

An IPSO-SVM Algorithm for Security State Prediction of Mine Production Logistics System

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Abstract. A theoretical basis for the regulation of corporate security warning and resources was provided in order to reveal the laws behind the security state in mine production logistics. Considering complex mine production logistics system and the variable is difficult to acquire, a superior security status predicting model of mine production logistics system based on the improved particle swarm optimization and support vector machine (IPSO-SVM) is proposed in this paper. Firstly, through the linear adjustments of inertia weight and learning weights, the convergence speed and search accuracy are enhanced with the aim to deal with situations associated with the changeable complexity and the data acquisition difficulty. The improved particle swarm optimization (IPSO) is then introduced to resolve the problem of parameter settings in traditional support vector machines (SVM). At the same time, security status index system is built to determine the classification standards of safety status. The feasibility and effectiveness of this method is finally verified using the experimental results.

1. Introduction

Security of mine production is beneficial to the people's livelihood and social stability. Although the situation is getting better now, mine production security cannot be ignored. According to statistics, the proportion of the reported mine accidents caused by production logistics system failures reaches as high as forty percent. Therefore, the further research on mine production logistics system security has important significance in practice.

In recent years, the development of mine production logistics in academia is mainly focused on the evaluation of production efficiency[1-2], the logistics system construction [3] and the informationization. The deficiencies on mine production logistics system security are obvious. Meanwhile, great achievements have been achieved when it comes to the research of mine security status prediction, which actually have great impact on our following works. For example, X.Star Wu and Ertugrul Topuz [4] presented two Operations Research models for optimization of ventilation control device locations and sizes in two different mine ventilation systems. The using of an essentially discrete-event simulation languages has been shown to effectively simulate the behaviour of a coal transportation system in a mine which has continuous characteristics [5].YIN Dong ling [6] reexamined these factors and built an evaluation index system of mine security, with its feasibility proved by quantitative analysis. Zhu et al. [7] constructed a comprehensive classification index system of mine risk from qualitative perspective. Besides, varies of Mathematical models existed so far in mine security prediction, and the most familiar ones including "regression analysis", "Markov Model", "Grey Model [8]", and "neural network [9]", et al. However, most models are not accurate



and adaptable currently, and these studied seldom have microscopic and dynamic security state prediction of mine production logistics system.

As a promising technique of machine learning based on statistical learning theory, support vector machines (SVMs) have received widespread attention in the field of mine security for their unique advantages in solving problems related to small samples, non-linear and high dimensions. The selections of model parameters and kernel functions in the SVM have an important influence on the classification performance in reality. Considering about this, this paper puts forward an improved particle swarm and SVM optimization algorithm by using radial basis function (RBF) as the fundamental kernel function. The proposed IPSO-SVM methods maximize the mine production logistics system security state for serving the growing demand of prediction modeling.

2. The IPSO-SVM algorithm

The method proposed in the present paper introduces the IPSO algorithm to optimize the relative parameters of SVM. It combines the features of the IPSO algorithm and the advantages of SVM at the same time. Figure 1 gives the flow diagram of the IPSO-SVM algorithm.

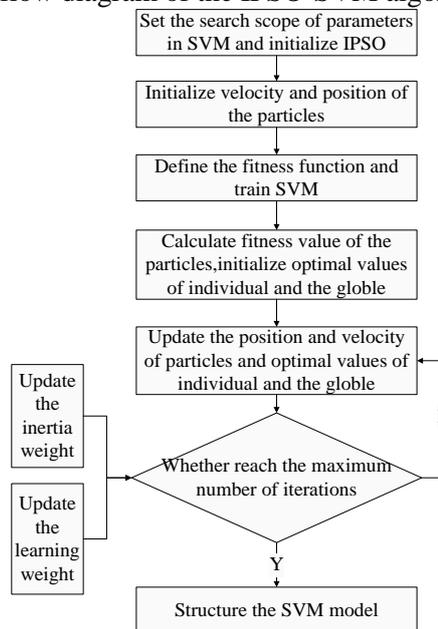


Figure 1.The flow diagram of IPSO-SVM algorithm

As can be seen, the procedure of the proposed IPSO-SVM algorithm is divided into the following seven steps:

STEP 1 Initialization of parameters. Search scopes of the parameters C and σ in SVM are set. Parameters of IPSO are initialized, including population dimension D , population size M , the maximum learning weight C_{max} , the minimum learning weight C_{min} , the maximum inertia weight W_{max} , the minimum inertia weight W_{min} , the maximum number of iterations T and the maximum velocity V_{max} .

STEP 2 Initialization of particle swarm. According to the search scope of C and σ , the model defined the initial position and speed of each particles randomly.

STEP 3 Definition of the fitness function. The average value of K models' classification accuracy is calculated by the K-CV method, which is used as a fitness function of IPSO algorithm expressed as Formula (1)

$$F(C, \sigma) = a_{K-CV} \quad (1)$$

The K-CV divides the initial data into K sets of groups. Firstly it selects a set of data as the target set, and others as the training sets. Then, each set of data will be set as a target set once one after another. The classification accuracy average of K target sets is the classification index of the SVM based on K-CV.

STEP 4 Training of the SVM. According to the value of the fitness function, the optimal value of individual species P_i and the global optimum P_g are initialized.

STEP 5 Updating the inertia weight, learning weight, positions and velocities of each particle, and optimal value of individual species and the global optimum. In details, the inertia weight is updated according to the Formula (2).

$$w = w_{\max} - (w_{\max} - w_{\min})t / T \quad (2)$$

Where w_{\max} and w_{\min} mean the maximum and minimum inertia weight, respectively. t and T are the number of iterations at present and the maximum number of iterations, respectively.

The learning weight is updated using the Formula (3).

$$c_1 = c_2 = c_{\max} - (c_{\max} - c_{\min})t / T \quad (3)$$

Where c_{\max} and c_{\min} are the maximum and minimum learning weight, respectively. Parameter t is the number of iterations at present and T is the maximum number of iterations.

The positions and velocities of each particle are updated on the basis of Formula (4).

$$\begin{aligned} v_i^d &= wv_i^d + c_1r_1(p_i^d - x_i^d) + c_2r_2(p_g^d - x_i^d) \\ x_i^d &= x_i^d + v_i^d \end{aligned} \quad (4)$$

Where the parameter $i = 1, 2, \dots, m$ and $d = 1, 2, \dots, D$, w is a nonnegative number called inertia weight, c_1 and c_2 are nonnegative constants called learning weight, r_1 and r_2 are random numbers in the range of 0 to 1. The movement velocity of every particle is set from $-v_{\max}$ to v_{\max} to prevent its velocity out of control.

Finally the optimal value of individual species and the global optimum are updated by comparison.

STEP 6The machine will determine whether the iterations have met the maximum number that has been set before. If so, the iteration will stop. Otherwise, the iteration will return back to STEP 5.

STEP 7 Optimal parameter values are obtained according to the results of calculation, and the SVM model is built in the end.

3. Example and analysis

3.1. The design of experiments

On the basis of the index system described above, 20 sets of typical data are selected from the safety monitoring data set of operational planning underground in a coal mining enterprise in Henan. After repeated experiments and demonstration analysis, numbers from 1 to 15 are chosen as the training sets, and numbers from 16 to 20 are chosen as the test sets. And the initial experiment parameters are set as: The range of penalty factor C is [0.1,100]; The range of the parameter σ is [0.1,50]; The dimension of particle D is 2; The size of particle swarm M is 100; The maximum number of iterations T is 200; The maximum learning weight c_{\max} is 1.7; The minimum learning weight c_{\min} is 0.9; The maximum inertia weight w_{\max} is 0.9; The minimum inertia weight w_{\min} is 0.4; The maximum velocity of particles v_{\max} is 1.2.

3.2. Analysis of experimental results

In order to verify the effect on training and prediction of the IPSO-SVM model, simulation experiment is performed in the simulation environments of Matlab 2014 (the fitness functions of IPSO algorithm are as Formula (1)).

In order to observe the effect of PSO algorithm after the intuitive improvement, values of the fitness function are recorded continuously during the process of iterative computations. Figures 2 and 3 are the convergence curves for the PSO and IPSO, respectively.

It is clearly seen from Figures 2 and 3 that the convergence speed and the accuracy of IPSO has significantly improved through linear adjustment of inertia weight and learning weigh. Besides, the convergence curve of IPSO is steadier compared with the counterpart of PSO, which verified the effectiveness of the IPSO to optimize parameters of the SVM.

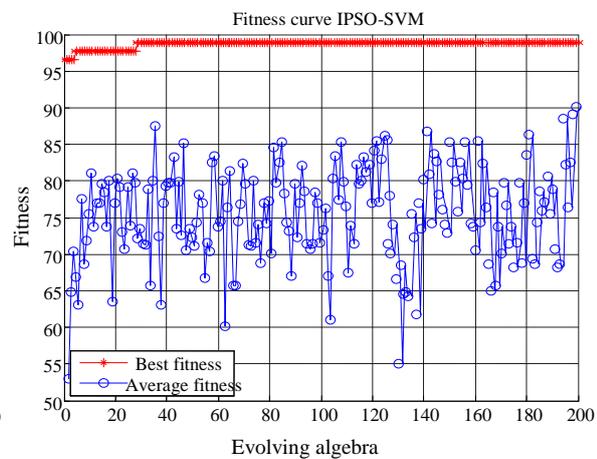
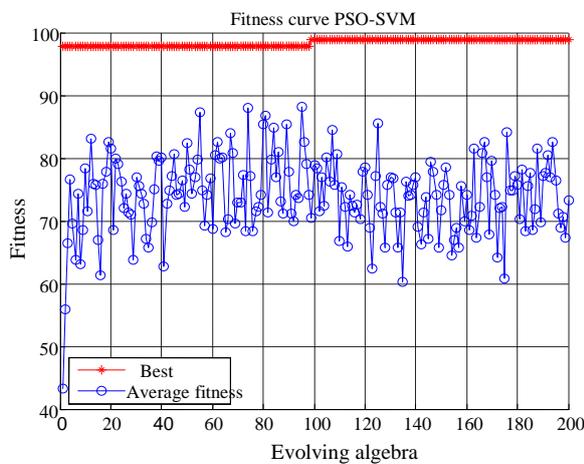


Figure 2.The convergence curve of PSO **Figure 3.**The convergence curve of IPSO

After fitting and studying the 15 sets of training samples, PSO-SVM and IPSO-SVM are used to forecast over 5 tested sample sets in experiments. The simulation and prediction results were demonstrated in Figures 4 and 5.

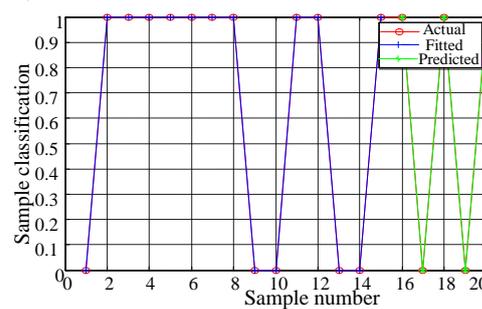
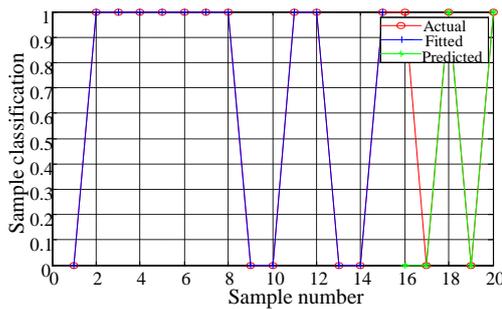


Figure 4.The classification effect of

Figure 5.The classification effect of

the PSO-SVM model the IPSO-SVM model

It is shown from Figures 4 and 5 that the PSO-SVM model has one mistake in the fitting and prediction process, while the IPSO-SVM model in this paper made no error in the whole process. Table 1 listed all the comparisons for two models. The results demonstrate the excellent performance of IPSO-SVM model in applications, which can even characterize small sample and complicated nonlinear ones in mine production logistics system.

Table 1. The comparisons of three results

Model	The number of sample	16	17	18	19	20	Accuracy	Parameters (C,σ)
PSO-SVM	Actual value	1	0	1	0	1	80%	(7.781,1.910)
	Predicted value	(0)	0	1	0	1		
IPSO-SVM	Actual value	1	0	1	0	1	100%	(8.181,2.350)
	Predicted value	1	0	1	0	1		

The precisions of PSO-SVM model are around 80 percent and make one error in classification, which shows the unique advantages of the SVM model in solving the nonlinear binary-class problems. In contrast, the IPSO-SVM model reaches 100 percent precision and show none error, which possesses excellent advantages in computing performance.

Above all, the experiments indicate that the IPSO-SVM is a promising model when used as security state prediction model in mine production logistics system. The model has better classification performance (none error in classification) and higher reliability (100% precision) compared with other two methods.

4. Conclusion

Combined with previous studies, The SVM theory is introduced into the prediction of security state for the characteristics of mine production logistics system. By integrating the traditional SVM model and the PSO after improvements of inertia weight and learning weight, this paper puts forward the IPSO-SVM prediction model of mine production logistics system security state. It is verified that the proposed IPSO algorithm improves dramatically the speed and accuracy of parametric optimization in the SVM. Meanwhile, the experimental results revealed that the IPSO-SVM model possesses excellent classification and prediction performance. Nevertheless, the model lacks adaptability when it comes to more complicated nonlinear problems. Therefore, the future research will focus on the introduction of nonlinear and self-adaptive parameter adjustment strategy in order to improve the search precision and speed of the particle group, and reduce the occurrence of premature phenomenon.

References

- [1] Wang J F,Zhai X Q,Feng L J. Efficiency optimization of coal mine production logistics under safety hard constraint. Chinese Journal of Management Science,2014,22(7):59-66.
- [2] Zhang Y L,Liu Y N,Wang J F. Research of coal mine production logistics system efficiency based on system dynamics. Industry and Mine Automation,2016,42(1):40-44.
- [3] Wang J F,Hu L N,Feng L J,ea al. Dynamic coordinated development degree model for safety and efficiency of coal mine production logistics system. China Safety Science Journal,2014,24(4):15-21.
- [4] X.Star Wu, Ertugrul Topuz. Analysis of Mine Ventilation Systems Using Operations Research Methods. International Transports Operation Research.1998,5(4):245-254.
- [5] Edwards, J.B.Mort, N.Holland, R.J. The use of animation in the simulation of coal mine production systems[C].Third International Conference of Competitive Performance Through Advanced Technology, 2002:278-284.
- [6] Yin D L,Chen Z B,Zeng J C,et al. Analysis of factors affecting coal mine operators' unsafe acts. China Safety Science Journal,2015,25(12):151-156.
- [7] Zhu J F, Yang D M. Research on mine risk classification and establishment of index system. China Mining Magazine, 2011,(20):110-112.
- [8] Wang L G, Pei A L. Applications of modified empenage residual error GM(1,1) model in the prediction of million tons death rate of coal mine. Science & Technology Review, 2013,(8):57-61.
- [9] Li J T. Overpressure distribution prediction of mine gas explosion based on artificial neural networks. Coal Safety, 2013,(2):157-159.