

Article

Prediction of Backfill Slurry Shrinkage Rate and Optimization of Roof-Contact Backfilling Based on an Optimized Neural Network Approach

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Abstract

In backfill mining of metal mines, the sedimentation and shrinkage of backfill slurry critically affect roof-contact quality and stope stability. This study investigates these characteristics for unsorted tailings backfill slurry from the Daye Iron Mine through laboratory experiments and develops a prediction model for the shrinkage rate. Tests examined the effects of cement-to-tailings ratio (1:4 to 1:20) and slurry concentration (65% to 71%) on shrinkage rate over curing time. A crested porcupine optimizer-backpropagation (CPO-BP) neural network model was developed to predict the shrinkage rate and compared with the traditional BP model. The robustness and generalization capability of the model were further verified by repeated five-fold cross-validation and by comparison with the GA-BP, PSO-BP, random forest, support vector regression, and XGBoost models. Results show that shrinkage predominantly occurs within the first 8 h and stabilizes after 24 h; high-concentration slurries stabilize earlier. At a fixed concentration, the shrinkage rate increases with decreasing cement-to-tailings ratio; at a fixed ratio, it decreases with increasing concentration. The CPO-BP model significantly outperforms the BP model, achieving a mean squared error (MSE) of 3.0767×10^{-6} , a mean absolute error (MAE) of 1.4528×10^{-3} , and a coefficient of determination (R^2) of 0.94946 on the test set. For the Daye Iron Mine, a slurry concentration of 69–71% reduces shrinkage height and improves roof-contact rate. This study reveals the evolution of shrinkage rate with curing time, cement-to-tailings ratio, and concentration, demonstrates the effectiveness of the CPO-BP model, and optimizes the backfilling scheme, providing a theoretical basis for roof-contact quality control in practice.



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Keywords: unsorted tailings backfill slurry; sedimentation–shrinkage characteristics; shrinkage rate; slurry concentration; prediction model

1. Introduction

In metal mines, the cut-and-fill mining method is widely adopted due to its high mining efficiency, high ore recovery rate, and low dilution and loss [1,2]. However, the quality of backfill roof-contact directly affects the stability of the goaf. When the roof-contact rate is low, the exposed area of the stope roof expands, posing a major safety hazard [3–7].

The dewatering and shrinkage rate of the backfill slurry is one of the key factors affecting roof-contact quality. In pipeline transport, the slurry concentration must be controlled at approximately 65% to enable gravity flow. However, at this concentration, the slurry contains a high proportion of free water, making it prone to sedimentation and shrinkage, which prevents the backfill body from fully contacting the stope roof [8–10].

Considerable research has been conducted on the sedimentation and shrinkage characteristics of backfill slurry [11–15]. Wang et al. [16] quantitatively characterized the sedimentation behavior of backfill materials, elucidated the intrinsic correlation mechanisms among slurry mass concentration, rheological properties, and sedimentation performance, and established a quantitative correlation model between pipeline rheological parameters and sedimentation behavior. Deng et al. [17], through systematic experimental testing, analyzed the bleeding and shrinkage characteristics of backfill slurry and found that the cement-to-tailings ratio and mass concentration exhibited significant negative correlations with both bleeding and shrinkage rates. Sun et al. [18], using tailings from a specific mine as the experimental material, focused on the dynamic process and evolution characteristics of bleeding and sedimentation in backfill slurry, examining the influence of slurry concentration and binder type on shrinkage behavior. Yang et al. [19], based on bleeding and shrinkage tests, reported that the mass concentration of backfill slurry is negatively correlated with its bleeding and shrinkage rates. Wu et al. [20], through laboratory experiments, analyzed the effects of binder and mass concentration on the shrinkage characteristics of backfill slurry and concluded that mass concentration exerts a greater influence than the binder. Shao et al. [21] designed a goaf backfilling simulation platform to investigate the flow and sedimentation patterns of gangue-based paste slurry. Hou et al. [22], using full tailings from an iron mine, conducted laboratory sedimentation–shrinkage tests on cemented full-tailings backfill slurry, regulating slurry concentration, binder type, and hydration conditions to explore their influence mechanisms on sedimentation and consolidation behavior. Lu et al. [23], based on the tailings characteristics of the Zhongguan Iron Mine, employed COMSOL 6.4 numerical simulation to study the sedimentation characteristics of backfill slurry in high-stage stopes and optimized the mine's backfilling technology based on the simulation results. Lu et al. [24] designed similarity simulation experiments on backfill slurry, revealing that the slurry in the stope could be divided into three zones with distinct properties according to its flow and sedimentation patterns.

Although laboratory experiments and numerical simulations have substantially elucidated the fundamental laws governing the sedimentation and shrinkage characteristics of backfill slurry, these studies are typically conducted under idealized curing conditions that may not fully represent the complex field environment. Wang et al. [25] reported that drainage conditions critically influence the evolution of backfill properties. Similarly, Cao et al. [26] demonstrated that curing humidity significantly affects the deformation and mechanical behavior of cemented paste backfill. Furthermore, Wang et al. [27] showed that flocculation and dewatering processes in thickeners determine the initial solids concentration and particle aggregation state, which subsequently govern the sedimentation behavior of the slurry. These findings indicate that multiple environmental and process-related factors can affect the sedimentation and shrinkage behavior of backfill slurry in ways that laboratory tests alone may not fully capture. Reliance on purely experimental approaches without a reliable predictive model makes it difficult to accurately estimate the final shrinkage rate under varying field conditions, thereby compromising the reliability of engineering design for roof-contact backfilling. Therefore, the development of an effective prediction model is essential to complement experimental investigations and to enhance the accuracy and robustness of engineering design in practical backfilling operations.

Among the existing prediction methods for backfill properties, empirical formulas and regression-based approaches remain the most commonly used. However, these methods often fail to capture the nonlinear relationships between material variables and shrinkage behavior. Artificial neural networks, particularly the BP neural network, have been applied to related problems due to their ability to learn complex nonlinear mappings through layered architectures [28]. Nevertheless, the BP algorithm relies on gradient descent for weight optimization, which makes its performance highly sensitive to the initial selection of weights and biases and prone to becoming trapped in local optima [29]. To overcome these limitations, various metaheuristic optimization algorithms have been developed to enhance neural network training by providing global search capabilities. Among these, the CPO is a recently proposed swarm intelligence algorithm that simulates the defensive behaviors of the crested porcupine, offering strong global exploration ability, fast convergence, and relatively few tunable parameters [30]. These characteristics make CPO particularly suitable for optimizing the initial weights and biases of BP networks. Therefore, this study attempts to apply the CPO algorithm to optimize a neural network for predicting the shrinkage rate of unsorted tailings backfill slurry, utilizing its global search capability to optimize the BP neural network and achieve accurate prediction of the shrinkage rate.

In summary, most existing studies have focused on individual factors affecting sedimentation and shrinkage through experiments or simulations. Systematic investigations under site-specific conditions remain limited, especially for accurate shrinkage rate prediction of unsorted tailings backfill slurry. To address this gap, the present study designs sedimentation–shrinkage experiments with varying cement-to-tailings ratios and slurry concentrations. Based on the experimental results, the shrinkage characteristics and influencing factors are analyzed, and a CPO-BP neural network-based prediction model for the shrinkage rate is proposed to achieve accurate prediction. The model is then applied to optimize the roof-contact backfilling scheme for large-volume stopes at the Daye Iron Mine, providing a scientific basis for improving roof-contact quality and optimizing backfilling process parameters.

2. Basic Physicochemical Properties of Unsorted Tailings Backfill Slurry

To ensure consistency between the tested samples and those collected from the field, the tailings slurry was sampled from the concentrator and transferred into plastic containers. After 24 h of static settlement, the clear supernatant water was decanted, and the remaining tailings were air-dried and transported to the laboratory. The sampling procedure is illustrated in Figure 1.



Figure 1. Tailings Sampling Procedure at the Mineral Processing Plant of Daye Iron Mine.

The tailings generated from the concentrator without any classification or desliming treatment are referred to as unsorted tailings. The physicochemical properties of unsorted tailings are fundamental factors influencing the sedimentation and shrinkage characteristics of backfill slurry. Particle size analysis of the unsorted tailings from the Daye Iron Mine was conducted using a Mastersizer 3000 laser diffraction particle size analyzer (Malvern Panalytical, Malvern, UK). The results show that the median particle size (d_{50}) of the tailings

is 12.1 μm , and the sorting coefficient (S_0) is 4.261, indicating that the tailings are classified as ultra-fine and poorly graded.

X-ray fluorescence (XRF) analysis reveals that the major mineral components of the tailings are CaO , Al_2O_3 , SiO_2 , and MgO , as presented in Table 1. Among these, CaO , Al_2O_3 , and MgO are reactive oxides that can promote cementitious reactions and thereby enhance the strength of the backfill body. SiO_2 , which accounts for the highest proportion, is an inert oxide that exhibits favorable sedimentation performance.

Table 1. Major chemical components of tailings from the Daye Iron Mine.

Mineral composition	CaO	SiO ₂	Fe ₂ O ₃	MgO	Al ₂ O ₃	K ₂ O	SO ₃	other
Proportion	31.3	31.2	12.4	9.7	0.45	2.1	1.8	2.5

The density of the unsorted tailings from the Daye Iron Mine was measured as $2.855 \text{ t}\cdot\text{m}^{-3}$ through laboratory tests. Based on this tailings density, the densities of the backfill slurry at different concentrations were calculated, and the results are presented in Table 2.

Table 2. Density of filling slurry with different mass concentrations.

Slurry Concentration (%)	Slurry Density (t/m^3)	Tailings Density (t/m^3)	Density of Solid Dry Materials (t/m^3)
65	1.746	2.855	2.915
67	1.787		
69	1.830		
71	1.876		

The cementitious binder used in the backfill slurry at the Daye Iron Mine is a specialized material for mine backfilling, supplied by a domestic professional manufacturer and conforming to the relevant standards for mine backfill materials. Its main oxide components are similar to those of ordinary Portland cement, primarily including CaO , SiO_2 , Al_2O_3 , Fe_2O_3 , SO_3 , and MgO , with a density of $2.931 \text{ g}\cdot\text{cm}^{-3}$.

3. Sedimentation–Shrinkage Experiment on Unsorted Tailings Backfill Slurry

3.1. Experimental Scheme

The preparation process of the backfill slurry is illustrated in Figure 2.

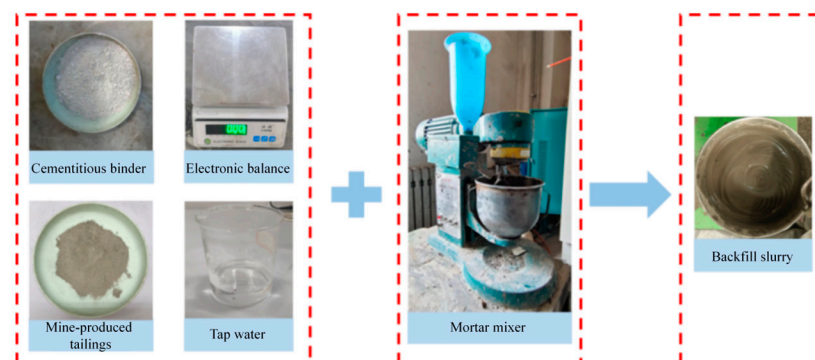


Figure 2. Backfill Slurry Preparation Process.

In this study, the slurry concentration is defined as the mass fraction of total solid particles (including tailings and cementitious material) to the total mass of the slurry mixture, expressed as a percentage. Sedimentation–shrinkage tests were designed for backfill

slurries with cement-to-tailings ratios of 1:4, 1:8, 1:12, and 1:20, and slurry concentrations of 65%, 67%, 69%, and 71%. The sedimentation performance of the backfill slurry was measured using transparent PC cylindrical containers with a diameter of 80 mm and a height of 200 mm. The shrinkage rate data were recorded at 4 h, 8 h, 12 h, 24 h, and 36 h after placement. The mixed proportions of the tested slurries are presented in Table 3.

Table 3. Mix proportions of slurries for sedimentation–shrinkage tests.

Slurry Concentration (%)	Cement-to-Tailings Ratio	Tailings (g)	Cementitious Material (g)	Water (g)
65	1:4	936.00	234.00	630
	1:8	1040.00	130.00	630
	1:12	1080.00	90.00	630
	1:20	1114.29	55.71	630
67	1:4	964.80	241.20	594
	1:8	1072.00	134.00	594
	1:12	1113.23	92.77	594
	1:20	1148.57	57.43	594
69	1:4	993.60	248.40	558
	1:8	1104.00	138.00	558
	1:12	1146.46	95.54	558
	1:20	1182.86	59.14	558
71	1:4	1136.00	284.00	580
	1:8	1262.22	157.78	580
	1:12	1310.77	109.23	580
	1:20	1352.38	67.62	580

3.2. Analysis of the Shrinkage Rate of Unsorted Tailings Backfill Slurry

The shrinkage rate (ϕ) is defined as the ratio of the volume reduction in the backfill body to its initial volume, and is calculated as follows:

$$\phi = \frac{V_1}{V_2} \times 100\% \quad (1)$$

where

V_1 —Volume of backfill body the shrinkage, m^3 ;

V_2 —Initial volume of backfill body, m^3 .

The shrinkage rate of the backfill slurry at concentrations of 65%, 67%, 69%, and 71% was measured and calculated at five specific time points: 4 h, 8 h, 12 h, 24 h, and 36 h after specimen preparation. At each time point, the slurry volume was measured at four different orientations around the transparent cylindrical container, and the average value was taken as the shrinkage rate for each concentration to improve measurement reliability. Each shrinkage-rate value reported in Table 4 is therefore the arithmetic mean of the four circumferential readings taken at the same recording time. The observed results of the sedimentation–shrinkage tests at 4 h and 36 h are presented in Figure 3.

Table 4. The 36-Hour Shrinkage Rate of Total Tailings Backfill Slurry.

Slurry Concentration (%)	Cement-to-Tailings Ratio	4 h	8 h	12 h	24 h	36 h
65	1:4	4.500%	6.250%	6.625%	6.750%	6.750%
	1:8	4.625%	6.375%	6.750%	7.000%	7.000%
	1:12	4.875%	6.500%	6.875%	7.250%	7.250%
	1:20	5.250%	7.875%	8.750%	8.875%	8.875%

Table 4. Cont.

Slurry Concentration (%)	Cement-to-Tailings Ratio	4 h	8 h	12 h	24 h	36 h
67	1:4	3.375%	5.375%	6.125%	6.250%	6.250%
	1:8	3.500%	5.500%	6.250%	6.375%	6.375%
	1:12	3.500%	5.500%	6.350%	6.650%	6.650%
	1:20	4.125%	6.375%	7.250%	7.750%	7.750%
69	1:4	2.500%	3.625%	4.375%	4.375%	4.375%
	1:8	2.500%	3.875%	4.250%	4.500%	4.500%
	1:12	2.625%	4.125%	4.750%	5.125%	5.125%
	1:20	2.875%	4.250%	5.000%	5.250%	5.250%
71	1:4	2.250%	3.500%	3.875%	3.875%	3.875%
	1:8	2.250%	3.375%	3.875%	4.000%	4.000%
	1:12	2.250%	3.625%	4.125%	4.250%	4.250%
	1:20	2.250%	3.625%	4.125%	4.375%	4.375%

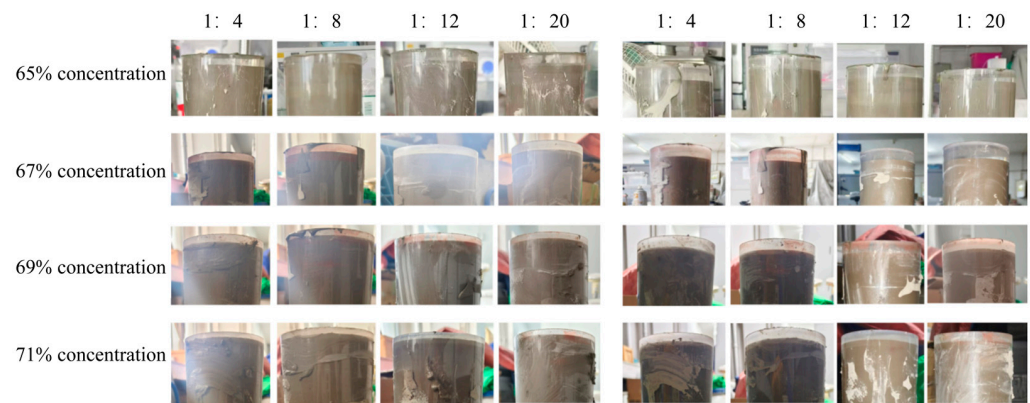


Figure 3. Observation results of the shrinkage experiments on backfill slurry with different Cement-to-tailings ratios and concentrations.

Through the 36 h sedimentation–shrinkage tests of the unsorted tailings backfill slurry, the data were observed and recorded, and the results are presented in Table 4.

3.3. Analysis of Sedimentation–Shrinkage Characteristics and Influencing Factors

The variation curves of the shrinkage rate versus time for the unsorted tailings backfill slurry with different cement-to-tailings ratios and slurry concentrations are shown in Figure 4. As illustrated in Figure 4, within the first 8 h, the sedimentation of particles in the backfill slurry is primarily governed by gravity. Owing to the high degree of particle dispersion and relatively low sedimentation resistance, the settling velocity of the slurry is relatively rapid. In this stage, coarse particles settle faster than fine particles, and the sedimentation resistance gradually increases with the enhancement of cementation. After 8 h, the slope of the curves decreases significantly, indicating a reduction in the shrinkage rate. After 12 h, the shrinkage rates of the slurries with a cement-to-tailings ratio of 1:4 and concentrations of 69% and 71% tend to stabilize, suggesting that the backfill body has completed the cementation and solidification process. In contrast, the shrinkage rates of the slurries with concentrations of 65% and 67% continue to increase slowly after 12 h, indicating incomplete cementation and solidification. After 24 h, the shrinkage rates of all slurries essentially stabilize, indicating that sedimentation has ceased. Furthermore, the shrinkage rates of slurries at different concentrations all reach stability after 24 h, and within the 0–36 h period, the rate of change in shrinkage rate gradually decreases over time. The differences in shrinkage rate between the slurries with concentrations of 65% and 67%

are relatively small, and similar observations apply to the slurries with concentrations of 69% and 71%.

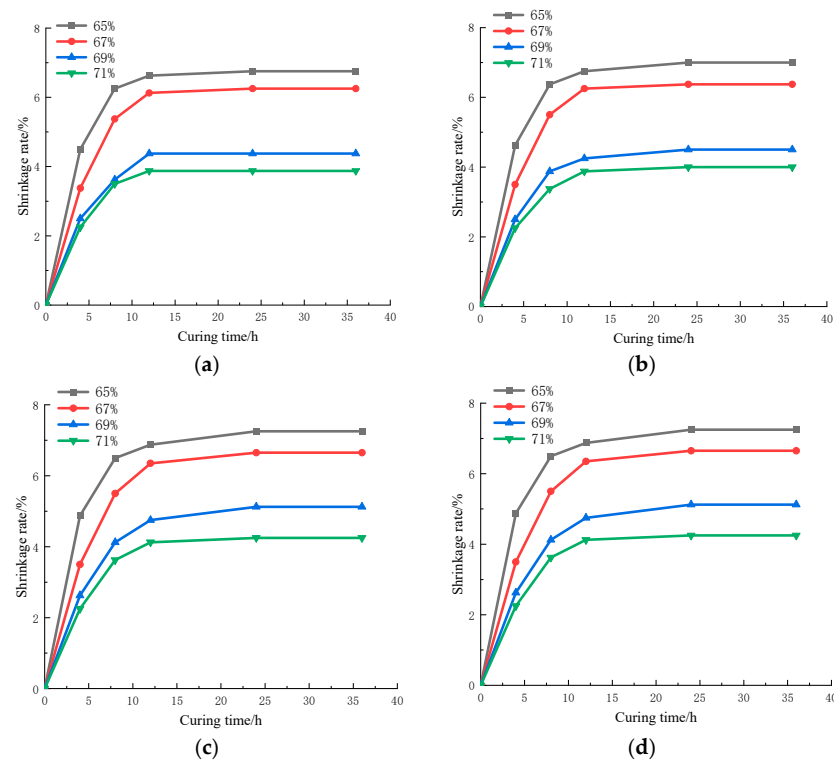


Figure 4. Time-Dependent Shrinkage Rate Curve of Total Backfill Slurry. (a) Cement-to-tailings ratio 1:4; (b) Cement-to-tailings ratio 1:8; (c) Cement-to-tailings ratio 1:12; (d) Cement-to-tailings ratio 1:20.

The variation curves of shrinkage rate with cement-to-tailings ratio for the unsorted tailings backfill slurry are shown in Figure 5. As illustrated in Figure 5, the shrinkage rate of the backfill slurry increases with decreasing cement-to-tailings ratio. For low-concentration slurries, the shrinkage rate increases rapidly when the cement-to-tailings ratio decreases from 1:12 to 1:20, whereas for high-concentration slurries, the increase rate is relatively slow. With variations in the cement-to-tailings ratio, the shrinkage rate of high-concentration slurries exhibits only minor changes, while that of low-concentration slurries shows significant variations, indicating that the cement-to-tailings ratio exerts a greater influence on the shrinkage rate of low-concentration slurries.

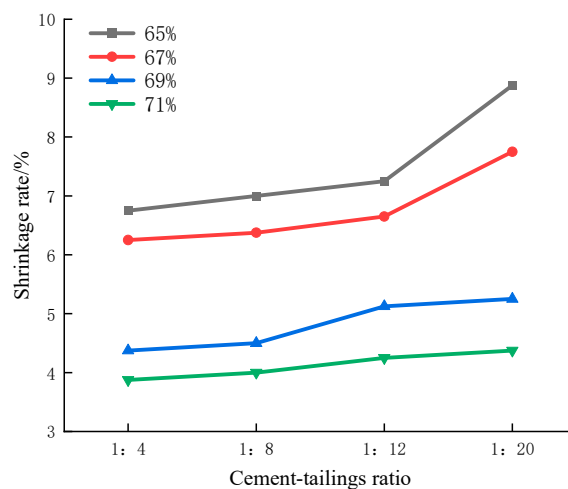


Figure 5. Cement-to-tailings ratio-Dependent Shrinkage Rate Curve.

The variation curves of shrinkage rate with slurry concentration for the unsorted tailings backfill slurry are shown in Figure 6. As illustrated in Figure 6, at a given cement-to-tailings ratio, the shrinkage rate decreases with increasing slurry concentration. When the slurry concentration increases from 65% to 67%, the reduction in shrinkage rate is relatively small. When the concentration increases from 67% to 69%, a more pronounced reduction is observed. However, when the concentration further increases from 69% to 71%, the reduction in shrinkage rate becomes relatively limited. Overall, the slurry concentration exerts a significant influence on the shrinkage rate of the backfill slurry.

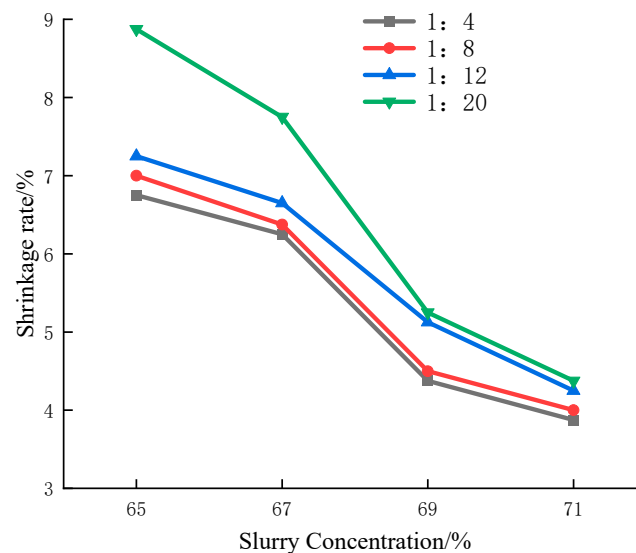


Figure 6. Slurry Concentration-Dependent Shrinkage Rate Curve.

3.4. Binary Linear Regression Analysis of the Shrinkage Rate of Backfill Slurry

Based on the above analysis, the sedimentation and shrinkage behavior of the backfill slurry essentially ceases after a curing time exceeding 24 h. Since the final shrinkage rate is the primary concern in mine backfill operations, this study focuses on the effects of the cement-to-tailings ratio and slurry concentration on the shrinkage rate. The variations in shrinkage rate with cement-to-tailings ratio and slurry concentration are presented in Figure 7.

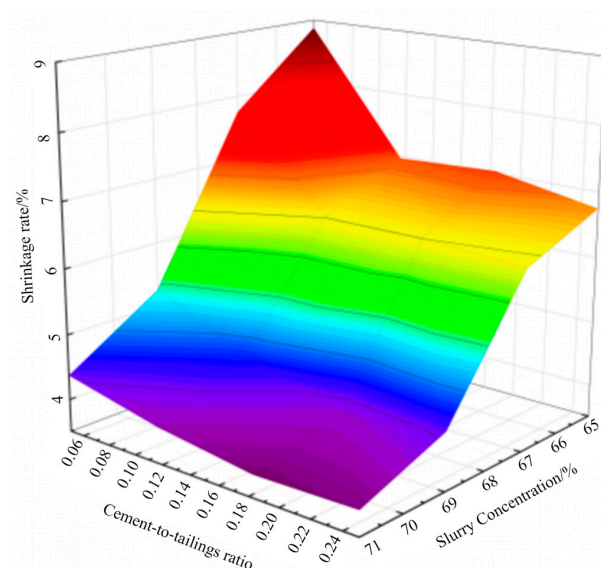


Figure 7. Cement-to-tailings ratio and Slurry Concentration Co-Dependent Shrinkage Rate Diagram.

A binary linear regression analysis was performed on the laboratory sedimentation–shrinkage test dataset using SPSS software 26.0, with the cement-to-tailings ratio and slurry concentration as independent variables and the shrinkage rate as the dependent variable. The results are presented in Table 5. The regression model yielded a coefficient of determination (R^2) of 0.8000, indicating that the cement-to-tailings ratio and slurry concentration together explain 80% of the variance in the shrinkage rate. The Durbin-Watson (DW) statistic was 1.753, the F-value was 30.956, and the p -value was less than 0.05, confirming that the regression model satisfies the independence assumption and is statistically valid.

Table 5. Binary linear regression analysis results.

Regression Model	R^2	Adjusted R^2	Durbin-Watson (DW)	F-Value	Significance
1	0.826	0.800	1.753	30.956	0.000 ^b

^b: The superscript indicates that the F-test is statistically significant ($p < 0.05$), confirming the validity of the regression model.

The variance inflation factor (VIF) is an important diagnostic parameter in multi-variate regression analysis, which is used to assess the degree of multicollinearity among the independent variables in a regression model. Based on the 80 datasets from the sedimentation–shrinkage tests, the coefficients of the binary linear regression model obtained through SPSS software are presented in Table 6. In Table 6, the “B” column presents the unstandardized regression coefficients, which represent the change in the dependent variable (shrinkage rate) for a one-unit change in each independent variable in the original measurement units. The “Standardized error” column represents the standard error of each coefficient, indicating the precision of the estimate; smaller standard errors relative to the coefficient magnitude indicate more reliable estimates. The “Beta” column presents the standardized coefficients, which allow direct comparison of the relative importance of each independent variable by removing the effects of different measurement scales. The “t” values are calculated as B divided by Standardized error, and the “Significance” values indicate the probability that each coefficient is actually zero. Smaller p -values (<0.05) indicate statistically significant effects. The “Tolerance” and “VIF” are collinearity diagnostics, with VIF values close to 1 indicating no multicollinearity issues. The VIF value is 1.000 for both independent variables, indicating that there is no multicollinearity issue between the slurry concentration and the cement-to-tailings ratio, and that the variances of the regression coefficients are not inflated, confirming the stability of the model. Furthermore, the independent variable of slurry concentration exerts a significant influence on the dependent variable of shrinkage rate.

Table 6. Regression Model Coefficients.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Significance	Collinearity Statistics	
	B	Standardized Error	Beta			Tolerance	VIF
Constant	46.573	5.187		8.978	0.000		
1 Concentration	−0.598	0.076	−0.907	−7.854	0.000	1.000	1.000
Cement-to-tailings ratio	−0.261	0.556	−0.054	−0.470	0.646	1.000	1.000

The normal P-P plot of the standardized residuals is shown in Figure 8. The data points are highly concentrated along the diagonal line, with no significant deviation or dispersion.

The slope of the diagonal line is close to 1 and the intercept is close to 0, indicating that the residual distribution conforms well to the standard normal distribution.

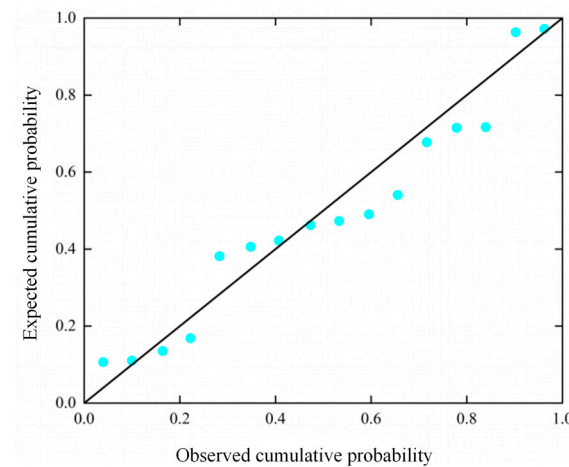


Figure 8. Normal P-P Plot.

To further quantify the reliability of the regression model, the 95% confidence intervals (CIs) of the regression coefficients were calculated from the estimates and standard errors in Table 6 with 13 degrees of freedom ($t_{0.975,13} = 2.160$). The 95% CI of the concentration coefficient is $[-0.762, -0.434]$, which excludes zero and confirms that the influence of slurry concentration on the shrinkage rate is statistically robust; the 95% CI of the cement-to-tailings-ratio coefficient is $[-1.462, 0.940]$, which contains zero and is consistent with its non-significant t -test result; and the 95% CI of the constant term is $[35.367, 57.779]$. In addition to the normal P-P plot, quantitative diagnostics of the model residuals were performed. The Shapiro–Wilk test yielded $W = 0.893$ ($p = 0.062 > 0.05$), so the normality assumption of the residuals is not rejected, and the Breusch–Pagan test yielded $LM = 3.573$ ($p = 0.168 > 0.05$), indicating no significant heteroscedasticity. An uncertainty analysis of the fitted model shows that the residual standard error is approximately 0.68 percentage points; accordingly, within the tested factor domain, the average half-width of the 95% confidence interval for the fitted mean response is about 0.62 percentage points, and that of the 95% prediction interval for a single new observation is about 1.60 percentage points (at most 1.70 percentage points).

4. Shrinkage Rate Prediction Model Based on the CPO-BP Neural Network

4.1. Principle of the CPO-BP Algorithm

The backpropagation (BP) neural network is a multilayer feedforward network with an input layer, hidden layer, and output layer, which adaptively adjusts the weights and biases of hidden layers through the error backpropagation mechanism [31,32]. The raw data are transmitted forward through the input layer and transformed via distributed representations in the hidden layer to generate the final output response. When the network output deviates from the target values, the error signals are propagated backward layer by layer, and the weight matrices are updated using gradient descent optimization, thereby progressively establishing an adaptive mapping between the input and output variables [33]. The schematic flowchart of the algorithm is presented in Figure 9.

The Crested Porcupine Optimizer (CPO) is a high-performance swarm intelligence-based optimization algorithm that possesses strong global search capability and fast convergence speed. It simulates various defensive behaviors of the crested porcupine in nature, including visual defense, sound defense, odor defense, and physical attack [34].

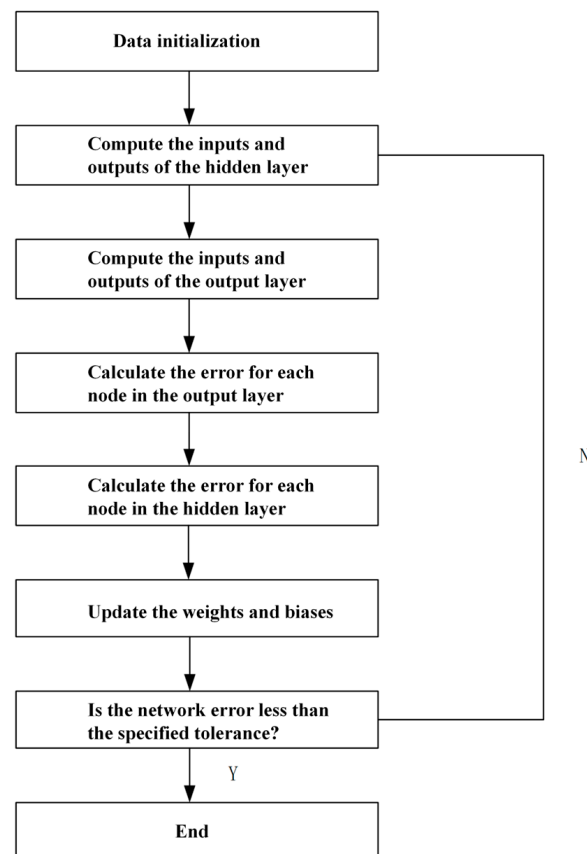


Figure 9. Backpropagation Neural Network Training Algorithm Flowchart.

In the CPO algorithm, population individuals are regarded as crested porcupines, and the objective function value is considered as the level of threat. When an individual is far from the predator, visual and sound strategies are employed for global exploration. When the predator is in close proximity, odor defense and physical attack are adopted for local exploitation. The defensive strategies are ranked from the least aggressive to the most aggressive, as illustrated in Figure 10. In addition, the algorithm incorporates a cyclic population reduction mechanism that retains superior individuals, eliminates inferior ones, and generates new individuals, thereby balancing population diversity and convergence speed. The CPO algorithm features few parameters, fast convergence, and strong global search capability, making it suitable for complex nonlinear optimization problems.

The prediction accuracy of the BP neural network is highly dependent on the selection of initial weights and biases, and random initialization can easily cause the model to fall into local optima [35]. To overcome the performance limitations of the conventional BP neural network caused by sensitivity to initial parameters, this study develops a crested porcupine optimizer-backpropagation (CPO-BP) neural network optimization algorithm. By incorporating the dynamic adaptive mechanism of the Crested Porcupine Optimizer and leveraging its global search capability, the initial weights and biases of the BP neural network are optimized. The dual characteristics of global exploration and local exploitation effectively enhance the prediction accuracy of the model. The CPO-BP model was implemented with a single hidden layer containing six neurons, as determined by preliminary experiments. The Tan-sigmoid function was selected as the activation function for the hidden layer. The BP network was trained with a learning rate of 0.01 and a target minimum error of 10^{-6} . To prevent overfitting of the CPO algorithm, an early stopping strategy was adopted.

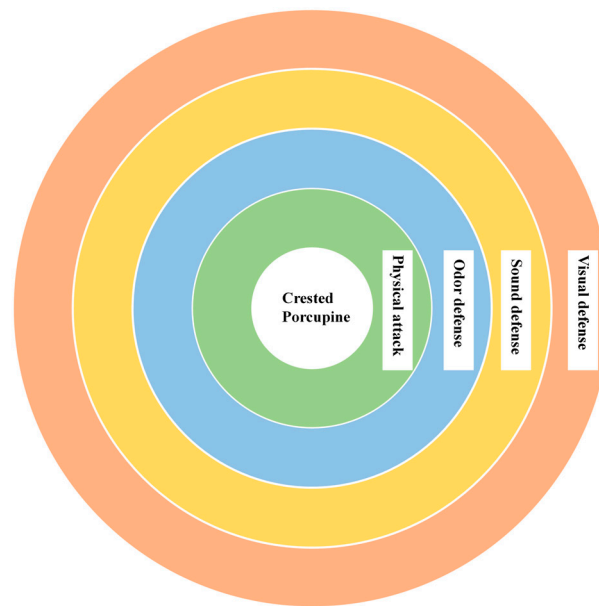


Figure 10. Crested Porcupine Defensive Strategies.

The procedure of the CPO-BP algorithm is as follows: the CPO algorithm is first employed to initialize the weights and biases of the BP neural network; the BP network is then trained and the error is calculated; subsequently, the error is used as the fitness function of the CPO algorithm to update the positions and quill sizes of the crested porcupines; these steps are repeated until the termination criterion is satisfied, as illustrated in Figure 11.

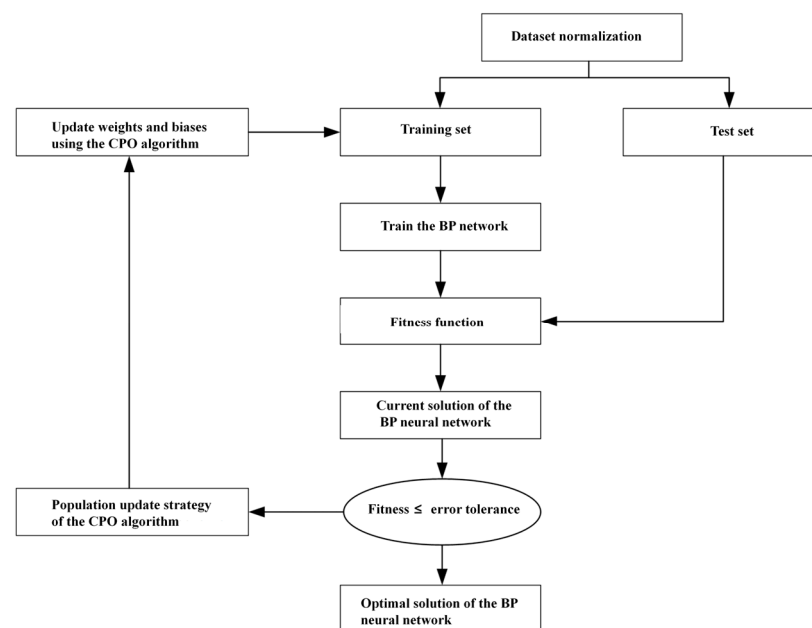


Figure 11. CPO-BP Algorithm Flowchart.

4.2. Shrinkage Rate Prediction Model

Based on the results of the sedimentation–shrinkage experiments, a total of 80 data sets were obtained for neural network training, of which 70 sets were used for training and 10 sets for validation. The input layer nodes correspond to slurry concentration, cement-to-tailings ratio, and curing time, while the output layer node corresponds to the shrinkage rate. According to the universal approximation theorem, the model adopts a three-layer neural network architecture with a single hidden layer.

The number of neurons in the hidden layer exhibits a significant nonlinear correlation with the generalization capability of the model, and its optimal configuration has not yet been fully established through a complete mathematical description. Empirical formulas are generally employed for estimation. In this study, the number of hidden layer nodes was calculated using Equation (2) in MATLAB (R2024a). The mean squared error (MSE) on the training set was computed for each of the 10 candidate node counts, and the number of neurons that yielded the minimum MSE was ultimately selected as the optimal value.

$$h = \sqrt{i + o} + f \quad (2)$$

where

h —There are h neurons in the hidden layer;

i —There are i neurons in the input layer;

o —There are o neurons in the output layer;

f — f is an empirical constant, generally ranging from 1 to 10.

The activation function is a key computational mechanism acting on neurons in the neural network. In this study, the Tan-sigmoid function was selected as the activation function.

In general, the training and validation samples involve multiple parameters with considerable variations in their data ranges. Given the specific requirements of the activation function regarding the input and output ranges, data normalization is essential during the model training stage. In this study, data preprocessing was performed using the mapminmax function built into MATLAB. Specifically, the input dataset was normalized to the range [0, 1], while the output data were normalized to [−1, 1]. The normalized results of the sample data are presented in Table 7.

Table 7. Sample Normalization Table.

Slurry Concentration	Cement-to-Tailings Ratio	Curing Time	Shrinkage Rate	Slurry Concentration	Cement-to-Tailings Ratio	Curing Time	Shrinkage Rate
0.00	1.00	0.00	−0.32	0.67	1.00	0.00	−0.92
0.00	1.00	0.13	0.21	0.67	1.00	0.13	−0.58
0.00	1.00	0.25	0.32	0.67	1.00	0.25	−0.36
0.00	1.00	0.63	0.36	0.67	1.00	0.63	−0.36
0.00	1.00	1.00	0.36	0.67	1.00	1.00	−0.36
0.00	0.38	0.00	−0.28	0.67	0.38	0.00	−0.92
0.00	0.38	0.13	0.25	0.67	0.38	0.13	−0.51
0.00	0.38	0.25	0.36	0.67	0.38	0.25	−0.40
0.00	0.38	0.63	0.43	0.67	0.38	0.63	−0.32
0.00	0.38	1.00	0.43	0.67	0.38	1.00	−0.32
0.00	0.17	0.00	−0.21	0.67	0.17	0.00	−0.89
0.00	0.17	0.13	0.28	0.67	0.17	0.13	−0.43
0.00	0.17	0.25	0.40	0.67	0.17	0.25	−0.25
0.00	0.17	0.63	0.51	0.67	0.17	0.63	−0.13
0.00	0.17	1.00	0.51	0.67	0.17	1.00	−0.13
0.00	0.00	0.00	−0.09	0.67	0.00	0.00	−0.81
0.00	0.00	0.13	0.70	0.67	0.00	0.13	−0.40
0.00	0.00	0.25	0.96	0.67	0.00	0.25	−0.17
0.00	0.00	0.63	1.00	0.67	0.00	0.63	−0.09
0.00	0.00	1.00	1.00	0.67	0.00	1.00	−0.09
0.33	1.00	0.00	−0.66	1.00	1.00	0.00	−1.00
0.33	1.00	0.13	−0.06	1.00	1.00	0.13	−0.62
0.33	1.00	0.25	0.17	1.00	1.00	0.25	−0.51
0.33	1.00	0.63	0.21	1.00	1.00	0.63	−0.51
0.33	1.00	1.00	0.21	1.00	1.00	1.00	−0.51
0.33	0.38	0.00	−0.62	1.00	0.38	0.00	−1.00

Table 7. Cont.

Slurry Con- centration	Cement-to- Tailings Ratio	Curing Time	Shrinkage Rate	Slurry Con- centration	Cement-to- Tailings Ratio	Curing Time	Shrinkage Rate
0.33	0.38	0.13	−0.02	1.00	0.38	0.13	−0.66
0.33	0.38	0.25	0.21	1.00	0.38	0.25	−0.51
0.33	0.38	0.63	0.25	1.00	0.38	0.63	−0.47
0.33	0.38	1.00	0.25	1.00	0.38	1.00	−0.47
0.33	0.17	0.00	−0.62	1.00	0.17	0.00	−1.00
0.33	0.17	0.13	−0.02	1.00	0.17	0.13	−0.58
0.33	0.17	0.25	0.24	1.00	0.17	0.25	−0.43
0.33	0.17	0.63	0.33	1.00	0.17	0.63	−0.40
0.33	0.17	1.00	0.33	1.00	0.17	1.00	−0.40
0.33	0.00	0.00	−0.43	1.00	0.00	0.00	−1.00
0.33	0.00	0.13	0.25	1.00	0.00	0.13	−0.58
0.33	0.00	0.25	0.51	1.00	0.00	0.25	−0.43
0.33	0.00	0.63	0.66	1.00	0.00	0.63	−0.36
0.33	0.00	1.00	0.66	1.00	0.00	1.00	−0.36

A total of 70 data sets from the overall dataset were used for network weight training, while the remaining 10 data sets were reserved to validate the engineering applicability of the model. The number of hidden layer nodes was calculated using Equation (2), yielding a range of 3 to 12. The learning rate was set to 0.01, and the target minimum error for training was set to 10^{-6} . The mean squared error (MSE) on the training set was computed for each candidate number of hidden layer nodes using MATLAB. A comparison of the MSE values is presented in Figure 12. The optimal number of hidden layer nodes was 6, at which the training set MSE reached its minimum value of 2.8742×10^{-6} .

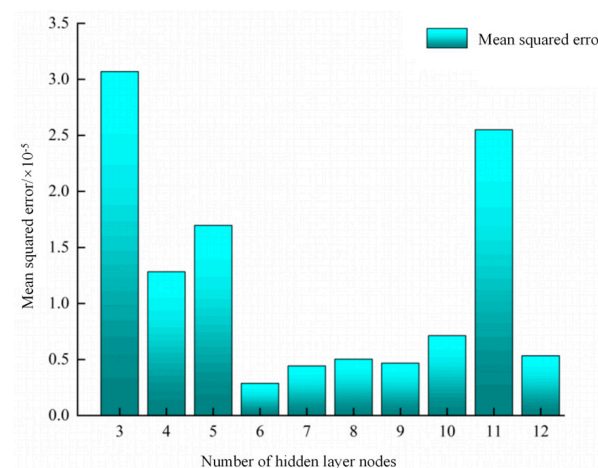


Figure 12. Mean Squared Error Comparative Plot.

The prediction performance of both the BP neural network-based and the CPO-BP neural network-based shrinkage rate prediction models was evaluated using three metrics: mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R^2). A comparison of the performance of the two models on the test set is presented in Table 8. The MSE and MAE reported in Table 8 were calculated based on the normalized output data, and thus are dimensionless. RMSE values have also been added to Table 8 for reference. And the predicted versus actual values are shown in Figure 13. As shown in Figure 13, the MSE on the training set decreases with increasing hidden layer nodes up to 6, reaching its minimum at 6 nodes, and then exhibits a peak at 11 nodes. This trend can be explained as follows: when the number of hidden layer nodes is insufficient, the network lacks the capacity to capture the complex nonlinear relationships in the data. Increasing

the number of nodes up to 6 enhances the network's representational ability, leading to lower prediction errors. Beyond the optimal number of nodes (6), the network becomes increasingly overparameterized, and the increased model complexity leads to a rise in prediction error, as observed at 11 nodes. Based on the above analysis, it can also be concluded that six nodes represent the optimal number of hidden layer nodes for the CPO-BP model, which is consistent with the result shown in Figure 12. As can be observed from Table 8 and Figure 13, the BP neural network model exhibited significant deviations from the actual values for samples 8, 9, and 10 in the test set, indicating relatively low prediction accuracy. In contrast, the CPO-BP neural network model demonstrated a significant performance advantage over the BP model: the MSE decreased from 9.0044×10^{-6} to 3.0767×10^{-6} , the MAE decreased from 2.2779×10^{-3} to 1.4528×10^{-3} , and the R^2 increased from 0.85208 to 0.94946. These results indicate that the CPO-BP neural network model possesses satisfactory accuracy and generalization capability, and can effectively predict the shrinkage rate of backfill slurry in mine stopes.

Table 8. Model Performance Comparison Table.

Model	MSE	RMS	MAE	R^2
BP	9.0044×10^{-6}	3.001×10^{-3}	2.2779×10^{-3}	0.85208
CPO-BP	3.0767×10^{-6}	1.754×10^{-3}	1.4528×10^{-3}	0.94946

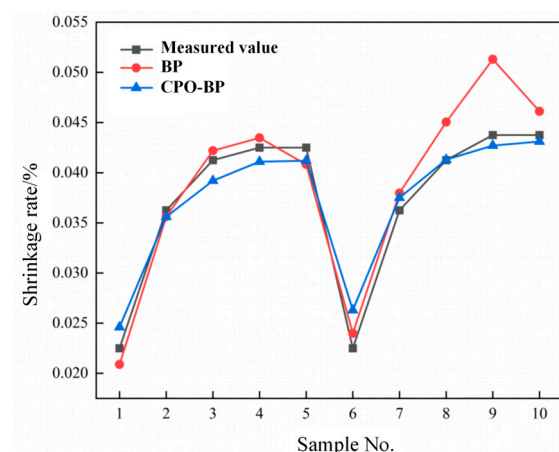


Figure 13. Test Set Predictive Results Comparative Plot.

It should be noted that the proposed CPO-BP model was developed using a limited dataset of 80 samples from a single mine site, with only three input variables (slurry concentration, cement-to-tailings ratio, and curing time) considered. This may restrict the generalizability of the model to other tailing types or field conditions. A more comprehensive evaluation of the model's robustness and generalization capability, including cross-validation and comparison with other machine learning methods, is presented in Section 4.3.

4.3. Cross-Validation and Comparison with Other Prediction Models

Considering that the prediction model was developed from a limited dataset of 80 experimental samples, the robustness and generalization capability of the proposed CPO-BP model were further examined by repeated k-fold cross-validation, and its performance was benchmarked against several widely used prediction models, namely the GA-BP and PSO-BP neural networks, random forest (RF) [36], support vector regression (SVR) [37], and extreme gradient boosting (XGBoost) [38]. A repeated five-fold cross-validation scheme (five random repetitions, 25 training-validation folds in total) was adopted, so that ev-

ery sample was used for validation five times and each fold contained about 64 training samples and 16 validation samples. The GA-BP, PSO-BP, and CPO-BP models shared the same network architecture, normalization method, and training settings as described in Section 4.2, with a population size of 30 and 60 iterations for the meta-heuristic optimizers; the hyperparameters of the SVR model (penalty coefficient, kernel width, and insensitive-loss margin) were tuned by grid search with an inner three-fold cross-validation, and the RF and XGBoost models each used 300 trees. The evaluation metrics (MSE, MAE, and R^2) were computed on the validation fold of each split, and the mean $\pm$ standard deviation over the 25 folds are reported in Table 9.

Table 9. Repeated five-fold cross-validation performance of different prediction models (mean $\pm$ standard deviation over 25 folds).

Model	MSE	MAE	R^2
BP	$5.10 \times 10^{-6} \pm 2.65 \times 10^{-6}$	$1.737 \times 10^{-3} \pm 0.382 \times 10^{-3}$	0.9790 ± 0.0122
GA-BP	$6.13 \times 10^{-6} \pm 4.70 \times 10^{-6}$	$1.793 \times 10^{-3} \pm 0.638 \times 10^{-3}$	0.9716 ± 0.0338
PSO-BP	$6.13 \times 10^{-6} \pm 3.83 \times 10^{-6}$	$1.858 \times 10^{-3} \pm 0.516 \times 10^{-3}$	0.9742 ± 0.0188
CPO-BP	$5.13 \times 10^{-6} \pm 3.11 \times 10^{-6}$	$1.740 \times 10^{-3} \pm 0.464 \times 10^{-3}$	0.9789 ± 0.0142
RF	$6.55 \times 10^{-6} \pm 4.27 \times 10^{-6}$	$1.763 \times 10^{-3} \pm 0.570 \times 10^{-3}$	0.9740 ± 0.0158
SVR	$24.55 \times 10^{-6} \pm 25.32 \times 10^{-6}$	$3.645 \times 10^{-3} \pm 1.652 \times 10^{-3}$	0.9091 ± 0.0734
XGBoost	$2.61 \times 10^{-6} \pm 2.34 \times 10^{-6}$	$1.014 \times 10^{-3} \pm 0.355 \times 10^{-3}$	0.9885 ± 0.0130

As shown in Table 9, all of the investigated models achieve satisfactory average accuracy on this dataset (mean $R^2 > 0.90$), indicating that the experimental dataset, although limited in size, exhibits a consistent and learnable mapping between the mix parameters and the shrinkage rate. Among the neural-network-based models, the CPO-BP model attains a mean R^2 of 0.9789 ± 0.0142 , outperforming the GA-BP and PSO-BP models in both average accuracy and fold-to-fold stability and performing on par with the fully trained BP baseline; this indicates that the benefit of the CPO initialization lies mainly in reducing the sensitivity of the network to its initial weights, thereby avoiding the occasional convergence to poor local optima that was observed for the conventional BP model in the fixed-split evaluation of Table 8. The RF and SVR models yield lower average accuracy than the CPO-BP model, whereas the XGBoost model achieves the lowest average errors (MSE of 2.61×10^{-6} and R^2 of 0.9885) on this regularly gridded dataset, reflecting the well-known strength of gradient-boosted trees on small tabular datasets. Nevertheless, tree-based models produce piecewise-constant response surfaces, which restricts their ability to represent the smooth and monotonic dependence of the shrinkage rate on slurry concentration and cement-to-tailings ratio when interpolating at untested factor levels—an ability that is essential for the continuous process optimization in Section 5. Taking the prediction accuracy, cross-validation stability, and smoothness of the fitted response surface into account, the CPO-BP model was retained for the optimization of the roof-contact backfilling scheme.

5. Optimization of the Roof-Contact Backfilling Scheme

The mining method adopted at the Daye Iron Mine is the sublevel open stopping with subsequent backfill method, with the extraction sequence following an alternating pattern of mining one stope while leaving the adjacent one unmined. Currently, the orebody at the -270 m to -360 m level is being extracted, while the -180 m to -270 m level has been fully mined out. In the -180 m to -270 m level, the stopes are divided from west to east into 10 ore blocks, each consisting of ore rooms and pillars. The sublevel height is 90 m, the ore block length ranges from 30 m to 45 m, and both the ore rooms and pillars are 15 m in width. Due to the increase in sublevel height (from 60 m to 90 m) and the greater mining

depth, the backfill body in the ore rooms has failed to make full contact with the roof, as illustrated in Figure 14.



Figure 14. Schematic Diagram of Backfill Failure to Reach the Stope Roof in Daye Iron Mine.

The Daye Iron Mine employs a cemented backfilling process for backfilling the goaves, in which cementitious materials are mixed with aggregates to form a high-strength backfill body after curing, effectively supporting the surrounding rock structure and controlling ground pressure. The typical goaves currently being mined are Stope #3 and Stope #4, and their cross-sections are shown in Figure 15. Stope #3 is approximately 40 m in length, 15 m in width, and 75 m in height, with an orebody dip angle of about 60° . Stope #4 is approximately 90 m in length, 15 m in width, and 75 m in height, with an orebody dip angle of about 70° .

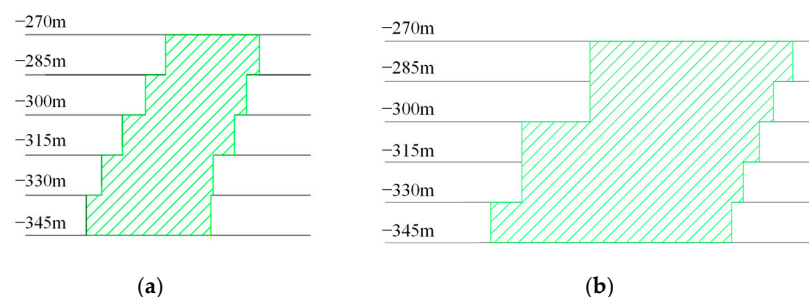


Figure 15. Cross-section of the goaf. (a) Stope #3, western district; (b) Stope #4, western district.

In the current backfilling scheme at the Daye Iron Mine, the cement-to-tailings ratio is 1:4 for backfilling the ore rooms and 1:20 for backfilling the pillars, with a slurry concentration of approximately 65%. Previous studies have shown that the 65% concentration slurry exhibits excellent fluidity but suffers from a relatively high shrinkage rate [39,40]. Field investigations indicate that the average roof-contact rate in the ore rooms of the eastern district is only 63.33%, while that in the western district is even lower, at less than 60%. Therefore, reducing the shrinkage rate of the backfill slurry is of critical importance.

The sedimentation–shrinkage test results indicate that the final shrinkage rate of the 65% concentration slurry after 36 h ranges from 6.75% to 8.75% (for cement-to-tailings ratios of 1:4 to 1:20), which is one of the primary reasons for the low roof-contact rate in the stopes. To reduce the shrinkage rate of the backfill slurry, it is necessary to increase the slurry concentration. The sedimentation–shrinkage test results, combined with the spreadability test data, show that increasing the concentration to 71% reduces the final shrinkage rate to 3.875–4.375%. When the concentration exceeds 71%, the shrinkage rate varies only slightly; however, the fluidity deteriorates significantly, rendering gravity-flow transport infeasible.

When the concentration is below 69%, the fluidity is relatively good, but the shrinkage rate remains high. Considering both the sedimentation–shrinkage characteristics and transport requirements, the optimal slurry concentration for the Daye Iron Mine is recommended to be in the range of 69–71%.

Using the optimized concentration range of 69–71% for backfilling, the shrinkage rate was predicted using the CPO-BP neural network model. A comparison of the backfill performance before and after optimization for cement-to-tailings ratios of 1:4 and 1:20 is presented in Table 10. It can be observed that after optimization, with a slurry concentration of 69–71%, the shrinkage rate was reduced by 2.375% to 3.875%, the shrinkage height was reduced by 1.78 to 2.91 m, and the roof-contact rate exceeded 90%. Therefore, it is recommended that the slurry concentration at the Daye Iron Mine be controlled within the range of 69–71%. The standard deviation of the CPO-BP-predicted shrinkage rates over ten independently trained models was within 0.07 percentage points (see Section 4.3), indicating that the optimization results in Table 10 are insensitive to the randomness of model training.

Table 10. Comparison table of optimization effects.

Cement-to-Tailings Ratio	Shrinkage Rate (%)		Shrinkage Height (m)		Roof-Contact Rate (%)
	Before Optimization	After Optimization	Before Optimization	After Optimization	
1:4	6.75	3.875~4.375	5.06	2.91~3.28	95.63~96.13
1:20	8.75	4.875~5.25	6.56	3.656~3.938	94.75~95.13

It should be noted that, due to the current mining schedule at the Daye Iron Mine, no stopes were available for immediate field backfilling trials during the course of this study. Therefore, full-scale industrial validation of the proposed concentration increase and pipeline spacing optimization could not be conducted. Nevertheless, the laboratory experiments and numerical simulations provide strong evidence for the expected improvement. Field verification of the optimized scheme is currently being planned and will be carried out in the upcoming mining phase.

6. Conclusions

Based on the sedimentation–shrinkage test results of the unsorted tailings backfill slurry, this study analyzed the sedimentation–shrinkage characteristics and influencing factors, developed a CPO-BP neural network-based prediction model, and performed optimization simulations on the pipeline spacing at the Daye Iron Mine. The main conclusions are as follows:

1. The sedimentation–shrinkage tests of the unsorted tailings backfill slurry revealed that the shrinkage rate increased rapidly within the first 8 h of curing time, and then decreased significantly between 8 and 12 h. After 12 h, the shrinkage rates of the slurries with concentrations of 69% and 71% tended to stabilize, while those of the slurries with concentrations of 65% and 67% continued to increase slowly. No further changes were observed after 24 h.
2. At a given concentration, the shrinkage rate increased with decreasing cement-to-tailings ratio, and this trend was more pronounced in low-concentration slurries. At a given cement-to-tailings ratio, the shrinkage rate decreased with increasing slurry concentration. Binary linear regression analysis revealed that the slurry concentration exerted a significantly greater influence on the shrinkage rate than the cement-to-tailings ratio, with a coefficient of determination (R^2) of 0.800.
3. The CPO-BP neural network-based shrinkage rate prediction model exhibited excellent performance, achieving an MSE of 3.0767×10^{-6} , an MAE of 1.4528×10^{-3} ,

and an R^2 of 0.94946 on the test set, significantly outperforming the conventional BP neural network. Repeated five-fold cross-validation and comparisons with the GA-BP, PSO-BP, random forest, SVR, and XGBoost models further confirmed the robustness of the proposed model, which achieved a mean R^2 of 0.9789 ± 0.0142 over 25 validation folds, outperforming the GA-BP, PSO-BP, RF, and SVR models and performing comparably to the gradient-boosting model while providing a smooth response surface suitable for backfilling process optimization. This demonstrates that the proposed model can effectively predict the shrinkage rate of unsorted tailings backfill slurry.

4. Based on the sedimentation–shrinkage test results and the predictions of the CPO-BP neural network model, increasing the slurry concentration from 65% to 69–71% resulted in a reduction of the shrinkage rate by 2.375% to 3.875%, a decrease in the shrinkage height by 1.78 to 2.91 m, and an improvement of the roof-contact rate to over 90%.
5. Several limitations of this study should be acknowledged. The proposed CPO-BP model was developed using a limited dataset of 80 samples from a single mine site, with only three input variables considered. This may restrict the model’s generalizability to other tailings types or field conditions. Additionally, independent replicate experiments were not performed for each mix proportion, although measurement reliability was enhanced through standardized procedures and four-orientation averaging. Future work will focus on expanding the experimental database with a wider range of tailings sources and conditions, incorporating additional influencing factors such as particle size distribution and binder type, and conducting field validation of the optimized backfilling scheme.

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