Research and Application of IPSO-SVM-Based Coal and Gas Outburst Prediction Model (Postprint)

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Abstract

Coal and gas outburst represents a significant safety hazard in China's mining operations, seriously threatening the lives of underground personnel and constraining mining efficiency. To address this issue, this paper comprehensively employs theoretical analysis, model construction, and practical application methods to investigate the occurrence mechanism and key influencing factors of coal and gas outbursts. Utilizing grey relational analysis combined with real-time mine monitoring data, quantitative correlation calculations were performed between ten pre-selected influencing factors and the target outburst intensity value. The calculations demonstrate the effect weight of each factor on outburst intensity, providing data support for index optimization. Building upon this foundation, an improved particle swarm optimization (IPSO) algorithm is innovatively proposed. By dynamically adjusting inertia weights and learning factors to enhance global optimization capability, the algorithm provides optimization support for parameter configuration of the support vector machine (SVM) model, forming an IPSO-SVM coupled prediction model. This model overcomes, to a certain extent, the deficiency of insufficient accuracy in traditional prediction methods, and enhances dynamic identification and early warning capabilities for outburst risks. The research findings provide theoretical basis and technical means for the scientific prevention and control of coal and gas outbursts. Furthermore, the findings can reduce accident incidence rates through risk prediction, promote intelligent upgrading of coal mine safety management systems, and achieve dual improvements in safety benefits and resource extraction efficiency.

Full Text

Research and Application of Coal and Gas Outburst Prediction Model Based on IPSO-SVM

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Abstract: Coal and gas outbursts constitute major safety hazards in China' s mining operations, posing severe threats to underground personnel and constraining extraction efficiency. To address this challenge, this paper comprehensively investigates the occurrence mechanism and key influencing factors of coal and gas outbursts through theoretical analysis, model construction, and practical application. Utilizing grey relational analysis combined with real-time mine monitoring data, we quantitatively calculated the correlation degree between ten preselected influencing factors and outburst intensity target values. The calculations demonstrate the effect weight of each factor on outburst intensity, providing data support for index optimization. Building upon this foundation, we innovatively propose an Improved Particle Swarm Optimization algorithm (IPSO) that enhances global optimization capability through dynamic adjustment of inertia weight and learning factors, thereby optimizing the parameter configuration of the Support Vector Machine (SVM) model and forming an IPSO-SVM coupled prediction model. This model addresses the accuracy limitations of traditional prediction methods to a certain extent and improves dynamic identification and early warning capabilities for outburst risks. The research findings provide theoretical basis and technical means for scientific prevention and control of coal and gas outbursts. Additionally, the results can reduce accident rates through risk prediction, promote intelligent upgrading of coal mine safety management systems, and achieve dual improvements in safety benefits and resource extraction efficiency.

Keywords: Coal and gas outburst; Support Vector Machine; Improved particle swarm optimization algorithm; Grey correlation degree; Prediction model

1 Introduction

China' s energy structure is characterized by being rich in coal but poor in oil and natural gas. Although renewable energy sources such as wind and solar power are developing rapidly, coal' s pivotal position in energy supply cannot be replaced in the short term. Particularly in the process of advancing carbon emission control goals, coal serves not only as a guarantee of energy security but also as a key support for stable supply. However, coal mine safety issues have become a pain point for the industry. Over the past six years, coal mine accidents have occurred frequently with persistently high casualty numbers, among which coal and gas outbursts are extremely destructive, causing casualties and production stoppages. The triggering factors for these accidents are complex, including sudden geological condition changes, gas pressure peaks, or coal structure fragility, any of which may lead to sudden disasters. To reduce accidents, reliance on empirical prevention and control alone is insufficient; scientific understanding of the underlying patterns and establishment of more accurate early warning measures are required.

To eliminate potential bias introduced by the original data order, 28 sets of typical coal and gas outburst monitoring data were selected from publicly available National Bureau of Statistics data to construct a sample set. The data were randomly shuffled using Matlab R2018b' s `randperm` function and divided into training and test sets at a 7:3 ratio, with 20 sets used for model training to learn feature patterns and adjust parameters, and the remaining 8 sets used to validate model prediction accuracy and generalization capability in actual scenarios, ensuring reliability under complex working conditions.

Outburst intensity is classified into four risk levels: Level 1 indicates no outburst risk and no outburst intensity; Level 2 represents general outburst risk with relatively low intensity; Level 3 indicates moderate outburst risk with medium intensity; and Level 4 represents severe outburst risk with relatively high intensity. This study employs the normalization function built into Matlab R2018 software to standardize the collected data, converting original data proportionally into dimensionless pure numerical values within the [0,1] interval to eliminate the influence of data units. The normalized results are shown in Table 1.2.

Extensive research on coal and gas outburst prediction has been conducted by scholars both domestically and internationally. Former Soviet scholar Frid discovered a strong correlation between electromagnetic radiation signal anomalies and outburst disasters through analysis of coal-rock fracture processes, providing a theoretical foundation for electromagnetic monitoring and early warning. Chinese scholar Wang Jian achieved precise prediction of outburst areas under small-sample conditions using a Particle Swarm Optimization-Support Vector Machine (PSO-SVM) model. Wang Pengfei improved algorithm convergence performance through an improved compression factor optimization strategy (FPSO). Shi Y et al. proposed a globally optimized particle swarm algorithm that further enhanced parameter optimization efficiency. The successful application of Support Vector Machine (SVM) and its improved models in fault diagnosis fields (such as diesel engine fault detection) also provides technical references for coal mine disaster prediction. However, existing methods still have significant limitations: SVM relies on manual experience for parameter selection, which easily leads to insufficient model generalization ability; traditional Particle Swarm Optimization (PSO) easily falls into local optima in complex problems and has slow parameter optimization speed. These issues constrain the accuracy and practicality of prediction models, necessitating breakthroughs through algorithmic innovation.

To address these problems, this paper proposes a coal and gas outburst prediction model based on Improved Particle Swarm Optimization (IPSO) optimizing Support Vector Machine (SVM), termed IPSO-SVM. This study employs grey relational analysis to quantify the correlation between ten major influencing factors and outburst intensity. As model inputs, core indicators such as gas content, ground stress, and coal hardness coefficient are excluded to reduce redundant data interference. By dynamically adjusting inertia weight and learning factors, the global search capability of the particle swarm optimization algorithm is enhanced to avoid premature convergence. The penalty coefficient and kernel function parameters of SVM are optimized to improve model fitting efficiency for nonlinear relationships. To verify model performance, this study comprehensively combines publicly available data from the National Bureau of Statistics with monitoring data from multiple excellent coal mines in Shanxi Province to conduct comparative training of three models: SVM, PSO-SVM, and IPSO-SVM. Experimental results demonstrate that IPSO-SVM improves learning speed by approximately 18% compared with traditional PSO-SVM, achieving a prediction accuracy of 93.7%. The model exhibits stronger adaptability to data from different working faces and demonstrates stable early warning capabilities, particularly under complex geological conditions. The successful application of IPSO-SVM not only provides a dynamic high-precision prediction tool for coal and gas outburst risk but also optimizes outburst prevention measures through real-time monitoring and early warning, substantially reducing accident rates. This achievement will provide technical support for the intelligent transformation of coal mine safety management and help the coal industry achieve both safety and sustainable development goals under the "dual carbon" targets.

1.1 Model Sample Data Selection and Preprocessing

[Continued Table 1.1]

Table 1 .1 Measured Data of Coal and Gas Outburst

1.2 Parameter Selection and Prediction Result Analysis

In constructing the nonlinear Support Vector Machine (SVM) classification model, the Radial Basis Function (RBF) was adopted as the kernel function, and parameter optimization was performed based on a grid search method combined with cross-validation strategy. Cross-validation (K=5) was established to evaluate model generalization capability, with the search space for penalty parameter C and kernel function parameter g defined as $[2^{-4}, 2^{4}]$ and search step size set to 1, achieving global optimization by traversing parameter combinations within this logarithmic space. To systematically analyze the influence of parameters on model classification performance, three-dimensional surface plots and contour maps of parameter optimization were simultaneously generated to visually characterize the variation 规律 of model accuracy under the synergistic action of C and g, revealing parameter-sensitive regions and optimal solution distribution characteristics to provide quantitative basis for subsequent algorithm improvement.

As shown in Figures 1.1 and 1.2, the first-round parameter optimization results indicate that the model' s cross-validation accuracy reaches 89.4737% based on grid search and cross-validation, with optimal solutions for penalty parameter C and kernel function parameter g being 1.0443 and 2.0885, respectively, confirming that this parameter combination can significantly improve the discrimination performance of the coal and gas outburst classification model.

A second-round refined parameter tuning was conducted to further improve cross-validation accuracy. In this stage, K=5 was maintained, while the optimization range for penalty parameter C was narrowed to [2^{-2}, 2^2], and the optimization range for kernel function parameter g was similarly narrowed to [2^{-2}, 2^2], with step sizes adjusted to 0.5 for both parameters.

The contour map and 3D view of the second SVC parameter selection are shown in Figures 1.3 and 1.4.

Figure 1 [Figure 1: see original paper].1 3D view of the first SVC parameter selection

Figure 1.1 Contour map of the first SVC parameter selection

Figure 1.3 Contour map of the second SVC parameter selection

After two rounds of refined parameter adjustment and cross-validation, the optimal parameter combination was determined as C=1.1892 and g=1.6818, which were applied to the Support Vector Machine (SVM) classification prediction model. As shown in Figure 1.5, although the optimal parameter combination was found through refined search using cross-validation, the prediction accuracy of traditional Support Vector Machine (SVM) for coal and gas outburst prediction still only reached 77.7778%, and the test results did not meet expectations.

Figure 1.4 3D view of the second SVC parameter selection

Figure 1.5 Test result graph of SVM highlighting prediction model

2.1 Inertia Weight Strategy Improvement

The inertia weight w is set to decrease nonlinearly with iteration 次数 to optimize particle swarm algorithm performance. In the early algorithm stage, particles are assigned a relatively large inertia weight to facilitate rapid global search and improve search efficiency. The inertia weight variation formula is:

$$w = w_o + (w_i - w_o)(1 + e)$$

where w_i is the initial inertia weight setting, w_o is the final determined inertia weight value, t is the current iteration number, and T is the maximum iteration number.

Figure 2 [Figure 2: see original paper].1 Variation curve of nonlinear inertia weight

Figure 2.1 shows the simulation results. As iteration 次数 increases, the decay rate of inertia weight gradually accelerates, which helps particles search within the global scope and maintain population diversity. In the later stage, inertia weight gradually decreases with accelerated decay rate, enhancing particles' local search capability and accelerating population convergence. The adaptive nonlinear decreasing strategy for inertia weight can effectively balance global and local search capabilities and optimize algorithm performance.

2.2 Population Initialization Strategy Improvement

To ensure population diversity while enhancing algorithm search capability, the Tent map from chaotic motion is employed to generate chaotic sequences. The generated chaotic sequence Qτ replaces random numbers for population initialization and is mapped to the search space to enhance population diversity and global search capability. This process can be mathematically expressed as:

$$Q_{\tau+1} = \begin{cases} 2Q_\tau, & 0 \le Q_\tau < 0.5 \\ 2(1 - Q_\tau), & 0.5 \le Q_\tau \le 1 \end{cases}$$

where Qτ+1 [0,1] is the generated chaotic sequence.

$$x_{iz} = up + Q_{\tau+1}(up + lp)$$

where up and lp are the upper and lower boundaries of the search space, respectively, which can be used to initialize population positions.

2.3 IPSO Optimization Process

The optimization steps of the Improved Particle Swarm Optimization (IPSO) algorithm are as follows:

Step 1: Initialize population positions xiz using the Tent map and initialize particle swarm parameters, including population size M, maximum iteration 次数 T, nonlinear inertia weight w, initial particle velocities and positions, individual learning factor c1, and social learning factor c2, while setting the search ranges for penalty parameter C and kernel function parameter g.

Step 2: Update the adaptive nonlinear inertia weight w.

Step 3: Calculate the current individual fitness value of each particle and the global optimal fitness value of the particle swarm.

Step 4: Update the velocity and position of each particle based on the objective function to determine individual optimal positions and global optimal positions.

Step 5: Check whether the algorithm termination conditions are satisfied. If satisfied, end iteration and output optimal parameters; otherwise, return to Step 3 to continue iteration.

Step 6: Successfully output the optimal parameters C and g found by the IPSO algorithm.

The flowchart is shown in Figure 2.2.

Figure 2.2 IPSO Optimization Flowchart

Optimization testing was conducted in the Matlab R2018b environment. Particle swarm size was set to 40, and maximum iteration 次数 was set to 1000. To comprehensively evaluate the performance of the Improved Particle Swarm Optimization (IPSO) algorithm, it was compared with Standard Particle Swarm Optimization (PSO) and Adaptive Particle Swarm Optimization (TACPSO). Testing was performed on functions F1, F2, and F3, with specific parameter settings shown in Tables 2 .3 and 2.4. To ensure result stability and reliability, each algorithm was independently run 30 times on each test function.

The three-dimensional diagrams and convergence curves of test results are shown in the figures: (a) 3D diagram and iteration curve of F1 test function.

2.3 Performance Testing of Improved Particle Swarm Algorithm

To verify the performance of the Improved Particle Swarm Optimization (IPSO) algorithm and evaluate its effectiveness in parameter optimization, benchmark test functions are used as evaluation tools. Five unimodal test functions and three multimodal test functions were selected, as shown in Tables 2.1 and 2.2, aiming to comprehensively compare and evaluate the optimization capability of the improved particle swarm algorithm.

Table 2.1 Unimodal Test Functions

Table 2.2 Multimodal Test Functions

(b) 3D diagram and iteration curve of F2 test function

(c) 3D diagram and iteration curve of F3 test function

In experiments on unimodal test functions F1 through F3, the Standard Particle Swarm Optimization (PSO) algorithm was observed to converge quickly in the early stage but with insufficient final solution precision, easily falling into local optima. Particularly on the F2 function, three improved algorithms—Modified Particle Swarm Optimization (MPSO), Improved Particle Swarm Optimization (IPSO), and Adaptive Particle Swarm Optimization (TACPSO)—showed similar performance with comparable convergence speeds and ultimately reached the same optimization precision. Notably, across these test functions, IPSO consistently achieved better solution precision than other algorithms, highlighting its significant advantage in local fine search capability.

2.3 Selection of IPSO-SVM Model for Coal and Gas Outburst Prediction

Using the three improved particle swarm optimization algorithms (MPSO, IPSO, and TACPSO) combined with Support Vector Machine (SVM), different coal and gas outburst prediction models were established respectively. The parameters for each particle swarm were initialized as follows: individual learning factor c1 set to 1.5, social learning factor c2 set to 1.7, model evolution iteration limit set to 100, and maximum population size set to 20, aiming to balance search breadth and efficiency. Additionally, the search range for SVM penalty parameter C was set to [0.1, 100], and the search range for kernel function parameter g was set to [0.01, 1000], as shown in Figures 4 [Figure 4: see original paper].11, 4.12, and 4.13.

Figure 2.3 Classification prediction results and fitness curve of TACPSO-SVM

Figure 2.5 Classification prediction results and fitness curves of IPSO-SVM

The TACPSO-SVM prediction model was observed to have a prediction accuracy of 88.8889% due to misclassifying test sample No. 9, as shown in Figure 4.11, exposing its limitation of easily falling into local optimization. In contrast, both MPSO-SVM and IPSO-SVM prediction models demonstrated excellent performance with perfect prediction accuracy of 100%, as shown in Figures 2.4 and 2.5.

To further investigate the prediction effects of IPSO-SVM and MPSO-SVM models, a detailed analysis of their optimization comparison diagrams was conducted. As shown in Figure 4.14, with increasing iteration 次数, the Improved Particle Swarm Optimization (IPSO) reached the optimal fitness value of the swarm first after 15 iterations, with its average fitness higher than that of the MPSO algorithm, directly revealing performance differences among different improved particle swarm algorithms when optimizing prediction models. Comprehensive analysis indicates that the IPSO-SVM prediction model took 0.7049 seconds for prediction, demonstrating excellent prediction performance.

Figure 2.4 Classification prediction results and fitness curves of MPSO-SVM

Figure 2.6 Comparison chart of optimization effects between IPSO and MPSO

3.1 Coal Mine Overview

The Shanxi Provincial Coal Industry Bureau identified coal seam No. 81 as an outburst-prone seam in 2009, and the China Coal Technology & Engineering Group Chongqing Research Institute identified coal seam No. 15 as an outburst-prone seam in 2012. The 2020 mine gas grade identification report shows that the mine' s absolute gas emission rate reached 106.75 m^3/min, with a relative emission rate of 78.78 m^3/t. Specifically, the maximum emission from the mining face reached 49.63 m^3/min, and the maximum from the excavation face was 2.29 m^3/min, all indicating substantial gas occurrence in the coal seams.

Due to the gas occurrence conditions and outburst risk of the mine' s coal seams, the drilling cuttings index method was adopted for outburst risk prediction in the coal roadway excavation face. The specific implementation scheme involves arranging no fewer than 3 prediction boreholes with a diameter of 4 mm, and the projected depth along the roadway axis direction is set to 10 meters.

The collected coal and gas outburst monitoring data of 4-5 groups are shown in Table 3 .1. Outburst intensity is divided into two levels: Level 1 represents no outburst risk, and Level 2 represents existing outburst risk.

Table 3.1 Coal and Gas Outburst Monitoring Data

[Continued Table 3.1]

Prediction results were obtained using Support Vector Machine (SVM), Particle Swarm Optimization-Support Vector Machine (PSO-SVM), and Improved Particle Swarm Optimization-Support Vector Machine (IPSO-SVM) models respectively.

Figure 3 [Figure 3: see original paper].1 Prediction results of the SVM prominence prediction model in Pingshu Mine

Figure 3.2 Prediction results of the PSO-SVM prominence prediction model in Pingshu Mine

Figure 3.3 Prediction results of the IPSO-SVM prominence prediction model for Pingshu Mine

The prediction accuracies of the three models for the test set of outburst monitoring data from the mine' s excavation face were 84.6154%, 92.3077%, and 100%, respectively. The IPSO-SVM prediction model demonstrates accuracy and reliability in predicting coal and gas outbursts in the Pingshu Mine excavation face in Shanxi Province, and can serve as an effective prediction tool for coal mine safety production.

Coal and gas outbursts are frequent and extremely destructive disasters in mine extraction, making rapid and accurate prediction crucial. Due to the often limited availability of practical sample data coupled with extremely high requirements for prediction accuracy, the Support Vector Machine (SVM) algorithm demonstrates unique advantages in handling such problems. Therefore, a novel prediction model is proposed: the SVM model based on Improved Particle Swarm Optimization (IPSO), termed IPSO-SVM. The core concept of this model is to use the IPSO algorithm to optimize the key parameters of SVM, aiming to improve prediction speed and accuracy. This new model was studied in detail and thoroughly trained and validated using actual field monitoring data from coal mines.

Validation confirms that the IPSO-SVM model exhibits excellent performance in coal and gas outburst prediction tasks, with high prediction accuracy and stable, reliable results. This model provides a new and effective prediction tool and technical approach for the field of coal mine safety production, contributing to enhanced mine disaster early warning capabilities.

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Note: Figure translations are in progress. See original paper for figures.