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Research paper

Concrete and strength analysis of different materials based on hybrid PSO

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Abstract: Concrete, as one of the most widely used structural materials in the construction industry, its strength and durability are directly related to the safety of the project. The study proposes a hybrid intelligent algorithm technique for analyzing the strength of concrete in engineering and construction. The process uses ultrasonic rebound technology to collect the concrete strength data, and the acoustic beam velocity calculation method of the ultrasonic instrument is set. The adaptation value of the particle is calculated from the adaptation function and dynamic inertia weights are introduced to balance the performance of the algorithm. The experimental results indicated that in the training efficiency analysis, the research method dropped to its minimum value at the 77th training session, which was in the range of 10^{-2} to 10^{-3}. When analyzing the compressive strength prediction residuals, the research method had a maximum predicted strength positive residual of only 108 kPa and a maximum predicted strength negative residual of only –56 kPa when analyzing concrete with a water-cement ratio of 0.6. The research method had the smallest error in 6 out of the 8 groups of lightweight ceramic granular aggregates for concrete strength analysis. This indicates that the research method is more efficient and can analyze the concrete strength more accurately. The study can provide technical support to the construction industry in analyzing the material properties.

Keywords: particle swarm optimization, concrete, strength analysis, dynamic inertia weights, ultrasonic rebound

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1. Introduction

With global urbanization accelerating, the construction industry is growing rapidly, with concrete being one of the most widely used materials due to its strong load-bearing capacity and construction efficiency [1,2]. Driven by technologies like big data and artificial intelligence, industries, including construction, are shifting towards automation and intelligence [3]. Concrete strength analysis, a complex issue involving material science, mechanics, and chemistry, has traditionally relied on methods like empirical formulas and experiments. While effective to some degree, these methods suffer from inefficiency, high costs, and imprecision [4,5].Huang et al. designed a method for analyzing the strength of concrete specimens based on the superposition model. The experimental results revealed that the proposed method had good accuracy in strength analysis [6]. Ali et al. designed an ensemble multi-model concrete strength analysis model to analyze the strength of concrete with different nano-silica mix ratios. The experimental results indicated that the proposed method has good results for compressive strength analysis [7]. Wu and Zhou proposed a support vector regression-based method for concrete two-way slab design, using design parameters and characteristic importance to adjust parameter weights. Their experimental results showed improved prediction accuracy [8]. Bassi et al. proposed a method incorporating machine learning techniques for the performance impact of concrete admixtures. Experimental results indicated that the proposed method had lower performance prediction error [9]. Ahmed et al. proposed a method incorporating a soft computing model for the prediction of concrete compressive strength. The experimental results indicated that the proposed method had strong reliability in predicting the results [10].

Advancements in information technology have enhanced data analysis and parameter inversion, using computers' data processing power to efficiently and accurately extract relationships and complete calculations. Particle Swarm Optimization (PSO), an algorithm inspired by animal behavior, offers strong global search capabilities and computational accuracy, making it valuable for complex concrete strength analysis. Several scholars have explored PSO in this context, recognizing its importance in the design and construction of engineering buildings. Demir and Sahin proposed a PSO-based technique for earthquake damage analysis in buildings, using a gradient enhancement model to simulate seismic energy diffusion and rank feature importance. Their experimental results showed high prediction accuracy [11]. Ankita Sahana designed a resource scheduling technique based on PSO algorithm to improve the performance of the computational network. The work of the algorithm was investigated in the study and the performance was evaluated through standard datasets. [12]. Flori et al. proposed an optimized PSO algorithm for the problem of setup search. Experimental results indicated that the proposed method had good search efficiency [13]. Lin et al. developed a PSO-based path planning technique to optimize both path length and smoothness, integrating fuzzy control for intelligent obstacle avoidance. Their experimental results showed that this method improved path planning quality [14]. Huang et al. proposed a PSO-based method for building strength analysis, using machine learning to analyze the relationships between structural properties and material features. Their experimental results showed high accuracy in shear strength analysis [15].

PSO optimizes objective functions through iterative collaboration of individual and population solutions, offering few parameters and fast convergence. However, traditional PSO may get stuck in local optima due to limited population diversity. To address this, hybrid PSO enhances global search by incorporating genetic algorithm operations (selection, crossover, mutation) and a dynamic inertia weight strategy to balance exploration and development. This method is more efficient than genetic algorithms and simulated annealing, especially for high-dimensional nonlinear problems like concrete strength analysis. The study combines ultrasonic rebound technology, dynamic inertia weights, and genetic algorithm to optimize concrete material ratio and strength analysis, improving population diversity and avoiding premature convergence while balancing global and local optimization.

2. Methods

2.1. Concrete strength data collection method based on ultrasonic rebound technology

Concrete strength is crucial for quality control and safety in construction, directly affecting project quality and building safety [16, 17]. To analyze the strength of concrete with different materials, it's essential to collect material data. Ultrasonic rebound technology, a non-destructive and easy-to-operate testing method, efficiently extracts the required testing parameters [18, 19]. In this study, ultrasonic rebound technology is used to collect the strength data of concrete. Ultrasonic rebound technology works with the effect of rebound meter as shown in Fig. 1.

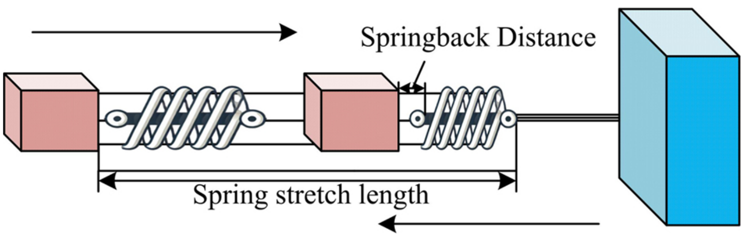


Fig. 1. Effect of rebound tester

In Fig. 1, the rebound hammer, powered by an internal spring mechanism, strikes a rod on the concrete surface, transferring energy to the concrete. This causes elastic deformation, with some energy absorbed by the concrete, leading to residual surface deformation. The energy from this deformation is transferred back to the hammer, causing it to rebound. The rebound tester records the rebound value, which correlates with the concrete's hardness and strength. The kinetic energy loss of the hammer is calculated as shown in Eq. (2.1).

$$\Delta E = \frac{1}{2}KL^2 - \frac{1}{2}KX^2 = E_k\left[1 - \left(\frac{X}{L}\right)^2\right] \tag{2.1}$$

In Eq. (2.1), ΔE represents the kinetic energy loss of the hammer. K represents the spring stiffness. L represents the spring extension length. X represents the rebound distance. E_k represents the kinetic energy of impact. The rebound value is calculated as shown in Eq. (2.2).

$$R = \frac{X}{L} \tag{2.2}$$

In Eq. (2.2), R stands for rebound value. The ultrasonic value of concrete acquired by the ultrasonic instrument is shown in Fig. 2.

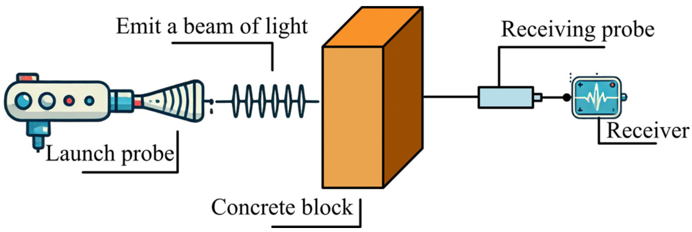


Fig. 2. Ultrasonic instrument collects ultrasonic values of concrete

In Fig. 2, during the acquisition of ultrasonic values of concrete using an ultrasonic instrument, the transmitting probe transmits an ultrasonic acoustic beam on one side of the concrete specimen. The ultrasonic beam velocity is calculated as shown in Eq. (2.3).

$$\begin{cases} V_P = \sqrt{\dfrac{\lambda + 2\mu}{\rho}} = \sqrt{\dfrac{E}{\rho} \cdot \dfrac{1-\sigma}{(1-2\sigma)(1+\sigma)}} \\ V_S = \sqrt{\dfrac{\mu}{\rho}} = \sqrt{\dfrac{E}{\rho} \cdot \dfrac{1}{2(1+\sigma)}} \end{cases} \tag{2.3}$$

In Eq. (2.3), V_P represents longitudinal wave velocity. V_S represents transverse wave velocity. ρ represents concrete density. σ represents material Poisson's ratio. λ represents Lamé elastic constant. μ represents shear modulus. E represents Young's modulus. To reduce the computational complexity in strength analysis, the study considers the propagation of the ultrasonic beam as passing through the cement and aggregate layers of concrete by the extreme method. The ultrasonic beam propagation velocity function is constructed as shown in Eq. (2.4).

$$\frac{1}{v_b} = \frac{V_a}{v_a} + \frac{V_m}{v_m} \tag{2.4}$$

In Eq. (2.4), v_b represents the ultrasonic beam propagation velocity in cement. V_a represents the relative volume occupied by the aggregate. v_a represents the ultrasonic beam propagation velocity in aggregate. V_m represents the relative volume occupied by cement. v_m represents the ultrasonic beam propagation velocity in concrete. The formula for calculating the average compressive strength of concrete is shown in Eq. (2.5).

$$f_{cm}(t) = \beta_{cc}(t) f_{cm} \tag{2.5}$$

In Eq. (2.5), $f_{cm}(t)$ represents the average compressive strength of concrete at the age of t-th day. $\beta_{cc}(t)$ represents the age coefficient of concrete. f_{cm} represents the average compressive strength of concrete at the age of four weeks. The age coefficient of concrete is calculated as shown in Eq. (2.6).

$$\beta_{cc}(t) = \exp\left\{s \cdot \left[1 - \left(\frac{28}{t/t_1}\right)^{1/2}\right]\right\} \tag{2.6}$$

In Eq. (2.6), e represents the Euler number. t represents one unit day. In analyzing the strength of concrete of different materials, the base parameters of concrete are obtained by ultrasonic rebound technology. Moreover, the average compressive strength of concrete is analyzed to provide data base for subsequent analysis.

2.2. Design of concrete strength prediction technique combining genetic algorithm and PSO

At the beginning of PSO, setting larger inertia weights helps the particles to explore the solution space. This allows the particles to take a greater pace during the search process and thus quickly localize to promising regions in the solution space. As the algorithm nears its end, decreasing the inertia weights helps to enhance the algorithm's localized search. Smaller inertia weights allow the particles to move more cautiously through the solution space, thus meticulously approximating the optimal solution. To balance the performance of the algorithm in performing concrete strength analysis, the study introduces dynamic inertia weights that vary with the number of iterations of the algorithm. The dynamic inertia weights are shown in Eq. (2.7).

$$w = w_e \cdot (w_s/w_e)^\wedge \left(\frac{1}{1 + 10 \cdot (i/mg)}\right)^2 \tag{2.7}$$

In Eq. (2.7), w represents dynamic inertia weights. w_e represents inertia weights as the algorithm approaches order. w_s represents initial inertia weights. i represents the number of iterations currently in place. mg represents the upper limit of the number of operations. The study introduces genetic algorithm to optimize PSO and improve the quality of concrete strength solution. The main operation flow of the genetic algorithm is shown in Fig. 3.

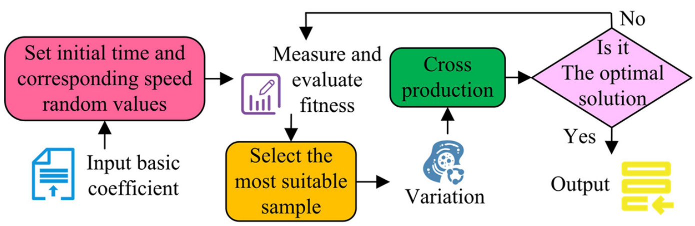


Fig. 3. Basic operation process of genetic algorithm

In Fig. 3, the genetic algorithm starts by setting base coefficients and creating an initial population. It then defines loop dimensions, initial time, and random speed values, followed by adaptation measurement and evaluation. Suitable samples are selected, and after crossover and mutation, the results are evaluated. If the optimal solution is found, the results are output; otherwise, the process repeats until the optimal solution is achieved. The solution process of the combined algorithm of genetic algorithm and PSO for concrete strength analysis is shown in Fig. 4.

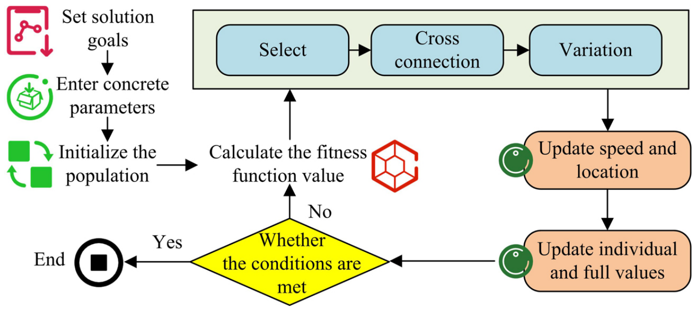


Fig. 4. The process of solving concrete strength analysis using algorithms

In Fig. 4, the algorithm begins by setting the solution objective and inputting concrete parameters. The population is initialized, and the fitness function is calculated. The algorithm updates values and checks if the individual and weight values meet the conditions or if the cycle limit is reached. If so, the solution results are output. The algorithm encodes material parameters into particle positions and iteratively approaches the optimal solution. This process addresses premature convergence issues in traditional PSO, balancing computational efficiency and accuracy. However, ultrasonic rebound data may contain anomalies due to material variations, affecting algorithm accuracy. To improve reliability, the Grubbs method is applied to filter out outliers, ensuring more accurate particle fitness calculations and enhancing the hybrid PSO technique. The Grubbs number of the maximum value anomaly is calculated as shown in Eq. (2.8).

$$G_n = \frac{X_n - \bar{X}}{S} \tag{2.8}$$

In Eq. (2.8), G_n represents the Grubbs number of the maximum value anomaly. X_n represents the maximum value in the acquired data. $\bar{X}$ represents the mean value of the acquired data. S represents the standard deviation of the data. The Grubbs number of the minimum value anomaly is calculated as shown in Eq. (2.9).

$$G'_n = \frac{\bar{X} - X_1}{S} \tag{2.9}$$

In Eq. (2.9), G'_n represents the Grubbs number of minimum value anomalies. X_1 represents the minimal value in the acquired data. The inertia coefficient expression is then reconstructed as shown in Eq. (2.10).

$$\omega^* = \omega_{\max} - \frac{4}{\pi} \arctan\left(\frac{k}{k_{\max}}\right) \cdot (\omega_{\max} - \omega_{\min}) \tag{2.10}$$

In Eq. (2.10), k represents the current evolutionary generation. $k_{\max}$ represents the preset maximum evolutionary algebra. The information updating equation of the particle individual after the introduction of the new inertia coefficient is changed as shown in Eq. (2.11).

$$V(i)_{k+1} = \omega^{*} V(i)_k + c_1 r_1 \left(P(i)_{\text{best}} - X(i)_k\right) + c_2 r_2 \left(G_{\text{best}} - X(i)_k\right) \tag{2.11}$$

When conducting the elimination of individuals with low fitness, the study designs a multiplicative standard deviation-based elimination mechanism for unfit individuals. The degree of dispersion is measured in terms of the mean squared deviation of the fitness values of the corresponding generation of the population, as shown in Eq. (2.12).

$$\sigma_k = \sqrt{\frac{1}{m_z} \sum_{i=1}^{m_z} \left[F\left(x(i)_k\right) - \mu\right]^2} \tag{2.12}$$

In Eq. (2.12), σ_k represents the mean squared error of the fitness value of the population in a given generation. $F\left(x(i)_k\right)$ represents the fitness value of the i-th individual in the population in a given generation. m_z represents the number of individuals in the population. The design variation rate control function is shown in Eq. (2.13).

$$\phi(k) = 1 - \frac{1}{1 + e^{-20\left(\frac{k}{k_{\max}} - 0.5\right)}} \tag{2.13}$$

In Eq. (2.13), $\phi(k)$ represents the variation rate control function. For concrete strength analysis using the hybrid PSO technique designed for the study, ultrasonic rebound technology is used to collect the data, and then the Grubbs method is applied to remove the anomalous data. The fitness value of each particle is calculated after setting the initial parameters, and the inertia weights are dynamically adjusted according to the number of iterations of the algorithm, and the selection, crossover and mutation operations are performed to optimize the particle population. It is judged whether the optimal positions of the particles and populations obtained by updating satisfy the termination conditions. If the termination condition is met, the optimal solution of the concrete strength analysis is output, and the strength prediction results are generated based on this solution.

3. Results

3.1. Performance testing based on hybrid PSO concrete strength analysis technique

To test the performance of the research-designed hybrid PSO when performing concrete strength analysis tests, the study collects historical data from a concrete strength test site as a data source, and extracts concrete of different ages and concrete of different material ratios for the tests, respectively. The population size is set to 30, the upper limit of training is 2000×. The research method is compared with PSO-back propagation network (PSO-BP) and PSO-support vector machines (PSO-SVM). The training efficiency of different methods is analyzed as shown in Fig. 5.

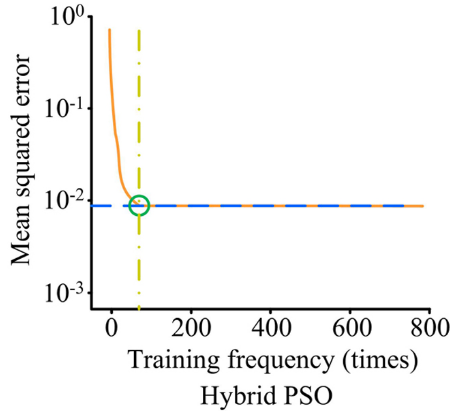


Fig. 5. Training efficiency analysis

In Fig. 5, the hybrid PSO maintains a better rate of decrease in mean square error during training, which decreases to a minimum value at the 77th training, between 10^{-2} and 10^{-3}. The rapid convergence of Hybrid PSO is due to the dynamic inertial weight strategy. In the early stage, high weight accelerates global exploration, and in the later stage, weight attenuation refines local search, making it approximate the optimal solution in low iterations. It shows that the research method has faster training speed and better training accuracy. The computational time consuming of different methods is analyzed as shown in Fig. 6.

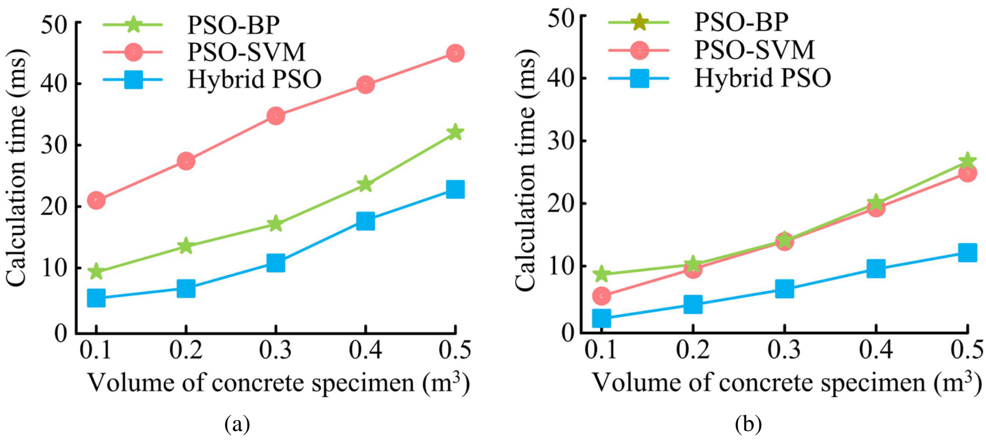
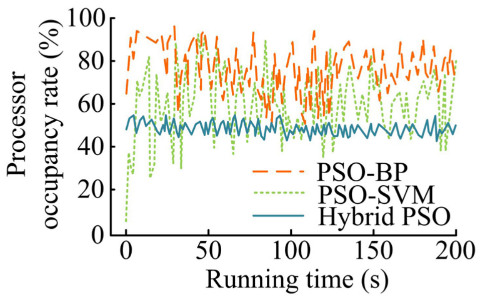


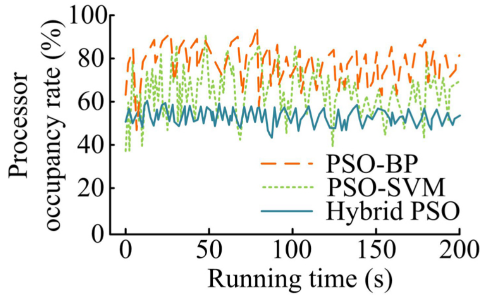
Fig. 6. Calculation time test: (a) Different ages, b) Different material rations

In Fig. 6a, when analyzing concrete of different ages, the computational elapsed time of PSO-BP increases to 32.4 ms when the volume of predicted concrete specimen increases to 0.5 m^3. The computational elapsed time of PSO-SVM is 21.0 ms when the volume of predicted concrete specimen is 0.1 m^3. The computational elapsed time of hybrid PSO is

5.7 ms when the volume of predicted concrete specimen is 0.1 m^3. The computational time consumed in predicting the concrete specimen volume increases to 22.9 ms. In Fig. 6b, when analyzing concrete with different material ratios, the computational time consumed by PSO-BP in predicting the concrete specimen volume of 0.1 m^3 is 9.2 ms. The computational time consumed in predicting the concrete specimen volume increases to 0.5 m^3 increases to 27.2 ms. The computation time of PSO-SVM increases to 24.8 ms when the volume of concrete specimen is increased to 0.5 m^3. The computation time of hybrid PSO is 2.1 ms when the volume of concrete specimen is predicted to be 0.1 m^3. The computation time of PSO-SVM increases to 11.9 ms when the volume of concrete specimen is predicted to be increased to 0.5 m^3. This indicates that the research method has better computational efficiency. The processor occupancy during the analysis is tested as shown in Fig. 7.



(a)



(b)

Fig. 7. Processor occupancy test: (a) Different ages, b) Different material rations

In Fig. 7a, the processor occupancy of PSO-BP fluctuates between 51% and 96% when analyzing concrete of different ages. The processor occupancy of PSO-SVM fluctuates between 7% and 92%. The processor occupancy for hybrid PSO fluctuated between 42% and 54%. In Fig. 7b, the processor occupancy of PSO-BP fluctuates between 47% and 93% when analyzing concrete with different material ratios. The processor occupancy of PSO-SVM fluctuated between 38% and 90%. The processor occupancy for hybrid PSO fluctuated between 44% and 60%. It shows that the research method can provide a more stable computing environment for the hardware and requires less computational performance from the hardware. To verify the reliability of the experimental results, normality tests were performed on the test data of training efficiency, calculation time and processor occupancy (Kolmogorov- Smirnov test, significance level $\alpha = 0.05$). The results show that the mean square error reduction process ($P = 0.213$) and calculation time ($P = 0.187$) of Hybrid PSO are in line with normal distribution, indicating that the data deviation is mainly caused by random factors rather than systematic errors. In addition, the stability of the method was evaluated by calculating the coefficient of variation (CV): the mean square error CV of the hybrid PSO was 8.7%, which was significantly lower than that of PSO-BP (CV = 23.5%) and PSO-SVM (CV = 18.9%), indicating that the training process of the hybrid PSO had higher repeatability.

3.2. Application of strength analysis techniques for concrete of different materials

To further determine the effectiveness of the research methodology in real- world scenarios, the study analyzes the application of the research methodology using several different materials of concrete. The residuals of compressive strength predictions from the different methods are analyzed as shown in Fig. 8.

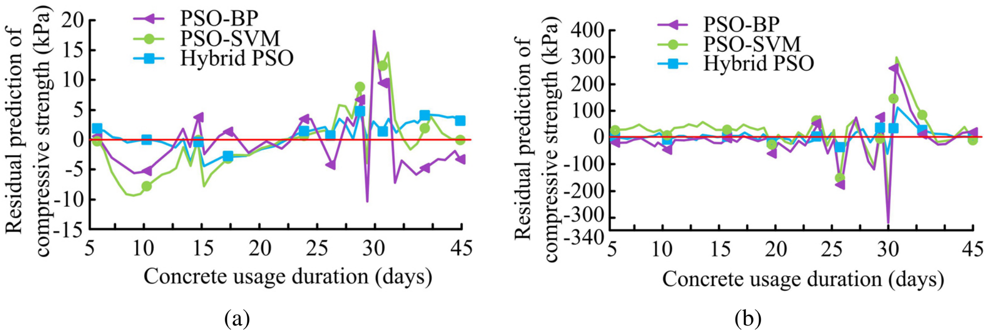


Fig. 8. Prediction residual analysis: (a) 0.3 water cement ration concrete, (b) 0.6 water cement ration concrete

In Fig. 8a, for the strength analysis of concrete with a water-cement ratio of 0.3, the maximum positive residual of the predicted strength of PSO-BP occurs when the number of days of use reaches 17.0 days, reaching 17.8 kPa. The maximum positive residual of the predicted strength of the hybrid PSO occurs when the number of days of use reaches 16.5 days, reaching 4.9 kPa. The maximum negative residual of the predicted strength occurs when the number of days of use reaches 11.1 days, reaching –4.6 kPa. 11.1 days, reaching –4.6 kPa. In Fig. 8b, in the strength analysis of concrete with a water-cement ratio of 0.6, the maximum positive residual of predicted strength for PSO-SVM occurs when the number of days of use reaches 17.5 days, reaching 296 kPa. The maximum negative residual of predicted strength occurs when the number of days of use reaches 17.0 days, reaching –236 kPa. The maximum positive residual of predicted strength for hybrid PSO occurs when the number of days of use reaches 16.5 days, reaching 296 kPa. positive residual of predicted strength occurs at 17.5 days of use and is only 108 kPa. The maximum negative residual of predicted strength occurs at 17.0 days of use and is only –56 kPa. The paired sample T-test ($\alpha = 0.05$) was used to verify the significant difference in the predicted residual. For concrete with a water-cement ratio of 0.6, the mean residual difference between Hybrid PSO and PSO-SVM is -188 kPa ($t = 5.32$, $P < 0.001$), and the confidence interval ([–244 kPa, –132 kPa]) does not contain zero value, indicating that the prediction accuracy of Hybrid PSO has statistical significance. At the same time, the Kurtosis (2.1) and Skewness (0.3) of the residual of the Hybrid PSO are close to normal distribution, indicating that the prediction error distribution is more concentrated and there is no systematic deviation. This indicates that the methodology has smaller fluctuations in the residual of predicted compressive strength. The compressive strength analysis of a class of concrete specimens with lightweight ceramic particles added as aggregates is shown in Table 1.

Table 1. Strength analysis of lightweight ceramic particle aggregate concrete

Group number	Compressive strength value (MPa)	Calculated strength value (MPa)		
		PSO-BP	PSO-SVM	Hybrid PSO
1	59.81	59.36	60.22	59.63
2	72.64	62.94	63.84	67.62
3	41.53	44.04	44.67	45.09
4	43.28	48.74	47.99	41.94
5	64.55	65.53	66.81	69.38
6	57.31	60.21	59.54	58.66
7	51.13	62.92	63.44	53.21
8	68.15	64.73	65.76	66.74

In Table 1, the analyzed values of the different methods in analyzing the compressive strength of concrete specimens with lightweight ceramic particles added as aggregates are in some error with the actual values. The study method is closest to the four-seasonal values in six of the eight groups. The error in the remaining 2 groups does not exceed 10%.The error of strength analysis of lightweight ceramite concrete was analyzed by one- way anOVA ($\alpha = 0.05$). The results showed that Hybrid PSO had no significant difference between groups ($F = 1.24$, $P = 0.296$), while PSO-BP ($F = 3.87$, $P = 0.012$) and PSO-SVM ($F = 2.95$, $P = 0.029$) had significant difference between groups. Combined with Bland-Altman consistency analysis, the error 95% consistency limit of Hybrid PSO is ([–2.8 MPa, +3.1 MPa]). The coverage was narrower than that of PSO-BP ([–5.4 MPa, +6.2 MPa]) and PSO-SVM ([–4.7 MPa, +5.5 MPa]), which verified that the predicted results were more consistent with the actual values. The combination of other experimental results indicate that the research method can effectively analyze the strength of concrete of different materials with better analytical accuracy.

4. Discussion

As one of the most commonly used structural materials in the construction industry, concrete's strength and durability directly affect the safety of the project. With the acceleration of global urbanization, the development of the construction industry is unprecedented, and higher requirements have been put forward for the accuracy and efficiency of concrete strength analysis. A PSO based concrete strength analysis technique has been proposed, which reflects the hardness of the concrete surface through rebound values and considers the propagation of ultrasonic beams as an extreme value method through the cement and aggregate layers in the concrete. Establish a concrete strength prediction model using PSO and introduce genetic algorithm to optimize PSO to improve the quality of concrete strength solutions. In addition, the

Grubbs method is introduced to eliminate the obtained abnormal data, and a mixed algorithm is used to solve the concrete strength value.

The research results indicate that the proposed hybrid PSO technique outperforms traditional PSO-BP and PSO-SVM methods in terms of training efficiency, computation time consumption, and processor utilization. Especially when dealing with concrete with different material ratios, this method shows faster training speed and better training accuracy. In addition, this method has a relatively small residual fluctuation in predicting concrete strength, indicating high reliability in practical applications. Compared with the methods of Bassi et al. [9] and Demir and Sahin [11], the advantage of this study lies in its innovative combination of ultrasonic rebound technology and dynamic inertia weight strategy, which improves the search ability and local search efficiency of the algorithm. Moreover, compared to the techniques of Huang et al. [15], the research method enhances the diversity of algorithms, which helps to avoid getting stuck in local optima.

5. Conclusions

A concrete strength analysis technique based on hybrid PSO is designed to investigate the properties of concrete with different materials. The process is reflected by the rebound value to reflect the hardness of the concrete surface, and the propagation of the ultrasonic beam is regarded as passing through the cement and aggregate layers of the concrete by the extremum method. The PSO is used to establish the concrete strength prediction model, and a genetic algorithm is introduced to optimize the PSO to improve the quality of the solution of concrete strength. The Grubbs method is introduced to reject the acquired anomalous data, and the concrete strength values are solved by the hybrid algorithm. The experimental results indicated that when performing the computational elapsed time test, the computational elapsed time of the research method increased to 11.9 ms when the volume of concrete specimens increased to 0.5 m^3 when analyzing concrete with different material ratios. When performing the processor occupancy test, the processor occupancy of the research method fluctuated between 42% and 54% when analyzing concrete of different ages. It indicated that the research method has more precise concrete analysis accuracy and less hardware and time requirements. The study does not account for measurement interference from concrete cavities after corrosion or the testing of damaged concrete. Future research will focus on concrete strength testing after corrosion, freeze- thaw cycles, and other environmental effects. It will also explore the relationship between ultrasonic rebound data and internal cracks, while developing a damage factor compensation model. Additionally, a multi- objective hybrid PSO framework will be created to optimize strength, durability, and economy, considering factors like construction cost and carbon emissions.

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