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Two Blasting Vibration Prediction Models Based on Optimized Machine Learning Algorithms

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Abstract: the blasting vibration of large open-pit mines has a great impact on the production safety of the mine and the stability of the slope rock mass, so ensuring that the prediction results of the blasting vibration speed are accurate is an important part to guarantee the safe and efficient production of the mine. However, the traditional machine learning method is difficult to accurately predict the velocity of blasting vibration. Therefore, the pso algorithm and gsm algorithm are introduced to optimize the parameters of the support vector machine (svm), and construct pso-svm algorithm and gsm-svm model to improve the prediction accuracy. 63 groups of blast monitoring data of a mine in eastern zambia is used to train and verify the two algorithms. The result show that the pso-svm blasting vibration prediction model has the most accurate prediction (87.71%), while the prediction accuracy of the gsm-svm blasting vibration prediction model is 86.53%. By contrast, the pso-svm type prediction has higher accuracy and stronger generalization ability, which provides a way of thinking for the prediction of blasting vibration speed.

1. Introduction

With the continuous development of machine learning, many classification algorithms and prediction algorithms have been successfully applied in many fields. In the prediction of mine blasting vibration speed, many prediction models based on machine learning algorithms have also been proposed. Rajabi uses an artificial neural network to build a prediction model, uses 80 sets of blasting data to train and verify, and obtains a 79.5% prediction accuracy [1]. Azimi proposes a hybrid evolutionary artificial neural network (ann) based on genetic algorithm optimization to predict the blasting vibration speed. Comparing the performance of the ga-ann model through statistical indicators, it indicates that the ga-ann model is relatively superior to the empirical predictor and neural fuzzy inference system [2]. Fang, qiancheng proposes a prediction model based on m5-rules and imperialist competition algorithm (ica), called ica-m5-rules technology, and its prediction accuracy of blasting vibration reaches 86.4% [3].

The rapid development of machine learning algorithms has made the prediction accuracy of blasting vibrations higher and higher, but for the input factors of the algorithm, most models still use the traditional Sadovsky influence factors as the standard.

In traditional engineering practice, regression analysis is mainly based on the vibration data measured on site, then the Sadovsky empirical formula is obtained, and finally the calculated formula is used to predict the subsequent blasting vibration velocity [4]. Most engineering tests prove that the Sadovsky formula has high accuracy in predicting the ground blasting vibration particle velocity under flat terrain conditions, but the formula does not take into account the effect of the height difference between the measurement point and the blast center, so the prediction accuracy of the blasting vibration is low if this formula is used when the topography and geomorphology of the blasting site change greatly [5]. Therefore, when establishing the prediction model, this work used the blasting elevation difference (the difference between the blasting area elevation and the measurement point elevation) as a part of the input factors, and the distance between measurement points and the blasting area, the elevation difference, the maximum

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single-hole charge and the number of gun holes are used as input variables. The peal vibration velocity of particles is used as the output variable, and two optimized blasting vibration speed prediction models are established using the optimized SVM algorithm.

2. Data Acquisition and Data Preprocessing

In order to verify the effectiveness and practicability of the optimized SVM model for the prediction of blasting vibration speed proposed in this work, a blasting experiment is carried out in a mine in Zambia, and 63 sets of blasting data are collected as learning and training samples and test samples for the two models built (Table 1). According to the needs of the SVM prediction model, the data set is divided into a training set and a test set according to a 7:3 ratio, and the blasting vibration speed data set is normalized. Considering that there are only four parameters affecting the blasting vibration speed, therefore, dimension reduction is not performed [6].

Table 1 Partial Blasting Vibration Data Set

Distance between measuring point and burst area / m	Elevation difference / m	Maximum single-hole dose / kg	Number of holes	Blasting vibration Speed (cm/s)
658.8	92.7	380	29	0.18
658.8	92.7	380	29	0.17
297	57.5	400	17	0.52
297	57.5	400	17	0.35
292	22.5	380	17	0.5
292	22.5	380	17	0.44
443	82.5	340	27	0.46
443	82.5	340	27	0.38
404	44.5	350	32	0.17
404	44.5	350	32	0.29
…	…	…	…	…

3. Pso-Svm Prediction Model of Blasting Vibration Velocity

When determining the blasting vibration velocity, the input variables of the SVM model are the distance between the measurement point and the blast area, the elevation difference (the difference between the blast area elevation and the measurement point elevation), the maximum single-hole charge and the number of gun holes, and the peak vibration velocity of the particle is used as an output variable to establish mapping based on this. 44 of the 63 blasting data samples collected are selected as training samples, and the remaining 19 groups are used as test samples. In the SVM regression problem, the penalty factor C determines the goodness of fit of the function. If the C value is too high, more support vectors will be obtained, but it will affect the regression performance of SVM. For this reason, it is important to choose a suitable penalty factor for regression predictive analysis [7]. Insensitive parameter g explains the accuracy of the regression curve, the greater the g, the lower the generalization performance of the regression curve. The sample training kernel function is the Radial Basis Function (RBF). Matlab is used to write a PSO optimized SVM model parameter program, the Libsvm support vector machine toolbox is combined, and the training sample cross-validation method is used to determine the support vector machine parameters g and C. The cross-validation fold is 10, and the Matlab particle swarm optimization algorithm toolbox is called to implement stepwise heuristic optimization. The control parameters are set as follows: the group size is 20, the maximum evolution algebra is 100, and the optimization interval of each parameter is set to: $C \in [0, 10^2]$, $g \in [0, 10^2]$, and the squared correlation coefficient (R^2) and the mean square error (MSE) are used as the final evaluation index [8].

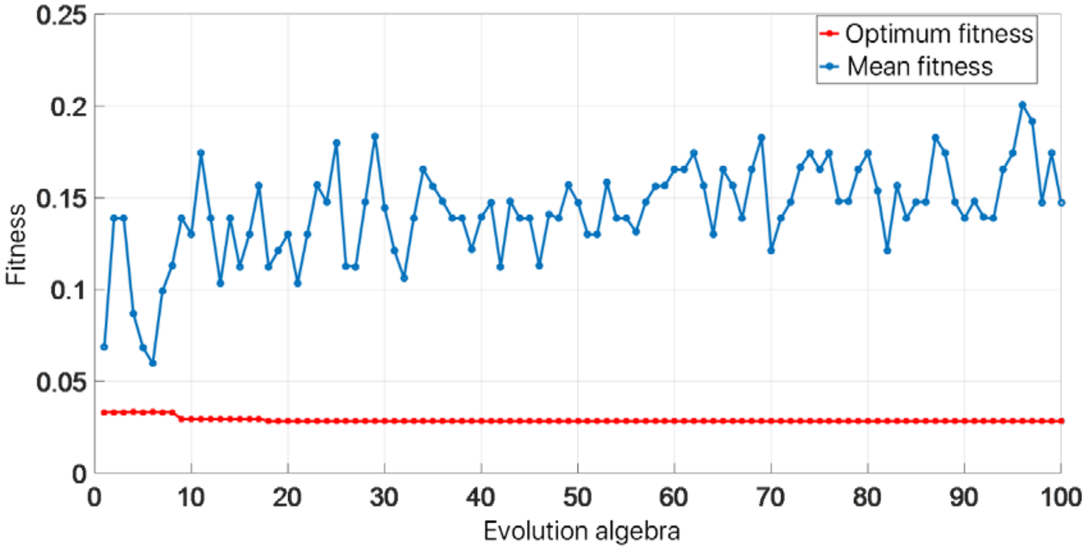

Fig.1 Selection Fitness Curve of Blasting Vibration Velocity Pso Parameter

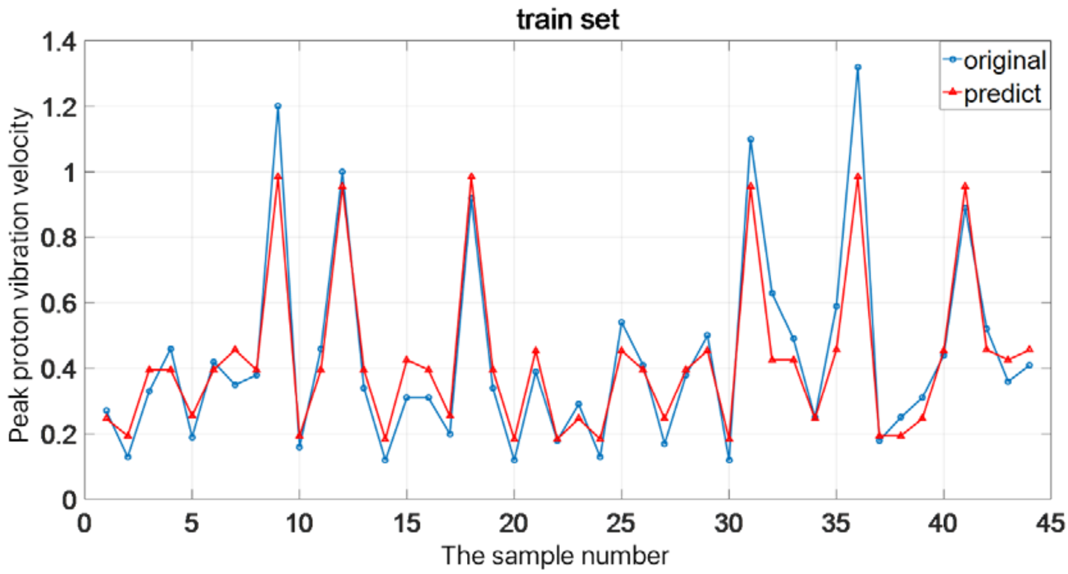

Fig.2 Comparison of Regression Prediction Results of Blasting Vibration Velocity (Train Set)

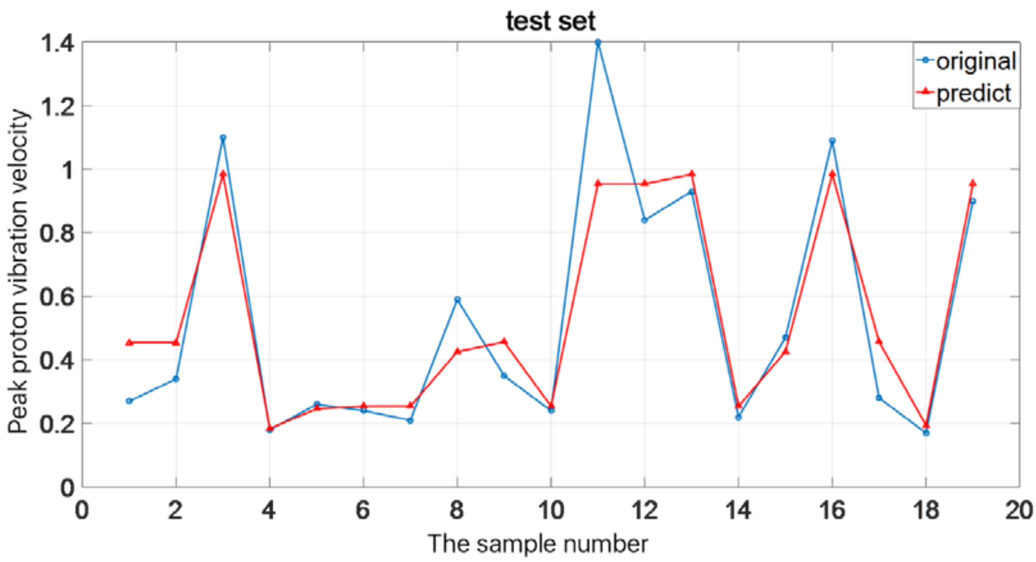

Fig.3 Comparison of Regression Prediction Results of Blasting Vibration Speed (Test Set)

It can be seen from Fig. 1 that the optimal fitness value gradually converges with the increase of the evolutionary algebra, which is exactly the effect of particle swarm optimization. Through calculation, when the blasting vibration velocity regression prediction model of the SVM hyperparameter is C = 0.83253, g = 100, the corresponding training sample R^2 is 92.03%, and the test sample R^2 = 87.71%; see Table 2 for details. As can be seen from Table 2 and Fig. 2, the predicted curve obtained from using PSO to optimize SVM has good fitting degree.

Table 2 the Best Values of the Parameters C and g in the Pso Optimized Svm and the Evaluation of the Regression Effect

	Ideal parameters of using PSO to optimize SVM		Train set		Test set	
PSO-SVM model	Best *C*	Best *g*	R^2	MSE	R^2	MSE
	0.83235	100	92.03%	0.0208	87.71%	0.0469

It is not difficult to find that combining PSO and SVM can not only exert the generalization ability of SVM, but also make SVM have a stronger learning ability. PSO algorithm borrows the idea of genetic algorithm and substitutes mutation operations into PSO algorithm. Re-initializing the unqualified intermediate variables makes the particles jump out of the local extreme value and search in a larger space can improve the calculation efficiency and accuracy of the SVM algorithm [9].

4. Gsm-Svm Prediction Model for Blasting Vibration Velocity

Using the same database, a GSM-SVM prediction model for blasting vibration velocity is established. Similarly, the input vectors of the SVM model are the distance between the measurement point and the explosion area, the elevation difference (the difference between the elevation of the explosion area and the elevation of the measurement point), the maximum value of single-hole dose and the number of gun holes. The peak vibration velocity of the particle is the output variable, and the mapping is established based on this. The optimized SVM model parameter program is written in Matlab by using GSM, the SVM regression function of the LIBSVM support vector machine toolbox is combined, and the crossover verification method is used to determine the support vector machine parameters g and C. After repeated experiments, C and g are set to the range: [2^{-8}, 2^8], and the support vector machine is set to perform 10-fold cross-validation. The best (C, g) value is determined according to the highest prediction accuracy rate. Squared correlation coefficient (R^2) and mean square error (MSE) are used as the final evaluation indicators.

Through calculation, the best parameter pair (C, g) = (C = 1,22.6274) can be obtained, and the optimal parameter C is finally determined to be 1, and g is 22.6274. At this time, the prediction accuracy of the training set can reach 92.55%, that is, using GSM to determine the parameter values of the SVM kernel function has an ideal effect with high prediction accuracy, and each group of parameters is decoupled from each other, which facilitates parallel computing and high operating efficiency. Therefore, the regression model can be considered to be very stable. The parameter selection results of the GSM-SVM model is as follows.

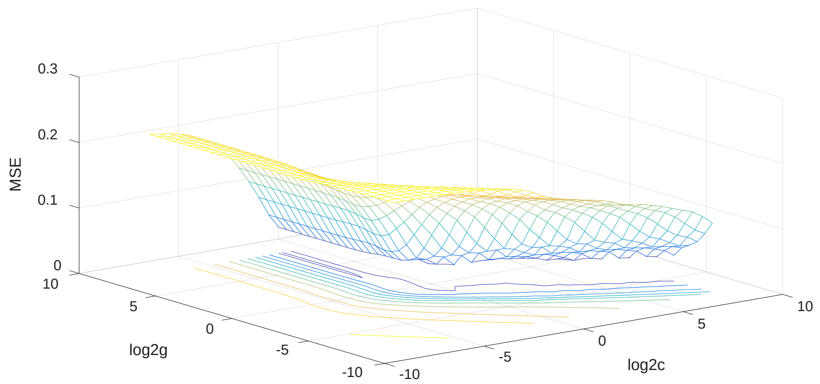

Fig.4 Result of Gsm Parameter Selection for Blasting Vibration Velocity Prediction Model

According to the well-learned GA-SVM model for prediction of blasting vibration velocity, 19 samples to be judged are discriminated. The discrimination result is consistent with the actual state result, and the accuracy rate is 86.53%. It can be seen that the GSM-SVM model can be used to predict blasting vibration velocity, and the prediction is completely reliable and effective. The specific prediction results are shown in Fig. 5-6 and Table 6.

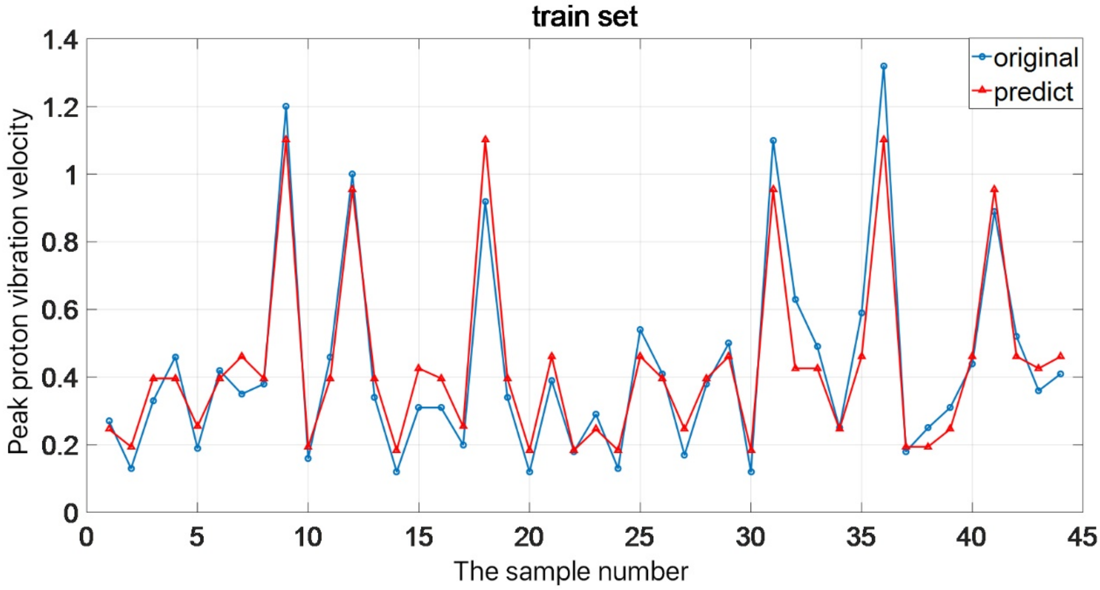

Fig.5 Comparison of Regression Prediction Results of Blasting Vibration Velocity (Training Set)

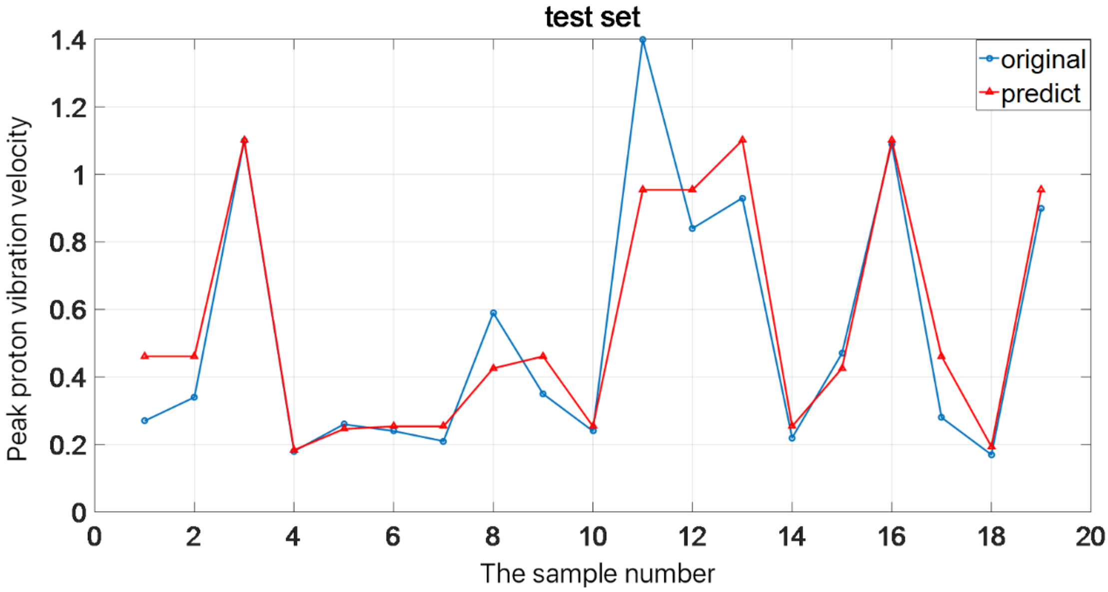

Fig.6 Comparison of Regression Prediction Results of Blasting Vibration Velocity (Test Set)

Table 6 the Best Values of Parameters C and g in Gsm Optimized Svm and Evaluation of Regression Effect

	Ideal parameters of using PSO to optimize SVM		Train set		Test set	
GSM-SVM model	Best *C*	Best *g*	R^2	MSE	R^2	MSE
	1	22.6274	92.55%	0.0167	86.53%	0.0480

5. Conclusion

According to the above two prediction models, the prediction results of GSM-SVM and PSO-SVM prediction vibration blasting models, the prediction accuracy in different situations and the corresponding SVM hyperparameter values are obtained. Through comparison and analysis, it can be seen that both optimization methods can be used for the construction of blasting vibration velocity prediction model. From the prediction accuracy of the training set, the GSM-SVM blasting vibration prediction model has the highest prediction accuracy of 92.55%, followed by the PSO-SVM blasting vibration prediction model with a prediction accuracy of 92.03%. From the prediction accuracy of the test set, the prediction accuracy of the PSO-SVM blasting vibration prediction model is the highest, which is 87.71%, followed by the GSM-SVM blasting vibration prediction model with a prediction accuracy of 86.53%; The relative prediction accuracy comparison chart is shown in Fig. 7.

Fig.7 Comparison of Prediction Accuracy of the Two Algorithms

It can be seen that the prediction accuracy of the two optimization algorithms on the training set is not much different, and the prediction accuracy can achieve the desired effect, but the PSO-SVM blasting vibration prediction model has the highest prediction accuracy on the test set, which is 87.71%. Since the set can well reflect the generalization ability of the prediction model, the use of PSO-SVM algorithm is recommended for the prediction of blasting vibration velocity. This work also provided an idea for the prediction of blasting vibration velocity, that is to consider the rationality and completeness of the input variables when establishing an excellent prediction model, so that the blasting vibration velocity can be accurately predicted under different operating environments.

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