios or viscosity modifying admixtures. On the other hand, the cost of SCC is one of the negative point of this type of concrete, due to needs to use of chemical admixtures and use of high volumes of Portland cement. High cement content usually introduces high hydration heat, high autogenous shrinkage and high cost. So, it cause to increase the consumption of cement and rise carbon dioxide emissions associated with cement production that can affect serious environmental impacts. Using some natural and artificial pozzolans like fly ash (FA) could be one of the best solution to reduce both the cost and cement that needs to create SCC [3, 4].

Many researchers [5, 6] has investigated the properties of SCC made with different amounts of fly ash. Among different pozzolans, FA has reported one of the best materials as SCMs to improve the mechanical properties and durability of concrete when used as a cement replacement material [7–9]. Most of researches in this area concentrated in incorporating nanoparticles on SCC which most of them have focused on using SiO_2 nanoparticles [10]. Using different types of nanoparticles like Al_2O_3 or TiO_2 in SCC has been addressed in some of studies [11–13]. Flexural performance and abrasion resistance of concrete containing TiO_2 nanoparticles for pavement were experimentally studied by Li *et al*. [14, 15]. The results were shown the significant improvement of flexural fatigue performance and abrasion resistance. Nazari and Riahi used different percentage of Al_2O_3 nanoparticles in concrete in order to investigate the influence of these particles [16]. The results appeared the strength improvement by using of nano–Al_2O_3 particles up to maximum replacement level of 2.0% produces concrete. However, the ultimate strength of concrete was gained at 1.0 wt% of cement replacement.

There are many factors to assess the performance concrete, and many research focused on the evaluation and prediction of these factor. The compressive strength of concrete has been considered as one of the most essential qualities of concrete. In order to save costs and time in important projects, developing accurate and reliable prediction models of the compressive strength has received great deal of attentions by many researchers. Therefore, soft computing techniques as the modern approach for constructing a computationally intelligent system been widely have been widely used. The most popular of the techniques consists of Artificial Neural Networks (ANNs), Evolutionary Computation (EC), Machine Learning (ML), Adaptive network–based fuzzy inference system (ANFIS) and Support vector machines. The successful applications of the techniques have been reported in the problems of engineering [17–22]. Sobhani *et al*. [23] presented a comparative study of prediction models such as ANN and ANFIS to estimate the compressive strength of no–slump concrete. The comparison of the results indicated that ANN and ANFIS models were more feasible than the proposed traditional regression models. Rofooei *et al*. [24] applied different

ANN models to estimate the vulnerability of sample of reinforced MRF concrete structures. Saridemir [25] investigated the use of genetic programming approach to predict the compressive strength of concretes containing rice hush ash. Behfarnia and Khademi [26] investigated the efficiency and accuracy of ANN and ANFIS models for the prediction of 28–day compressive strength of concrete with different usual mixture without any special additive. The results of this study revealed that the ANN model was the efficient model for prediction of compressive strength.

The main contribution of this work to investigate an accurate prediction model of the compressive strength of self–compacting concrete (SCC) by utilizing soft computing techniques. The techniques consist of ANFIS, ANN and the hybrid of particle swarm optimization with passive congregation (PSOPC) and ANFIS, which called PSOPC–ANFIS. In order to find the best prediction model of the compressive strength of SCC, a comparative study of the models are implemented. In this study, SCC mixtures containing different percentage of nano–SiO_2 (NS), nano–TiO_2 (NT), nano–Al_2O_3 (NA), also binary and ternary combining of these nanoparticles are selected. The numerical results demonstrate that the PSOPC–ANFIS model in comparison with the ANFIS and ANN techniques obtains an improvement in term of generalization and predictive accuracy. Furthermore, the ANFIS and ANN techniques are a suitable model for this purpose.

2. DATASET DESCRIPTION AND MATERIALS

In order to attain the aim purpose of this study, the experimental data sets containing of 82 samples of SCC are obtained from different previous studies [27, 28]. All of the mixture were produced with constant water/binder ratio of 0.4 and the amount of fly ash was 25 wt.% of the cement in all samples. In this study, NS, NA and NT are the abbreviation of SiO_2, Al_2O_3 and TiO_2 nanoparticles, respectively and combination of S, A and T denote the binary and ternary mixture of these nanoparticles. Table 1 shows the experimental data set used in this study. Each of these sample contains cement (C), sand (S), NS, NA, NT, superplasticizer dosage (SP) and time (D) as input variables of the database, the compressive of SCC as the output variables of the database.

Table 1: Experimental data sets

Label	Cement	Fly ash	Nano SiO_2	Nano TiO_2	Nano Al_2O_3	Water	Sand	SP	Age
Control	525	175	0	0	0	280	1210	4.5	3
1NA	518	175	0	0	7	280	1198	4.20	3
3NA	504	175	0	0	21	280	1176	4.00	3
5NA	490	175	0	0	35	280	1153	4.00	3
1NS	518	175	7	0	0	280	1198	4.5	3
3NS	504	175	21	0	0	280	1176	4.2	3
5NS	490	175	35	0	0	280	1153	4.2	3
1NT	518	175	0	7	0	280	1153	4.20	3

5NT	490	175	0	35	0	280	1176	3.90	3
Control	525	175	0	0	0	280	1210	4.5	7
	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.
Control	525	175	0	0	0	280	1210	4.5	28
	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.
Control	525	175	0	0	0	280	1210	4.5	90
	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.
1NSA	518	175	3.5	0	3.5	280	1153	4.20	3
3NSA	504	175	10.5	0	10.5	280	1198	4.20	3
5NSA	490	175	17.5	0	17.5	280	1176	4.00	3
	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.
1NSAT	518	175	2.3	2.3	2.3	280	1198	3.80	3
3NSAT	504	175	7	7	7	280	1176	3.80	3
5NSAT	490	175	11.7	11.7	11.7	280	1153	3.50	3
	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.

Furthermore, Table 2 illustrates the range of input and output data sets.

Table 2: Statistical description of concrete components

Factors	Notation	Unite	Min	Max	Mean
Cement	C	kg/m^3	490.00	525.00	504.95
Nano SiO_2	NS	kg/m^3	0.00	35.00	6.68
Nano TiO_2	NT	kg/m^3	0.00	35.00	6.68
Nano Al_2O_3	NA	kg/m^3	0.00	35.00	6.68
Sand	S	kg/m^3	1153.00	1210.00	1178.40
SP	SP	kg/m^3	3.50	4.50	4.04
Ages	D	days	3.00	90.00	32.00
Compressive strength	Output	*MPa*	11.90	60.67	34.05

3. BACK–PROPAGATION TRAINED ARTIFICIAL NETWORK

Back–propagation (BP) algorithm has been presented as a type of ANN methods. In this model, the input values to a neuron are obtained by multiplying the output of the connected neuron by the synaptic strength of the connection between them [29]. The weighted sums of the input components x_i are calculated as follows:

$$(net)_j = f(\sum_{i=1}^{n} w_{ij}x_i + b) \tag{1}$$

where $(net)_j$ is the output from neuron, w_{ij} is connection's weights, b is thresholds, n is the number of neurons or processing elements (PE) in each layer and f is the activation function as follows:

$$O_j = f(net)_j = \frac{2}{1+\exp\left(2(net)_j\right)} - 1 \tag{2}$$

BP–ANN operates in two steps. First, the data are fed into the input layer and processed by transfer functions through the layers until the network's response is computed at the output layer. Second, the network's response is compared at the target and an error is generated. Based on this error signal, connection weights between layer neurons are updated until the network reaches a pre–defined performance goal. The back–propagation algorithm is used to accelerate the convergence of this algorithm. BP algorithm adjusts the weights in the steepest descent direction where the performance function decreases more rapidly.

4. ADAPTIVE NETWORK–BASED FUZZY INFERENCE SYSTEM

One of types of fuzzy inference system (FIS) has been introduced as a nonlinear mapping from the input space to the output space [30]. The mechanism of this system has been basically adopted as the conversion of inputs from numerical domain to fuzzy domain with using the three functional components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions (MFs) used in the fuzzy rules and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output. The adaptive neuro–FIS (ANFIS) is a FIS implemented in the framework of adaptive networks. The architecture of ANFIS with two input variables is shown in Fig. 1.

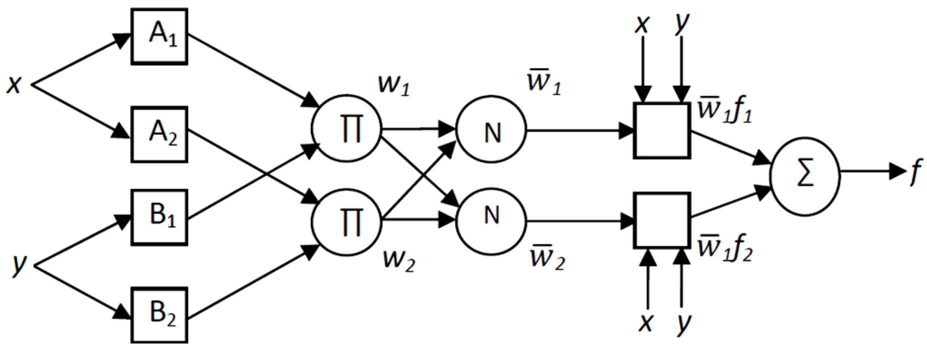


Figure 1. Architecture of ANFIS [20]

The ANFIS approach consists of the human–like reasoning style of FIS by the use of input–output sets and incorporates of two fuzzy if–then rules based on Takagi and Sugeno's type [35]:

$$\begin{aligned} &Rule\ 1:\ \ If\ \ x\ \ is\ \ A_1\ \ and\ \ y\ \ is\ \ B_1,\ then\ \ f_1 = p_1 x + q_1 y + r_1 \\ &Rule\ 2:\ \ If\ \ x\ \ is\ \ A_2\ \ and\ \ y\ \ is\ \ B_2,\ then\ \ f_2 = p_2 x + q_2 y + r_2 \end{aligned} \tag{3}$$

where A_1, A_2, B_1 and $B_2$are representing MFs for the inputs x and y, respectively. Also, p_i, q_i and r_i ($i = 1, 2$) are incorporating parameters of the output MFs (consequent parameters).

The final structure of ANFIS consists of fixed square nodes and adaptive circle nodes that those parameters are changed during the training process. A hybrid learning algorithm of ANFIS is employed by the parameters of MFs of input variables and linear parameters of the output variable that are optimized with gradient descent (GD) approaches and finally can be calculated as follows [30]:

$$f = \sum_i \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i}, \quad for\ \ i = 1, 2 \tag{4}$$

$$w_i = \mu A_i(x) \times \mu B_i(x) \quad for\ \ i = 1, 2 \tag{5}$$

where w_i represents the firing strength of rule I, $\mu A_i(x)$ and $\mu B_i(x)$ are the membership degrees of x and y in A_i and B_i, respectively. Gaussian functions with maximum and minimum equals to 1 and 0, respectively, are selected for the membership degrees as:

$$\mu A_i(x) = \frac{1}{1 + (\frac{x - c_i}{a_i})^{2b_i}} \tag{6}$$

$$\mu B_i(y) = \frac{1}{1 + (\frac{y - d_i}{e_i})^{2g_i}} \tag{7}$$

where {a_i, b_i, c_i} and {d_i, e_i, g_i} are the premise parameters set that used to adjust the shape of MF.

5. INTELLIGENCE ANFIS MODEL

The ANFIS approach utilizes both the advantages of neural networks and fuzzy systems. However, training the parameters of the ANFIS model is considered as a main challenge when ANFIS is employed for the real–world problems. Furthermore, the GD approaches are utilized as the training methods of ANFIS, which are known to be local search approaches and their performances generally depend on initial values of parameters. Since the optimal design of fuzzy systems (FSs) can be considered as an optimization problem, many researchers have proposed metaheuristic approaches such as genetic algorithms (GAs) and PSO for the optimal design of FSs [32, 33].

The performance and accuracy of the ANFIS model depend on the premise parameters and the consequent parameters which need to be trained. Recently, Khatibinia and Mohammadizadeh [33] have introduced a intelligent ANFIS approach. In this approach, the premise parameters i.e. $\{a_i, b_i, c_i\}$ have been estimated by the particle swarm optimization with passive congregation (PSOPC). The intelligent ANFIS approach been has called as PSOPC–ANFIS. The flowchart of the proposed intelligent ANFIS method is shown in Fig. 2.

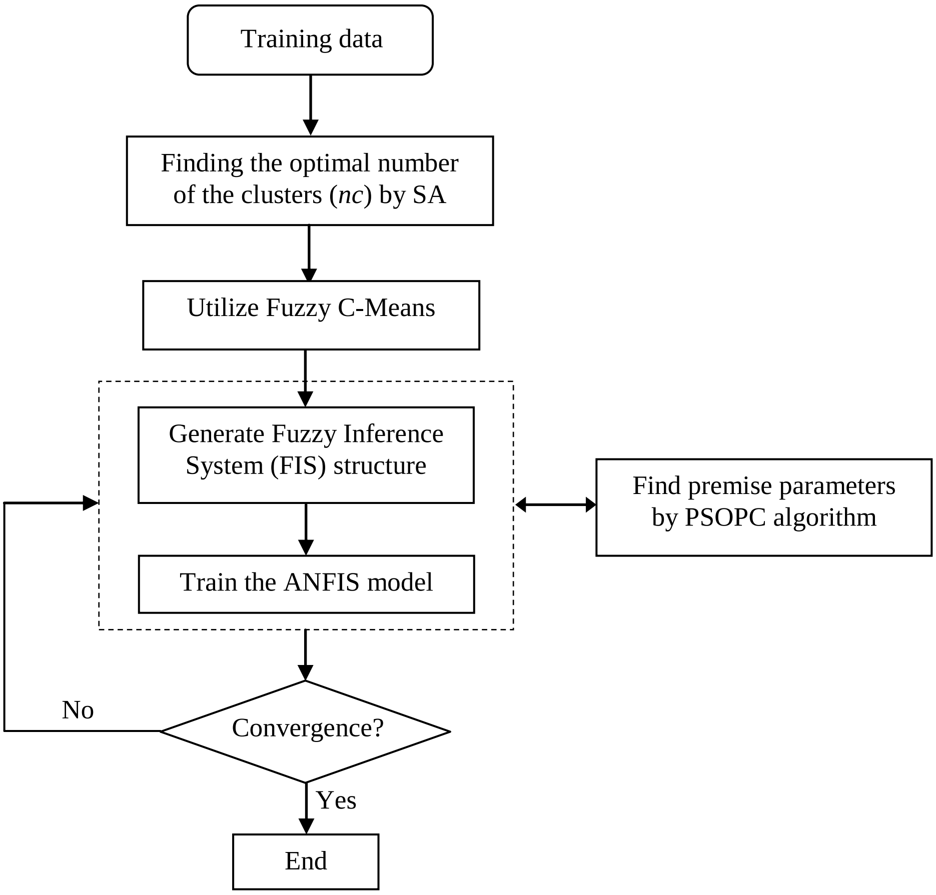


Figure 2. Flowchart of the proposed intelligent ANFIS model

In this model,the premise parameters are considered as the design variables of optimization problem. Furthermore, the consequent parameters are calculated by the least squares estimation (LSE). To evaluate the accuracy of the PSOPC–ANFIS approache, the root mean squared error (*RMSE*) between actual output and desired output is considered as the objective function, which can be expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - \bar{O}_i)^2}{n_t}} \tag{8}$$

where O and $\bar{O}$ are the measurement values and the predicted values, respectively; and n_t is the total number of test data. In fact, *RMSE* can calculate the variation of errors in the proposed model and is very useful when large errors are undesirable.

In order to overcome the overfitting problem in the PSOPC–ANFIS approache, the subtractive algorithm (SA)is utilized to find the optimum number of the fuzzy rules. The fuzzy c–means (FCM) approach also creates a fuzzy inference system for the antecedents and consequents. The details of the SA and FCM approaches can be found in the work of Khatibinia *et al*. [21].

6. RESULT AND DISCUSION

6.1 Scaling database

To evaluate the effectiveness and accuracy of the ANN, ANFIS and PSO–ANFIS approachs, the compressive of SCCis estimated using the PSOPC–ANFIS and RCGA–ANFIS approaches. In order to achieve this purpose, the database of laboratory testing results for 88 samples outlined in Table 1 is selected. Before dividing database into training and testing sets, the values of the input variables are normalized between 0.2 and 0.8 as follows [33]:

$$\bar{x}_i = b_1 \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} + b_2 \tag{9}$$

where $\bar{x}_i$, $x_{\max}$ and $x_{\min}$ are the normalized, maximum and minimum values of the input variables, respectively. In this study, b_1 and b_2 are assumed to be equal to 0.6 and 0.2, respectively.

6.2 Evaluating accuracy of the soft computing methods

To evaluate the performance of all of the soft computing methods, three criteria are chosen. The coefficient of determination (R^2) represents that how well the independent variables considered account for the measured dependent variable [33] as follows:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n_t}(O_i - \bar{O}_i)^2}{\sum_{i=1}^{n_t}\bar{O}_i^2}\right) \tag{10}$$

Also, the prediction relationship relative root mean squared error (*RRMSE*) between actual output and desired output is considered as the objective function that can calculate the variation of errors in the proposed model expressed [33]:

$$RRMSE = \sqrt{\frac{n_t \sum_{i=1}^{n_t} (O_i - \bar{O}_i)^2}{(n_t - 1) \sum_{i=1}^{n_t} O_i^2}} \tag{11}$$

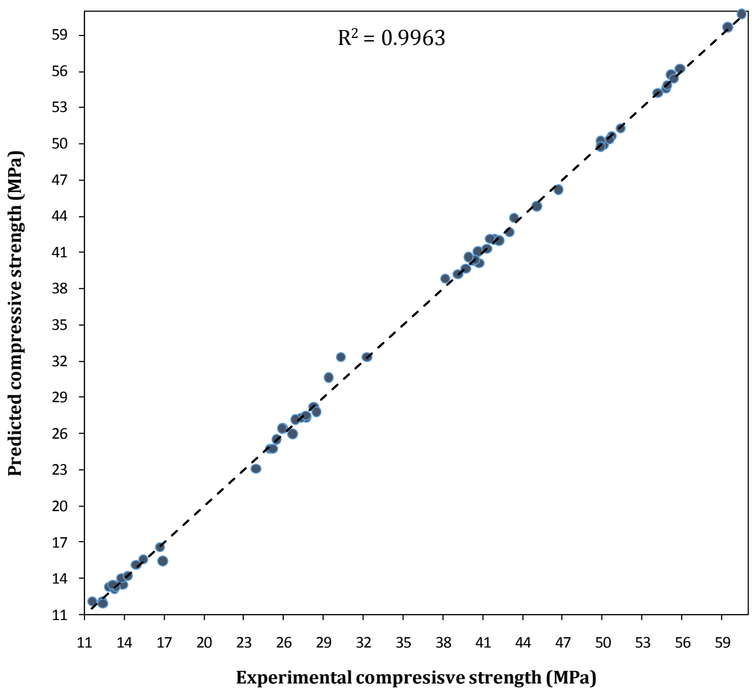
Moreover, the mean absolute percentage error (*MAPE*) are computed as following [33]:

$$MAPE = \frac{1}{n_t} \sum_{i=1}^{n_t} 100 \times \left| \frac{O_i - \bar{O}_i}{O_i} \right| \tag{12}$$

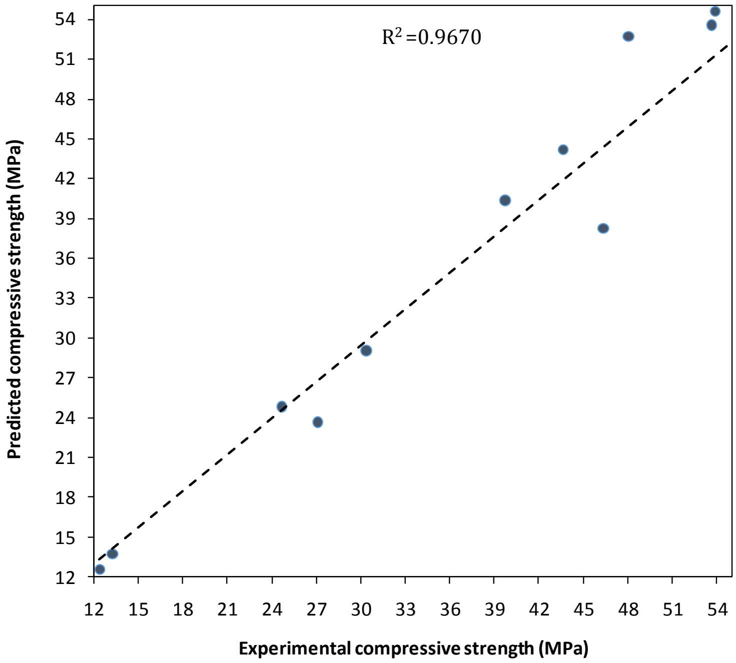
6.3 Results of the ANN model

In order to provide the ANN model, 70% of the data is randomly considered as the training data. Furthermore, The number of the validating and testing data are selected to be equal to 15%. Figure 3 shows the correlation between the target values(experimental compressive strength)and output values (estimated compressive strength) for the training, validating and testing and data.

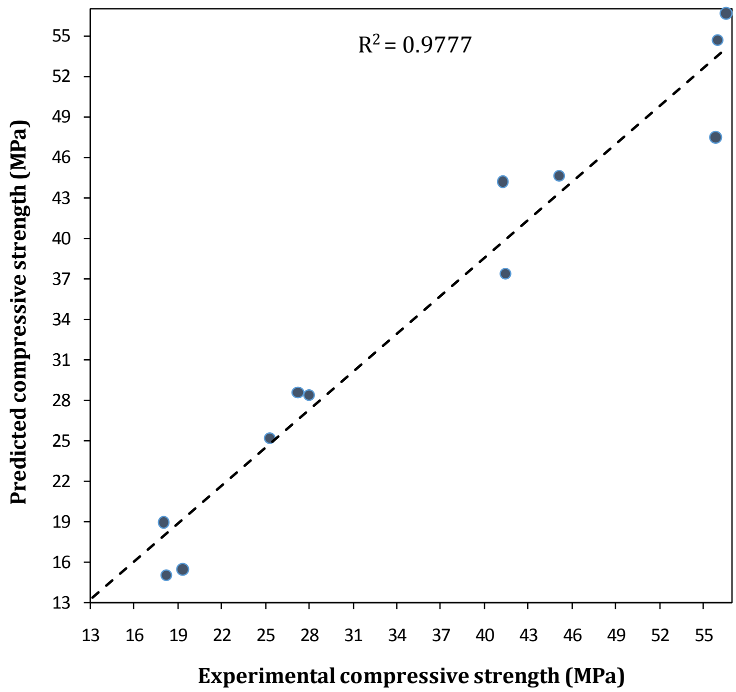
In accordance with Fig. 3, all of R^2 show the desirable ability of this method to use for prediction problems. It is found from Figure 3 that, ANN model has correlation coefficient almost one. Therefore, this shows that this model has high degree to experimental data.



(a)



(b)



(c)

Figure 3. Results of predicting compressive strength by the ANN model for (a)training data, (b)testing data and (c)validating data

6.4 Results of the ANFIS and PSOPC–ANFIS models

The experimental data are divided into two sets for the training and testing the networks, where, 70% of the experimental data are used to train the networks, and the rest (30%) are used to test the accuracy of the trained models.The performance and the accuracy of the ANFIS and PSOPC–ANFIS models are graphically shown in Figs. 4 through 7.

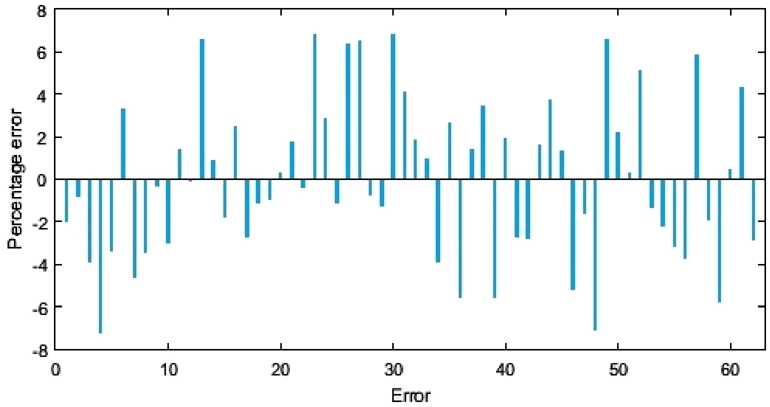


Figure 4. Percentage of error values of the ANFIS model in the training process

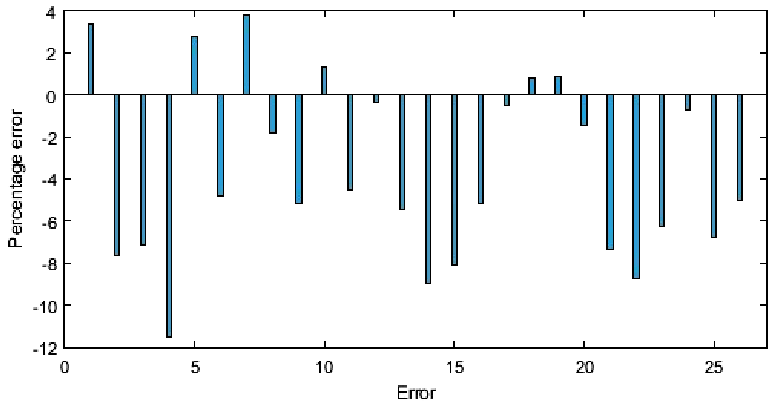


Figure 5. Percentage of error values of the ANFIS model in the testing process

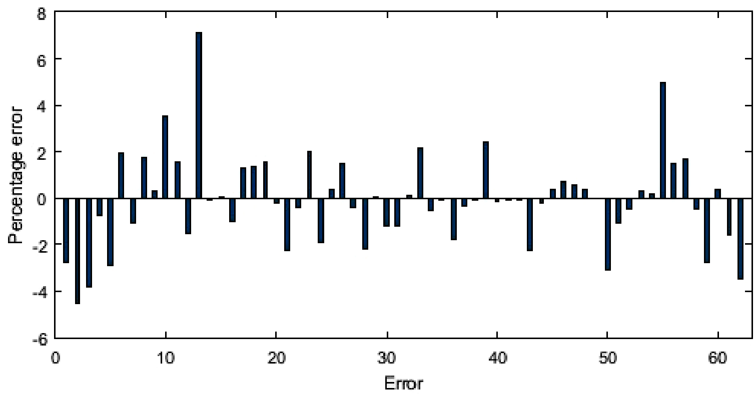


Figure 6. Percentage of error values of the PSOPC–ANFIS model in the training process

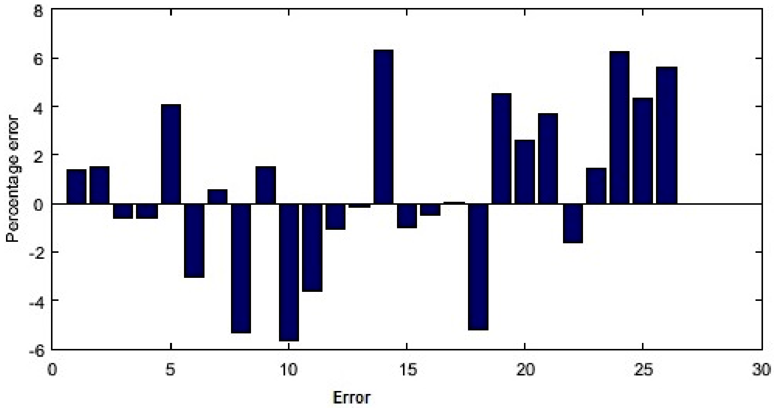


Figure 7. Percentage of error values of the PSOPC–ANFIS model in the testing process

It is observed from Figs. 4 through 7, the PSOPC–ANFIS model in comparison with the ANFIS model predicts the compressive strength of SCC at high accuracy rate. Furthermore, Figs. 8 and 9 show the histogram for distribution of error values in the testing process of the ANFIS and PSOPC–ANFIS models, respectiviely.

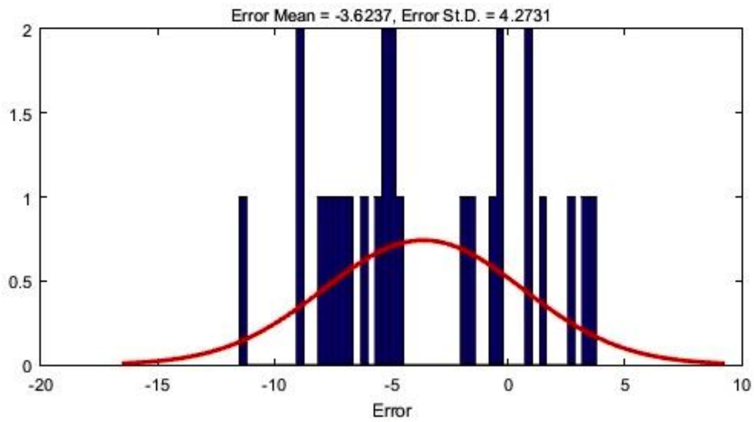


Figure 8. The histogram for distribution of error values in the testing process of ANFIS

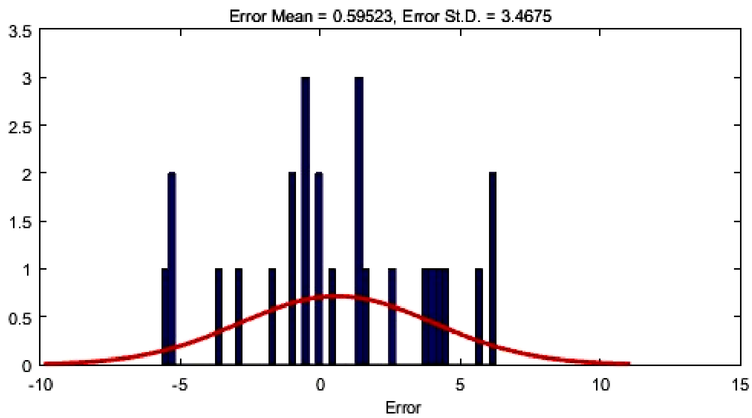


Figure 9. The histogram for distribution of error values in the testing process of PSOPC–ANFIS

The histogram of PSOPC–ANFISin comparing with that of ANFIS represented is close to the normal distribution, which illuminate the robust prediction using the PSOPC–ANFIS model.

6.5 Comparison of the ANN, ANFIS and PSOPC–ANFIS models

This section presents the comparison of results obtained by the ANN, ANFIS and PSOPC–ANFIS and RCGA–ANFIS.For this purpose, at first, each of the performance criteria is normalized to a value of 1 for the best performance and 0 for the worst. Then, the RI is obtained by calculating the average of every normalized performance criteria as shown in Eq. (13) [33].

$$RI = \frac{MAPE + RRMSE}{2} \tag{13}$$

Also, Eq. (14) is used for normalizing theperformance criteria as:

$$f_{norm,i} = \frac{f_{\max,i} - f_i}{f_{\max,i} - f_{\min,i}} \tag{14}$$

Table 3 shows the results from the proposed methods, the ANFIS, ANN and PSOPC–ANFIS techniques for comparison purposes.

Table 3. Performance measurement results of various prediction techniques

Process	Performance	Model		
		PSOPC–ANFIS	ANFIS	ANN
Train	*MAPE*	1.3971	4.6305	0.3407
	RRMSE	0.0517	0.1524	0.0139
	R^2	0.9974	0.9812	0.9998
Test	*MAPE*	2.7705	3.0215	2.9872
	RRMSE	0.1029	0.0988	0.1285
	R^2	0.9890	0.9903	0.9857
	RI	0.930	0.500	0.068

Based on the *RI* index obtained for testing process, the PSOPC–ANFIS method outperform the ANN and ANFIS model. Therefore, the PSOPC–ANFIS model can be a powerful technique with high accuracy as compared with the ANN and ANFIS techniques.

7. CONCLUSIONS

In this paper, the accuracy and efficiently of the ANN, ANFIS and PSOPC–ANFIS models as soft computing methods wereinvestigated to find the best method for predictingthe compressive strength of SCC by knowing the mixture properties materials and percentage of each of them. Results of the models were discussed based on *RI*which was normalized to a value of 1 for the best performance and 0 for the worst. The following results could be drawn from this study:

- The results of the analyses indicate that the hybrid of PSOPC and ANFIS outperform the ANN, ANFIS models. By adopting the hybrid model, there is no need to go through time–consuming laboratory tests.
- PSOPC is applied to optimize the premise parameters of ANFIS, to acquire a global optimal solution and a reliable model in prediction of the compressive strength of CCS.

The ANFIS and ANN models can be a reliable model for predicting the compressive strength of CCS.

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