

Article

Prediction and Optimization of Open-Pit Mine Blasting Based on Intelligent Algorithms

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Abstract: Blasting prediction and parameter optimization can effectively improve blasting effectiveness and control production energy consumption. However, the presence of multiple factors and diverse effects in open-pit blasting increases the difficulty of effective prediction and optimization. Therefore, this study takes blasting fragmentation as the prediction indicator and proposes a hybrid intelligent model based on multiple parameters. The model employs a least squares support vector machine (LSSVM) optimized by a genetic algorithm (GA) for prediction. Additionally, the performance of GA-LSSVM was compared with LSSVM optimized by rime optimization algorithms (RIME-LSSVM) and by particle swarm optimization algorithms (PSO-LSSVM), unoptimized LSSVM, and the Kuz–Ram empirical model. Furthermore, considering both blasting fragmentation and blasting cost, a multi-objective particle swarm optimization (MOPSO) algorithm was used for blasting parameter optimization, followed by field validation. The results indicated that the GA-LSSVM model provided the best prediction of blasting fragmentation, achieving optimal evaluation metrics: a root mean square error (RMSE) of 1.947, a mean absolute error (MAE) of 1.688, and a correlation coefficient (r) of 0.962. Moreover, the MOPSO optimization model yielded the optimal blasting parameter combination: a burden of 5.5 m, spacing of 4.3 m, specific charge of 0.51 kg/m³, and subdrilling of 2.0 m. Field blasting tests confirmed the reliability of these parameters. This study can provide scientific recommendations for open-pit mine blasting design and cost control.



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Keywords: blasting; fragmentation prediction; GA-LSSVM; cost; multi-objective; parameter optimization

1. Introduction

Blasting is the most commonly used method in open-pit mining operations. Its quality and efficiency not only affect the overall productivity of the mining process but also determine the economic benefits for the enterprise [1]. Prediction and optimization before blasting are crucial means of controlling blasting outcomes, which has prompted a series of studies by researchers.

In the blasting process, ore fragmentation is a critical indicator of blasting effectiveness [2]. Researchers often use the mean particle size (P_{50}) to represent the overall degree of fragmentation. Early predictions of blast fragmentation relied heavily on empirical models. The Kuz–Ram model is considered the most commonly used model for predicting blast fragmentation [3]. This model is widely used and continuously revised to improve prediction accuracy [4–9]. However, empirical models are limited in their consideration of parameters, leading to deficiencies in prediction accuracy and optimization effectiveness [10]. There is growing research focused on predicting fragmentation using intelligent algorithms, such as support vector machines [11,12], BP neural networks [13], artificial neural networks [14], gradient-boosting trees [15,16], etc.

In recent years, improved intelligent algorithms have become increasingly popular in blasting prediction research [17–21]. For instance, Yari et al. [22] used the jellyfish search optimization (JSO) algorithm to optimize the hyperparameters of the Light-GBM model, establishing a hybrid model to predict blast fragmentation. Zheng et al. [23] employed multiple meta-heuristic algorithms to optimize the hyperparameters of LSSVM, demonstrating that the LSSVM-BFO model has the best prediction efficiency. Ding et al. [24] developed four improved artificial intelligence models and determined that the cascade forward neural network (CFNN) model optimized by the Levenberg–Marquardt algorithm (LMA) was the best, using root mean square error (RMSE) as the statistical indicator. This also indicates that established hybrid models can predict blast fragmentation more accurately. However, these predictions mainly serve as reference data for field personnel and do not provide practical blasting design parameters to directly guide on-site production work.

Therefore, many researchers have conducted in-depth studies on the optimization of blasting parameters [25–27]. Given the nonlinear and multi-factor nature of blasting operations, multi-objective intelligent optimization algorithms have been widely used. Sadrossadat et al. [28] utilized a particle swarm optimization algorithm to establish a multi-objective optimization model for cemented backfill, incorporating strength, regional stress, and filling cost and used multiple regression to establish surrogate models for each objective, achieving the optimal design parameters. Bakhtavar et al. [29] developed a stochastic multi-objective planning model to optimize multiple blasting outcomes in open-pit metal mines, ultimately determining the optimal adjustable parameters for the best blasting scheme. Moreover, multi-objective particle swarm optimization (MOPSO) can optimize multiple indices in blasting operations [30]. It is noteworthy that the feasibility of the prediction and optimization results in production also needs to consider cost factors, as costs limit the realization of optimization effects.

Therefore, using intelligent algorithms to establish efficient blasting prediction and optimization models is of significant practical importance, as it helps in finding blasting design parameters that achieve the optimal balance between fragmentation and blasting cost. This study established an intelligent hybrid model (GA-LSSVM) to predict rock blast fragmentation (P_{50}). Using the root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (r) as evaluation metrics, the GA-LSSVM was compared with RIME-LSSVM, PSO-LSSVM, LSSVM, and the Kuz–Ram model. Additionally, a multi-objective optimization model that integrates blast fragmentation and blasting cost was established, providing optimal blasting design parameters to ensure the efficient operation of blasting activities.

2. Project Overview

A certain iron mine is located in Yueyang City, Hunan Province, and is engaged in the mining and beneficiation of iron ore. The mining method employed is open-pit mining. The mineral reserve in the mining area amounts to 320 million tons, with an annual production capacity of 2.33 million tons of iron ore. The ore types mainly include magnetite, hematite, and small amounts of limonite. The mine uses deep-hole bench blasting with continuous charge structures. The blasting parameters are shown in Figure 1. The blast hole inclination angle is 90° , and the designed bench height (H) is 12 m. The actual specific charge (q) ranges between 0.33 kg/m^3 and 0.54 kg/m^3 , the burden (B) ranges from 4.0 m to 4.8 m, the spacing (S) ranges from 5.0 m to 5.8 m, and the subdrilling (H_0) ranges from 0.5 m to 2.5 m. The wide range of blasting design parameter values indicates a strong reliance on subjective experience.

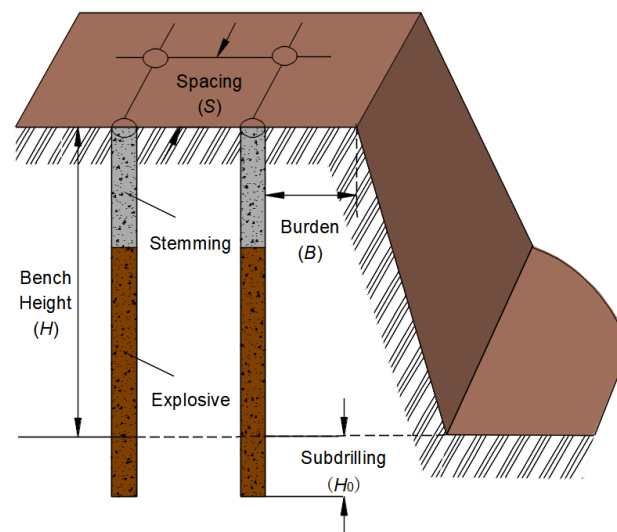


Figure 1. Rock blasting parameters.

3. Data Collection

This study formulated a data collection scheme that includes four adjustable blasting parameters: spacing (S), burden (B), specific charge (q), and subdrilling (H_0), along with blast fragmentation (P_{50}). A total of 37 blasts were recorded at the mining site, primarily targeting magnetite ore in the mining area. Additionally, the rock mass conditions (T) at the mining site, which include fractured and intact states, were assigned values of 1 and 2, respectively, and incorporated into the blast fragmentation prediction model. Thus, there are a total of 37 sets of data encompassing blasting parameters, rock mass conditions, and blast fragmentation. The data are presented in Table 1. The first 30 data sets in Table 1 are used as the training set, while the remaining 7 data sets are used as the test set.

Table 1. Blasting parameters and blasting fragmentation data from the mine.

No.	S (m)	B (m)	q (kg/m ³)	H_0 (m)	T	P_{50} (cm)
1	5.8	4.3	0.45	0.8	1	35.77
2	5.8	4.3	0.49	1.2	1	31.43
3	5.8	4.3	0.49	2.2	1	31.80
4	5.8	4.3	0.47	2.0	1	32.43
5	5.8	4.8	0.41	1.5	1	39.74
6	5.8	4.8	0.38	2.0	2	45.05
7	5.8	4.3	0.46	0.5	1	34.95
8	5.8	4.3	0.48	2.5	1	31.74
9	5.8	4.3	0.36	1.5	2	48.06
10	5.8	4.8	0.33	1.5	1	53.07
11	5.5	4.3	0.48	1.5	1	32.14
12	5.8	4.3	0.51	1.5	1	29.82
13	4.3	5.5	0.36	1.5	2	44.36
14	5.5	4.5	0.35	0.5	1	45.8
15	5.8	4.3	0.40	2.5	1	40.63
16	5.8	4.8	0.32	0.5	1	55.78
17	5.5	4.3	0.40	2.5	1	39.87
18	5.8	4.3	0.42	1.0	1	39.12
19	5.5	4.3	0.40	1.0	2	40.17
20	5.8	4.5	0.39	1.5	2	44.76

Table 1. Cont.

No.	S (m)	B (m)	q (kg/m ³)	H_0 (m)	T	P_{50} (cm)
21	5.8	4.5	0.37	1.5	1	50.55
22	5.5	4.3	0.42	2.0	2	38.84
23	5.5	4.5	0.39	2.0	1	44.13
24	5.5	4.3	0.45	2.0	1	35.05
25	5.8	4.3	0.42	1.5	1	39.50
26	5.8	4.3	0.37	1.5	1	48.63
27	5.8	4.3	0.41	1.5	1	40.24
28	5.5	4.3	0.49	2.0	2	30.87
29	5.5	4.3	0.47	1.5	1	49.56
30	5.8	4.5	0.37	2.0	1	51.60
31	5.5	4.5	0.36	1.5	1	48.90
32	5.5	4.3	0.39	1.5	1	43.16
33	5.5	4.5	0.40	1.5	1	39.66
34	5.5	4.3	0.39	1.5	2	43.37
35	5.8	4.8	0.39	1.5	1	46.47
36	5.0	4.0	0.54	2.0	1	29.54
37	5.5	4.3	0.40	2.0	1	40.90

4. Methods

4.1. Least Squares Support Vector Machine

Support vector machine (SVM) is a machine learning algorithm used for classification and regression tasks [31]. The core idea of SVM is to identify a hyperplane that maximizes the margin between classes. This means finding the optimal boundary between two classes such that the distance from the closest points to this boundary is maximized [32]. The schematic diagram of its structure is shown in Figure 2 [33].

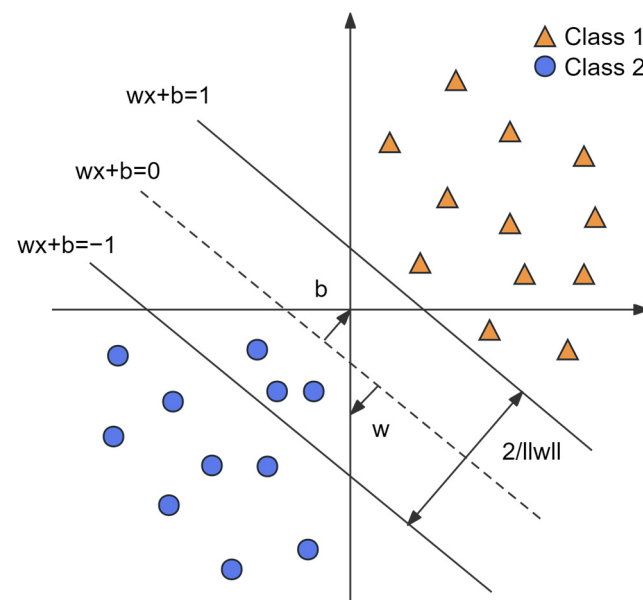


Figure 2. The schematic diagram of SVM structure.

Least squares support vector machine (LSSVM) is a method based on SVM [34]. In LSSVM, data are fitted by minimizing the sum of squared errors, and the decision function is constrained by introducing Lagrange multipliers. This method obtains model parameters by solving the dual problem rather than solving the primal problem as in traditional support vector machines. The following is the principle of LSSVM:

Given a training sample set $\{(x_i, y_i), i = 1, 2, \dots, N\}$, where $x_i \in R^d$ (R^d is a d -dimensional input vector) and $y_i \in R$ is its corresponding predicted value. The optimization problem of LSSVM for the sample set is formulated as follows:

$$\begin{aligned} \min J(\omega, e) &= \min\left(\frac{1}{2}\|\omega\|^2 + \frac{\gamma}{2} \sum_{i=1}^N e_i^2\right) \\ \text{s.t. } y_i(\omega^T \phi(x_i) + b) &= 1 - e_i, i = 1, 2, \dots, N \end{aligned} \quad (1)$$

Among the variables, ω is the weight vector, e_i is the slack variable, y_i is the label, $\phi(x_i)$ is the feature mapping, b is the bias term, and γ is the regularization parameter.

The optimization problem is addressed by constructing the Lagrangian function:

$$L(\omega, b, e, \alpha) = \frac{1}{2}\|\omega\|^2 + \frac{\gamma}{2} \sum_{i=1}^N e_i^2 - \sum_{i=1}^N \alpha_i [y_i(\omega^T \phi(x_i) + b) + e_i - 1] \quad (2)$$

Among the variables, α_i is the Lagrange multiplier.

By setting the partial derivatives of the Lagrangian function with respect to ω, b, e_i to zero [35], we obtain the dual problem [36]:

$$\begin{bmatrix} 0 & y^T \\ y & \Omega + \gamma^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad (3)$$

Among the variables, y is the label vector, α is the Lagrange multiplier vector, Ω is the kernel matrix, and I is the identity matrix.

By solving the linear equations above, we can obtain b and α . The final expression of the LSSVM model is

$$f(x) = \sum_{i=1}^N \alpha_i y_i K(x_i, x) + b \quad (4)$$

where $K(x_i, x_j)$ is the kernel function, which plays a crucial role in LSSVM [37,38].

$$K(x_i, x_j) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \quad (5)$$

where σ is the width parameter of the kernel function. Both σ and the regularization parameter (γ) are key parameters of the LSSVM model and have a significant impact on the model's performance and generalization ability [39].

4.2. Optimization of LSSVM by Genetic Algorithm

Genetic algorithm (GA) is an optimization algorithm based on natural selection and genetic mechanisms that is used to solve various complex optimization problems [40]. Using GA to optimize the LSSVM algorithm can fully leverage its advantages, such as global search capability, strong adaptability, and ease of parallelization, to find better combinations of model parameters, thus enhancing the performance of the LSSVM model. The process of optimizing hyperparameters in the LSSVM model using GA is illustrated in Figure 3. During the optimization process, the objective function is to minimize the prediction error on the training set, and the RMSE is selected to establish the fitness function, as shown in Equation (6).

$$\text{fit}(\gamma, \sigma) = \sqrt{\frac{1}{N} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (6)$$

Among the variables, N is the number of training samples, y_i is the actual value, and $\hat{y}_i$ is the predicted value.

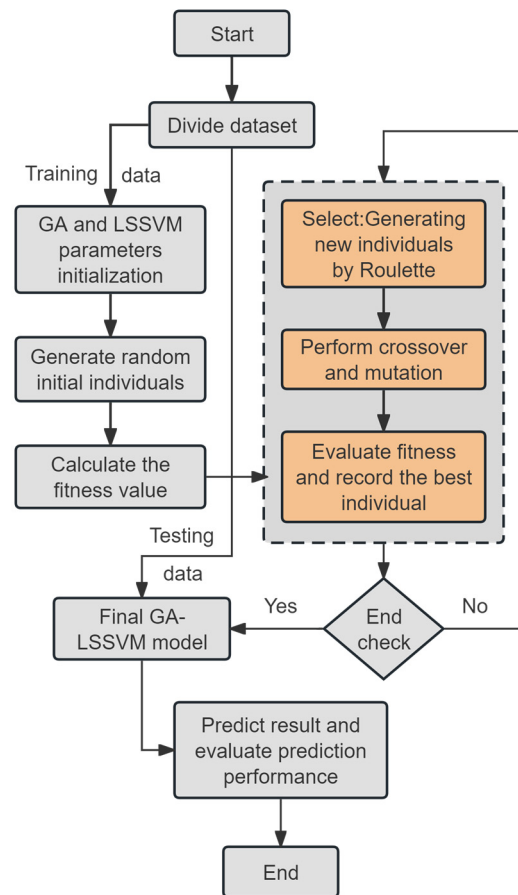


Figure 3. GA optimization LSSVM model process.

4.3. Multi-Objective Particle Swarm Optimization

Particle swarm optimization (PSO) is an optimization technique based on swarm intelligence and is characterized by its simplicity, high precision in optimization results, and fast convergence [41]. PSO simulates the movement of particles in the search space to find the optimal solution [42]. Multi-objective particle swarm optimization (MOPSO) was developed based on conventional particle swarm optimization algorithms, initially proposed by Coello et al. [43]. MOPSO has the advantages of efficient search and a well-distributed Pareto front, and it is widely used to optimize mathematical problems in engineering applications [28]. The basic principle involves particles dynamically adjusting their velocity and position for the next step based on their own optimal position and the globally known optimal position, with the fitness function determining the fitness value of particles.

In this study, blast fragmentation (P_{50}) and blasting cost (C) are optimized. Therefore, the GA-LSSVM model serves as one of the proxy models. Additionally, the blasting cost calculation model serves as another proxy model, represented by Equation (7) [44]. The optimization process of MOPSO is shown in Figure 4.

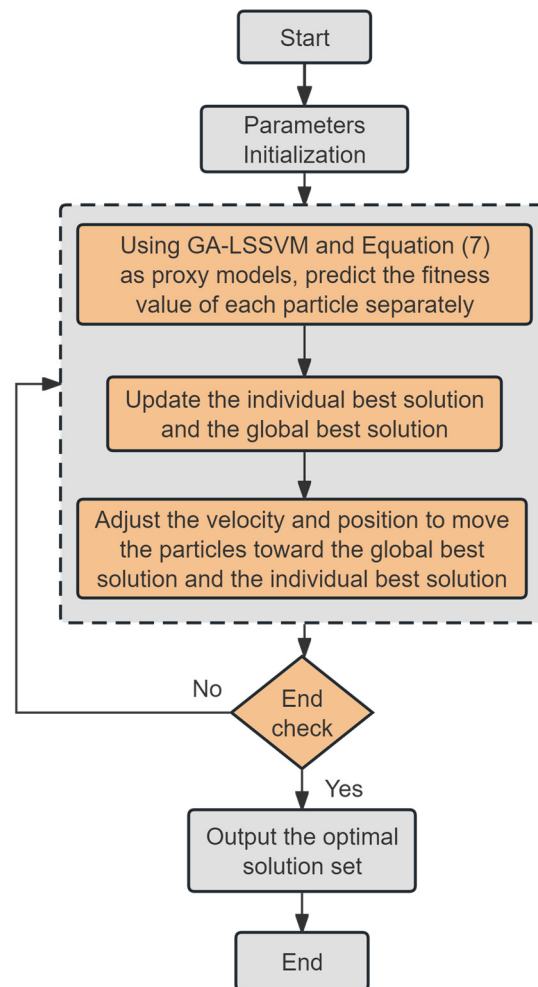
$$C = \frac{L_m \cdot (H + H_0)}{S \cdot B \cdot H \cdot \rho_r} + \frac{q \cdot E_m}{\rho_r} + \frac{N_D \cdot D_m}{S \cdot B \cdot H \cdot \rho_r} + R_1 + R_2 \quad (7)$$

Among the variables, L_m is the unit price of drilling, ρ_r is the density of ore, E_m is the unit price of explosives, N_D is the average number of electronic detonators used per blast hole, D_m is the unit price of detonators, R_1 is the labor cost for drilling, and R_2 is the labor cost for loading explosives.

The collected mining production data and the constants in Equation (7) are shown in Table 2.

Table 2. The constant parameters of the blasting cost model.

L_m (CNY)	ρ_r (t/m ³)	E_m (CNY)	N_D (Per)	D_m (CNY)	R_1 (CNY)	R_2 (CNY)
31.78	3.3	10.5	1.13	35	0.042	0.165

**Figure 4.** The optimization process of MOPSO.

5. Results and Discussion

5.1. Modeling for Prediction

The models for predicting blast fragmentation were trained using the training dataset, resulting in four intelligent prediction models (GA-LSSVM, RIME-LSSVM, PSO-LSSVM, LSSVM). After incorporating relevant parameters, the Kuz–Ram model was adjusted. Additionally, integrating GA-LSSVM with blast cost formulas into the MOPSO optimization model facilitated the optimization of mining blast parameter design, providing precise and reliable guidance for engineering applications.

5.1.1. GA-LSSVM Model

To enhance the prediction accuracy of the GA-LSSVM model, multiple iterations were conducted to determine the maximum number of iterations ($I_{\max}$) and the population size (n_{pop}). RMSE was employed as both the fitness function and the evaluation metric for the predictive model. There exists a negative correlation between prediction performance and RMSE; smaller RMSE values indicate better predictive efficacy. Multiple iterations were performed, as illustrated in Figure 5. After 100 iterations, the minimum RMSE value corresponded to a population size of 60, and stability was achieved after approximately

70 iterations. Therefore, the final choice for n_{pop} was determined to be 60. Taking into account iteration redundancy, the value of I_{max} was set to 90.

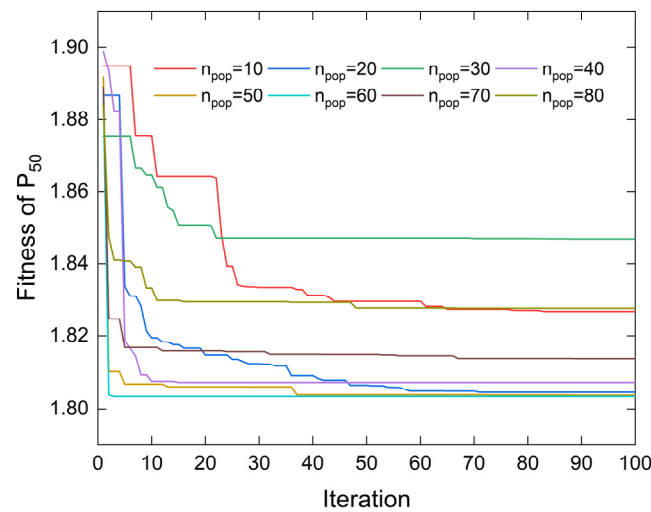


Figure 5. The selection of the maximum number of iterations and population size.

When the blast fragmentation (P_{50}) is taken as the output indicator, the optimal values for γ and σ^2 are 468.69 and 287.23, respectively. The regression fitting effect of the final GA-LSSVM model on the sample data is shown in Figure 6. We can see that the predicted values of the model are very close to the test values, with an RMSE value of 1.805. This indicates that the GA-LSSVM model has a good fitting effect on P_{50} .

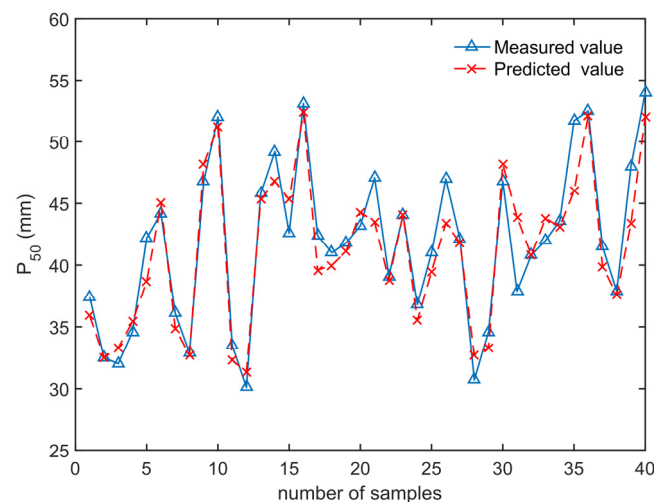


Figure 6. The regression fitting effect of GA-LSSVM.

5.1.2. Comparative Models

RIME-LSSVM, PSO-LSSVM, LSSVM, and the Kuz–Ram model were developed to compare with the GA-LSSVM model and assess its predictive performance. LSSVM has been described earlier in the text, with γ and σ^2 taken as (95, 16).

RIME-LSSVM is an LSSVM model optimized using the rime optimization algorithm. By optimizing LSSVM with RIME, it enhances various aspects of the model's performance, including improving prediction accuracy, enhancing generalization capability, boosting robustness, and adapting to complex data structures [45]. This makes LSSVM more efficient and reliable in handling real-world problems. In RIME, the parameter (ω) controlling the

number of segments in the step function is set to 5, resulting in optimized values of γ and σ^2 as (51, 30), respectively.

The PSO-LSSVM model combines the global search capability of PSO with the powerful modeling capability of LSSVM, enabling it to achieve good results in many machine learning and optimization problems. Using an intelligent model optimized by particle swarm algorithm to predict mine blasting vibration is considered efficient [30]. In the model construction process, the individual learning coefficient (c_1) and the global learning coefficient (c_2) of PSO were set to (1.5, 1.7), resulting in optimal values of γ and σ^2 as (81, 75).

The Kuz–Ram model is widely applied in the prediction of blast fragmentation [4,46]. The basic formula of the Kuz–Ram equation, which relates the average fragmentation size to the specific charge, is as follows:

$$P_{50} = K \cdot \left(\frac{V_0}{Q}\right)^{0.8} \cdot (Q)^{\frac{1}{6}} \cdot \left(\frac{115}{E}\right)^{\frac{19}{30}} \quad (8)$$

Among the variables, K is the rock coefficient, typically taken as 7 for medium rocks, 10 for hard rocks with developed fissures, and 13 for hard rocks without developed fissures; V_0 represents the volume of crushed rock per hole; Q denotes the TNT equivalent energy of explosive charge per hole, which can be obtained by multiplying the line explosive density (ql) by the explosive length (h); and E represents the relative weight power of the explosive, taken as 100 for ammonium nitrate fuel oil and 115 for trinitrotoluene. To achieve the desired blasting effect, a high-velocity emulsion explosive with a cartridge diameter (d) of 140 (mm) and ql of 11.4 (kg/m) is used.

Considering the engineering context, the blasting parameter design for the open-pit iron mine needs to take into account the maximum size of ore blocks after blasting. Therefore, according to reference [47], the parameter of maximum allowable fragmentation size ($X_m = 0.7$ m) is introduced to modify the following equation:

$$P_{50} = K \cdot \sqrt{X_m} \cdot \frac{V_0^{0.8}}{Q} \cdot (Q)^{\frac{1}{6}} \cdot \left(\frac{115}{E}\right)^{\frac{19}{30}} \quad (9)$$

5.1.3. MOPSO Model

The GA-LSSVM model and blasting cost formula (Equation (7)) were used as objective functions in MOPSO. This dual-objective optimization strategy requires consideration of four variables: spacing (S), burden (B), specific charge (q), and subdrilling (H_0). Combining with the literature [48] and based on multiple repeated experiments, the parameter values for MOPSO were determined as shown in Table 3.

Table 3. MOPSO optimization model parameter settings.

Initial Parameters	n_V	n_P	n_R	n_G	c_1	c_2	w_d	ω
value	4	200	100	7	1	2	0.99	0.5

Among the variables, n_V is the number of decision variables, n_P is the number of particles in the swarm, n_R is the size of the external archive, n_G is the number of grids, c_1 is the individual learning coefficient, c_2 is the global learning coefficient, w_d is the decay factor of the inertia weight, and ω is the inertia weight.

5.2. Performance Evaluation of Prediction Models

Using the same set of training and testing samples, the prediction performance of RIME-LSSVM, PSO-LSSVM, LSSVM, and Kuz–Ram models was compared with that of the GA-LSSVM model. RMSE, MAE, and r were selected as evaluation metrics for prediction performance.

The calculated evaluation metrics for the prediction performance on both the training and test samples are shown in Table 4.

Table 4. Calculation results of prediction performance metrics.

Models	Training Datasets			Test Datasets		
	RMSE	MAE	r	RMSE	MAE	r
GA-LSSVM	1.805	2.088	0.925	1.947	1.688	0.962
RIME-LSSVM	2.067	1.639	0.904	2.967	2.344	0.958
PSO-LSSVM	3.008	2.113	0.889	3.870	2.564	0.959
LSSVM	3.324	2.656	0.876	3.869	2.584	0.921
Kuz–Ram	4.240	3.646	0.751	4.800	3.871	0.833

Figure 7 visually displays the evaluation metric values for the five models on the training and test sets. It is evident that the models based on intelligent algorithms (GA-LSSVM, RIME-LSSVM, PSO-LSSVM, and LSSVM) show lower prediction errors and better fit compared to the Kuz–Ram empirical model. Additionally, the hybrid models (GA-LSSVM, RIME-LSSVM, PSO-LSSVM) exhibit better prediction performance than the single model (LSSVM). Using the prediction metrics of LSSVM as a reference, it can be observed that LSSVM optimized by GA outperforms LSSVM optimized by RIME and PSO. These data demonstrate that GA-LSSVM has the best prediction performance among the compared models.

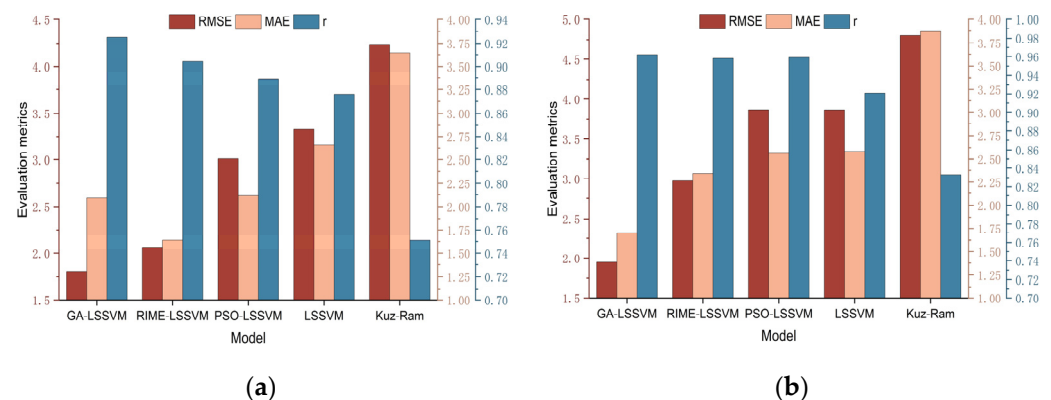


Figure 7. Evaluation metric results: (a) training sets; (b) testing sets.

Figure 8 illustrates the predicted values and their fitting curves for both the training and testing sets, as well as the degree of fit between the fitted curve and the reference curve ($Y = T$). It can be observed that the predicted values from the intelligent models GA-LSSVM, RIME-LSSVM, PSO-LSSVM, and LSSVM exhibit a high degree of fitting with the actual values, while the Kuz–Ram empirical model performs poorly. It is noteworthy that the predicted values from GA-LSSVM are closer to the actual values, indicating a better-fitting degree. The r values for the training set and the test set are 0.925 and 0.962, respectively, demonstrating the superior predictive performance of this model.

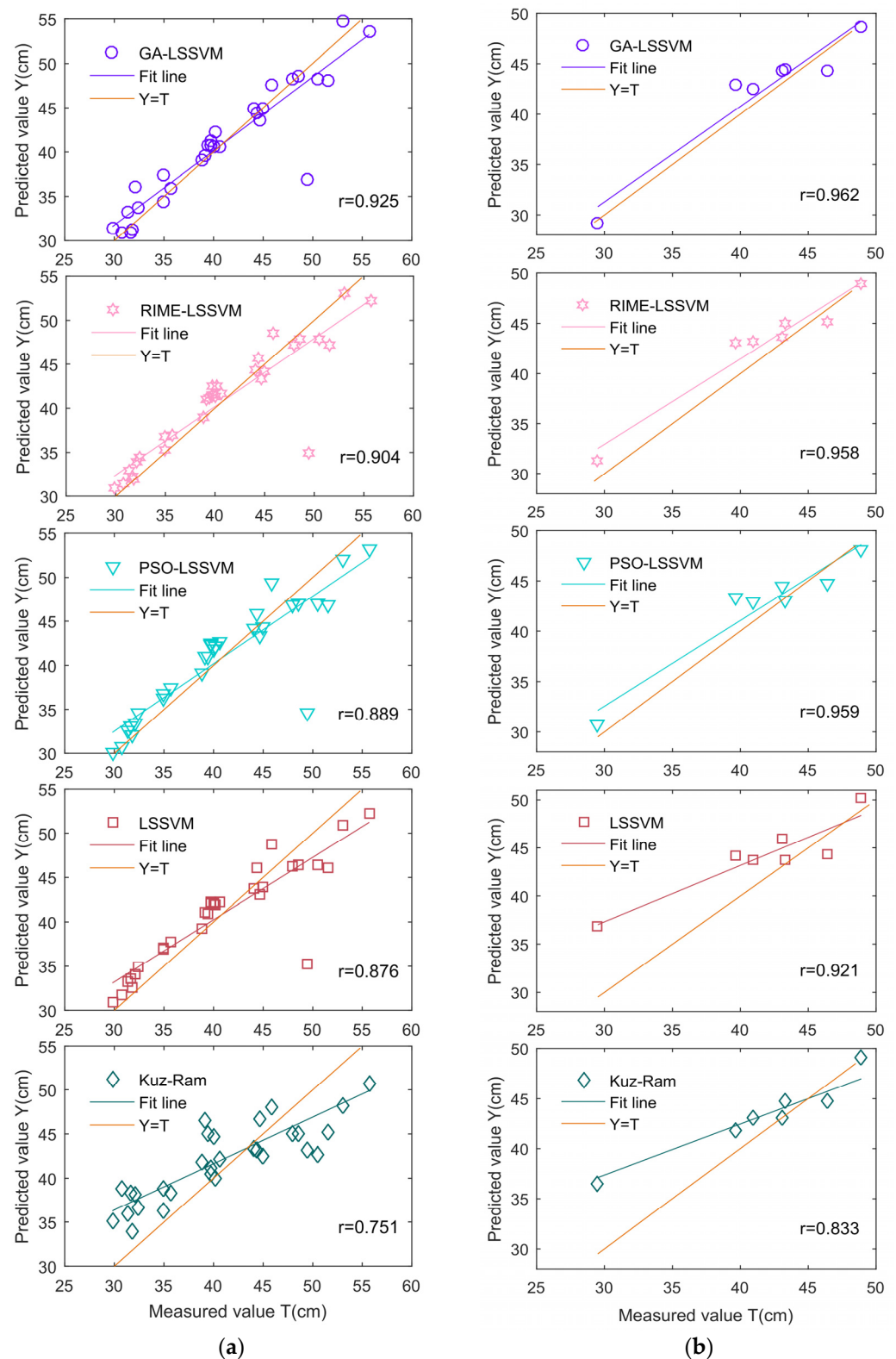


Figure 8. Comparison of predicted results: (a) training sets; (b) testing sets.

5.3. Blasting Parameters Optimization

Reducing the size of ore fragmentation in blasting operations can help control hazardous factors and facilitate ore handling. However, smaller fragmentation implies higher blasting costs. Therefore, it is crucial to find blasting parameters that strike an optimal balance between fragmentation and cost. In this section, we established blasting fragmenta-

tion and blasting cost models related to blasting parameters, respectively serving as two objective functions for blasting parameter optimization. The Pareto front representing the relatively optimal conditions was obtained. By the 90th iteration, a stable Pareto front was formed, resulting in a Pareto optimal solution set for different blasting design parameters, as shown in Figure 9. The distribution of the optimal solution set in the graph indicates uniformity, demonstrating that the surrogate model obtained accurate optimization results in the MOPSO algorithm.

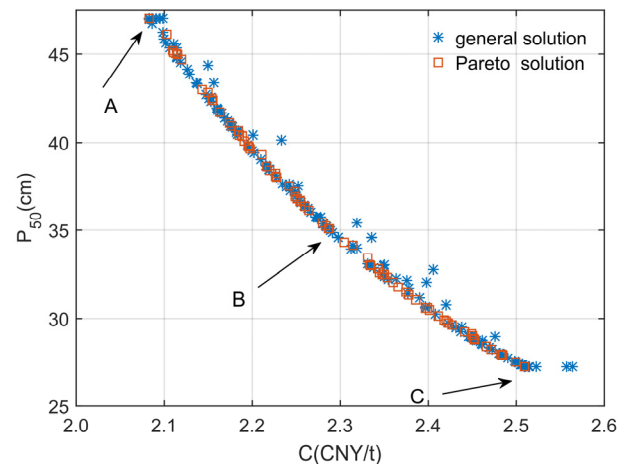


Figure 9. Two-objective Pareto optimal solution set for fragmentation and cost.

Three sets of typical Pareto optimal solutions were extracted, and the blasting parameter optimization values corresponding to the variable denormalization are shown in Table 5. The optimal solutions at points A and C have characteristics where one objective is relatively small while the other is relatively large. Point B, with its two objectives balanced between the optimization extremes, corresponds to a more balanced blasting fragmentation and blasting cost. The blasting design parameters extracted at this point represent the ideal blasting design scheme for this mine, satisfying the relatively optimal solution. Therefore, considering the optimized blasting design parameters at point B in the blasting plan can further enhance the overall production efficiency of the mine. The corresponding optimized blasting design parameters are $S = 5.5$ m, $B = 4.3$ m, $q = 0.51$ kg/m³, and $H_0 = 2.0$ m.

Table 5. Three typical solutions from the Pareto front.

No.	Characteristic Points		S (m)	B (m)	q (kg/m ³)	H_0 (m)
1	A	Variable Values	1.000	0.447	0.848	0.529
		Parameter Values	5.800	4.800	0.450	1.200
2	B	Variable Values	0.782	0.643	1.000	0.338
		Parameter Values	5.500	4.300	0.510	2.000
3	C	Variable Values	0.457	0.515	1.000	0.936
		Parameter Values	5.000	4.000	0.550	2.500

6. Field Verification

Through the optimization of blasting parameters, Scheme B has been identified as the ideal set of blasting design parameters. Therefore, the optimized parameters were incorporated into the blasting design scheme for this mine, and field verification of the blasting optimization effect was conducted. In the mine area, areas with thick magnetite ore veins and relatively intact rock layers were selected for blasting optimization tests. These include platforms 584, 596, and 608, which were chosen to control the influence of varying rock layer properties. Each platform conducted one blasting test, and a total of three blasting results were analyzed. The blasting design scheme is shown in Table 6. The field operations are illustrated in Figure 10.

Table 6. Field test blasting design parameters.

D (mm)	S (m)	B (m)	q (kg/m ³)	H_0 (m)	H (m)
140	5.5	4.3	0.51	2.0	12

Among the variables, D represents the diameter of the blast hole.

**Figure 10.** Field operations.

The results of blasting fragmentation after detonation at platforms 584, 596, and 608 are shown in Table 7. The P_{50} for the three blasting tests were 34.27 cm, 33.66 cm, and 35.34 cm, respectively, which were lower than the mine's average blasting block size of 40.91 cm, indicating a significant improvement in the blasting optimization effect. Furthermore, according to mine statistics, the monthly average cost changes before and after optimization are shown in Table 8. Although the blasting monthly cost increased by CNY 67,600 compared to the previous statistics, the total cost of the entire mining operation chain (blasting, loading, transportation, and crushing) decreased by CNY 139,400, resulting in an annual saving of CNY 1,672,800. This is because reducing the blasting fragmentation comes at the cost of increased expenditure. However, reducing the fragmentation degree of the ore blasting can significantly improve loading and transportation efficiency and reduce costs. The crushing and grinding costs during beneficiation will also decrease substantially with the reduction in feed size. Therefore, the on-site blasting tests demonstrated that the proposed blasting parameter design scheme in this study is reliable, enabling the mine to effectively improve blasting performance and reduce overall costs.

Table 7. Analysis results of P_{50} .

Areas	584	596	608
P_{50} (cm)	34.27	33.66	35.34

Table 8. Change in monthly cost before and after optimization.

Production Phases	Cost before Optimization (10,000 CNY)	Cost after Optimization (10,000 CNY)	Change in Monthly Cost (10,000 CNY)
Blasting	149.92	156.68	+6.76
Loading	72.68	68.76	−3.92
Transportation	139.48	130.62	−8.86
Crushing	121.93	114.04	−7.92
All phases	484.01	470.07	−13.94

7. Conclusions

Blasting prediction and optimization are essential means for achieving controlled blasting and low-cost production in open-pit mines. Reliable prediction and optimization models can provide scientific blasting design parameters to guide actual production in mines. Therefore, this study proposed a GA-LSSVM prediction model and a MOPSO optimization model. The following conclusions are drawn:

1. The GA-LSSVM model, compared with the RIME-LSSVM, PSO-LSSVM, unoptimized LSSVM, and Kuz–Ram empirical model, exhibited more accurate predictive performance in predicting ore blasting fragmentation. It had smaller error metrics and a larger fitting coefficient (RMSE = 1.947, MAE = 1.688, $r = 0.962$), significantly outperforming other prediction models;
2. By using MOPSO to solve the two-objective optimization model of blasting fragmentation and blasting cost, the blasting parameters were optimized as follows: burden (B) = 4.3 m, spacing (S) = 5.5 m, specific charge (q) = 0.51 kg/m³, and subdrilling (H_0) = 2.0 m. The reliability of the scheme was verified through on-site blasting tests, which improved the blasting effect of the mine while reducing the overall cost;
3. There are many factors influencing blasting effects. To effectively carry out blasting prediction and optimization, in addition to increasing the necessary factors, the importance and relationships between different influencing factors should be considered. Furthermore, obtaining more sample data and finding better intelligent models are crucial for obtaining accurate data.

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