

Research on blasting vibration prediction based on BFO-LSSVM and its engineering application

Yong Yang², Zhongyuan Qi², Jian Liu², Peng Li³, Zhaowei Yang^{1,3,*}

¹ Hubei Key Laboratory of Blasting Engineering of Jiangnan University, Wuhan, 430056;

² Wuling Power Corporation LTD. Changsha 410010;

³ Key Laboratory of Geotechnical Mechanics and Engineering of Ministry of Water Resources, Changjiang River Scientific Research Institute, Wuhan 430010;

Abstract. In order to realize the accurate prediction of blasting vibration, the LS-SVM optimization model based on BFO algorithm is constructed with the help of bacterial foraging algorithm (BFO) and least squares support vector machine (LS-SVM) theory. 30 groups of blasting data are used as training samples to test the prediction accuracy of the model, and the main factors affecting the propagation of blasting vibration are selected as the input factors, such as single shot charge, blasting center distance, elevation difference, blockage, hole depth and other factors as the input factors, and blasting vibration as the output factor of the prediction model. The results show that the prediction accuracy of BFO-LSSVM model is higher than that of LS-SVM model under the same sample size. Taking the measured vibration data of excavation blasting of Wuqiangxi power station as an example, the average error of BFO-LSSVM model is 5.57%, which verifies the feasibility and practicability of the prediction model.

Keywords: Blasting vibration; forecast; Support vector machine; BFO-LSSVM;

1. Introduction

In order to serve the goals of peaking carbon emissions and achieving carbon neutrality, as well as building a new type of power system, State Grid actively promotes the construction of pumped storage power stations. In the construction process of pumped storage power stations, it is inevitable to face excavation construction of rock slopes and underground power plants. Drilling and blasting technology, with its advantages of high efficiency and economy, is still the most important technical means in rock excavation in China. However, during the explosion process, the energy released by explosives is not only used for rock fragmentation, but also partially propagates in the form of seismic waves, causing certain damage to facilities, equipment, and buildings along the propagation path. This increases the difficulty of construction to a certain extent and also affects social stability [1-2]. Therefore, how to quickly and accurately predict blasting vibration is of great significance for the safety production of pumped storage power station construction.

In recent years, domestic and foreign researchers have conducted detailed research on the prediction of blasting vibration. Sun Saisai et al. [3] conducted a prediction analysis of blasting vibration at different elevations by introducing a standard normal distribution and using probability formulas. The prediction results were significantly better than the Sadovsky formula. Qin Xiaoxing et al. [4] conducted an analysis of the attenuation law of blasting vibration propagation under the influence of conditions such as step terrain based on the measured vibration data of step model blasting. Scholars such as Jiang Nan and Chen Ming [5-6] have also conducted detailed research on the impact of terrain and landforms on blasting vibration. The above research is mostly based on the traditional Sadovsky formula or improved on it. In practical engineering, the Sadovsky formula considers fewer factors and has a large prediction error, which can only be applied to specific blasting projects. With the development of computer network technology, domestic and foreign scholars have developed a large number of soft science methods with strong nonlinear processing ability and real-time learning characteristics, such as BP neural network, bacterial foraging algorithm, and support vector machine. Khandelwal and Singh et al. [7-11] respectively studied the application of BP neural network and support vector machine in blasting vibration prediction. They

trained and optimized the prediction model using a large amount of measured blasting vibration data as samples, and compared the prediction results with traditional empirical prediction formulas, confirming the superiority of the prediction model. Shi Xiuzhi et al. [12] effectively reduced the prediction space of neural networks, accelerated the efficiency of model operation, improved prediction accuracy, and applied the model to predict the amplitude of blasting vibration by introducing rough sets. Wang Tao et al. [13] conducted research on the prediction of millisecond blasting vibration using the BP neural network method, further demonstrating the effectiveness of the BP neural network prediction model.

In summary, achieving accurate and rapid prediction of blasting vibration by comprehensively considering factors such as rock mass properties, explosive types, and blasting parameters has become one of the hot topics in the field of engineering blasting, and has achieved relatively rich results. However, the existing prediction models based on empirical formula method consider fewer factors, and the prediction results of artificial neural network method are greatly affected by the number of hidden layer nodes, resulting in poor learning performance.

Based on this, this article relies on measured blasting vibration data and introduces the bacterial foraging algorithm (BFO) into the least squares support vector machine (LSSVM). By utilizing the strong global search ability of the bacterial foraging algorithm, the parameters of the LSSVM are optimized, and a BFO-LSSVM blasting vibration prediction model is constructed to accurately predict the peak of blasting vibration.

2. least squares support vector machine algorithm

2.1 Support Vector Machine

Support Vector Machine is a two-level classification model proposed by Vapnik et al. SVM has the characteristics of high model accuracy, excellent adaptability, and excellent robustness and generalization ability. In the prediction of blasting fragmentation results, due to the numerous factors that affect the distribution of fragmentation, SVM method is used to map the nonlinear relationship between the results of fragmentation distribution and multiple influencing factors such as rock properties, explosive types, and blasting parameters into a high-dimensional linear relationship by selecting a mapping function (kernel function), thereby achieving accurate prediction of blasting fragmentation.

2.2 Least Squares Support Vector Machine

Least Squares Support Vector Machine [42] [43] is an improved algorithm for SVM, which uses the square term of the comparison objective function error as the optimization evaluation criterion for the algorithm, and transforms the constraint conditions in the calculation process into equality constraints to reduce the difficulty of solving and improve the efficiency of solving. The basic principle is as follows:

For the samples (x_i, y_i) , using the same algorithm theory as support vector machines, the objective function of the least squares support vector machine is constructed as follows:

$$\min \frac{1}{2} \|\omega\|^2 + \frac{1}{2} \gamma \sum e_i^2 \quad (1)$$

In the formula, e_i represents the error; γ is a regularization parameter that can control error accuracy; By introducing the Lagrange operator, equation (2) can be transformed into:

$$\begin{aligned} \min J = & \frac{1}{2} \|\omega\|^2 + \frac{1}{2} \gamma \sum e_i^2 - \\ & \sum \lambda_i [\omega^T \varphi(x_i) + b + e_i - y_i] \end{aligned} \quad (2)$$

Further solving can lead to

$$\left\{ \begin{array}{l} \frac{\partial J}{\partial \omega} = 0 \rightarrow \omega = \sum \lambda_i \varphi(x_i) \\ \frac{\partial J}{\partial b} = 0 \rightarrow \omega = \sum \lambda_i = 0 \\ \frac{\partial J}{\partial e_i} = 0 \rightarrow \lambda_i = \gamma e_i \\ \frac{\partial J}{\partial \lambda_i} = 0 \rightarrow \omega^T \varphi(x_i) + b + e_i - y_i = 0 \end{array} \right. \quad (3)$$

Solving a system of linear equations yields:

$$\begin{bmatrix} b \\ \lambda \end{bmatrix} = \begin{bmatrix} 0 & E^T \\ E & K + \frac{1}{\gamma} \end{bmatrix} \begin{bmatrix} 0 \\ \gamma \end{bmatrix} \quad (4)$$

Among them, $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_n]^T$, $E = [1, 1, \dots, 1]^T$ is the unit column vector, and K refers to the kernel function; $E = [1, 1, \dots, 1]$ is the identity matrix. According to this equation, the values of λ_i and b can be calculated, and then the prediction model of LS-SVM can be calculated. The expression is as follows:

$$y = \sum \lambda_i K(x_i, x_j) + b \quad (5)$$

3. BFO-LSSVM model

3.1 Bacteria Foraging Optimization

The bacterial foraging optimization algorithm is an intelligent optimization algorithm proposed by Passion in 2002 based on the foraging behavior of *Escherichia coli*. A large amount of data analysis shows that this algorithm has advantages such as strong global search ability and strong robustness. This algorithm solves engineering problems based on four basic behaviors of foraging: tendency, aggregation, replicability, and migration.

(1) Tendency: During the foraging process of *Escherichia coli*, there are two actions: rotation and swimming. Rotation is to find a new direction of motion, while swimming is to continue moving in the previous direction. The essence of directional operation is to simulate these two actions.

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i) \Delta(i)}} \quad (6)$$

In the formula: represents the position of bacteria i after the j -th chemotaxis, k -th replication, and l -th dispersal.

(2) Aggregation: During the foraging process of bacteria, different individuals have two forces: repulsion and attraction. repulsion forces bacteria to forage alone in a certain area, while attraction forces bacteria to gather in a specific area. The mathematical expression for its aggregation is:

$$J_{cc}(\theta, P(j, k, l)) = \sum J_{cc}(\theta, \theta^i(j, k, l)) \quad (7)$$

(3) Reproduction: The evolutionary process of bacteria follows the principle of survival of the fittest, with bacteria with strong foraging abilities replicating. The expression is:

$$J^i = \sum J(i, j, k, l) \quad (8)$$

(4) Migration: When a bacterial environment undergoes a mutation, the algorithm provides a certain probability to simulate the bacterial migration process, allowing the bacterial individual to generate a new individual under the condition of probability of death. This behavior is beneficial for the algorithm to jump out of the local optimal solution.

3.2 LSSVM model based on BFO optimization

Adopting the BFO algorithm to optimize LS-SVM parameters, and using the optimized LS-SVM to predict the peak value of blasting vibration. Firstly, read the measured data of blasting vibration, divide the data into training samples and prediction samples, and then use the BFO algorithm to calculate the optimal parameters of LS-SVM. Then, substitute the obtained values of the optimal parameters into LS-SVM to train the training samples. Finally, analyze the predicted samples and calculate the corresponding results.

4. Engineering Case Analysis

4.1 Project Overview

The Wuqiangxi Hydropower Station is located in the middle and lower reaches of the Yuanshui River, within the territory of Yuanling County, Hunan Province. The upstream is 73km away from Yuanling County and the downstream is 108km away from Changde City. The Wuqiangxi Hydropower Station is a first-class (I) type project that focuses on power generation and has comprehensive benefits such as flood control and navigation. The installed capacity of the power station is 1200MW (5×240 MW, with an average annual power generation of 5.329 billion kW · h, annual utilization hours of 4441 hours, and a water utilization rate of 80.94%.

The intake adopts a shore tower layout, and the intake cofferdam adopts a reserved rock ridge+concrete cofferdam method. The minimum straight-line distance from the Wuqiangxi Dam is about 80m, and the building level is level 4. The flood design standard is once every 10 years, and the corresponding design water level is 108.00m. Considering wave height and minimum safety superelevation, the top elevation of the intake cofferdam is 110.00 meters. The layout plan of the reserved rock slope and concrete cofferdam at the water inlet is shown in Figure 1, and the cross-sectional view of the reserved rock slope and concrete cofferdam is shown in Figure 2.

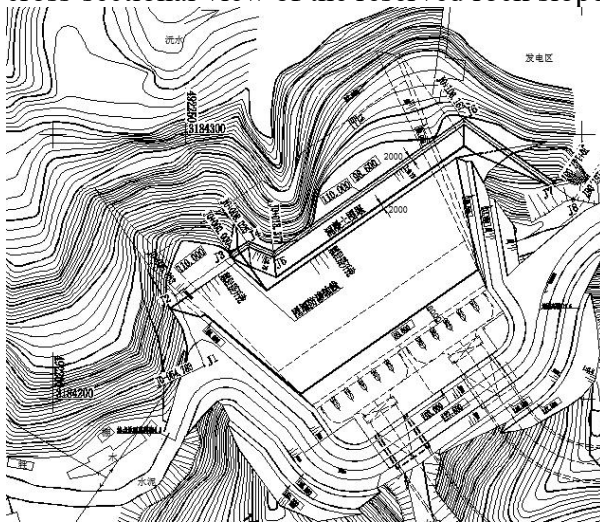


Fig. 1 Layout plan of reserved rock ridges and concrete cofferdams at the water inlet

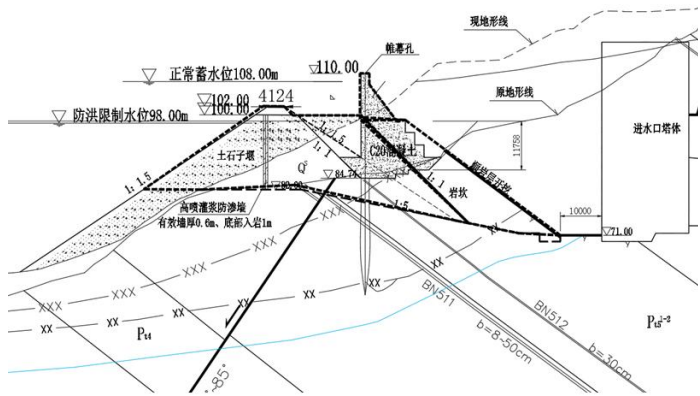


Fig. 2 Cross section diagram of reserved rock ridges and concrete cofferdams

To further evaluate the degree of damage to adjacent buildings under the action of blasting seismic waves, on-site blasting vibration monitoring is required. The blasting test results are shown in Table 1.

4.2 Analysis of Prediction Results

Take 30 sets of measured vibration data from the demolition blasting of the cofferdam at Wuqiangxi Hydropower Station. The first 25 sets of data are training samples, and the last 5 sets are model prediction accuracy verification test samples. Relative error and average absolute error are

taken as calculation indicators to evaluate the prediction accuracy of LS-SVM and BFO-LSSVM prediction models. The measured blasting vibration data is shown in Table 1. The predicted results of each model are shown in Table 2 and Figure 3.

Table 1 List of Measurement of Blasting Vibration Data

	maximum charge amount among delays groups /kg	horizontal distance/m	vertical distance /m	PPV/(cm/s)
1	19.8	82	0	0.54
2	19.8	124	0	0.40
3	19.8	176	0	0.14
4	19.8	223	0	0.15
5	19.8	280	0	0.13
6	19.8	46	0	1.13
7	8.8	34	0	2.01
8	8.8	84	0	0.39
9	8.8	134	0	0.25
10	8.8	184	0	0.09
11	19.8	223.60	238.80	0.073
12	19.8	249.71	232.31	0.091
13	19.8	284.15	227.02	0.093
14	19.8	380.80	212.15	0.035
15	19.8	574.86	149.37	0.015
16	19.8	255.26	232.42	0.104
17	19.8	284.15	227.02	0.054
18	19.8	335.67	220.29	0.067
19	19.8	380.80	212.15	0.051
10	19.8	574.86	149.37	0.026
21	8.8	223.60	238.80	0.029
22	8.8	255.26	232.42	0.040
23	8.8	335.67	220.29	0.037
24	8.8	380.80	212.15	0.016
25	8.8	594.53	145.80	0.014
26	19.8	223.60	238.80	0.069
27	19.8	249.71	232.31	0.051
28	19.8	284.15	227.02	0.080
29	19.8	707.60	138.22	0.031
30	19.8	574.86	149.37	0.032

Table 2 Comparison of Prediction Results of Various Models

Serial Number	measured value	LS-SVM		BFO-LSSVM	
		predictive value	relative error	predictive value	relative error
26	0.069	0.057	-18.07%	0.059	-14.16%
27	0.051	0.048	-6.21%	0.051	-0.96%
28	0.08	0.077	-3.48%	0.078	-2.85%
29	0.031	0.033	7%	0.033	6.63%
30	0.032	0.016	-50.65%	0.031	-3.26%

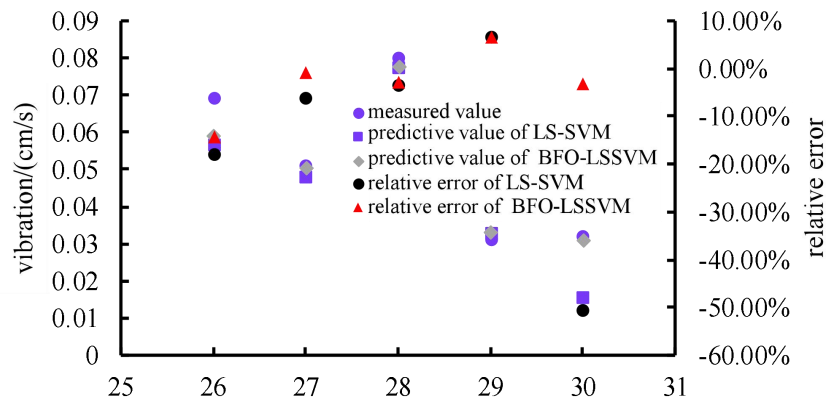


Fig. 3 Prediction results of each model

Based on on-site measurement of blasting vibration results and corresponding blasting design parameters, a BFO-LSSVM prediction model was established to predict the peak value of blasting vibration, and compared with the measured values.

From Table 2, it can be seen that the average absolute relative errors of the two different prediction methods are 16.98% and 5.57%, respectively. From Figure 3, it can be seen that the BFO-LSSVM model has a high degree of fit. Except for the relatively large relative error of the predicted values in the first group, the other four groups of prediction results are quite good; On the other hand, the LS-SVM model has low prediction stability and there is a problem of large errors in individual predicted sample values. In summary, the LSSVM model optimized by BFO has higher prediction accuracy and stronger data fitting ability than the original model, which can meet the practical needs of engineering.

5. Conclusion

(1) A blasting block size prediction model based on BFO-LSSVM was constructed using the least squares support vector machine theory. By comparing the prediction results of the LS-SVM model and the BFO-LSSVM model, the results show that the BFO algorithm can optimize the performance of the LS-SVM model to a certain extent, reducing the error from 16.98% to 5.57%. That is to say, the BFO-LSSVM model has higher prediction accuracy than the LS-SVM model in predicting the peak value of blasting vibration.

(2) Based on the BFO-LSSVM block size prediction model, peak prediction was conducted on the measured blasting vibration data during the cofferdam demolition process, with an average prediction error of 5.57%. This further proves the feasibility of peak prediction of blasting vibration under determined blasting parameters and on-site rock conditions, and is of great significance for blasting vibration control in the excavation process of underground power plants.

(3) When predicting the peak value of blasting vibration based on small samples, the accuracy of training sample data has a significant impact on the accuracy of model prediction results. At the same time, the application process of the BFO-LSSVM model did not consider the influence of structural surfaces on vibration propagation attenuation. The next step will be to conduct research in this area.

Declaration of Competing Interest: No

Acknowledgements

The authors are grateful for the supports from the National Natural Science Foundation of China (Nos. 52109148, 52079009 and 52279093), the Foundation of Hubei Key Laboratory of Blasting Engineering (No. BL2021-14).

Reference

- [1] Song Guangming, Shi Xiuzhi, Chen Shouru. New method for determining blasting vibration damage criterion on open-pit slope and its application [J]. Journal of central south university technology, 2000, 31(6):485—488.
- [2] Khandelwal M, Singh T N. Evaluation of blast-induced ground vibration predictors[J]. Soil Dynamics and Earthquake Engineering, 2007, 27(2):116—125.
- [3] Sun Saisai, Chi Enan, Niu Guoting, et al. Application of standard normal distribution in evaluation and prediction of blasting vibration[J]. Mining Research and Development, 2020, 40(4):35-40.
- [4] Qin Xiaoxing, Pu Chuanjin, Xu Jingui, et al. Propagation and predictive analysis of blasting vibration in step slope[J]. Nonferrous Metals(Mining Section), 2018, 70(3):45-50.
- [5] Jiang Nan, Zhou Chuanbo, Ping Wen, et al. Altitude effect of blasting vibration velocity in rock slopes [J]. Journal of Central South University (Science and Technology), 2014(1):237-243.
- [6] Chen Ming, Lu Wenbo, Li Peng, et al. Elevation amplification effect of blasting vibration velocity in rock slope[J]. Chinese Journal of Rock Mechanics and Engineering, 2011, 30(11).
- [7] Singh T N, Singh V. An intelligent approach to prediction and control ground vibration in mines[J]. Geotechnical & Geological Engineering, 2005, 23(3):249-262.
- [8] Khandelwal M, Singh T N. Prediction of blast induced ground vibrations and frequency in opencast mine: A neural network approach[J]. Journal of Sound and Vibration, 2006, 289(4-5):711-725.
- [9] Iphar M, Yavuz M, Ak H. Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system[J]. Environmental Geology, 2008, 56(1):97-107.
- [10] Khandelwal M, Singh T N. Prediction of blast-induced ground vibration using artificial neural network[J]. International Journal of Rock Mechanics and Mining Sciences, 2009, 46(7):1214-1222.
- [11] Khandelwal M. Blast-induced ground vibration prediction using support vector machine[J]. Engineering with Computers, 2011, 27(3):193-200.
- [12] Shi Xiuzhi, Xue Jianguang, Chen Shouru. A fuzzy neural network prediction model based on rough set for characteristic variables of blasting vibration[J]. Journal of shock and vibration, 2009, 28(7):73-76.
- [13] Wang Tao, Zhang Jianhua. Millisecond Blasting Vibration Prediction based on BP Neural Network[J]. Blasting, 2015(2):144-147.