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Developing a New Procedural Binary Particle Swarm Optimization Algorithm to Estimate Some Properties of Local Concrete Mixtures

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Abstract: Artificial intelligence techniques have lately been used to estimate the mechanical properties of concrete to reduce time and financial expenses, but these techniques differ in their processing time and accuracy. This research aims to develop a new procedural binary particle swarm optimization algorithm (NPBPSO) by making some modifications to the binary particle swarm optimization algorithm (BPSO). The new software has been created based on some fresh state properties (slump, temperature, and grade of cement) obtained from several ready-mix concrete plants located in Aleppo, Syria to predict the density and compressive strength of the regional concrete mixtures. The numerical results obtained from NPBPSO have been compared with the results from BPSO and artificial neural network ANN. It has been found that BPSO and NPBPSO are both predicting the compressive strength of concrete with less number of iterations and more accuracy than ANN (0.992 and 0.998 correlation coefficient in BPSO and NPBPSO successively and 0.875 in ANN). In addition, NPBPSO is better than BPSO as it prevents the algorithm from falling into the problem of local solutions and reaches the desired optimal solution faster than BPSO. Moreover, NPBPSO improves the accuracy of obtained compressive strength values and density by 30% and 50% successively.

Keywords: concrete; binary particle swarm algorithm; artificial neural networks; compressive strength; density

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1. Introduction

To determine the strength of concrete mixtures using the traditional approach, the following steps are required: (1) Identify the components of the mixture, such as the types and amounts of sand, gravel, cement, and auxiliary materials. (2) Determine the correct amount of water to add to the mix, considering local evaporation factors. (3) Implement the mix using appropriate procedures and steps, considering ambient temperature and humidity. (4) Fill molds with the mixture according to the prescribed shapes and dimensions. (5) Allow the mixture to harden and form a concrete base by leaving it inside the mold for 7 to 28 days. (6) Extract the concrete beam from the mold and expose it to external forces using special testing devices to determine its compressive strength. (7) After completing the experiments, remove any waste resulting from the examination process [1–5].

Due to the speed of artificial intelligence (AI) techniques in solving engineering problems, there has been a tendency to use these techniques in various fields of civil engineering, including designing construction materials (concrete mixtures for example) or estimating their properties. As it is hard to predict the compressive strength of concrete due to the different nonlinearities inherent in the mixture designs, various concrete companies are continuously looking to use new methods and technologies to predict the compressive strength. Such methods include numerical modelling and artificial intelligence due to their advantages. These methods are efficient and environmentally friendly, as there is no waste in the testing process. In addition, they are more economical since there is no need for test means, test materials, or even laboratory employees. Moreover, these methods are flexible since many parameters can be taken into consideration, along with the speed of their implementation. It is crucial to accurately predict and evaluate the compressive strength of concrete mixtures, as it is one of the most important features of concrete [6,7].

Several recent studies focused on evaluating compressive strength using machine learning (ML) practices [8] which involve regular, big, and complete information. However, collecting this information is restricted due to the lack of data corresponding to the diverse input characteristics [9]. The concept of utilizing particle swarm optimization (PSO) begins by resetting particles within the search space randomly. Then, the particles construct upon their previous successful attempts and those of their neighbors to discover the optimal particle state. This is achieved by resetting the particle's location and updating its velocity [10]. Furthermore, the parameters of PSO can be easily modified, making it suitable for a wide range of practical problems [11]. In simpler terms, particle velocity in each cycle is determined by three factors: (1) the particle's current location, (2) the best location it has ever been, and (3) the best location within the entire group. This concept is explained in greater detail in reference [12]. PSO is a widely used procedure in the field of Swarm Intelligence that relies on optimization [13]. The goal of the optimization process is to find the best possible solutions to specific problems while taking into account any relevant constraints [14].

For this paper, the binary particle swarm optimization (BPSO) algorithm was selected due to its high level of adaptability and simplicity. Throughout the research, this algorithm has faced some challenges, stemming from local solutions and time constraints. In order to solve these issues, the BPSO algorithm was modified, and a new procedural binary particle swarm (NPBPSO) algorithm was obtained, which was able to overcome the obstacle of local solutions and is able to achieve a reduction in the required time to reach the optimal solution.

2. Literature Review

Concrete has several advantageous characteristics, including high wear resistance, low water permeability, and good compressive strength, and it is widely used in civil structures [15–18]. To maintain resident safety and structure durability, construction engineers are mainly concerned with the quality of building materials, notably the compressive strength of concrete. One typical method of evaluating the concrete's other physical and mechanical characteristics is measuring its compressive strength, which acts as a significant and trustworthy indicator of whether or not a concrete mixture conforms with engineering design criteria [16,17]. The process of precisely measuring the compressive strength of concrete mixtures is difficult, time-consuming, and associated with multiple problems [18–20]. Although statistical and experimental models incorporate a lot of data from laboratory tests, the results' accuracy is still poor [20].

Artificial intelligence models (AIMs) have been proposed as an alternative method to address the challenges of compressive strength prediction connected to the impact of various mixed design parameters [21–26]. By predicting the compressive strength of the concrete, a project's time and expense can be reduced. As a result, AIMs can be used to identify this important characteristic [27].

A mathematical model for estimating the compressive strength of concretes with additives was developed by Kandiri et al. [28] using an artificial neural network (ANN) technique. In the testing phase, the proposed model showed acceptable accuracy with a mean absolute percentage error of 11.10%. Ngo et al. [29] used artificial neural networks (ANNs), support vector regression (SVR), linear regression (LR), and M5P techniques for the prediction of axial strength in circular steel tube confined concrete columns. The authors outlined key distinctions between the techniques and concluded that the M5P was the best artificial intelligence (AI) model for predicting experimental results when compared to others. Goutham and Singh [30] used support vector regression (SVR) to predict the compressive strength of concrete. By comparing the analytical results with those of a non-destructive test, the authors concluded that SVR can be successfully used to predict the compressive strength of concrete.

Using four artificial intelligence models (AIMs), namely ICA-XGBoost, AIM ICA-ANN, ICA-SVR, and ICA-ANFIS, Duan et al. [31] evaluated the compressive strength of concrete made by recycled aggregates. The ICA-XGBoost model is the best one for determining the compressive strength of concrete, according to the findings. According to the authors, the proposed method can be used to verify that recycled concrete has the required mechanical characteristics in structural engineering [31].

Another study by H. N. Muliauwan et al. [32] determined the most exact Input/Output (I/O) connections between the components of concrete mixtures by employing many AIMs. The three AIMs employed in this investigation were support vector machines, linear regression, and artificial neural networks. The simulation's results using roughly 1030 compressive strength test values demonstrated that AIMs can facilitate the development of precise predictive models for concrete properties without the need for substantial expenditures on costly laboratory experiments.

Using six different types of AIMs, Cihan [27] employed AI to forecast the compressive strength of concrete. The adopted techniques were linear regression, classification and regression trees, K-nearest neighbor and extreme learning machine, adaptive neuro-fuzzy inference system (ANFIS), random forest, and SVR. The correlation factor, absolute mean error, root mean squared, and mean were used as standards to evaluate the efficiency of these approaches. Comparative results showed that the ANFIS outperforms the competition as a prediction model. The findings of the random forest model were nearly identical to those of the ANFIS, while the classification and regression tree had the lowest level of correctness. To estimate compressive strengths, Nafees. et al. [33] used three models namely genetic programming (GEP), ANFIS, and MLPNN that is a form of ANN. The results of the study showed that GEP models for data predictions are more precise than machine learning (ML) and that a new mathematical formula might be created and utilized to estimate additional database properties. The strength of lightweight concrete was predicted by Kumar et al. [25] using six machine learning algorithms: GPR, EL, SVMR, enhanced SVMR and GPR, and ensemble learning (EL). The results of this study showed that the optimized GPR model had the greatest accuracy. Furthermore, the improved GPR and SVMR models showed excellent behavior. K. Nasrollahzadeh and E. Nouhi, 2016 [34], applied the fuzzy inference model to improve a new precise procedure and to evaluate the square concrete columns' strength and strain subjected to a vertical load strengthened by fiber polymer wraps. An experimental compressive strength of 261 and a crucial experimental strain of 112 were gathered from the previous studies. The outputs of the finally proposed (Takagi–Sugeno) fuzzy inference models were well agreed with the experimental data of both strain and strength [34].

In order to estimate the density and compressive strength of local concrete mixtures based on the specific properties of their constituents, this work aims to develop the binary particle swarm algorithm (BPSA) with a new procedure. Because the experimental data currently available may be regarded as discrete space, and since the binary particle swarm approach is quick to reach the best answer with fewer iterations than other algorithms, it was chosen for this investigation.

Moreover, artificial swarm intelligence (ASI) may considerably improve prediction accuracy and collective insights.

3. New Procedural Binary Particle Swarm Optimization (NPBPSO)

3.1. Binary Particle Swarm Optimization

Binary particle swarm optimization was devised by Eberhart and Kennedy in 1995 [35,36]. This technique produces a swarm of particles through a random process, each of which stands for a potential solution to the problem. Thus, to find the best particle, the approach must search iteratively using two equations [37]. The first is the particle velocity equation (speed equation)

$$V_{ij}^{t+1} = WV_{ij}^{t} + c_1 r_{1j}\left(pbest_i^t - X_{ij}^t\right) + c_2 r_{2j}\left(gbest_i^t - X_{ij}^t\right) \quad (1)$$

where i denotes the particle number; j: the number of elements inside the particle; V_{ij}^{t}: the velocity of the particle i in the previous instant t; V_{ij}^{t+1}: the velocity of the particle i in the next instant t + 1; $pbest_i^t$: the most appropriate value reached by the i-particle until the iteration t; $gbest_i^t$: the most appropriate value within the swarm has been reached up to repetition t,

$$gbest_i^t = max\left(pbest_1^t\ pbest_2^t \ldots pbest_{55}^t\right)$$

r_{1j} and r_{2j}: random values to ensure diversity of investigation and fall within the range [0, 1]; X_{ij}^t: the position of the particle i in the previous instant t; W: a variable representing a percentage of the particle velocity at the previous moment; c_1 and c_2 acceleration variables that control the speed of reaching the best solution. In applications that use this algorithm, the variables c_1 and c_2 and W are calibrated experimentally [38,39].

W's value is constrained to the range [0.3–0.9], while the fields for the two variables $\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ are [0.4–2]. As a result, a series of experiments were carried out to arrive at the correct values. The probability of a change in the values of the constituent parts of the particle is determined by Equation (1). Equation (2) represents the particle's new state.

$$X_{ij}(t+1) = \begin{cases} 1 \text{ if} & u_{ij} < sig\ \left[v_{ij}\ (t+1)\right] \\ 0 \text{ if} & u_{ij} \geq sig\ \left[v_{ij}\ (t+1)\right] \end{cases} \quad (2)$$

u_{ij}: a random value within the interval [0, 1] generated according to an equal probability function at the beginning of each iteration.

$$sig\left(v_{ij}(t)\right) = \frac{1}{1 + e^{-v_{ij}(t)}} \quad (3)$$

Sigma function $sig(v)$ aims to narrow the numeric values into confined space [0, 1] in order to improve the performance of the algorithm [40]. Figure 1 shows a systematic diagram for working of the binary optimization particle swarm.

The algorithm used here operates differently than neural networks. It begins by creating a swarm of potential solutions, referred to as "particles." With the use of two mathematical equations, the speed equation and the new state equation, the algorithm continually enhances these solutions. Following each iteration, an evaluation function is used to assess the resulting solutions and identify the most optimal one. For the particle, after each iteration, all the resulting "particle" solutions are evaluated using a special function called the evaluation function, by which the best particle "optimal solution" is reached. The data in this algorithm are not divided into "training, checking, testing" groups as it is in the neural networks' algorithm. Rather, all the data are applied to the algorithm, and through the evaluation function, we can identify the best particle, the "best solution", and ensure that the algorithm is able to reach the optimal solution.

Even though the binary particle swarm optimization algorithm shows good accuracy regarding to other AI techniques such as ANN, it still suffers from the phenomenon of immature convergence (falling into a local solution) in which the search process may get stuck in a region that contains an optimal value, which results in a loss of diversity [41].

In addition, the new procedural binary particle swarm optimization algorithm NPBPSO provides the optimum solution with fewer iterations.

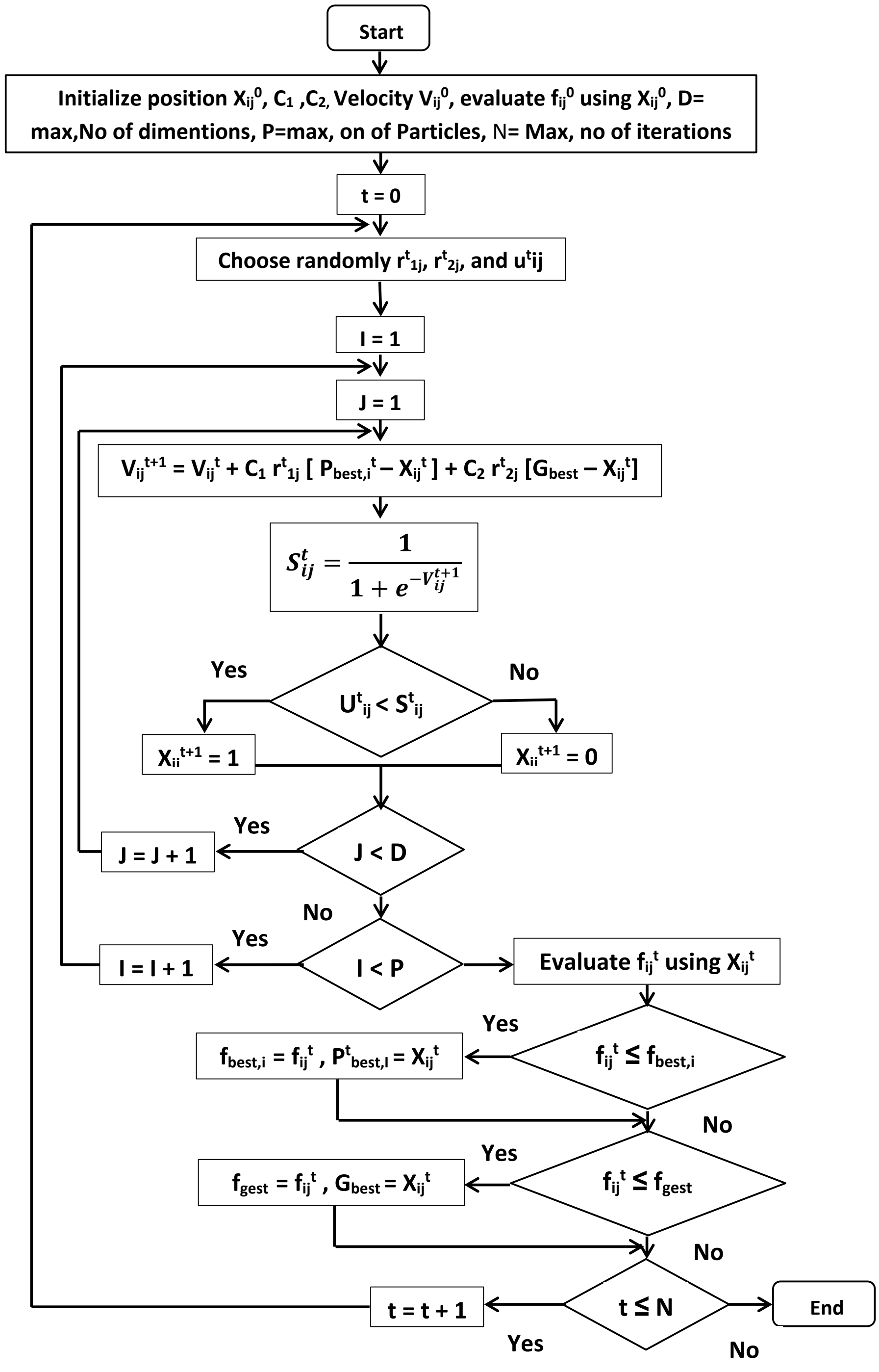

Figure 1. The flowchart of binary particle swarm optimization algorithm [42].

3.2. New Procedural Binary Particle Swarm Optimization (NPBPSO)

To address the issue of immature convergence in the binary particle swarm optimization (BPSO) algorithm, a new approach called NPBPSO has been proposed in this research. Immature convergence occurs when the search process becomes trapped in a local solution, leading to a loss of diversity and optimal value. Figure 2 depicts the modifications made to the procedural binary particle swarm optimization technique to prevent immature convergence. Figure 2 illustrates the modifications applied to the new procedural binary particle swarm optimization technique to avoid immature convergence.

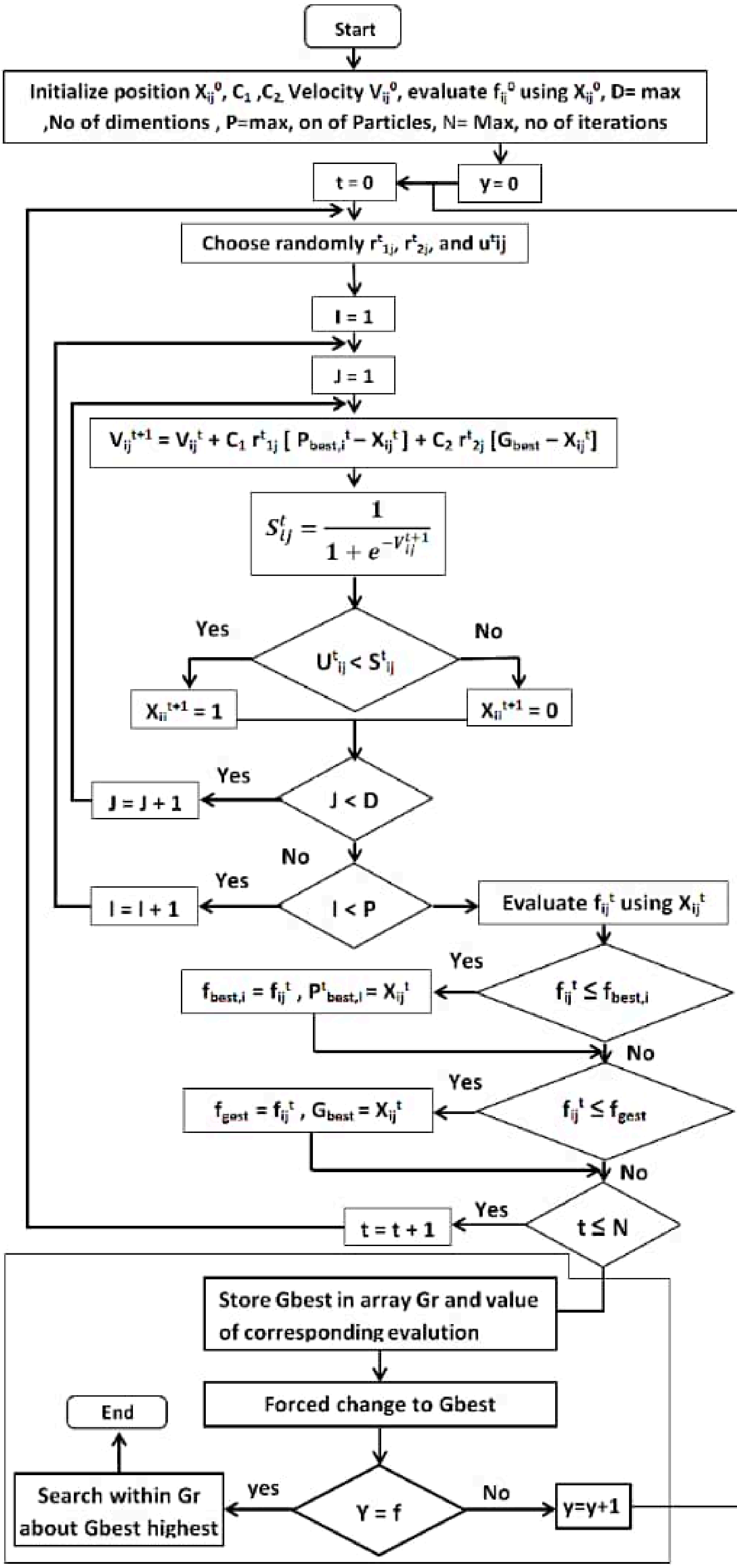

Figure 2. The flowchart of the new procedural binary particle swarm optimization algorithm.

3.3. Function of the Suggested Evaluation

The evaluation function was created using the target formula [43] since the constraints of the problem of the compressive strength of the mixture are independent of one another (slump, temperature, and cement grade). Whenever the value given by equation 4 is higher, the solution is considered to be better, and the particles on the next iteration will move towards that solution.

$$Fitness = \sum_{j=1}^{n} (Q + CL + T)j \quad (4)$$

where Q, CL, and T denotes the grade of cement, the slump, and the temperature, respectively.

3.4. Piloting Tests

A total of 60 iterations of the particle swarms' program were completed before the mean value of those results was calculated and represented. Table 1 expresses the conventions used during program piloting.

Table 1. Conditions adopted during the piloting of programs.

Processor	1.7–1.73 GHzCore
memory	12 G Byte
operating system	Windows 7

4. Methodology and Materials

The database used for the investigation in this study contains 163 concrete mixtures. Some of them were from the experimental works of the laboratories of the faculty of civil engineering at the University of Aleppo, and the others were from the prefabricated concrete factory of the industrial region of Aleppo City in Syria. These data include the grade of cement, slump, temperature, density, and compressive strength at 7 and 28 days where the density was between 2350 and 2550 kg/m3, cement grade values were N20, N25, N32, and N40, fresh slump was within the range of 40–125 mm, the exterior temperature was varying from 10 to 30 °C, the compressive strength at 7 days was between 10 and 40 MPa, and the compressive strength at 28 days was between 22 and 57 MPa. The statistical distribution of the measurements is shown in Figure 3.

In the next step, the binary particle swarm optimization algorithm was developed using cement grade, slump, and temperature as input to obtain the density and compressive strength as output by means of the evaluation function.

Then, some modification to the binary particle swarm optimization algorithm was made to improve the procedure of having results by avoiding local solutions of BPSO and having the optimum solution with fewer iterations. The modified algorithm is named the new procedural binary particle swarm optimization algorithm NPBPSO.

Later, the NPBPSO was run using the same inputs to get the density and compressive strength at 7 and 28 days.

Finally, the results of BPSO and NPBPSO were compared with ANN and investigated in order to know the best one to be used for estimating the density and compressive strength of local concrete mixtures.

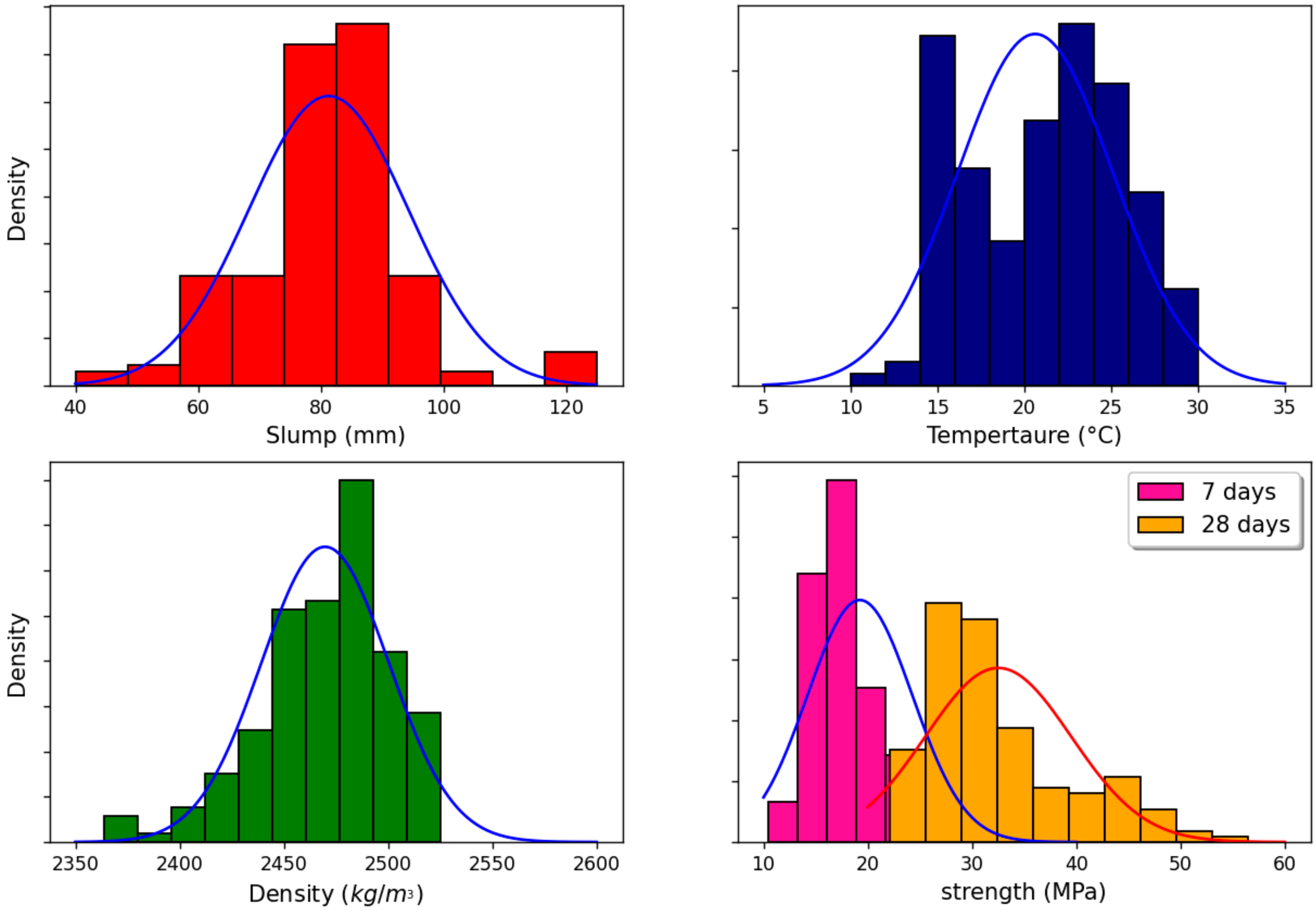

Figure 3. Statistical distribution of database values.

5. Results and Discussion

In the previous research [44], the neural network algorithm was used to estimate the compressive strength of cement concrete for each period of 28 days.

In that research, a neural network was designed consisting of three layers: the first layer was the "input layer", which contained twenty neurons; then, the second layer was the "hidden layer", which consisted of ten neurons; the third layer was the output layer, which consisted of five neurons. The algorithm used in training the neural network was the rapid deployment algorithm, and the number of training sessions for this network was 1000 training sessions, where in each training session, the weights of neurons within the network layers were adjusted in order to reach the optimal solution and reduce errors to the lowest possible extent.

The same data of experimental mixtures were entered into the network (163 mixtures from the experimental works of the laboratories of the faculty of civil engineering at the University of Aleppo and a prefabricated concrete factory of the industrial region of Aleppo City in Syria). The used input data of the neural network were temperature, slump, and cement grade, and the output was the density and the compressive strength at 7 and 28 days of concrete.

The data of experimental mixtures were divided into three groups: The first group, containing 111 mixtures of data, was used to train the network. The second group, containing 25 mixtures of data, was used to audit the training results. The third group, containing 25 mixtures of data, was used to test and to ensure that the neural network received sufficient training and was able to show satisfactory results.

As the correlation coefficient is quite low, $R^2 = 0.875$ (even though it is acceptable regarding other research [45–47]), the results presented in Figure 4 indicate that the selected

ANN technique does not fit the experimental data well in terms of compressive strength; there was a need to use different AI techniques, and as for the reason mentioned above, the authors selected the BPSO and then improved it to NPBPSO.

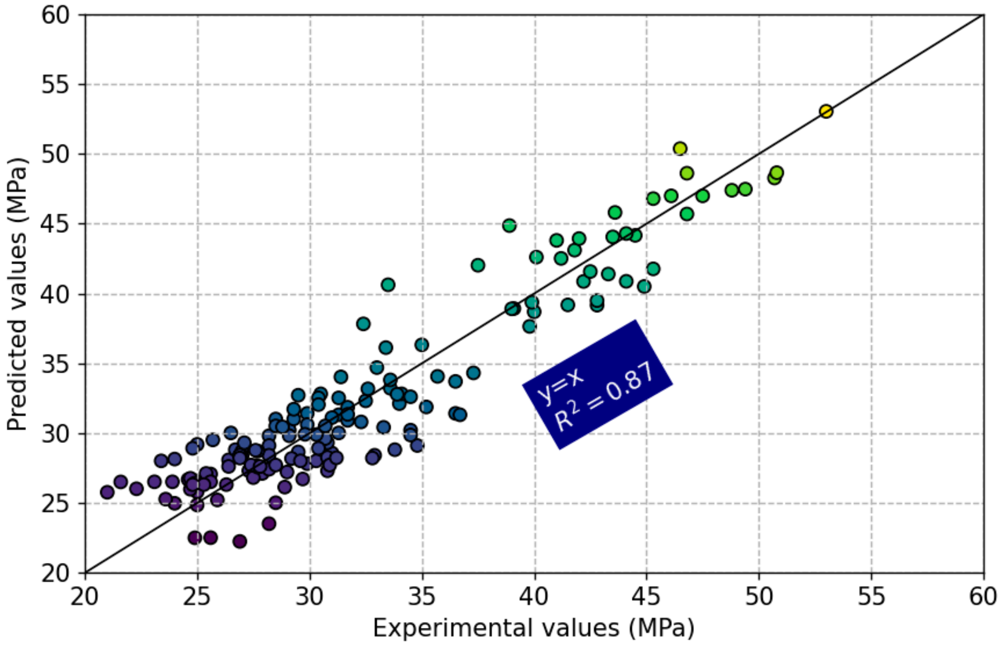

Figure 4. Comparison of the neural network results with the real values of the test data in the resistance condition after 28 days.

The results of the neural networks algorithm, related to estimating the resistance of concrete for 28 days, showed that there was a shift between the experimental values (in the laboratory) and the values generated by the neural networks with a capacity of (1.91 Mpa). We also notice that there is a large dispersion in the values generated by the neural network algorithm.

Figure 5 presents experimental compressive strength measurements and BPSO results obtained after 7 and 28 days, respectively. The predicted compressive strength values at the age of 7 and 28 days have been found to be extremely close to those experimentally achieved with a shift of (0.01112 MPa).

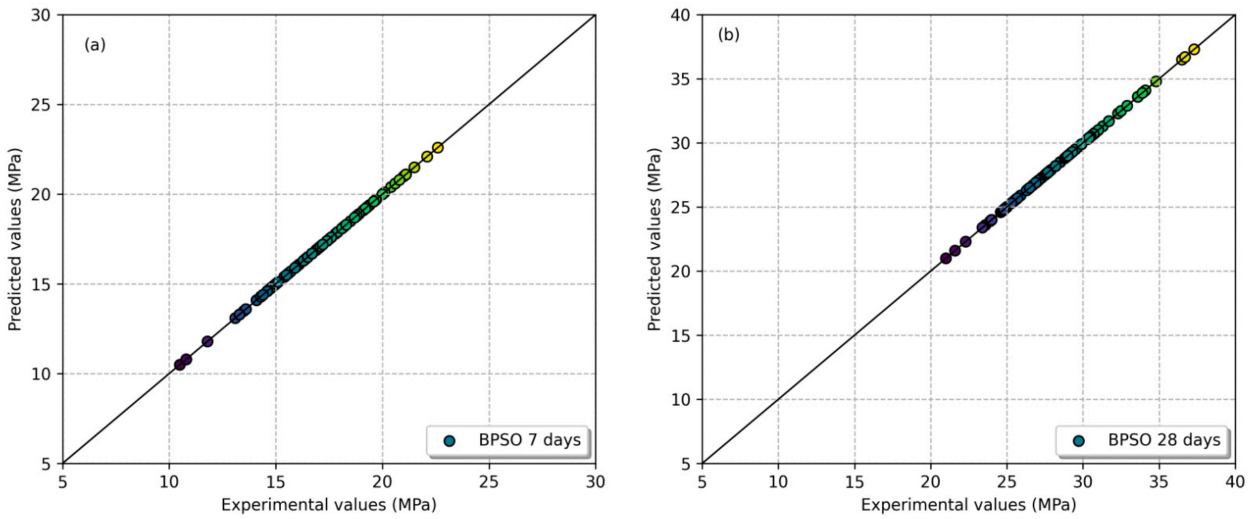

Figure 5. Experimental versus predicted compressive strength using BPSO (**a**) after 7 days, (**b**) after 28 days.

Figure 6 shows the differences between experimental compressive strength values and others resulting from applying the new procedural binary particle swarm optimization NPBPSO after 7 and 28 days, respectively, where it has been noticed that most of the values resulting from NPBPSO matched the experimental ones. As for the points that did not match, the shift ratio reached (0.00798 MPa); in other words, the accuracy of the values resulting from artificial intelligence has been improved by almost 30%.

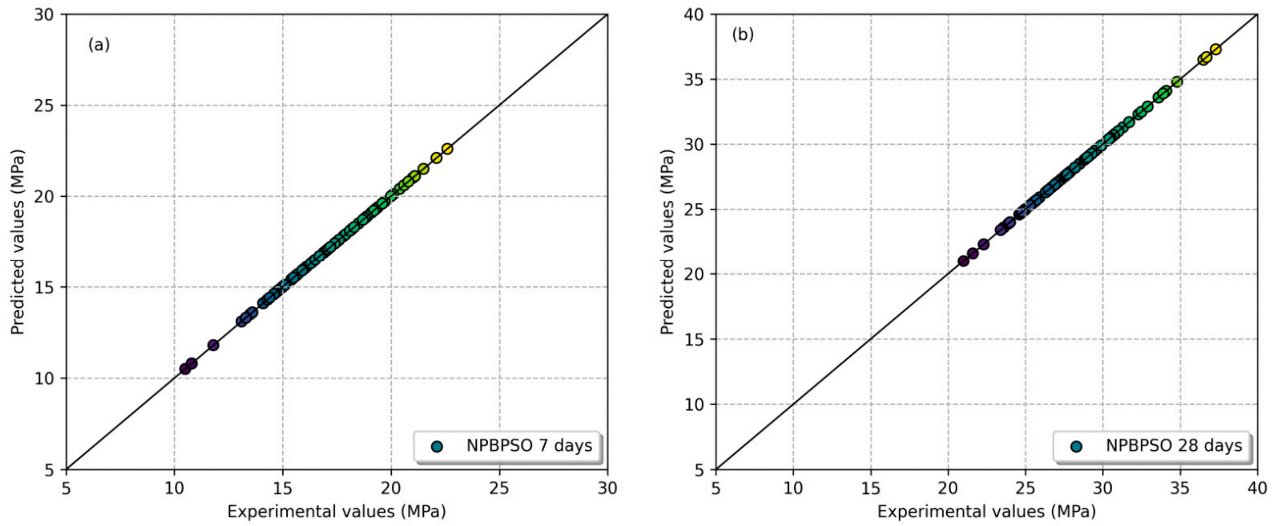

Figure 6. Experimental versus predicted compressive strength using NPBPSO (**a**) after 7 days, (**b**) after 28 days.

Finally, Table 2 shows an improvement in the results after using the improved version of the algorithm (NPBPSO), as shown in the last column of the table.

Figure 7 shows the differences between average density and others resulting from applying the new procedural binary particle swarm optimization NPBPSO after 28 days, where it has been noticed that most of the values resulting from NPBPSO matched the experimental ones. As for the points that did not match, the shift ratio reached (1 Kg/m^3),

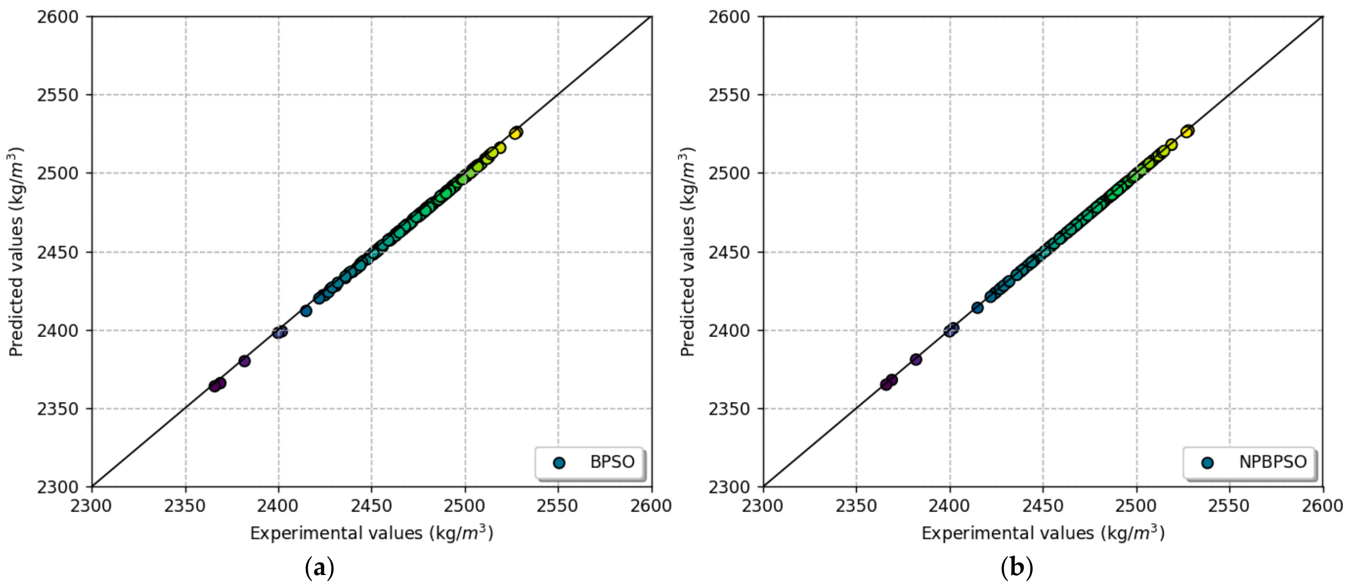

Figure 7. Experimental versus predicted values of the density at 28 days (**a**) using BPSO, (**b**) using NPBPSO.

Table 2. Statistics evaluation of compressive strength results.

		Standard Deviation	Variance	R^2	Experimental/ Predicted Average
7 days	BPSO	5.26	27.66	0.999451	1.0005
	NPBPSO	5.26	27.66	0.999423	1.0004
28 days	BPSO	7.24	52.52	0.999653	1.0003
	NPBPSO	7.24	52.52	0.999784	1.0002

Table 3 shows, through the fourth column, that the values resulting from the modified algorithm (NPBPSO) are close to the experimental values, and therefore, the proposed modification of the algorithm achieved the desired results, while the last column shows significant improvement in the time to reach the results

Table 3. Statistics evaluation of density results.

	Standard Deviation	Variance	R^2	Experimental/ Predicted Average	Execution Time
BPSO	28.77	828.12	0.992211	1.0010	60 iterations
NPBPSO	28.79	829.36	0.998454	1.0004	25 iterations

6. Conclusions

By comparing the results shown by the neural networks algorithm to obtain the compressive strength of concrete for 7 days and 28 days, respectively, (1.413 MPa—7 days and 1.91 MPa—28 days) and the results shown by the binary particle swarm algorithm BPSO (0.01112) MPa—7 and 28 days), the great superiority of the BPSO algorithm over the neural networks algorithm appears in two main important points: the first is the number of cycles or iterations that the algorithm needs to reach the results (i.e., the time to obtain the results), and the second point is the accuracy of the results that the algorithm shows.

The binary particle swarm algorithm was developed with a new procedure (NPBPSO) in order to estimate the strength of concrete and the compressive strength. Through this development, we were able to achieve two goals. One is to prevent the algorithm from falling into the problem of local solutions that the algorithm can fall into. The other is that the speed of the algorithm reaches the desired optimal solution.

After that, the new algorithm (NPBPSO) was converted into a computer program using a high-level programming language, where the data of the experimental compressive strength tests of the concrete mixtures that were conducted in the laboratories of the Faculty of Civil Engineering at the University of Aleppo and the ready-mixed concrete factory were entered.

BPSO and NPBDSO compressive strength and density outputs were obtained.

With an average shift (0.01112 MPa) in compressive strength, it was discovered that the solutions obtained using the binary particle swarm technique are close to the experimental values. However, the new procedural binary particle swarm algorithm (0.00798 MPa) shows a shift from the experimental values with approximately 30% improvement in accuracy.

The density results for BPSO and NBPSO show a shift rate of 2.311 kg/m^3 and 1.001 kg/m^3, respectively, with an accuracy improvement of about 50%. As a result of this research, it can be found that both BPSO and NBPSO techniques provide good results with better accuracy than NPBPSO because of the modification made to avoid local solutions and reduce the number of iterations.

The intensity results for both BPSO and NBPSO show a significant improvement in the speed of Al-Khwarizmi's access to optimal solutions, as the number of iterations needed to reach the optimal solution in the version (BPSO) decreased from (60 iterations) to (25 iterations) in the modified version of the algorithm (NPBPSO).

Finally, it can be found that BPSO and NBPSO AI techniques are good at predicting some properties of concrete such as compressive strength and density, which means that they can be highly recommended due to their speed, accuracy, and low cost.

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