Prediction of Mine Gas Emission Rate using Support Vector Regression and Chaotic Particle Swarm Optimization Algorithm

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***Abstract*—Forecasting of gas emission rate in mine is a complicated problem due to its nonlinearity and the small quantity of training data. Support vector regression (SVR) can solve the problem with small samples, nonlinear and high dimensions. However, the precision of SVR is significantly affected by its parameter. In order to improve the mine gas emission rate accurately, an optimal selection approach of support vector regression parameters is proposed based on the chaotic particle swarm optimization algorithm (CPSO）. A model based on the CPSO-SVR to predict the mine gas emission rate is established and the optimal parameters of SVR is searched by CPSO. The experimental data from a coal mine in China is used to illustrate the performance of proposed CPSO－SVR model. The results show that the proposed prediction model has better results than the artificial neural network (ANN) and traditional SVR algorithm under the circumstances of small sample. This indicates that the precision can meet the requirement of practical production and demonstrates that the CPSO is an effective approach for parameter optimization of SVR.**

***Index Terms*—support vector regression, chaotic particle swarm optimization, mine gas emission rate**

I. Introduction

In China, 95% of coal mine accidents were gas incidents. As the coal mining, gas pressure of coal seam was from the relatively stable into pressure instability, leading to sudden gas emission increase in the moment[1].Therefore, the gas emission rate whose characteristics are complex and highly nonlinear has a major impact to the mine design, construction and mining. At the same time, gas emission rate is the primary indicators to determine mine ventilation, so accurate prediction of gas emission has important practical significance to guide the mine design and production safety. Many scholars have used various methods such as statistics theory, grey theory, Geological model, different-source method, regression theory etc. to forecast the coal gas emission rate [2-3]. Those methods could not play the excellent role in forecasting coal gas emission rate because the factors used for forecasting coal gas emission rate are known to be nonlinear. To improve the performance of nonlinear forecasting coal gas emission rate, artificial neural network (ANN) is employed. However, the ANN method realizing the dynamic prediction has the shortcomings, such as selecting the influencing factors of gas emission rate subjectively, have difficulties to acquire some accurate parameters. Furthermore, when the sample size is small, neural network can hardly make good predication [4].

Support Vector Machine (SVM) was proposed by Vladimir Vapnik [5] and his cooperators at the AT&T Bell Laboratory. Support vector machine as a small sample method based on statistical learning theory are one of the significant developments in overcoming shortcomings of ANN mentioned above. SVM not only implement the empirical risk minimization (ERM) principle to minimize the training error, but also apply the structural risk minimization (SRM) principle to minimize an upper bound on the generalization error. These differences make SVM a greater ability to generalize. It is shown that SVM has provided better performance than traditional learning techniques [5-6]. SVM is also well known for its superiority in solving nonlinear problems with kernel function, which automatically carries out a nonlinear mapping to a feature space. Originally, SVM was developed to solve pattern recognition problems. With the introduction of ε-insensitive loss function, SVM was extended to solve nonlinear regression estimation problems especially in situations where the training

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samples are small, such new techniques known as support vector regression (SVR), which have been shown to exhibit excellent performance [7].

To construct the SVR model efficiently, SVR's parameters must be set carefully [8]. However, the feasibility of SVR is effected due to the difficulty of selecting appropriate two parameters (C andσ). Although, some scholars had given some advices on appropriate setting of SVR parameters [9], however, those approaches do not simultaneously consider the interaction effects among the two parameters. Recently, Kennedy and Eberhart [10] inspired by the social behavior of organisms such as fish schooling and bird flocking, introduced particle swarm optimization (PSO). It is initialized with a population of random solutions in PSO .A randomized velocity flown through hyperspace to look for the optimal position to land is assigned to each particle. PSO can find a global optimal, at the same time, this method does not require gradient of the objective function but use values of the function itself. Nowadays PSO has gained much attention and wide applications in solving continuous nonlinear optimization problems due to its simple concept, easy implementation and quick convergence. But PSO is easy to trap into local optimum. Chaotic particle swarm optimization (CPSO) is a kind of improved PSO, which can not only avoid being trapped into local optimum in search , but also can help search the optimum quickly by using chaos queues [11].

This paper applies CPSO algorithm to choose the suitable parameter combination for a mine gas emission rate forecasting SVR model. A forecasting model of mine gas emission rate, called CPSO-SVR model, was established. The experiment s showed that the application of CPSO-SVR to forecast the mine gas emission rate is feasible and preferable.

II. Support Vector Regression

Here give a brief description of SVR. Detailed descriptions of SVR can be found in Vapnik [5,12,13], Sch□lkopf and Smola [14] and Cristianini and Shawe-Taylor [15].

The basic concept of SVR is to map nonlinearly the original data x into a high-dimensional feature space, and to solve a linear regression problem in this feature space. A nonlinear mapping φ is defined to map the training data set as Eq.(1) into a high dimensional feature space.Then, in the high dimensional feature space, there theoretically exists a linear function f to formulate the nonlinear relationship between input data and output data. Such a linear function, namely SVR function, is as Eq. (2).

$$(y_1, x_1), \cdots, (y_l, x_l) \in R^N \times R \tag{1}$$

$$f(x) = w^T \varphi(x) + b, \quad w, x \in R^N, b \in R \tag{2}$$

Where x_i is the input vectors and y_i is the associated output values of x_i; $f(x)$ denotes the forecasting values; φ (x) denotes the high-dimensional feature space, w denotes the weight vector and b denotes the bias term.

The generalization accuracy is optimized over the empirical error and the flatness of the regression function which is guaranteed on a small w by the SRM principle. Therefore, the objective of SVR is to include training patterns inside a ε-insensitive tube (ε-tube) while keeping the norm $\| w \|^2$ as small as possible. An optimization problem can be formulated as the following soft margin problem:

$$\min \frac{1}{2} \| w \|^2 + C \cdot \sum_{i=1}^{l} (\xi_i + \xi_i^*), \tag{3}$$

Subject to $y_i - ((w \cdot \phi(x_i)) + b) \le \varepsilon + \xi_i, \quad i = 1, \cdots, l,$ (4)

$$((w \cdot \phi(x_i)) + b) - y_i \le \varepsilon + \xi_i^*, \quad i = 1, \cdots, l, \tag{5}$$

$$\xi_i, \quad \xi_i^* \ge 0, \quad i = 1, \cdots, l, \tag{6}$$

Where C, ε, and ξ_i (ξ_i^*) are a trade-off cost between the empirical error and the flatness, the size of the ε-tube, and slack variables, respectively. Two positive slack variables ξ_i and ξ_i^* represent the distance from actual values to the corresponding boundary values of the e-tube measure the error of the up and down sides, respectively.

The above formulae indicate that increasing ε decreases the corresponding ξ_i and ξ_i^* in the same constructed function, thereby reducing the error resulting from the corresponding data points.

By adding Lagrangian multipliers α_i and α_i^*, the QP problem can be optimized as a dual problem. The dual form of this optimization problem is usually obtained through the minimization of the Lagrange function, constructed from the objective function and the problem constraints. This constrained optimization problem is solved using the following Lagrangian form:

$$\mathrm{L} = \sum_{i=1}^{l} y_i (\alpha_i - \alpha_i^*) - \varepsilon \sum_{i=1}^{l} (\alpha_i^* + \alpha_i) \tag{7}$$

$$\max - \frac{1}{2} \sum_{i,j=1}^{l} (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)(x_i \cdot x_j) + \mathrm{L} \tag{8}$$

$$\text{s.t.} \quad \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0, \quad \alpha_i, \alpha_i^* \in [0, C], i = 1, \ldots l, \tag{9}$$

The Karush–Kuhn–Tucker (KKT) conditions are fulfilled in this condition. We do not detail this process for simplicity; the interested reader can consult [14] for reference. The function $K(x_i, x_j)$ is formed by the evaluation of a kernel function equivalent to the dot product $\varphi(x_i)\varphi(x_j)$ is the kernel matrix.

Finally, the decision function of SVR is described as follow:

$$f(x)=\sum_{i=1}^{l}(a_i-a_i^*)K(x_i,x)+b \quad (10)$$

Based on the Karush–Kuhn–Tucker's conditions of solving quadratic programming problem, $(\alpha_i - \alpha_i^*)$ in Eq. (10), only some of them are non-zero values. These approximation data point errors on non-zero coefficient equal to or larger than ε, and are referred to as the support vector. That is, these data points lie on or outside the ε-bound of decision function. According to Eq. (10), the support vectors are clearly the only elements of the data points employed in determining the decision function as the coefficient $(\alpha_i - \alpha_i^*)$ of other data points are all equal to zero. Generally, the larger the ε value, the fewer the number of support vectors. Nevertheless, increasing ε decreases the approximation accuracy of training data. In this condition, ε determines the trade-off between the sparseness of representation and closeness to the data [16].

The kernel function's value equals the inner product of two vectors x_i and x_j in the feature space. The kernel function is intended to handle any dimension feature space without the need to calculate $\varphi(x)$ accurately [16]. If any function can satisfy Mercer's condition, it can be employed as a kernel function [5]. The typical examples of kernel function are the following:

Polynomial kernel: $K(x,x_i)=[(x,x_i)+1]^q$ （11）

RBF kernel: $K(x,x_i)=\exp(-\gamma\|x-x_i\|^2)$ （12）

Sigmoid kernel: $K(x,x_i)=\tanh(v(x\cdot x_i)+c)$ （13）

It is reported that RBF kernel function produces better results than polynomial kernel function and sigmoid kernel function in the previous studies[17], so RBF kernel function is selected as the kernel function of SVR in our experiments, where σ denotes the width of RBF kernel function.

Here, C and σ are user-determined parameters, the election of the parameters plays an important role in the performance of SVR.

III. The Prediction Model based on CPSO-SVR

A. Particle Swarm Optimization

PSO performs searches using a population of individuals, named particles that are updated from iteration to iteration [18].

The particles' population is initialized. Every particle has a random position within the D-dimensional space and has a random velocity for each dimension. The D-dimensional position for the *i-th* particle at iteration t can be represented as $x_i=(x_{i1},x_{i2},...,x_{iD})$, x_{ij} is limited in the range $[a_j, b_j]$. The best previous position of particle is represented as below:

$$pbest_i=(pbest_{i1},pbest_{i2},...,pbest_{iD}). \quad (14)$$

The best particle in the population is represented as (15):

$$gbest=(gbest_1,gbest_2,...,gbest_D) \quad (15)$$

The velocity which is also an D-dimension vector can be described as(16):

$$v_i=(v_{i1},v_{i2},...,v_{iD}) \quad (16)$$

After finding the two best values, to search for the optimal solution, each particle changes its velocity and position according to the cognition and social parts as follows:

$$v_{id}=\omega v_{id}+c_1r_1(pbest_{id}-x_{id})+c_2r_2(gbest_d-x_{id}) \quad (17)$$

$$x_{id}=x_{id}+v_{id} \quad (18)$$

where d is the *D*-th dimension of a particle, c_1 and c_2 are two positive constants, c_1 indicates the cognition learning factor; c_2 indicates the social learning factor ,and r_1 and r_2 are random numbers uniformly distributed in U(0,1). [19]

B. Chaos Particle Swarm Optimization

PSO algorithm is easy to realize, but the method is easy to trap into local optimum [20-23]. Therefore, in order to enrich the searching behavior and to avoid being trapped into local optimum, chaotic dynamics is incorporated to improve particle swarm optimization algorithm. Ergodicity, randomicity and regularity are the character of chaos. Chaos queues can experience all the states in a specific area without repeat, so chaotic search becomes a novel tool used as an optimizer.Logistic equation is employed to obtain chaos queues in this paper, which is described as follows [24]:

$$z_{n+1}=\mu z_n(1-z_n), n=0,1,2\cdots,N \quad (19)$$

Where μ is the control parameter, the system of (19) has been proved to be entirely chaotic. Chaos queues z ($0\le z\le 1$) are generated by iteration of Logistic.

C. CPSO-SVR Prediction Model

The election of the parameters C and the width of the RBF kernel σ have a great influence on the performance of the nonlinear SVR in this study. The 2-dimensional parameters influence the number of support vectors. Parameters (C,σ) are two attributes of each particle. The two attributes determine its position and velocity. C and σ are set in the ranges: C = $[1,10^3]$, σ= $[10^{-3},10^3]$. The fitness function is employed to evaluate the quality of every particle which must be designed before searching for the optimal parameters [25]. Here, Mean Square Error (MSE) given by Eq. (20) is employed as the fitness function.

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(f_i-y_i)^2 \quad (20)$$

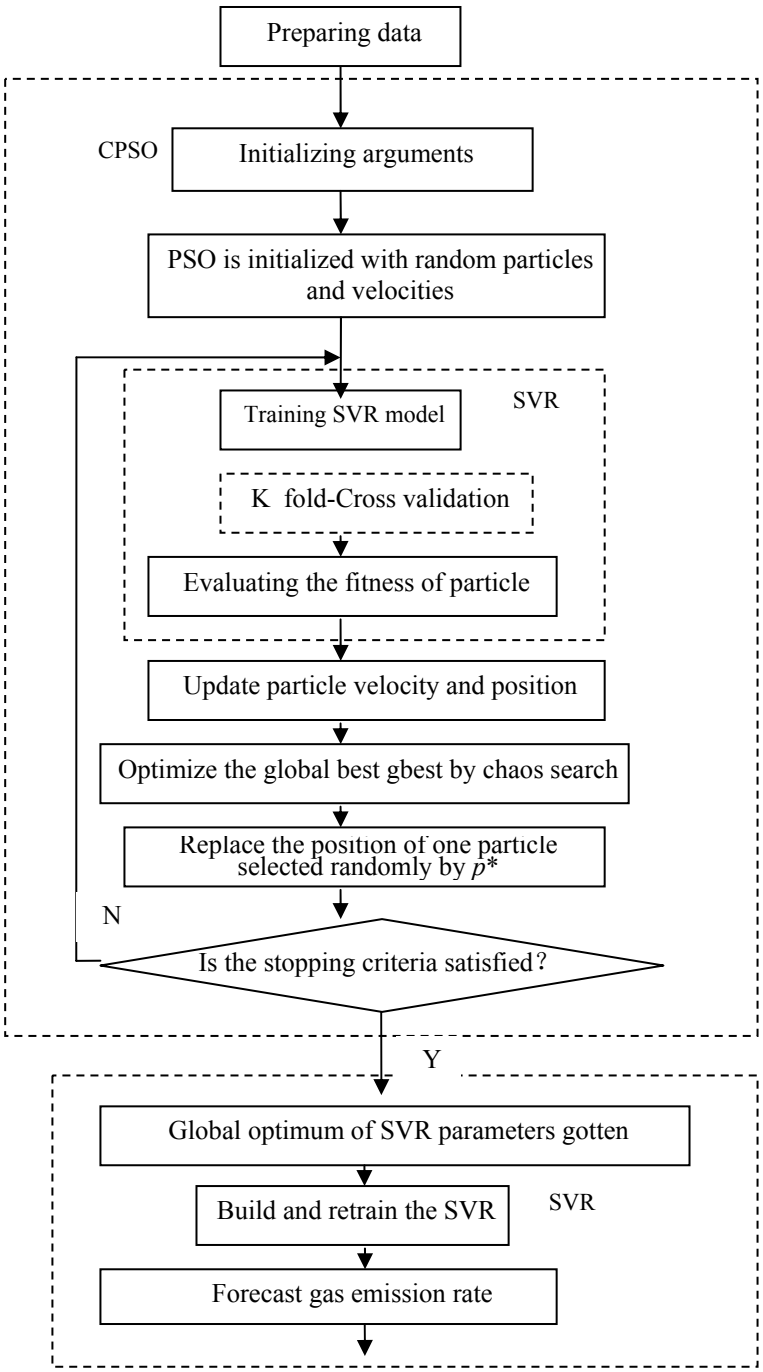

Figure 1. The process of optimizing the SVR parameters with CPSO optimization

Where n is the number of forecasting points, y_i and f_i represent the actual and forecasting values, respectively.

As CPSO algorithm can not only avoid the search being trapped in local optimum and but also help to search the optimum quickly. Therefore, the method is applied to determine the two parameters (C,σ) in the SVR. The basic steps of prediction algorithm CPSO-SVR are described as Figure 1.

IV PREDICTION OF MINE GAS EMISSION RATE BASED ON CPSO-SVR

A. Data Descriptions

Gas emission rate is variation physical factors with the geological condition, coal occurrence, mining technology and time, etc. The main controlling factors of gas emission rate are different for different mines. According

to the analysis of main mining seam in Kailuan coal mine which located in Hebei Province, China, the parameters affecting gas emission rate were selected including: coal seam depth(x1), coal seam dip angle(x2)、coal seam thickness(x3)、the ratio of diffusion layer within the extent of 50 m from coal seam roof(x4)、permeability of coal seam roof(x5)、permeability of coal seam floor(x6), dip angle variation(x7)、thickness variation(x8) and major structural(x9). These indexes were quantitated using the technology of Kriging interpolation, surface spline function interpolation, mathematical model and spatial analysis theory. Detailed descriptions of quantization process can be found in [2].These nine factors were the input factors and the gas emission rate was adopted as the target value in our model. In this study, the samples are the same data sets as in [2], listed in Table 1. There are 14 samples all together. All samples in the dataset are divided into two sets, the 1373, 1373W, F275 working faces are used for testing samples to estimate the predicting capacity of the CPSO-SVR model and the remaining 11 are used for training of the model.

TABLE I.
SAMPLES USED FOR GAS EMISSION RATE PREDICTION [2]

working face	x_1/m	x_2/m	x_3 (°)	x_4	x_5	x_6	x_7	x_8	x_9	relative gas emission rate /(m^3/t)
1371	415.195	4.209	10.447	0.062	0.143	0.501	0.462	0.5	1	0.7
1373	455.611	4.257	9.428	0.123	0.066	0.464	0.589	0.375	1	0.7
1377	549.071	5.328	7.085	0.098	0.066	0.443	1	0.264	1	0.5
1378	566.077	4.919	6.278	0.07	0.027	0.416	1	0.53	1	0.5
1177E	459.725	3.57	10.663	0.119	0.153	0.39	1	1	0	0.8
1178E	486.449	3.629	11.985	0.028	0.171	0.364	1	1	0	0.8
1274E	309.299	6.484	5.791	0.258	0.119	0.496	0.369	0	1	0.6
1277E	373.662	4.72	11.86	0.095	0.147	0.495	0.632	0.667	1	0.5
1371W	406.638	4.114	9.804	0.186	0.195	0.533	0.45	0.612	0	1.4
1372W	433.835	4.595	10.033	0.064	0.106	0.478	0.667	0.6	0	1.4
1373W	461.871	4.558	10.019	0.037	0.122	0.5	0.4	0.358	0	1.4
F274	339.681	3.983	5.857	0.099	0.017	0.353	1	0.563	0	0.6
F275	358.032	4.179	6.059	0.062	0.02	0.306	1	1	0	0.8
F276	376.015	4.211	8.437	0.141	0.079	0.376	1	1	0	1.1

B. System Implementation Details

Main parameters of CPSO are set as follows: the size of number of particles N is set to 20, particle dimension Mis set to 2, set acceleration coefficients c1is 2 and c2 is 2, number of maximal iterations I is set to200. MatlabR2009b which is a mathematical development environment is employed as the implementation platform, Libsvm version 2.82 which is originally designed by Chang and Lin [26] extends MatlabR2009b.

C. Data Normalization

Normalization not only can avoid attributes in greater numerical ranges dominating those in smaller numerical ranges but also can avoid numerical difficulties during the calculation [23, 26]. According to experimental results feature value normalization can help increase SVR accuracy. The data of all factors are normalized to the range [0, 1] to improve the treatment effect according to the following formula:

$$x^{'} = (x_i - x_{\min})/(x_{\max} - x_{\min}) \tag{21}$$

Where x' is normalization data. $x_{\max}$ is the maximum in the series data, $x_{\min}$ is the minimum in the series data. This normalization for original data points will help to improve the predicting accuracy.

D. Experimental Results and Analysis

The 11 training samples are inputting into the CSPO-SVR model, the CPSO algorithm is used to search the optimal parameters(C,σ) in the SVR while we set ε is 0.0001, and the searching process is operated with 200 generations in total. Figure.2 illustrates the convergence process of CPSO for seeking the optimal parameters during evolution process. Figure.2 shows that fitness values are decreased as the generations increasing. When

the sample evolution to generation 54, the fitness value (MSE) of training samples was reached 7.36978e-008. Thus, the individual at generation 54 produced the optimal parameters, which were C=49.69 and σ=0.21.

These optimal parameter sets were applied to construct the SVR models. Table 2 shows forecasting results in the training phases while the optimal parameters (C,σ) = (49.69, 0.21). It is observed that the proposed CPSO-SVR model fits this particular data set very well.

The three testing samples are used to examine the accuracy of the forecasting model. In order to compare the forecasting accuracy with other methods, the results of CPSO-SVR model, traditional SVR model and ANN model are shown in Table 3.

Table 3 shows that the average errors were equal to 17.56%, 16.62%, and 3.99% for the ANN, AVR, and CPSO-SVR strategies, respectively. It shows that the results made by the CPSO-SVR models have extremely small deviations between the predicted and actual values and were superior to those from the other models. The ability of CPSO-SVR is significantly stronger than that of ANN and traditional SVR, its results are stable. Thus prove that optimizing the model parameters of SVR by CPSO is feasible and superior. If more data were applied for ANN model training, ANN will have greater generalization ability and study ability.

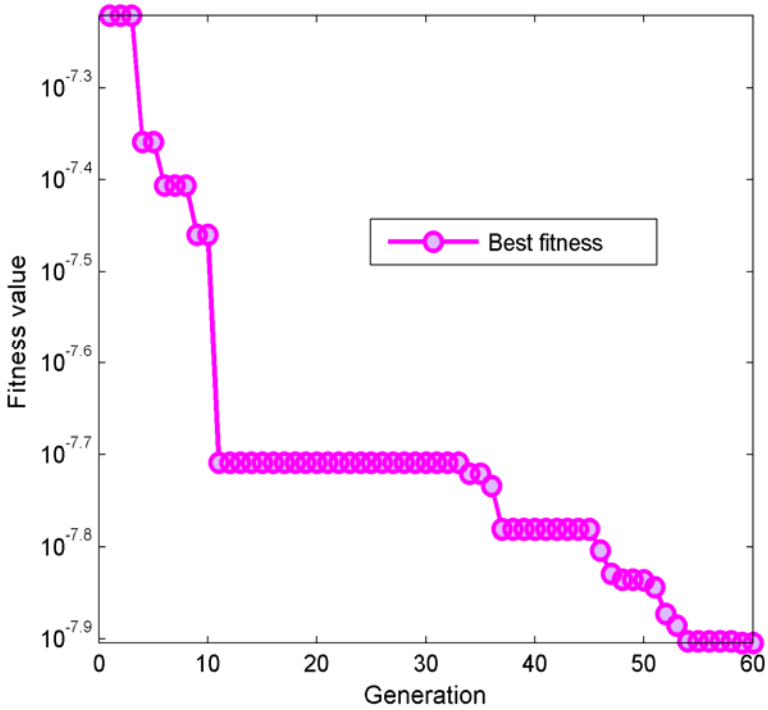

Figure 2. The fitness alternation during optimization process (60 generations).

TABLE II.
FORECASTING RESULTS IN THE TRAINING PHASES

working face	relative gas emission	Prediction relative gas emission
1371	0.7	0.6999
1377	0.5	0.4999
1378	0.5	0.4998
1177E	0.8	0.8001
1178E	0.8	0.7999
1274E	0.6	0.6001
1277E	0.5	0.5001
1371W	1.4	1.4000
1372W	1.4	1.4001
F274	0.6	0.6000
F276	1.1	1.0997

TABLE III.
COMPARISON OF RESULTS BETWEEN THREE ALGORITHMS (M^3/T)

working face	actual value	ANN[2]			SVR			CPSO-SVR	
		prediction value	error/ %		prediction value	error/%		prediction value	error/ %
1373	0.7	0.61	12.86		0.8303	18.6		0.6575	6.07
1373W	1.4	1.59	13.57		0.9842	29.7		1.3679	2.30
F275	0.8	0.59	26.25		0.8126	1.58		0.7712	3.6
Average error/%		17.56			16.62			3.99	

But obtaining a sufficiently large set of gas emission rate data is often difficult. In that sense, CPSO-SVR also has certain advantages that it needs only a small set of training data.

V. CONCLUSIONS

The relationship between the factors which affect gas emission rate is highly nonlinear and complex and difficult to handle. In this paper, CPSO–SVM is applied to forecast gas emission rate in coal mine. In the CPSO–SVM approach, CPSO is used to select suitable parameters of SVR, which avoids over-fitting or under-fitting of the SVR model occurring because of the improper determining of these parameters. CPSO is an optimization method, which not only has strong global search capability, but also is very easy to implement. So it is very suitable for parameters selection of SVR. The real data sets are used to investigate its feasibility in forecasting gas emission rate in coal mine. Results show that the CPSO–SVR method for forecasting gas emission rate can achieve greater forecasting accuracy than artificial neural network and traditional SVR method under the circumstances of small sample. CPSO-SVR method for forecasting gas emission rate is simple and worth being popularized.

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REFERENCES

[1] Gui Xiang-you and Yu Zhong-ming, “Risk Evaluation of Gas Outburst Fatalness Based on Grey Relation Analysis”, Journal of Mining & Safety Engineering, vol.23, no.4, pp.464-467,2006.

[2] Ma Shangquan, Wang Yibo and Liu Demin, “Mine gas emission rate predicted with automatic geological index quantitative and nervous network”, Coal Science and Technology, vol.34, no.12, pp.84-88, 2006.

[3] Gu Song, Cui Hongqing and Feng Wenli, “Mine gas gushing forecasting based on grey model and wavelet neural network”, Journal of China Coal Society, vol.39,no.9,pp.964-966,2007.

[4] MENG Qian, WANG Yongsheng and ZHOU Yan, “Prediction of spontaneous combustion in caving zone based on Rough Set and SVM”, Journal of china coal society,vo1.35, No.12,pp.2100-2104, 2010.

[5] Vapnik.V.N, The Nature of Statistical Learning Theory, Springer-Verlag, New York, 1995.

[6] Christopher J.C. Burges, “A Tutorial on Support Vector Machines for Pattern Recognition”, Data Mining and Knowledge Discovery, vo1.2, No2,pp. 121-167,1998.

[7] Giorgos Mountrakis, Jungho Im and Caesar Ogole, “Support vector machines in remote sensing: A review”, Journal of Photogrammetry and Remote Sensing no.66, pp247-259, 2011.

[8] Kuan-Yu Chen, “Forecasting systems reliability based on support vector regression with genetic algorithms”,Reliability Engineering and System Safety, no. 92 , pp.423-432,2007.

[9] Cherkassky V,Ma Y, “Practical selection of SVM parameters and noise estimation for SVM regression”,Neural Networks, vo1.17, no.1,pp.113-135,2004.

[10] Eberhart R and Kenndy J, “A new optimizer using particle swarm theory”,Proceedings of the Sixth International Symposium on micro machine and human science,pp.39-43, 1995.

[11] Alatas, B., Akin, E. and Bedri Ozer, A. , “Chaos embedded particle swarm optimization algorithms”,Chaos, Solitons & Fractals,vol.40,no. 4, pp.1715–1734,2009.

[12] Vapnik VN, Golowich S and Smola A, “Support vector method for function approximation, regression estimation and signal processing”, Advance in neural information processing system, vol. 9,pp.281-287,1997.

[13] Vapnik VN, Statistical learning theory, Wiley, New York, 1998.

[14] Schölkopf B and Smola AJ, Learning with Kernels, MIT Press,Cambridge, 2002.

[15] Cristianini N. and Shawe-Taylor J, An Introduction to support vector machines and other Kernel-based learning methods, Cambridge University Press, Cambridge, UK, 2000.

[16] Tay FEH and Cao L, “Application of support vector machines in financial time series forecasting”, Omega,vol.29,no.4,pp.309-317,2001.

[17] Huang, Z., Chen, H., Hsu, C.J., Chen, W.H. and Wu, S. , “Credit rating analysis with support vector machines and neural networks: a market comparative study”,Decision Support Systems,vol.37,no.4,pp.543-558,2004.

[18] Pedrycz, W., B. J. Park, and N. J. Pizzi. 2009. Identifying core sets of discriminatory features using particle swarm optimization. *Expert Systems with Applications* 36 (3 PART 1): 4610-4616.

[19] Huachao Yang,Shubi Zhang,Kazhong Deng and Peijun Du, “Research into a Feature Selection Method for Hyperspectral Imagery Using PSO and SVM”, Journal of China University of Mining and Technology, vol.17,no.4, pp.473-478, 2007.

[20] Niu wei ,Wang guoqing and Zhai zhengjun, "prediction of chaotic time series based on rough sets and support vector machine", International Journal of Digital Content Technology and its Applications, vol.5, no. 9, pp.145-152,2011.
[21] Wang xiaohua and Zhang yongmei, "chaotic quantum-behaved PSO algorithm for power system economic load dispatch", International Journal of Digital Content Technology and its Applications, vol.5, no.8, pp. 290-297, 2011
[22] Zhong Shaobo and Zhongshi H.E. , "Application of particle swarm optimization algorithm based on classification strategies to grid task scheduling", Journal of Software, Finland:Academy ,vol. 7, no. 1, pp. 118-124, 2012
[23] Mo, Yuanbin, Xin-quan Zhao, and Shu-jian Xiang, "Application of particle swarm optimization in figuring out non-differentiable point of function",Journal of Computers, Finland: Academy , vol. 7, no. 10,pp2542-2548.,2012
[24] Zhao Chenglin, Sun Xuebin and Sun Songlin, "Fault diagnosis of sensor by chaos particle swarm optimization algorithm and support vector machine. Expert Systems with Applications,vol.38 ,pp.9908–9912,2011.
[25] Meng, Qian, Xiaoping Ma, and Yan Zhou, "Application of the PSO-SVM model for coal mine safety assessment", 8th International Conference on Natural Computation, China: IEEE Computer Society,pp393-397,2012
[26] Chih-Chung Chang and Chih-Jen Lin, "LIBSVM : a library for support vector machines",2009. Software available: http://www.csie.ntu.edu.tw/~cjlin/libsvm

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