Prediction of gas emission in mining face based on GA-PSO-SVM

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Abstract—In order to prevent the gas from exceeding the limit and accurately and effectively predict the gas emission, this paper puts forward a prediction method of gas emission in mining face based on GA-PSO-SVM. The historical data of a coal mine is analyzed by comprehensively considering five factors that affect the gas emission from the working face. By predicting the gas emission from the test set, the values of MSE, MAE and RMSEP of GA-PSO-SVM model in the return gas concentration prediction are 0.029942, 0.001323 and 0.036378, respectively, and the three indexes are superior to the other three prediction models, indicating that the combined model is better than the single GA-SVM and PSO.

1.Introduction

Gas overrun is a major threat to coal mine production, and its frequent occurrence will have a serious impact on people, lives and property. Gas emission is one of the most obvious characteristics of gas overrun. The prediction of gas emission can effectively reduce or even avoid the occurrence of gas overrun in coal mines, and improving the prediction accuracy of gas emission is the basic work to realize effective management of gas overrun and ensure safe production in coal mines.

C.Özgen Karacan[1]The porosity and permeability of coal are analyzed by gamma ray, density and sound wave, and the prediction and early warning analysis is made by formula experience according to the field data. Then the prediction method based on hierarchical classification and regression tree (CART) is studied.[2], geostatistical evaluation[3]And wavelet transform model.[4]Equal gas emission prediction method and a gas prediction software MCP are developed.[5]To predict and warn the gas emission. Tutak M[6]According to the gas monitoring data, a multi-layer artificial neural network model is established to predict the gas emission, and the results show that the error is only 0.1%. Zhang[7]The improved gas concentration prediction model based on grey theory GM (1,1) and BP neural network can effectively improve the prediction accuracy by taking advantage of the advantages of less sample data required by grey model and simple algorithm, and combining with the fact that BP neural network is suitable for predicting nonlinear systems. Fan[8]In this paper, the sample data of gas emission is decomposed by LMD method, and the obtained components are modeled by SVM. The predicted value of gas emission is obtained by overlapping prediction results. When the model is applied to actual mines, the average error is only 2.35%. Feng[9]Aiming at the lack of dynamic tracking optimal solution in particle swarm optimization (PSO) and the randomness of artificial neural network parameters, an improved time-varying particle swarm optimization (TVPSO) is proposed to dynamically track the optimal solution, and the least square support vector machine (LSSVM) is used to select model parameters, which improves the efficiency of dynamic prediction.

The above prediction methods greatly improve the accuracy of gas emission prediction to a certain extent, but there are still many inevitable problems, such as: although neural network has strong learning ability and approximation ability to nonlinear functions, it is easy to fall into local optimal solution, which leads to slow convergence; Support vector machine (SVM) has strong learning ability for small sample and nonlinear problems, but it is prone to over-fitting. Although the application of wavelet theory in gas prediction improves the prediction accuracy, it is only applicable to the case of single gas emission. In order to predict the gas emission more accurately, this paper puts forward a GA-PSO-SVM prediction model to predict the gas emission in the case of few samples, insufficient data and many influencing factors with irregular distribution, which provides some research ideas for preventing gas from exceeding the standard.

2 Gas Emission Analysis of Influencing Factors

(1) The air volume has a great influence on the gas emission of the mining face, and it is a direct influence. When the air volume of the working face fluctuates, it will break the pressure balance of the goaf and make the gas concentration change with the followers, especially when the air volume of the working face increases, the pressure in the roadway becomes smaller, and a large amount of gas is emitted, resulting in return air and gas overrun.

(2) Gas drainage in goaf is an effective technology to

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control the gas overrun in working face, but it is easy to induce spontaneous combustion in goaf due to excessive gas drainage and large air leakage in goaf; If the gas extraction amount is too small, it can't meet the gas emission requirements.

(3) The faster the working face advances, the greater the gas emission. The coal mining rate of the coal mining face is low, and there are more residual coal in the goaf, and gas is continuously released. The influence of recovery rate is mainly reflected in the level of recovery rate. At present, the mining technology is basically fully mechanized top-coal caving, and the recovery rate is relatively high, which can reach more than 90%. Therefore, the coal loss rate is greatly reduced, and the influence on gas emission in goaf and roadway is relatively small, and the absolute gas emission is inversely proportional to the recovery rate.

(4) The advancing speed is very important for the safe production of coal mines. If the advancing speed is too fast, the time of the scattered coal blocks in the working face will be reduced, and the residual gas content of the coal blocks will increase, which will lead to excessive gas emission and increase the possibility of accidents.

(5) When the working face is mined, when the main roof reaches the limit span, it will break and form a three-hinged arch balance. With the continuous advancement of the working face, new strata fracture appears at the top of the roadway, which forms a uniform balance between these strata, and the fracture zone at the top of the roadway appears a periodic process from stability to instability and finally to stability.

3. Theory and Algorithm

3.1 Support Vector Machine Theory

Support Vector Machine (SVM) is a machine learning method based on statistical learning theory, which was introduced in 1995.[10]. It uses the structural risk minimization in statistical theory and VC theory, indirectly maps the image vector from the low-dimensional feature space to the high-dimensional feature space by introducing kernel function, and then constructs the optimal classification hyperplane in the high-dimensional feature space to obtain the linear optimal decision function, thus solving the quadratic programming problem. Support vector machine has unique advantages over traditional statistical methods in identifying small data samples and high-dimensional models, and solving problems such as over-fitting and dimension disaster. High learning efficiency and high generalization ability make it one of the most widely used machine learning methods. In this paper, support vector machine (SVM) is used to predict gas overrun prediction and early warning.

3.2 Combination of Particle Swarm Optimization and Genetic Algorithm

In practical application, the two optimization algorithms mentioned above have certain results, but with the refinement and complexity of practical problems, the results of simple particle swarm optimization and genetic algorithm cannot meet the needs of solving. The efficiency of genetic algorithm decreases in the later optimization process, and the individuals of the population mature earlier, which is easy to fall into the defect of local optimization. Particle swarm optimization (PSO) is that all particles move in the optimal direction, which makes the direction of particle movement more and more consistent, so the convergence speed of PSO is getting slower and slower in the later stage, and it is easy to fall into local optimization.

3.3GA-PSO-SVM process

GA-PSO combined algorithm proposed in this paper is based on genetic algorithm and embedded with particle swarm optimization. By introducing particle swarm speed, particle value and all particle values of particle swarm optimization to improve genetic algorithm, the problems of low convergence speed of genetic algorithm and premature convergence of particle swarm optimization can be solved, and the optimization performance of the algorithm can be improved. The specific implementation process is as follows:

(1) Initialize the population and set parameters.
(2) Calculate the fitness value of the population.
(3) carry out selection operation.
(4) Cross operation.
(5) carrying out mutation operation.
(6) update the group speed and position.
(7) Update the speed and position of the individual.
(8) Stop when the number of iterations reaches, and obtain the optimal solution.

Algorithm setting: population number pop is 20; The maximum number of iterations is 50; The crossover probability is 0.6; The mutation probability is 0.03, and the cross-validation setting is 10% off.

4.Model and Analysis

4.1 Field data

In this paper, 50 groups of samples were randomly selected according to the actual situation and the influencing factors of gas emission. Among them, the first 40 groups are used as training sets and the last 10 groups are used as test sets. The selected factors that affect the gas emission from the working face are goaf drainage, air distribution, working face recovery rate, footage from the last weighting and advancing speed, and the prediction index is the return gas concentration. As shown in Table 1.

Table 1 Sample data

Goaf extraction volume (m3/h)	Air volume (m3/min)	Coal mining rate of the coal mining face (%)	From the last footage (m)	Propulsion speed (m/d)	Return air gas concentration(%)
9.8	1309	0.93	19.2	4.15	0.43
9.4	1309	0.94	44.1	4.46	0.47
9.1	1309	0.955	14	4.56	0.48
8.9	1309	945	13	4.67	0.49
8.7	1309	0.934	15	4.35	0.5
8.4	1309	0.94	12	3.44	0.51
7.8	1309	0.93	12.3	3.23	0.54
7.3	1309	0.94	12.6	3.69	0.5
8.8	1302	0.923	13.6	3.28	0.45
8.3	1302	0.933	7.8	4.03	0.44
8.1	1302	0.92	17.5	3.35	0.43
8.0	1302	0.97	11.2	2.87	0.4
7.9	1302	0.953	10.2	3.66	0.4
9.3	1302	0.945	13	4.12	0.41
8.2	1302	0.93	19.8	4.11	0.47
10.1	1302	0.94	10.8	4.15	0.48
16.9	1302	0.94	11.4	4.36	0.49
16.4	1302	0.955	15.6	4.67	0.5
18.5	1309	0.95	15.6	4.26	0.43
19.4	1302	0.92	17.1	3.23	0.46
22.7	1296	0.93	15.8	3.48	0.49
21.6	1296	0.89	18.7	4.02	0.5
21.8	1296	0.94	16.4	3.34	0.47
22.1	1296	0.92	10.1	2.88	0.42
22.3	1296	0.923	10.3	2.68	0.45
22.5	1296	0.81	15.1	2.43	0.48
22.6	1296	0.85	11.3	2.77	0.49
22.8	1296	0.886	17	2.67	0.5
21.6	1296	0.89	9.0	2.72	0.51
20.5	1296	0.902	10.5	4.12	0.53
20.1	1309	0.95	17.4	2.8	0.55
19.6	1309	0.93	13	4.43	0.58
18.9	1309	0.93	9.3	4.41	0.6
19.1	1309	0.91	8.3	4.03	0.52
19	1309	0.941	14.1	4.17	0.4
18.6	1309	0.92	9.0	3.36	0.39
18.3	1309	0.89	16.3	3.21	0.36
18.1	1309	0.92	15.9	4.55	0.4
17.4	1302	0.911	12.4	4.67	0.42
17	1302	0.934	11.3	4.29	0.42
16.4	1302	0.92	16.5	4.03	0.5
16.1	1302	0.91	13.9	3.87	0.53
15.2	1302	0.93	15.1	3.47	0.5
14.2	1302	0.941	10.3	3.76	0.4
12.7	1302	0.936	11.5	2.87	0.46

12.4	1302	0.92	16.7	2.59	0.44
12.1	1302	0.93	14.5	2.11	0.42
12	1302	0.93	12.4	2.98	0.41
11.9	1309	0.94	11.4	3.17	0.43
11.6	1302	0.92	10.1	4.58	0.4

4.2 Model analysis

After the same training times, 10 groups of data are selected as the test set, and the gas emission is predicted by the support vector machine model simulated by MATLAB software, the support vector machine model optimized by genetic algorithm, the support vector machine model optimized by particle swarm optimization and the improved support vector machine prediction model optimized by genetic algorithm, respectively. The performance of these prediction models is compared by three indicators, namely RMSE, MAE and MSE, as shown in Table 2.

Table 2 Calculation results of different models

Sequence	SVM	GA-SVM	PSO-SVM	GA-PSO-SVM
One	0.364613	0.464245	0.424351	0.465523
Two	0.364524	0.464107	0.410262	0.465523
Three	0.399881	0.464374	0.451783	0.466672
Four	0.500276	0.464373	0.472900	0.462623
Fve	0.459570	0.464292	0.449848	0.455375
Six	0.421078	0.464319	0.453325	0.458930
Seven	0.371198	0.464372	0.460122	0.446635
Eight	0.475924	0.464249	0.452650	0.465643
Nine	0.394327	0.465882	0.446694	0.466105
Ten	0.617116	0.464376	0.483587	0.465098
MAE	0.088813	0.042914	0.052303	0.029942
MSE	0.012129	0.0021987	0.003867	0.001323
RMSEP	0.11013	0.04689	0.062189	0.036378

It can be seen from Table 2 that among the 10 groups of measured data, the MAE value of GA-PSO-SVM model is 0.058871, 0.012972 and 0.039331 lower than that of SVM model. It shows that GA-PSO-SVM model has high goodness of fit and improved prediction accuracy. Secondly, the MSE value of GA-PSO-SVM model is 0.010806, 0.002199 and 0.003867 lower than that of SVM model. Finally, the RMSE value of GA-PSO-SVM model is 0.073752 lower than that of SVM model, 0.010512 lower than that of GA-SVM model and 0.025811 lower than that of PSO-SVM model. The smaller the values of MSE, MAE and RMSEP, the higher the accuracy of the data predicted by this model. It shows that GA-PSO-SVM model has high goodness of fit and improved prediction accuracy. Combined model is more suitable for gas emission prediction than single GA-SVM and PSO-SVM models.

5.Summary

A gas emission prediction model based on GA-PSO-SVM algorithm was established and successfully applied in a coal mine. Practice has proved that the prediction model has higher accuracy and credibility, and the main conclusions are as follows: the MSE, MAE and RMSEP values of GA-PSO-SVM model in the prediction of return gas concentration are 0.029942, 0.001323 and 0.036378, respectively, and the three indexes are superior to the other three prediction models, so the prediction accuracy of GA-PSO-SVM model is the highest. It shows that the combined model is more accurate than the single GA-SVM and PSO-SVM models to predict the gas emission in coal mines, and it has certain effect on the gas overrun in mining face.

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