ARTICLE

Prediction Model for Gas Outburst Intensity of Coal Mining Face Based on Improved PSO and LSSVM

Haibo Liu[1,*], Yujie Dong[2] and Fuzhong Wang[1]

[1]School of Electric Engineering and Automation, Henan Polytechnic University, Jiaozuo, 454000, China
[2]College of Computer Science and Technology, Henan Polytechnic University, Jiaozuo, 454000, China
[*]Corresponding Author: Haibo Liu. Email: liuhaibo09@hpu.edu.cn

ABSTRACT

For the problems of nonlinearity, uncertainty and low prediction accuracy in the gas outburst prediction of coal mining face, the least squares support vector machine (LSSVM) is proposed to establish the prediction model. Firstly, considering the inertia coefficients as global parameters lacks the ability to improve the solution for the traditional particle swarm optimization (PSO), an improved PSO (IPSO) algorithm is introduced to adjust different inertia weights in updating the particle swarm and solve the fitness to stagnate. Secondly, the penalty factor and kernel function parameter of LSSVM are searched automatically, and the regression accuracy and generalization performance is enhanced by applying IPSO. Finally, to verify the proposed prediction model, the model is applied for gas outburst prediction of Jiuli Hill coal mine in Jiaozuo City, and the results are compared with that of PSO-SVM model, IGA-LSSVM model and BP model. The results show that the relative errors of the proposed model are not greater than 2.7%, and the prediction accuracy is higher than other three prediction models. The IPSO-LSSVM model can be used to predict the intensity of gas outburst of coal mining face effectively.

1 Introduction

In recent years, with the increasing depth and intensity of mine exploitation in China, the number of dangerous mines with gas outburst has increased rapidly, and coal mine gas explosions and outburst accidents have occurred frequently, which has brought serious impact on coal mine safety production and economic benefits [1]. How to predict the occurrence of coal mine gas outburst accurately and reliably and prevent it effectively has become an important direction in the research of coal mine safety production technology, and also a problem to be solved urgently in the field of safety production.

Coal and gas outburst is the destabilizing release of broken coal and gas stored in coal seam, which shows that a large amount of coal and gas are thrown into the production space in a very short time, which may induce gas explosion and cause greater disasters [2,3]. The cause of gas outbursts is fairly complicated and involves many influencing factors, such as *in-situ* stress, gas content, gas pressure, firmness coefficient and geological structure and so on. The relationship between the gas outburst and influencing factors has the characteristics of non-linearity, randomness and fuzziness, which make it

impossible to use classical mathematical theory to establish accurate prediction model. Since the traditional empirical model and deterministic model have certain limitations, many researchers have tried to develop many prediction methods to improve low accuracy and efficiency of coal and gas outburst prediction, including fuzzy theory [4,5], grey theory [6], neural network [7,8], support vector machine (SVM) [9,10], data mining and fusion [11–15], double coupling algorithm [16] and machine learning [17–20] and so on. In [6], Guo et al. proposed a grey theory and neural network method to predict coal and gas outburst. Main controlling factors were filtered by the grey correlation method, and the mathematical model and systematic structure of artificial neural network were established. Qu [7] proposed to apply the BP neural network method to predict, used the neural network method to train the main outburst controlling factors, and established an artificial neural network mathematical model. Liu [8] used the combination of fuzzy neural network and D-S theory to obtain a gas outburst evaluation strategy by two fusions of sample data. As the development of the techniques mentioned above, many advanced prediction models for gas outburst are obtained in the literature. However, it should be pointed out that gas outburst of coal mining face are complex non-linear dynamic systems, establishing fast and effective prediction models and making evaluations on outburst risk are still a challenging problem.

2 Related Work

During the last several decades, a great deal of efforts has been devoted to gas prediction of coal mining face. Hence, remarkable results have been proposed in the literature [6–10,16,17,21–27]. In [9], on basis of the strong recognition ability of SVM in the case of small samples, the gray correlation analysis was introduced in outburst influencing factors, the feature vector was extracted, and SVM prediction model was obtained. In [10], to improve the classification accuracy and generalization ability of SVMs, a parameter selection model for SVMs with RBF kernel was proposed based on adaptive differential evolution (ADE) algorithm, which can adjust parameters automatically and promote the searching ability for local optimal values. By applying BPNN to set up identification model and introducing D-S theory to fuse the identification results in the time domain and the spatial domain, a gas outburst prediction model based on data mining and information fusion was proposed which effectively improved the accuracy of prediction in [11]. Xu [15] presented a method of combining wavelet principal component analysis (KPCA) and improved extreme learning machine (IQGA-ELM), KPCA was used to extract the principal component sequence of the primate index, using the IQGA to optimize the input weight and the hidden layer threshold of ELM. The model had strong generalization performance and improve the accuracy of prediction. In [19], the main influence factors were analyzed and extracted by gray correlation and factor analysis model, and the quantum genetic algorithm (QGA) was applied to optimize the parameters of the least squares support vector machine (LSSVM). The QGA-LSSVM model was established and can effectively predict the outburst type. In [25], an outburst fragmentation index was developed based on a new surface theory by analyzing the ejected coal, which can be linearly fitted with the relative intensity of outburst nonlinearly. Thus the η prediction method was proposed, and the relationship with f prediction method was analyzed. These scholars have achieved fruitful results on gas outburst prediction. However, it should be noted that, most of them require more input factors, and the kernel function and penalty parameter in [9,10] are selected based on experience and traditional PSO, which will affect the classification effect of prediction model significantly. Therefore, there are still rooms for further enhancement on the feasible region of coal and gas outburst prediction for mining face.

On basis of the above discussion, considering the complex non-linear relationship between gas outburst and influencing factors, an IPSO-LSSVM model for coal mine gas outburst prediction is established. Firstly, considering the inertia coefficients as global parameters lacks the ability to improve the solution at the later stage of evolution, an IPSO algorithm is introduced, which can adjust different inertia weights in updating the particle swarm and solve the fitness to stagnate. Secondly, by applying the IPSO algorithm, the penalty factor

and kernel function parameter of LSSVM are searched automatically, and the regression accuracy and generalization performance is enhanced. Finally, the proposed model is applied for gas outburst prediction of Jiuli Hill coal mine in Henan Province, China, which has higher accuracy and reliability by comparing with PSO-SVM model, IGA-LSSVM model and BP model.

3 Methodology

3.1 Least Squares Support Vector Machine (LSSVM)

SVM is a kind of classification algorithm, which can improve the generalization ability of learning machine by seeking the structural risk minimization and realize the minimization of empirical risk and confidence range [9]. In 1999, Suykens introduced least squares into SVM and proposed LSSVM, which used the least squares linear system as the loss function to transform the quadratic programming problem into solving linear equations in standard SVM training [11].

Suppose training set $\{x_i, y_i\}$, $i = 1, \cdots, m$, where $x_i \in R^n$, $y_i \in R$, regression estimation by following equation:

$$y = f(x, w) = w^T \phi(x) + b \tag{1}$$

where, $\phi(\cdot)$ is the nonlinear mapping to map the input data to the high-dimensional feature space; w^T is the transpose of the weight vector w, b is the real constant parameter threshold, $b \in R$. The optimization problem of LSSVM is expressed as follows:

$$\min_{w,b,e} J(w, e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma e^T e \tag{2}$$

The constraint is:

$$y_i = w^T \phi(x_i) + b + e_i, \quad i = 1, \cdots, m \tag{3}$$

Introducing the Lagrangian operator $\alpha = [\alpha_1, \cdots, \alpha_m]^T$, define the Lagrang function as:

$$L(w, b, e, \alpha) = J(w, e) + \sum_{i=1}^{m} \alpha_i [y_i - (w^T \phi(x_i) + b + e_i)] \tag{4}$$

The optimum conditions are as follows:

$$\begin{cases} \dfrac{\partial L}{\partial w} := 0 \Rightarrow w = \sum_{i=1}^{m} \alpha_i \phi(x_i) \\ \dfrac{\partial L}{\partial b} := 0 \Rightarrow \sum_{i=1}^{m} \alpha_i = 0 \\ \dfrac{\partial L}{\partial e_i} := 0 \Rightarrow \alpha_i = \gamma e_i \\ \dfrac{\partial L}{\partial \alpha_i} := 0 \Rightarrow w^T \phi(x_i) + b + e_i - y_i = 0 \end{cases} \tag{5}$$

where, $i = 1, \cdots, m$. Eliminate the variables e and w, the following matrix equations can be obtained.

$$\begin{bmatrix} 0 & 1 \\ 1 & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{6}$$

where I is the unit matrix, $1 = [1, \cdots, 1]^T$, $y = [y_1, \cdots, y_m]^T$, Ω is the kernel matrix. The existence of mapping function ϕ and kernel function $K(\cdot, \cdot)$ makes the following equation hold.

$$\Omega_{jk} = [\phi(x_j)]^T [\phi(x_k)] = K(x_j, x_k) \quad j, k = 1, \cdots, m \tag{7}$$

Let $A = \Omega + \gamma^{-1}I$. A^{-1} exists for any $\gamma > 0$. Solving the linear equation for Eq. (6) gives:

$$\alpha = A^{-1}(y - bI) \quad b = \frac{I^T A^{-1} y}{I^T A^{-1} I} \tag{8}$$

By substituting w in the first fraction of Eqs. (5) and (4) into Eq. (1), a least squares support vector regression estimate can be obtained:

$$f(x, w) = y(x) = \sum_{i=1}^{m} \alpha_i K(x, x_i) + b \tag{9}$$

where, α_i and b are given by Eq. (8), depending on the γ and kernel matrix. In order to avoid solving complex non-linear mapping functions, radial basis function (RBF) is introduced to replace the point product operation in high-dimensional space, which can greatly reduce the computational complexity. Moreover, RBF kernel function can easily realize the optimization process of SVM, and support vectors and weights can be obtained by an algorithm. The kernel function is:

$$K(x, x_k) = \exp\left(-\frac{\|x - x_k\|^2}{2\sigma^2}\right) \tag{10}$$

where, σ is the kernel width, then the linear regression equation of LS-SVM becomes:

$$y(x) = \sum_{i=1}^{n} \alpha_i \exp\left(-\frac{\|x - x_k\|^2}{2\sigma^2}\right) + b \tag{11}$$

3.2 Improved Particle Swarm Optimization Algorithm (IPSO)

PSO is a swarm intelligence search algorithm proposed by J Kennedy and R Eberhart in 1995 to find the optimal solution through cooperation and information sharing among individuals in the swarm [10]. It is relatively simple and easy to implement, and has been widely used in many fields.

In PSO, a population consisting of m particles is distributed in the D-dimensional space, $x_i = [x_{i1}, x_{i2}, \cdots, x_{iD}]^T$ is the positional information of the i-th particle in space, $v_i = [v_{i1}, v_{i2}, \cdots, v_{iD}]^T$ is the velocity information of the i-th particle, $p_i = [p_{i1}, p_{i2}, \cdots, p_{iD}]^T$ represents the optimal position of the i-th particle passing at time t, $p_g = [p_{g1}, p_{g2}, \cdots, p_{gD}]^T$ is optimal position that particle swarm can search, $i = 1, 2, \cdots, m$. The particles update their speed and position by means of Eqs. (12) and (13). After multiple iterations, the individual's optimization in free space is finally realized.

$$v_{iD}(t+1) = \omega v_{iD}(t) + c_1 r_1 [p_{iD} - x_{iD}(t)] + c_2 r_2 [p_{gD} - x_{iD}(t)] \tag{12}$$

$$x_{iD}(t+1) = x_{iD}(t) + v_{iD}(t+1) \tag{13}$$

where, ω is the inertia coefficient, r_1 and r_2 are the random numbers in [0,1]; c_1 and c_2 are the acceleration factors, the position range and velocity interval of the particles can be set to appropriately constrain the motion.

The setting of inertia coefficients in PSO algorithm directly affects the balance between global and local search ability of particles. Taking the inertia coefficients as global parameters lacks the ability to improve the solution at the later stage of evolution, which will cause the fitness to stagnate. In [18], a new strategy of inertia weight adjustment and the corresponding PSO were proposed, different inertia weights are used in updating the particle swarm in the same generation in the new PSO. The particle individual sets are

sorted in descending order according to the size of the fitness value, and a new set of individual particles is arranged in order. Since the fitness value of particle in the first position of the new individual set is the largest, it is called a good particle. The position of i-th particle in the individual particle set is called the best particle distance of the individual i, and the inertia weight adjustment model is established as follows:

$$\omega(i,x) = u(d_i,x) * [\omega_s + (\omega_e - \omega_s) * cIter/MaxIter] \tag{14}$$

where, $cIter$ and $MaxcIter$ is the current and maximum iteration number respectively, ω_e and ω_s are the initial and end values of ω, respectively; $u(d_i, x)$ is the control factor of the individual inertia coefficient of the particle. The specific form is as follows:

$$u(d_i,x) = \begin{cases} 1 + \alpha, & d_i \leq S_1 N \\ 1, & S_1 N < d_i < S_2 N \\ 1 - \beta, & d_i \geq S_2 N \end{cases} \tag{15}$$

where N is the population size, S_1 and S_2 are control parameters, and α and β are adjustment parameters, $S_1 < S_2 < 1$, $\alpha > 0$, $\beta > 0$.

3.3 Gas Outburst Prediction Model Based on IPSO and LSSVM

The main geological factors affecting outburst are gas pressure, coal seam thickness, permeability coefficient of coal seam, destruction type and geological structure type of coal. The relationship between gas outburst and its influencing factors is complex and non-linear, so it is difficult to express it in explicit mathematical form. This is described by $LSSVM (x_1, x_2, \ldots, x_n)$.

$$\begin{cases} LSSVM(X) : R^n \rightarrow R \\ Y = LSSVM(X) \\ X = (x_1, x_2, \cdots, x_n) \end{cases} \tag{16}$$

where, $X = (x_1, x_2, \ldots, x_n)$ is the factor affecting gas outburst, such as coal seam thickness, geological structure type of coal, and Y is the intensity of gas outburst. The actual representative data samples are used for LSSVM learning to establish a non-linear relationship model.

The process of IPSO-LSSVM model is as follows:

1. Input and preprocess the sample data.
2. Initializing the IPSO-LSSVM, including the particle dimension n, the population size m, the number of iterations p, randomly giving the initial space position x_i^0 and initial velocity v_i^0 of the particle ($i \leq m$).
3. Predict the test sample through LSSVM model corresponding to each particle vector, and the prediction error is used as the individual fitness to reflect the generalization and prediction ability of LSSVM.
4. Comparing the fitness value calculated by each particle with $pbest_i$ of the current individual optimal solution, if $S_i(x) < pbest_i$, the current individual optimal solution is replaced by the particle, $pbest_i = S_i(x)$, $xpbest_i = x_i$.
5. Comparing the fitness value $pbest_i$ of each particle's current individual optimal solution with $gbest$ of current population optimal solution, if $pbest_i < gbest$, the particle will replace the original population optimal solution, $gbest=pbest_i$, $xpbest_i = x_i$.
6. After the whole population particle calculation, the termination condition is judged. If not, the particle moves according to Eqs. (12, 13) to generate a new population and return to Step (2). If the termination requirement is satisfied, the calculation is completed and the calculation results are output.

The IPSO-LSSVM prediction model of coal mine gas outburst is shown in Fig. 1.
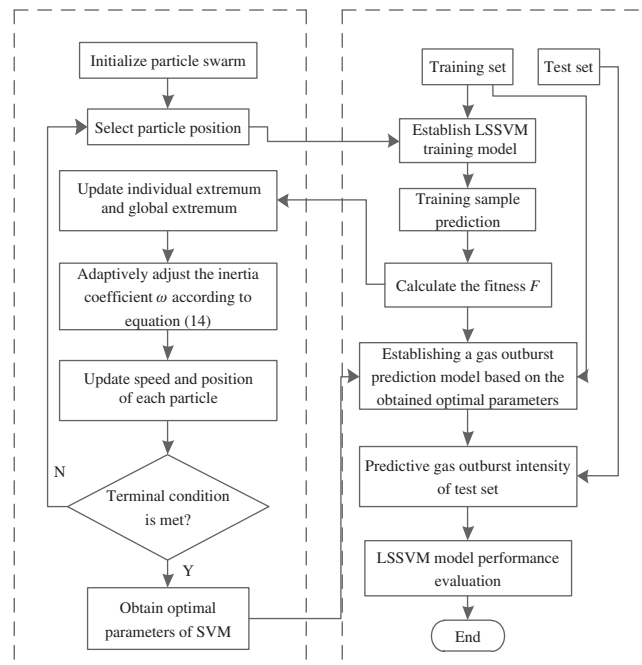
Figure 1: The flowchart of IPSO-LSSVM gas outburst prediction model

4 Results Analysis

4.1 Selection of Influencing Factors for Prediction

The occurrence of gas outburst in coal mining face is affected by many geological factors and is an extremely complex dynamic process involving coal, rock and gas. When predicting the gas outburst in the coal mining face, first select the typical factors that affect the gas outburst. According to the comprehensive hypothesis of outburst mechanism and site conditions, this paper selected coal seam thickness (p_1), gas pressure (p_2), gas content (p_3), initial speed of methane emission (p_4), firmness coefficient (p_5), geological structure (p_6), failure type of coal (p_7) and coal seam permeability coefficient (p_8) as gas outburst influence factors. The scale of coal and gas outburst is quite different. The scale of gas outburst is usually expressed by outburst intensity. The outburst intensity refers to the amount of coal (t) thrown out and the amount of gas (m^3) emitted in each outburst. Since the amount of gas in the process of outburst is difficult to accurately measure, the amount of coal (rock) outburst is used as the basis for classification usually. In general, there are four prediction types: I ($0\sim1t$), II ($1\text{-}50t$), III ($50\sim100t$) and IV ($100t$ or more). Among them, I represents negligible risk, II represents low risk, III represents medium risk and IV represents high risk [25]. The four prediction types are used as the evaluation set, which is the output result of LSSVM model.

In order to establish the IPSO-LSSVM gas outburst prediction model, the historical gas outburst data of 2306 working face of Jiuli Hill No. 1 Coal Mine of Jiaozuo Coal Group in Henan Province was collected and taken as the basic data source. The working face is the first caving face in 23 mining areas. The mining object is 2# coal seam in the middle and lower part of Henan Formation. The average thickness of coal seam is 5.45 m. During the production process, the gas emission amount is 29.63 m^3/min, the gas pressure is 0.5 MPa, the gas content in coal seam is 5.85–8.20 m^3/t, the average is 6.98 m^3/t, and the gas emission amount from the working face of the roadway is 9 m^3/t. The mining area is a typical high gas mining area, and high gas has become the main problem of the mining area. A total of 60 representative samples were selected from the entire sample data set. Some original training samples are shown in Tab. 1.

Table 1: Partial original training sample data

No.	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	Outburst intensity
1	3.8	0.95	0.5	6.0	0.25	5	1	0.3	II
2	4.5	2.75	0.7	18.0	0.30	3	4	0.6	IV
3	4.1	1.20	0.5	17.0	0.16	3	2	0.2	II
4	4.4	3.95	0.4	14.0	0.23	3	1	0.3	II
5	3.5	1.17	0.5	5.0	0.61	1	1	0.1	I
6	5.2	1.25	0.6	8.0	0.37	3	5	0.4	III
7	4.6	2.00	0.6	7.0	0.46	1	2	0.1	I
8	4.5	2.80	0.6	8.0	0.58	3	3	0.3	II
9	5.4	3.95	0.7	14.0	0.23	3	4	0.8	IV
10	5.3	2.90	0.7	4.0	0.50	5	5	0.7	II
11	4.7	1.30	0.7	6.0	0.43	3	5	0.8	IV
12	3.2	1.40	0.4	4.0	0.58	3	1	0.2	I
13	4.9	0.95	0.5	6.0	0.24	3	3	0.4	III
14	4.5	2.16	0.6	14.0	0.33	4	2	0.3	II
15	4.1	2.39	0.4	11.0	0.26	3	1	0.2	I

4.2 Data Preprocessing

For eliminating the influence of different data dimensions on the performance of prediction model, the sample data of each factors should be normalized before modeling. The Min–Max normalization approach is used to preprocess the original sample data in this paper, which is a linear transformation and ensure the result is mapped between [0,1]. The normalized equation is as follows:

$$\bar{p}_i = \frac{p_i - p_{\min}}{p_{\max} - p_{\min}} \tag{17}$$

where $\bar{p}_i$ is the normalized value, p_i is the initial value of the salient factor, and $p_{\max}$ and $p_{\min}$ are the maximum and minimum values of salient factor, respectively.

4.3 Prediction Result Analysis

In this paper, LIBSVM is selected as the training and testing tool for the LSSVM model, and the simulation experiment is carried out in MATLAB. Under the condition that other parameters are set at the default value of the system, the relative error and standard deviation of the gas outburst prediction model established by the three kernel functions in the training process are compared, as shown in Tab. 2.

Table 2: Relative error and standard deviation of models with different kernel function

Kernel functions	Relative error %	Standard deviation %
POLY_kernel	0.152	0.146
LIN_kernel	0.063	0.055
RBF_kernel	0.052	0.047

As can be seen from Tab. 2, the relative error and standard deviation of the prediction model established by RBF_kernel function are less than model established by Poly_kernel and LIN_kernel function. Therefore, RBF_kernel function is used in this paper.

When training the training samples with IPSO, the parameters are set as follows. The first 45 groups were selected as the training samples from the 60 sets of sample data, and the last 15 groups were used as test samples to test the prediction accuracy of model. C and kernel function parameters of LSSVM are optimized by changing the parameters c_1 and c_2 of IPSO and the number of iterations. The main parameters are as follows: $N = 20$, particle dimension is 2, $c_1 = 1.5$, $c_2 = 1.7$, the maximum number of iterations is 100. The optimized parameters were obtained, and the IPSO-LSSVM model was used to predict the intensity of gas outburst. The fitness curve of IPSO is shown in Fig. 2, which shows that after 20 iterations, the optimal fitness reaches 90%. Tab. 2 shows α of the partial sample support vectors.
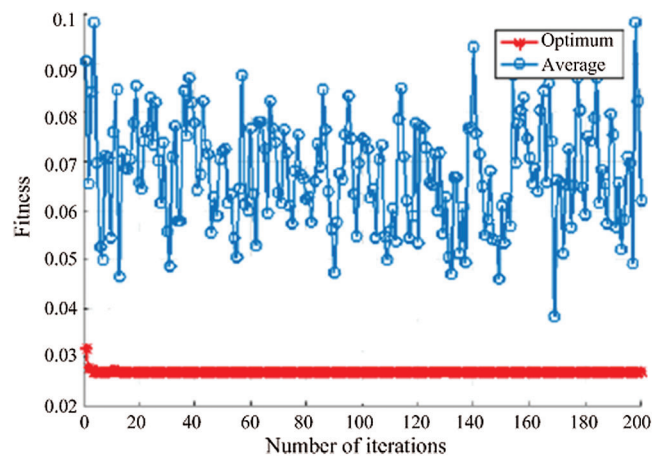

Figure 2: Fitness curves of IPSO

Table 3: The α of support vector of each sample

No.	α	No.	α	No.	α
1	1.4578	6	3.5420	11	1.6301
2	6.9112	7	4.3308	12	−3.7235
3	0.6896	8	−1.4427	13	2.8490
4	6.9112	9	−2.2555	14	−1.2445
5	−6.0703	10	3.9833	15	2.3281

According to the optimal penalty parameters and the optimal kernel function parameters obtained, the IPSO-LSSVM gas outburst prediction model is used to predict the test samples. The results of some test samples are shown in Tab. 4.

Tab. 4 shows that the predicted results of test samples are in good agreement with the actual results, indicating the validity of the proposed model. In order to verify the superiority of IPSO-LSSVM gas outburst prediction model, the model is compared with the BP model [13], IGA-LSSVM model [15] and PSO-SVM model [26] through simulation experiments. The results are shown in Fig. 3.

Table 4: Prediction results of test sample

No.	Predict results	Actual intensity	No.	Predict results	Actual intensity
46	II	II	54	IV	IV
47	IV	IV	55	II	II
48	II	II	56	III	III
49	II	II	57	I	I
50	I	I	58	III	III
51	III	III	59	II	II
52	I	I	60	I	I
53	II	II			
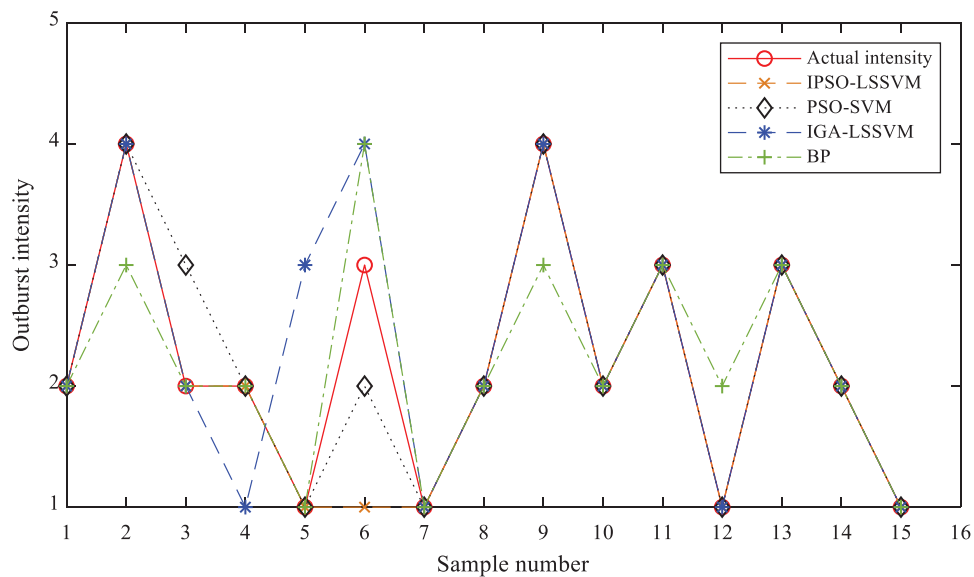
Figure 3: Gas outburst prediction results of four methods

Fig. 3 shows that the accuracy of BP neural network prediction is 60%, PSO-SVM model prediction is 78% and that of IGA-LSSVM model prediction is 80%, indicating that the IPSO-LSSVM model has higher accuracy compared with the other four prediction methods. From Fig. 4, one can clearly see that the relative errors of the four predicted methods are 2.7%, 5.6%, 5.9% and 7.8% respectively, and our results provides smaller relative error than those in [12,13,26]. Compared with the general LSSVM model, an IPSO algorithm is introduced which can adjust different inertia weights in updating the particle swarm in the same generation and solve the fitness to stagnate. And the penalty factor and kernel function parameter of LSSVM are searched automatically and optimized by IPSO, which enhance the regression accuracy and generalization performance of LSSVM models and improve the prediction accuracy. The comparison results indicate that the proposed prediction model in this paper has higher accuracy and can be applied to other coal mines in the future.
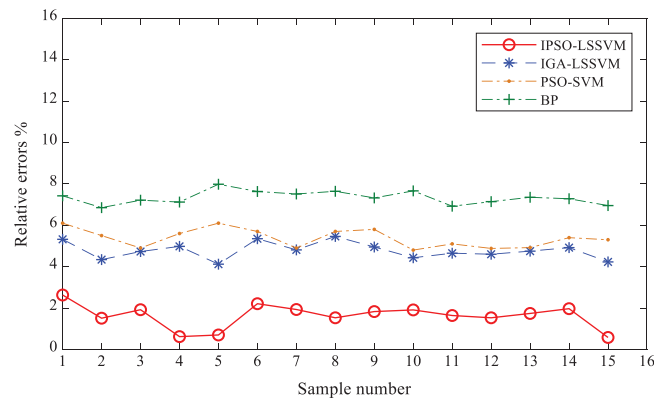
Figure 4: Relative errors comparison of four methods

5 Conclusion

In this paper, a new IPSO-LSSVM prediction model for gas outburst of mining face is proposed. The proposed model establishes the mapping relationship between gas outburst and influencing factors effectively, and improves the prediction accuracy. The main conclusions are as follows:

1. Considering the inertia coefficients as global parameters lacks the ability to improve the solution for traditional PSO, an IPSO algorithm is introduced which can adjust different inertia weights in updating the particle swarm and solve the fitness to stagnate.
2. By applying the IPSO algorithm, the penalty factor and kernel function parameter of LSSVM are searched automatically, and the regression accuracy and generalization performance of LSSVM models are enhanced.
3. Based on a comprehensive analysis of influencing factors of gas outburst, eight influencing factors are selected. Then, the prediction model based on IPSO and LSSVM is established, and is applied for gas outburst prediction of Jiuli Hill coal mine in Jiaozuo City, China. The results show that the relative errors of the proposed model are not greater than 2.7%, and the prediction accuracy is higher than other three prediction models.

Conflicts of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

1. Zhu, L. Y., Lv, W. S., Yang, P., Wang, Z. K., Wang, K. (2018). Statistical analysis and occurrence laws of coal mine accidents of China from 2007 to 2016. *Safety in Coal Mines, 49(7),* 237–240.
2. Zhao, X. S., Ning, X. L., Zhang, Q. H., Ma, G. L. (2018). Discussion on early warning method of coal and gas outburst. *Industry and Mine Automation, 44(1),* 6–10.
3. Black, D. J. (2019). Review of coal and gas outburst in Australian underground coal mines. *International Journal of Mining Science and Technology, 29(6),* 815–824. DOI 10.1016/j.ijmst.2019.01.007.
4. Grychowski, T. (2014). Multi sensor fire hazard monitoring in underground coal mine based on fuzzy inference system. *Journal of Intelligent & Fuzzy Systems, 26(1),* 345–351. DOI 10.3233/IFS-120743.
5. Liu, H. B., Wang, F. Z., Dong, Y. J. (2018). Application of fuzzy data fusion in prediction of gas outburst in mining face. *Process Automation Instrumentation, 39(5),* 89–92.

6. Guo, D. Y., Li, N. Y., Pei, D. W. (2007). Prediction method of coal and gas outburst using the grey theory and neural network. *Journal of University of Science and Technology Beijing, 29(4),* 354–357.

7. Qu, F., Zhang, L., Li, Y. Y. (2012). Development of coal and gas outburst prediction system based on BP neural network. *China Safety Science Journal, 22(1),* 11–16.

8. Liu, H. B., Li, Y. B., Wang, F. Z. (2016). Evaluation strategy of gas outburst based on fuzzy neural network and evidence theory. *Journal of University of Shanghai for Science and Technology, 38(2),* 168–171.

9. Chen, Z. Y., Zhang, G. Z., Wu, C. F. (2010). Research on coal and gas outburst prediction based on support vector machines. *Industrial Safety and Environmental Protection, 36(5),* 33–36.

10. Xie, G. M., Shan, M. Z., Liu, M. (2016). Coal and gas outburst intensity prediction of FOA-SVM model and application. *Chinese Journal of Sensors and Actuators, 29(12),* 1941–1946.

11. Suykens, J. A., Vandewalle, J. (2000). Recurrent least squares support vector machines. *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications, 47(7),* 1109–1114. DOI 10.1109/81.855471.

12. Liu, H. B., Dong, Y. J., Wang, F. Z. (2020). Gas outburst prediction model using improved entropy weight grey correlation analysis and IPSO-LSSVM. *Mathematical Problems in Engineering, 2020(7),* 1–10. DOI 10.1155/2020/8863425.

13. Wu, Y. Q., Gao, R. L., Yang, J. Z. (2020). Prediction of coal and gas outburst: A method based on the BP neural network optimized by GASA. *Process Safety and Environmental Protection, 133,* 64–72. DOI 10.1016/j.psep.2019.10.002.

14. Rudakov, D., Sobolev, V. (2019). A mathematical model of gas flow during coal outburst initiation. *International Journal of Mining Science and Technology, 29(5),* 791–796. DOI 10.1016/j.ijmst.2019.02.002.

15. Wang, Z. H., Qiao, N. (2015). Prediction model of coal and gas outburst intensity based on IGA-LSSVM. *Journal of Liaoning Technical University: Natural Science, 34(7),* 791–796.

16. Xu, Y. S., Qiu, W., Wang, Z. G. (2018). Based on the wavelet KPCA with IQGA-ELM coal and gas outburst prediction research. *Chinese Journal of Sensors and Actuators, 31(5),* 720–725.

17. Fu, H., Feng, S. C., Gao, Z. B., Yang, Y. G. (2018). Study on double coupling algorithm based model for coal and gas outburst prediction. *China Safety Science Journal, 28(3),* 84–89.

18. Huang, L., Du, W. W., Ding, L. X. (2012). Particle swarm optimization algorithm based on adaptive Sigmoid inertia weight. *Application Research of Computers, 29(1),* 32–34.

19. Wen, T. X., Sun, H. J., Zhang, B., Shao, L. S., Kong, X. B. (2015). Prediction model for outburst of coal and gas based on QGA-LSSVM. *Journal of Safety Science and Technology, 11(5),* 5–12.

20. Rudakov, D., Sobolev, V. (2019). A mathematical model of gas flow during coal outburst initiation. *International Journal of Mining Science and Technology, 29(5),* 791–796. DOI 10.1016/j.ijmst.2019.02.002.

21. Wen, T. X., Yu, F. E., Shao, L. S. (2018). Probabilistic neural network prediction model of coal and gas outburst based on grey relational entropy. *Application Research of Computers, 35(11),* 3326–3329.

22. Papalexakis, E. E., Faloutsos, C., Sidiropoulos, N. D. (2017). Tensors for data mining and data fusion: Models, applications, and scalable algorithms. *ACM Transactions on Intelligent Systems and Technology, 8(2),* 1–16.

23. Kursunoglu, N., Onder, M. (2019). Application of structural equation modeling to evaluate coal and gas outbursts. *Tunnelling and Underground Space Technology, 88,* 63–72. DOI 10.1016/j.tust.2019.02.017.

24. Zhi, S., Elsworth, D. (2016). The role of gas desorption on gas outbursts in underground mining of coal. *Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 2(3),* 151–171. DOI 10.1007/s40948-016-0026-2.

25. Zhu, Z. J., Zhang, X. Y. (2014). Research on coal and gas bursting models based on BP and RBF neural networks. *Journal of North University of China (Natural Science Edition), 35(5),* 571–575.

26. Zhang, C. L., Wang, E. Y., Xu, J., Peng, S. J. (2020). A new method for coal and gas outburst prediction and prevention based on the fragmentation of ejected coal. *Fuel, 2020,* 1–10. DOI 10.1016/j.fuel.2020.119493.

27. Yan, Z. G., Yao, K., Yang, Y. X. (2016). A novel adaptive differential evolution SVM model for predicting coal and gas outbursts. *Journal of Difference Equations and Applications, 23(1-2),* 238–248. DOI 10.1080/10236198.2016.1214725.