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Hybrid Artificial Intelligence Model Development for Roller-compacted Concrete Compressive Strength Estimation

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ABSTRACT

This study implemented the artificial bee colony (ABC) metaheuristic algorithm to optimize the Artificial Neural Network (ANN) values for improving the accuracy of model and evaluate the developed model. Compressive strength of RCC was investigated using mix design materials in three forms, namely volumetric weight input (cement, water, coarse aggregate, fine aggregate, and binder), value ratio (water to cement ratio, water to binder ratio, and coarse aggregate to fine aggregate ratio), as well as the percentage of mix design values of different ages. A comprehensive, proper-range dataset containing 333 mix designs was collected from various papers. The accuracy of the research models was investigated using error indices, namely correlation coefficient, root-mean-square-error (RMSE), mean absolute error (MAE), and developed hybrid models were compared. External validation and Monte Carlo simulation (MCS)-based uncertainty analysis was also used to validate the models and their results were reported. The experimental stage of the prediction of compressive strength values showed significant accuracy of the ANN-ABC model with (MAE=11.49, RMSE=0.920, RME=5.21) compared to other models in this study. Besides, the sensitivity analysis of predictor variables in this study revealed that the variables “specimen age,” “binder,” and “fine aggregate” were more effective and important in this research. Comparison of the results showed that the improved proposed model using the ABC algorithm was more capable and more accurate in reducing the error rate in providing computational relations compared to the default models examined in the prediction of the compressive strength of RCC and also tried in simplifying computational relations.

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1. INTRODUCTION

Over the past few years, our country has been moving rapidly towards the construction of roads and streets using concrete to achieve economic growth benefits and consider environmental problems. Concrete road construction has become even more prominent, especially over the last decade, during which sustainable development and environmental problems have been much discussed. The cost of concrete pavement construction is lower than that of asphalt pavements and has a much longer shelf life. In addition, other advantages such as high compressive strength, desirable tensile and shear strength at low thickness, high corrosion and water penetration resistance, high abrasion resistance, and ease of maintenance have made it possible to justify the use of relevant devices to implement it. However, the relatively short life span of this type of pavement and the complex design of this type of concrete necessitates the need for strong scientific support in the design and optimization of mix design. The problem of concrete mix design and achieving optimum strength to perform various engineering issues including dam construction, pavement, high-rise buildings, and large foundations (including hospitals, stadiums, etc.) has a long history. Nevertheless, this is achieved by spending a lot of money and time due to the specific complexities involved in selecting the type of constituents and their ratio to prepare the concrete with a certain strength. The importance and necessity of this issue become apparent when a

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substantial amount of time and money is allocated to the concrete mix design in a project similar to RCC.

Roller-compacted concrete (RCC) is a zero-slump concrete that becomes stiff due to roller vibration. Two types of RCC are used in construction work: low-cement mass RCC (mass RCC with low cement content) for the construction of dams and mass structures such as retaining walls, heavy foundations, and embankments where high strength is not required. For the relatively high-cement RCC (RCC with relatively high cement content) is used for rapid application of highway pavement layers and similar coatings; where high mechanical and wear strength is required. The main advantage of this type of concrete is its low cost [1].

Numerous methods have been proposed to determine the RCC mix ratios by concrete associations and committees, which are generally experimental, quasi-experimental, and based on theoretical methods. Nonetheless, soil compaction and liquidity (performance) approaches are generally used in different mix ratio design methods. These two approaches are defined based on optimizing the dry density of the sample by optimum moisture content and mix design by absolute volume, respectively.

Therefore, artificial intelligence methods are nowadays widely used to model and predict problems in civil engineering due to its significant benefits. On the other hand, among the things that have made it necessary to present a model for the RCC mix design are the range of materials used in this type of concrete, the complexity of the mix design, the effect of different parameters on the mix design, as well as finding the relationships between the various parameters of its mix design. Predicting and modeling the mix design or the resistance of these types of concrete is particularly complex in accordance with effective parameters similar to other types of concrete. On the other side, concrete mix design has become more complex as a result of the introduction of a variety of pozzolans, new materials added to the mix design of this type of concrete, as well as the impact of various concrete methods on this concrete, mix, and compaction. Moreover, the models that are trained can be used to predict the compressive strength of this type of concrete for engineering predictions and to obtain the most economical or optimal mix design using optimization techniques.

Here, we refer to a number of studies that have been conducted on modeling the mechanical properties of RCC using artificial intelligence methods. In a study, Ni and Wang [1] showed that it is possible to predict resistance at different ages and RCC vibration time in a very short time with acceptable accuracy using neural networks obtained. In a study, Ashrafian et al. [2] demonstrated that the ANN model is more capable than the adaptive neural fuzzy inference system (ANFIS) models and SVM in predicting the compressive strength of RCC. Furthermore, the resistances estimated by ANN and the SVM have the highest and lowest compliance with the actual compressive strength, respectively.

In their study, Amlashi et al. [3] observed that compressive strength will increase with an increase in the cement content as the rate of increase in strength decreases with an increase in the amount of fine RAP according to the results of the model sensitivity analysis. In addition, the compressive strength will increase with a decrease in the amount of fine RAP or an increase in curing time at a fixed amount of coarse aggregate. It was also observed that the effect of curing time on compressive strength decreases with an increase in the percentage of fine RAP.

Ayaz et al. [4] studied the indices of compressive strength and ultrasonic pulse velocity (UPV) as a criterion to detect the quality of concrete containing natural additives using artificial intelligence methods. This study used tree modeling algorithms to predict these two components using 40 data collected from 10 mix designs. The results of the samples were examined at the ages of 3, 7, 28, and 120 days.

Ashrafian et al. [5] used intelligent data-driven methods to estimate the compressive strength and UPV in nano-silica concrete. Five data-driven methods including linear regression, SVM, ANN, tree model, and multivariate adaptive regression splines (MARS) were investigated to provide computational relations of compressive strength and pulse velocity and prediction models were presented with high accuracy. Additionally, a number of computational relations have been introduced to estimate this type of concrete or nano property using the MARS method and the tree model.

Al-Sudani et al. [6] investigated the prediction of water flow using the MARS method coupled with differential evolution (DE) algorithm (hybrid DE-MARS). The results of this hybrid model were compared with those of classical data-driven modeling (DDM) models such as SVMs and simple MARS. The results presented in the form of error indices showed that the model quality was improved as a result of using a metaheuristic algorithm.

Mansouri et al. [7] evaluated the behavior of Fiber Reinforced Polymer (FRP) (also called fiber-reinforced plastic) using a variety of artificial intelligence methods. 3042 laboratory data from 253 different studies were selected to develop models, 60% of which were used for training, 20% for testing, and 20% for validating the presented models. The results of this study, presented in the form of RMSE statistics, showed that the tree model and MARS method performed better than the neural network and fuzzy neural network.

Kaveh et al. [8] estimated the properties of self-compacting concrete (SCC) containing fly ash (also known as pulverised fuel ash in the United Kingdom) using the MARS method and the tree model. This study presented 114 data collected from various literature review articles and computational relations to predict

SCC properties including compressive strength, tensile strength, flexural strength, and modulus of elasticity (MOE). The results indicate that artificial intelligence methods are considered reliable to predict the mechanical properties of this type of concrete.

Asteris et al. [9] conducted a study to provide computational relations to predict the compressive strength of SCC containing metakaolin (MK). In this study, they considered and analyzed the size of the largest aggregate as an input for the first time. In this regard, they used the nonlinear and non-parametric MARS method as well as the M5p tree model to develop estimated relationships and presented the relationship-based models.

In a study, Ashrafian et al. [10] investigated their newly developed model to estimate the compressive strength of lightweight concrete and compared its results with those of classical data-driven modeling techniques including ANN, SVMs, and MLR. In this study, the appropriate combination of inputs was used in the dataset using Mallow's Cp evaluation and a suitable structure was chosen for the inputs. The results of this study reported a more accurate and appropriate performance of the developed model compared to other methods.

Regarding the background to the prediction and modeling of the compressive strength of RCC, it can be stated that only few studies have attempted to model the compressive strength of this type of concrete and find a solution to estimate this mechanical component. Thus, it is necessary to propose a modeling approach for predicting and modeling the compressive strength of RCC. Furthermore, previous studies have shown that using the neural network method alone yields poor performance (esp. determination of optimal model parameters). Hence, it is necessary to develop new models to solve the problem. In this regard, the central question (major problem) of the present study is whether the metaheuristic algorithms are considered as a suitable solution to increase the accuracy of artificial intelligent models for estimating the compressive strength of RCC. Research sub-questions include:

How much increase in accuracy and decrease in error is observed in the proposed ANN-ABC method compared to the ANN method and other regression methods? Which component in the RCC mix design has the largest impact on compressive strength?

In addition, the assumptions of the present study for modeling a 28-day RCC resistance are as follows:

- For modeling, the laboratory moisture and temperature of the concrete samples are not found in the model.
- Influential factors such as concrete construction, curing, transfer, and placing are not found in the model.
- The grading of each fine and coarse aggregate constituting RCC is assumed to be uniform.

2. MATERIALS AND METHODS

This study evaluates the ANN and ANN-ABC models in terms of performance accuracy, and compares and contrasts the model with the best results as the preferred model for each method to determine the best method for predicting the compressive strength of pavement RCC. It should be noted that modeling aims to evaluate the capability of these methods in predicting the compressive strength of pavement RCC. The results were then compared with those of the MLR model.

2. 1. Development of Hybrid ANN-ABC Model

The ABC algorithm is used in a wide variety of fields, including in the training of feedforward ANNs, which is considered one of the most interesting applications. Applying the ABC algorithm to train ANNs is a simple and convenient method. The multidimensional search space employed by the ABC algorithm is the space associated with the weights of network connections and neurons. Food resource competency is measured by the standard measure of network output performance, including SSE of the “network training set” data. The most important advantage of this algorithm is the simultaneous search of the entire solution space.

The present study has used the ABC algorithm as a method for learning ANN to overcome the disadvantages created by the recursive extension algorithm in ANN training. The ABC algorithm is selected as an optimization tool because it can find optimal solutions along with relatively moderate computations. In addition, the ABC algorithm is used in the process of training ANNs to achieve the desired parameters such as network weight and bias to minimize the error function. These parameters are updated gradually to achieve the desired convergence criterion. Figure 1 shows the process of optimizing the values of ANN parameters by the ABC algorithm.

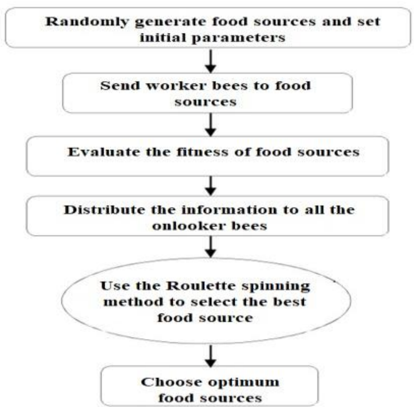

Figure 1. Artificial Bee Colony Algorithm Used in ANN Training

It seems that using swarm intelligence (SI)-based algorithms such as ABC algorithm is an appropriate solution to optimize the performance of ANNs, given the limitations of the backpropagation training algorithm.

2. 2. The Dataset Used in the Present Study A comprehensive laboratory database is needed to estimate the compressive strength of pavement RCC using the above models. Thus, 333 laboratory datasets were collected from published and validated laboratory studies for modeling the compressive strength of the pavement RCC [11–21]. Of the total data, 75% (i.e., 250 data) were considered to perform the training phases and 25% (i.e., 83 data) to perform the test phases, respectively. Figure 2 shows the flowchart of the implementation steps of this research during the modeling, analysis, and validation processes.

3. RESULTS AND DISCUSSION

3. 1. Selection of Input Parameters to Develop the Proposed Models According to Table 1, three scenarios with different input combination arrangements under different conditions are considered to select the optimal input state to develop the proposed model. In this evaluation, three different input types of values were evaluated as volumetric weight (dimensional), the ratio of values to each other (dimensionless), and percentage of values.

According to Table 2, Scenario 1 presented the most optimal results based on statistical analysis with respect to the results of statistical indices. In this analysis, the Mallows index is a function of the predictor variables in Scenario 1 considering the compressive strength (CS) in this study, as shown in Equation (1). Accordingly, according to Equation (1), predictor inputs for model development are compressive strength (CS) of pavement RCC including cement (C), coarse aggregate (CA), fine aggregate (FA), water (W), binder (cement + pozzolan) (B), and specimen age (AS). In this selected combination, the specimen age unit is presented on a daily basis and the rest of the input variables are in kg/m^3.

$$\mathrm{CS} = f\ (CA, FA, C, W, B, AS) \tag{1}$$

3. 2. Statistical Analysis of Input and Output Parameters in the Present Study A large standard deviation (SD) indicates a significant data sparsity (dispersion). According to Table 3, the data collected in this study have a significant sparsity over the study area and have facilitated the modeling process.

3. 3. Development of Multivariate Linear Regression Model In this section, the modeling process is performed using the MLR method to compare the values with the results of other developed methods. Hence, the configuration structure derived from the six predictor inputs is used. The MLR method structure used the "minimum mean square error (MMSE)" algorithm to optimize the weights and parameters of the model values to establish a linear relationship between the input variables and the output variables. Model learning process performed in MATLAB using training data and

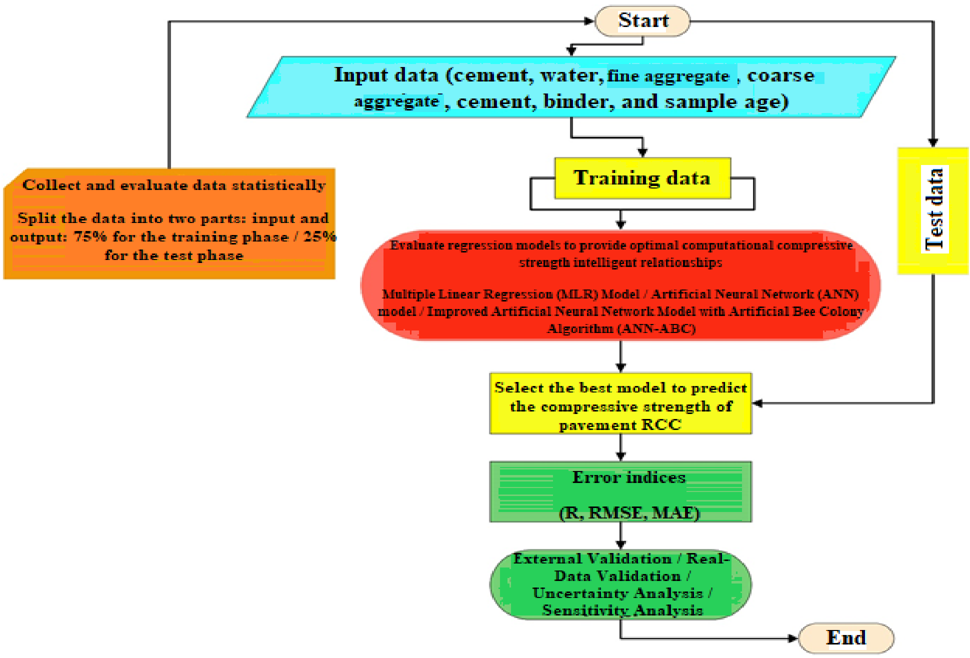

Figure 2. Flowchart of the implementation steps of the modeling process in this study

TABLE 1. Predicted scenarios for selecting the best input state for model development

Scenario	Input Values	Description
1	6	$CS = f\ (CA, FA, C, W, B, AS)$
2	4	$CS = (\frac{W}{B}, \frac{W}{C}, \frac{CA}{FA}, AS\ )$
3	6	$CS = (\%CA, \%FA, \%C, \%W, \%B, AS\ )$

TABLE 2. Results of investigation of scenarios to select the best input state in Minitab

Scenario	1	2	3
C_p	7.86	9	**9.11**
R^2	76.18	69.55	**67.60**

TABLE 3. Statistical analysis of predictor variables

Variables	Mode	SD	Mean	Min Value	Max Value
Coarse Aggregate	1095	178.09	1058.01	585	1316
Fine Aggregate	807	197.67	801.56	272.50	1263
Binder	295	67.98	310.71	200	672.50
Water	114	41.22	128.77	78	336.25
Cement	400	91.02	211.12	49	400
Specimen Age	28	44.58	47.549	7	180
Compressive Strength	24	15.23	37.78	6.80	75.50

a developed linear relationship has been reported below as Equation (2) to predict compressive strength with a correlation coefficient of 0.59:

$$CS = 0.14\ AS + 0.0002FA + 0.0644C - 0.1531W + 0.0555B + 19.894 + 0.0001CA \tag{2}$$

3. 4. Development of the Artificial Neural Network Model

This study used a multilayer perceptron (MLP) neural network, which has a hidden layer. Fifty neural network models were constructed and evaluated to determine the optimal number of nerves in hidden layers. To do this, the number of nerves is added up one by one in the first hidden layer (n = 1-50) and the performance of each model was examined. The Levenberg-Marquardt (LM) algorithm was used to train the neural network. This algorithm is often considered as the fastest backpropagation algorithm and is strongly recommended as the first choice in supervised learning algorithms. Tangent sigmoid, logarithmic sigmoid, and logarithmic linear functions were used to determine the appropriate excitation function in the hidden and output layers. The best result was related to the tangent sigmoid function in the hidden layer and the linear function in the output layer.

75% (n = 250) and 25% (n = 83) of the information were used to train and test networks, respectively. Table 4 presents the results of the performance evaluation of each step. The final model is determined based on its performance in the test phase. It should be noted that different weights are assigned to the network with each analysis of the ANN model in MATLAB; thus, a different solution is obtained with each analysis. To overcome this problem, neuron analysis was performed in hidden layers for 50 times for each ANN model. Table 4 reports fifteen appropriate performance results. The Neural Network 6 (with six neurons in the hidden layer) is the best developed model selected as the final model. In this study, the optimal model has a training rate of 0.25, a momentum index of 0.3, and 2000 repeats. As can be deduced from (Table 4), the six nerves in the hidden layer (i.e., the architecture of the network 1-6-6) yielded the best results and the Neural Network 6 Model is the best ANN model.

Figure 3 shows the evaluation criteria in each ANN model in the form of a graph. High values of parameter R and low values of RMSE indicate the high performance of the model.

Moreover, Figure 4 shows the architectural structure of the developed neural network model. The computational time of the ANN model in the

TABLE 4. Neural network performance evaluation criteria in the training phase

Model	Training Stage		Test Stage	
	R	RMSE	R	RMSE
NN1	0.808	85.900	0.829	**71.452**
NN2	0.811	83.122	0.844	**62.480**
NN3	0.812	83.117	0.840	**63.623**
NN4	0.811	83.122	0.848	**63.442**
NN5	0.801	90.618	0.854	**66.263**
NN6	**0.861**	76.68	**0.857**	**65.41**
NN7	0.770	95.329	0.805	**78.946**
NN8	0.766	95.800	0.800	**80.976**
NN9	0.741	95.612	0.745	**88.845**
NN10	0.722	98.845	0.722	**91.013**
NN11	0.720	98.010	0.711	**96.852**
NN12	0.733	93.621	0.739	**89.999**
NN13	0.800	900.60	0.718	**93.569**
NN14	0.819	84.329	0.822	**73.699**
NN15	0.800	900.060	0.839	**64.020**

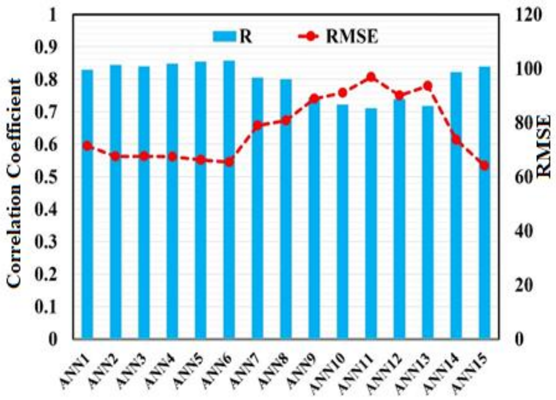

Figure 3. Evaluation criteria for ANN models

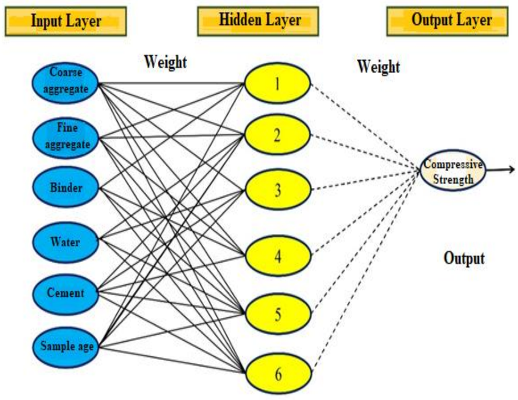

Figure 4. Architecture structure of the developed neural network model

computational analysis of this study is 9.12 seconds and the time spent for model structure formation is 0.62 seconds.

3. 5. Development of an Improved ANN Model Using ABC Algorithm

Evaluations showed that the optimal network has a 6-8-6 architecture with eight neurons in the hidden layer, six neurons in the input layer, and one neuron in the output layer. Table 5 shows the parameters for the ABC algorithm to optimize the network weights and biases. The number of iterations was assumed 1000 at each time and the initial population to be 50.

TABLE 5. ABC algorithm parameters to optimize network values

Parameter	Value
Initial population size	10-100
No. of repetitions	10-1000
Maximum number of cycles	100
Local search	15

Furthermore, Figure 5 evaluates the convergence of the ABC algorithm in combination with the neural network model to achieve optimal values. Due to the convergence process, the algorithm takes a constant trend at the 140th iteration that turns into a linear process from the 480th iteration and optimal values are found from the solutions.

3. 6. Comparison of Models Developed to Predict the Compressive Strength of RCC

According to Table 6, the correlation coefficients at the training phase are 0.603, 0.821, and 0.938 for the LRM, ANN, and neural network improved with the ABC algorithm, respectively. In addition, the RMSE values at this stage are 145.47, 76.68, and 39.97 MPa for the proposed MLR, ANN, and ANN-ABC models, respectively. Furthermore, the MAE for the ANN-ABC (4.71) model was better than the other three models. Thus, the statistical indices show that the proposed ANN-ABC model has a better performance and higher accuracy at the training stage than the other models. Applying a metaheuristic algorithm approach to model learning has played a fundamental role in better estimating the intelligent model. At the test stage, the newly developed ANN-ABC model with a correlation coefficient of 0.920 and RMSE and MAE values of 49.11 and 5.21 MPa, respectively, had more significant accuracy compared to the other two models. Additionally, the ANN-ABC model reduced the error generation process by 105.52 and 16.3 to reduce the error rate of the models presented in this study.

As shown in Figure 6, the neural network model, in combination with the ABC algorithm, involves less error in training compared to multiple regression and ANN in predicting the compressive strength values of pavement RCC. In a qualitative comparison, most compressive strength values are concentrated on the bisector (i.e., ideal line) and only a few of these points are outside the focus area (outliers). As shown in Figure 6c, in the model evaluation, a deviation of more than 20% was observed in the prediction of the estimated points in the range of

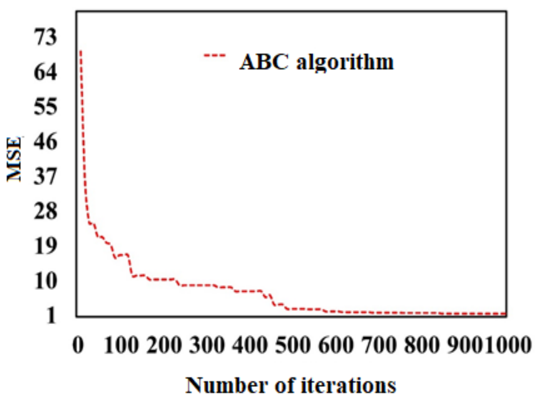

Figure 5. Evaluation of convergence in the iteration of the ABC algorithm

TABLE 6. Performance evaluation of the proposed models

Stages	Models	R	RMSE	MAE
Training	MLR	0.603	145.47	9.86
	ANN	0.821	76.68	6.47
	ANN-ABC	**0.938**	**39.97**	**4.71**
Test	MLR	0.590	154.63	10.32
	ANN	0.857	65.41	5.90
	ANN-ABC	**0.920**	**49.11**	**5.21**

20-40 MPa which was reduced severely using the ABC metaheuristic algorithm. The predicted values in this range were mostly higher than the actual values; however, the estimates were largely lower than the laboratory values with an increase of more than 50 MPa in values. Overall, the methods used in this study were well-trained for evaluation.

According to Figure 7, the compressive strength values of the models are predicted with good accuracy in the test phase. In predicting these values, the computational error was mainly less than 20% and the correlation between actual and predicted laboratory values was more than 85%. Furthermore, due to the percentage of the absolute error in the test phase, the combination of a metaheuristic algorithm with the ANN model reduced the error by 11.69%.

As shown by red dashed lines in Figure 8, the weak-prediction data (i.e., less fitness) are mainly over-estimated or under-estimated in the calculation of the reference values. This error rate has been reduced by applying refinement methods to the model, such as hybrid algorithms (i.e., hybrid models) and a more efficient and accurate model.

Based on the time series plot, the local minima and maxima predictions are better evaluated in the training and testing stages shown in Figure 9. The MLR and ANN

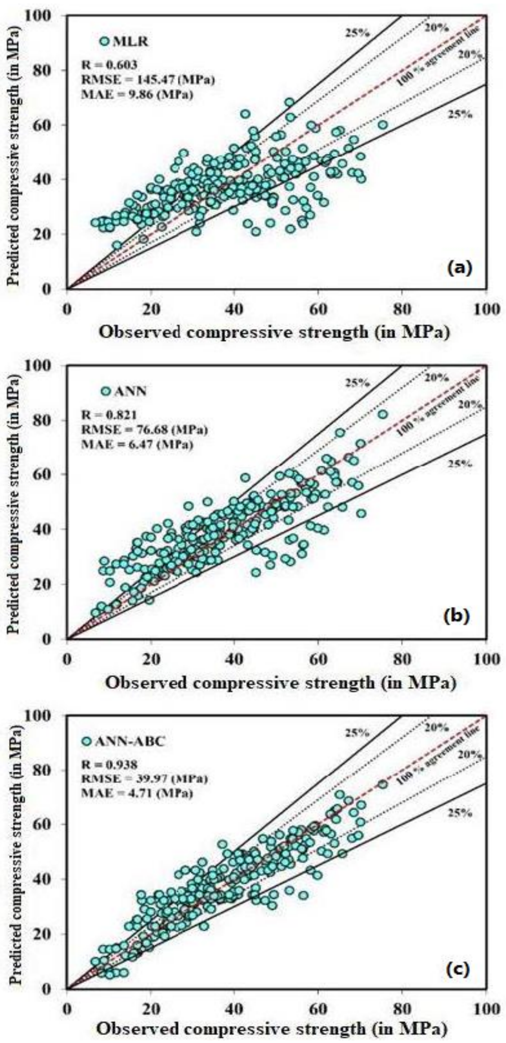

Figure 6. Scatter plot of the compressive strength values in the training phase for the proposed models

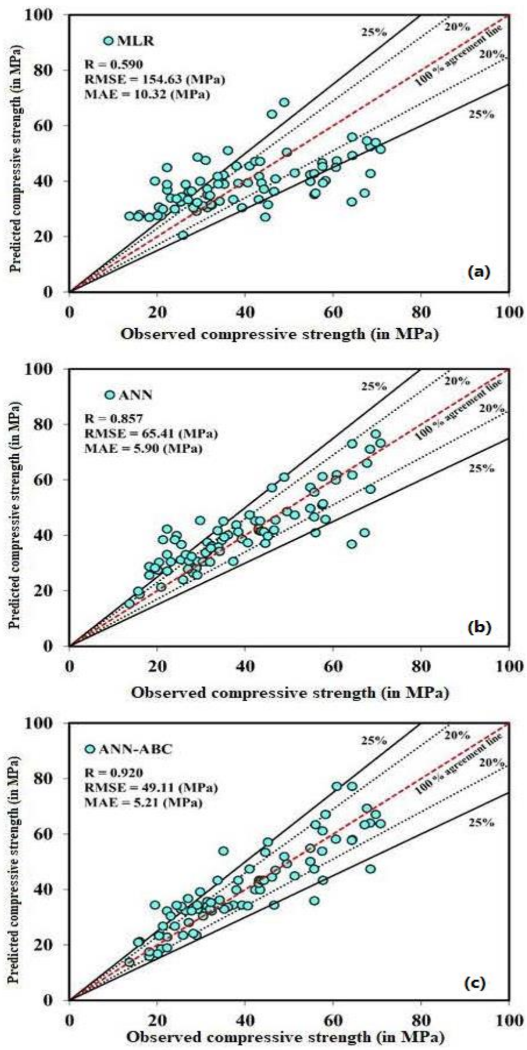

Figure 7. Scatter plot of the compressive strength values in the test phase for the proposed models

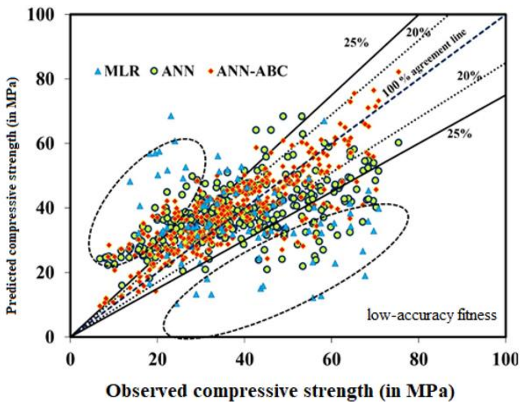

Figure 8. Compressive strength values of RCC in the test phase for all the proposed models

methods had relatively poor performance compared to the developed ANN-ABC model in this study. The hybrid ANN-ABC algorithm has been more successful in estimating local maxima and minima in the test phase. Moreover, the analysis of the presented models shows that local maxima are predicted with a greater error with an increase in the compressive strength values. This weakness is largely remedied by improving the neural network model by combining it with the ABC metaheuristic algorithm.

Figure 10 shows the error distribution values of the three methods used. The error distribution was mainly in the range of -20 to -30. Besides, the error range in the ANN-ABC model was between -10 and 10.

3. 7. Sensitivity Analysis This study has selected the ANN-ABC model (i.e., the best model in this study)

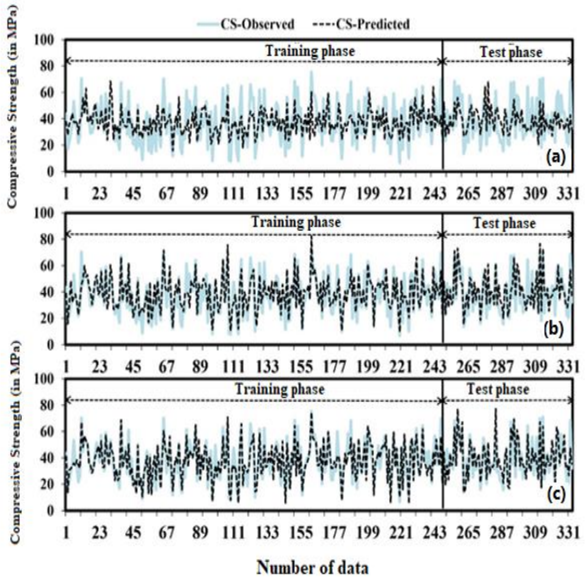

Figure 9. Time series plot of the proposed models; A: MLR, B: ANN, C: ANN-ABC

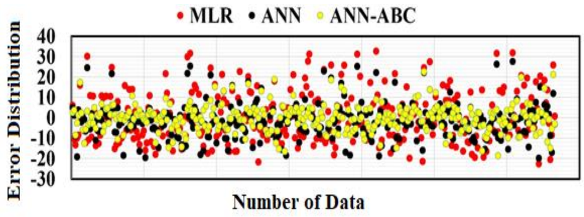

Figure 10. Error distribution values for the three methods used

to perform a sensitivity analysis to determine the effect of each input parameter on the compressive strength of pavement RCC. According to Table 7, the results of the sensitivity analysis show that the omission of the predictor variable "specimen age" with the correlation coefficient of R = 0.601 and MAE = 9.383 had the largest effect on the proposed ANN-ABC model in estimating the compressive strength of pavement RCC. Furthermore, among the mix design variables, the variables "binder" and "fine aggregate" had the greatest impact on the compressive strength, with a 22.1% and 17.7% decrease, respectively, in the result of the correlation coefficient at the experimental stage.

3. 8. External Validation of the Proposed Models

A new external validation criterion is presented to evaluate the proposed models based on their performance with the test dataset. Accordingly, at least one slope of the regression line from the origin for the predicted values to the observed values (K) or vice versa (K′) should be close to 1 as stated in Equations (3) and (4) [22].

$$K = \sum_{i=1}^{n}(O_i \times P_i)/P_i^2 \tag{3}$$

$$K' = \sum_{i=1}^{n}(O_i \times P_i)\ /\ O_i^2 \tag{4}$$

In addition, using the coefficient of determination (R^2) resulted from Equations (5) and (6), the regression line from origin should be less than 0.1.

TABLE 7. Sensitivity analysis of predictor parameters in compressive strength

Input Parameters	R	MAE
The omission of "Binder" variable	0.699	7.031
The omission of "Water" variable	0.823	5.796
The omission of "Cement" variable	0.780	6.873
The omission of "Fine aggregate" variable	0.743	7.893
The omission of "Coarse aggregate" variable	0.745	7.234
The omission of "Specimen age" variable	0.601	9.383

$$m = (R^2 - R_0^2)\ /\ R^2 \tag{5}$$

$$n = (R^2 - R_0'^2)\ /\ R^2 \tag{6}$$

where R_0^2 is the square of the correlation coefficient from origin between the predicted and observed values, and $R_0'^2$ is the square of the correlation coefficient between the observed and predicted values calculated via Equations (7) to (9) as follows [23]:

$$R_m = R^2 \times \left(1 - \sqrt{|R^2 - R_0^2|}\right) > 0.5 \tag{7}$$

$$R_0^2 = 1 - \sum_{i=1}^{n} P_i^2 (1-K)^2 / \sum_{i=1}^{n} (P_i - \bar{P})^2 \tag{8}$$

$$R_0'^2 = 1 - \sum_{i=1}^{n} O_i^2 (1-K')^2 / \sum_{i=1}^{n} (O_i - \bar{O})^2 \tag{9}$$

As can be seen in Table 8, the ANN-ABC model performed well within the scope of this validation based on validation criteria. Therefore, this method has high prediction accuracy and the amount of correlation between predicted and observed values in this method has not been estimated randomly.

Proposed models can be used to predict natural events if some or all of the validation conditions are valid for them. Accordingly, the R_m parameter for each of the improved models is greater than 0.5. The coefficients of determination of n and m are also less than 0.1 for all models. As can be seen from Table 8, the methods used can be introduced as predictor models by satisfying the relevant validation criteria. In addition, this correlation between the predicted and observed values of compressive strength cannot be random [24].

3. 9. Uncertainty Analysis

Simply put, uncertainty refers to what happens outside human control. In this section, a quantitative evaluation is presented of uncertainties based on the Monte-Carlo simulation (MCS) approach using intelligent models to estimate the compressive strength of pavement RCC. The uncertainty analysis is implemented for 333 laboratory data used in this dissertation (thesis for MSc) with 250,000 iterations. Besides, this analysis can add to the advantages of the proposed intelligent methods over empirical relationships. The relevant analysis is performed using the following equations that consider uncertainty in the range of less than 35% as acceptable [25], as shown in Table 9. Mean absolute deviation and uncertainty can be derived using Equations (10) and (11) as follow:

- Mean Absolute Deviation (MAD):

$$MAD = \frac{1}{M} \sum_{i=1}^{M} |P_i - Median(P)| \tag{10}$$

- Uncertainty%:

$$Uncertainty\% = \frac{100 \times MAD}{Median(P)} \tag{11}$$

TABLE 8. External validation criterion for predicting compressive strength

Model	*K*	*K'*	*m*	*n*	R_m
MLR	1.04	0.914	-0.446	-0.400	0.444
ANN	1.02	0.936	-0.364	-0.334	0.533
ANN-ABC	0.973	0.999	-0.244	-0.252	0.565
Conditions	(85/0< K, K' <1.15)		(*m*, *n* <0.1)		(R_m > 0.5)

3. 10. Validation of the Proposed Models Using Real Data

This study used eight unused pavement RCC data at 7, 28, 90, and 180 days of age that were not used in model development to validate models and to control their reliability conditions, whose values are described in Table 10. Input data for this evaluation are collected from Ref. [26–28].

The results of this evaluation, presented in Table 11, clearly show that the real and computational values are consistent for each of the six samples and the accuracy of the predictions is accompanied by an acceptable error. The MARS-ABC model with RMSE and MAE of 21.85 and 4.79, respectively, and a correlation coefficient above 0.8, which is an acceptable correlation condition (0.94), is validated at this stage. Based on the results, the proposed models, the accuracy of the predicted values of the developed models, and the accuracy of their estimation have been validated. [29, 30].

TABLE 9. Monte Carlo uncertainty analysis for the proposed models

Models	Median	MAD	Uncertainty %
MLR	33.62	14.23	58.47
ANN	38.90	10.26	33.40
ANN-ABC	40.96	9.11	26.63

TABLE 10. Input data for validation of the model prediction

	AS	CA	FA	C	W	B
A	7	841	1235	150	105	250
B	7	1209	801	295	114	295
C	90	1209	801	175	130	295
D	90	772	1158	330	105.6	330
E	90	1095	807	125	94	313
F	180	1209	801	295	114	295
G	28	1095	807	193	103	322
H	90	633.75	427.78	210	165	300

TABLE 11. Evaluation of the models at the validation stage

Sample (Specimen)	Actual Compressive Strength	Calculated Compressive Strength	Error Rate	R	RMSE	MAE
A	21.8	23.65	-1.857	0.94	21.85	**4.79**
B	26.5	31.29	-4.798			
C	70.25	56.33	13.917			
D	45	46.84	-1.847			
E	54.3	58.08	-3.788			
F	53.4	54.21	-0.811			
G	48.8	47.53	1.2626			
H	40.35	41.99	-1.649			

4. CONCLUSIONS

This study utilized novel data-driven modeling techniques, namely Multiple Linear Regression (MLR) and Artificial Neural Network (ANN), as well as a newly developed ANN-ABC approach to predict the comprehensive strength of pavement RCC. Initially, three different scenarios were defined to extract the parameters affecting the compressive strength of this type of concrete. The best combination of input variables, including six input parameters, namely coarse aggregate, fine aggregate, cement, water, binder, and specimen age, were used to develop the proposed models based on Cp mallow and R^2 indices in Minitab. According to the error statistical indices in the training phase, the ANN-ABC model (RMSE = 39.97, R = 0.938) performed better in estimating the compressive strength of the pavement RCC than ANN (RMSE = 76.68, RR = 0.821) and MLR (RMSE = 145.47, R = 0.603). Furthermore, the MAE statistical index for the improved ANN (4.71 MPa) reported a lower mean error. As a result, the statistical indices show that the proposed ANN-ABC model has a better performance and higher accuracy in the training phase than the other models. In other words, the application of metaheuristic algorithms to the model learning process improves the accuracy of the developed model. At the experimental stage, the compressive strength values of the models are predicted with good accuracy. The ANN-ABC model (MAE = 5.21, RMSE = 49.11, R = 0.920) reported significant accuracy compared to the other models used in this study. Sensitivity analysis results show that the omission of the predictor variable "specimen age" with the highest correlation coefficient of R = 0.601 and MAE = 9.383 had the highest effect on the proposed ANN-ABC model (i.e., the best model in this study) in estimating the compressive strength of pavement RCC. Furthermore, the mix design variables, namely the variables “binder” and “fine aggregate,” had the greatest impact on compressive strength, with a 22.1% and 17.7% decrease, respectively, in the result of the correlation coefficient at the test stage. The validity of the developed compressive strength models was evaluated using external validation, Monte Carlo uncertainty analysis, and validation of real laboratory values. The results suggested that the models presented are within the acceptable range of the indicators of this evaluation and are valid.

5. SUGGESTIONS FOR FUTURE RESEARCH

In recent years, great attention has been devoted to laboratory analyses and resulting modeling given the importance of RCC in industries and the attainment of appropriate resistance. This section offers a number of suggestions for future research and continuing the path of data-driven research:

Emerging concrete such as geopolymer concrete, heavy concrete, and SCC containing nanomaterials can be considered in the data-driven modeling process due to the multiplicity of influential materials.

Considering the structure of the MSE method in artificial neural models, it is suggested to use other metaheuristic algorithms such as ant colony optimization (ACO), particle swarm optimization (PSO) and genetic algorithm (GA) to improve performance and evaluate accuracy and speed.

Other data-driven models such as Model Tree (MT), Support Vector Machine (SVM), and Evolutionary Polynomial Regression (EPR) can be used to estimate the compressive strength of pavement RCC.

Consideration of other experiments on the properties of pavement RCC may also be of interest to continue this study.

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Persian Abstract

چکیده

در این پژوهش، به منظور بهبود بخشیدن دقت مدل ارائه شده، الگوریتم فراابتکاری کلونی زنبور عسل مصنوعی (ABC) برای بهینه کردن مقادیر روش شبکه‌ی عصبی مصنوعی (ANN) پیاده‌سازی شده و مدل توسعه‌داده‌شده ارزیابی شد. مقاومت فشاری بتن غلتکی با استفاده از مصالح طرح اختلاط در سه فرم ورودی وزنی حجمی (سیمان،آب، درشت دانه، ریزدانه و چسباننده)، نسبت مقادیر (نسبت آب به سیمان، نسبت آب به چسباننده، نسبت درشت‌دانه به ریزدانه) و همچنین درصد مقادیر طرح اختلاط در سنین مختلف بررسی گردید. مجموعه‌ی جامع و دارای محدوده‌ی مناسب داده‌ها شامل ۳۳۳ طرح اختلاط از مقالات مختلف جمع‌آوری شد. دقت مدل‌های این پژوهش با استفاده از شاخص‌های خطا شامل ضریب همبستگی، ریشه‌ی میانگین مربعات خطا، میانگین خطای مطلق بررسی و مدل‌های ترکیبی توسعه داده شده، مقایسه گردید. همچنین، برای اعتبار سنجی مدل‌ها، اعتبارسنجی خارجی و تحلیل عدم قطعیت مونت کارلو انجام و نتیجه گزارش گردید. در مرحله‌ی آزمایش پیش‌بینی مقادیر مقاومت فشاری، معلوم شد که مدل شبکه‌ی عصبی مصنوعیِ بهبودیافته با الگوریتم کلونی زنبور عسل (ANN-ABC) با (R=۰/۹۲۰, RMSE=۱۱/٤۹, MAE=۵/۲۱) در مقایسه با دیگر مدل‌های این مطالعه دقت قابل توجهی داشته است. همچنین، تحلیل حساسیت متغیرهای پیش‌بین در این مطالعه مشخص کرد که سن نمونه، چسباننده و ریزدانه متغیرهایی با اثرگذاری و اهمیت بیشتر در این تحقیق بوده است. مقایسه‌ی نتایج نشان‌گر این است که مدل بهبودیافته‌ی پیشنهادی با الگوریتم کلونی زنبور عسل مصنوعی در ارائه‌ی روابط محاسباتی توانایی بیشتری در کاهش خطا و دقت بالاتری نسبت به مدل‌های پیش‌فرض بررسی شده در پیش‌بینی مقاومت فشاری بتن غلتکی نشان داده و همچنین سعی در ساده سازی روابط محاسباتی داشته است.