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Prediction of Ground Vibration Velocity Induced by Long Hole Blasting Using a Particle Swarm Optimization Algorithm

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Abstract: Obtaining accurate basic parameters for long hole blasting is challenging, and the resulting vibration damage significantly impacts key surface facilities. Predicting ground vibration velocity accurately and mitigating the harmful effects of blasting are crucial aspects of controlled blasting technology. This study focuses on the prediction of ground vibration velocity induced by underground long hole blasting tests. Utilizing the fitting equation based on the US Bureau of Mines (USBM) formula as a baseline for predicting peak particle velocity, two machine learning models suitable for small sample data, Support Vector Regression (SVR) machine and Random Forest (RF), were employed. The models were optimized using the particle swarm optimization algorithm (PSO) to predict peak particle velocity with multiple parameters specific to long hole blasting. Mean absolute error (MAE), mean Squared error (MSE), and coefficient of determination (R^2) were used to assess the model predictions. Compared with the fitting equation based on the USBM model, both the Support Vector Regression (SVR) and Random Forest (RF) models accurately and effectively predict peak particle velocity, enhancing prediction accuracy and efficiency. The SVR model exhibited slightly superior predictive performance compared to the RF model.

Keywords: rock blasting; long hole blasting; peak particle velocity prediction; particle swarm optimization (PSO); Support Vector Regression (SVR); Random Forest (RF)

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1. Introduction

Long hole blasting offers significant benefits, including a large blasting scale, substantial ore yield per blast, and low explosive consumption. Nevertheless, inadequate control of long hole blasting can result in intense vibrations in crucial surface facilities, jeopardizing mine safety and causing legal disputes between enterprises and local communities. The adverse impact of blasting vibrations, particularly on rock mass [1], nearby structures, and essential facilities [2], has garnered increasing attention.

The safety criteria for assessing the seismic effects of blasting primarily focus on the peak particle vibration velocity, frequency, and duration. Typically, regression analysis is applied to the measured blasting vibration data, and empirical formulas are employed to predict the peak particle vibration velocity. However, disparities often arise between the predicted values and the actual measurements on site. This discrepancy can be attributed to the influence of various factors on the site attenuation coefficient k and the α value, making it challenging to accurately represent real results. The effective parameters in the empirical formula are relatively limited, further complicating the situation. Li et al. [3,4] explored the factors influencing blasting vibration attenuation and the energy attenuation law of seismic waves, indicating that rock mass and terrain conditions exert a more substantial influence compared to the blasting conditions.

Researchers have proposed various experiments and techniques to estimate the peak particle velocity (PPV) induced by blasting. The overall objective of experimental studies is to establish empirical equations [5–8] based on the relationship between PPV measurement distance (D) and the amount of explosive charge per delay (W) for each blast, including the Sadowsky formula, USBM formula, U·B formula, Indian formula, and Japanese formula. Although empirical formulas for PPV prediction are convenient and quick, they may not accurately predict under certain specific conditions and may fail to provide high-quality prediction results.

The rapid advancement of artificial intelligence technologies, including genetic algorithms, fuzzy mathematics, neural networks, classification and regression tree methods, and intelligence committee machines, has significantly enhanced the prediction of production blasting vibration velocity in the field of blasting ground vibration analysis. These methods have notably improved prediction accuracy and efficiency. Khandelwal et al. [9–11] and Monjezi et al. [12] utilized various mathematical empirical formulas and BP neural networks to predict on-site blasting-induced ground vibrations, finding the ANN model to be more accurate. In the context of open-pit mines in India, Khandelwal et al. [13,14] conducted research on blasting vibrations, considering factors such as the maximum single-segment charge and distance from the blasting working face to the test point. They utilized the support vector machine (SVM) model, demonstrating its superior accuracy. The SVM model, when based on dual input parameters, outperformed its counterpart utilizing single-input parameters. Hasanipanah et al. [15] applied SVM to predict ground vibrations from blasting at the Bakhtiari Dam in Iran, highlighting the superior predictive performance of the method, particularly concerning peak particle vibration velocity. Cheng [16] established blasting vibration prediction models using generalized regression neural networks and support vector machines. Through an analysis of signals from underground long hole blasting vibrations, the peak particle vibration velocity and main vibration frequency and duration were predicted, finding that the SVM model exhibited the best predictive performance. Xu [17] conducted principal component analysis on multiple factors influencing blasting safety. Utilizing support vector machines, a vibration velocity prediction model was developed. The generalization ability of the model was enhanced by reducing input information dimensions, and the feasibility of increasing blasting charge experiments was assessed. Additionally, Hajihassani et al. [18] and Shang et al. [19] developed ICA-ANN models based on imperial competition algorithms and FFA-ANN models based on firefly algorithms for quarry blasting ground vibration prediction.

Several scholars [20–23] have proposed hybrid models integrating the firefly algorithm (FFA), genetic algorithm (GA), and particle swarm optimization (PSO) with Support Vector Regression (SVR) and artificial neural networks (ANNs) to enhance the accuracy of blasting vibration velocity predictions. Wang et al. asserted that the PSO-SVR model provides a more precise estimation of blasting vibration intensity. Nguyen et al. identified the GA-SVR-RBF model as the optimal method for estimating peak particle velocity (PPV). Additionally, Yang et al. and Chen et al. found the FFA-SVR model to be both efficient and reliable. Zhou et al. [24] employed feature selection methods to identify primary input variables and developed two prediction models, FS-RF and FS-BN, for predicting ground vibrations resulting from quarry blasting, and the FS-RF model exhibited marginally superior accuracy compared to the FS-BN model. Azimi [25] introduced a second-order polynomial intelligent committee machine (SPICM) for open-pit mine bench blasting vibration prediction, which proved to be more accurate and reliable than previous empirical formulas and neural network models. The SPICM model represents a novel advancement in machine learning technology for blasting vibration prediction. Zhang et al. [26] utilized PSO to optimize the hyperparameters of XGBoost for predicting ground vibration. Additionally, several researchers [27–30] have integrated intelligent optimization algorithms with neural networks to build optimized network models for fly-rock distance prediction in blasting scenarios. Fattahi [31] combined relevance vector regression (RVR) with grey wolf optimization (GWO) to establish the RVR-GWO model and incorporated the bat algorithm (BA) to create two intelligent models, RVR-GWO and RVR-BA, aiming to improve the efficiency of ground vibration prediction.

However, it is noteworthy that there are limited studies focusing on the application of the particle swarm optimization algorithm in predicting the environmental effects of mine blasting, such as peak particle velocity. Additionally, there is a gap in the research landscape concerning the PSO-RF intelligent hybrid learning model. Innovative development in the domain of intelligent hybrid learning models based on the particle swarm optimization algorithm remains a crucial area for future exploration.

The objective of this study is to forecast the peak vibration velocity of mass points in underground long hole blasting. This prediction is based on mathematical empirical formula regression, wherein the original blasting test data are partitioned into training and testing sets. Employing the particle swarm optimization (PSO) algorithm to optimize model hyperparameters, two machine learning models, PSO-SVR and PSO-RF, tailored for small sample datasets, are developed. These models are specifically designed for predicting the peak vibration velocity of mass points in underground long hole blasting, considering multiple parameter indicators. The reliability of these machine learning models is assessed using metrics such as the mean absolute error (MAE), mean squared error (MSE), and coefficient of determination (R^2).

2. Long Hole Blasting Vibration Test

Long hole blasting exerts a significant impact on surface structures, necessitating an evaluation and analysis of blasting vibration test data to ensure compliance with relevant national standards regarding blasting vibration hazards. This study focuses on the Hongling Lead–Zinc Mine in Chifeng. The mining method is the stage open stoping method in the room stopes, and the pillar stopes utilize the caving method. Currently, mining operations span from the production midsection at 805 m to 905 m. Mining activities for stopes above 905 m have been completed. During the overall collapse blasting of mine pillars, noticeable surface vibrations occur, profoundly affecting buildings in the mine.

To mitigate the adverse effects of blasting vibrations, tests were conducted at strategic locations on the surface to analyze the impact of the blasting on nearby buildings. The blasting vibration velocity tests were performed using the Mini-Blast I type blasting vibration tester, which comprises sensors, blasting vibration measurement, and microcomputers, among other components (Figure 1). Six measurement points were strategically positioned around the building on the ground surface within the impact area. These points were arranged in a straight line, aligning with the surface testing points and the distribution of long hole blasting cores, as depicted in Figure 2. A total of 138 sets of valid data were collected from nine ground-blasting vibration tests, encompassing 46 sets of valid data related to vertical particle vibration velocity (Table 1). The recorded parameters commonly include the charge weight, the number of delays, the horizontal distance and elevation difference between the blast point and the measurement point, and the peak particle velocity in the vertical direction.

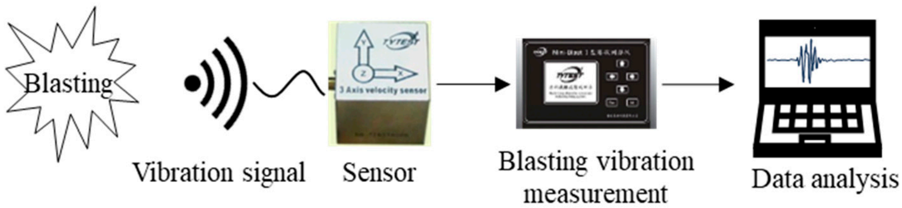


Figure 1. Blasting vibration monitoring system.

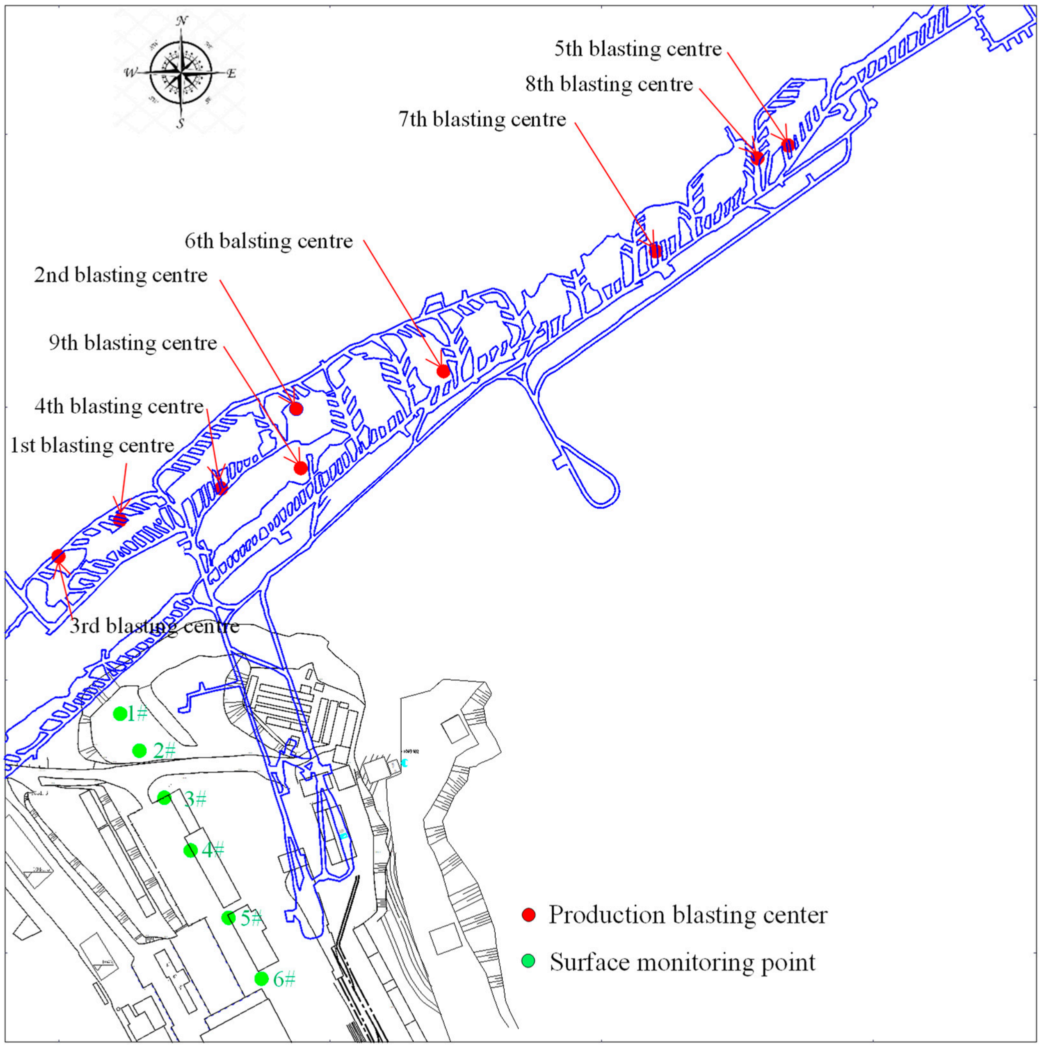


Figure 2. Distribution of monitoring points on the surface and blasting centers in the subsurface.

Table 1. Basic statistics for blasting measurement datasets.

Parameters	Minimum Value	Maximum Value	Mean Value	Standard Deviation
The charge weight (kg)	1500	7198	3153.50	1641.2208
Maximum charge per delay (kg)	319	830	510.09	163.8998
The number of delays	5	17	8.87	3.4616
The horizontal distance between the blasting point and the measurement point (m)	125.98	723.33	400.86	180.8581
The elevation difference between the blasting point and the measurement point (m)	76.00	187.50	160.46	40.1046
The peak particle velocity in the vertical direction (cm/s)	0.0068	1.7200	0.4742	0.4104

3. Mathematical Model of Long Hole Blasting Vibration Velocity

The primary safety control standards for blasting seismic effects are the peak particle vibration velocity and the main vibration frequency. Typically, the prediction model for blasting vibration velocity is a function of the maximum charge weight in a single section and the distance from the blasting working surface to the test point. Its general form is the following:

$$V = kQ^{\alpha}R^{\beta} \tag{1}$$

where V is the blasting vibration intensity (velocity or acceleration); Q is the maximum charge per delay; R is the distance between the blasting working surface and the test point; and k, α, and β are constants relating to geological terrain.

Various situations necessitate different constants (α and β), leading to the derivation of Formula (1) suitable for specific contexts, such as the Sadowsky formula, USBM formula, U·B formula, Indian formula, and Japanese formula. The Sadowsky empirical formula is commonly utilized for predicting the peak vibration velocity of particles. However, discrepancies often exist between the predicted values and the measured values. The literature [32–34] extensively compares different fitting formulas and indicates that the results obtained using the US Bureau of Mines (USBM) formula [6] closely align with reality. This comparison offers valuable insights when exploring the most accurate fitting formula for predicting vibration velocity. In this study, we employ the fitting equation based on the USBM formula for fitting analysis of blasting test data.

The peak particle velocity (PPV) is primarily influenced by factors including the maximum charge per delay (Q), the distance from the blasting working face to the test point (R), the scaled distance (SD), and the site attenuation coefficients (k and α). It can be expressed by the following:

$$\mathrm{PPV} = k(SD)^{\alpha} \tag{2}$$

$$SD = \frac{R}{Q^{1/2}} \tag{3}$$

Forty-six sets of vertical particle vibration velocity correlation monitoring data were employed to establish a relationship between the proportional distance and vertical particle vibration velocity. The site attenuation coefficients, which are related to terrain and geological conditions from the explosion center to the measuring point, were determined. A vertical particle vibration velocity model was formulated, as depicted in Figure 3a. Utilizing this model, the predicted peak vibration velocity of the particle was calculated, resulting in a coefficient of determination (R^2) of 0.2587 between the predicted and measured values. The USBM fitting formula is $V = 72.28(\frac{R}{Q^{1/2}})^{-1.863}$, and the fitting equation is $V = 72.28 \times SD^{-1.863}$.

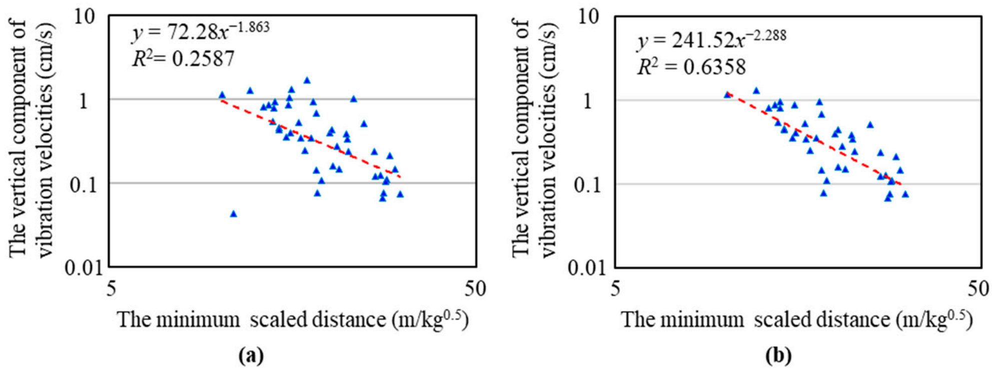


Figure 3. Logarithmic relation between the vertical component of vibration velocities and scaled distances: (**a**) the test data; (**b**) the data excluding five sets of noisy data.

After excluding five sets of noisy data with significant accuracy errors, a vertical particle vibration velocity model within the monitoring range was established, as illustrated in Figure 3b. This model was employed to obtain the predicted peak vibration velocity of the particle, yielding a coefficient of determination (R^2) of 0.6358. The USBM fitting formula is $V = 241.52(\frac{R}{Q^{1/2}})^{-2.288}$, and the fitting equation is $V = 241.52 \times SD^{-2.288}$. In the follow-up, this fitting result was compared and analyzed.

4. Machine Learning Model

The Support Vector Regression (SVR) machine represents a new generation of learning systems tailored for small sample data, characterized by robustness and strong generalization abilities, particularly for unstable data. The hyperparameters of kernel function, penalty factor (C), kernel function deviation (g), and insensitive loss parameter (ε) significantly impact the prediction accuracy of the SVR model. In contrast, RF, an ensemble learning method, employs decision trees (CART) as its basic unit. These trees are trained with randomly selected data and combined feature types, making RF invaluable for estimation, inference, and mapping. Notably, it requires fewer parameter adjustments than the SVM method. Despite these advantages, existing learning models face challenges such as slow learning speeds and susceptibility to local minima. To address these limitations, the particle swarm optimization algorithm, known for its superiority, is employed to optimize the hyperparameters of the model [35]. This optimization enhances the performance of the machine learning model and subsequently improves the accuracy of predicting the particle vibration velocity induced by blasting.

4.1. Support Vector Regression Model

The support vector machine (SVM), introduced by Cortes and Vapnik [36] based on statistical theory, was designed for small sample data. SVM utilizes nonlinear transformations to map original variables into high-dimensional feature spaces. It constructs linear classification functions within these high-dimensional spaces and subsequently transforms them into quadratic programming problems to yield globally optimal solutions. The topological structure of SVM is entirely defined by support vectors. Vapnik et al. introduced the insensitive loss function ε through support vector classification (SVC) and developed SVR. The resulting mathematical model is represented as a curve within a multidimensional space. By employing the insensitive loss function ε, an "ε-tube" enveloping the curve and training points is derived. Sample points situated on the tube wall are termed "support vectors". In regression fitting analysis using SVR, it seeks an optimal classification plane that minimizes the error of all sample points to the optimal plane. SVR demonstrates high accuracy and robustness when addressing small sample sizes, nonlinear, high-dimensional complex problems, and local optimal problems. Figure 4 illustrates the nonlinear SVR.

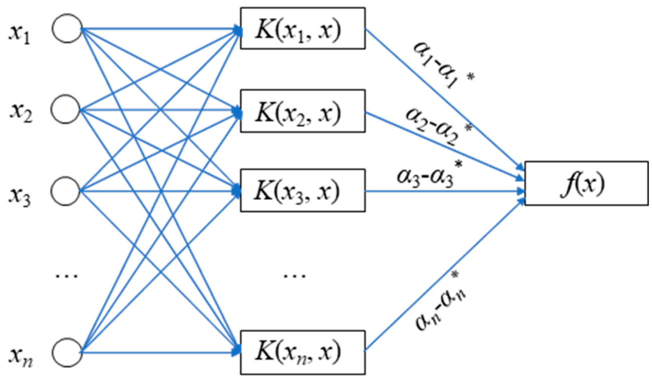


Figure 4. Basic model of nonlinear Support Vector Regression.

4.2. Random Forest Model

The Random Forest algorithm [37,38] represents a novel machine learning approach capable of integrating predictions from multiple decision trees with exceptional accuracy. First, the bootstrap [39] sampling technique with replacement is applied to randomly extract k subsets from the original dataset, with each subset comprising 2/3 of the original dataset, thus averting overfitting. Second, regression decision trees are derived from the random subsets, leading to the formation of a forest consisting of k regression decision trees. During the development of each tree, m features ($m \leq N$) are randomly chosen from all N feature variables, and the optimal attribute for internal node branching is determined based on the minimum Gini coefficient principle. Each branch represents the output subset of a specific value range in the characteristic attribute test. Third, the prediction outcomes of the k decision trees are merged, and the mean value of the decision tree predictions establishes the anticipated value of the new sample. In each sampling iteration, approximately 1/3 of the data remains untouched, and these out-of-bag (OOB) data are utilized for internal error estimation (OOB error). The RF method enhances the prediction accuracy of the model without significantly escalating the computational load. Moreover, the introduction of randomness heightens the dissimilarities between the trees, thereby augmenting the model's generalization capability (Figure 5).

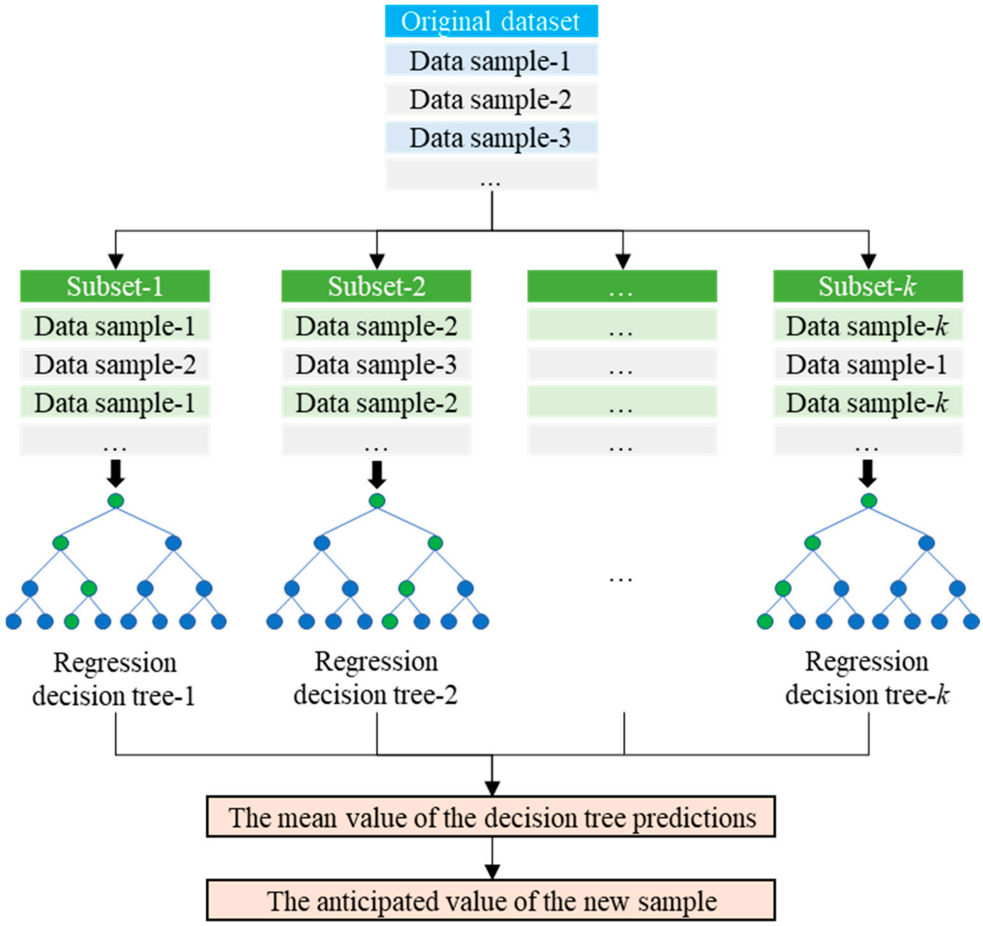


Figure 5. Random Forest algorithm model.

4.3. Hyperparameter Optimization

The selection of hyperparameters in machine learning significantly influences both learning and generalization capabilities, making the choice of optimal model parameters a pivotal concern. In the SVR model established on the RBF kernel function, key parameters include the C and g. When the C value is high, the result is overfitting, while the C value being low yields a simpler learning machine but carries higher risks. The kernel function deviation g is intricately linked to the input space range and the width of the learning sample. In constructing the RF model, the number k of decision trees and the number m of random variables used for node division are crucial customizable parameters that require optimization. Intelligent optimization algorithms, such as the PSO algorithm [40–42], are inspired by biological evolution and physical phenomena, employing a random search strategy to mimic the search behavior of individuals. Throughout the search process, each individual adapts their search strategy based on personal and global experiences, aiming to identify optimal parameters within the solution space. The PSO algorithm, rooted in swarm intelligence theory and emulating the foraging behavior of birds, achieves optimization objectives through cooperative efforts among group members. Due to its straightforward logic, ease of implementation, parallel global search capabilities, and intelligent search approach, the PSO algorithm was selected to optimize the internal parameters of the machine learning model. Figure 6 illustrates the specific process of optimizing the model parameters using the PSO algorithm.

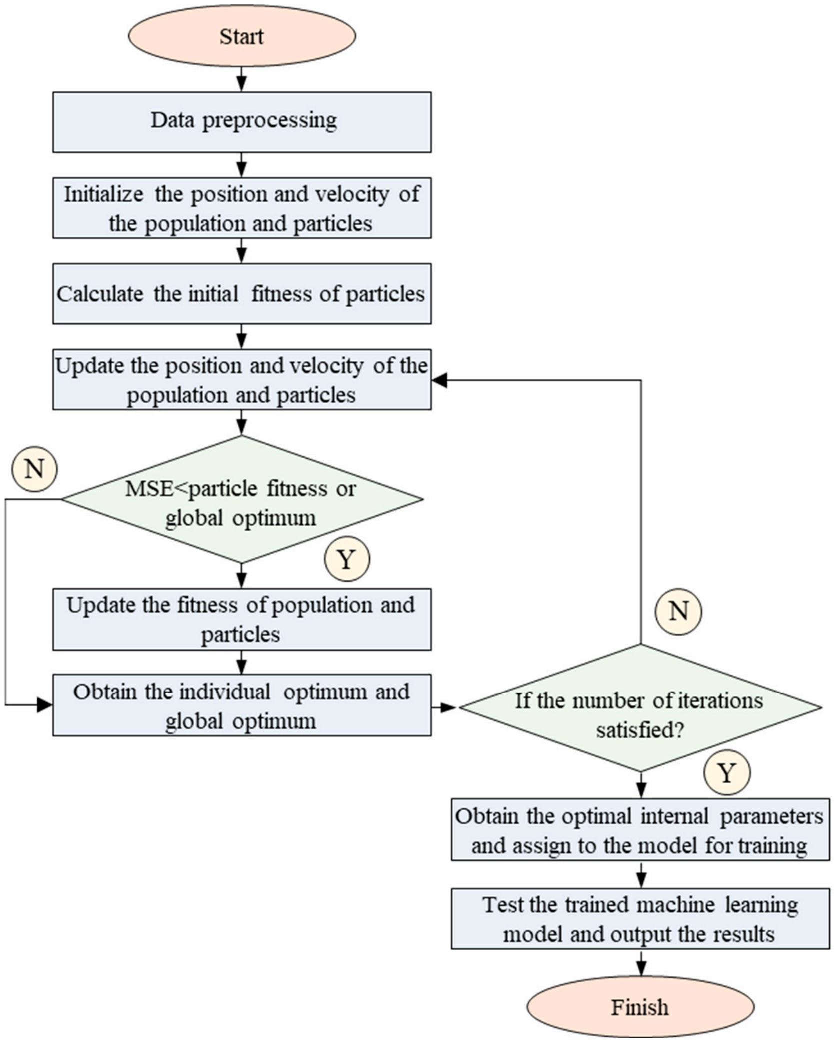


Figure 6. Flowchart of particle swarm optimization-based machine learning.

4.4. Model Performance

The following main statistical indicators are used to evaluate the predictive performance of machine learning models and mathematical empirical formulas.

Mean Absolute Error (MAE): MAE quantifies the average magnitude of errors in the predictions, compared to actual values.

$$\text{MAE} = \frac{1}{n}\sum_{i}^{n}\left|x_i^{\text{real}} - x_i^{\text{pred}}\right| \tag{4}$$

Mean Squared Error (MSE): MSE computes the average squared discrepancies between predicted and actual values.

$$\text{MSE} = \frac{1}{n}\sum_{i}^{n}\left(x_i^{\text{real}} - x_i^{\text{pred}}\right)^2 \tag{5}$$

Coefficient of Determination (R^2): R^2 represents the proportion of variance in the dependent variable that can be explained by the independent variables.

$$R^2 = 1 - \frac{\sum_i^n \left(x_i^{\mathrm{real}} - x_i^{\mathrm{pred}}\right)^2}{\sum_i^n \left(x_i^{\mathrm{real}} - \overline{x^{\mathrm{real}}}\right)^2} \tag{6}$$

Here, n is the total number of data points; x_i^{real} and x_i^{pred} are the measured values and predicted values, respectively; and $\overline{x_i^{\mathrm{real}}}$ is the mean value of the measured values.

5. Vibration Velocity Prediction of Long Hole Blasting

5.1. Peak Particle Velocity Prediction Using the Support Vector Regression Model

To process the 41 sets of blasting test data, 35 sets derived from the first seven long hole blasting events constituted the training set, and the remaining six sets from the eighth and ninth events were designated as the test set, all of which underwent normalization. The radial basis function was chosen as the kernel function, and the MSE served as the initial fitness metric for the model. Employing the PSO intelligent algorithm with parameters detailed in Table 2, 5-fold cross-validation technology was applied. The 35 training datasets were randomly split into five groups, with four groups utilized for training and one group for model verification. This process was repeated five times, optimizing the model using the C and g resulting in the smallest MSE. The PSO-SVR model was employed for predictions involving 12 mass point peak vibration velocities. The optimized model yielded C ranging from 1.8746 to 170.8970 and g ranging from 0.1957 to 4.2967 (Table 3). Interestingly, penalty factor C and kernel function deviation g exhibited a negative correlation, with an R^2 of 0.6011. Utilizing these optimized parameters, an SVR model was constructed. Predictions were made for both the training and test sets, and comparisons were drawn against measured values. The MAE, MSE, and R^2 for the predicted and measured peak vibration velocities of the mass point in the training set were 0.0796, 0.0172, and 0.8525, respectively. The main indicator curves demonstrated relative stability (Figure 7). Correspondingly, the mean MAE, MSE, and R^2 for the predicted and measured peak vibration velocities of the mass point in the testing set were 0.1426, 0.0416, and 0.8023, respectively. Notably, the fourth dataset exhibited superior performance (testing set, MAE: 0.1022, MSE: 0.0252, and R^2: 0.9645).

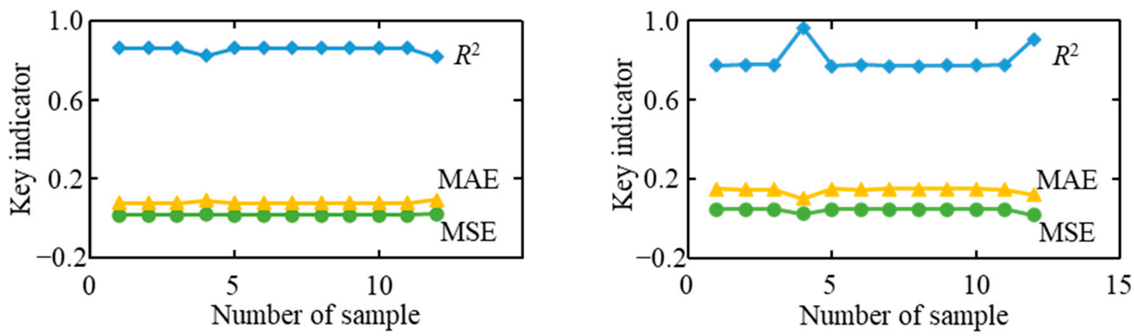
Table 2. Main parameters of the PSO.

Parameters	Value
Number of iterations (m)	1000
Number of particles (n)	500
Penalty factor C_1	2
Penalty factor C_2	2
Inertia weight (ω_{ine})	0.8
Constrained weight (ω_{con})	0.5

In this study, an SVR model with a penalty factor C of 15.2756 and kernel function deviation g of 0.6742 was employed, which is determined by the result of the fourth dataset. In contrast, utilizing the fitting equation based on the USBM formula resulted in test set indices of 0.0948, 0.0275, and 0.7877, respectively (Table 4). Comparing the results, the MAE increased by 7.78%, the MSE decreased by 8.37%, and the R^2 increased by 22.44%. Figure 8 illustrates the curve representing the predicted and measured peak vibration velocities of the testing set, while Figure 9 depicts the comparison curve between the predicted and measured peak vibration velocities, with an impressive R^2 value of 0.9645.

Table 3. Key indicators in predicting PPVs by the PSO-SVR model.

Number	Training Set (35 Groups)					Testing Set (6 Groups)		
	Penalty Factor, C	Kernel Function Deviation, g	MAE	MSE	R^2	MAE	MSE	R^2
1	1.8831	4.2451	0.0779	0.0166	0.8587	0.1498	0.04589	0.7735
2	2.0851	4.1060	0.0772	0.0165	0.8595	0.1473	0.04537	0.7795
3	2.0450	4.1143	0.0775	0.0166	0.8590	0.1474	0.04533	0.7790
4	15.2756	0.6742	0.0885	0.0205	0.8219	0.1022	0.0252	0.9645
5	1.8746	4.2967	0.0776	0.0165	0.8594	0.1506	0.04617	0.7709
6	2.0812	4.1041	0.0773	0.0165	0.8594	0.1473	0.04534	0.7793
7	1.9725	4.2509	0.0771	0.0164	0.8603	0.1499	0.04607	0.7726
8	1.9340	4.2496	0.0775	0.0165	0.8597	0.1498	0.04598	0.7730
9	2.0254	4.1934	0.0771	0.0165	0.8601	0.1488	0.04579	0.7746
10	1.9608	4.1986	0.0776	0.0165	0.8592	0.1490	0.04573	0.7750
11	2.0773	4.1084	0.0773	0.0165	0.8594	0.1473	0.04536	0.7789
12	170.8970	0.1957	0.0929	0.0208	0.8138	0.1213	0.01635	0.9074
Mean value	-	-	0.0796	0.0172	0.8525	0.1426	0.0416	0.8023



(**a**) Training set (**b**) Testing set

Figure 7. Key indicator curves in predicting PPVs by the PSO-SVR model.

Table 4. Key indicators in predicting PPVs for testing datasets.

MAE	MSE	R^2	Model
0.0948	0.0275	0.7877	The fitting equation based on USBM formula
7.78%	−8.37%	22.44%	PSO-SVR
7.99%	−0.52%	2.17%	PSO-RF

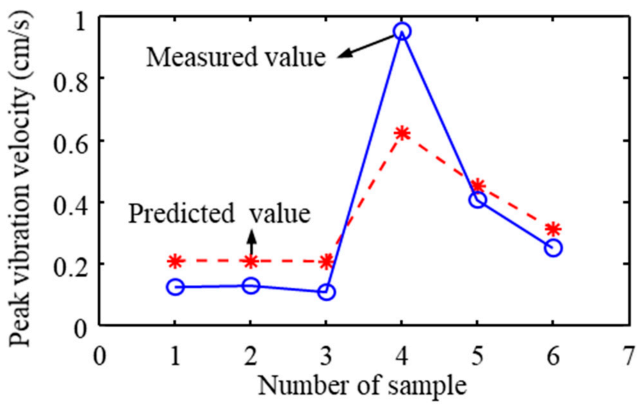


Figure 8. The relation between PPVs predicted by the PSO-SVR model and measured PPVs for testing datasets.

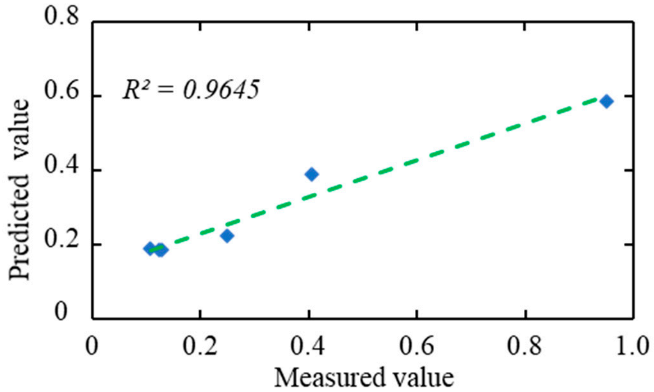


Figure 9. Predicted PPVs by the PSO-SVR model versus measured PPVs.

5.2. Peak Particle Velocity Prediction Using Random Forest Model

The training process for the RF aligned with the methodology used for SVR. Employing the PSO algorithm (main parameters listed in Table 2), the training set data were iteratively optimized to determine the number of decision trees (k = 23) and the random variable number for splitting nodes (m = 3) in the RF model. Utilizing these optimized parameters, an RF model was constructed to predict the test set data, and the results were compared with the measured values. The MAE, MSE, and R^2 between the final prediction values of the peak particle vibration velocity for the testing set and the measured values were 0.1024, 0.0274, and 0.8048, respectively (Table 5). Comparing the results with those of the fitting equation based on the USBM formula, the MAE increased by 7.99%, the MSE decreased by 0.52%, and the R^2 increased by 2.17% (Table 4).

Table 5. Key indicators in predicting PPVs by the PSO-RF model.

The Number of Decision Trees, *k*	The Random Variable Number for Splitting Nodes, *m*	MAE	MSE	R^2
23	3	0.1024	0.0274	0.8048

The optimized RF model, characterized by a decision tree count (k) of 23 and a random variable number (m) of 3 for splitting nodes, was employed. Figures 10 and 11 depict the prediction curve for the mass peak vibration velocity in the test set compared with the measured values. The correlation curve between the predicted and measured values is also presented in Figure 11, demonstrating an R^2 of 0.8048.

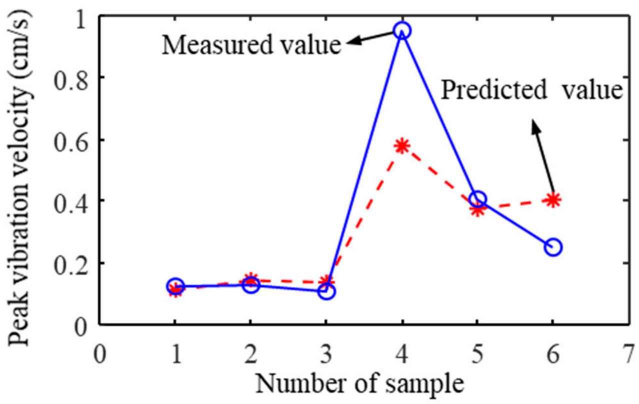


Figure 10. The relation between PPVs predicted by the PSO-RF model and measured PPVs for testing datasets.

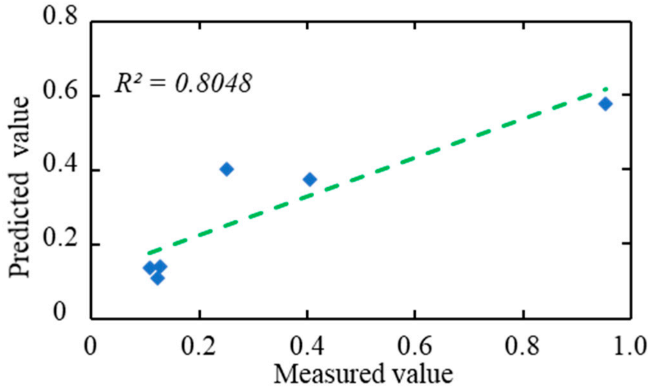


Figure 11. Predicted PPVs by the PSO-RF model versus measured PPVs.

6. Conclusions

(1) Vibration monitoring tests were conducted on underground long hole blasting at critical surface facilities. The measured data of the long hole blasting vibration velocity were fitted using the fitting equation based on the USBM formula, which demonstrated smaller errors. Subsequently, a vertical mass point peak vibration velocity model was established specifically for the Hongling Lead–Zinc Mine. After eliminating noise data, the R^2 between the predicted and measured values of the mass point peak vibration velocity increased by 0.3771.

(2) Leveraging the particle swarm intelligence optimization algorithm, two machine learning model programs tailored for small sample data, PSO-SVR and PSO-RF, have been meticulously crafted. Through iterative optimization using the training set data, the penalty factor C of the SVR model was determined to be 15.2756, and the kernel function deviation g is 0.6742. Simultaneously, the decision tree count (k) of the RF model is set as 23, and the number of random variables for splitting nodes (m) is set as three.

(3) Two machine learning models, PSO-SVR and PSO-RF, were developed with optimized parameters to predict the peak vibration velocity of particles resulting from underground long hole blasting. Compared to the fitting equation based on the USBM formula, both the PSO-SVR and PSO-RF models notably improve the precision. Specifically, the PSO-SVR model (with an impressive R^2 value of 0.9645) exhibits slightly superior performance in predicting the test set data compared to the PSO-RF model (with an R^2 value of 0.8048).

(4) The prediction of extreme points of measured values by PSO-SVR and PSO-RF for both the training and test sets did not meet ideal results. This discrepancy could be attributed to the complexity of the correlation between the input and output parameters in the test data, as well as the limited number of measured data points. The challenges need to be further studied to address this. Despite these limitations, both learning models remain effective and suitable tools for predicting the particle vibration velocity resulting from blasting activities. Importantly, they offer viable alternatives to performing time-consuming and cumbersome tests on site.

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