Prediction of compressive strength of concrete based on IABC-MLP algorithm

Ping Li
Anhui University of Technology
Yanru Zhang (18855561253@163.com)
Anhui University of Technology
Jiming Gu
Anhui University of Technology
Shiwei Duan
Anhui University of Technology

Article

Keywords: Concrete, Compressive strength prediction, Improved artificial bee colony algorithm, Multilayer perceptron

Posted Date: January 11th, 2024

DOI: https://doi.org/10.21203/rs.3.rs-3842431/v1

Additional Declarations: No competing interests reported.

Prediction of compressive strength of concrete based on IABC-MLP algorithm

Ping Li [1], Yanru Zhang [1*], Jiming Gu [1],Shiwei Duan [1]

[1] School of Mechanical Engineering, Anhui University of Technology, Ma'anshan 243032, China
* Correspondence: 18855561253@163.com

Abstract: There are many factors that affect the compressive strength of concrete. The relationship between compressive strength and these factors is a complex nonlinear problem. Empirical formulas commonly used to predict the compressive strength of concrete are based on summarizing experimental data of several different mix proportions and curing periods, and their generality is poor. This article proposes an improved artificial bee colony algorithm (IABC) and a multilayer perceptron (MLP) coupled model for predicting the compressive strength of concrete. To address the shortcomings of the basic artificial bee colony algorithm, such as easily falling into local optima and slow convergence speed, this article introduces a Gaussian mutation operator into the basic artificial bee colony algorithm to optimize the initial honey source position and designs an MLP neural network model based on the improved artificial bee colony algorithm (IABC-MLP). Compared with traditional strength prediction models, the ABC-MLP model can better capture the nonlinear relationship of the compressive strength of concrete and achieve higher prediction accuracy when considering the compound effect of multiple factors. The IABC-MLP model built in this study is compared with the ABC-MLP and particle swarm optimization (PSO) coupling algorithms. The research shows that IABC can significantly improve the training and prediction accuracy of MLP. Compared with the ABC-MLP and PSO-MLP coupling models, the training accuracy of the IABC-MLP model is increased by 1.6% and 4.5%, respectively. This model is also compared with common individual learning algorithms such as MLP, decision tree (DT), support vector machine regression (SVR), and random forest algorithms (RF). Based on the comparison of prediction results, the proposed method shows excellent performance in all indicators and demonstrates the superiority of heuristic algorithms in predicting the compressive strength of concrete.

Key words: Concrete; Compressive strength prediction; Improved artificial bee colony algorithm; Multilayer perceptron.

1. Introduction

Concrete is one of the most commonly used materials in construction engineering, and its compressive strength is an important reference index for structural design and construction. As a multiphase composite material, the complex and diverse composition of concrete, differences in curing time and environment, and nonlinear coupling relationships between its constituent materials pose many challenges to the establishment of compression strength prediction models. Currently, in engineering applications, engineers mostly conduct mechanical performance tests on concrete materials and establish empirical-type compression strength prediction models based on the test data. However, such models are often based on the empirical summaries of test data for one or two types of concrete. When changing one of the constituent materials or curing time, the accuracy of this prediction model will greatly reduce. Therefore, these concrete strength prediction models based on specific constituent materials and curing conditions are often one-sided.

With the development of artificial intelligence, machine learning has drawn the attention of civil engineers. Machine learning methods, due to their ability to identify patterns or judgment rules hidden in extensive data sets and construct models with the aid of manual experience adjustment, are a new path for overcoming the limitations of empirical regression models in traditional mix design and predicting the relationship between concrete mix and performance[1-5]. Artificial neural networks (ANNs) are an important algorithm in machine learning, and more and more scholars are using neural networks for engineering prediction and damage identification[6-12], especially multilayer perceptron (MLP) networks. Wang[13] trained an ANN using the bark beetle algorithm and established a BAS-MLP concrete strength prediction model, which was compared and analyzed with the SCE-MLP, MVO-MLP coupling algorithms, and individual learning algorithms ANN and SVM. The results showed that combining the heuristic algorithm and ANN can better solve such problems. Kovačević[14] comprehensively overviewed machine learning methods available for estimating the compressive strength of self-compacting reinforced concrete, including multilayer perceptron artificial neural networks (MLP-ANN), the ensemble of MLP-ANN, regression tree ensembles (random forest, boosting, and bagging regression trees), support vector regression (SVR), and Gaussian process regression (GPR). Moodi[15] studied the effectiveness of three different machine learning methods, including radial basis function neural networks (RBNN), multilayer perceptron (MLP), and support vector regression (SVR), in predicting the ultimate strength of square and rectangular concrete columns. The research results show that MLP and RBNN achieve higher accuracy and have the best model prediction performance. Ghunimat[16] used three models, including multilayer perceptron network (MLP), random forest regression (RFR), and k-nearest neighbor regression (KNN) methods to estimate the compressive strength of concrete mixtures. By comparing the accuracy and stability of the three methods in predicting compressive strength, it was found that RFR and MLP have better performance and the results are closest to the actual values compared to KNN. Although some progress has been made in the above research, the setting of the initial parameters of the neural network greatly affects the results. When facing large or complex nonlinear problems in data sets, neural network algorithms still have shortcomings such as overfitting and dependence on initial values. Often, further improvement and more accurate prediction results require the use of optimization algorithms.

Artificial intelligence optimization algorithms, such as genetic algorithms, particle swarm optimization, ant colony optimization, and artificial bee colony algorithm, are popular parameter optimization algorithms. In the research of Karaboga, it has been demonstrated through numerous experiments that the artificial bee colony algorithm outperforms the above-mentioned algorithms in terms of optimization performance. It has the characteristics of few control parameters, strong local optimization ability, and fast convergence speed. Currently, scholars have applied this modeling approach of using the artificial bee colony algorithm to optimize neural network parameters for predicting the mechanical behavior of civil engineering materials and components. For example, Zhou[17], applied the artificial bee colony (ABC) algorithm and support vector machine (SVM) algorithm to optimize concrete mix design, and established an optimized concrete mix design model. The rationality and applicability of the model were verified through concrete slump and strength tests. Imran[18], used the artificial bee colony (ABC) algorithm and cascade forward neural network (CFNN) to develop a novel hybrid model for predicting the compressive strength of concrete. The model was validated using performance indicators, and it was found that the proposed hybrid model outperformed other models in all performance indicators. However, the ABC algorithm, as a random optimization algorithm, shares similar disadvantages with other evolutionary algorithms, such as slow convergence speed and susceptibility to local optima. In recent years, various improvement strategies have been proposed for the basic ABC algorithm. Shao[19], introduced a Gaussian mutation operator into the basic artificial bee colony algorithm to optimize the initial honey source position, and designed and established an improved RBF neural network model based on the improved artificial bee colony algorithm (IABC-RBF), which comprehensively improves the prediction ability of the neural network. Leng[20], improved the artificial bee colony algorithm in terms of search method and follower bee selection probability by introducing the global optimal solution and adaptive judgment factor. The improved algorithm's convergence speed and accuracy were found to be enhanced in three function test results. Yao[21], improved the algorithm from three aspects: swarm initialization, fitness function, and position update formula, overcoming the randomness of the initial algorithm and susceptibility to local optimal solutions. Inspired by the particle swarm optimization algorithm, Zhu[22], introduced the global best solution (gbest) information into the solution search equation and proposed an improved ABC algorithm, the GABC algorithm, to improve the development rate of the algorithm. Gao[23], first used a population initialization method based on chaotic opposition to improve global convergence, and then combined DE with GABC by evaluating strategies to try to use more prior search experience to improve development efficiency. They designed a new method called DGABC to improve the performance of ABC. These improved ABC algorithms have improved the algorithm's performance to some extent, but have not yet achieved adapted learning of the mechanical properties of materials from engineering materials testing data while avoiding premature convergence of the algorithm to improve the efficiency and accuracy of material strength prediction models.

Therefore, this paper conducts research on the concrete compressive strength prediction problem and proposes an improved artificial bee colony algorithm. The algorithm is improved from two aspects of the swarm: initialization and honey source update formula, overcoming the randomness of the honey source's random initialization and the disadvantage of easily falling into a local optimal solution. The improved artificial bee colony algorithm is combined with MLP neural network to solve the problem of poor global search ability of the MLP algorithm. The simulation experimental results of applying the model to two strength prediction datasets demonstrate the effectiveness of the algorithm, greatly improving the optimization efficiency and performance, and providing certain practical value in engineering project applications.

2. Model and Optimization Algorithm

2.1 MLP neural network

The multilayer perceptron (MLP) is a feedforward supervised learning neural network that includes an input layer, an output layer, and at least one hidden layer. In the MLP model, each layer contains several neurons, and there is no direct connection between neurons in the same layer. The neurons between adjacent layers are fully connected through the addition of weights. Except for the input layer, each layer's neurons have a nonlinear activation function. The multilayer perceptron inputs data through the input layer, and the hidden layer neurons analyze and process the data, and finally, the output layer outputs the results, which achieves multi-layer optimization processing of data.

MLP has excellent capabilities for nonlinear mapping, high parallelism, and high fault tolerance. Compared to other machine learning algorithms, it performs well in the presence of noise, nonlinearity, and high-dimensional data. At the same time, it can adapt to specific problem requirements by adjusting the number of layers and nodes in the model. In the research problem of concrete strength prediction, it can predict the compressive strength of concrete by learning the nonlinear mapping relationship between input features and outputs. During the training process, known concrete mix proportions, water-cement ratio, age, and other feature parameters are used as input, and their corresponding compressive strength is used as output. The backpropagation algorithm is used to optimize the network parameters, resulting in a more accurate prediction model.

Therefore, compared to other neural network models, the multilayer perceptron has outstanding advantages in nonlinear modeling, training speed, and handling of input variable correlations in concrete strength prediction. Its model structure is shown in Figure 1. Circles usually represent neurons or nodes, and the connecting lines represent connections between neurons, with arrows on the connecting lines indicating the direction of signal transmission from one neuron to another.

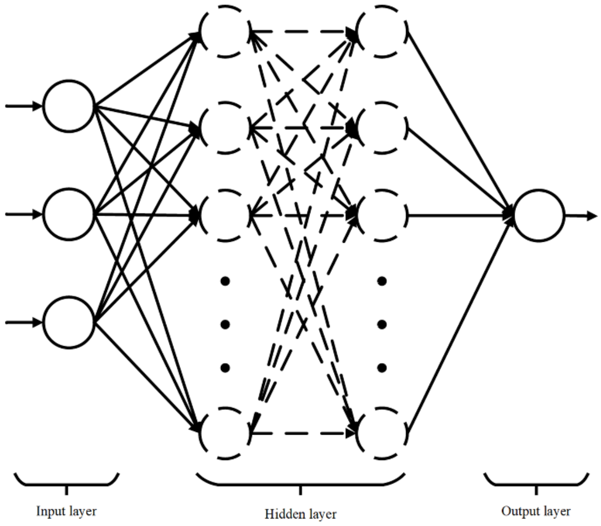


Figure 1 Structure diagram of MLP model

MLP determines the number of neurons in the input and output layers based on the target requirements, while the number of neurons and layers in the hidden layer are determined based on the error requirements set. In the MLP model, the output formula for the $j\text{-}th$ neuron in the $i\text{-}th$ layer is:

$$y_j^{(i)} = f_j^{(i)}(W_j^{(i)} \cdot y^{(i-1)} + b_j^{(i)}) \tag{1}$$

In the equation, $W_j^{(i)}$ is the weight vector of the $j\text{-}th$ neuron in the $i\text{-}th$ layer, with direction from the $((i-1)\text{-}th$ layer to the $i\text{-}th$ layer and the $j\text{-}th$ neuron; $y^{(i-1)}$ is the output vector of the $(i-1)\text{-}th$ layer; $b_j^{(i)}$ is the bias vector of the $j\text{-}th$ neuron in the $i\text{-}th$ layer; and $f_j^{(i)}$ is the activation function of the $j\text{-}th$ neuron in the $i\text{-}th$ layer.

All the parameters of the MLP model are the weights and bias quantities between each layer. The selection of these parameters affects the prediction performance of MLP to a certain extent. Therefore, it is necessary to optimize the weights and bias quantities of MLP, to make the output of the MLP model closer to the true value, thus improving the prediction accuracy of the model.

2.2 Basic Artificial Bee Colony Algorithm

There are currently many algorithms inspired by the behavior of insect colonies in nature, simulating the foraging behavior of insect colonies under the "survival of the fittest" rule. Artificial Bee Colony Algorithm is one of them, evolved from the foraging behavior of bees in nature. In 2005, Professor Karaboga first modeled the behavior and division of labor of bee colonies in foraging in literature and proposed the Artificial Bee Colony Algorithm model. Due to its ease of implementation, few control parameters, and strong stability, the algorithm performs both global and local searches in each iteration, which increases the likelihood of finding the optimal solution. Compared to other swarm intelligence algorithms, it converges faster and quickly gained attention and research from many researchers.

The Artificial Bee Colony Algorithm can simulate the actual honey bee foraging behavior, with the location of the food source representing the solution to the problem, the quality of the pollen representing the fitness of the solution, and the spatial position of a food source representing a set of feasible solutions. The colony is divided into three types of bees: employed bees, which are responsible for randomly searching for food around the hive and carrying information on food sources; follower bees, which follow employed bees to collect nectar; and scout bees, which randomly search for other food sources when a food source has been over-exploited. The individual behavior of bees in the colony is simple, but they coordinate with each other, communicate and cooperate to make the system run smoothly. The workflow is shown in Figure 2.

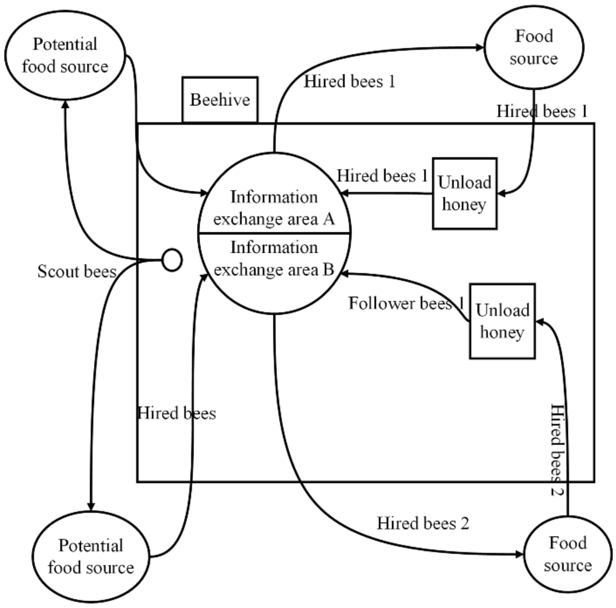


Figure 2 Workflow diagram of the bee colony

The basic model of the ABC algorithm includes four stages: the initialization stage, the employed bee stage, the onlooker bee stage, and the scout bee stage. Below is a detailed introduction to each stage of the artificial bee colony algorithm.

Stage 1: Initialization Phase: set the dimension of the solution space d, the size of the bee colony NP, the number of leading bees $NP/2$, the control parameter "*limit*" for abandoned food sources, and the maximum number of algorithm iterations Max Iterations. The ABC algorithm randomly generates $NP/2$ initial solutions x_i, $i = 1, 2, \ldots, NP/2$, each of which is a d-dimensional vector, and constructs the fitness function to evaluate the goodness of each food source.

Stage 2: Employed Bee Phase: each honey source represents a solution to the problem being solved. At the beginning, the honey source $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$ can be randomly generated according to the following equation:

$$v_{ij} = L_{ij} + r_1 \times (U_{ij} - L_{ij}) \tag{2}$$

where v_{ij} represents the $j\text{-}th$ variable of the $i\text{-}th$ honey source, $i \in (1, 2, \ldots, NP/2)$, $j \in (1, 2, \ldots, d)$, U_{ij} and L_{ij} are the upper and lower bounds of g_{ij}, and r_1 is a random number between 0 and 1, which is used to control the range of the neighborhood.

Stage 3: Follower Bee Phase: Follower bees select the honey source to search next based on the fitness of the honey source, using roulette wheel selection. The selection probability for honey source i is calculated according to the following equation:

$$p_i = \frac{fit_i}{\sum_{j=1}^{NP/2} fit_j} \tag{3}$$

where fit_i represents the fitness of the $i\text{-}th$ solution, which is the amount of nectar of the $i\text{-}th$ honey source, and " p_i " represents the probability of the $i\text{-}th$ honey source being selected. As can be seen from the equation, the probability of selecting a food source increases as its fitness increases. Once a follower bee selects a employed bee to follow, it searches in the neighborhood of the food source using equation (2) to find a better food source, which corresponds to the optimal fitness.

Stage 4: Scout bee stage: In the bee algorithm, if a local optimum is reached after t iterations of search and the threshold $limit$ for the number of attempts is reached without finding a better quality honey source, the bee responsible for that source becomes a scout bee. The scout bee generates a new honey source according to equation (4).

$$v_i^{t+1} = \begin{cases} L_i + r_1 \times (U_i - L_i) \ , & t \geq limit \\ v_i^t \ , & t < limit \end{cases} \tag{4}$$

It can be seen that the ABC algorithm has excellent global search capability and adaptability, and has a wide range of applications in scientific research and industry. It is suitable for predicting the strength of concrete. However, it has weaknesses in terms of slow convergence speed and a tendency to get stuck in local optima.

2.3 Improvements to the Artificial Bee Colony Algorithm

In order to enhance the optimization accuracy and convergence speed of the ABC algorithm, this study proposes improvements in two aspects: the optimization of the initial solution space and the honey source search mechanism.

(1) Honey Source Initialization

The initialization of honey sources has a significant impact on the speed and quality of the solution. In the basic Artificial Bee Colony algorithm, the positions of honey sources are randomly initialized, resulting in an uneven distribution of honey sources in the entire target space. However, chaotic sequences based on chaotic theory possess the properties of traversing the entire space and dynamism. Therefore, using chaotic sequences to improve the initialization of honey sources in the ABC algorithm overcomes the disadvantages of uneven distribution caused by random initialization.

A logistic mapping equation is used to generate chaotic sequences, as shown below:

$$x_k = \mu x_{k-1}(1 - x_{k-1}) \tag{5}$$

In the equation: μ represents the growth rate, and when μ =4, the system is in a fully chaotic state. x_0 is the initial value, and x_k represents the value of the algorithm at iteration k. According to chaotic theory, when the initial value x_0 is not equal to 0, 0.25, 0.5, 0.75, or 1.0, the sequence is in a chaotic state, which can expand the search range of the algorithm.

After introducing the chaotic sequence, the equation (1) can be improved as follows:

$$v_i = L_i + x_i \times (U_i - L_i) \tag{6}$$

where $i \in (1, 2, ..., \mathrm{NP}/2)$, U_i , and L_i are the upper and lower bounds of g_i ; x_i represents the d -dimensional chaotic sequence after a certain number of iterations.

(2) Honey Source Search Mechanism:

In order to improve the local search ability of the artificial bee colony algorithm, a Gaussian mutation mechanism is introduced. After each iteration, the fitness function values of the honey sources are sorted, and the worst $n \times \eta$ honey sources are selected for Gaussian mutation, where n is the number of honey sources and η is the mutation ratio. Empirically, η is set to 1/12; μ is the mean, and η is the standard deviation. After the worst $n \times \eta$ honey sources have been subjected to the Gaussian mutation, the formula for generating a new honey source is as follows:

$$v_{new}^{t} = v_{i}^{t} + Gauss(\mu, \sigma^{2}) \tag{7}$$

where v_i^t and v_{new}^t are the positions of the bee colony before and after mutation, respectively. The improved artificial bee colony algorithm flow is shown in Figure 3.

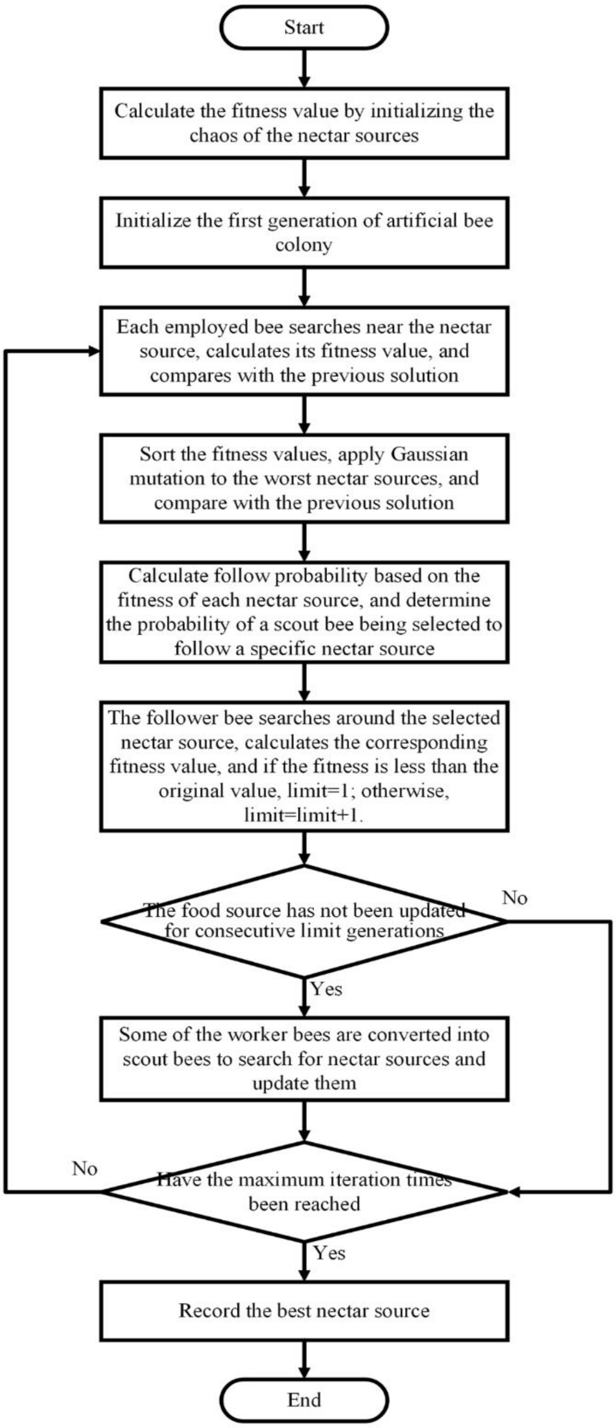


Figure 3 Improved artificial bee colony algorithm flowchart

3. Strength Prediction Model based on IABC-MLP

3.1 Model framework for prediction

MLP is a feedforward artificial neural network that has the advantage of processing complex nonlinear relationships and is therefore introduced for predicting the strength of concrete. In the research of predicting the compressive strength of concrete, its prediction results are easily affected by the model structure and fitting ability, which may lead to problems such as underfitting or overfitting, resulting in inaccurate prediction results. Therefore, in this paper, an improved artificial bee colony algorithm is used to search for the optimal initial weights and thresholds of the MLP neural network, which is then applied to the pre-defined network to construct the final algorithmic training model. It can overcome the problems of MLP neural network such as poor stability and easy falling into local optimum. This paper proposes a coupling model for predicting concrete strength using an improved artificial bee colony algorithm to optimize the multilayer perceptron network. In IABC-MLP, the IABC algorithm is used to find the best weights and biases to minimize prediction errors, so that the new model has stronger global search capability and can search for optimal solutions from a wider range of areas, while avoiding the limitations of traditional multilayer perceptron network that rely on the selection of initial weights and gradient descent, thereby improving the accuracy and stability of the model.

Specifically, in the ABC algorithm, individual bees optimize the weights and biases of the MLP through search and selection operations. Each bee represents a solution, which includes a set of values for weights and biases. Bees evaluate solutions based on the performance of the objective function (i.e., prediction error) and perform search and exploration based on a certain probability. The "employed bees" phase in the ABC algorithm is used to improve the current solution through information exchange with other worker bees. The "follower bees" phase is used to search for new solutions and compare them with the current solution for selection. By optimizing the weights and biases of MLP using the ABC algorithm, the performance and prediction accuracy of the model can be improved, thereby achieving more accurate prediction of concrete strength.

The specific flow of the IABC-MLP prediction model is shown in Figure 4.

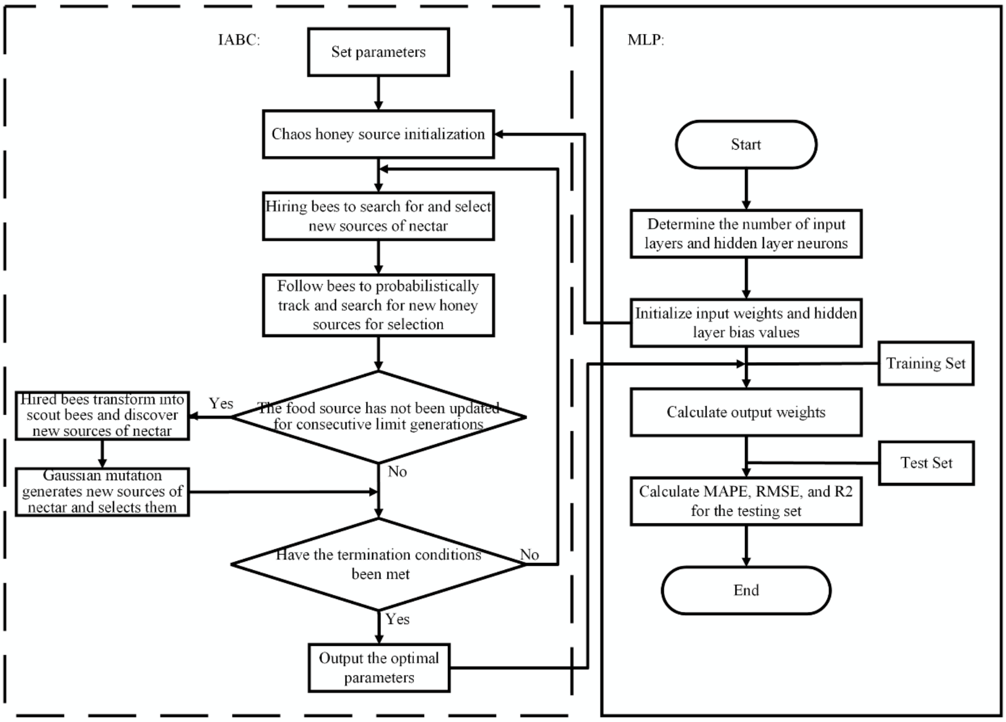


Figure 4 Flowchart of ABC-MLP algorithm

3.2 Model evaluation index

The evaluation of the accuracy of the model established in this paper is comprehensively assessed using mean absolute error (MAE), root mean square error ($RMSE$), and correlation coefficient (R^2) as performance indicators for model prediction.

MAE represents the average absolute error between the predicted value and the actual value, reflecting the average size of the predicted value error. The smaller the MAE value, the more accurate the prediction of the model. Its expression is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left| y_i - \hat{y}_i \right| \tag{8}$$

$RMSE$ represents the square root of the mean of the sum of squares of the difference between the predicted value and the true value, and is more sensitive to outliers because it amplifies the square of larger prediction errors. The smaller the value of $RMSE$, the more accurate the prediction of the model. Its expression is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left| y_i - \hat{y}_i \right|^2} \tag{9}$$

R^2 indicates the correlation between the predicted result and the true value. The value of R^2 ranges from 0 to 1, indicating the correlation between the predicted result and the true value. The closer the value is to 1, the better the model effect is. Its expression is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i \right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y} \right)^2} \tag{10}$$

Where: y_i is the measured value; $\hat{y}_i$ is the predicted value; $\overline{y}$ is the mean; n is the number of measured values.

4. Case Study Analysis

4.1 Data Acquisition

Concrete, as a composite material, its compressive strength depends mainly on two factors. Firstly, it depends on the proportion of various materials added during the mixing process, such as cement, slag, ash, water, superplastic, coarse aggregate, and fine aggregate, etc. Secondly, the mixed concrete needs to undergo chemical reactions in the natural environment after mixing in order to harden, so there is a significant correlation between the age of the concrete and its compressive strength.

Based on previous research and analysis of a large number of relevant literature and engineering experience, this paper chooses to consider the influence of concrete material proportion and age on its compressive strength and constructs a compressive strength regression prediction model based on MLP. The computer configuration used in this experiment is as follows: 16GB of memory, AMD R7 processor, CPU frequency of 3.2GHz, operating system Windows 11 (64-bit), and Python 3.9 as the programming language.

Dataset 1 is sourced from the Concrete Compressive Strength dataset of the UCI Machine Learning Repository. This dataset consists of 1030 samples, with each sample having 8 influencing factors: cement content, fly ash content, blast furnace slag content, superplasticizer content, water content, coarse aggregate, fine aggregate, and concrete age. Additionally, there is one target output value, which is the compressive strength of the concrete. Table 1 provides descriptive statistical data for dataset 1.

Table 1 Descriptive statistics of concrete compressive strength and key factors in dataset 1

Parameters	Descriptive indicators						
	Mean	Median	Standard Deviation	Variance	Minimum	Maximum	Skewness
Cement ($kg.m^{-3}$)	281.17	272.90	104.46	10910.98	102.00	540.00	0.51
Slag ($kg.m^{-3)}$	73.90	22.00	86.24	7436.90	0.00	359.40	0.80
Ash ($kg.m^{-3}$)	54.19	0.00	63.97	4091.64	0.00	200.10	0.54
Water ($kg.m^{-3}$)	181.57	185.00	21.34	455.56	121.80	247.00	0.07
Superplastic ($kg.m^{-3}$)	6.20	6.40	5.97	35.65	0.00	32.20	0.91
Coarse aggregate ($kg.m^{-3}$)	972.92	968.00	77.72	6039.81	801.00	1145.00	-0.04
Fine aggregate ($kg.m^{-3}$)	773.58	779.50	80.14	6421.95	594.00	992.60	-0.25
Age (d)	45.66	28.00	63.14	3986.56	1.00	365.00	3.26
Strength (MPa)	35.82	34.45	16.70	278.81	2.33	82.60	0.42

4.2 Input Variable Selection and Data Preprocessing

In order to reveal the extent of correlation between each type of input variable and the final output variable, and thereby optimize the input variables to achieve better predictive performance, we selected 8 initial variables from dataset 1 and calculated their importance indices for the output variable using a random forest algorithm via Python software. The results and importance index rankings are shown in Table 2.

Table 2 Feature importance ranking

Serial number	Features	Importance score	Serial number	Features	Importance score
1	Age	0.335511	5	Superplastic	0.071511
2	Cement	0.321780	6	Fine Aggregate	0.036973
3	Water	0.106932	7	Coarse Aggregate	0.029245
4	Slag	0.081184	8	Ash	0.016864

As shown in the table, it can be observed that among the input variables, the age of the concrete has the highest correlation with the output variable, which means that the duration of the age has the greatest impact on the compressive strength of the concrete. This is consistent with the empirical experience in engineering. The influence of cement content and water content on the output is secondary, as the cement content, water content, and water-cement ratio, which is one of the important indicators affecting concrete strength, are closely related. Therefore, the relationship between the calculated inputs and outputs based on this method is reasonable.

Furthermore, the correlation between the input variables and the compressive strength of concrete is analyzed using the heatmap method in Python. This is done to validate the importance scoring of the input variables calculated based on the random forest algorithm. The analysis results are shown in Figures 5 and 6. The coefficient size and color depth in the figures represent the degree of correlation between two variables.

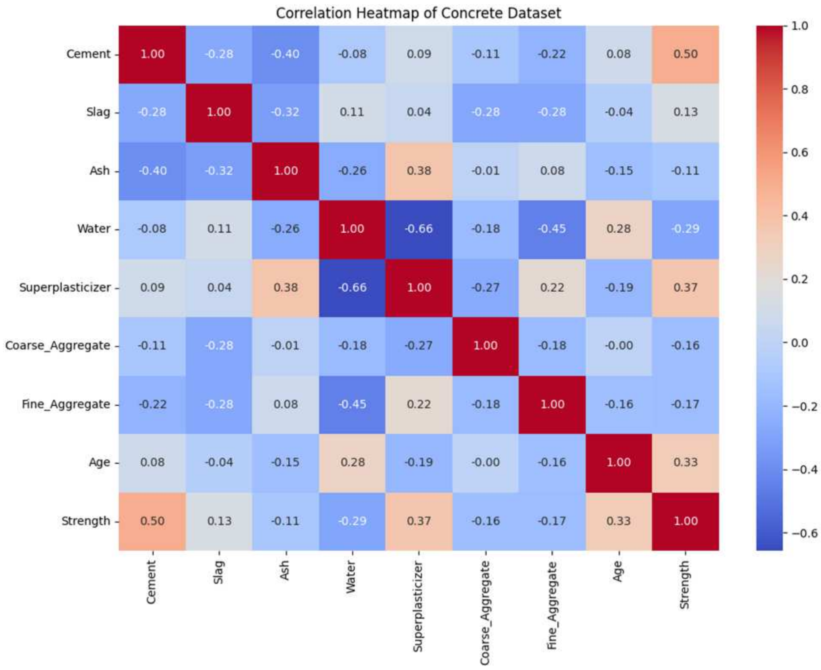


Figure 5 Heatmap of variable correlation

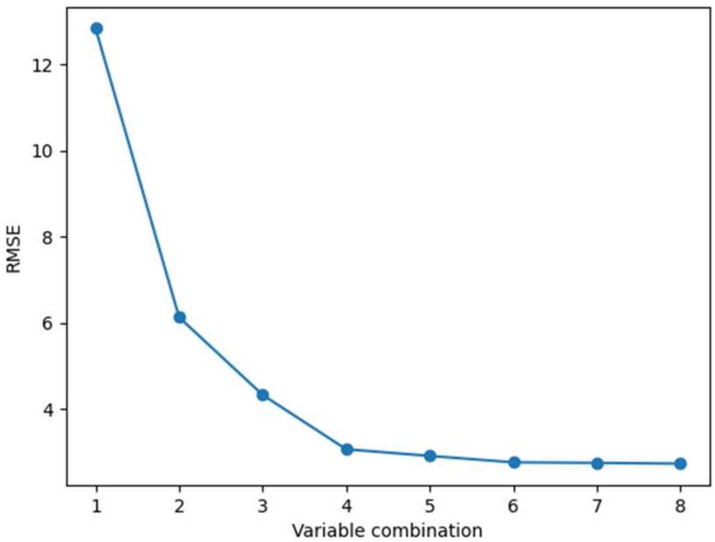


Figure 6 RMSE trend chart of different variable combinations

After traversing all feature variables, the optimal combination of variables is determined to be 8. At this point, the root mean square error is minimized and the predictive accuracy of the model is highest. Therefore, all 8 influencing factors in dataset 1 are used as input variables for the concrete compressive strength prediction model.

The machine learning method divides the original dataset into two subsets, the training set and the validation set, in a ratio of 8:2. Specifically, 824 randomly selected samples are used to build the concrete strength prediction model and evaluate the fitting performance of the ABC-MLP model. The remaining 206 samples are used as the validation set to test the generalization ability of the concrete strength prediction model. Both the ABC-MLP model and the other control group models are trained and validated according to this standard.

From the statistical description of the data, it can be observed that there are significant differences in concrete compressive strength and the physical values of various key factors, and the units are not standardized. Therefore, it is necessary to normalize the samples in order to improve the accuracy of the model training. In this paper, the (0,1) normalization method is selected as the normalization technique, with the following expression:

$$Y = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{11}$$

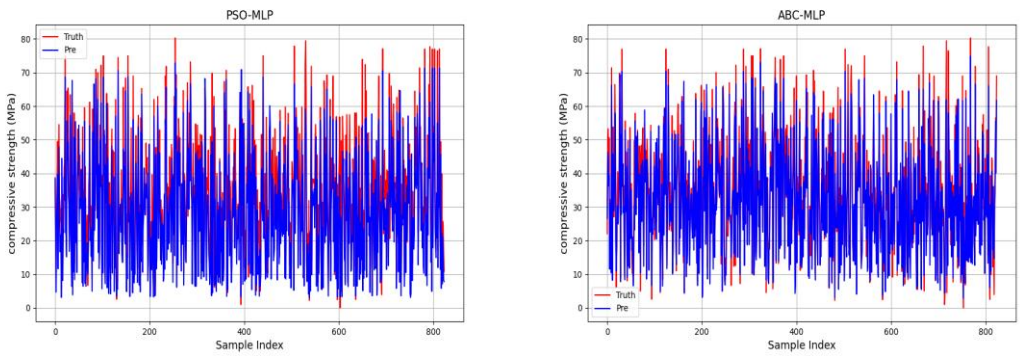
In the formula: Y represents the result of normalization; $X_{\min}$ is the minimum value in the sample; $X_{\max}$ is the maximum value in the sample; X is the sample value that needs to be normalized.

5. Model Comparison

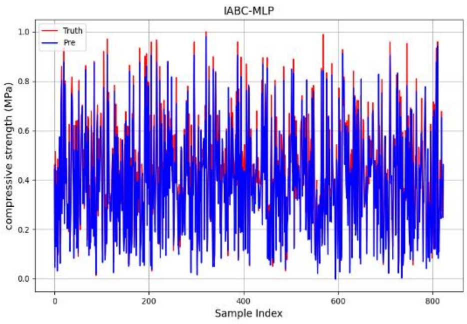
5.1 Comparison with the Coupled Model.

The particle swarm optimization (PSO) algorithm is a swarm intelligence algorithm that imitates the collaboration between particles to search for optimal solutions. Each particle updates its position and velocity continuously by interacting with other particles until the optimal solution is found. In the PSO algorithm, the interaction information between particles includes the current position, velocity, and the optimal position. Similar to the artificial bee colony (ABC) algorithm, the PSO algorithm can simultaneously consider global and local optimal solutions, and converge to the optimal solution quickly. Therefore, to verify the effectiveness of the IABC-MLP coupled model, we compared the IABC algorithm proposed in this paper with the basic ABC algorithm and the PSO algorithm.

The normalized concrete strength training set is input into the MLP for training, and the PSO algorithm, ABC algorithm, and improved ABC algorithm are used to optimize the weights and biases of MLP, respectively. This leads to the establishment of three concrete strength prediction models, and the training set is fitted to obtain the concrete strength fitting result as shown in Figure 7. To test the generalization ability of the concrete prediction model, the predicted results of the concrete strength test set are shown in Figure 8.

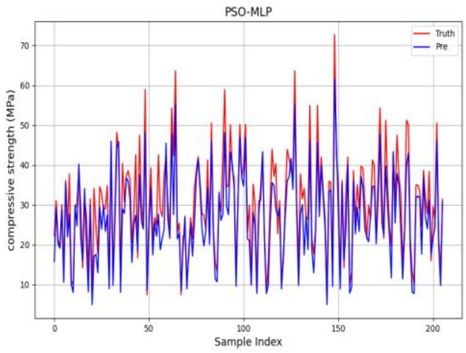


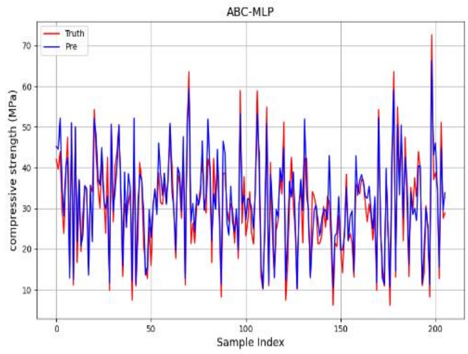
(a) PSO-MLP training sample fitting effect diagram (b) ABC-MLP training sample fitting effect diagram



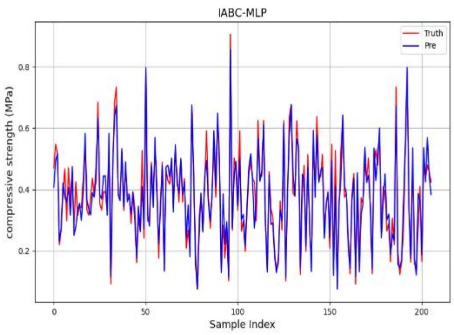
(c) IABC-MLP training sample fitting effect diagram

Figure 7 Three models training sample fitting effect diagram





(a) PSO-MLP testing sample fitting effect diagram (b) ABC-MLP testing sample fitting effect diagram



(c) IABC-MLP testing sample fitting effect diagram

Figure 8 Three models testing sample fitting effect diagram

Table 3 Results of evaluation indicators for each coupling model

Model	评估指标		
	MAE / MPa	*RMSE* /MPa	R^2
IABC-MLP	2.504	3.408	0.973
ABC-MLP	3.053	4.070	0.958
PSO-MLP	3.799	5.070	0.931

From Figures 7 and 8, it is evident that regardless of the training set or the testing set, the IABC-MLP model has smaller variations in prediction bias, higher goodness of fit, and can effectively fit the nonlinear relationship between predicted and actual values of concrete strength. According to the evaluation indicators in Table 3, it is found that the goodness of fit of IABC-MLP can reach over 97%, which is 1.5% and 4.2% higher than ABC-MLP and PSO-MLP, respectively. The average absolute error and root mean square error are also smaller, indicating better accuracy in fitting the prediction of concrete strength. Additionally, the particle swarm algorithm has slow convergence speed and is sensitive to parameter selection. In contrast, the artificial bee colony algorithm can quickly adapt to environmental changes, has strong robustness and high search efficiency, making it applicable to various fields and problems.

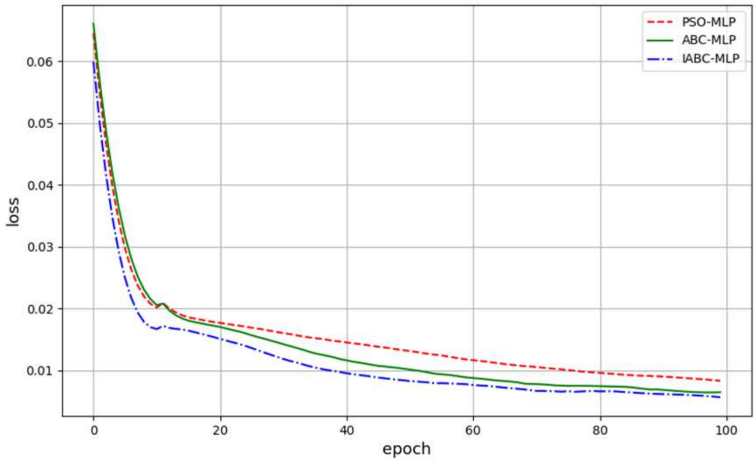
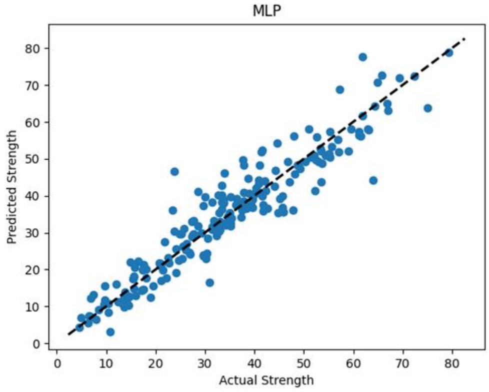


Figure 9 Loss iteration graph

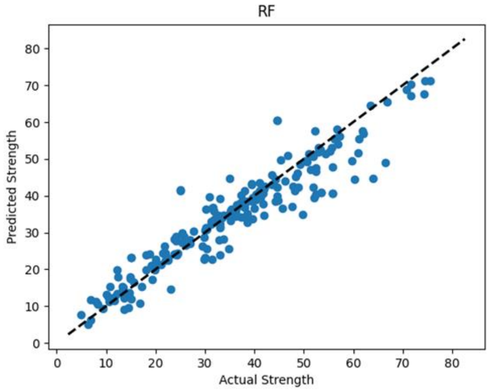
Convergence speed is an important indicator of the performance of optimization algorithms. Figure 9 shows the convergence curves of PSO-MLP, ABC-MLP, and IABC-MLP algorithms. In the figure, epoch represents the iteration times and loss represents the loss value. Comparing the loss values of the three coupled model algorithms after each iteration, it can be seen that the original ABC algorithm has a certain degree of slow convergence speed and is prone to getting stuck in local optimal solutions. Compared with the original algorithm, the PSO algorithm has faster convergence speed and fewer iterations, but weaker global optimization ability. This paper's IABC algorithm adopted the optimization of initial solution space and honey source search mechanism to avoid problems such as the randomness of initialization of food source positions and being prone to getting stuck in local optimal solutions. The algorithm enables bees to quickly move to the region where the optimal food source is located through the Gaussian mutation operator. Therefore, the IABC algorithm has significantly improved in both iteration speed and global optimization ability. After about 100 iterations, the test error tends to stabilize. Compared with the ABC-MLP algorithm and the PSO-MLP algorithm, the IABC-MLP neural network algorithm is superior in both optimization accuracy and convergence speed in the same number of iterations and can well predict the compressive strength performance of concrete.

5.2 Comparison with Single Model

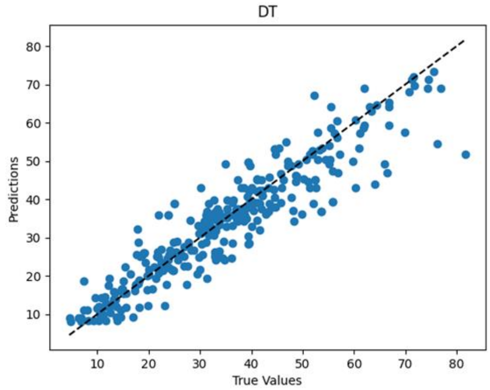
To further observe the prediction effect of the IABC-MLP model, this study also selected four single models for concrete strength prediction experiments: Multi-Layer Perceptron (MLP), decision tree (DT), Support Vector Regression (SVR), and Random Forest (RF). Figure 10 shows the fitting effect of the predicted values and actual values of each model, where it can be visually seen that the DT model has the worst fitting effect compared to other models, and the sample points are not concentrated on the regression line. The performance of all models was measured using evaluation metrics such as mean absolute error, root mean squared error, and correlation coefficient. The calculation results of all models are shown in Table 4.



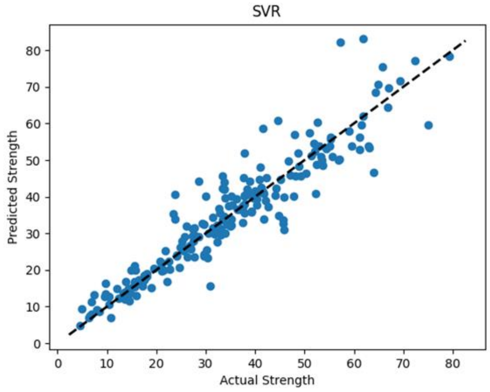
(a) MLP Model



（b）RF Model



（c）DT Model



（d）SVR Model

Figure 10 Fitting diagram of predicted values and actual values of each model

Table 4 Evaluation metrics results of each single model

Model	Evaluation metrics		
	MAE / MPa	*RMSE* /MPa	R^2
MLP	3.837	5.183	0.898
DT	4.340	6.151	0.860
SVR	3.901	5.814	0.872
RF	3.738	5.472	0.884

From Table 4, it can be seen that the goodness of fit values of the four single models from highest to lowest are: MLP>RF>SVR>DT. Compared to the single MLP model, the ABC-MLP model increased the R^2 value by 8.35%. This means that ABC adapts and optimizes the model based on the characteristics of the data, overcoming the curse of dimensionality and improving the prediction accuracy and stability of the MLP model.

In addition, compared to the other three classical models, the IABC-MLP model shows significantly better prediction performance. The reason is that DT, SVR, and RF are individual learning algorithms, which require a large number of weights and thresholds when dealing with a large number of samples, resulting in low accuracy. On the other hand, IABC-MLP is a coupled metaheuristic algorithm that does not require excessive parameter tuning. It has a fast convergence speed and strong global optimization ability, enabling accurate prediction of concrete compressive strength.

6. Model Performance Verification

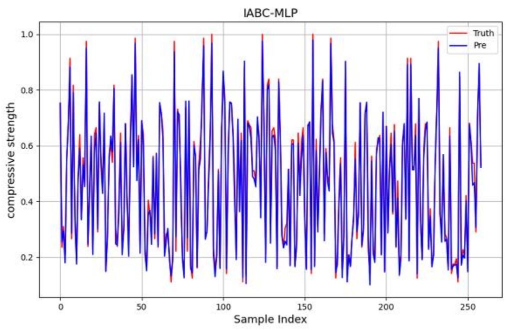
In order to further validate the generalization performance of the IABC-MLP neural network model and test its feasibility in practical construction, a new dataset 2 is selected for validation. It is applied to the dataset publicly available in the paper by Al-Shamiri [24], which consists of 324 sets of concrete samples obtained in their laboratory. This dataset has fewer types of input variables, so there is no need for variable optimization. The input variables are the cement, superplastic, water, coarse aggregate, fine aggregate, with the concrete compressive strength as the output variable.

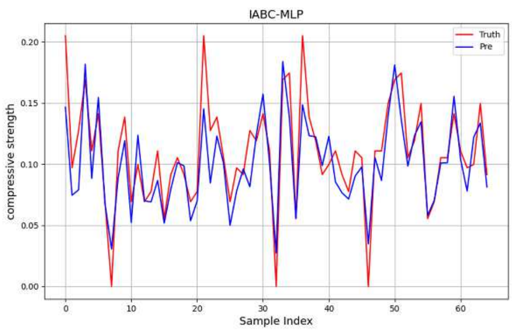
This dataset is used to verify the generalization of the proposed model in this paper, and its descriptive statistical data are shown in Table 5.

Table 5 Descriptive statistics of concrete compressive strength and key factors for Dataset 2

Parameters	Descriptive indicators						
	Mean	Median	Standard Deviation	Variance	Minimum	Maximum	Skewness
cement ($kg.m^{-3}$)	417.81	411	76.91	5914.77	284	600	0.41
water ($kg.m^{-3}$)	170	170	8.16	66.67	160	180	0
superplastic ($kg.m^{-3}$)	0.90	1.0	0.56	0.32	0.00	2.0	0.09
coarse aggregate ($kg.m^{-3}$)	898.51	898.00	43.75	1914.08	845.00	989.00	0.02
fine aggregate ($kg.m^{-3}$)	767.63	769.5	85.39	7291.25	552.00	951.00	-0.19
Strength (MPa)	51.93	48.90	9.43	88.95	37.5	73.6	0.44

The fitting effect on the training set and the test set is shown in Figure 11.





(a) Fitting graph of the training samples (b) Fitting graph of the testing samples

Figure 11 Fitting effect graph of IABC-MLP strength

From Figure 11, it can be seen that both the actual strength curve and the predicted strength curve are extremely close for both the training and validation samples, indicating an excellent fitting effect. According to the calculation results, the fitting accuracy reached 99.2%, with average absolute error and root mean square error of 0.713 and 0.964, respectively. In summary, the IABC-MLP model has demonstrated its effectiveness and universality for predicting the strength of concrete, providing a new approach and method for predicting the compressive strength of concrete in practical engineering applications.

7. Conclusion

In response to the high requirements for real-time and accuracy of compressive strength prediction of concrete on construction sites, this study adopts the multilayer perceptron (MLP) with higher predictive fit as the modeling method. Due to the significant influence of parameters on the predictive performance of MLP, the process of hyperparameter optimization is time-consuming. In this study, the basic artificial bee colony (ABC) algorithm is improved by introducing the Gaussian mutation operator and optimizing the initial solution space to establish an MLP neural network model based on the improved artificial bee colony algorithm optimization. By applying the improved artificial bee colony algorithm to optimize the parameters of the MLP neural network model, the extensive mapping capability of neural networks and the global search capability of optimization algorithms are fully utilized.

The newly established IABC-MLP model for predicting compressive strength of concrete is experimentally simulated on two public datasets and compared with models using ABC, particle swarm optimization (PSO) for hyperparameter optimization, as well as commonly used individual learning algorithms such as MLP, decision tree (DT), support vector machine regression (SVR), and random forest algorithm (RF). The experimental results show that the proposed IABC-MLP model in this study can complete the prediction process more quickly and accurately compared to other models, and it has good generalization ability and is suitable for predicting the compressive strength of concrete on actual construction sites. However, the prediction research in this study mainly focuses on the prediction of concrete under standard conditions at room temperature, and further research is needed for the prediction of compressive strength of concrete under different temperatures, moisture content, and other conditions.

Data availability

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Reference

[1] Wang R , Wu S C , Geng X J ,Sun J L , Zhang X Q . Strength prediction of steel fiber shotcrete based on machine learning[J/OL]. *Journal of Kunming University of Science and Technology(Natural Science)*. 2023, 1-15. http://doi.org/10.16112/j.cnki.53-1223/n.2023.06.482

[2] Long W J , Luo S Y , Cheng B Y , Feng G L , Li L X . Research progress of th e use of machine learning algorithm in performance design of self-compacting concrete [J/OL]. *Materials Reports*. 2023, 1-17.http://kns.cnki.net/kcms/detail/50.1078.TB.20230509.1319.006.html

[3] Liu X , Wang S M , Lu L , Chen M Z , Zhai Y , Cui S . Development on machin e learning for durability prediction of concrete materials [J/OL]. *Journal of the Chinese C eramic Society*. 2023, 08, 1-12. http://doi.org/10.14062/j.issn.0454-5648.20220973

[4] Luo G B , Hong C Y , Cheng Z L ,Sun L . Study on prediction of concrete compr essive strength based on BP and GA-BP neural network [J]. *Concrete*. 2023, 03, 37-41. ht

tp://doi.org/10.3969/j.issn.1002-3550.2023.03.007
[5] Xu X H , Hu Z L , Liu J P , Li W W, Liu J Z . Concrete strength prediction of the three gorges dam based on machine learning regression model [J]. *Materials Reports*. 2023, 37(02), 45-53. http://doi.org/10.11896/cldb.22010068
[6] Zhang J , Liu X D. Prediction of concrete strength based on least square support vector machine optimized by chaotic particle swarm optimization [J]. *Journal of Jilin University(Engineering and Technology Edition)*. 2016, 46(04), 1097-1102. http://doi.org/10.13229/j.cnki.jdxbgxb201604013
[7] Fan X Q , Liu J D , Shi C Y , Fe F . Innovative idea on fracture analysis of FRP reinforced concrete using artificial neural network [J]. *Journal of Disaster Prevention and Mitigation Engineering*. 2023, 43(03), 626-636. http://doi.org/10.13409/j.cnki.jdpme.20210429003
[8] Long X , Mao M H , Lu C H , Su T X , Jia F R . Prediction of dynamic compressive performance of concrete-Like materials subjected to SHPB based on artificial neural network [J]. *Journal of Nanjing University of Aeronautics & Astronautics*. 2021, 53(05), 789-800. http://doi.org/10.16356/j.1005-2615.2021.05.017
[9] Huang W , Zhou L , Ge P , Yang T . A comparative study on compressive strength model of recycled brick aggregate concrete based on PSO-BP and GA-BP neural networks [J]. *Materials Reports*. 2021, 35(15), 15026-15030. http://doi.org/10.11896/cldb.20070041
[10] Jin L , Zhao R , Du X L . Neural network prediction model of concrete compressive strength size effect [J]. *Journal of Beijing University of Technology*. 2021, 47(03), 260-268. http://doi.org/10.11936/bjutxb2020010020
[11] Yu H , Zheng J , Lin Q . Strength prediction of seawater sea sand concrete based on artificial neural network in python[J]. *Materials Research Express*. 2023, 9(03), 035201. http://doi.org/10.1088/2053-1591/ac5957
[12] Asteris, P G, Mokos, V G. Concrete compressive strength using artificial neural networks[J]. *Neural Computing and Applications*. 2020, 32(15), 11807-11826. http://doi.org/10.1007/s00521-019-04663-2
[13] Wang S R , Hu P , Chen S B , Xiao Y . Prediction of concrete compressive strength based on coupled beetle search algorithm [J/OL]. *Journal of Building Materials*. 2023, 1-15. http://kns.cnki.net/kcms/detail/31.1764.TU.20230308.1421.004.html
[14] Kovačević, Miljan, Lozančić, Silva, Nyarko E K, Hadzima-Nyarko M. Modeling of Compressive Strength of Self-Compacting Rubberized Concrete Using Machine Learning[J]. *Materials* .2021, 14(15), 4346. https://doi.org/10.3390/ma14154346
[15] Moodi Y, Ghasemi M, Mousavi S R. Estimating the compressive strength of rectangular fiber reinforced polymer–confined columns using multilayer perceptron, radial basis function, and support vector regression methods[J]. *Journal of Reinforced Plastics and Composites*. 2022, 41(3-4), 130-146. http://doi.org/10.1177/07316844211050168
[16] Ghunimat D , Alzoubi A E , Alzboon A , Hanandeh, S. Prediction of concrete compressive strength with GGBFS and fly ash using multilayer perceptron algorithm, random forest regression and k-nearest neighbor regression[J].*Asian Journal of Civil Engineering*. 2023, 24(1), 169-177. http://doi.org/10.1007/s42107-022-00495-z
[17] Zhou H , Chen B , Meng M L. Optimization of concrete mix proportion based on SVM-ABC model[J]. *Water Resources and Power*. 2021, 39(06), 127-130.
[18] Imran, M, Khushnood R A, Fawad M. A hybrid data-driven and metaheuristic optimization approach for the compressive strength prediction of high-performance concrete[J]. *Ca*

se Studies in Construction Materials. 2023, 18, e01890. https://doi.org/10.1016/j.cscm.2023.e01890
[19] Shao G C , Zhang K , Wang Z Y , Wang X J , Lu J. Groundwater depth prediction model based on IABC-RBF neural network[J]. *Journal of Zhejiang University(Engineering Science)*. 2019, 53 (07): 1323-1330. https://doi.org/10.3785/j.issn.1008-973X.2019.07.011
[20] Leng X , Zhang S Q , Lei Z Y . Application of improved artificial bee colony algorithm in neural network[J]. *Computer Engineering and Applications*, 2016,52(11):7-10. https://doi.org/10.3778/j.issn.1002-8331.1407-0164
[21] Yao G, Wu Y, Huang X, et al. Clustering of typical wind power scenarios based on K-means clustering algorithm and improved artificial bee colony algorithm[J]. *IEEE Access*, 2022, 10: 98752-98760. https://doi.org/10.1109/access.2022.3203695
[22] Zhu G, Kwong S. Gbest-guided artificial bee colony algorithm for numerical function optimization[J]. *Applied mathematics and computation,* 2010, 217(7): 3166-3173. https://doi.org/10.1016/j.amc.2010.08.049
[23] Gao W, Huang L, Wang J, et al. Enhanced artificial bee colony algorithm through differential evolution[J]. *Applied soft computing*, 2016, 48: 137-150. https://doi.org/10.1016/j.asoc.2015.10.070
[24] Al-Shamiri A K, Kim J H, Yuan T F, et al. Modeling the compressive strength of high-strength concrete: An extreme learning approach[J]. *Construction and Building Materials*, 2019, 208: 204-219. https://doi.org/10.1016/j.conbuildmat.2019.02.165

Acknowledgements

The authors would like to acknowledge the financial support by National Natural Science Foundation of China (Nos.11802001 and 12102002).

Author Contributions

Y.Z.: methodology; S.D.: investigation; P.L.: writing—original draft; J.G.: writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Additional information

Correspondence and requests for materials should be addressed to Y.Z.