Regression analysis of friction resistance coefficient under different support methods of roadway based on PSO-SVM

Ying Song¹, Meng Zhu¹, Ning Wei² and Lijun Deng³,⁴

¹College of Management Science and Engineering, Shandong Technology and Business University, Shandong Yantai 264005, China
²China Construction First Bureau (Group) Co. Ltd, Hebei Tangshan 063300, China
³College of Safety Science and Engineering, Liaoning Technical University, Liaoning Huludao 125105, China
⁴Key Laboratory of Mine Thermo-motive Disaster and Prevention, Ministry of Education, Liaoning Huludao 125105, China

Corresponding author and e-mail: Ying Song, 201613602@sdtbu.edu.cn

Abstract. In order to solve the problem of large test workload by using the traditional mine ventilation measurement methods, the impact of support methods on the ventilation resistance coefficient was analyzed emphatically. The Particle Swarm Optimization Support Vector Machine(PSO-SVM) algorithm was used to model three types of supported roadways: wood-supported roadways, I-steel-supported roadways, and bolt-net-supported roadways. The roadway attribute parameters of the concrete supported roadway were analyzed, and the PSO-SVM regression model of the supporting parameters and the friction resistance coefficient under the specific supporting method was established, and its regression performance was analyzed. The results showed that the average relative errors of the regression results of wood-supported roadway, I-steel-supported roadway, and bolt-net-supported roadway were: -2.542%, 0.483%, and 1.605%. The friction resistance coefficient and the supporting parameters of the corresponding supporting roadway all showed a high degree of correlation. The research showed that the PSO-SVM regression model can more accurately regress the ventilation resistance coefficient and provide a new intelligent algorithm for the regression of ventilation resistance coefficient, which could have these important guiding significance for practical application.

1. Introduction
In the mine ventilation system, the ventilation resistance coefficient is an important basic parameter of the network calculation. It can be obtained theoretically according to the empirical formula (1) (2) [1], but there will be a large deviation. In the actual calculation, the ventilation resistance coefficient is calculated inversely according to formula (3). In the actual measurement process, the resistance and air volume of each roadway need to be measured. Although the actual measurement is relatively accurate, the mine tunnels are complex and the number of tunnels is huge. The actual measurement workload is huge and time-consuming. With the continuous deepening of underground mining, the shape of the roadway will be slightly deformed, which will lead to slight changes in the attributes of the roadway, and there will be a problem of "always changing and inaccurate" in the resistance coefficient of
underground ventilation [2]. Long-term measurement will also make the actual measurement deviation. Due to the correlation between the mine ventilation resistance coefficient and the roadway attributes (roadway section, perimeter, and support method), it is necessary to explore a method that can overcome the shortcomings of traditional methods to obtain the mine ventilation resistance coefficient, and achieve the purpose of saving time and effort and being able to accurately obtain the mine ventilation resistance coefficient.

\[ R = \frac{\alpha LU}{S^3} \]  
\[ \alpha = \frac{\lambda g}{8g} = \frac{\lambda g}{8} \]  
\[ h = R Q^2 \]  

In the current research on the ventilation resistance of roadways, Ma Heng and others [3] used the maximum and minimum values of the field and the mean filtering method to filter the measured data of coal mines, and explored and found that the frictional resistance of 100 meters and the cross-sectional area of the roadway showed an exponential function relationship. The simplified calculation formulas for frictional wind resistance of semicircular arch roadways and trapezoidal roadways are determined. Pi Zikun [4] studied the cluster analysis of mine tunnel wind resistance characteristics and support methods, and statistically summarized the friction resistance coefficient of mine tunnels under different support methods. Li Yucheng and others [5] introduced an analytical calculation method for node pressure energy, using two sets of air volume data passing through the same roadway under different conditions and part of the node pressure energy to accurately calculate the wind resistance of the roadway to be sought.

In recent years, artificial neural networks and Support Vector Machines (SVM) have good predictive effects in regression analysis for nonlinear samples. Zhang Pan [6] proposed to use an improved BP neural network algorithm model to simulate the friction resistance coefficient. Wang Siyi [7] used BP neural network to recognize and predict the frictional resistance coefficient of different types of roadways. Wei Ning and others [8] proposed a method of using SVM to predict mine ventilation resistance coefficient. Deng Lijun [2] used least square method, genetic algorithm and particle swarm algorithm to carry out inversion research on the ventilation resistance coefficient, and compared and analyzed the advantages and disadvantages of each method, and concluded that the particle swarm algorithm is the most suitable for the actual mine ventilation resistance.

In summary, the application of the SVM model can effectively establish a regression model between the ventilation resistance coefficient and the roadway cross-sectional area, perimeter, and support methods. However, the problem with the model is that the support method in the input variable is characterized by the value of the friction resistance coefficient, and the friction resistance coefficient is obtained by the traditional method and the friction resistance coefficient needs to be obtained by looking up the table. In view of the large amount of testing existing in traditional measurement methods, this paper uses Particle Swarm Optimization Support Vector Machine (PSO-SVM) algorithm to analyze the roadway attribute parameters of specific supported roadways, and establish PSO-SVM regression model of friction resistance coefficient with the supporting parameters under the specific supporting methods, and analyze its regression performance.

2. PSO-SVM model

2.1. SVM nonlinear regression machine
The basic idea of SVM regression is to map data samples to a high-dimensional space through a nonlinear mapping, and to achieve linear regression in the high-dimensional space [8]. Suppose training samples \( \{(x_i, y_i) | i = 1, 2, \cdots, n\} \), \( x_i \in \mathbb{R}^n \) and \( y_i \in \mathbb{R} \) are sample input and sample output. The
sample input is mapped to the high-dimensional feature space to construct the required model, and nonlinear mapping is used to construct the regression function:

\[ f(x) = w^T \varphi(x) + b \]  

(4)

In the formula, \( w \) is the weight, \( \varphi(x) \) is the nonlinear mapping, and \( b \) is the threshold.

In the regression support vector machine model, the key role is the selection of the kernel function of the regression model. Under the action of the kernel function, the support vector machine is not subject to linear separability, but uses nonlinear mapping to map the low-dimensional space nonlinear function to the high-dimensional space. This process does not need to know the specific conditions of the mapping. Therefore, the most widely used radial machine kernel function is adopted [9]:

\[ K(x, x_i) = \exp\left\{-\frac{|x - x_i|^2}{\sigma^2}\right\} \]  

(5)

The discriminant is formula (6):

\[ f(x, \alpha) = \text{sgn}\left\{ \sum_{i=1}^{m} \alpha_i y_i \exp\left\{-\frac{|x - x_i|^2}{\sigma^2}\right\} - b \right\} \]  

(6)

2.2. The parameters of PSO-SVM

The particle swarm optimization algorithm is used to optimize the kernel function parameters \( \sigma \) and penalty factor \( C \) [10]. The parameter optimization steps are as follows:

Step 1: Initialize the algorithm control parameters. The particle parameters in the particle swarm algorithm are set as: \( C \in [1,100] \), \( \sigma \in [0.01,0.1] \), the population size of the particle swarm is 180, the maximum number of iterations is 15, the acceleration coefficient \( c_1=1.5, c_2=1.7 \).

Step 2: Initialize the group of particles, mainly random position and velocity.

Step 3: Calculate and evaluate the fitness value of each particle.

Step 4: Compare the fitness value of each particle with the fitness value of the best position in history, and select the best as the individual optimal value.

Step 5: Compare the individual optimal value of each particle with the best global experience position fitness value, and select the best as the global optimal value.

Step 6: Update the particle velocity and position according to the calculated inertia weight.

Step 7: Determine whether the termination condition is met. If the condition is met, the optimization process ends, otherwise skip to step 3 and continue the search.

Step 8: Send the optimized parameters obtained by optimization to the SVM regression model.

3. Regression analysis of friction resistance coefficient under specific support

3.1. Regression of friction coefficient of wood-supported roadway

The specific support parameters in the wood-supported roadway mainly include the horizontal diameter, vertical diameter, and wooden pillar diameter of the roadway support. The supporting method plays an important role in the roughness of the roadway, so it is the main factor affecting the ventilation resistance coefficient. Therefore, determine the wooden column diameter \( d \), the longitudinal diameter of the support \( \Delta \), the transverse diameter of the support \( \varepsilon \), and the perimeter \( u \) of the supporting part as the input variables of the PSO-SVM regression model, and the output variable is the friction resistance coefficient. The sample data of the model comes from the actual mine production, and 66 sets of data under the wood support method are selected as the sample data, of which 58 sets are training samples and 8 sets are test samples.

The PSO-SVM algorithm performs regression analysis on the friction resistance coefficient of wood-supported roadway. The optimal combination parameters of the PSO-SVM are: \( C=62.9593, \sigma \)
The relative error between the regression value and the measured value in the test sample is mostly between 5% and -5%. The average relative error of the PSO-SVM model test sample is -2.542%. The number of test samples that the absolute value of the relative error is less than or equal to 5% is 7 groups, accounting for 87.5% of all. Therefore, the accuracy of using PSO-SVM to return the
The coefficient of friction resistance is 87.5%, and it has the ability to accurately return the coefficient of friction resistance.

Comparing and analyzing the measured values and regression values in Figure 1, the PSO-SVM regression model also has good regression performance on the friction resistance coefficient, and can also achieve a more accurate regression analysis, indicating that the use of support parameters for wood-supported roadways can more accurately perform regression calculations on the frictional resistance coefficient.

3.2. Regression of friction resistance coefficient of I-steel supported roadway
The specific support parameters in the I-steel-supported roadway mainly include the horizontal and vertical diameters of the roadway support, and the surrounding support conditions of the roadway. According to the specific support parameters of the I-beam support and the attribute parameters of the roadway, four parameters such as the size of the support, the longitudinal diameter of the support, the transverse diameter of the support and the circumference of the support part are determined as the input variables of the regression model, and the output variable is the ventilation resistance coefficient. The sample data of the model comes from the actual mine production, and the data structure is balanced. 83 groups of data under the I-beam support method are selected as sample data, of which 67 groups are training samples and 16 groups are test samples.

The PSO-SVM algorithm performs regression analysis on the friction resistance coefficient of I-steel-supported roadway. The optimal combination parameters of PSO-SVM are: $C=25.7756$, $\sigma=0.0784$, and the square correlation coefficient of the training model is 0.9846. The number of vectors is 61, of which the number of boundary support vectors is 42, the test sample results are shown in Table 2 and Figure 3, and the relative error analysis of the test sample is shown in Figure 4.

| $d/$(cm) | $u/(m)$ | $\Delta$ | $\varepsilon$ | Measured value | Regression value | Relative error /($) |
|---|---|---|---|---|---|---|
| 10 | 2.13 | 4 | 0.052 | 0.11760 | 0.11482 | 2.365 |
| 10 | 3.2 | 5 | 0.035 | 0.11776 | 0.11756 | 0.170 |
| 10 | 2.61 | 4 | 0.042 | 0.11760 | 0.10795 | 8.202 |
| 10 | 2.39 | 3 | 0.047 | 0.09310 | 0.09378 | -0.732 |
| 12 | 2.82 | 8 | 0.047 | 0.17640 | 0.17585 | 0.312 |
| 12 | 3.37 | 4 | 0.039 | 0.11525 | 0.11571 | -0.401 |
| 12 | 3.02 | 4 | 0.044 | 0.12074 | 0.11936 | 1.146 |
| 14 | 3.2 | 3 | 0.049 | 0.10179 | 0.10787 | -5.975 |
| 14 | 2.39 | 8 | 0.065 | 0.21103 | 0.20806 | 1.408 |
| 16 | 3.02 | 4 | 0.059 | 0.14948 | 0.14842 | 0.710 |
| 16 | 2.39 | 5 | 0.074 | 0.19861 | 0.19738 | 0.620 |
| 16 | 2.82 | 5 | 0.063 | 0.18816 | 0.18891 | -0.396 |
| 18 | 2.61 | 4 | 0.076 | 0.17836 | 0.18096 | -1.455 |
| 18 | 2.39 | 3 | 0.084 | 0.14275 | 0.14423 | -1.036 |
| 18 | 2.39 | 3 | 0.084 | 0.14275 | 0.14423 | -1.036 |
| 18 | 2.39 | 8 | 0.084 | 0.27309 | 0.26264 | 3.826 |
The relative error between the regression value and the measured value in the test sample is mostly between 5% and -5%. The average relative error of the PSO-SVM model test sample is 0.483%. The number of test samples that the absolute value of the relative error is less than or equal to 5% is 15 groups, accounting for 93.75% of all. Therefore, the accuracy of using PSO-SVM to return the coefficient of friction resistance is 93.75%, and it has the ability to accurately return the coefficient of friction resistance.

Comparing and analyzing the measured values and regression values in Figure 3, the PSO-SVM regression model also has good regression performance on the friction resistance coefficient of the I-steel-supported roadway, and can also achieve a more accurate regression analysis, indicating that the use of support parameters for I-steel-supported roadway can more accurately perform regression calculations on the frictional resistance coefficient.

### 3.3. Regression of friction resistance coefficient of bolt-net-supported roadway

The specific supporting parameters in the bolt-net-supported roadway mainly include the smoothness of the bolt-net, the distance between the bolts, the anchoring length, etc. According to the anchor net support parameters and the basic parameters of the roadway, determine the roadway width, height, anchor net smoothness $R_a$, bolt row distance $D$, and anchor length $l$ as the input variables of the SVM regression model, and the output variable is the ventilation resistance coefficient. The sample data of the model comes from the actual production of the mine, and the data structure is balanced. 82 groups of data under the wood support method are selected as sample data [7], of which 66 groups are training samples and 16 groups are test samples.
The PSO-SVM algorithm performs regression analysis on the friction resistance coefficient of bolt-net-supported roadway. The optimal combination parameters of the PSO-SVM are: $C=52.657$, $\sigma =0.0831$, and the square correlation coefficient of the training model is 0.9314. The number of vectors is 58, of which the number of boundary support vectors is 37, the test sample results are shown in Table 3 and Figure 5, and the relative error analysis of the test sample is shown in Figure 6.

### Table 3. Regression results of test samples of bolt-net-supported roadway.

| Width /cm | Height /cm | Bolt row distance $D$/m | Anchor length $l$/m | Anchor net smoothness $R_a$ | Measured value | Regression value | Relative error/(%) |
|----------|-----------|------------------------|--------------------|---------------------------|----------------|------------------|-------------------|
| 3.2      | 2.8       | 0.5                    | 0.4                | 8                         | 0.10048        | 0.097            | 3.25544           |
| 3.8      | 2.8       | 0.5                    | 0.25               | 9                         | 0.01362        | 0.014            | 0.528597          |
| 3.2      | 2.5       | 0.5                    | 0.25               | 10                        | 0.08994        | 0.092            | -2.82727          |
| 3.4      | 2.8       | 0.6                    | 0.25               | 7                         | 0.00668        | 0.007            | -1.02985          |
| 4.2      | 2.8       | 0.6                    | 0.25               | 7                         | 0.23704        | 0.228            | 3.719218          |
| 3.5      | 2.3       | 0.6                    | 0.3                | 8                         | 0.09550        | 0.099            | -3.61056          |
| 3.9      | 2.6       | 0.6                    | 0.3                | 8                         | 0.03463        | 0.033            | 4.183527          |
| 4.6      | 2.6       | 0.7                    | 0.3                | 6                         | 0.38602        | 0.351            | 8.95637           |
| 3.3      | 3         | 0.7                    | 0.3                | 10                        | 0.16069        | 0.169            | -5.40065          |
| 2.7      | 1.8       | 0.7                    | 0.35               | 6                         | 0.05117        | 0.049            | 4.833606          |
| 4.4      | 3.3       | 0.7                    | 0.35               | 8                         | 0.07004        | 0.067            | 4.429464          |
| 4.7      | 3.3       | 0.7                    | 0.35               | 7                         | 0.17210        | 0.180            | -4.38726          |
| 4.3      | 2.7       | 0.8                    | 0.35               | 7                         | 0.10778        | 0.103            | 4.794793          |
| 4.1      | 2.8       | 0.8                    | 0.4                | 10                        | 0.01822        | 0.017            | 3.974161          |
| 3.7      | 2.8       | 0.8                    | 0.4                | 9                         | 0.00974        | 0.009            | 2.833724          |
| 4.1      | 2.2       | 0.8                    | 0.4                | 8                         | 0.01271        | 0.013            | 1.424202          |

![Figure 5. Test results of bolt-net-supported roadway.](image)

![Table 3. Regression results of test samples of bolt-net-supported roadway.](image)
The relative error between the regression value and the measured value in the test sample is mostly between 5% and -5%. The average relative error of the PSO-SVM model test sample is 1.605%. The number of test samples that the absolute value of the relative error is less than or equal to 5% is 14 groups, accounting for 87.5% of all. Therefore, the accuracy of using PSO-SVM to return the coefficient of friction resistance is 87.5%, and it has the ability to accurately return the coefficient of friction resistance.

Comparing and analyzing the measured values and regression values in Figure 5, the PSO-SVM regression model also has good regression performance on the friction resistance coefficient of the bolt-net-supported roadway, and can also achieve a more accurate regression analysis, indicating that the use of support parameters for bolt-net-supported roadway can more accurately perform regression calculations on the frictional resistance coefficient.

4. Conclusions
Taking wood-supported roadway, I-steel-supported roadway and bolt-net-supported roadway as the research objects, a PSO-SVM regression model of roadway friction resistance coefficient and roadway attribute parameters of specific supported roadway was established. The input of the model was determined according to the support parameters of the specific supported roadway, and the output was the friction resistance coefficient. The regression performance of the PSO-SVM model was analyzed. Under the specific support method, the support parameters of the specific supported roadway can better return the friction resistance coefficient. The average relative errors of the regression results of the wood-supported roadway, the I-steel-supported roadway, and the bolt-net-supported roadway were respectively -2.542%, 0.483%, 1.605%, all <5%. The friction resistance coefficient and the supporting parameters of the corresponding supporting roadway showed a high degree of correlation. The research showed that it was feasible to use PSO-SVM algorithm to analyze the friction resistance coefficient of the specific supported roadway, and had high accuracy, which can provide a certain method guidance for the regression analysis of the mine ventilation resistance coefficient.

Acknowledgement
Fund Project: The Natural Science Foundation of Shandong Province (ZR2020QE125); The Key R&D Program (Soft Science Project) of Shandong Province (2020RKB01167)

References
[1] HUANG Yuanping. Mine ventilation [M]. Xuzhou: China University of Mining and Technology Press, 1986.
[2] DENG Lijun. Study on mine ventilation resistance coefficient inversion [D]. Fuxin: Liaoning
[3] MA Heng, XU Chao, LI Zongxiang, et al. Calculation and research on friction wind resistance of mine ventilation shaft [J]. Journal of safety and environment, 2011, 11(05): 172-174.

[4] PI Zikun. Study on the clustering analysis of ventilation resistance characteristics & supporting pattern of mine roadway [D]. Fuxin: Liaoning Technical University, 2013.

[5] LI Yucheng, LIU Tianqi, ZHOU Yang, et al. Study of node pressure energy analytical method based on inversion from air volume to wind resistance [J]. Journal of China Coal Society, 2015, 40(05): 1076-1080.

[6] ZHANG Pan. The research of new methods to compute coefficient of mine roadway's frictional resistance [D]. Fuxin: Liaoning Technical University, 2001.

[7] WANG Siyi. Calculation of mine tunnel friction coefficient based on multilayer feedforward neural networks [D]. Fuxin: Liaoning Technical University, 2014.

[8] WEI Ning, SUN Yashengnan, DENG Lijun, et al. Influence factors analysis and prediction on mine ventilation resistance coefficient based on SVM [J]. Journal of Safety Science and Technology, 2018, 14(04): 39-44.

[9] FENG Guohe. Comparison of SVM kernel function and parameter selection [J]. Computer Engineering and Applications, 2011, 47(03): 123-124+128.

[10] CHEN Xin. Research of security state prediction of coal production logistics system based on improved particle swarm optimization-support vector machine [D]. Zhengzhou: Zhengzhou University, 2014.